Predicting Wildfires and Measuring their Impacts: Case Studies in British Columbia

by

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M.A., Beijing Forestry University, 2009
B.A., Beijing Forestry University, 2006

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Supervisory Committee

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Abstract

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As the most destructive forest disturbance in British Columbia, wildfire becomes more worrisome for increasing uncertainty due to climate change. The current study investigates the potential to predict wildfire occurrence using climate indexes and quantify its marginal prices for property values at the municipal level, so as to provide a quantitative indicator for decision making in regard to influences of wildfire occurrence in the near future. First, significant correlations between monthly temperature and precipitation and large fire occurrence with distinctions in terms of distances to municipalities are proved by statistical analysis. Monthly wildfire occurrence are then statistically estimated with the four-month lags of the El Niño index and predicted using count models with regional differences. At last, the hedonic pricing model shows distance based positive impact of fire frequency and negative impact of fire size in neighbouring areas on property values.

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Dedication

This manuscript is dedicated to my wife, my parents and my soon-to-born child. My lovely wife, Yuan, supported my research with her thoughtfulness and encouragement. Thanks her for understanding all the compromise and sacrifice that I had to make on our marriage in order to pursue my academia. My parents also deserve special appreciation. They have been silently but firmly supporting me all the time for every step in my academic life, although they know little about my research. At last, I am so fortunate that I am going to be entitled a father when I finish this dissertation.

Chapter 1: Introduction

1.1 Introduction to Research

As one of British Columbia's most important natural resources, forests are nature-dependent and renewable in the long-run. Such characteristics make forests vulnerable to climate change and natural disturbances such as wildfires, particularly in the BC Interior. Wildfire is a natural process and an essential part of a forest ecosystem. Naturally occurring wildfires help maintain healthy and diverse forests by keeping insects and disease in check, and periodically changing the composition and density of forests. However, wildfires in BC have also resulted in huge timber losses and high economic costs due to extremely severe fire seasons with high numbers of fires and large burn areas.

Among others, one primary concern about severe wildfire occurrence is its impact on residential areas. During 2000-2009, wildfire occurrence in BC seemed to have been far more destructive than that in the rest of Canada (Wotton et al. 2010). In 2009 in particular, severe fires again threatened areas around Kelowna as in 2003; many residents of the southern and central interior areas were on evacuation alert or actually evacuated from their homes in small towns. Fires struck again in 2010. By mid-August, heavy smoke from 93 fires first affected southwestern BC and later Edmonton and Calgary; smoke was so thick in Kamloops at one point that it was impossible to see the opposite side of the North Thompson River. A province-wide ban on outdoor fires was in place during both the 2009 and 2010 camping seasons, a number of homes were destroyed, and, in 2010, two firefighters lost their lives. In contrast, the 2011 fire season was quiet.

Such uncertain and unexpected wildfire occurrence has enraged the pundits, blaming the government for not having done enough to mitigate wildfires or prevent their spread once they are underway, destroying wilderness areas and threatening private properties.

One essential perspective related to uncertain wildfire occurrence is the climate. Previous studies have shown that wildfires are strongly influenced by both local weather conditions and the global climate (Flannigan and Wotton 2001; Hely et al. 2001; Wotton et al. 2003; Flannigan et al. 2005; Nitschke and Innes 2008; Tymstra et al. 2007). These studies generally conclude that a warmer climate may result in a much more severe wildfire occurrence in the future. However, among existing studies of the long-run causes of fire, the influence of the changing climate is quite complex and little consensus has been achieved on how exactly climate change affects wildfire occurrence (Dale et al. 2001). Except for methodological discrepancies in terms of various assumptions and scenarios, the processes as to how climate change may affect wildfires *per se* are quite complicated. On the one hand, a warmer climate may result in more frequent fires in the summer and lengthen the fire season. Also, a higher CO_2 concentration in the atmosphere could accelerate the growth rate of vegetation, which accumulates more biomass as fuel. On the other hand, climate change might increase precipitation, which has a negative impact on wildfires. Overall, these factors likely make future fire occurrence harder to predict – they increase uncertainty.

Except for local weather conditions, like monthly temperatures and precipitation, wildfire occurrence can also be affected by the global climate via different climate oscillations and changing cycles, such as the El Niño Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) (Nitschke and Innes 2008; Balshi et al. 2009;

Meyn et al. 2009). Historically, abnormal climate conditions and, more recently, certain periodically changing climate events, have been blamed in the annual reports for each fire season, for higher total numbers of wildfires and increased area burned. Additionally, influences of climate change on regional weather vary considerably with complex terrain like that found in BC (Meyn et al. 2010). Thus, an analysis of potential spatial effects is then required when considering weather conditions across varying terrains. Lastly, as another major forest disturbance in BC forests, the mountain pine beetle (MPB) outbreak can may also be related to climate oscillations, especially those that impact the severity of weather during winter months (Stahl et al. 2006); indeed, it is possible that there is an interaction between the MPB and wildfire, with the MPB having increased potential fuel load and vulnerability to ignition agencies (i.e., lightning strikes and human activities). However, evidence in this regard remains mixed and we are unaware of any literature linking the mountain pine beetle outbreak to enhanced incidence of wildfire.

In general, the research interest of the current study relates to how wildfires in BC are affected by climate and the effect of wildfire on the value of properties in the BC interior. Using case studies, the main objectives of the research include investigating the main features of wildfire occurrence in BC and their relation to weather conditions; exploring the potential to predict long-term wildfire occurrence using climate indexes; and examining indirect impacts of historic wildfire occurrence on residential property values. Three case studies are conducted based on different geographic information system (GIS) models, and various statistical regression models. Monte Carlo simulation and probability distribution functions are also used to deal with the underlining uncertainty in wildfire occurrence. By estimating regression models, we intend to provide a perspective to simply model possible relationships between uncertain wildfire occurrence and the climate, as well as its impacts on residential properties, so that decision makers can be somehow more proactive in dealing with possible changes resulting from uncertain wildfire occurrence. To be specific, on the one hand, being directly affected by climate conditions, wildfire occurrence varies greatly across fire seasons. We believe that climate indexes representing ocean oscillations can serve as a simple but reasonable indicator of possible wildfire occurrence prior to a certain period. On the other hand, wildfires also exert long-term indirect influences on economic activities. We take property values in real estate markets as an example to demonstrate how spatial distribution and fire size may affect homebuyers' expectations in a ten-year period.

1.2 Dissertation Structure

This study consists of a general discussion between wildfire occurrence and climate conditions and two separate case studies, which are organized in three main chapters. Although the data and spatial analyses are separately employed in different chapters using different models, we begin by discussing and analyzing the underlying data in the context of a GIS model. Two case studies are then developed to address uncertainty of wildfire occurrence in temporal and spatial contexts. In one case climate indexes are used to predict wildfire occurrence; in the other, the impact of historic fire occurrence on property values is examined.

Following the introductory chapter, we first define and describe the interior area of BC in Chapter 2 from the perspectives of wildfire management and forest management, respectively. Then we introduce all of the data employed in this study, followed by some techniques and indexes for spatial analysis used in processing weather data and testing spatial autocorrelation. Finally, we discuss more generally the influences of local weather conditions and the possible implications for firefighting expenditures in BC based on two linear regression models.

In Chapter 3, two count models, that is, a zero-inflated negative binomial model for monthly number of fires and a general Pareto model for associated total area burned, are introduced to take account of the randomness in wildfire occurrence across months. Climate indexes are employed in the former to predict wildfire occurrence with a 4-month lag. A sensitivity analysis is conducted in terms of hypothetical changes in the climate index.

The last case study is discussed in Chapter 4, in which the indirect influence of historic wildfire occurrence on property values is examined in Kelowna. With a relatively small study area, the impacts of wildfire occurrence are investigated in terms of the location and size of each single fire event rather than the aggregated values in a larger scope (i.e., forest district or fire zone). Particularly, spatial autocorrelation in property values and marginal prices of wildfires in regard to different distances to properties are addressed by a spatial regression model using maximum likelihood estimation.

We conclude in Chapter 5 by summarizing the main findings in each case study. Some shortcomings of the current study and possible future work are also discussed.

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Chapter 2: Wildfire in British Columbia Interior and Relation to Climate

2.1 Introduction

In February 2012, the BC Forest Service celebrated its centennial birthday. During the last 100 years, wildfires have been continually challenging forest management in British Columbia and appear to be even more of a problem in recent years due to climate change. In this study, we mainly focus on the interior area of the province, given that wildfires are a much less important disturbance on coastal regions than for the interior regions. We argue why most fire events concentrate in the interior regions from the perspectives of terrain features and associated climate conditions.

The main purpose of this chapter is to profile wildfire occurrence in general and describe the data. We also provide some background spatial analyses that are employed in this chapter and case studies in later chapters. In particular, we first briefly describe the interior areas of BC from the perspective of this study; then we focus on the wildfire occurrence in those areas by demonstrating some spatial and temporal features. This is followed by a detailed description of the data that we employed in this study and discussion of spatial analysis in examining the relations between wildfires and the climate. Lastly, we discuss the relationships between large fires and weather conditions by conducting a simple statistical analysis, and examine some implications for predicting firefighting expenditures for the upcoming fire season.

The spatial analyses are discussed based on geographic information system (GIS) models that are built using vector layers, which employ vector features such as polygons, polylines and points to project information visually. Generally, GIS models are built by merging original vector layers representing different contents such as region boundaries, fire events or weather stations into one vector layer, so that attributes from various data sources are synthesized, and correlations between them, such as location based statistics and distances, can be analyzed. We build three GIS models in this study: (1) a GIS model for the interior area of BC based on forest districts, fire events, weather stations and municipalities for the analysis of relationships between wildfires and weather conditions; (2) a GIS model for the BC interior consisting of fire zones and fire events for the first case study in Chapter 3; and (3) a model for the City of Kelowna in Chapter 4 that uses city and fire prone area boundaries, fire events and residential properties to describe the study region. Since the procedures are similar for all GIS models, later in this chapter we describe procedures for building a GIS model in detail using the first as an example.

2.2 The British Columbia Interior

2.2.1 Scope

The British Columbia Interior roughly consists of the inland area between the Coastal Mountains and the Rocky Mountains, and the northeast area – part of the Prairies within BC. The exact scope of the BC Interior varies slightly for different purposes, while in terms of this study, it is defined from the perspective of wildfire management.

British Columbia is currently divided into six fire centres with 27 fire zones to facilitate wildfire management in different areas (Figure 2.1). Considering each fire centre is responsible for wildfire management within their area of responsibility, we simply define the BC Interior to embrace five fire centres - Northwest, Prince George, Cariboo, Kamloops and Southeast, without any further modifications at the fire zone level. The BC Interior defined by fire centres is employed in the case study in Chapter 3.

Figure 2.1: The BC Interior in Wildfire Management

Since the weather data we employ to analyze relationships between wildfires and climate conditions are provided by forest regions, we use forest regions rather than fire centres to define the BC Interior, particularly in this chapter for discussions related to the climate. In BC, there used to be three forest regions: the Northern Interior, Southern Interior and Coastal (Figure 2.2). Such classification was re-categorized into eight regions by the Ministry of Forests, Lands and Natural Resource Operations (MFLNRO) in 2011. In order to facilitate data analyses, and since most data are for the period before 2011, we still employ the previous classification here. The BC Interior from the prospective of forest management, therefore, refers to the Northern and Southern Interior Forest Regions (the shaded area in Figure 2.2), but excluding the Coastal Region. Although such a classification is not identical to that in wildfire management, most of their components (forest districts) are identical to the corresponding fire zones or reintegrated with different combinations.

Figure 2.2: The BC Interior in Forest Management

Source: Ministry of Forests, Lands and Natural Resource Operations.
http://www.for.gov.bc.ca/mof/maps/regdis/regdismap.pdf

2.2.2 Topography

The geographical landscape changes dramatically in the BC Interior due to the north-south-oriented Cordilleran Maintain System (including the Coast Mountains and the Rocky Mountains). Generally, from south of Prince George to the Canada-U.S. border, two mountain ranges run from southeast to northwest in parallel, making the area between them a basin. Towards the north, the basin area becomes wider and flatter but vanishes quickly in the north of Prince George, where two mountains join each other, leaving the northwest BC as rolling prairie. The northeast area, however, is out of this mountain system - it actually becomes the very northwest part of Canada's western grain belt. The complex topography in BC province means great fluctuation in elevation (Figure 2.3), which has an overwhelming influence on climate conditions and wildfire occurrence.

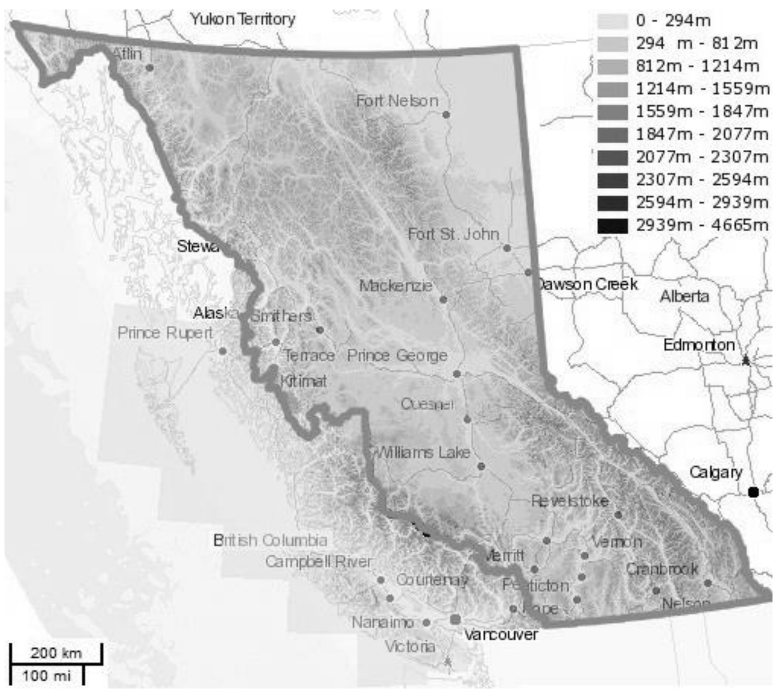

Figure 2.3: Elevation in the BC Interior

Source: Hectare BC. http://hectaresbc.org/app/habc/HaBC.html

2.2.3 Climate

Climate conditions in the BC Interior vary greatly due to the unique topography. Temperature is firstly affected by elevation. There is about 3000-meter drop in height and more than 15°C difference in mean annual temperature from the mountain tops to the lower valleys. Latitude also plays a positive role in affecting the temperature as the province goes across more than 10 degrees in latitude. Though precipitation has a similar spatial pattern in terms of the terrain, unlike temperature it also displays a significant west-east gradient as the Cordilleran Mountain System serves as barriers for both westward flows of cold continental arctic air masses from the rest of Canada and moisture-laden east-flowing winds from the Pacific Ocean (Meyn et al. 2009). In fact, for the entire Interior of BC, such mountainous topography is considered as a primary climate modifier that creates a rain shadow in the west foothills of the Coastal Mountains and the flat area in the northeast, and a wet belt in the east foothills of the Rocky Mountains and most of the BC northwest (Figure 2.4).

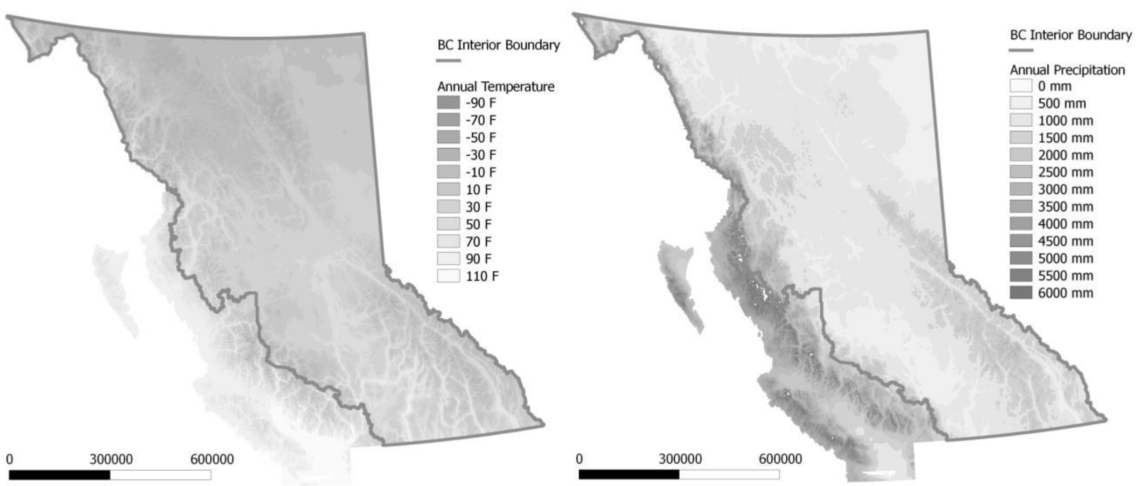

Figure 2.4: Mean Annual Temperature and Precipitation in the BC Interior

Source: Climate Normals (1961-2009), Hectare BC. http://hectaresbc.org/app/habc/HaBC.html

2.3 Wildfire in the BC Interior

Wildfire activities in the Interior of BC are quite severe in general but vary greatly across fire centres. According to wildfire statistics from the Wildfire Management Branch (WMB) of the MFLNRO, there is roughly an average of 2,000 fires annually throughout

BC, burning more than 100,000 hectares on average. Nearly 60% of the fires were caused by lightning strikes, with the remainder mainly the result of human activities.

2.3.1 Spatial Distribution

The spatial distribution of fire events indicates a correlative pattern to the distributions of elevation and annual temperature and precipitation (see Figures 2.3, 2.4 and 2.5). As with other regions in British Columbia (e.g., Peace River region in the northeast but on the east side of the Rocky Mountains), the Central and Southern Interior of BC are especially vulnerable to wildfires, as average summer temperatures in this region are higher than elsewhere in the province while average summer precipitation is lower due to the rain shadow (Figure 2.5). The annual fire occurrence density (measured in terms of number of fires per 100 square kilometers) across fire centres is distributed in a highly uneven fashion, as indicated in Figure 2.6. The Central and Southern Interior consists of the Cariboo, Southeast and Kamloops fire centres, each of which must deal with above-average fire occurrence densities. Categorized by causes, lightning-caused fires are less clustered than human-caused fires because most human activities are relatively close to populated areas (most of which are located in the Southern Interior) while lighting strikes are more dispersive across BC, even if the Southern Interior also has the most frequent lightning events.

Figure 2.5: Spatial Distribution of All Fires Events during 1950-2012

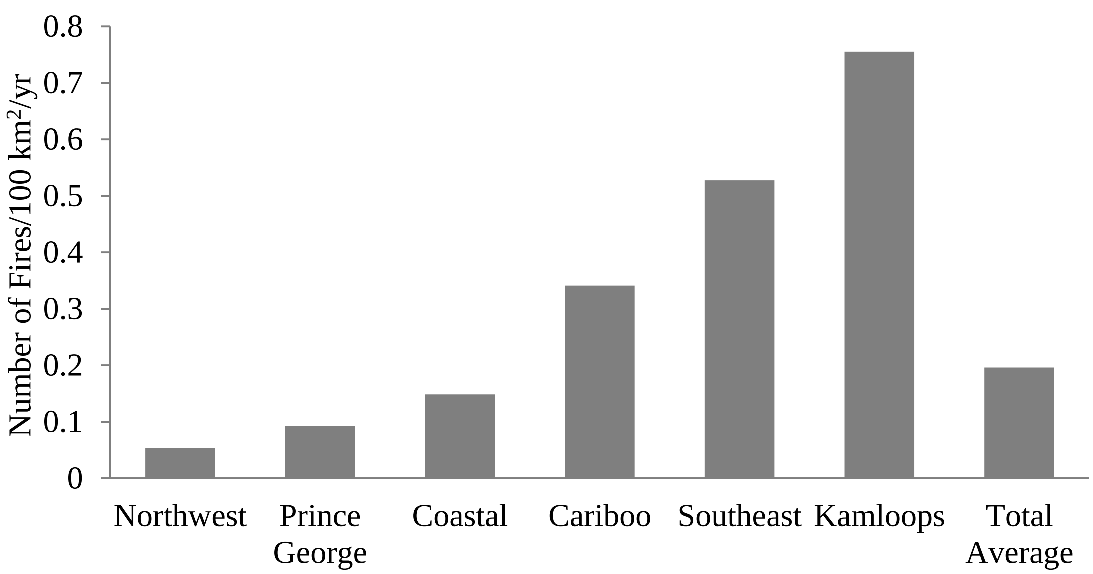

Figure 2.6: Fire Occurrence Density by Fire Centres, 1950-2012

In terms of fire size, however, fire events with large sizes (greater than 100 ha) are not only concentrated in the Central and Southern Interior of BC, but also the

Northern Interior. It indicates that the spatial distribution of large fires seems to be less clustered than those relatively small ones which compose the majority of all fire events. This is mainly because more than two thirds of large fires are caused by lightning strikes in mountainous regions, where fires are more likely to go bigger due to multiple ignitions at the same time, as well as the tough firefighting environment. Although large fires are quite rare, really large fire events, say the largest 3% in total fires, contribute to more than 97% of the area burned across Canada (Kurz et al. 2008) and most of the economic losses. In Figure 2.7, we take fire events greater than 100 hectares for the same period as an example. It seems that the larger the fire size is, the less clustered is the distribution. For those extremely large ones (>10,000 ha), the distribution seems to be random all over the BC Interior. In terms of fire causes, lightning is responsible for more than 80% of large fires, which is overwhelmingly high compared to the proportion when all fire events are considered. Large fires caused by human activities, on the other hand, are mainly located in the east side of the Coastal Mountains in the Southern Interior of BC – the east parts of the Cariboo Fire Centre and the Kamloops Fire Centre, as these areas are among the driest areas in BC according to Figure 2.7.

