Development of GIS-based Methods for Modeling Fire Hazard - A Large Scale Empirical Investigation

by

Mohamed Mansour Elshabrawy

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in
Transportation Engineering

Department of Civil and Environmental Engineering
University of Alberta

Abstract

Wildland fires are natural occurrences in the woodland landscape that play a vital ecological role in Canada's boreal forest region. However, they also endanger human life and can disrupt timber resources and other economic assets. Recently, wildfires have ravaged areas of British Columbia, Alberta, California, and other parts of North America, Europe, and Australia. Loss of human life, the economic repercussions in terms of suppression expenses and property damage have been staggering. Many of these fires have occurred near the wildland-urban interface, mostly natural regions increasingly subject to human development. As the population in these areas grows, there is a greater risk of economic impact and human loss. As a result, it is critical to provide an accurate classification of the green spaces as well as which areas pose the greatest risk of fire depending on the ignition sources found in the forested areas. Consequently, developing a fire risk assessment model can be used to effectively locate high risk areas/zones and form a foundational building block for conducting future research for fire prevention strategies or evacuation plans, and policy intervention. This model would also help in locating the low-risk areas/zones to be developed since they could add to the destructive consequences if ignored in the planning and expansion process.

To develop an effective assessment model, this thesis has three main tasks. The first task is to provide a thorough review of existing literature, followed by background information that will help to build a contemporary, urban fire risk model. As a case study to form the basis of a fire risk model, this research uses anthropogenic, biologic, topographic, and climatic data from the City of Edmonton (CoE). This is then layered and mapped onto the City’s geographic location using ArcGIS and Python scripting language and then combined with data obtained from large datasets. The datasets in this research are satellite imaginary, aerial LiDAR dataset, urban Primary

Land and Vegetation Inventory (uPLVI), and Road Weather Information Systems (RWIS) data, used to extract 12 variables that represent the fire risk assessment model. Fire risk assessment maps are subsequently generated by processing and analyzing all the datasets using the analytical hierarchy process (AHP) technique. The output of this research effort is a fire risk model that identifies the locations with the highest risk of wildfire within the CoE.

Secondly, this study forecasts the wildland fire risk for 2050 and 2080, given the climatic projections from IPCC RCP4.5 and RCP8.5 (Representative Concentration Pathway). This analysis offers a better understanding of the forecasted climate change by highlighting transportation development and evacuation planning and integrating a multitude of data sources, including temperatures, precipitation, wind speed, and humidity levels. Results indicate that from 2021 to 2050, the fire risk may increase by almost 20%. Furthermore, the risk will increase by another 11% from 2050 to 2080 for the City of Edmonton.

Finally, a comprehensive discussion that illustrates all the findings of the fire risk maps, current and forecasted, is presented. The fire risk map and the road map of the CoE are overlayed to facilitate insight into transportation development and evacuation planning. To help create a climate resilient municipality, an ecological vulnerability classification map is constructed to identify developable areas and areas that should remain under preservation. Since creating awareness for climate adaptation and zone resiliency is a shared goal among stakeholders, a brief discussion on the role of each stakeholder is provided. The discussion covers strategies for fire prevention and mitigation in high-risk areas/zones, as well as establishing several cornerstones for strategic planning and action to strengthen climate resilience and the transportation development foundation of urban communities.

Dedication

In dedication to my dearest parents: Mr. Mansour Elshabrawy and Prof. Eman Hegazy, my dearest wife: Mrs. Nada Elhawary, and my dearest sons: Youssuf and Zein, who always inspire me to fulfil my goals and motivate me to never give up when faced with life's challenges. These beautiful and unforgettable experiences would not have occurred without their unending affection, motivation, understanding, and unwavering encouragement.

Acknowledgments

First and foremost, I want to share my heartfelt gratitude, admiration, and a note of thanks to my supervisors, Prof. Karim El-Basyouny and Prof. Tae J. Kwon. They have been this research's most ardent supporters and greatest leaders. I am grateful to my supervisors for allowing me to study in their research group. Their patience, advice, and brilliant research suggestions have been very enlightening. They have made this journey mean more than a mere supervisor/assistant relationship. Even though this research was conducted entirely remotely during the COVID-19 pandemic, it was completed and exceeded expectations thanks to their expanded experience and management skills.

I would like to thank Prof. Farook Hamzeh and Prof. Stephen Wong for being part of my examination committee.

I am very grateful to all my colleagues and friends, especially Karim Habib and Maged Gouda, for their ideas, support, and motivation. I had a fantastic and unforgettable time with them all.

In addition, I would also like to thank the City of Edmonton and the University of Regina for providing me with all the necessary datasets. Thanks also go out for the members of the CoE/UofA project support committee for providing me with constructive and positive feedback during our regular meetings.

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Nomenclature

Acronyms

AHP	Analytical hierarchy process
AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy interface systems
ANN	Artificial neural networks
ASE	Average-standard error
ASP	Aspect
BR	Biologic risk
BRT	Boosted regression tree
CART	Classification and regression tree
CoE	City of Edmonton
CR	Climatic risk
DE	Differential evolution
ELE	Elevation
FA	Firefly algorithm
FT	Forest type
GA	Genetic algorithm
GAM	Generalized adaptive model
GHG	Greenhouse Gas
GIS	Geographic information system

GWLR	Geographically weighted logistic regression
HR	Anthropogenic risk
HVRA	Highly valued resources and asset
ICA	Imperialist competitive algorithm
KPI	Key performance indicator
LiDAR	Light detection and ranging
LU	Land use
MCDA	Multi-criteria decision analysis
MLP	Multi-layer perception
MLP-Net	Multilayer perception neural network
MOA	Meta-heuristic optimization algorithms
NBCC	National building code of Canada
NDVI	Normalized difference vegetation index
PCP	Precipitation
PRXR	Proximity to road
PRXW	Proximity to water
PSO	Particle swarm optimization
RCP	Representative Concentration Pathway
RF	Random forests
RMS	Root-mean-square
RMSE	Roo-mean-square error
RMSS	Root-mean-square standardized
RMSSE	Root-mean-square standardized error

RWIS	Road weather information system
SFLA	Shuffled frog leaping algorithm
SLP	Slope
SVMC	Support vector machine classifier
TMP	Temperature
TR	Topographic risk
uPLVI	Urban primary land vegetation index
VAP	Humidity
WS	Wind speed
WUI	Wildland–urban interface

1. Introduction

1.1. Background & Motivation

Municipalities in Canada have accommodated growing populations by expanding their city and land limits. As cities expand, so does the span of their wildland-urban interface (WUI), which is the area where houses contact or intermingle with undeveloped wildland vegetation. What is noteworthy for the present study is that the WUI is particularly at risk of wildfires due to the increased probability of human-nature interaction, as made evident by Mietkiewicz et al. (2020). Hence, the risk of wildfires potentially encroaching upon urban centers increases significantly. Canada has a sizeable number of wildfires (or wildland fires) that occur annually, which, given the interspersion of populated areas within vast wilderness and expansive rural regions across the country (Coops et al. 2018; Hanes et al. 2019). This is particularly evident in Figure ***1-1***, which depicts every wildland fire occurrence in Canada between 1980 and 2018.