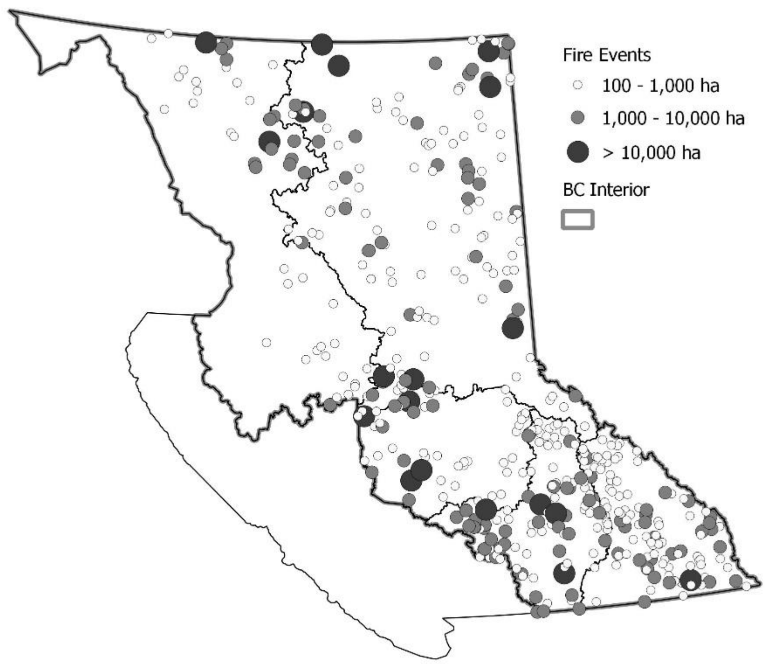

Figure 2.7: Spatial Distribution of Large Fires during 2000-2009

In terms of elevation, more than 88% of wildfires occur below 1,500 m. Fire events are most frequent in areas between 600 m and 1,200 m, although fires can even occur in places as high as 3,000 m (Figure 2.8). For the period since 1950, the average elevation of human caused fires turns out to be a little bit lower than that of lightning caused fires, which implies that fires caused by humans tend to be closer to areas with low to moderate elevations as these areas are relatively easier to access. As illustrated in Figure 2.5, the spatial distribution of all fire events during 1959-2012 clearly indicates that most fires are located in valleys between mountain ranges, especially in the Southern Interior.

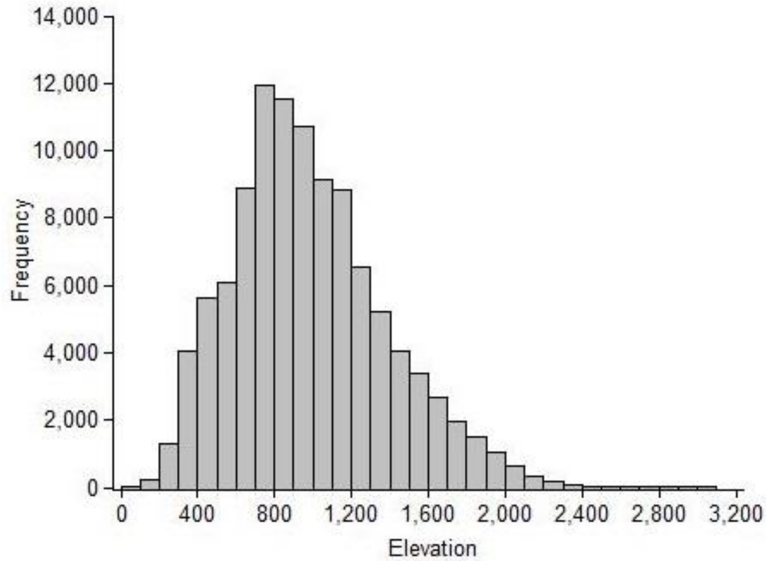

Figure 2.8: Histogram of Elevations at Hot Spots

2.3.2 Temporal Trend

In addition to spatial features, wildfires in BC also present strong trends over time. In each fire year, most fires occur between April and October, which constitutes the fire season, and the number of fires peaks either in July or August (Figure 2.9).[1] By contrast, there are few fires occur during the winter months. The monthly means of total area burned also follows a very similar trend. Statistics by fire causes show that, during a fire season, lightning is the overwhelming cause of wildfires during June, July and August, but human activities are responsible for the majority of wildfire occurrence in the other four months. This observation coincides with monthly cloud-to-ground lightning statistics from Environment Canada (Figure 2.10).

[1] According to the BC government's Wildfire Management Branch, a fire year is defined as the 12 consecutive months from April 1 to March 31.

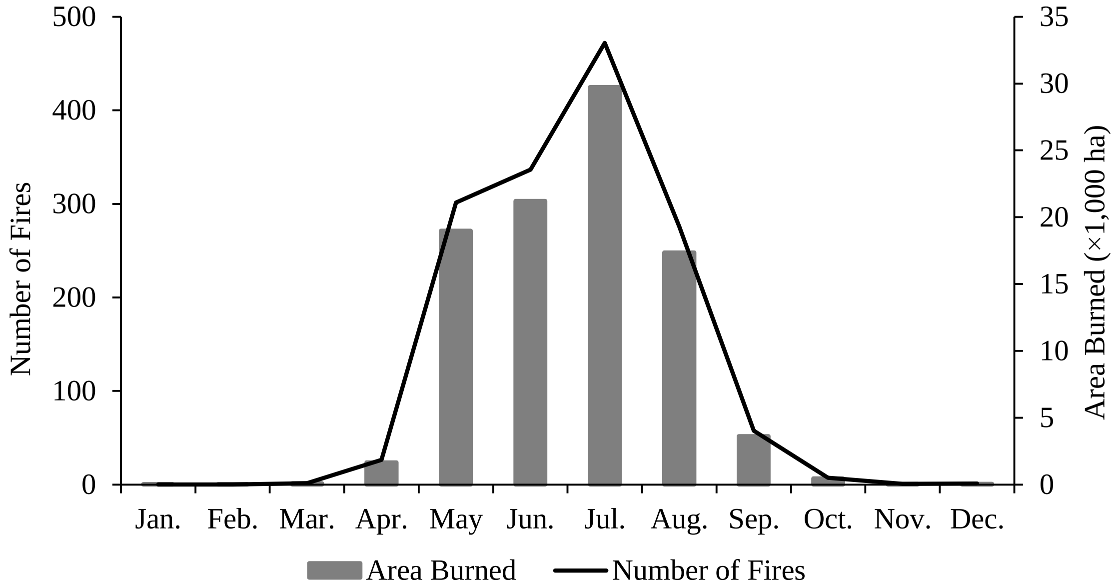

Figure 2.9: Average Number of Fires and Total Area Burned by Month, 1950-2012

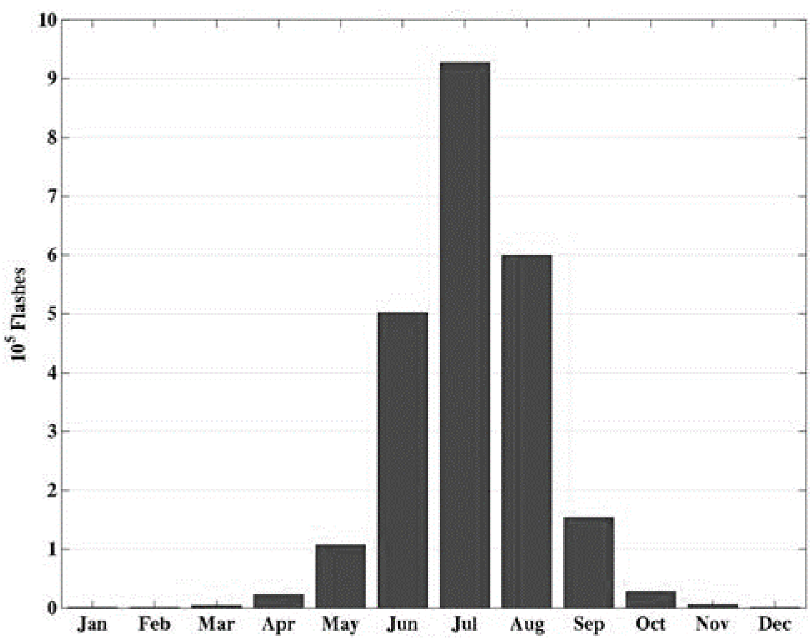

Figure 2.10: Average Monthly Cloud-to-Ground Lightning in Canada, 1999 – 2008

Source: Environment Canada, http://www.ec.gc.ca/foudre-lightning/default.asp?lang=En&n=C4E86962-1

In terms of inter-annual changes, we aggregate numbers of fires and total area burned annually, with results presented in Figure 2.11. Among others, wildfire occurrence in the BC Interior during the last six decades can be characterized by: (1) large variability in both fire frequency and area burned; and (2) many fire events that are less than one hectare in size, and much fewer large fires that account for the vast majority of the total area burned. The fire season with most number of fires appeared in 1970 with 4,002 fires in total, while the year with the fewest fire events is quite recent – 655 fires in 2011. As to area burned, wildfires in 1958 swept away more than 855,000 ha in total, which makes that fire season the most catastrophic one in history. In contrast, a total area of 2,960 ha in 1997 is the smallest area burned by wildfires in a single fire year. It is worth mentioning that, after 18 years with annual area burned less than 80,000 ha since 1985, approximately 250,000 ha and 300,000 ha that were burned in 2003-2004 and 2009-2010, respectively, make those fire seasons most destructive and costly since the early 1990s when aircrafts began to be commonly used for firefighting in BC.

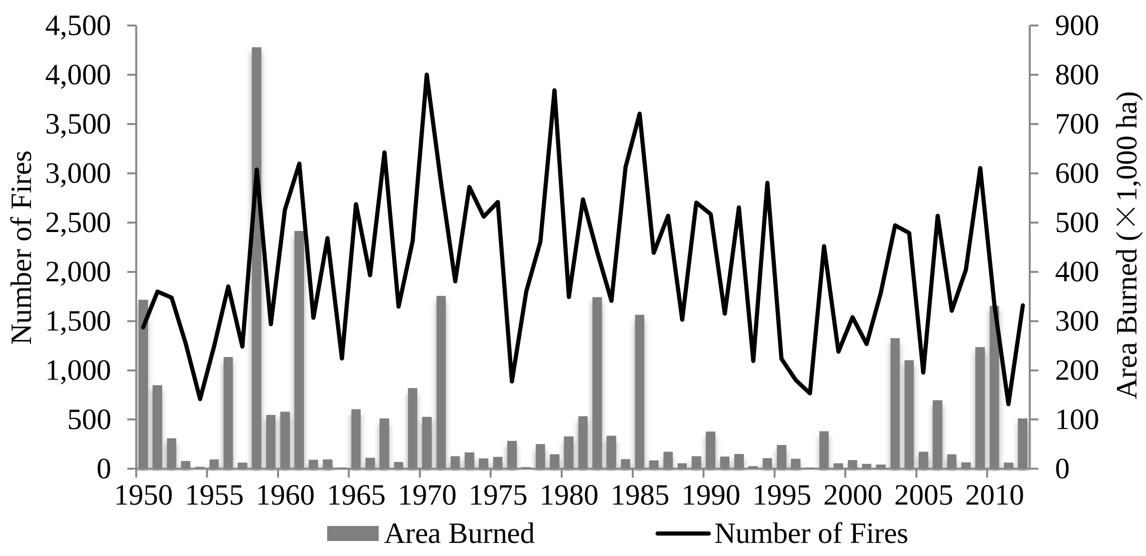

Figure 2.11: Annual Number of Fires and Total Area Burned, 1950-2012

2.4 Data Description

Analyses of relationships between wildfires and climate conditions and potential impacts based on regression models require a large amount of data that come with different formats, time spans, data types and launch tools. To generate required datasets for statistical analysis, we synthesize different raw datasets in GIS models to create datasets with required attributes by, for example, filtering observations, calculating statistics, measuring distances and merging attributes according to their spatial locations. In general, five raw datasets are collected: 1) vector layers indicating boundaries of certain areas, such as forest districts and fire zones; 2) records of historical wildfires; 3) weather station data in the Interior of BC; 4) daily data of various weather conditions from weather stations; and 5) monthly data of global climate events.

2.4.1 Spatial Layers of BC Interior

As described before, the BC Interior based on forest regions are employed in this study. Forest regions are employed to analyze the general relationship between wildfires and weather conditions, which is discussed at the end of this chapter; data at the level of fire centres are mainly used in the first case study in Chapter 3, in which relationships between wildfire occurrence and climate indexes are examined.

According to the classification of forest regions and districts as of 2010, the two forest regions in our study area were further divided into 21 forest districts. We keep such a classification in this study, with only one necessary modification. The Skeena Stikine District actually consists of two separate pieces: Skeena Stikine and Dease Lake. For convenience, we consider this district as two separate ones. In total, therefore, there are

22 districts in our study area. Such modification greatly simplifies the spatial categorization of weather stations and fire events.

The district layer was obtained from the GeoBC service desk provided by the Integrated Land Management Bureau (http://geobc.gov.bc.ca/). It provides various geographic data and information services from multiple ministries and agencies. The data pertaining to forest districts include the boundary information used for categorizing fire events and weather conditions and the elevation of the centroid of each district. Each forest district is identified by a unique ID number and a related name.

The spatial layers for the boundaries of fire centres and zones in BC were acquired by request from the WMB of MFLNRO, as those data are not currently available online. Useful attributes in those layers include the name of each fire centre and associated fire zones within it, headquarter names, area and boundary length. Similarly, we use the name to identify each polygon.

In addition, we also obtained the spatial layer of municipalities in BC to calculate distances between municipalities and nearby fire events. In the map, municipality boundaries are provided in polygons and are available to the public from DataBC (http://www.data.gov.bc.ca/). Finally, the spatial layer for boundaries of the City of Kelowna (located in southern interior of BC) was also obtained by request from the local government in order to study the regional impacts of wildfires. Details pertaining to the spatial layer are described in the case study in Chapter 4.

2.4.2 Wildfire Data

We obtained historical wildfire data also from the WMB. The data are part of the provincial wildfire database that contains detailed information of all fire events (including actual fires, suspected fires, nuisance fires and smoke chases) tracked by the WMB since as early as 1930s. The fire data for this particular study only include the actual fires during 1950-2012. The data are formatted as a vector layer in which each fire event is represented by a point located by a pair of GIS coordinates. The data include the following useful attributes for each fire event: the date when the fire was discovered, its location and elevation, its ultimate size (at the time it was put out), the cause of the fire, and the total cost of suppressing the fire (if applicable). The raw data for this study include more than 130,000 observations in total. We further filtered the data by restricting the locations to the BC Interior and eliminating all observations with incomplete or incorrect information. This leaves only 106,077 observations, each of which is uniquely identified by an ID number. To investigate how large fires particularly may relate to climate conditions and their roles in firefighting expenditures, we classified the fire data by fire sizes – fires with 100 ha or greater sizes (sizes when fires are put out) are marked as large fires (2.7% of the total fire events). Notice that the data for fire events occurred within or near the City of Kelowna employed in the case study in Chapter 4 is also from this dataset. We introduce that part of the data in detail in Chapter 4.

2.4.3 Weather Station Data

To investigate relationships between wildfires and weather conditions, we employ historic weather data recorded by weather stations in the province. To obtain weather data, we need to explore the weather station data throughout BC first and then filter the data using certain criteria. We employ a dataset that includes 1,997 weather stations as provided by both the BC Forest Service and Environment Canada (EC) since 1950. The reason that we use weather stations from different sources is that none of those datasets can cover all the BC Interior for such a long time, given that most weather stations only last for several years. Therefore, only weather stations in current use and those archived with start and decommission dates are considered. We excluded weather stations located outside the boundary of the BC Interior, and those used for recording wind conditions only. As a result, there are 1,229 weather stations left and we use weather data from those stations to estimate regional weather conditions at the forest district level. Each data record includes ID number, name, location and elevation of a weather station. We filed these stations into a panel dataset which categorizes them by time and forest district according to their operation periods and spatial locations.

2.4.4 Weather Data

The weather and weather station data come from the same database, which is daily data for 1950-2009 and formatted as a panel identified by date and related weather stations. This huge database contains various attributes, including mean temperatures, total precipitation, wind speed, wind direction, relative humidity. Considering potential impacts on wildfire occurrence, all five features should be considered. However, we only selected mean temperatures and total precipitation for the statistical analysis, because we assume that wind speed and direction only have instant impacts on area burned (i.e., no lagged effects) rather than on fire incidence, and that relative humidity is highly related to precipitation. We investigated this hypothesis by running a linear regression model with our existing data, and it turned out that relative humidity is highly correlated to precipitation, as expected, while the impact of wind speed appears to have an insignificant impact on both fire frequency and area burned.

We aggregated the daily data to monthly data for each weather station since we intend to investigate the long-term impact of climate conditions on wildfire occurrence. For some station records, one problem is that temperature and precipitation data are not always available for all days in each month, we only employ the monthly data from those weather stations that have valid data for more than 20 days. Another problem is that we have two weather data sources with different weather station identification systems. The only way we can unite them is to identify their longitude-latitude coordinates. We then synthesized those weather data mainly based on the EC datasets and fill missing gaps in EC data with WMB data.

2.4.5 Climate Index Data

To take the potential impacts of global climate events into account, we collected data for different climate indexes that are listed in Table 2.1. These data are also monthly with different time spans. Since climate events are expected to exert their impacts over a much larger spatial landscape rather than only at a regional level, we assume that the impacts of these climate events are identical in the entire BC Interior and only change over time. They serve as the integral circumstance responding to the long-term periodic effects of climate events on wildfires, and are expected to affect the long-term trend of changes in fire occurrence. So basically, climate indexes affect wildfire occurrence with a certain period lag but without spatial differences. Also, predicting fire occurrence in the near future also requires that we need to use lagged variables with historic data. Among other, the El Niño Southern Oscillation indexes are believed to have significant lagged influences on BC's wildfires (Wang et al. 2010). The data for climate indexes are monthly based during 1950 and 2012, and were collected from different sources.

Specifically, we gathered ENSO indexes from the National Oceanic and Atmospheric Administration (NOAA) at four different regions, i.e. Niño 1+2 (0°-10°S, 80°W-90°W), Niño 3 (5°N-5°S, 90°W-150°W), Niño 3.4 (5°N-5°S, 120°W-170°W) and Niño 4 (5°N-5°S, 160°E-150°W), and examined the impact of Niño 1+2 on wildfire occurrence in Chapter 4.

Table 2.1: Description of Climate Indexes

Index	Description	Data Source
ENSO	El Niño Southern Oscillation index, sea surface temperature anomaly (SSTA) at four different regions	Climate Prediction Center, National Oceanic and Atmospheric Administration
PNA	Pacific/North America Pattern index, difference of normalized sea level pressure (SLP) at North Pacific Ocean polar ward of 20°N-90°N	University Corporation for Atmospheric Research
SOI	Southern Oscillation Index, difference of normalized SLP at Tahiti minus Darwin	University Corporation for Atmospheric Research
NAO	North Atlantic Oscillation index, normalized SLP difference between Ponta Delgada, Azores and Stykkisholmur/Reykjavik, Iceland	University Corporation for Atmospheric Research
PDO	Pacific Decadal Oscillation index, SSTA at North Pacific Ocean polar ward of 20°N	Joint Institute for the Study of the Atmosphere and Ocean

2.5 Spatial Analysis

As described in the last section, most of the original datasets need to be reformatted or transformed to reflect spatial attributes before they are employed for statistical analysis. In this section, we discuss some spatial analytic methods and techniques in detail using a GIS model, including spatial interpolation of weather data at the forest district level, combining different spatial attributes from multiple layers, and testing for spatial autocorrelation in fire incidence across forest districts.

2.5.1 Building a GIS Model

The procedures for building an underlining GIS model using multiple spatial layers for data categorization and interpolation are illustrated in Figure 2.12. In general, there are four base maps involved in the entire process, i.e. spatial layers of fire events, forest districts, weather stations with weather data, and municipalities. All procedures are conducted using the Quantum GIS (QGIS), which is a user friendly open source GIS software developed by the Open Source Geospatial Foundation (http://www.qgis.org).

Specifically, fire events represented by vector points in the BC Interior are first filtered to eliminate void or incorrect observations and merged into corresponding forest districts according to their locations; and then, we combine the layer of fire events by district with the municipality layer in order to measure the distance from a fire event to the centroid of the corresponding nearest town.

Next, the polygons for the Coastal Forest Region are deleted from the vector layer of forest districts in BC to obtain the vector layer for the BC Interior. The left polygons are then transformed to Thiessen polygons for convenience (we discuss that in the following). Centroids of forest districts are determined and merged with the filtered weather station layer to estimate weather conditions at the centroids, which represent weather conditions for entire forest districts. The weather data pertaining to each weather station are weighted based on the distance to the corresponding centroid and also adjust for elevations. We discuss that in the following as well.

Finally, the estimated weather conditions for each forest district and fire events with the associated distances are integrated to one single spatial layer to generate the weather and fire data at the forest district level.

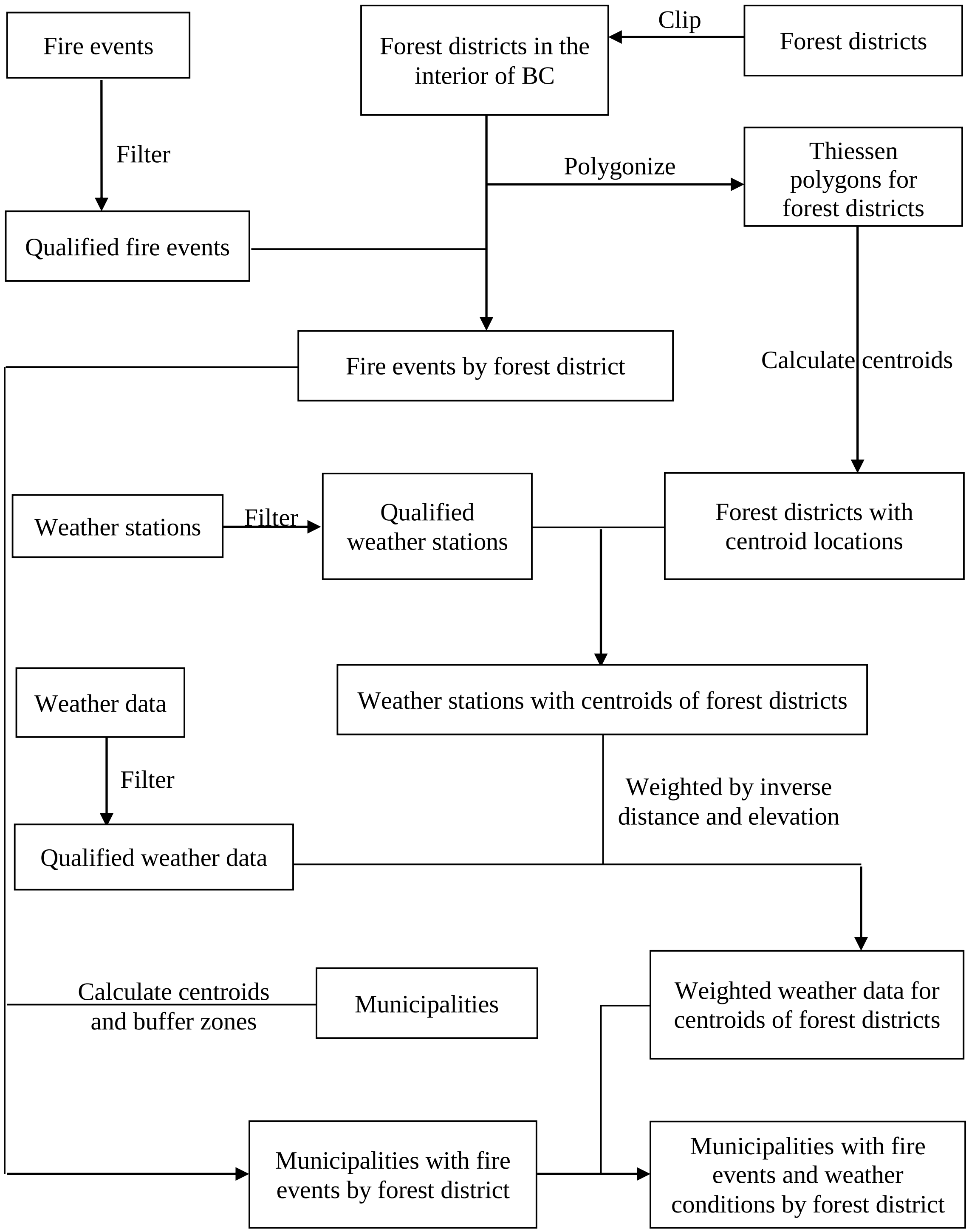

Figure 2.12: Data Transformation with Multiple Spatial Layers

Intersections of arrows represent the combination of layers during which selected attributes in different layers are combined into one single attribute table. Such procedures are achieved using the “joint attributes by locations” function for vector layers provided by QGIS.