Wildfire events are one of the costliest natural hazards in Canada, as evidenced by Alberta's 2016 Fort McMurray Wildfire. This incident resulted in approximately \$3.8 billion in insured losses—the highest-ever loss for a single year in Canadian history at the time (Insurance Bureau of Canada 2020). Due to rapid climate changes, it is likely that wildfires will not only continue to occur but will be more frequent and burn longer (Kives 2019; Climate Atlas 2020). A recent study forecasted that Western Canada is expected to experience a 50% increase in the number of dry, windy days, which will likely contribute to widespread fires in the region (Wang, 2017). For instance, CBC News (2021) reported that the province of British Columbia has recorded

2021 as the third-worst wildland fire season on record, with many fires burning dangerously near communities.

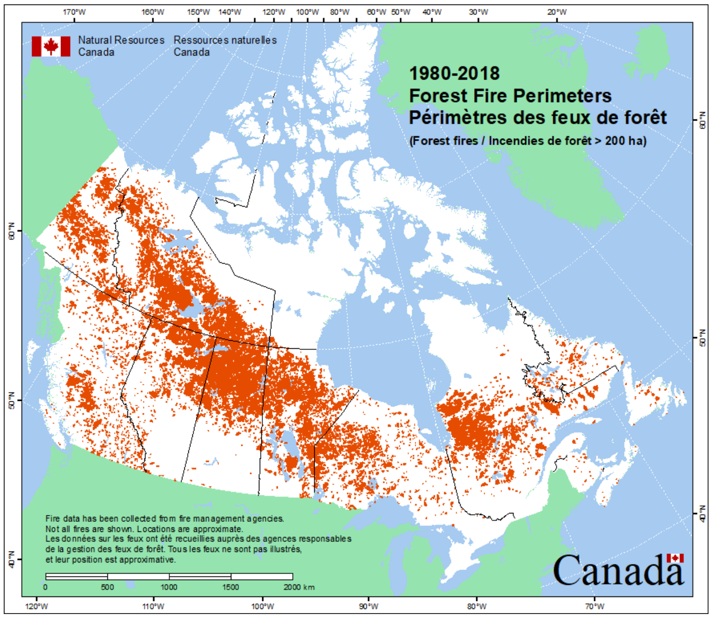


Figure 1-1: All wildland fire occurrences in Canada between 1980 and 2018 (adopted from the Canadian National Fire Database, CNFDB)

The City of Edmonton (CoE) is one of North America's greenest cities with the longest connected stretch of urban parkland in any of the continent's urban areas. The city is also the northernmost metropolis with at least 1 million residents (CALDO 2020). Despite the significant amenities and quality of life derived from the parklands, they can be classified as WUIs and therefore come with increased risk for wildfire events. Hence, the protection and preservation of Edmonton's green spaces and neighbouring urban infrastructure have become a significant concern for the city.

Of course, wildfire is not an issue unique to Edmonton. Many other cities around the globe have developed frameworks to manage wildfires, some of which include Mount Wuyi in China (You, 2017), Urbión in Spain (González-Olabarria, 2012), Provence-Alpes-Côte d'Azur in France (Varela, 2019), Espírito Santo State in Brazil (Eugenio, 2016), Vikos-Aoos parks in Greece (Petrakis, 2005), Apulian region in South Italy (Semerato et al., 2016), and Trieste in northeast Italy (Poldini et al., 2018), California in USA (Wong, 2020). Nonetheless, there continues to exist significant gaps in knowledge that would help develop a unified yet transferrable methodological framework that can identify high-risk zones in urban metropolitan areas.

1.2. Problem Description

The main difficulty for municipal planners is understanding how wildland fires might behave in their particular urban settings. Certainly, both the natural and anthropogenic aspects to the environment have a significant effect on the behaviour of fires as they burn and spread. Climate change factors such as higher winds, more prolonged droughts, and rising temperatures must also be accounted for (Linder, 2010), as they would affect fire intensity, frequency, and movement. Hence, it is in the best interest of any municipality to have a comprehensive and detailed database that inventories all the significant elements of their WUIs, including, but not limited to, vegetation, topography, climate, land use, roads, zoning, and population statistics. This database may be interpreted in a way that would benefit the city's transportation development, for example. As such, it could have a significant positive impact on communities, including transportation safety, transportation operations, and evacuations, to name a few.

Wildland fires are naturally occurring ecological and abiotic events with diverse features being classified by the surrounding terrestrial ecosystem. It is a globally important process that significantly and dynamically affects the ecosystems (Pausas, 2019). Lightning is the primary natural cause for many wildfires, but increasingly forest fires have become the result of anthropogenic (or human) activities. Typically, the anthropogenic causes can be classified into three main categories: (1) culpably or carelessness; (2) arson or the intentional act of starting a fire; and (3) unknown or unlinkable causes (Syphard, 2014).

In addition to anthropogenic causes, catastrophic wildland fire losses owing to increased incidences of extreme climate trends and occurrences are on the upswing. Certainly in North America, increased climate risk is noticeable. For example, Swiss Re, one of the world's largest reinsurance, insurance, and other insurance-based risk transfer companies, reports that 74% of global weather losses and 94% of global assurance weather losses took place in North America in 2012. The U.S. insured losses were 91% connected with extreme weather, including Hurricane Sandy and the severe drought in the Midwest (Bevere, 2013). Future losses will place further tension on the already-strained US and Canadian public finances, particularly if they occur in places with significant property and business value, such as major municipalities.

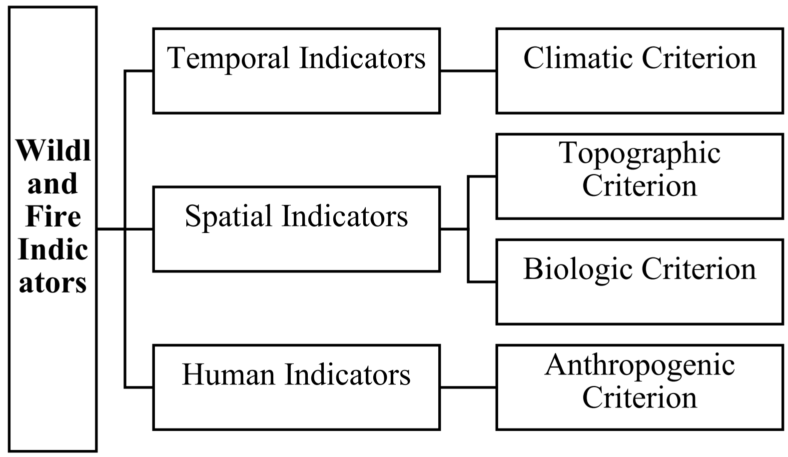


Figure 1-2 Summary of the three common wildland fire indicators

Based on the increased frequency of observed extreme climate events, there are two paths forward for government agencies: continue business-as-usual practices or develop innovative mitigation strategies for at-risk areas. The latter is to strengthen their resilience to climate events, save lives, improve quality of living, and increase safety, to name a few, and generally speaking, preserve or even enhance insurability in those places (Brugmann, 2012). As one of the fastest-growing Canadian municipalities, Edmonton currently faces difficult infrastructure and climate decisions. The city has warmed up at one of the quickest rates of any municipality over the last 50 years. While Edmonton historically has only had one day each year above +30°C, predictions suggest this will increase to more than 15 days by the 2040s and 33 days by the 2070s (Roszko, 2020). Edmonton may also see unprecedented high temperatures never before observed (Martin, 2012; Roszko, 2020). Based on all these factors, it is therefore critical to consider fire risk management in the context of climate resiliency.

Given the growing risk of forest fires within Canada, a surge of research into wildfire prevention/reduction methods have been observed, such as land-use planning that creates buffer areas (or defensible spaces) next to fire-prone areas (Syphard, 2014). In order to develop the proper preventative measures and maximize their impact, it is of paramount importance to identify high fire-risk locations that require intervention. As a result, these locations would benefit from greater transportation planning and safety infrastructure, which would aid in future development and evacuation scenarios.

To develop effective and efficient transportation systems and operations that aid in fire prevention strategies or evacuation plans, the spatial distribution of high fire-risk zones needs to be mapped and presented to planners (Jung, 2013). The availability of such datasets will allow city planners and engineers to develop plans and policies for zoning, evacuation, emergency responses, and firefighting. Wildfire indicators may be grouped into three categories, namely, spatial, temporal, and human (Eskandari, 2017; Tien Bui, 2018; Hong, 2019; Kumari, 2020), as depicted in Figure 1-2.

1.3. Research Objectives

Based on the importance of modeling fire risk hazards for major municipalities as outlined above, the primary research question that will be addressed is:

"How can municipalities model the unique risks of wildfires in highly urbanized environments to better inform evacuation planning and transportation design and operations?"

which leads to a follow-up question stating:

"What are the data requirements for developing a fire-risk model capable of capturing both current and forecasted variable dynamics in order to aid city authorities in setting appropriate emergency planning and response, such that any municipality can improve its climate resiliency and is prepared in the event of any wildland fire?"

This thesis seeks to answer the above questions based upon three objectives:

1. Provide an extensive literature review of past efforts on the topic of wildland fire risk modeling. The information collected and presented comes from a myriad of sources, most of which are from scientific publications that provide an extensive and solid background into wildfire modeling and risk assessment.
2. Develop a wildfire risk map using a multitude of data collected from various sources to identify the city's highest fire-risk areas. These data sources include aerial LiDAR images, satellite

images, urban Primary Land Vegetation Index (uPLVI), and climatic RCP4.5 and RCP8.5 datasets.

3. Identify operational actions municipalities can take to not only adapt their proposed zoning and building regulations, but also develop and understand the necessary transportation infrastructure development in accordance with how wildfire risk has increased due to climate change.

To integrate multiple datasets and map their outcomes, this thesis uses ArcGIS, one of the most widely used geographic information systems (GIS) software. Additionally, a weight assignment method, namely, the analytic hierarchy process (AHP), is introduced where factor weights are assigned to 12 variables that contribute to fire ignition and triggering. The AHP was chosen for its ability to overcome the subjectivity problem in weight assignment (Busico, 2019). Furthermore, a brief discussion on the role of climate change and the future of fire-risk modeling is provided. Concepts into fire-risk management in policies, zoning, and building regulations are briefly introduced, as well as addressing fire-risk management from the perspective of climate resiliency.

This thesis, therefore, serves as a building block for future research on improving evacuation plans and emergency responses in the event of a fire outbreak by highlighting and prioritizing the high-risk areas in the City of Edmonton. In the case of emergency planning, it allows city planners to simulate, plan, and handle concurrent transportation concerns. Some of these concerns include the necessity for urban evacuations, a pre-disaster strategy, and a risk assessment of transportation infrastructure and road networks. Ultimately, this research will facilitate the development of plans that can improve a city’s climate resiliency and enhance citizen readiness (i.e., mobility) in the case of a citywide wildfire.

1.4. Thesis Outline

The remainder of this thesis is divided into five chapters.

Chapter 2 summaries the current literature by: identifying and exploring the variables that affect fire risks; defining fire-risk and their associated unit of analysis; comparing urban and rural fire models; presenting a summary of fire-risk management and policies, as well as zoning and building regulations; and, finally, investigating the impact of climate change on fire risk.

Chapter 3 outlines the datasets used, their sources, and preprocessing requirements.

Chapter 4 provides the methodological framework used for building the fire-risk assessment model. This provides all the necessary information about the various datasets and features (how the factors and variables were extracted from each dataset, an overview of the analytical hierarchy process and weight assignment, followed by an analysis of the fire-risk model, and, finally, the climate predictions and forecasting interpolation).

Chapter 5 presents the results obtained from the fire-risk modeling. It also discusses the key research findings, such as the classification of the vulnerable areas, identification of mitigation factors, and discussion of management cornerstones to create climate resiliency.

Finally, Chapter 6 will summarize the key findings and research contributions and provide suggestions for transportation planning and future research recommendations.

2. Literature Review

Divided into six subsections, this chapter provides an extensive literature review of the previous studies and discusses their limitations. The first subsection (2.1) aims to identify the variables that affect fire risks. The second (2.2) looks at fire-risk models with fire-risk definition and their associated unit of analysis. The third (2.3) compares urban and rural fire models. The following subsection (2.4) presents fire-risk management and policies, as well as zoning and building regulations due to fire risk. The fifth (2.5) subsection investigates the impact of climate change on fire risk. The final subsection (2.6) provides a summary of the literature review findings.