2.5.2 Thiessen Polygons for Forest Districts

We start our spatial analysis by generating the Thiessen polygons for the forest districts in our study area. Considering most of the forest districts have irregular shapes, it might be biased to aggregate weather data for a district using information from all the weather stations located in that district, because some stations may be much farther from the centroid than others in adjacent district. To correct such bias, we transform the forest districts to so-called Thiessen polygons based on the locations of their centroids.

Thiessen polygons can be constructed based on a set of points as shown in Figure 2.13. A boundary of a Thiessen polygon is determined by a perpendicular line (solid lines) through the midpoint of the line (dash lines) connecting two points (triangles). Transforming to Thiessen polygons is a common approach to determine spatial boundaries between certain observation spots. Such approach can make sure that any location inside the boundary has the nearest distance to the centroid of the same polygon.

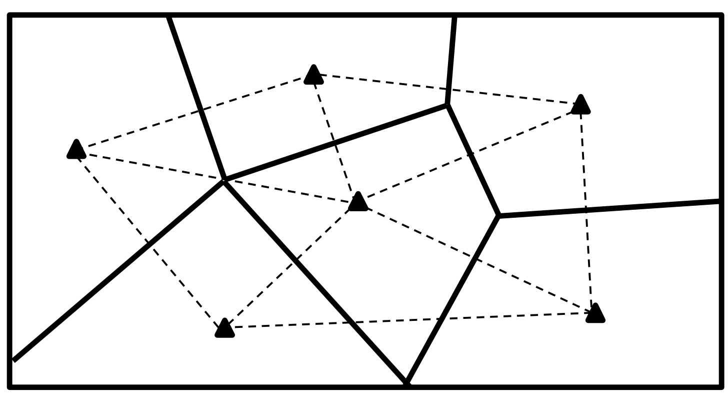

Figure 2.13: Boundary Determination of a Thiessen Polygon

By transforming to Thiessen polygons, we ensure that the aggregated weather data at the centroid of each forest district come from the nearest stations. In this way, relatively more accurate weather forecasts are expected. Figure 2.14 gives the transformed Thiessen polygons generated by QGIS for all forest districts in the BC Interior.

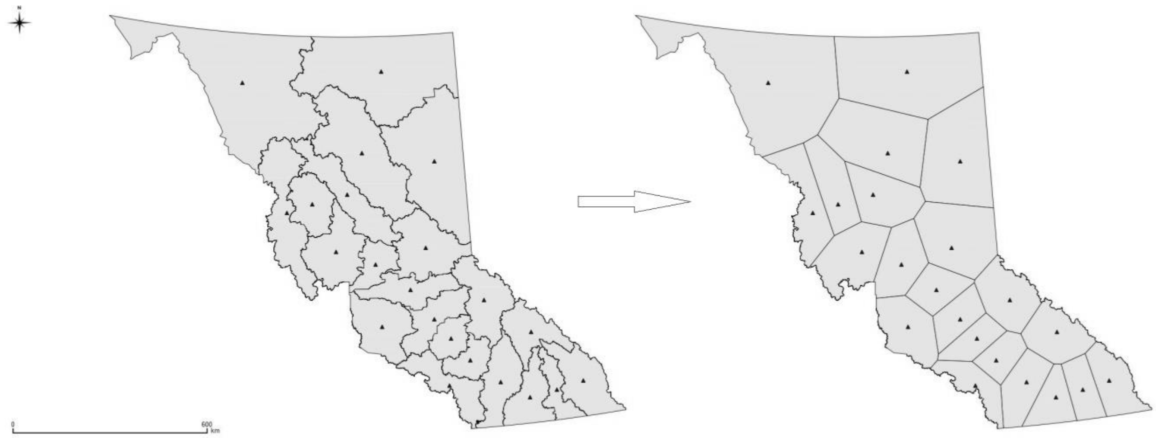

Figure 2.14: Transforming Forest Districts to Thiessen Polygons based on Centroids

2.5.3 Spatial Statistics of Fire Events

To obtain the monthly numbers of fires in each forest district, we clip the fire layer with the forest district layer and join the attributes together from the two layers by locations to identify the forest district to which each fire event belongs. By summarizing fire events in each forest district by month, we get the total monthly number of fires and area burned. Then we use the centroid of each patch to represent the municipalities and measure distances between each fire event and the nearest municipality centroid. Such distances can be treated as a measurement of potential threats or fire risks to residential properties in municipalities, and it is expected to be negatively related to fire threats. Using the synthesized spatial layer in the final step in Figure 2.12, we also create a 5 km buffer zone for each municipality as a possible threshold to identify the near-town fire events (see Figure 2.15 for example). Notice that each fire and the nearest town to it are not necessarily located in the same district.

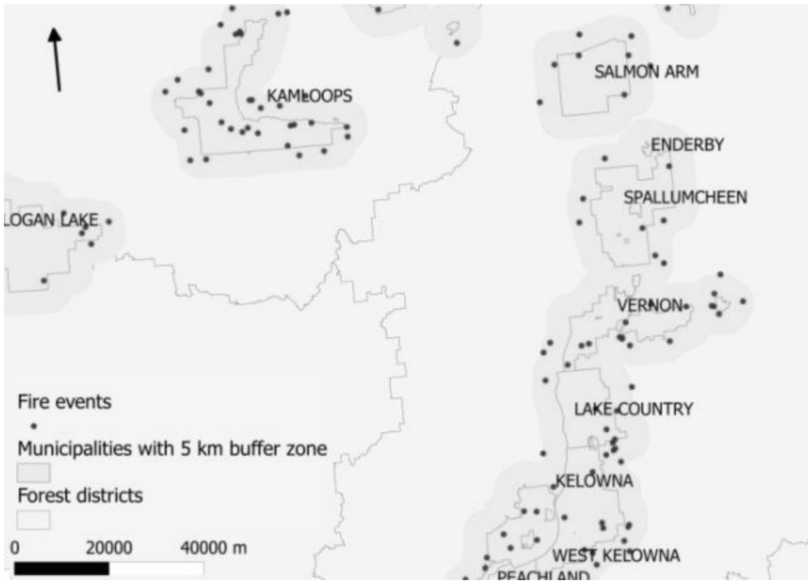

Figure 2.15: Fires within the 5-km Buffer Zone of Municipalities

2.5.4 Testing Spatial Autocorrelation

Using the combined spatial layer of fire events and district boundaries, we examine the distribution pattern of fire events, spatial autocorrelation in fire frequency and area burned between forest districts throughout the entire BC Interior. This could be a concern given that neighboring districts are likely to share similar forest types and weather conditions. Therefore, if severe wildfires occur in one district, it could increase the risk of large fires in adjacent districts. First of all, we use the nearest neighbor analysis provided by QGIS to examine the evenness of the spatial distribution of fire events in each year. Then we use Geary's C and Moran's I indexes to test potential autocorrelations between the fire frequency and area burned in one district and that in their neighbors.[2]

[2] Neighbors of a forest district could be an edge neighbor (sharing one or more edges with the district), a node neighbor (sharing one or more nodes with the district), or a combined one (sharing both edges and nodes with the district).

The nearest neighbor analysis uses the Nearest Neighborhood Index (NNI) to evaluate how observations of interest are distributed across a certain area. Basically, the value of NNI ranges from 0 to 2.15. The closer NNI is to zero, the more clustered is the distribution; in contrast, values close to 2.15 are indicative of an even distribution, while the value of 1 represents a random distribution. There are two different formulae for NNI calculation; here we use the one that is employed by Corral-Rivas et al. (2010):

[2-1] $$NNI = \frac{\sum_{i=1}^{n} d_{ij} \big/ n}{\frac{1}{2}\sqrt{S/n}}, \quad 0 < i, j \leq n; n, s > 0$$

In Equation [2-1], the numerator refers to the average distance of all *n* fires to their nearest neighbors with d_i denoting the distance of fire *i* from its nearest neighbor *j*. *S* refers to the area of the minimum square that embraces all fire events. To coincide with our data structure, we calculate the NNIs for all fires greater than 100 ha in every year, as well as the moving averages, as shows in Figure 2.16. Compared to the entire range, the fluctuation with an overall average of 0.785 shows a primarily random distribution with a mild clustered tendency, which means that the spatial distribution pattern for large fires is random in general in most of years. It implies that, in the long run, no districts are significantly more risky than others in terms of large fires. This could potentially contribute to the uncertainty in firefighting expenses, given that firefighting resources (e.g. attack bases) are not evenly distributed for all districts. Notice that we only examine the NNI for large fires, the distribution of all fires could differ from this result, given that the occurrence of large fires are expected to be more restrained in terms of both physical conditions, such as more fire fuel and management activities. For example, more fire fuel reduction may be addressed if large fires show an obvious clustered distribution in a certain area; moreover, even with a large amount of fuel, the fuel would be consumed quickly by large fires *per se*.

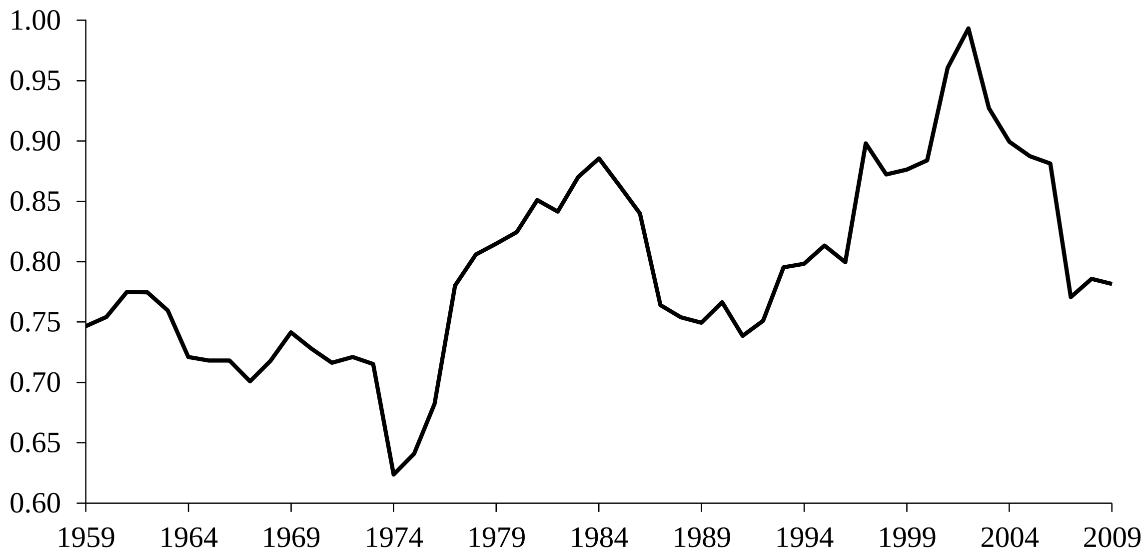

Figure 2.16: Ten-Year Moving Average of NNI, 1959-2009

Take fire frequency among districts for example, we calculate the values of both Geary's C (Geary 1954) and Moran's (Moran 1950) I with Equations [2-2] and [2-3]:

$$\text{[2-2]} \quad \text{Geary's C} = \frac{(n-1)\times\sum_{\mathrm{i}}\sum_{\mathrm{j}}[w_{ij}\times(x_i - x_j)^2]}{2\times\sum_i\sum_j w_{ij}\times\sum_i(x_i-\bar{x})^2}$$

$$\text{[2-3]} \quad \text{Moran's I} = \frac{n\times\sum_{\mathrm{i}}\sum_{\mathrm{j}}[w_{ij}\times(x_i-\bar{x})\times(x_j-\bar{x})]}{\sum_i\sum_j w_{ij}\times\sum_i(x_i-\bar{x})^2}$$

Here n refers to the number of forest districts; x_i and x_j refer to the number of fires in districts i and j, respectively; w_{ij} is the neighborhood dummy indicating whether district i and district j are adjacent or not (they are defined to be adjacent only if they share at least one node); and $\bar{x}$ is the overall average of fire frequency per district in the study area. We calculate such indexes for every year and the values are expected to determine whether fire frequency in one district would be affected by its neighbors. The value of Geary's C changes from 0 to 2, with values smaller than 1 indicating positive autocorrelation and values greater than 1 indicating negative autocorrelation. In contrast, the value of Moran's I ranges from -1 to 1, with negative values indicating a uniform distribution and positive values indicating a clustered distribution.

According to the results in Figure 2.17, we find that fire frequency at the forest district level is just slightly affected by neighbors. For total area burned, even weaker autocorrelation can be detected across districts due to the randomness of locations of large fires. It indicates that spatial autocorrelations of wildfire occurrence across forest districts are not significant.

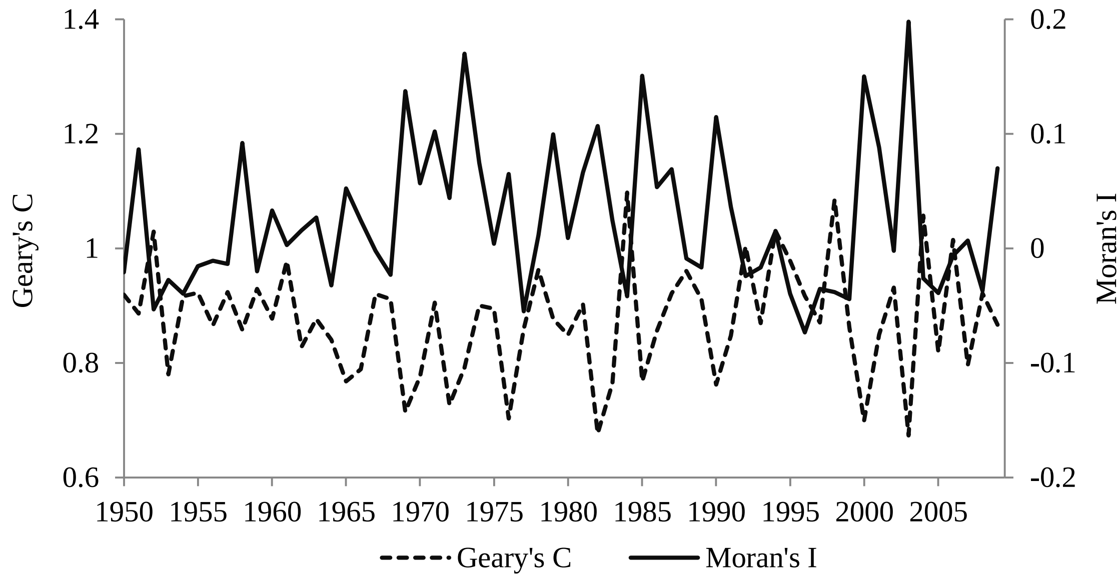

Figure 2.17: Spatial Autocorrelation of Fire Frequency among Districts

2.5.5 Weather Data Interpolation

There still remain some difficulties in aggregating weather conditions for each district even with Thiessen polygons. Problems in this regard relate to the determination of appropriate weather stations and the need to adjust for distance and elevation during the interpolation of weather data.

There are two ways to determine the weather data for each district. One is aggregating with all the stations in the BC Interior according to distances to the centroid of each district; the other is aggregating only with the stations in the same polygon. Since we have hundreds of weather stations available in each month (see Figure 2.18 for instance), if we use all of them, aggregated weather conditions in two adjacent districts could be very similar to each other, especially for those districts with relative fewer stations. Therefore, we choose the latter. Because the number and the spatial distribution of weather stations in use for each district are very likely to vary across months due to their different life spans, we first group the weather stations as a panel by district and month, and then check each panel cell to make sure that there is at least one available weather station; otherwise, we have to interpolate the weather data for that district only with data from stations in neighboring districts. Fortunately, this is automatically satisfied when we combine the weather stations from the WMB and EC.

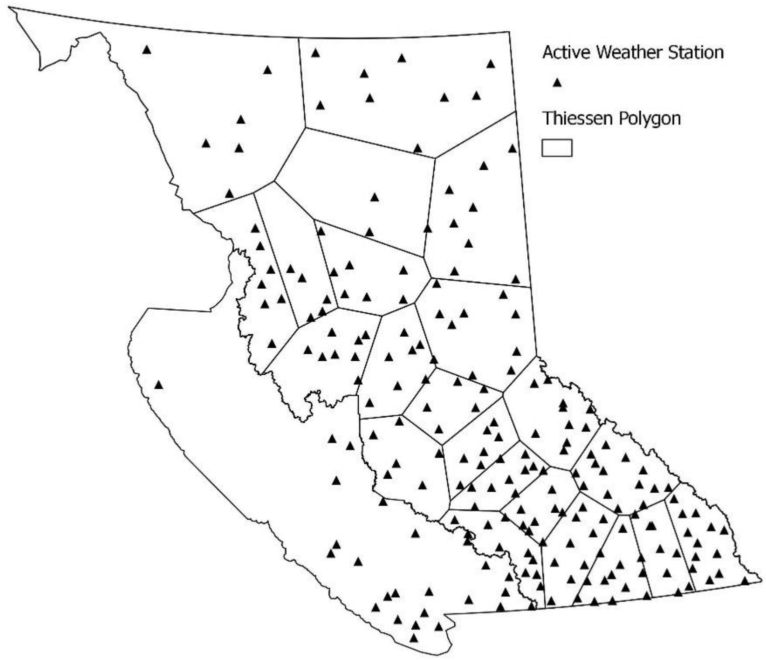

Figure 2.18: Active Weather Stations across BC in July, 2009

We estimate the monthly average temperature and total monthly precipitation at the centroid of a forest district to represent the weather conditions for that district. This is done by using a simplified version of the weighted moving average approach. A weighted moving average is usually used to spatially interpolate missing data for certain points on a map. Generally, there are two ways to calculate the moving average. One can search for some consistent number of weather stations that are nearest to the observation spot, or include all the weather stations located within a circle with a pre-determined radius from the centroid (Figure 2.19). To interpolate discrete points, such an approach can estimate the value for each point based on the values and distances to its neighborhood. The method shown in the left panel is more convenient to employ for those districts where weather stations are relatively intensive, while the one on the right is more appropriate for those districts containing relatively fewer stations. In this chapter, however, we modify the approach to an even simpler version rather than employing either of those two ways. We determine the number of stations for each district using the boundary of the Thiessen polygon. Though such modification varies the number of stations among different districts, we do not need to preset a fixed criterion for all districts, as in that case we may lose the accuracy of interpolation in the districts with relatively fewer stations or smaller areas.

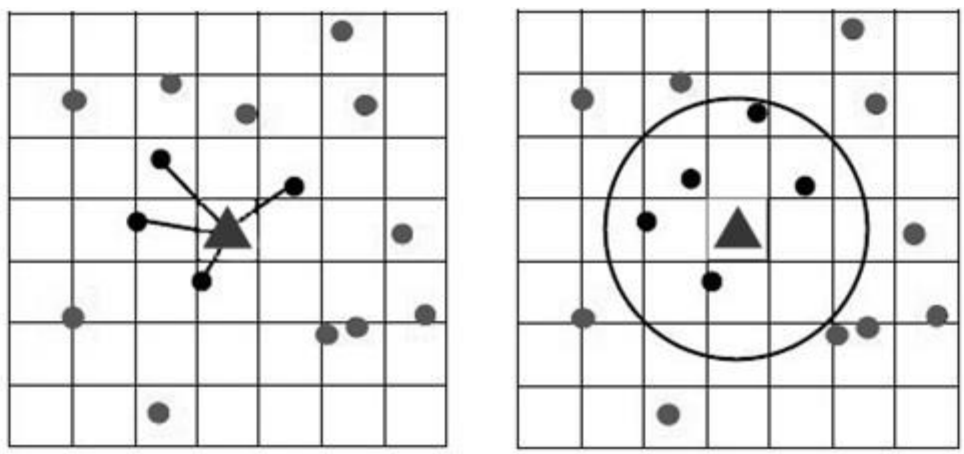

Figure 2.19: Spatial Interpolation with Number of Stations and Radius

As an example consider the Quesnel Forest District indicated in Figure 2.20. We first find the centroid for this district and obtain the distances between the five stations in this district and the centroid. We then use an inverse-distance weight to aggregate the weather data from these stations to estimate the weather conditions for the entire district. Notice that the number of stations and their locations vary among different months as most stations in our dataset are archived ones with certain start and decommission dates. Thus we need to examine the available weather stations from our candidates by forest districts for every month.

Figure 2.20: Determination of Weather Conditions for Quesnel Forest District

In addition to the distance adjustment, we also need to consider the gradient changes in temperatures resulting from elevation differences (we assume that precipitation has no such elevation related problem, at least it is not a significant influencing factor in this study). Adjustment for elevation in some previous studies has been done using specific lapse rates, such as 6.5°C/km or by calculating monthly lapse rates in terms of different seasons and meteorological conditions (Stahl et al. 2006). Here, we simply use the global standard of 6.5°C/km.

For temperature data, however, we need to decide the sequence of distance and elevation adjustments. There are three possible ways to do this: (1) first adjusting for distance and then for elevation; (2) first adjusting for elevation and then for distance; or (3) synthesizing elevation and distance together and then adjusting simultaneously. Apparently, the first method is not practical for our data as the distance measurement of two points in our spatial layer does not consider the elevation difference, which means that the distance is just a two-dimension projection of a 3D map rather than the real distance between them. In that case, it is impossible to determine the elevation after the distance adjustment has been made. For the third method, we use the Euclidean norm, i.e., constructing a triangle with elevation and distance as the two right-angle sides and using the hypotenuse as the new weighted factor. However, when distance is compared with elevation, the elevation differences are so small that elevation has no noticeable impact even though the influence of elevation is actually much greater than that of distance. Therefore, we employ the second method - first adjust the temperature data from all weather stations in each district with respect to the elevation at the centroid (i.e., all weather stations are adjusted to the same elevation), and then adjust the data using the weighted moving average of distance.

We develop a weighted matrix W_t in which all distances d_{ijt} in time t between the centroid of forest district i and all J available weather stations in the same district are measured as weighted index W_{ij}. For any given month t,

$$W_t = \begin{bmatrix} W_{11} & \cdots & W_{1J} \\ \vdots & \ddots & \vdots \\ W_{I1} & \cdots & W_{IJ} \end{bmatrix}$$

in which

$$W_{ij} = \frac{w_{ij}}{\sum_{j=1}^{J} w_{ij}} \quad \text{and} \quad w_{ij} = \frac{1}{d_{ij}^{\beta}}, \quad \beta \geq 1$$

where W_{ij} is the inverse of distance between weather station j and the centroid of forest district i; and β is a smooth parameter that adjusts the rate of changes in the impact of weather data when distances from weather stations change. If β is greater than one, it means that less weight is given to farther stations compared to the linear condition (β =

1); similarly, more weight will be given to far away stations if β is smaller than 1. In this study, we assume β = 1. With such a weighted matrix, weather data in any given month t can then be weighted as:

$$X_t = \begin{bmatrix} x_{11} & \cdots & x_{1J} \\ \vdots & \ddots & \vdots \\ x_{I1} & \cdots & x_{IJ} \end{bmatrix} \times \begin{bmatrix} W_{11} & \cdots & W_{1J} \\ \vdots & \ddots & \vdots \\ W_{I1} & \cdots & W_{IJ} \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} \sum_{j=1}^{J} W_{1j} x_{1j} & & \\ & \ddots & \\ & & \sum_{j=1}^{J} W_{Ij} x_{Ij} \end{bmatrix},$$

where, for example, x_{ij} is the temperature recorded at station j in district i. In the last matrix, the elements in the diagonal are weighted weather data for each related forest district. Notice that some of the weather stations in a forest district used for interpolation may present a clustered distribution, which will make the inverse distance weights biased since more weights will be put on the clustered weather stations whose representative regions are mostly overlapped.

2.6 Relation to Climate

In this section, we briefly discuss the potential impacts of weather conditions on large wildfire occurrence in the BC Interior and possible implications for firefighting expenditures. We employ statistical analysis using regression models. We focus on fires larger than 100 ha as large fires are responsible for most timber damage, economic loss, and firefighting expenditure. Since climate forecasts based on the Global Circulation Models (GCMs) indicate that average temperature across Canada will increase by 3-5℃ by the end of this century (Lempriere et al. 2008), and thus decrease soil and fuel moisture, it is believed that longer and more severe fire seasons are to be expected in the next few decades. Moreover, increased CO_2 in the atmosphere accelerates tree growth and improves water-use efficiency, which produces more biomass and thus more fuel that makes forests a greater fire risk (Dale et al. 2001). However, some researchers argue that a warmer climate could also result in an increase in precipitation that neutralizes the positive effect of higher temperature (Bergeron and Archambault 1993). Some others insist that predicted changes in precipitation from GCM projections are distinct for different areas (Flannigan et al. 2000) and projections are much less confident than those of temperature (Wotton et al. 2010). Inaccuracy in precipitation projections also lowers the reliability of predictions.

2.6.1 Statistical Analysis

We employ a simple linear regression model in which fire frequency greater than 100 ha and associated area burned are functions of weighted temperatures and precipitation that are generated based on multiple spatial layers, inverse distance to the nearest town, and district dummy variables:

[2-4] $$N100_{it} = a_0 + a_1 \times TEMP_{it} + a_2 \times PREC_{it} + a_3 \times D100_{it} + \sum_{\mathrm{k}=1}^{21} a_{k+3} \times D100I_{it} \times D_k + u_i^n + \varepsilon_{it}^n$$

[2-5] $$S100_{it} = b_0 + b_1 \times N100_{it} + b_2 \times D100_{it} + b_3 \times TEMP_{it} + b_4 \times PREC_{it} + \sum_{\mathrm{k}=1}^{21} b_{k+4} \times D100_{it} \times D_k + u_i^s + \varepsilon_{it}^s$$

where $N100_{it}$ and $S100_{it}$ are, respectively, the number of fires greater than 100 ha and related area burned at time t in district i. $TEMP_{it}$ and $PREC_{it}$ are the respective monthly mean temperature and monthly total precipitation at time t in district i. $D100_{it}$ and $D100I_{it}$

are the average distance of all fires in district *i* to the nearest town in month *t* and its inverse value, respectively. Notice that, since zero values in *D100* also mean zero values in *N100*, using *D100I* will drop all zero observations in Equation [2-4]; also, *S100* in Equation [2-5] is also calibrated to zeros if *N100* equals zero. D_k is a dummy variable that capture the district-dependent effects of distances in $D100_{it}$ and $D100I_{it}$; while u_i is addressed to represent the fixed effect specific to district *i* for each equation, and ε_{it} refers to the error term.

The models are estimated using Panel Least Squares and the unit-root test for panel data indicates that data for number of fires and area burned are stationary. Main results are listed in Table 2.2. Temperatures and precipitation are both very significant in explaining the number of fires; while precipitation is a little bit less significant in terms of the area burned where the overall R^2 value is also lower. One possible reason is that, once ignition spots appear, except for temperatures and precipitation which determine soil moisture and dryness of fuel load above ground, the primary influencing factors on spreading speed also include some instant conditions, such as transient wind speed and relative humidity. The number of fires also strongly affects the area burned in the same period but the latter is not significant in estimating the former.

As indicated in Table 2.2, the global effect of average distance seems to be positive for both two dependent variables, indicating that large fires are more likely to occur in remote areas due to lightning activities; while the within-district effects vary, presenting a strong negative impact (positive in terms of the inverse distance) on the number of fires but a much weaker impact on area burned. Specifically, for the districts where the fire prone areas are far from towns in which firefighting facilities are located, there seem to be fewer fires than that where the fire prone areas are close to town, which can be partly explained by the pattern of human activities, especially for those districts in the south where human activities are more likely to be dominant regarding to fire causes, although lightning activities also seems to be more frequent in Southern BC. For the northern part, lightning activities tend to become the main reason for large fires (which are more likely in remote areas). This can be seen from the negative signs for district 1 (the Skeena Stikine Forest District) and district 5 (the McKenzie Forest District) where most areas are quite mountainous, and only a few municipalities are located in marginal areas.

As to the area burned, while the relationship seems to be insignificant in most districts, similar situations to the number of fires can be recognized for those districts with significant coefficients. For example, district 11 (the Headwaters Forest District) and district 13 (the Columbia Forest District) are located in the south, where human activities have more influences on large fires; however, these two districts also part of the Rocky Mountains, which means that some lightning-caused fire scenes may be quite difficult to reach for initial attack crews (sometimes even for rapattack and parattack crews), which gives fires a longer time to get bigger, even though they are not far from the nearest town. In that case, the relation between distance to the nearest town and area burned could be negative. On the contrary, the coefficient for district 3 (the Fort Nelson Forest District) in the north presents a positive sign as less human activities become less involved in triggering large fires, leaving lightning-caused ones with more random distributions.

Table 2.2: Estimated Coefficients for Number of Fires and Area Burned (>100 ha)[a]

Number of Fires	Coef.	Std. Error	Burned Area	Coef.	Std. Error
D100	0.0176***	0.0015	N100	115.7256***	18.4065
TEMP	0.0027***	0.0004	D100	13.4110***	3.6929
PREC	-0.0006***	0.0001	TEMP	0.5953***	0.1366
D100I × D1	-722.3231***	122.3490	PREC	-0.0330**	0.0140
D100I × D2	27.4769***	8.7006	D100 × D1	-6.6756*	3.8631
D100I × D3	73.5830**	32.4887	D100 × D2	-5.0924	4.7202
D100I × D4	75.3505***	13.3609	D100 × D3	16.7978**	8.0444
D100I × D5	-237.4656***	52.6949	D100 × D4	11.8722	12.0118
D100I × D6	7.9111	6.0079	D100 × D5	-3.7623	4.1808
D100I × D7	12.3996**	5.9773	D100 × D6	-7.9659*	4.2223
D100I × D8	7.1036***	2.4571	D100 × D7	-8.0350	5.4086
D100I × D9	3.8558	2.5172	D100 × D8	0.1311	5.4201
D100I × D10	8.1841**	3.8812	D100 × D9	-0.2248	5.9039
D100I × D11	12.0852	7.3798	D100 × D10	-1.5216	5.2597
D100I × D12	23.6328***	5.1972	D100 × D11	-9.8254**	4.1191
D100I × D13	78.6852***	24.3274	D100 × D12	-9.4427**	3.9427
D100I × D14	19.7120***	7.4156	D100 × D13	-11.7405***	4.0777
D100I × D15	-16.5884	39.2857	D100 × D14	2.2181	8.5427
D100I × D16	1.9575***	1.3655	D100 × D15	-5.8178	4.9396
D100I × D17	11.3440***	1.7484	D100 × D16	6.7258	7.0575
D100I × D18	17.0397***	2.9996	D100 × D17	13.3085	14.5140
D100I × D19	9.0189***	2.6213	D100 × D18	0.1241	5.5236
D100I × D20	34.2180***	9.4616	D100 × D19	-0.5147	6.2675
D100I × D21	9.7914***	1.5550	D100 × D20	-7.7796*	4.2678
			D100 × D21	10.5173	7.1378
R-square:	*0.4475*			*0.3578*	

[a] For all tables, *, **, *** denote significance at 0.1, 0.05, 0.01 levels, respectively.

2.6.2 Implications for Firefighting Expenditures

Generally, expenditures that the provincial government incurs on firefighting come from two budgets, the fire preparedness budget and the direct fire budget. The former takes care of the fixed firefighting expenditures in any fiscal year; examples include firefighter wages, training, equipment maintenance, and long-term contract services, while the direct budget addresses the direct firefighting costs, short-term or casual contract services, and overtime wages. Sometimes expenditures that are supposed to be paid from the fire preparedness budget can also be paid from the direct fire budget when the fire preparedness budget is exhausted during severe fire seasons (MFLNRO, 2012).

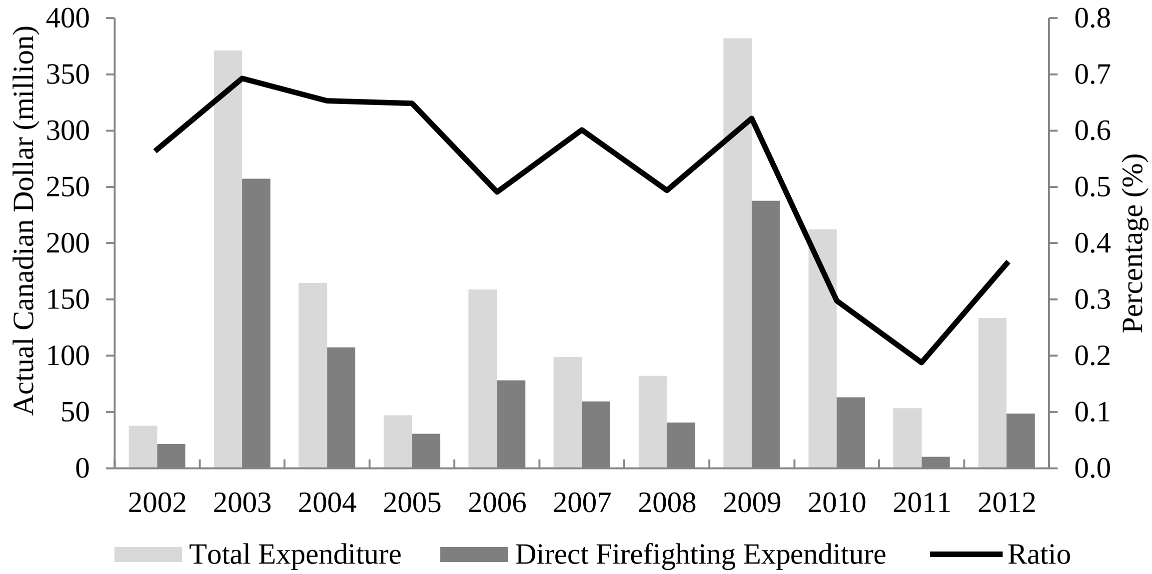

Figure 2.21: Direct Firefighting Expenditure vs. Total Expenditure, 2002-2012

Since the early 1990s, several catastrophic fires led the province to increase fire suppression efforts with several new measures. Among others, according to the WMB, the province began to share firefighting resources with other provinces and even with the U.S. to suppress most potentially threatening fires. Moreover, aircraft (primarily helicopters and airtankers) were also extensively used in firefighting, particularly for remote fires. While this implies that more large fires were suppressed, more expenses were also needed accordingly. Therefore, firefighting expenditures from the direct fire budget are expected to change sometimes dramatically across fire years. From Figure 2.21, we see that the proportions of direct firefighting cost in total cost follow a decreasing trend during 2002-2012 but with great fluctuations.

Simple statistical analyses using our fire data indicate that direct firefighting expenditures largely depend on the number of large fires and related area burned, especially in the last several decades. Spatial autocorrelations in expenditures between neighbouring forest districts do not arise mainly because wildfire occurrence resulting from either lightning or human activities is uncertain, even though forest conditions and weather conditions may be similar. A significant relationship between wildfire occurrence and firefighting expenditure implies that we could use historically observed climate data such as monthly temperatures and precipitation to predict large fire occurrence and thus firefighting expenses several months ahead; however, the determination of number of fires and possibilities of large fire occurrence in each month and the possible locations becomes crucial in this case. Further study is required to improve estimates of wildfire occurrence, which would help to predict an economic variable (e.g., direct firefighting expenditures) and facilitate budget planning by provincial decision makers. Ideally the methods employed need to be based, in the final analysis, on one or more variables that are readily observable in advance and could be easily understood by policy makers. That is, the state variables for predicting firefighting expenses need to constitute several simple series that are readily available to the public.

In BC, the current wildfire prediction system is the Canadian Forest Fire Danger Rating System (CFFDRS), which has been in operation since 1968. This fire rating system is mainly used for short-term (mostly daily) predictions at a landscape level on the basis of regional weather conditions and fuel types (Stocks et al., 1989). Although it can give a relatively accurate connection between weather conditions and wildfire occurrence, it is not appropriate for long term wildfire prediction at a provincial scale and thus firefighting budget planning due to the complicated input data. Therefore, in the next chapter, a simple approach to model future wildfire occurrence using statistical tools is provided.

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Chapter 3: Estimating Wildfires in British Columbia using Count Models: Predicting Climate Change Impacts

3.1 Introduction

With the exception of the recent mountain pine beetle outbreak, wildfire has been the primary natural disturbance in most of British Columbia's forests and is predicted to be an increasing problem in the future due to climate change. During the past decade, an average of 1,644 wildfires burned more than 128,000 hectares at an annual cost to taxpayers of $82 million, excluding the cost of lost timber. Factors influencing wildfire occurrence include not only natural factors, such as temperature, precipitation, lightning, vegetation and soil condition, but also human activities related to fuel load management, timber harvest and outdoor activities (viz., campfires, cigarettes, etc.). Combined influences from various factors make wildfire occurrence quite uncertain. Thereby, wildfire occurrence in any given fire season is very difficult to predict, as is the associated size of the forest that is subsequently destroyed.

Efforts to estimate future wildfire occurrence with a sufficiently long lead time have commonly examined correlations to climate indexes (Chu et al. 2002), long-term averages of temperature and precipitation (Preisler et al. 2011), and/or the Palmer Drought Severity Index (Westerling et al. 2003). On a global scale, seasonal temperature and precipitation anomalies across years are partly driven by certain climate circulation patterns that can be characterized by different climate indexes, such as the ENSO phenomenon that is measured by differences in sea surface temperatures (SSTs) across multiple regions in the Pacific Ocean. Given that climate circulation patterns affect seasonal weather conditions with delays, it may be possible to predict potential changes in wildfire events by monitoring climate indexes. Chu et al. (2002), for example, examined the relationship between area burned by wildfire in Hawaii and the Southern Oscillation Index (SOI). Likewise, Collins et al. (2006) examined the impact of both the SOI and the Pacific Decadal Oscillation (PDO) on the annual area burned in the interior of the western U.S. Meanwhile, McKenzie et al. (2004) used a bilinear regression model with summer temperatures and precipitation to estimate the (log of) burned area in California and Nevada. Also, warmer winters resulting from climate oscillations such as the ENSO phenomenon (e.g., the 1998 El Niño event) may promote mountain pine beetle infestations, thus potentially affecting wildfire occurrence. However, since the interaction between mountain pine beetle outbreaks and wildfires has not been clearly detected (Kulakowski and Jarvis 2011), we do not consider the impact of mountain pine beetle infestation in the current study.

Unlike these studies, in this chapter we estimate the effect of climate indexes on historical wildfire occurrence, as measured by the monthly number of fires and area burned, using two different count models – one for occurrence and the other for area burned. Our intent is to investigate whether and to what extent climate indexes can be used to predict monthly wildfire occurrence and the overall area burned by wildfire. To do so, we assume that monthly fire frequency follows the zero-inflated negative binomial (ZINB) distribution, while monthly area burned by fire follows the generalized Pareto (GP) distribution with a certain threshold. We regress historic wildfire occurrence on climate indexes and several important control variables to estimate the parameters of the ZINB distribution, and we estimate the occurrence of large fires that exceed a certain threshold area using a combination of a logistic regression model and the estimated GP distribution. Finally, we examine the sensitivity of total fires and associated area burned during a given fire season to hypothetical changes in the climate index.

We employ the BC Interior defined by fire centres as the study area (Figure 3.1). Wildfire data for the period 1950-2012 were obtained by request from the WMB, MFLNRO. Using the GIS spatial layers of fire centres and zones, which were also obtained from the WMB, we calculate the monthly number of fires and total area burned in each fire zone according to fire locations and discovery dates.

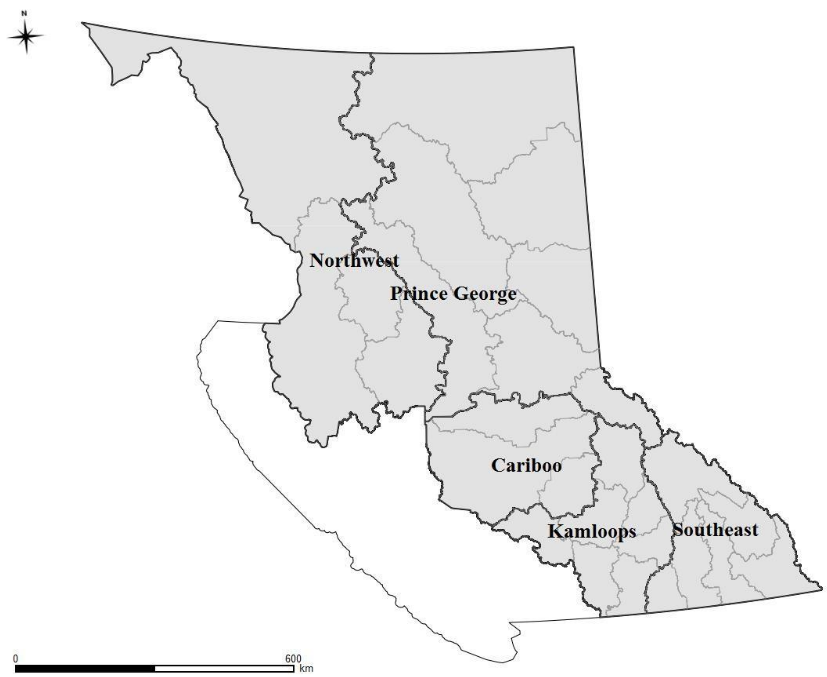

Figure 3.1: The BC Interior with Fire Centres

3.2 Estimating Monthly Fire Occurrence

A histogram of the monthly fire occurrences over the period 1950-2012 is provided in Figure 3.2, as are some basic statistics. These indicate that the standard deviation of fire occurrence is greater than the mean, suggesting over-dispersion of the count data. Further, there is a spike at zero as there are many months in the seven-month (April – October) fire season and 12-month fire year when no fires are recorded. Two types of models are commonly applied in these circumstances – the two-step or 'hurdle' model, and the ZINB model. Each employs a different process to generate the zeros. The hurdle model requires a clear distinction between zero and non-zero observations, which might be oversimplified in some cases and thus requires a different approach (Sheu et al. 2004). In the current analysis, monthly occurrence of wildfire does not solely depend on any single explanatory variable, but on the inter-play of many factors. Therefore, we consider the ZINB regression model to be more appropriate for our estimation; it allows zero observations in processes that are determined by different explanatory variables.

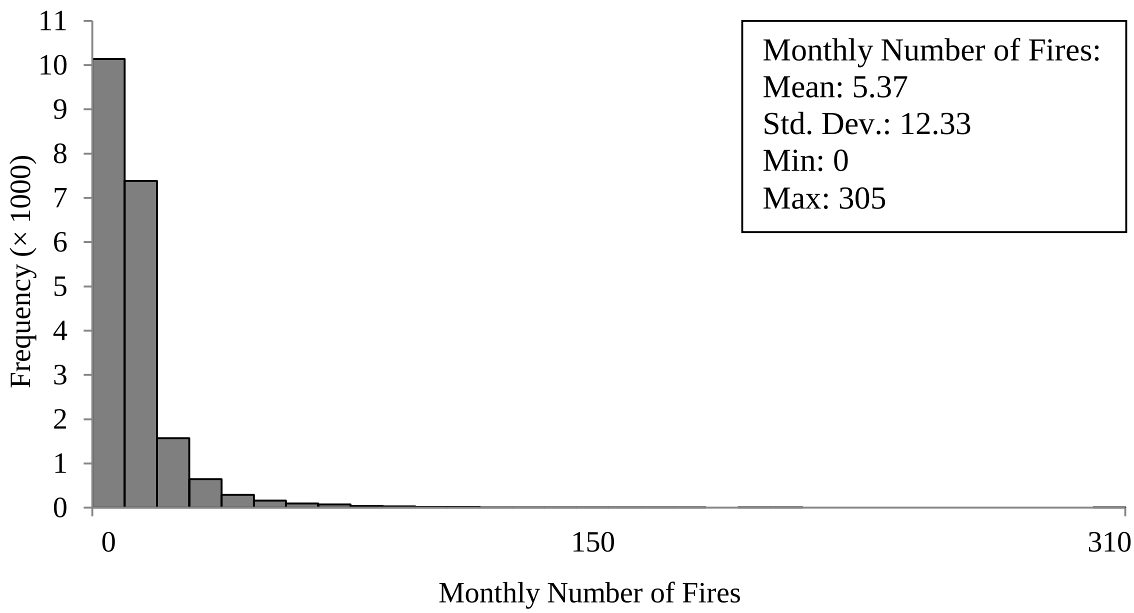

Figure 3.2: Histogram of Monthly Number of Fires, 1950-2012

The ZINB model assumes that all zeros in a dataset come from two different processes: one is the negative binomial distribution, and the other is a binary process that is usually determined from a logit or a probit model. Following Lambert (1992) and Redout et al. (2001), the ZINB model can be specified as:

$Y = 0$ with probability p

$Y \sim$ negative binomial (r,k) with probability $1-p$

Thus, the probability that $Y = y$ is given by:

$$\Pr(Y = y) = \begin{cases} p + (1\text{-}p)(1+\lambda/r)^{-r} & , y = 0 \\ (1\text{-}p)\left[\dfrac{\Gamma(y+r)}{\Gamma(y+1)}\Gamma(r)\right]\left(1+\dfrac{\lambda}{r}\right)^{-r}\left(1+\dfrac{\lambda}{r}\right)^{-y} & , y > 0, \end{cases}$$

where Γ refers to the Gamma distribution. Then, the mean and variance of Y are:

$$\mathrm{E}(Y) = (1-p)\lambda$$

and

$$\mathrm{Var}(Y) = (1-p)(1+p\lambda+\frac{\lambda}{r})\lambda\ ,$$

where $\lambda = \dfrac{rk}{1-k}$ is the mean of the underlying negative binomial distribution, and $\dfrac{1}{r}$ is the dispersion parameter. When $r \to \infty$, the negative binomial distribution reduces to the Poisson distribution.