2.1. Factors Affecting Fire Risk

Wildfire risk modeling highly depends on a range of factors and variables, which makes this process critical. As introduced earlier in Figure 1-2, the three wildland fire indicators can be divided into four sub-criteria for modeling: climatic, biological, topographic, and anthropogenic. Each of these criteria has been shown to influence and contribute to the fire season duration, likelihood, frequency, intensity, severity, and extent of a wildfire. Climate and environmental criteria of wildland forest regions control the nature of the fire regimes (Gedalof, 2011). In tandem, the biologic criterion will dictate the spread and intensity of fires in progress, since they include factors such as vegetation type and density, leaf litter depth and moisture, and soil characteristics (Eskandari, 2017). This subsection summarizes the variables used in wildland fire modeling, as shown in Figure ***2-1***.

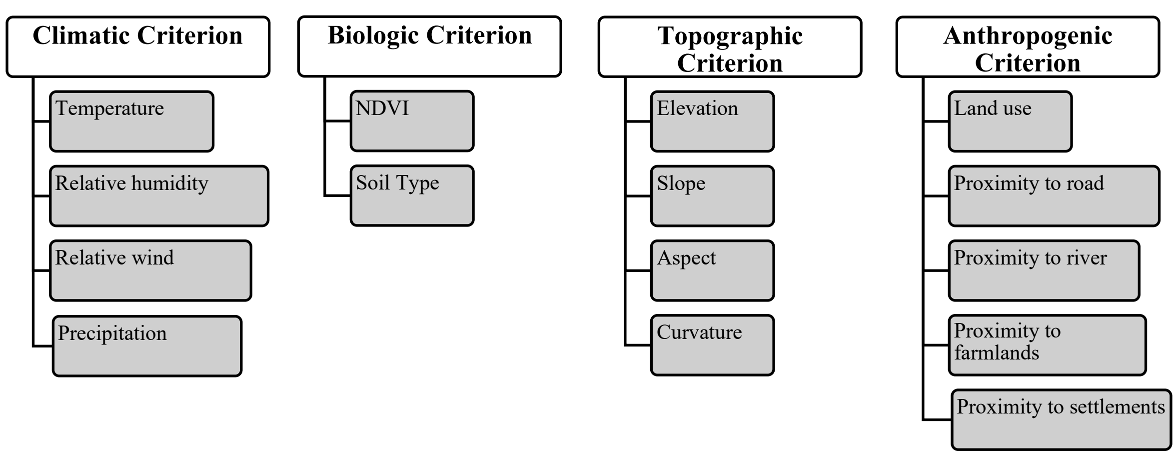


Figure 2-1 Summary of criteria and factors influencing wildland fire

2.1.1. Climate Conditions

Climate plays an essential role in the life cycle of wildfires. Climate patterns such as temperature, relative humidity, and wind speed are correlated with the chance of a fire occurring. Unsurprisingly, hot, windy, and dry conditions result in a higher likelihood for a fire to ignite (Scott, 2013; Chang, 2013; Thach, 2018; Tien Bui, 2018; Hong, 2019; Kumari, 2020). Precipitation has been another critical point of interest for its role in forest fire risk (Eskandari, 2015). Often, precipitation is high in winter but drops significantly in spring and summer, leading to dry conditions (Jaafari, 2018). Since dryness increases fire ignition potential, the precipitation factor should be considered in fire risk assessment.

2.1.2. Biological Factors

Biologic factors strongly influence the potential for ignition and propagation of wildland fires, including the rate of spread, size, and severity. Vegetation is the primary fuel source for wildland fires and, thus, can be considered the most crucial variable in this criterion, represented by vegetation type and density, leaf litter depth, and moisture and soil characteristics (Eskandari, 2017; Bright, 2017; Hong, 2019; Jaafari, 2019; Jaafari, 2019a). For instance, previous studies showed that LiDAR data could capture structural information related to quantitative canopy fuel characteristics (Scott, 2013; Kelly, 2015; Yavari, 2018). Another important measurement is the Normalized Differential Vegetation Index (NDVI), which is a highly dominant factor and can solely determine the biological criterion where a wildfire has occurred (Tien, 2018; Thach, 2018; Hong, 2019).

2.1.3. Topographical Factors

Topographical features may also influence the potential for ignition and propagation of wildfires. Examples of these factors include elevation, slope, and aspect, which were the predictors for wildfire occurrences in many studies (Scott, 2013; Kelly, 2015; Wang, 2017; Thach, 2018; Hong, 2019; Jaafari, 2019). Slope controls the rate of spread—the steeper the slope, the faster the fire propagates (Zhou, 2007). Aspect, or exposure direction, influences the moisture that relates to fire behaviour. Elevation influences solar radiation, temperature, and evapotranspiration of the terrain, related indirectly to forest fires (Camp, 1997). Another topographical feature that affects wildfire propagation is the local curvature of fire. This can be described as the boundary or perimeter line that represents the interface between burnt and unburnt regions. Previous studies have found that the lower the curvature, the higher the rate of fire spread (Hilton, 2017; Thach, 2018).

2.1.4. Anthropogenic Factors

The last factor affecting fire spread and occurrences is the anthropogenic factor (i.e., human indicator). This factor represents the potential for fire ignition and ramification (Thach, 2018). A highly visible example of anthropogenic influences on wildfires is electrical infrastructure. Ma et al. (2020) showed that most fires caused by power infrastructures were often outside the control of the utility company, where a system or piece of equipment fails when overstressed beyond design limits because of adverse conditions. Nonetheless, the devastating Camp's wildland fires in California in 2018 were blamed on PG&E's (Pacific Gas & Electric) failure to properly manage vegetation and upgrade electrical infrastructure along transmission and distribution lines (Kohn, 2021). Certainly, unintended vegetation contact with and ignition from the power lines are rare. However, as this example shows, it can indeed cause fires, particularly with tall vegetation that has not been cut back to maintain a safe clearance zone as per industry best practices. Any risk preparedness plan must, therefore, include electrical utility companies, especially if they have exposed infrastructure. While the interaction of electrical infrastructure, wildfires, and transportation is beyond the scope of this thesis, future work will be needed to better identify risks and needs.

The main anthropogenic variables to be considered are distances or proximities to roads, and types of land use (Thach, 2018; Tien Bui, 2018; Hong, 2019; Jaafari 2019). Other variables that have displayed some influence over the extent of fire spread, such as distances from settlements or farmlands were also introduced (Ward, 2017). In addition, the distances from rivers have been shown to affect the extent of fire spread (Wang, 2017). Also, house structure and building materials influence fire ignition and propagation, potentially leading to structure-to-structure fire propagation, discussed in detail in Section 2.3.

2.2. Fire-Risk Models

Fire-risk models can be divided into four main analytical categories: spatial, nonspatial, parametric, and nonparametric models. In this section, the methods will be thoroughly discussed and differentiated. The method providing the best resolution and accuracy for fire-risk modeling is crucial for future city planning and development. Achieving a higher resolution and better accuracy usually comes at the expense of data needs, computation expense and precise results. This depends upon the dataset availability, which, in most cases, is not available. Hence, simple model fire risk modeling could provide the municipality's experts' required insights.