The ZINB model is commonly employed in health care studies, but few have employed it in the study of wildfire. One exception is Chen (2013), who used a ZINB model to estimate annual fire ignitions caused by lightning across counties in Florida. In the current study, we estimate monthly fire occurrence using a univariate ZINB regression model with the ENSO index as the main explanatory variable and monthly lightning frequency for the zero inflation.

According to the U.S. National Oceanic and Atmospheric Administration (NOAA), the ENSO is the most important interactive phenomenon that causes interannual global climate variability. Since it reflects interactions between oceans and the atmosphere, the ENSO is expected to affect regional climate in BC, and thereby wildfires albeit with delays. We examine four different monthly ENSO indexes: Niño 1&2, Niño 3, Niño 3.4 and Niño 4, which describe the SST differences in various regions of the Pacific Ocean. By regressing the monthly fire frequency with respect to those indexes, we find that the four-month lag of the El Niño 1&2 index (ENSO within 0°-10°S, 80°W-90°W) constitutes the most relevant ENSO climate index for our model, because it has the strongest seasonal trend and the four-month delay is also the longest (and thus potentially more valuable for prediction purposes). In the ZINB model, the effect of the El Niño 1&2 index is assumed to be the same across fire zones and is expected to explain the fluctuations in wildfire occurrence in the negative binomial component.

The data for average monthly cloud-to-ground lightning frequency were collected during 1999-2008 by the Canadian Lightning Detection Network of Environment Canada.[3] It indicates that more than 500,000 cloud-to-ground lightning strikes occur every year during June, July and August, while the numbers are extremely low in December, January and February. Since most zeros in fire frequency data also occur during these three months, we employ cloud-to-ground strikes as the estimator to account

[3] For data in graph see: http://www.ec.gc.ca/foudre-lightning/default.asp?lang=En&n=C4E86962-1.

for excessive zeros in the ZINB model. While the zero-fire situation in winter results from the combined influence of lower temperatures, higher precipitation, fewer lightning strikes and less human activity that might cause fires, the lightning frequency provides a similar fluctuation to monthly fire frequency in a fire season. Since no statistically significant correlation exists between annual total lightning strikes and the average ENSO index, we assume lightning strikes to be an independent process that is unaffected by the ENSO and therefore does not change across years. This assumption is reasonable as lightning is a much more random and local phenomenon, much like precipitation compared to temperature. We also include the monthly dummy variables for April-October and zonal dummy variables to explain the unobservable effect in each month of the fire season and potential fixed-effects across fire zones, respectively.

For our purposes, the expected mean λ of the negative binomial distribution and the probability of the non-fire situation in the ZINB model can be estimated as:

$$\log(\lambda) = X'\beta + v$$

$$\text{logit}(P) = \log\left(\frac{P}{1-P}\right) = Z'\gamma + u$$

where $P \in \{0, 1\}$ is a vector of binary probabilities (P); X and Z represent matrixes of covariates for the negative binomial and the logit components, respectively; β and γ are the corresponding vectors of parameters to be estimated; and v and u refer to the error terms. In this study, except for the vector of constants, matrix Z includes only one covariate – the monthly number of lightning strikes. Since the probability distributions of lightning frequency are assumed to differ only across the months of each year, the probabilities in P generated by the logit model follow the same pattern. The matrix of independent variables X consists of vectors representing the constant, the four-month lags of the El Niño 1&2, and the zonal and monthly dummy variables. In the ZINB model, each component λ_{it} of matrix λ represents the expected mean in the negative binomial of the number of fires in fire zone i in month t. It is modeled as an exponential function of the linear predictor, namely $\exp(X'\beta)$.

Summary statistics for the variables used in the analysis are provided in Table 3.1. The data for the monthly number of fires are directly employed as the dependent variable since they are statistically stationary. Robust standard errors are applied due to heteroskedasticity across zones. We also test possible spatial autocorrelation using Moran’s I in the residuals. The results indicate that there is no significant spatial autocorrelation related to the dependent variable. The regression model is then applied to the monthly data for the 755 months from May 1950 to March 2013 (nearly 63 years) in five fire centres constituting 27 fire zones in the BC Interior.

Table 3.1: Variables and Summary Statistics

Variable	Mean	Std. Dev.	Range [Min; Max]
Monthly Number of Fires	5.3	12.33	[0; 305]
Monthly El Niño 1&2	23.1	2.24	[18.95; 29.24]
Monthly Lightning Frequency	1.97	2.95	[3×103; 9.29×105]
Zone Dummies	0.04	0.19	[0; 1]
Month Dummies	0.08	0.28	[0; 1]

The results of the ZINB regression are provided in Table 3.2. As expected, the ENSO index has a statistically significant and positive impact on wildfire occurrence, while lightning frequency is strongly and negatively correlated with the number of zeros, indicating that, during the months when there is a much reduced chance of having cloud-to-ground lightning, the number of fires and area burned are more likely to be zero.

Table 3.2: ZINB Regression Model Results[a]

Variable	Coefficient	Standard Error
ENSO Index at Region 1&2	0.06	0.01
Constant	-1.45	0.28
Logit Model:		
Lightning Frequency	-56.85	11.51
Constant	4.01	0.35
Ln(α)	-0.07	0.02

[a] Results for the control variables are omitted for convenience. All estimated parameters are statistically significant at the 1% level. Parameter α is the dispersion parameter for a Poisson distribution.

The results indicate that the ZINB model is the preferred model for estimating monthly fire occurrence. First, Ln(α) in Table 3.2 refers to the natural log of the dispersion parameter α; a Poisson regression model would be more appropriate than the ZINB model if $\alpha = 0$, or that Ln(α) = $-\infty$. Based on the statistical significance of the parameter estimate for Ln(α) in the regression, it is clear that the use of a standard Poisson model is unwarranted. Further, a likelihood-ratio test comparing the ZINB model to the zero-inflated Poisson (ZIP) model, presented in Table 3.3, also indicates that α is significantly different from zero; this implies that the ZINB model is preferred to the ZIP model. Finally, the Vuong (1989) test to determine whether the ZINB model is preferred to a standard negative binomial model, which can be employed for the ZINB and ZIP models because they are not nested (Greene 1994), indicates that the ZINB model is preferred to a standard negative binomial model.

Table 3.3: Goodness-of-Fit Tests of the ZNIB Regression

Test	Value[a]
ZIP likelihood-ratio test (χ^2): ZINB vs. ZIP	0.0006
Vuong test (z): ZINB vs. standard negative binomial[b]	15.11

[a] All test statistics are significant at the 1% level.
[b] ZINB preferred to a standard negative binomial if the z-value is greater than 1.96, and vice versa if it is smaller than –1.96 (see Long and Freese 2003).

3.3 Estimating Monthly Area Burned

Compared to monthly fire occurrence, estimation of the area burned each month is more difficult, because the data have much greater variability and include a large proportion of small values (the smallest recorded fire event burned only 0.009 ha). In the BC Interior during 1950-2012, for instance, nearly half of the months had zero area burned, while nearly one-third of months with non-zero area burned had total burns of less than 1 hectare. The single largest fire, on the other hand, burned more than 320,000 hectares. The non-zero observations are summarized in the histogram provided in Figure 3.3, where all burned areas exceeding 10,000 ha are combined for convenience. Clearly, the distribution has a heavy tail, in which case a log-normal or generalized Pareto distribution might be appropriate. Upon fitting a log-normal distribution, we find the estimated parameters of the distribution of total monthly area burned still lead to a result that underestimates the extreme end of the tail. Considering that most of the extreme values result from a few very large individual fire events that have a substantial economic and ecosystem influence, we decide to focus only on those months when large total burns occurred, which requires that we fit the GP distribution with a certain threshold.

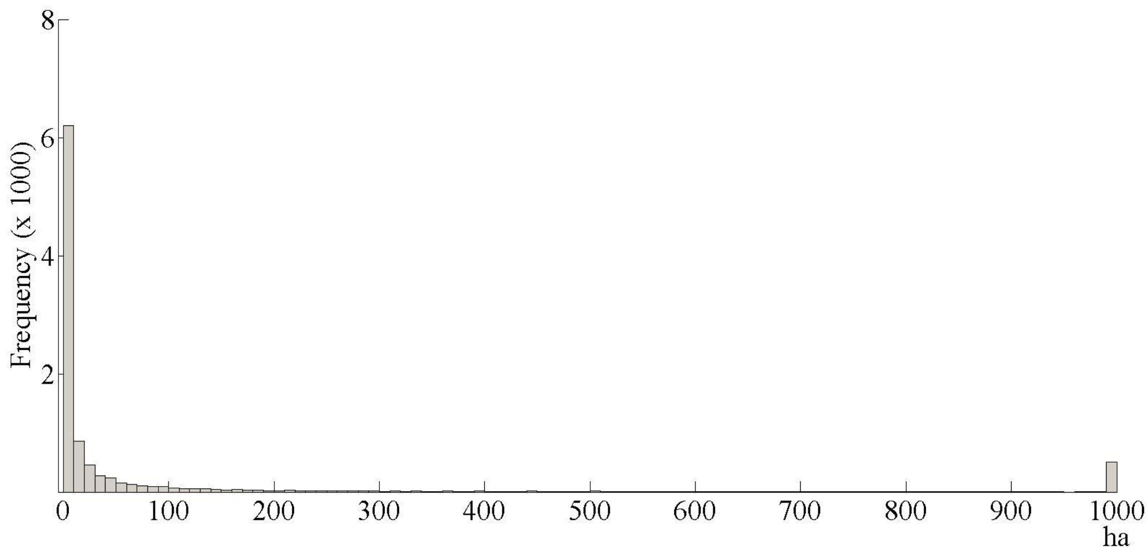

Figure 3.3: Histogram of Non-Zero Monthly Area Burned, 1950-2012

The GP distribution is commonly used to describe the tails of another distribution. In terms of wildfire, fire sizes have been consistently modeled by the heavy-tailed generalized Pareto distribution (Strauss et al. 1989; Cumming 2001). Given that we deal with observations on the basis of fire zones rather than single fire events, we simply assume that the sum of the sizes of all fire events in a fire zone also follows the GP distribution. We fit the GP distribution using monthly burn size data aggregated for each fire zone to examine possible correlation to the ENSO index.

To fit the GP distribution, a threshold for identifying extreme values is required. We determine the threshold by drawing a mean residual life plot (see Coles 2001). The GP distribution provides a valid approximation to observations beyond the threshold point where the sample mean of the values that exceed the threshold becomes a linear function of the corresponding threshold value (Holmes et al. 2008). As indicated in Figure 3.4, the mean residual life plot becomes approximately linear around 1,700 ha of burned area, suggesting that this is a plausible threshold. We verify this conclusion by examining the stability of parameter estimates when fitting the GP distribution for a range of possible thresholds (Coles 2001). As evident from Figure 3.5, the 95% confidence interval of predicted values from the fitted GP distribution widens rapidly beyond the 1,700 ha threshold, which confirms that this is a reasonable choice. Further, we examine the goodness-of-fit of the GP model for observations beyond 1,700 ha by providing probability and quantile plots in Figure 3.6. As argued by Coles (2001), the GP model is reasonable, because the relation between the observed and predicted values for monthly burned area is approximately linear in both plots.

The 380 observations that exceeded the threshold are used to estimate the constant shape parameter (σ = 4401.4) and scale parameter (k = 0.6894) of the GP distribution. The estimated value of the scale parameter indicates that the fitted distribution has a heavy tail with a finite mean (Holmes et al. 2008). A covariate model treating the scale parameter as a linear function of the seasonal El Niño 1&2 values is also examined, but the estimated coefficient turns out to be statistically insignificant, which indicates that, for the fire seasons 1950-2012 and across all fire zones, monthly area burned greater than 1,700 ha can be predicted from the same GP distribution.[4] That is, changes in the SST anomaly do not necessarily result in changes in the number of cases where monthly area burned exceeds the threshold. This is not unexpected given that large aggregated fire size results primarily from a few single large fire events, and that once a fire gets started, its size depends on local weather conditions (particularly winds) and suppression efforts.

[4] When looking at fire occurrence, we employed data for a fire year, but, when examining area burned, we needed only data for a fire season.

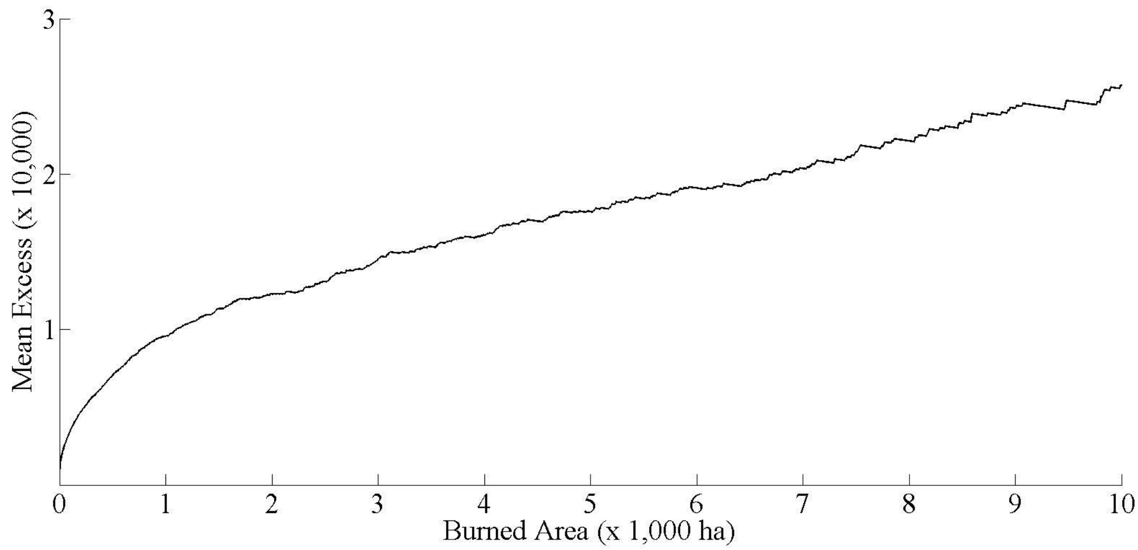

Figure 3.4: Mean Residual Life Plot for Monthly Burned Area

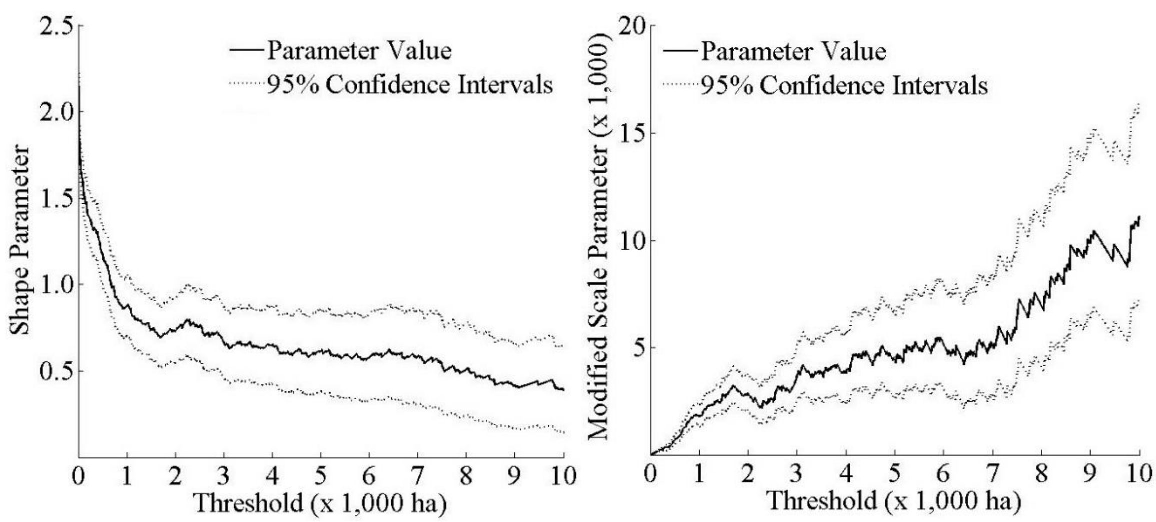

Figure 3.5: Parameter Estimates against Threshold

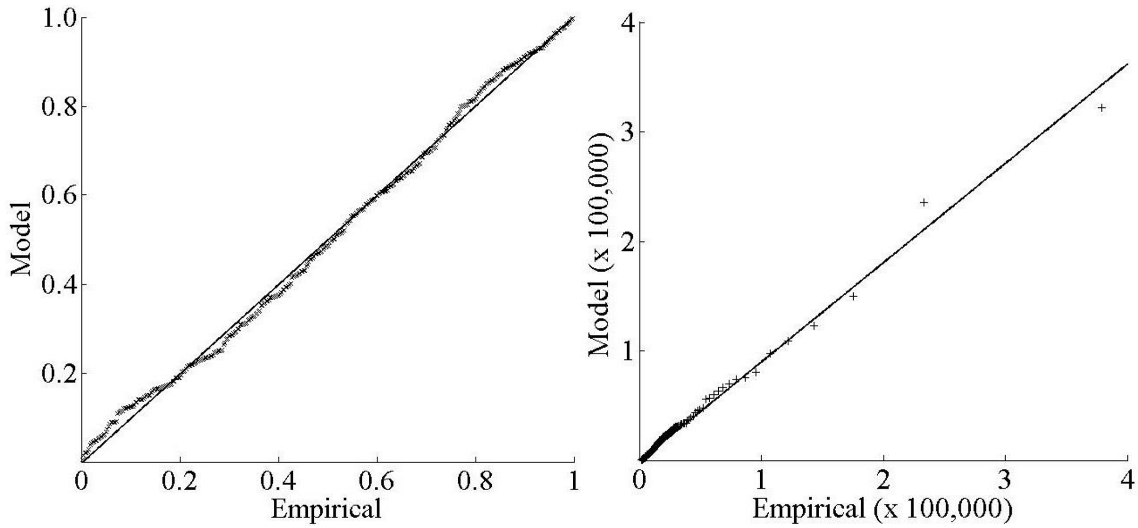

Figure 3.6: Probability Plot (Left) and Quantile Plot (Right)

The GP model provides estimates of monthly burns exceeding 1,700 ha. Now we want to investigate the probabilities of the occurrence of such large burns in each fire zone. By analyzing the spatial distribution of large fire events (> 1,700 ha) in the BC Interior using GIS, we find that large fires are randomly distributed across fire zones in general, but with clusters in some particular zones. Therefore, we employ a logit model with zonal dummy variables as follows to capture the zone-dependent effects:

$$\Pr(S > 1{,}700)_{it} = \beta_0 + \beta_1 \times N_{it} + \beta_2 \times NINO_t + \beta_3 \times D_i + \varepsilon_{it},$$

where S is the monthly area burned in each zone; N_{it} is the total number of fires in zone i in month t; $NINO_t$ refers to the monthly, 4-month lagged El Niño 1&2 value in the t month; and D_i refers to the dummy variable for zone i. The results are provided in Table 3.4. As expected, more fires and a higher SST anomaly increase the risk of burned areas exceeding 1,700 ha at the fire zone level. However, this risk declines with time, indicating that fire suppression activities have become more effective over time.

Table 3.4: Logit Model Estimation Results

Variable	Coefficient	Std. Error	Variable	Coefficient	Std. Error
CONSTANT	-17.0609	0.8841	D_{14}	-0.0648	0.7592
N	0.0547***	0.0042	D_{15}	0.7119	0.7067
NINO	0.4433***	0.0253	D_{16}	1.7155**	0.6666
D_2	-0.0055	0.7628	D_{17}	3.0687***	0.6328
D_3	-0.3409	0.9702	D_{18}	0.7052	0.7441
D_4	0.9191	0.7482	D_{19}	1.4542**	0.6914
D_5	3.2070***	0.6318	D_{20}	0.0541	0.7457
D_6	0.9280	0.6706	D_{21}	0.0974	0.8093
D_7	0.9656	0.7127	D_{22}	1.8977***	0.6728
D_8	-0.8140	0.9453	D_{23}	0.9595	0.7675
D_9	-0.0351	0.8749	D_{24}	0.2715	0.8456
D_{10}	2.7282***	0.6393	D_{25}	-0.4022	0.9200
D_{11}	3.5380***	0.6216	D_{26}	1.7027**	0.6704
D_{12}	2.8218***	0.6372	D_{27}	-1.1659	0.9952
D_{13}	1.3487*	0.7074			
Log Likelihood:		*-1292.76*			

Although large fires are less clustered than small ones, for zones that have a statistically significant impact on the probability of exceeding the threshold of 1,700 ha, the impact is always positive (Table 3.4) – the probability of large monthly burns during fire season increases compared that of zones that are statistically insignificant. This is consistent with the observed distribution of large fires shown in Figure 3.7, where the fire zones that significantly affect the occurrence of large burns in the logit model are illustrated as the darkened areas. In addition, single fire events during 1950-2012 that exceeded 1,700 ha are shown in Figure 3.7, as such fire events immediately imply that the total area burned in the corresponding fire zone exceeds the threshold. The fire-zone dummy variables in Table 3.4 are also indicative of the spatial distribution of firefighting resources and expenditures, given that large fires are responsible for the most part of firefighting efforts in BC.

From Figure 3.7, fire events are more likely to grow bigger in fire zones in northern BC, which is mainly because they are relatively far from fire suppression resources. According to the WMB, there are only 7 out of 47 attack bases with 18 out of 132 initial attack crews including 10 parachute-attack crews located within those fire zones. Further, in those zones hot spots are quite difficult to identify quickly and then access, especially those where lightning-caused fires occur.

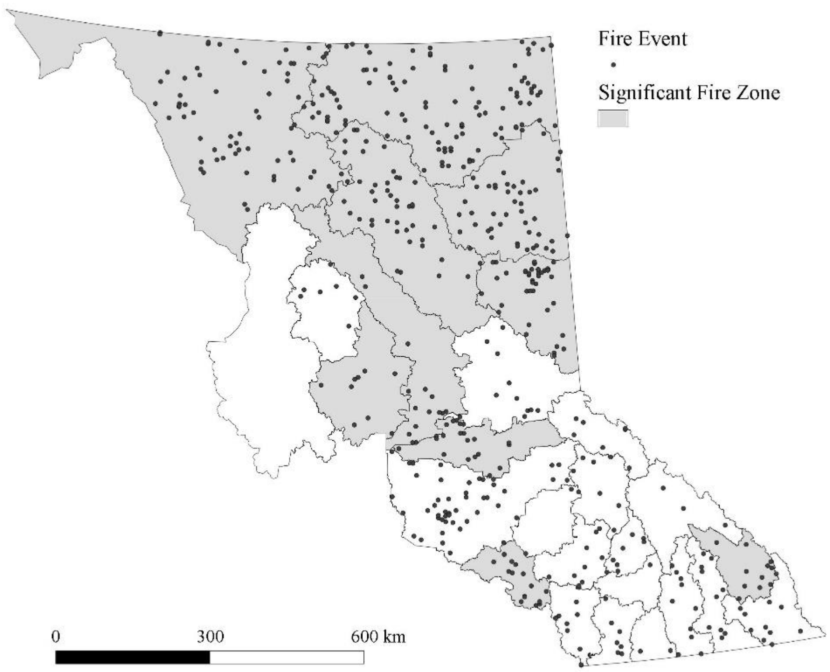

Figure 3.7: Significant Fire Zones and Fire Events > 1,700 ha, 1950-2012

3.4 Wildfire Prediction from Count Model Estimates

Using the estimated coefficients and parameters from the count models, we are able to predict monthly wildfire occurrence and total area burned for each fire zone. For the former, it is done by re-sampling random numbers from the binary and negative binomial distributions; for the latter, we simply combine the predicted probability from the logit model along with the random values generated from the estimated GP distribution.

As discussed by Long and Freese (2003), the ZINB model computes observed probabilities based on three steps: (1) modeling of the probabilities of zero (non-zero) in a binary process, (2) modeling the probabilities following the negative binomial distribution, and (3) computing the observed probabilities as the combined probabilities of the first two steps. In this study, we employ a similar procedure. We first describe the negative binomial distribution using the Poisson distribution whose mean (= λ) follows the Gamma distribution with a shape parameter r and a scale parameter $\frac{k}{1-k}$. This can be described as:

$$Y'_{it} \sim f(\lambda_{it}) \text{ (Poisson)}$$

$$\lambda_{it} \sim \Gamma(r, \frac{k}{1-k})$$

where Y'_{it} refers to the random value of monthly fires that are generated from the underlining negative binomial distribution in fire zone i for the t^{th} month.

Since the dispersion parameter $\frac{1}{r} = \alpha$ (and estimated in Table 2), we use it to describe the Gamma distribution:

$$\lambda_{it} \sim \Gamma(\frac{1}{\alpha}, \frac{k}{1-k}) \text{ and } E[\lambda_{it}] = \frac{rk}{1-k} = \exp(x'_{it}\beta_{it}),$$

Thus, $\lambda_{it} \sim \Gamma[\frac{1}{\alpha}, \alpha \times \exp(x'_{it}\,\beta_{it})]$. Since both α and $\exp(x'_{it}\beta_{it})$ can be obtained from the regression model, we are able to combine the negative binomial distribution with the binary process by multiplying the random values by a zero-value probability that can be estimated from the regressions. This is done by comparing the estimated probabilities in the logit model against random values generated from a standard uniform distribution $U(0,1)$. Since any random value $\pi \sim U(0,1)$ has an identical probability, whether Y_{it} equals zero or a random sample from the negative binomial distribution Y'_{it} can be determined by comparing π_{it} and the corresponding estimated p_j:

$$Y_{it} = \begin{cases} 0 & \text{if } \pi_{it} > p_j \\ Y'_{\text{it}} & \text{if } \pi_{it} \leq p_j \end{cases}$$

Using the above process, we hindcast the monthly occurrence of fires and their associated size for each fire zone for the 62 years of available information, 1951-2012. We employ Monte Carlo simulation with 1,000 iterations to calculate the mean frequency that the monthly number of fires is zero (or too small to register) and, for ‘non-zero’ fires, allocate these into bins or intervals of tens ranging to a final bin of 400 or more fires. The histograms of both historical and predicted fires are provided in Figure 3.8. With the exception of the 1-10 and 11-20 bins, the historic actual and predicted fire counts track very closely, indicating that the ZINB model prediction is an appropriate model of fire occurrence. The simulated averages by zones and by months of a fire year also provide a good estimation of the historical situation; however, interannual variability is underestimated because the number of fires shows a larger variance than that of the El Niño 1&2 index.

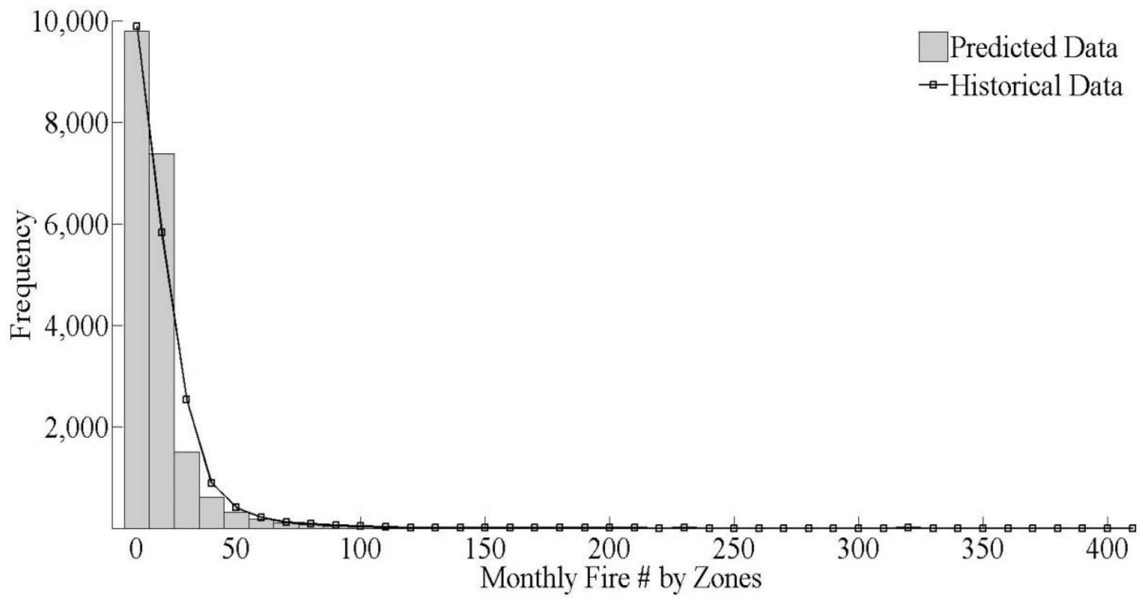

Figure 3.8: Histograms of the Monthly Wildfire Occurrence

Compared to fire occurrence, it is easier to predict the cumulative area burned because observations are assumed to follow the same GP distribution. The probabilities that predicted total areas burned by fire exceed the threshold are estimated by the logit model using predicted monthly fire occurrence from the ZINB model. The probabilities are then used to generate random binary values (0/1) to determine the occurrence of large burns. Finally, the binary values are multiplied by randomly generated values from the estimated GP distribution to predict the monthly aggregated area burned in each fire zone. In this way, the predicted area burned (S_{it}) are described as either zeros or random values (S'_{it}) truncated at 1,700 ha:

$$S_{it} = \begin{cases} 0 & \text{if } S_{\text{it}} \leq 1{,}700 \text{ ha} \\ S'_{it} \sim \text{GP distribution} & \text{if } S_{\text{it}} > 1{,}700 \text{ ha} \end{cases}$$

We predict the monthly area burned in each fire zone for the period 1951-2012. Again, using simulation, we plot the histograms of the predicted above-threshold burned areas and the historic values in Figure 3.9 for comparison. The ratio between the number of zero values and non-zero values in the prediction is quite similar to the actual number, implying that the logit model provides a good estimate of the occurrence of large burns exceeding the threshold. In general, the GP model presents a similar data structure to the historic one; however, similar to the prediction of the number of fires in a month, the predicted data also overestimate values near the threshold while underestimating the frequency of larger aggregated burns. For instance, the average frequencies of extremely large values greater than 90,000 ha are less than one, which means that less than one such monthly event occurs in the 62-year simulation on average. In practice, however, seven such cases occur, which is over twice as many as the upper bound on the 95% confidence interval.

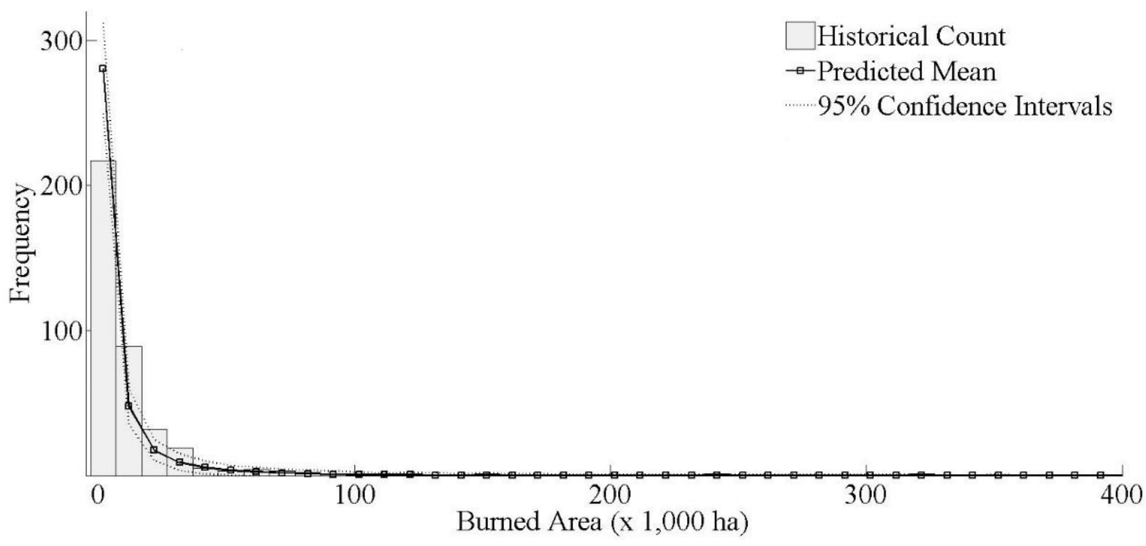

Figure 3.9: Histograms of Non-Zero Monthly Burned Area

By aggregating the simulated means according to fire zones, we find that the model predicts the historical data rather well, given that zonal dummy variables are employed to catch the zone-specific effects. However, our method fails to predict the extreme value in the Fort Nelson Fire Zone because the associated dummy variable can only capture whether total area burned exceeds the threshold rather than the actual total size of the aggregated area burned. We also compare the prediction by the 12 months, given that such a seasonal trend is estimated by the climate index in the logit model; the result indicates that the El Niño 1&2 index provides a good approximation of the seasonal trend of the historical means with 95% confidence.

3.5 Sensitivity Analysis

Finally, sensitivity analysis is used to examine the responsiveness of our predictions to changes in the monthly El Niño 1&2 index. Using the ZINB model and the logit model (recalling that the GP distribution is uncorrelated with the Niño 1&2 index), we simulate the average monthly fire frequency from the ZINB model and predict the probabilities that large fires occur monthly across fire zones. In doing so, we assume increases of 0.1ºC, 0.5ºC and 1ºC in the SST anomaly. The simulated average monthly number of fires for each fire zone rises from 5.37 to 5.42, 5.56 and 5.71, respectively. Aggregated to an annual basis, the actual average number of fires in a fire season (April - October) is 1,734 in the BC Interior, but for 0.1ºC, 0.5ºC and 1ºC increases in the SST anomaly, the numbers increase to 1,747, 1,785 and 1,841, respectively. This indicates that an increase in the mean of the climate index will result in a small increase in the average annual number of fires. However, considering the large variance, actual changes in the total number of fires with a positive monthly El Niño 1&2 anomaly could also be dramatic.

The same scenarios are then used to predict changes in the probability that large burns occur. We use the logit model to predict new probabilities of fire and illustrate the extent to which the El Niño affects the probabilities of larger fires. Our model predicts obvious changes in the monthly probabilities of significant fires occurring throughout the BC Interior, with average increases of 0.71%, 3.71% and 7.78% with 0.1ºC, 0.5ºC and 1ºC increases in the SST anomaly, respectively; in July and August, however, an increase of 1ºC can raise the occurrence of fire by upwards of 16%. This indicates that the risk of large fires is not very sensitive to changes in the El Niño 1&2 index in general, but that there is a strong seasonal trend.

Although average changes in the probabilities of significant fires occurring across zones are small, with upwards of a 3.2% increase in the + 1ºC scenario, distinctions across fire zones are significant. In Figure 3.10, we group the 27 fire zones into four risk categories according to the standard deviation of changes in probabilities under the + 1ºC scenario. As discussed in relation to the prediction of aggregate area burned, the Fort Nelson Fire Zone is most sensitive to potential changes in the climate index followed by the other four zones in the northwest. Fire zones located in the Central Interior are less sensitive, with those in the relatively drier rain shadow of the coastal mountains projected to be somewhat more prone to fires in this scenario compared to those to the east and northwest (along the coast). Most areas in the Southern Interior, on the other hand, are less sensitive to higher El Niño values, even though one would expect fire events to be more likely in this region in the summer. The reason for this seemingly contradictory finding relates to the location of firefighting resources. Since the Southern Interior is more densely populated, greater effort is made to suppress fires once they ignite.

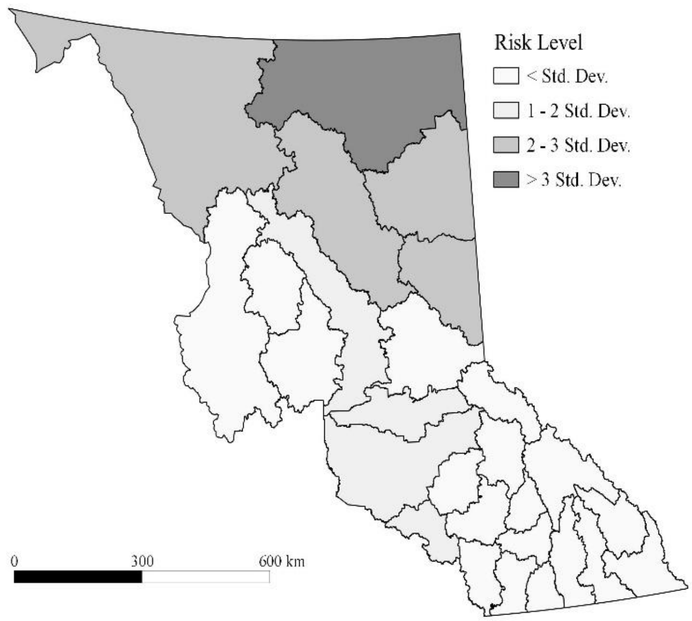

Figure 3.10: Spatial Distribution of the Changes in Probabilities of Large Fires

3.6 Conclusions

In this study, we estimated the relationship between historic wildfires and the ENSO index at the fire zone level using count models. Our results illustrate the merits of the zero-inflated, negative binomial regression model in estimating data with large numbers of zero values, as was the case for monthly wildfire frequency. The negative binomial distribution is appropriate for estimating randomness in the number of fires, and the lightning frequency provides a good predictor for months without fires. The occurrence of large aggregate monthly area burned by fire zone can be approximately estimated by the combination of the generalized Pareto distribution and the logit model. Using these models, significant spatial differences are also found across fire zones.

Our results indicate that the El Niño 1&2 index appears to have a significant effect on monthly number of fires as well as the extent of area affected by wildfire across zones. Since there is a four-month lag between the El Niño 1&2 index and the fire season, it is possible to use it as a simple wildfire predictor for an upcoming fire season. Further, using dummy variables, we could also estimate spatial differences between zones and the seasonal trend within a fire year can also be estimated. The use of the GP distribution proved to be an effective way to estimate monthly total burns exceeding 1,700 ha. This has potential implications, such as predicting expected firefighting expenditures, given that large fires play a more important role than small ones in many respects in wildfire management. The sensitivity analyses indicate that, in general, the average monthly fire frequency and the occurrence of large burns are not likely to change dramatically if a relatively large sea surface temperature anomaly occurs during a fire season; however, there remain significant distinctions across zones, and large temporal and spatial variations, that could lead to more extreme fire activities, especially in northern BC.

There are at least two shortcomings in this study. One is that inter-annual fluctuations in wildfires are underestimated with both count models because of the relatively small variability in the El Niño 1&2 index across years. This might be solved by including some spatial-specified climate conditions, such as the Palmer Drought Severity Index, although a shorter lag period or projected data may be required if the objective is to forecast the situation for the upcoming fire season. The other drawback is that, since we consider the uncertainty of wildfires at the zonal level rather than a grid with much higher resolution, some location based factors, such as vegetation and elevation, have been ignored, although these might exert an important effect on the probability that a wild fire starts and, once ignited, how quickly and how large it grows. These are considerations future research will need to take into account.

3.7 References

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Chapter 4: Living with Wildfire: The Impact on Property Values in Kelowna, British Columbia

4.1 Introduction

Every summer, British Columbia suffers moderate to severe damage from wildfires, resulting in large direct loss of commercial timber stocks and indirect economic costs that are related to lost amenity values, adverse health impacts from smoke, anxiety, loss of neighborhood unity, et cetera (Butry et al. 2001; Kochi et al. 2010). One approach for measuring the indirect costs is through their impacts on residential property values. Because wildfire results in lost amenity values and, near urban areas, poses a potential threat to property per se, house prices are believed to be sensitive to wildfire occurrence and nearness to fire-prone regions (Huggett 2003; Troy and Romm 2007). Among current studies, one basic assumption is that, if homebuyers are aware of the risks of wildfire in their own or neighbouring areas, the disamenities arising from past wildfires and the threat of future ones, among others, will show up in households' willingness-to-pay (WTP) for residential properties, which, in turn, can be measured by property values in real estate markets.

In studies of wildfire and property values, the 'wildland urban interface' (WUI) is used to refer to the place where residential and commercial development co-exist with wilderness that contains flammable vegetation (Ministry of Forests & Range and Ministry of Public Safety & Solicitor General 2008). Wildfires in the WUI tend to be more devastating than those in rural areas because of their greater potential threat to properties and the surrounding environment from which urban residents often receive significant amenity values.

In British Columbia, most wildfires occur in rural areas of the interior and far from residential properties, principally because 95% of the province's timberlands are publicly owned. Even though only a small proportion of wildfires occur in the WUI, losses can still be substantial; damage to buildings and reduced recreational, viewing and other amenity values negatively impact property values. During the 2003 fire season, the Okanagan Mountain Park Fire destroyed 238 homes around the City of Kelowna, and more than 33,000 people were evacuated. Later in the same year, 72 homes and 9 businesses were destroyed in the communities of McLure, Barriere and Louis Creek by the McLure Firestorm, which was larger than the earlier fire. Wildfires occurring outside the WUI are also believed to alter homebuyers' WTP by increasing risk perceptions and decreasing amenity levels or environmental values (Huggett et al. 2008).

Because several recent severe fire seasons in the western United States resulted in catastrophic losses, more attention is now paid to the impact of wildfire on property values (Donovan et al. 2007). In British Columbia, the 2003 and 2009 fire seasons led to record-breaking property damage and the largest evacuations in history. This is partly attributable to increasing housing density in the WUI because, despite the relatively higher wildfire risks, these areas also provide the amenities residents desire (Hammer et al. 2007). Further, it is possible that many homebuyers may not even be aware of the potential wildfire risks when they make purchase decisions, particularly if there has been no recent experience with wildfires in the region and/or records of property damages from wildfire (Champ et al. 2008). Even when people are aware of wildfire risks, homebuyers might underestimate the risks of rare but devastating wildfires, given that they are random events spread over time and spatially across a broad landscape.

Finally, although many factors affect wildfire risk, including forest management strategies and fuel load reduction efforts, climate change is also expected to result in more frequent wildfires (Westerling et al. 2006). As a consequence, knowledge of the relationship between wildfire occurrence and property values is important as a guide to decision makers regarding wildfire mitigation efforts. The purpose of this chapter, therefore, is to make a contribution to knowledge about this relationship; in particular, we employ a spatial hedonic pricing model to examine the potential effect of ten years of wildfire occurrence on residential property values in the British Columbia interior. We begin with a brief background discussion of the hedonic pricing method, followed by a detailed description of the study area and the data. We then provide the empirical model for this particular study and summarize the regression results. We end with concluding remarks.

4.2 Hedonic Pricing Method

Risk of wildfire occurrence has an indirect impact on property values that can be determined quantitatively using the hedonic pricing method (HPM). The hedonic pricing method is an indirect approach to measuring non-market values that relies solely on market evidence. Briefly, the hedonic curve regarding a certain characteristic (z) of a good is described as the envelope, $P(z)$, between the tangencies of bid functions ($\theta_1, \theta_2, \theta_3$) of consumers and offer functions ($\varphi_1, \varphi_2, \varphi_3$) of producers (Figure 4.1). The bid function describes the maximum amount of money that a consumer is willing to pay for a certain amount of a good (i.e., bid price), and the offer function refers to the minimum price at which a producer is willing to offer the good (offer price).

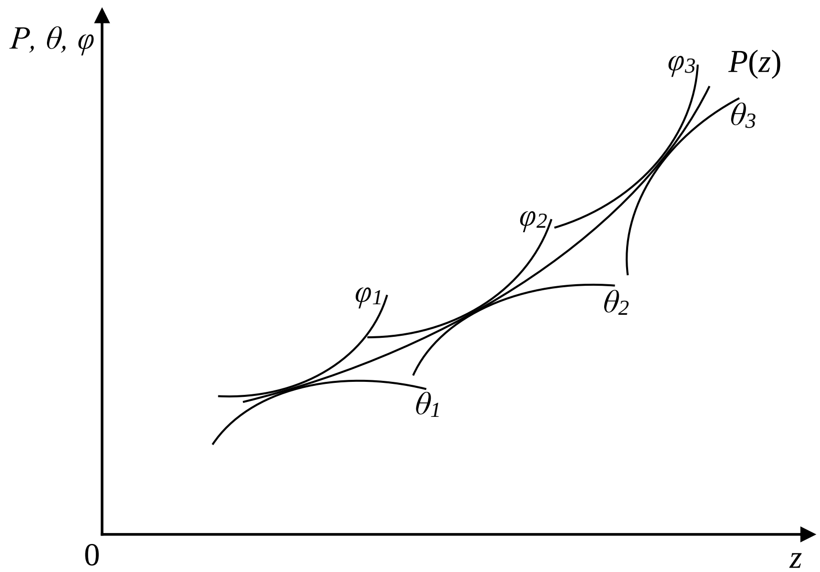

Figure 4.1: Hedonic Price Function

The conventional HPM usually takes the form of a two-stage procedure, although the second stage is relatively rare (Freeman 2003). In the first stage, it is assumed that the utility a consumer receives from purchasing a residential property can be measured by its characteristics – the marginal WTP or demand is determined by the levels of the property's features or characteristics. Then the marginal WTP for a property can be represented by its market value *V* as a function of its *n* various features $z_1, \ldots, z_n$:

[4-1] $V = f\,(z_1, z_2, \ldots, z_n)$

Equation [4-1] is the hedonic price equation, which could be linear, logistic, semi-log, quadratic or even a Box-Cox transformation function (Stetler 2008). The implicit marginal effect of any feature *i* can be derived as $\partial V/\partial z_i\,(i < n)$, which is a constant if (1) is linear. In the case of linearity, each additional unit of the characteristic, say, number of bedrooms, adds the same value to the house regardless of how many bedrooms are already present.