2.2.1. Non-Spatial Models

Non-spatial models are used to attribute the effects of independent variables to a dependent variable considering no spatial aspect of the variables. This means that the locations or spatial separations of the data points are not considered as contributing factors in the modeling process. The non-spatial models, therefore, rely solely upon measurable or recordable variables without considering their locational attributes.

One of the most widely used non-spatial fire-risk modeling techniques is the Analytic Hierarchy Process (AHP). The AHP method is a combination of qualitative and quantitative, systematic, and hierarchical analyses (Saaty, 1977). Advantages that characterize AHP are its simplicity and transparency; however, its primary advantage is the hierarchical framework that allows research users to consider and measure the relative importance of the indicators. AHP was implemented by Zhang (2013) to establish a fire-risk assessment system, which included three hierarchies of indicators: three first-level indicators (i.e., risk of urban fire, urban vulnerability, and urban anti-fire capability), thirteen second-level indicators (e.g., risk of fire accidents in the past, potential fire risk, meteorological factors, features of the city, evacuation protocols, the safety of buildings, etc.), and forty eight third-level indicators (e.g., number of fires per ten thousand persons, fire deaths per ten thousand persons, relative humidity, rainfall, wind speed, population density, etc.). The Gray Correlation Degree method gives equal weight to each evaluation indicator, enabling researchers to select these indicators objectively. This method was also applied to set up the weight's coefficient and quantify the indicators (Zhang, 2013). The major limitation of this study was the lack of visualization power of the risk levels in the model (i.e., missing a fire-risk hazard map). The association of uncertainty and subjectivity to all available information is another limitation, which requires a researcher with extensive experience in wildfire risk modeling to set up the required accurate weights coefficients and quantify all indicators.

There are also nonspatial simulation methods available, such as the Canadian Fire Behaviour Prediction (FBP) and the U.S. BEHAVE systems. The Canadian FBP is an empirical model developed based on wildfire and prescribed burning data, used to determine the behaviour of surface and crown fires. On the other hand, the U.S. BEHAVE system is a deterministic model based on the properties of fuels studied in laboratories rather than from field data and is used to determine the behaviour of surface fire. This model is deemed to have more realistic predictions as it is based on fuel loading rather than fuel type. A relevant study by Hély (2001) concluded that the BEHAVE system was not suited to predict realistic quantitative fire behaviour, whereas the FBP system was deemed to be an efficient fire behaviour prediction system for the boreal ecosystem.

2.2.2. Spatial Models

Spatial models consider the spatial aspects of the data as a possible influential variable that can affect the outcome of the model. Such models are constructed under a reasonable assumption that the location of the data points, as well as the separation distance between these points, are factors in and of themselves. Data that have an inherent correlation with themselves based on the distance between data points are said to be autocorrelated, where this distance factor can interpolate or predict values at unmeasured locations using the surrounding measured data.

There are several studies for wildland fire-risk modeling using spatial models. The essential component of the modeling framework is the geospatial analysis that is an important initial step to define a consistent geospatial definition for the data. Key factors influencing the success of wildland fire-risk assessment efforts are the level of resources committed as well as the sufficiency and availability of scale-appropriate geospatial data (Scott, 2013). For instance, FARSITE (Fire Area Simulator) is a tool that can describe and simulate temporal and spatial differences of fire behaviour and spread with the support of the Geospatial Information Systems (GIS) (Rothermel, 1972). FARSITE simulation can determine spread, intensity, as well as fuel consumption rate for different seasons (Kanga, 2014).

GIS can be integrated with a fuzzy AHP (Analytical Hierarchy Process) in a decision-making algorithm to model wildland fire areas and identify their associated risk factors. Hence, this model was constructed in two phases. The first phase analyzed the importance of the major criteria in wildland fire risk, such as obtaining the fuzzy weights for each criterion. In the second phase, the spatial data of seventeen sub-criteria were provided and organized in GIS to obtain the sub-criteria maps. Each sub-criterion map was converted to a raster format, where it was reclassified based on the associated risk of its classes for the potential of a fire occurrence. Then, all sub-criteria maps were converted to a fuzzy format using a fuzzy membership function in GIS. The fuzzy map of fire occurrence risk was obtained by overlaying all the major criteria fuzzy maps (Eskandari, 2017). The obtained fuzzy map of each major criterion also had a fuzzy format with a range of values from 0 to 1. The findings suggested that the fuzzy AHP had a high predictive capability for wildland fire detection and prediction for the Hyrcanian forest in Iran. Another recent study by Nuthammachot (2019) concluded that researchers should continue to investigate the potential of the AHP technique in this domain since few studies combined AHP with GIS for fire risk assessment.

By interpreting Landsat 8 satellite images in ArcGIS, vegetation types with a radiant heat flux can be the reference source of ignition in a wildland fire. This method can determine forest fire danger caused by anthropogenic factors and thunderstorm activities (Yankovich, 2019). For instance, the classification of forest vegetation was effectively computed and estimated using the Sentinel 2 images. The estimated accuracy was 77% for vegetation classification (Kupková, 2017). However, one of the major limitations in relying solely on satellite images is that they can only provide information on the terrain, texture, and radiation.

By combining LiDAR data and spatial analysis, one study used simple measurements about the canopy height as well as canopy cover and area to study the complex process of how a forest would restructure itself depending on fire severity (Kane, 2014). The proposed approach focused on tree clumps and openings, which were found to contribute to fire spread in dry forests. Two limitations were introduced when using discrete LiDAR data. First, there is a limitation on pre-fire structural measurements; smaller trees and understory are difficult to map reliably because of the underestimation in the density of trees less than 65 feet (20 meters) tall (Kelly, 2015). Second, the accuracy of the estimated fire risk and severity was also limited. In other words, gaining highly accurate LiDAR data, if available, is costly. Therefore, the data collected using low accuracy LiDAR scanners were limited in their ability to reflect the actual factors and criteria values.

The fusion of LiDAR and aerial satellite imagery datasets has shown dramatic improvement in the accuracy in measuring canopy height and biomass, as well as aiding in tree crown identification, tree species identification, and surface fuel mapping (Erdody, 2010). By merging satellite images with LiDAR data, the accuracy of vegetation classification increased by 88% (Sánchez, 2018). Integrating satellite imagery with LiDAR data leads to large amounts of information that can be gathered with greater accuracy for the identification of vegetation type and height (Gopalakrishnan, 2015). Taheriazad (2018) conducted fire-risk modeling for the CoE's Parkland natural area using airborne LiDAR, satellite images, and urban Primary Land and Vegetation Inventory (uPLVI) datasets by layering polygons in different layers in GIS and calculating an associated score. These scores were compared to certain thresholds to be classified accordingly to a certain risk category. From these studies, it can be shown that combining LiDAR and satellite datasets can improve the accuracy and precision of the mapping results from spatial modeling.

2.2.3. Parametric Models

In statistics, a parametric model is a class of statistical models where a family of probability distributions has a finite number of parameters. Using parametric models in wildfire risk modeling has shown promising prediction and analysis results.

A logistic regression, one of the most well-known statistical regression models, is more commonly used to map wildfire ignition probability over a vast spatial scale, as compared to some nonparametric algorithms, such as weights-of-evidence, classification and regression tree (CART), and random forests (RF) (Vasconcelos, 2001; Taylor, 2005; Chang, 2013; Satir, 2016). This is because of its reasonability and flexibility in accepting a mixture of continuous and categorical variables, as well as non-normally distributed variables (Bisquert, 2012; Chang, 2013). Logistic regression was determined to be more successful than nonparametric multi-layer perception (MLP) algorithms (Catry, 2009; Satir, 2016).

A more recent study used logistic regression in combination with GIS to predict the wildland fire occurrence in a grid of 1x1 km cell, using the set of explanatory variables from Shanxi Province in China. The developed model could predict wildland fire occurrences and zones accurately, and thus may provide a scientific basis for fire prevention and mitigation, and emergency evacuations (Pan, 2016). As a continuation, another model was developed in a separate study using logistic regression at the 1km grid resolution as a basic unit of analysis. This model was implemented to develop a future fire prediction model to allocate fire management resources efficiently to potential fire zones, of which they could do so with a high level of accuracy (Guo, 2017).

Guo (2016) also compared logistic regression to geographically weighted logistic regression (GWLR), an expansion of the standard logistic regression where it incorporates geographical location data, thereby including a spatial aspect to the regression model. The GWLR modeling depends on the weighting function determination for estimating the local parameters. Upon comparing the results between the two regression methods on a spatial 1x1 km grid, the author found GWLR had more insights into the parameter's weight assignment and provided better predictions for wildland fire occurrences.

In another study, logistic regression, and artificial neural networks (ANNs) were compared. ANN is a sophisticated network of individual learning units called neurons that are combined into different layers to learn and generalize complex relationships from their input variables. These two different modeling techniques were used to predict the fire occurrence in a 1 km square grid. The results showed that even though ANN and logistic regression are quite different, as the former is nonparametric while the latter is parametric, both models performed similarly in terms of their fire occurrence prediction (de Bem, 2019).

A wildland fire-risk occurrence predictor was developed using logistic regression that also showed promising results in accurately predicting fire occurrences. The model's unit of analysis was a one-kilometer square pixel. The model developed for the Niassa reserve in Mozambique could predict fire occurrence efficiently, and the accuracy of the model was further validated by referencing different logistic regression models, which were all showing high accuracy in fire occurrence prediction (Nhongo, 2019).

2.2.4. Non-Parametric Models

Wildland fires can also be estimated using non-parametric modeling techniques, where the major advantage is that they do not require any distributional assumptions on the fire records. The benefits associated with non-parametric models are 1) flexibility in fitting many functional forms without having to gain any prior knowledge and 2) greater performance, in terms of model speed and complexity, for predictions.

Different machine learning-based models have been developed to analyze spatial fire distribution and to produce fire-danger maps. ANN was extensively investigated and proven to be a robust approach in predicting wildland fires. A recent study by Tien (2018) implemented a hybrid machine learning algorithm based on the ANN with a novel hybrid training algorithm in a GIS platform to spatially model wildland fire danger. The developed model was found to enhance the accuracy of predicted solutions and the convergence rate. The results from the hybrid machine learning algorithm outperformed other nonparametric models in terms of classification and prediction accuracy of wildland fire danger. This model was used to approximate the tropical forest fire danger in the Lam Dong province of Vietnam.

In another example of non-parametric modeling, a basic machine learning algorithm was developed to compute and predict wildland fire models by using a decision tree (Stojanova, 2006; Pourtaghi, 2016). The purpose of implementing machine learning algorithms was to perform the features selection to reveal the variables that contributed the most to fire occurrences. The boosted regression tree (BRT), generalized adaptive model (GAM), and random forest (RF) were used to discriminate between fire or no fire occurrence, and it was found that GAM showed a better performance peak compared to BRT and RF (Pourtaghi, 2016). One limitation associated with decision trees can be attributed to the availability of the data resources as smaller municipalities have fewer, which leads to poorer accuracy (Guerreiro, 2018).

A map of wildland fires was estimated using a nonparametric *K*-modes clustering algorithm to determine fire-scars and to predict fire occurrences (Tutmez, 2017). The fundamental characteristic of this algorithm is that it does not become computationally intense even when the number of categories to be clustered is substantial, such as meteorological and topographical data. However, solutions generated by this method do not always converge to global optimal. Another drawback is the determination of the optimal number of clusters as there is no valid and reliable research dedicated to finding an optimal number of clusters in the observed data (Tutmez, 2017).

Non-parametric spatial fire-risk modeling was further developed by Than (2018), who used three advanced machine learning algorithms with GIS software. The algorithms implemented include Support Vector Machine classifier (SVMC), random forests (RF), and Multilayer Perceptron Neural Network (MLP-Net). Here, these were compared to more conventional methods. Eventually, it was revealed that all the test algorithms outperformed conventional methods. The results also showed that MLP-Net provided better fire occurrence predictions over the RF and SVMC algorithms based on the results of statistical significance testing conducted (Than, 2018).

Artificial intelligence (AI) has been under development for quite some time and has recently emerged as an effective prediction modeling tool for several applications, such as natural hazards. As introduced, wildfires are one of the costliest natural hazards in Canada, and AI methods have been implemented in modeling wildfires. The models included are ANN, adaptive neuro-fuzzy interface systems (ANFIS), SVMs, RF, and CART. AI methods can also provide extensive information on fire occurrence and their spatial patterns, thus making it an indispensable tool for fire-risk management and planning. Furthermore, what gives AI the upper hand over other methods are its capability to be coupled with many other methods to enhance model quality.

Metaheuristic optimization algorithms (MOA) are methods that can significantly enhance the performance of AI-based hybrid models. From the comparison study conducted by Jaafari (2019a), four different MOAs were hybridized with the chosen base AI models (ANFIS). The study area was Minudasht, in the eastern part of the Hyrcanian ecoregion of northern Iran. The four MOAs included genetic algorithm (GA), particle swarm optimization (PSO), shuffled frog leaping algorithm (SFLA), and imperialist competitive algorithm (ICA). What Jaafari (2019a) found was that of all the hybrids, ANFIS-ICA provided the best performance for spatially explicit wildfire prediction and mapping for the dataset used.