In practice, property values are regressed on the property's characteristics, including identifiable (and measurable) environmental amenities, with the estimated coefficients assumed to represent the implicit prices of the characteristics (Freeman 2003). Examples of environmental features or amenities include air quality (Pearce and Markandya 1989), water availability (Loomis and Feldman 2003), damage to forest landscapes by pests (Price et al. 2010), and presence of urban trees (Mansfield et al. 2005; Donovan and Butry 2011).

Forest fires also impact residential values. The main factor that has been extensively considered to impact homebuyers' willingness to pay (WTP) is the vicinity's wildfire history, particularly their number (occurrence) and size. Stetler et al. (2010) investigated the effect of wildfire size on home values for 256 fires by employing an HPM framework. They found that fire size together with a property's proximity to hotspots had a significantly negative impact on residential values. Some other studies focused only on the potential effect of a single severe wildfire event on property values. For instance, Loomis (2004) found that there was a statistically significant decline in property values when a major wildfire had occurred within two miles of a property. Studies also looked at the value of information about wildfire risk. For example, Donovan et al. (2007) examined the effect of disclosure of wildfire risk ratings for 35,000 residential parcels within the WUI in Colorado Springs, Colorado, concluding that such information has a statistically discernible effect that offset some of the positive amenity values and neighbourhood characteristics of these properties.

Because property values may be related in a spatial sense, spatial autocorrelation has to be taken into account in the hedonic price model. In this study, a spatial autoregressive model is employed to include a spatial lag variable determined by a weight matrix in the regression analysis. Spatial lag dependence describes correlations between the value of one property and that of neighbouring properties. For a linear function, this type of correlation can be expressed as:

[4-2] $V = \alpha + \rho\, W V + \beta Z + \varepsilon,$

where α is an intercept term, W is a user-defined spatial-weights matrix describing the spatial covariance structure among the samples of neighbouring properties, Z is a vector of property characteristics (features, amenities), ρ and β refer to the vectors of associated coefficients to be estimated, and ε represents the error structure. This kind of model is appropriate for explicitly testing the existence of spatial dependency in the dependent variable (Anselin 2007). If spatial autocorrelation exists, OLS estimates will be biased and inconsistent, although the spatial-weights matrix W might well take into account the spatial autocorrelation among neighbouring properties. In this regard, the spatial autocorrelation parameter ρ should be included in estimating the marginal effects of the characteristics in question. The spatial-weights matrix W can be developed on the basis of various factors, such as the Euclidean distance between properties, number of adjacent neighbours, or varying numbers of nearest neighbours within a specified radius of each property (Ham et al. 2012). Price et al. (2010), for example, employed a distance-based weights matrix in their hedonic model to estimate the implicit marginal price of the mountain pine beetle infestation for property values in Colorado.

4.3 Study Area and Data

Our study area is the City of Kelowna, which is located on the east side of Okanagan Lake in the southern interior of British Columbia (Figure 4.2). The study region has an area of 220 km^2 and average elevation of 334 m. We chose Kelowna because it lies in the central Okanagan Valley and the rain shadow of BC's Coastal Mountains. The region has the warmest and driest climate in BC and, compared to the surrounding mountains, the seasonal climate in the valley during summer time is even hotter and drier, which makes the valley vulnerable to wildfires. Further, given that Kelowna is the largest city in the Okanagan Valley and one of BC's fastest growing communities (City of Kelowna 2011), significant development is occurring near or within the WUI – in dry forested areas and, especially, within the Wildfire Development Permit Area (WDPA) in Figure 4.2.[5] Clearly, properties located in the WDPA carry a moderate to high risk of being impacted by wildfires (City of Kelowna 2011). Moreover, since the WDPA is located in the immediate vicinity of public lands (e.g., provincial or federal crown forestlands, or national, provincial or local parks), certain development standards for new construction have to be met (District of West Kelowna 2013).

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[5] See wildfire development permits of district of West Kelowna for detailed definition of WDPA, which is available from: http://www.districtofwestkelowna.ca/Modules/ShowDocument.aspx?documentid=1912

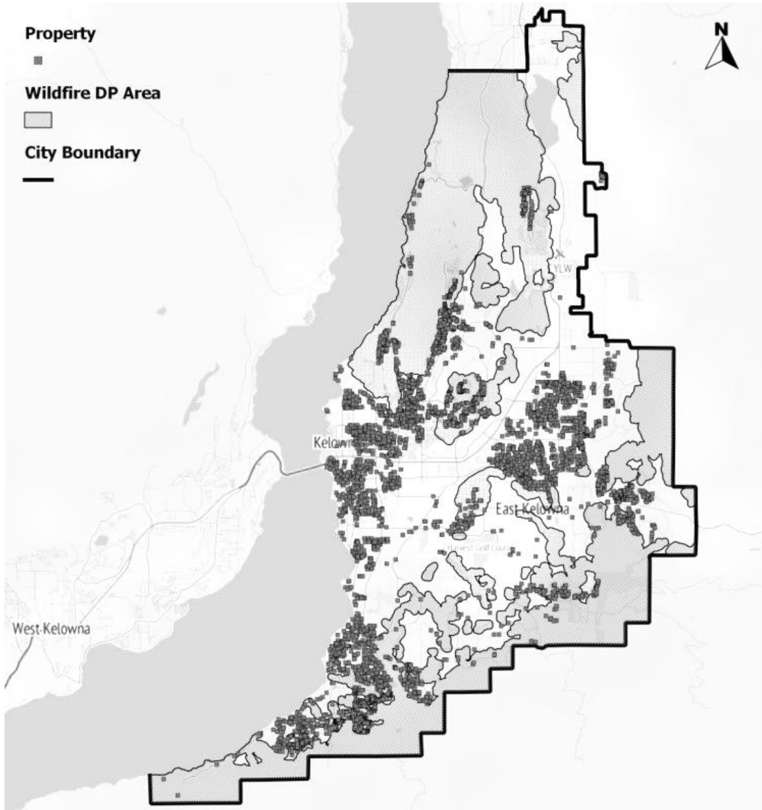

Figure 4.2: The City of Kelowna and Property Distribution[6]

Almost every summer, wildfires threaten communities in and around Kelowna, but the severity of the threat varies substantially across years. During the 2003 fire season, eight wildfires were recorded within the City of Kelowna, seven of which occurred in the WDPA; in the same season, the catastrophic Okanagan Mountain Park Fire destroyed 25,600 hectares of forestland and 238 homes on the southern edges of Kelowna (Filmon 2004). Although there were only two wildfires in 1998, one of them burned about 20 hectares of forestland only 4 km from downtown Kelowna.

As of 2011, more than 117,000 people lived in the 10 sectors into which Kelowna is divided, with most concentrated in Central City (central west), Rutland (central east),

[6] The base maps in all figures are from the Stamen Terrain-USA/OSM layer.

and North and South Okanagan Mission in the southwest (Figure 4.3). According to Statistics Canada's census data for 2006, there are 44,915 occupied private dwellings in the city of Kelowna (72% occupied by their owners), with an average value of $376,151 (Community Information Database 2006). More frequent catastrophic wildfire events during the past decade led the provincial government and local fire departments to put more effort into fire prevention and education. A Community Wildfire Protection Plan was created in 2011 and standards for fuel treatments and recommendations were developed as part of fire-free future community planning. An interactive manual for developers and homeowners, the 'FireSmart Wildland/Interface Planner', was also developed and made available online to help homeowners mitigate wildfire risk.[7] However, areas most vulnerable to wildfire remain in the northern sections of the city and along the southern boundary (see Figure 4.2).

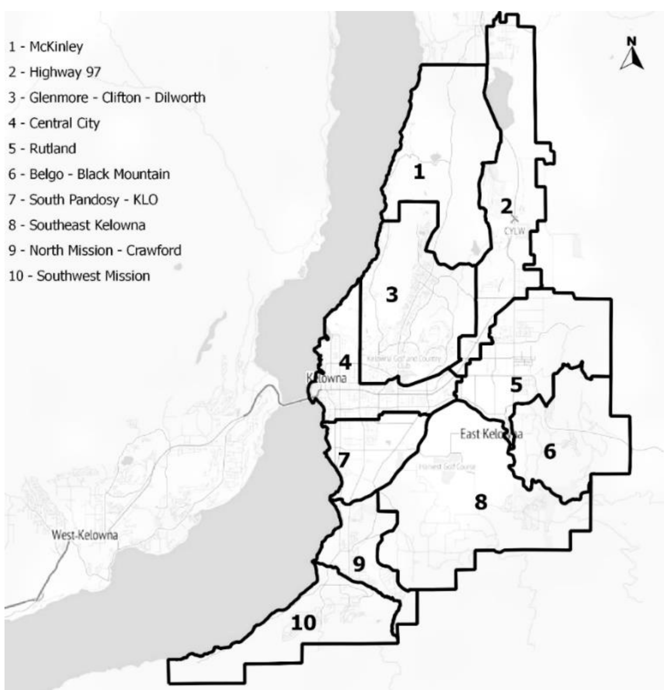

Figure 4.3: City Sector Map of Kelowna

[7] See http://www.kelowna.ca/CM/page384.aspx (viewed on 13 May 2013).

Three datasets are employed in this study. First, real estate data for Kelowna consist of property information (e.g., location, actual use type, and other attributes associated with residential structures) and detailed sales information (price, date and transaction number) for properties sold between 2004 and 2009. Since we can only identify the location of properties using the owners' physical addresses, all rental properties have to be excluded from the sample because the owner did not reside at that location. For remaining observations, we translated the physical addresses to geographic coordinates and then further verified their locations using Google maps. We also excluded those properties whose actual use type was not single-family dwelling to focus attention on house attributes for which we had information. This left 6,496 properties (shown in Figure 4.2) for estimating our hedonic pricing model.

Our second dataset constitutes the historical wildfire dataset from DataBC, provided by the WMB, MFLNRO.[8] This point-based GIS dataset contains detailed information of each wildfire event since 1950. For this particular study, given that our real estate data are available only from 2004 and we intend to analyze the effect of wildfires that occurred in the decade before properties were sold, we employ the size, date, location and total incidence of wildfires that took place during the period 1994 through 2009; the spatial distribution of these wildfires is provided in Figure 4.4. Unfortunately, the wildfire events that occurred on the west side of the Okanagan Lake (including West Kelowna) are not included in the analysis for lack of real estate data.

[8]Supported by the BC provincial government, DataBC is a comprehensive open-access database for public government data, applications and services that is available from: http://www.data.gov.bc.ca/.

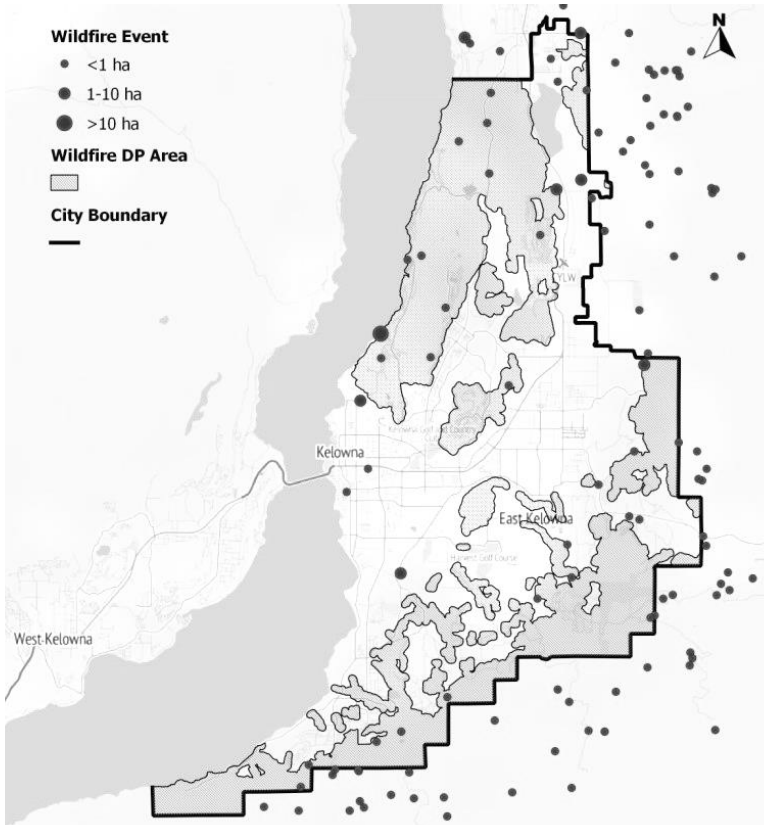

Figure 4.4: Wildfire Events within and around the City of Kelowna, 1994-2009

Our final dataset constitutes the GIS spatial layers for the City of Kelowna and the WDPA that are used in Figures 4.2 and 4.4. These maps are formatted as shapefiles and can be downloaded from the City of Kelowna website. We use the city boundary to identify wildfire occurrence within Kelowna and treat the WDPA as a dummy variable in the regressions (which marks 1,361 properties within such areas). Our objective is to explain the marginal effect of wildfires on property values in those areas.

4.4 Empirical Model

We utilize a semi-log hedonic price equation to investigate the potential effect of historic wildfire occurrence on homebuyers' WTP for houses in Kelowna. Logarithmic property values are employed because property values have a much larger variance compared to the explanatory variables in the model. Further, a Box-Cox test comparing the linear and the semi-log functional forms indicated that the latter is preferred. Thus, the model is specified as:

$$[4\text{-}3] \quad \ln(P_j) = \beta_0 + \beta_1 W_{ij} \ln(P_j) + \beta_2 S_j + \beta_3 A_j + \beta_4 D_j + \beta_5 F_j + \varepsilon_j, \quad \forall\, i \neq j,$$

where P_j is the value of the last available sale of property j, W_{ij} is a measure of distance between property i and j (a spatial-weights matrix); S_j and A_j are vectors of structural and environmental amenity characteristics, respectively, for property j; D_j is the year when the property was last sold; F_j is a vector of fire occurrences; and ε_j refers to the error structure. The data used in the model are summarized in Table 4.1.

Table 4.1: Variables and Summary Statistics

Attribute	Mean	Std. Dev.	Range [Min; Max]
Property Value			
Sales value ($'000s)	412.86	249.48	[3; 6,100]
Unit price ($ per m^2)	492.71	260.87	[3.37; 3,234.06]
House Structure and Location			
Area (acres)	0.25	0.26	[0.04; 12.51]
Age[a]	21.78	19.86	[-3; 106]
Number of storeys	1.24	0.41	[1; 1.5; 2; 3]
Number of bedrooms	3.51	1.01	[1; 13]
Number of car garages	0.85	0.46	[0; 3]
Pool (1=Yes; 0 otherwise)	0.09	0.28	[0; 1]
Other buildings (1=Yes; 0 otherwise)	0.002	0.05	[0; 1]
Corner lot (1=Yes; 0 otherwise)	0.11	0.31	[0; 1]
Waterfront (1=Yes; 0 otherwise)	0.007	0.09	[0; 1]
Environmental Amenity			
Prime view (1=Yes; 0 otherwise)	0.08	0.28	[0; 1]
Good view (1=Yes; 0 otherwise)	0.08	0.28	[0; 1]
Fair view (1=Yes; 0 otherwise)	0.07	0.25	[0; 1]
Dummy variable for year of sale			
2004	0.16	0.36	[0; 1]
2005	0.2	0.4	[0; 1]
2006	0.2	0.4	[0; 1]
2007	0.24	0.43	[0; 1]
2008	0.16	0.36	[0; 1]
2009	0.04	0.21	[0; 1]
Wildfire Occurrence			
Number of fires within 500m	0.07	0.26	[0; 2]
Average size within 500m	0.05	0.79	[0; 20]
Number of Fires within 1 km	0.24	0.5	[0; 2]
Average size within 1 km	0.22	0.35	[0; 20]
Number of fires within 2 km	0.83	0.91	[0; 4]
Average size within 2 km	0.48	1.39	[0; 10]
Number of fires within 5 km	3.44	1.7	[0; 10]
Average size within 5 km	1.86	2.1	[0; 7.2]
Total number of fires	15.05	2.85	[12; 21]
Total average size	0.73	0.12	[0.6; 0.92]
WDPA (1=Yes; 0 otherwise)	0.21	0.41	[0; 1]

[a] Negative values included in *AGE* indicate incomplete developments that were under construction at the time of sale and would not be completed by 2010.

We employ two dependent variables for property value: 1) the actual sales value of the property ($) and 2) the property's unit price ($\$/m^2$), which is obtained by dividing the sales value by the area of the land on which the house is located. The latter variable permits us to identify a more explicit impact of environmental amenities on property values because it adjusts for sprawling estates in the data set.

As indicated in Table 4.1, information on properties includes the area occupied by the property, age of the house, the numbers of storeys, bedrooms and car garages (including single and multi), and extra attributes (e.g., a swimming pool). In addition, the data include location factors such as whether the property is on a street corner or waterfront. In addition to wildfire-related amenity values (e.g., fire occurrences, whether a property lies within the WUI), additional amenity variables are represented by dummy variables for each of three different view categories of the lot on which a house is located. There are also dummy variables representing six sale year categories beginning in 2004.

The potential effect of historic wildfire occurrence is primarily modeled in terms of two factors – the number of fires that occurred in the 10 years before a property was sold and their associated average size. These two factors are then further classified according to the distance between wildfires and properties.[9] This is done using concentric circles with radii of 500 m, 1 km, 2 km and 5 km from a property, with nearby wildfires assumed to have a stronger impact on property values than more distant ones. For comparison, we also estimate a model that examines the effect of any wildfire occurrences in the study area. Intuitively, since a negative correlation might be expected

[9] Note that distances between wildfires and properties are not included in the spatial weight matrix, which accounts for spatial autocorrelation among properties (see below).

between the two variables (many small fires or a few large ones), we test for correlation between them. However, we do not find significant correlations in terms of any radii.

A dummy variable is used to identify properties located in a Wildfire Development Permit Area (WDPA) as the values of such properties are expected to differ from properties elsewhere, ceteris paribus. The expected impact of locating in a WDPA is not known a priori. A potential purchaser of a home in a WDPA would be aware of the fire risk, and thus would reduce their WTP. However, houses in the WDPA might be more attractive than similar ones elsewhere because of the added environmental amenities associated with the wildland-urban interface, which is often identical to the WDPA. Therefore, the dummy variable can be used to estimate the combined effects of the two inverse impacts.

A spatial matrix W is used to account for possible spatial autocorrelation in property values. In general, there are at least two popular ways to measure spatial autocorrelation: one is using a spatial matrix with binary values identifying the nearest neighbours; the other one is to construct a matrix of weights based on inverse distances (or to certain powers controlled by a smoothing parameter) between a particular observation and all the others. Because our data consist of properties from densely-populated urban areas and plus more sparsely-populated WUI areas, the majority of observations are densely clustered with the remainder more sparsely spread out over the study region (Figure 4.2). Thus, the mean distance between properties and their nearest neighbours tends to be quite small but the variance is great. Particularly in this study, properties in sparsely-populated areas might exhibit greater price variability among neighbors than those located in the densely-populated areas. We address this by combining the method of inverse distances and the method of choosing only properties within a certain radius of the property in question. That is, we only use inverse distances (which are standardized so the sum of a row in the weights matrix equals to 1) between a property and its neighbours within a certain radius of the property and exclude properties outside this radius (instead of including all properties as in the standard inverse distance approach). When calculating the matrix of weights, we choose a radius of 100 meters ruling out properties farther away; a circle with radius of 100 m around each property ensures that 95% of our observations have at least one nearest neighbour. By doing so, the size of the spatial matrix W is $n \times n$, where n is the number of observations, and the diagonal elements and those row elements outside the circle around the corresponding properties are set to zero.

We then multiply the logarithmic value of each property value by its associated matrix of weights (corresponding row vector of the matrix W), where the number of neighbours used to calculate the weights matrix varies according to the sample density. Thus, the logarithm of the weighted property values within a 100-meter neighbourhood is used as an independent variable to account for potential spatial autocorrelation among property values. We test for potential spatial autocorrelation in both the sales value and unit price models. Finally, we assume that there is no spatial autocorrelation among non-price features.

In the regressions, we employ maximum likelihood estimation (MLE) because, when we have spatial lags of the two dependent variables (i.e., the weighted sales values and the unit prices of nearby properties), the ordinary least squares (OLS) estimators could potentially be biased. Upon testing for serial correlations among the independent variables prior to running the final regressions, we found no significant correlation.

4.5 Results

The regression results for the dependent variables, sales value ($) and per unit value ($\$/m^2$), are provided in Tables 4.2 and 4.3, respectively. In each table, we present coefficient estimates for five regression equations, one equation for each of the four concentric circles around a property in which fires might occur and an equation for all fires regardless of distance from the property (but within the study region).

The estimated coefficients on most of the housing characteristics are statistically significant and have the anticipated sign in both regression models. For the sales value, characteristics like age, area, numbers of bedrooms, car garages and storeys, and whether there is a pool or it is waterfront have the expected signs (Table 4.2). There is no apparent impact on the sales value from being on a corner, nor does there seem to be any benefit in having other buildings on the property. For the unit price, corner lot and number of car garages are not significant. Contrary to what one might expect, additional bedrooms and whether there is a pool or other buildings in addition to the residence have a negative impact on per unit sales value. In the case of other buildings, this is explained by the fact that their value is lower than the value of the residence, while their area is included in the determination of per unit price. Likewise, on a per unit basis, the marginal value of a swimming pool or bedroom is less than the average value of a property, so one would expect a negative sign on these characteristics in the regressions reported in Table 4.3.

Table 4.2: Estimation Results: Sales Value ($) as Dependent Variable

Variable	Coefficient (Std. Dev)				
	0.5km radius	1km radius	2km radius	5km radius	All Area
Age	-0.0015***	-0.0015***	-0.0015***	-0.0014***	-0.0016***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Area	0.1014***	0.1025***	0.1012***	0.1009***	0.1019***
	(0.0174)	(0.0174)	(0.0174)	(0.0174)	(0.0173)
# of bedrooms	0.0192***	0.0199***	0.0195***	0.0203***	0.0189***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0010)
Corner lot	0.0004	0.0002	0.0006	-0.0015	-0.0014
	(0.0141)	(0.0141)	(0.0141)	(0.0140)	(0.0140)
Fair view	-0.0289	-0.0293	-0.0295*	-0.0352**	-0.0347**
	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0177)
Good view	0.0066	0.0050	0.0055	0.0041	0.0076
	(0.0161)	(0.0161)	(0.0162)	(0.0161)	(0.0161)
Prime view	0.0787***	0.0791***	0.0794***	0.0856***	0.0771***
	(0.0159)	(0.0159)	(0.0161)	(0.0160)	(0.0158)
# of car garages	0.0731***	0.0734***	0.0736***	0.0724***	0.0730***
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0102)
Other buildings	0.1021	0.1012	0.1007	0.0977	0.0920
	(0.1034)	(0.1034)	(0.1034)	(0.1031)	(0.1029)
Pool	0.2210***	0.2221***	0.2197***	0.2122***	0.2201***
	(0.0159)	(0.0159)	(0.0159)	(0.0159)	(0.0158)
# of storeys	0.0583***	0.0559***	0.0563***	0.0478***	0.0571***
	(0.0110)	(0.0111)	(0.0111)	(0.0111)	(0.0109)
Waterfront	1.2525***	1.2549***	1.2548***	1.2557***	1.2509***
	(0.0570)	(0.0570)	(0.0570)	(0.0568)	(0.0567)
Neighbour[a]	0.3116***	0.3111***	0.3087***	0.2897***	0.3150***
	(0.0155)	(0.0155)	(0.0157)	(0.0159)	(0.0154)
# of fires	0.0252	0.0217**	0.0091	0.0103***	0.0361***
	(0.0204)	(0.0111)	(0.0056)	(0.0031)	(0.0049)
Fire size	-0.0466	0.0010	-0.0067	-0.0243***	0.1796***
	(0.0355)	(0.0156)	(0.0068)	(0.0055)	(0.0551)
WDPA	0.0476***	0.0479***	0.0498***	0.0395***	0.0495***
	(0.0112)	(0.0112)	(0.0113)	(0.0113)	(0.0112)
Y2004	-0.3629***	-0.3623***	-0.3629***	-0.3595***	-0.2440***
	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0239)
Y2005	-0.2050***	-0.2048***	-0.2049***	-0.2026***	-0.1274***
	(0.0135)	(0.0135)	(0.0135)	(0.0134)	(0.0174)
Y2006	0.1971***	0.1971***	0.1961***	0.1912***	0.1236***
	(0.0129)	(0.0129)	(0.0129)	(0.0129)	(0.0187)
Y2007	0.3175***	0.3165***	0.3151***	0.3009***	0.1828***
	(0.0144)	(0.0144)	(0.0145)	(0.0147)	(0.0276)
Y2008	0.1954***	0.1933***	0.1926***	0.1764***	-0.0100
	(0.0226)	(0.0226)	(0.0226)	(0.0228)	(0.0412)
Intercept	8.5650***	8.5674***	8.5977***	8.8499***	7.8643***
	(0.1992)	(0.1993)	(0.2012)	(0.2059)	(0.2189)
Log Likelihood	-2120.56	-2119.58	-2120.26	-2104.03	-2063.19

[a] Neighbour indicates the weighted sales value of neighbouring properties within 100-meter radius.

Table 4.3: Estimation Results: Unit Price ($\$/m^2$) as Dependent Variable

Variable	Coefficient (Std. Dev)				
	0.5 km radius	1 km radius	2 km radius	5 km radius	All Area
Age	-0.0047***	-0.0045***	-0.0048***	-0.0047***	-0.0050***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
# of bedrooms	-0.0436***	-0.0411***	-0.0425***	-0.0436***	-0.0448***
	(0.0063)	(0.0063)	(0.0063)	(0.0063)	(0.0063)
Corner lot	0.0257	0.0251	0.0247	0.0228	0.0246
	(0.0203)	(0.0203)	(0.0203)	(0.0203)	(0.0203)
Fair view	0.0172	0.0128	-0.0014	0.0014	0.0027
	(0.0258)	(0.0257)	(0.0258)	(0.0257)	(0.0257)
Good view	-0.1289***	-0.1378***	-0.1406***	-0.1356***	-0.1311***
	(0.0233)	(0.0232)	(0.0233)	(0.0233)	(0.0233)
Prime view	-0.1584***	-0.1564***	-0.1802***	-0.1570***	-0.1646***
	(0.0230)	(0.0229)	(0.0232)	(0.0231)	(0.0229)
# of car garages	-0.0034	-0.0029	-0.0049	-0.0047	-0.0048
	(0.0149)	(0.0148)	(0.0149)	(0.0149)	(0.0149)
Other buildings	-0.3403**	-0.3448**	-0.3305**	-0.3454**	-0.3493**
	(0.1494)	(0.1490)	(0.1494)	(0.1494)	(0.1494)
Pool	-0.0503**	-0.0452**	-0.0522**	-0.0635***	-0.0540**
	(0.0228)	(0.0228)	(0.0228)	(0.0229)	(0.0228)
# of storeys	0.0907***	0.0793***	0.0920***	0.0822***	0.0933***
	(0.0159)	(0.0160)	(0.0160)	(0.0161)	(0.0159)
Waterfront	0.7516***	0.7629***	0.7451***	0.7501***	0.7407***
	(0.0822)	(0.0820)	(0.0822)	(0.0822)	(0.0822)
Neighbour[a]	0.1424***	0.1403***	0.1489***	0.1223***	0.1511***
	(0.0224)	(0.0223)	(0.0226)	(0.0231)	(0.0223)
# of fires	0.1589***	0.1141***	0.0238***	0.0173***	0.0344***
	(0.0294)	(0.0160)	(0.0081)	(0.0044)	(0.0071)
Fire size	-0.1208**	0.0185	0.0367***	-0.0227***	0.2600***
	(0.0512)	(0.0225)	(0.0099)	(0.0080)	(0.0800)
WDPA	-0.1306***	-0.1287***	-0.1317***	-0.1383***	-0.1260***
	(0.0161)	(0.0161)	(0.0162)	(0.0163)	(0.0161)
Y2004	-0.4092***	-0.4068***	-0.4077***	-0.4065***	-0.2747***
	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0347)
Y2005	-0.2317***	-0.2318***	-0.2327***	-0.2302***	-0.1491***
	(0.0195)	(0.0194)	(0.0195)	(0.0195)	(0.0253)
Y2006	0.1854***	0.1858***	0.1849***	0.1787***	0.1284***
	(0.0186)	(0.0186)	(0.0187)	(0.0187)	(0.0272)
Y2007	0.3323***	0.3276***	0.3285***	0.3106***	0.2231***
	(0.0209)	(0.0208)	(0.0210)	(0.0213)	(0.0401)
Y2008	0.2096***	0.2001***	0.2091***	0.1862***	0.0416
	(0.0326)	(0.0326)	(0.0327)	(0.0331)	(0.0598)
Intercept	4.4203***	4.4336***	4.3200***	4.6719***	3.6201***
	(0.2876)	(0.2871)	(0.2905)	(0.2982)	(0.3177)
Log Likelihood	-4441.22	-4425.49	-4440.17	-4442.32	-4441.55

[a] Neighbour indicates the weighted unit price of neighbouring properties within 100-meter radius.

The impact of the quality of views is somewhat mixed. A 'prime' view has a significantly positive impact on the value of a house, while a much poorer ('fair') view pulls down the property value and an in-between ('good') view has no statistically significant impact on property values. However, when we consider the unit price of a property (Table 4.3), a 'fair' view becomes insignificant while the other two variables tend to pull down the value of property. This can also be explained by the area, that is, a better view is usually associated with a larger lot (greater privacy). Once property values are adjusted by size, the benefits brought by higher environmental amenities are cancelled out by the larger area.

The estimated coefficients on all of the year dummy variables are consistent across the regressions results reported in Tables 4.2 and 4.3; the estimated coefficients are all highly statistically significant. They indicate that, compared to average prices, those in 2004 and 2005 were lower and those in more recent years were higher. This means that property values were rising throughout the period, even after controlling for wildfire effects.

Finally, consider the impact of wildfire on property values. The occurrence of wildfires in the ten years prior to the sale of a property generally has a positively significant impact on property values. On the other hand, however, the estimated coefficients on size of wildfires are quite mixed and not statistically significant in the sales value equations (Table 4.2), except in the case of the regression equation for the 5 km radius and the entire study area. By contrast, the impact of locating in the WDPA increases the sales value in a statistically significant way (Table 4.2), but actually reduces the per unit value of houses (Table 4.3).

Following Price et al. (2010), we also calculated the associated marginal effects of wildfires on both dependent variables, taking into account the effect on values of spatial autocorrelation among neighbouring properties (Table 4.4). Although the effect of number of fires is only significant in some regressions, the results still reveal a trend: an additional wildfire during the past decade would increase rather than decrease the average value of a property, but the extent of the increase is smaller if a greater neighbouring area is considered. For example, the marginal increase within a 1-km neighbourhood is \$13,005 (or \$65.43/m^2), while the value drops to \$5,987 (or \$9.72/m^2) if the neighbourhood radius increases to 5 km. However, if all fire events in Kelowna are considered, such marginal effects again rise, to \$21,758 or \$19.98/m^2. The results also indicate that a hectare increment in the average size of a wildfire occurring within the past 10 years and no more than 5 km from the property could actually decrease the average value of a property by \$14,124 or the per unit value by \$12.75 per m^2. The decreases in the unit price are even higher had the fire been within 500 m of the property, while the marginal impact of fire size actually increases property value when the entire study area is considered, adding \$108,249 to a property's value, or \$150 per m^2. Note that, for most observations, average fire sizes in our data are generally smaller than 1 hectare.

Table 4.4: Marginal Effects of Wildfire on the Average Sales Value and Unit Price

Variable	0.5 km radius		1 km radius		2 km radius		5 km radius		All Area	
	Sales value (\$)	Unit Price (\$/m^2)	Sales value (\$)	Unit Price (\$/m^2)	Sales value (\$)	Unit Price (\$/m^2)	Sales value (\$)	Unit Price (\$/m^2)	Sales value (\$)	Unit Price (\$/m^2)
# of fires	–[a]	91.35	13,005	65.43	–	13.79	5,987	9.72	21,758	19.98
Fire size	–	-69.44	–	–	–	21.26	-14,124	-12.75	108,249	151
WDPA	28,548	-75.08	28,707	-73.8	29,742	-76.29	22,959	-77.68	29,835	-73.17

[a] – indicates no value is calculated because of the insignificance.

More evidence regarding the impact of risk of wildfire comes from the data on the WDPA. Homes located within the WDPA are worth roughly $28,000 more than comparable homes outside this zone. However, the results also suggest that there is a negative impact of some $75 per m^2. We further discuss those results below.

4.6 Discussion and Conclusions

The regression results concerning wildfire occurrence have several interesting implications. First, wildfire occurrence does have a significant influence on unit prices at almost all distances, while its influence on sales values is significant only when wildfires within a 5-km radius (or all fires) are considered. This is mainly because, compared to the unit price, the sales value of a property largely depends on the lot size – land value usually constitutes the largest proportion in the total assessed value of a property. While land values within the same neighbourhood are likely to be similar, house structures might vary significantly within the neighbourhood and even between adjacent neighbours. Thus, the sales value may vary considerably among neighbours as well. Moreover, when small radii like 0.5 km or 1 km are considered, wildfire occurrence is also less variable (e.g., there are mostly 0s and 1s for the number of fires). Therefore, the correlations between wildfire occurrence and sales value is less pronounced when the neighbourhood is relatively small.

Second, while number of fires that occurred in the past decade does have significant influence on both sales values and unit prices, the impact is positive, which appears to contradict the results of some previous studies. According to the marginal effects of past fire frequency at different distances, the homebuyer likely considers the risk of fire to be reduced in proportion to the number of nearby fires – there is now a smaller risk that their property will be affected by wildfire in the near future if more fires occurred in the past decade, but such a perception becomes weaker when fires are farther away. One possible explanation is that, if more fires have occurred in the past decade, there is a perceived lower risk that there will be a future wildfire that will affect the property – homebuyers behave as if wildfire is unlikely to strike two or more times in the same general location. Likewise, when all wildfires in Kelowna are considered, the property values increase.

For fire size, on the other hand, the impacts on both dependent variables are mixed. The influence of fire sizes at distances within a 5-km radius of the property in question, and the influence of all fire sizes more generally, are statistically significant but with opposite signs. Unlike the number of fires, this implies that homebuyers treat the average fire size in the last decade that occurred within a 5-km radius as posing a potential future risk to properties. Larger average fire size in the nearby seems to imply a greater possible threat to future property damage. By contrast, such influences become positive when all fire events are included, which is consistent with the estimated signs on the coefficient on the number of fires. We believe the reasons for this are similar to those for the number of fires: when it comes to the entire city of Kelowna, homebuyers may not consider large fire size as a direct threat to nearby areas; rather, they may perceive that larger average fire size in the past lowers the risk of a similar situation in the near future. The estimated effects for smaller radii seem to contradict each other, probably because too few fire events are included in those areas (as noted earlier).

Third, as indicated by Tables 4.2 and 4.3, there is significant spatial autocorrelation in both sales values and unit prices. This implies that the aggregate price at which neighbouring properties previously sold has an effect not only on what the homebuyer is willing to pay, but on standardized per unit property values. In this regard, the unit price does present a distance-based gradient at the neighbourhood level, which implies that such influences from neighbours do not only depend on the lot size, but many other factors, such as location and nearby environmental amenities.

Finally, houses located within Kelowna's WDPA are relatively more valuable in terms of the sales value but less valuable in standard or per unit price terms due to higher fire risks. For the former, there are two potential reasons. First, as argued above, amenity values of locating in the WDPA have a positive impact on property values that exceeds the downward pressure on values associated with the greater risk of fire in these areas. For example, most parks and golf clubs in Kelowna are located in the WDPA in northwest Kelowna, which also has more convenient access to downtown than the southwest. Second, the homes located in the WDPA are required to meet certain 'fire-proofing' standards that increase the costs of construction which, in turn, get capitalized in the property value and/or reduce the perceived risk of damage from wildfire. For the latter, since amenity values are apportioned by larger lot sizes while fire risks are not, and compared to those properties located in urban areas with high values but relatively small lot sizes, per unit price is expected to be negatively affected if located in the WDPA.

The results of this study provide some indication as to how wildfires affect residential property values in Kelowna. However, because we find some inverse influences on property values between number of fires and average fire size, further research is required to determine why this might be the case. In this regard, it would be useful to expand the study to other cities in BC, and include additional environmental amenities in the regression analyses as control variables. It might also be useful to survey residents in the WUI, and outside it, to determine attitudes, perceptions of fire risk, et cetera, and include these variables in the hedonic pricing model. Important in this regard is knowledge about any perceived and realized public subsidies from which homeowners in the WUI might benefit. Public policy related to wildfire mitigation (fuel load management) and suppression (firefighting efforts), zoning laws, building codes, provision of public services (school buses, electricity, sewage, etc.), and property rights impact the willingness of homebuyers to live in the WUI and these too need to be investigated further.

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Chapter 5: Conclusions

5.1 Summary of the Study

Uncertainty of wildfire occurrence in BC is considered to be increasing over time due to climate change, with greater variability across fire seasons a likely outcome. This does not only imply that the occurrence of more extreme and catastrophic events during dryer and hotter summers will increase, but also that there could be a chance of having even milder fire seasons caused by abnormally more precipitation. In the case studies, temporal lags between climate indexes and wildfire occurrence, randomness in terms of monthly and inter-zonal distributions in monthly wildfire prediction, as well as distance-based spatial effects of historic wildfire occurrence were discussed. While previous studies have developed more comprehensive wildfire forecasting models with detailed results, the research presented here offered a different perspective with relatively straightforward statistical models, as well as readily available and easy-to-use data. Therefore, the analysis of wildfire occurrence and its influences examined in this study are expected to provide policymakers and home buyers with useful information for making decisions that reduce the adverse impacts of future wildfires.

In Chapter 2, wildfires in the BC Interior and geographical conditions associated with wildfires were discussed in detail. One main feature was illustrated: wildfire occurrence is uncertain in both temporal and spatial dimensions. Discussion of the data used in this study and procedures using GIS models provided a spatial perspective in preparing data and conducting necessary tests for regression models. Based on monthly temperature and precipitation data from large numbers of weather stations, a simple statistical analysis examined the strong correlations between monthly wildfire occurrence and local weather conditions. The regression models also captured the spatial differences across forest districts in terms of distances between hot spots and associated nearest municipalities.

Many previous studies argued that number of wildfires in a certain period usually follow a Poisson or negative binomial distribution rather than a Gaussian distribution. Therefore, the wildfire occurrence and associated burned areas were estimated in Chapter 3 using two count models. Zonal random effects were also included in estimating firefighting expenditures. Compared to the discussion of the impacts of monthly weather conditions at the end of the previous chapter, the model employed in Chapter 3 investigated the relationship between monthly wildfire occurrence and the climate index. The case study found that the ENSO index at regions 1+2 with a four-month lag provides statistically significant estimates of monthly number of fires in the BC Interior, with lightning frequency as the estimator for extremely low fire occurrence in winter. The study also found that the general Poisson model provides a good appropriation in estimating monthly burns larger than 1,700 ha, the probabilities of which were estimated by the ENSO index as well. Moreover, fire zones in the Northern Interior, especially the Northeast, are relatively more likely to witness large wildfires. This coincides with the findings in Chapter 2 that more large fires occur in remote, less populated districts where the need and the ability to suppress wildfires is less urgent. As a corollary, areas around municipalities in the south tend to experience more frequent small fire events as both the identification of wildfire ignition and efforts to fight wildfires are easier in more densely populated areas.

In Chapter 4, we were not interested in simulating and predicting wildfire events. Rather, we investigated the distance-based effects of wildfire occurrence on property values directly using historic data. This is unlike the impacts on firefighting expenditures: since wildfire occurrence is only a minor contributor to changes in property values compared to many other factors, a hedonic pricing model was used to determine the explicit impact of fires. In terms of different distances to properties, we found that homebuyers discount the impact of fire frequency on their purchase even if wildfires occurred relatively nearby – as if fires do not strike twice in the same region; however, large average fire size in nearby areas would adversely affect homebuyers' willingness-to-pay. Mostly important for policy purposes, the evidence suggested that amenities available in the wildland urban interface add more value to residential properties than that lost as a result of wildfire risk.

5.2 Contributions

The approach in Chapter 3 provided a new perspective regarding the uncertainty of wildfire occurrence, namely, that climate indexes had an important impact on the potential to forecast wildfire occurrence several months in advance of fire season. However, based on count models, we argued that future occurrence of wildfires cannot be predicted precisely; rather, it is more like a random process that is affected by several uncertain factors (e.g., climate conditions, fuel load, lightning and human activities). Modeling wildfire frequency based on the negative binomial distribution is preferred to that based on the Poisson distribution, as it is very likely to be the case that the expected mean of fire frequency for a given period and region is smaller than the associated standard deviation, while the Poisson distribution always assumes that the mean and standard deviation are identical. Unlike many other studies that focus on total burns, we modeled burn areas by paying more attention to the characteristics of large burns that are rarer but also more catastrophic. To our knowledge, there are few studies that make use of the generalized Pareto distribution to model large burn areas. The good approximation of monthly large burns using a GP model in this study provides supportive evidence of the potential for modeling large burn areas.

By constructing statistical relationships between wildfires and climate conditions, we believe that it is possible to predict future occurrence of wildfires at a large scale using a top-down approach by focusing on only several simple variables, rather than a bottom-up approach with complex input data that are specified for different ecosystems and require a considerable degree of computation. The underlining argument is that, since many factors that affect the occurrence of wildfires (e.g., climate conditions and lightning activities) are expected to be quite uncertain when a relatively small scale is considered (e.g., at a landscape level), it is nearly impossible to predict the exact location and the time of occurrence of a fire event. Therefore, long-term future wildfire occurrence for the BC Interior that is obtained by aggregating predicted situations at the landscape scale may not necessarily be more accurate than the prediction made directly using explanatory variables at the provincial level.

We also believe that the statistical relationships estimated by the count models can be used as a simple indicator for predicting firefighting expenditures for the upcoming fire season, which are significantly related to number of fires and total wildfire area, with especially large fires accounting for the greatest expenditures. Forecasts at this scale are possible employing long-term forecasting weather data from Environment

Canada or other climate models. Further, since fires with large burns are more responsible for the high firefighting expenditures, predictions based on count models of the occurrence of large fires and associated areas burned for an upcoming fire season might contribute to the budget planning. This is particularly important as firefighting expenses are an important component in the province's contingency fund of the annual budget, and better predictions of wildfire occurrence can help reduce the chance that the provincial government runs up unexpected deficits.

In terms of the impacts of wildfires on property values, the significant but inverse effects between fire frequency and fire size implied that policy makers should pay more attention to the control of large burns if they want to lower the impact of past fires on real estate markets. Also, the finding in this study suggested that local municipalities in the BC Interior might need to adopt some policies to make potential fire risks in the WUI better known to the public, so that real estate markets can better quantify such risks and homebuyer's willingness-to-pay via, for example, insurance premiums. The local government maybe also need to make some stronger measures to lower fire risks in the WUI, such as more strict inspections to ensure areas are fire-proofed.

5.3 Limitations and Future Work

The current study examined several possible ways to predict wildfire occurrence and estimate its impacts. While the results were promising, there are limitations. The discussion of the relationship between weather conditions and wildfire occurrence in Chapter 2 is sensitive to the assumption that the error term is normally distributed (i.e., Gaussian). Many previous studies argued that the number of large fires and the associated size are usually quite skewed so that residuals are not approximately normal (Genton et al. 2006). This is partly refined in Chapter 3 by using count models with different probability distributions. However, the estimation of inter-annual changes in wildfire occurrence still does not fit the historic data well because of the relatively small variance in the ENSO index. For possible future work, more physical conditions about forestlands in local areas could be used to improve the statistical fit and thus predictions. In addition, a de-clustering procedure for weather station data may be required in terms of weather data interpolation for forest districts.

Particularly for the relationship between weather conditions and wildfire occurrence, finer spatial layers (e.g., grid maps with higher resolutions) could allow us to embrace more variables in the model, while also facilitating the use of detailed historic weather data. For example, some long-term historic weather data are available in gridded format from Environment Canada, National Centers for Environmental Prediction North American Regional Reanalysis, and from ClimateBC. We can also aggregate historical wildfire occurrence to annual or even decadal scales, so that predictions of potential wildfire severity for longer periods (e.g., several years or decades) could be possible using projected weather conditions from climate models (e.g., ClimateBC). Further research might examine the potential to construct financial weather derivatives based on the estimated relationship between weather outcomes and wildfire occurrence. For example, the provincial government might be able to utilize certain financial means (e.g., weather insurance) to reduce possibly unexpectedly high firefighting costs due to uncertain wildfire occurrence.

Finally, as a follow-up study, the estimated marginal impacts of wildfire occurrence on property values in Chapter 4 can be used to estimate possible changes in property values as a result of wildfire occurrence in nearby areas. However, as mentioned in the text, more environmental amenities as well as homebuyers' risk preferences should be considered in the model. Additionally, analyses of the potential impacts on economic activities (e.g., home purchase) of a single extremely large fire event are also necessary.

5.4 References

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