In another MOA comparison study, the development and validations of two-hybrid AI models were done between the GA and firefly algorithm (FA) for the spatially explicit prediction of wildland fires probabilities. The study took place in the Zagros ecoregion in Iran and used ten explanatory variables (i.e., elevation, slope, aspect, land use, rainfall, soil order, temperature, wind effect, and distance to roads and human settlements). The model assigned weights to each class of variables depending on the strength of the spatial association between the class and the probability of fire occurrence. The results from this study concluded that ANFIS-GA was the better performer of the two (Jaafari, 2019).

In this final study, ANFIS was combined with the MOA called differential evolution (DE) and was compared to ANFIS-GA and ANFIS- PSO. The results showed that ANFIS-GA was the superior hybrid AI in both recognizing the pattern and predicting fire events (Moayedi, 2020).

2.2.5. Fire Risk Model Review

While the earlier fire-risk models developed were non-spatial due to computational limitations, recent advances in geographic information systems (GIS) have allowed for the development of spatial fire-risk models (Hirsch *et al.*, 2001; Loehle, 2004). A significant benefit associated with spatial models is the advantages it offers to city planners. Landscape planning and prioritization efforts require spatial and quantitative information to determine locations where there is a risk of a fire igniting. Furthermore, assessing wildland fire-risk supports the overall understanding of the likelihood of fire occurrences, the impact on highly valued resources and assets (HVRAs), and their magnitude of response to fire. These spatiotemporal analyses could only be executed effectively using the highly accurate dataset (Thompson, 2015). The most accurate fire-risk model estimation and prediction depend on how detailed the available spatial data are and how efficiently they could be interpreted. The fusion of satellite images and LiDAR data has shown promising results in that regard. Hence, spatiotemporal data accuracy and availability are crucial to building a reliable wildland fire- risk model.

Nonparametric and parametric models showed promising results as well. Drawbacks experienced in nonparametric models were the complexity of the development of the model and the validation process. Parametric models, on the other hand, are different as they are based on simplicity and flexibility in accepting a mixture of continuous and categorical variables, as well as non-normally distributed variables (Bisquert, 2012; Chang, 2013). It should be noted that when parametric and nonparametric models were compared, with logistic regression and ANN, respectively, it was found that they had similar performance metrics in fire occurrence prediction (de Bem, 2019).

By reviewing the research conducted in the past, it is proposed that a combination of both the spatial and parametric modeling approaches be used to develop a reliable fire risk model. Even though non-parametric modeling with AI seems to be promising, its lack of transparency with the calculations makes it difficult to understand in greater detail how each variable plays a role in the modeling process. The new modeling method proposed in this thesis, on the other hand, will benefit from both the parametric modeling method's ability to use a wider variety of variables while preserving their distinct spatial relationships. Together, this combination is expected to provide promising results in model development, calibration, and estimation of wildland fire occurrences.

2.3. Urban vs. Rural Fire Models

Modeling urban fires pose a distinct set of challenges not seen in rural fire models. One of the most significant differences is the fire's behaviour from a burning structure in an urban setting to a widespread brush or forested fire. Fires in the rural area propagate via surface spreading and crown fires, where there is little restriction to flame spread and fuel for the flames is immediately available at the propagation front (Quintiere 2016).

Fires in dwellings or urban settings differ in that they can be compartment fires or fires contained within a room, zone, or region. Modern structures contain fires within the compartments for a set "burn time" for safety, as it allows time for people to exit the structure and for firefighters to arrive (Quintiere 2016). In a large-scale disaster, such as the aftermath of an earthquake, urban fire models regard multiple buildings together as an ensemble, since damaged or collapsed buildings will cause a fire to spread more easily from one building to another in all directions through fire-spread methods (Thomas, 2002; Cousins, 2002; Cousins, 2003; Himoto, 2003).

Fire-spread methods are pathways for which fire can spread from one structure to another and include openings, collapsed buildings, flame brands, direct flame contact, emitted radiation through fuel, fire temperature and compartment properties, and radiative heat transfer (Carlsson, 1999; Heron, 2003). Fire-spread via openings and radiated heat is the most common fire-spread method between non-contiguous buildings. Radiation heat spread can occur if there is a straight line between the radiating and receiving buildings (Heron, 2003). Fire-spread via collapsed or damaged buildings often occurs because of an earthquake. In earthquakes, collapsed buildings with a non-combustible cladding may have combustible contents which will be exposed, allowing for a continuous fuel bed over which the fire may spread (Heron, 2003). Flame brands are the extremely hot pieces emitted from burning materials blown in air which may travel far distances. Fitting external surfaces with fire-resistant claddings is a way of protection from flame brands (Carlsson, 1999). Direct flame contact occurs through projected flames. It is possible that the flame from an opening can hit a nearby building and cause a fire (Carlsson, 1999). The flame itself has a high level of heat, and if the projection is large enough for the flame to reach a nearby building, ignition may result (Heron, 2003). Radiation ignition is the most common method of spreading fire amongst buildings and can occur at greater distances than by direct flame contact (Carlsson, 1999).

Two conventional models used in urban fire modeling are the static fire model and dynamic fire model. The static fire-spread model is based upon the "critical separation" concept, which is defined as the maximum critical distance that a fire can be transferred from one building to the other, and it can be computed and identified using GIS, as shown in Figure ***2-2*** (Cousins, 2003). Static models assume that the fire will keep spreading in all directions from one zone to another until the fire encounters a separation distance greater than the critical separation (Thomas, 2002). The critical separation distance serves as a fire break between buildings, potentially halting fire spread, assuming that there is no wind and that there are no other structures or flammable materials within the critical separation zone. However, this model does not take into consideration some biasing factors, such as the slope and active suppression (Thomas, 2002).

On the other hand, the dynamic fire-spread model is constructed based upon the "cellular automation" technique to model the fire spread over time using GIS (Cousins, 2002; Cousins, 2003). GIS divides the map into equal-sized cells, where each cell then allocates the properties of whatever it has. For instance, if a cell has a building, then it is considered a fuel cell and takes the properties of a building. On the other hand, a cell that lies over a roadway, grassland, or paved areas is considered an empty cell as it will hinder the spread of the fire. The dynamic model includes a factor for wind; however, like its static model counterpart, it does not consider some biasing factors, such as the ground slope and active suppression (Thomas, 2002; Cousins, 2002).

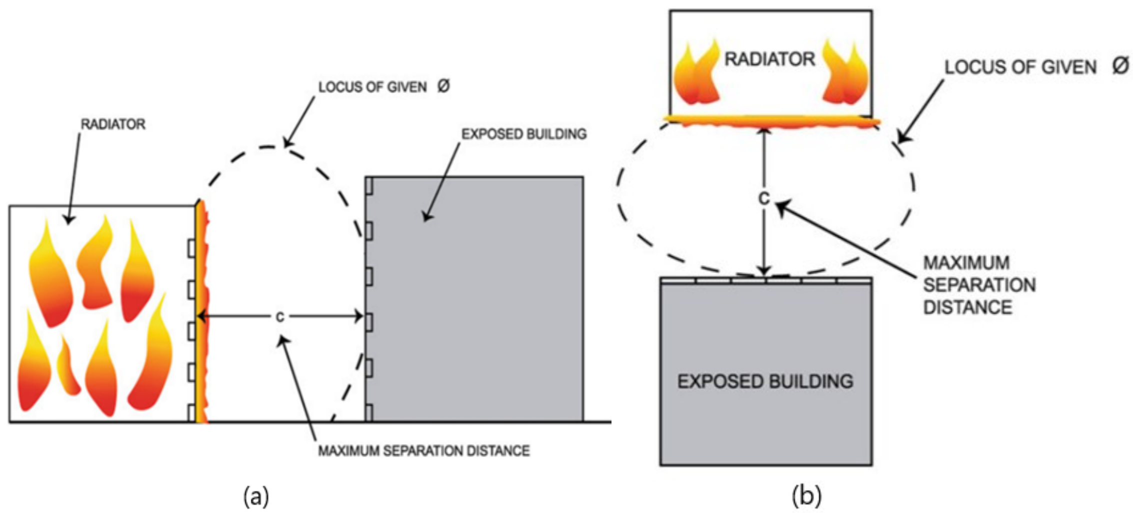


Figure 2-2 Generalized concept of critical separation. (a) Vertical section. (b) Horizontal section (adopted from O'Connor, 2016).

In determining the safe separation distances between buildings, the predicted fire temperature in the compartment and the levels of emitted radiation are essential parameters (Carlsson, 1999). An urban fire model is developed using two sub-models. One model predicts the building fire behaviour based on the exposure to heat coming from other building fires, while the other models the thermal environment caused by building fires (Himoto, 2003). The building fire model is based on a single zone, such that when the temperature of the building exceeds a specific heat flux, whether the heat source is from within or from another building nearby, the fire loads into the compartment, ignites, and burns. The thermal environment model considers the fire thermal radiation and fire-induced plume as the primary fire spreading factor in building-to-building. Simulations have shown that roof burn-through has little effect on the overall losses from a fire, while fire losses can increase dramatically by up to 430% through broken windows, as shown in Figure ***2-3*** (Himoto, 2003; O'Connor, 2016).

Vegetation growth between buildings or other structures may aid in the fire spreading between them as it acts as a fuel source within that separation gap. This type of vegetation growth should, therefore, be included in urban fire modeling, either statically or dynamically; otherwise, the model will probably underestimate the losses (Heron, 2003).

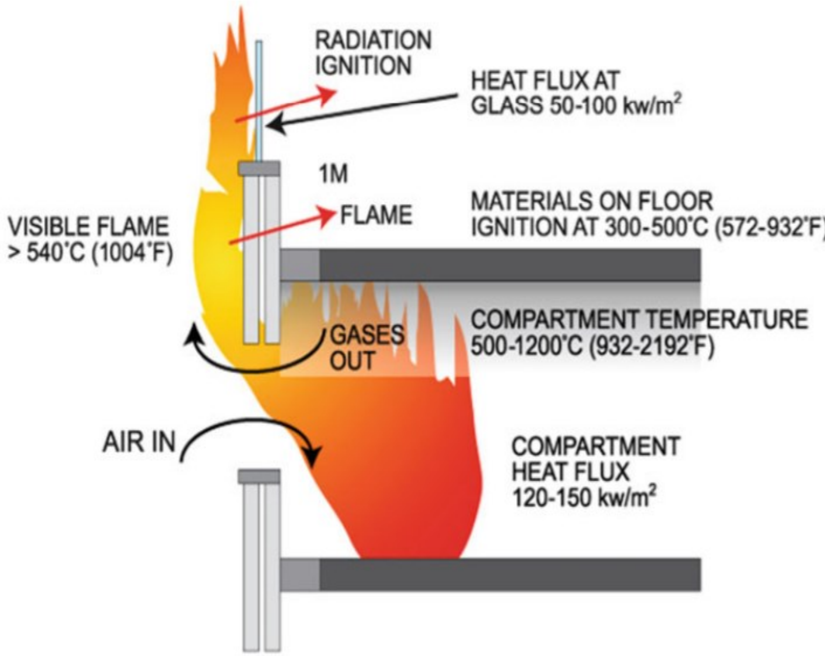


Figure 2-3 Difference between intact and broken windows (adopted from O'Connor, 2016).

2.4. Fire Risk Management and Building Regulations

Risk can be defined in a variety of ways based on context. Risk is the probability of having an undesired event, or the realization of a hazard and its outcomes (Simpson, 1989; Fourie and Burger 2000; Purdy, 2010). Risk can be measurable or unmeasurable, where the latter refers to the uncertainty with the risk, and, therefore, uncertainty should be distinguished from measurable risk (Fourie and Burger 2000). This subsection will define risk in wildland fire. The ISO 31000 risk management definition is the identification, assessment, and prioritization of risks (Purdy, 2010). Put succinctly, if there is a risk of wildland fires, then there will be a fire-risk assessment and fire-risk management, which are also covered in this section.

2.4.1. Wildland Fire Risk Definition

Wildland fire risk is the probability of a wildland fire occurring at a specific location under specific circumstances and conditions, together with its expected outcome as defined by its effects on the object, i.e., risk = likelihood of a fire occurrence × the impact or outcome of the fire (Bachmann, 2001; Chalkin, 2010; Johnston, 2020). It is critical to manage the risk and the trade-off qualitatively and effectively when accounting for the likelihood of a fire and its potential effects. To calculate the fire risk, the conditional probability of a wildland fire occurrence, the chance of ignition, and the directional fire spread of the ignited fires must be included in the equation. This can be expressed as:

$$Risk = \sum_{i}^{n} p(F_i)[B_i - L_i] \tag{1}$$

where risk is represented as the sum of the probability of fire at the i^{th} wildland fire behaviour $p(F_i)$, multiplied by the difference between the potential benefits (B) and losses (L). Including both the benefits and losses reflects the change in perception that "all fire is bad" mentality and is crucial in determining the full impacts of a fire (Hardy 2005; Miller and Ager 2013).

Equation 1 can be expanded to determine the risk of a variety of values, such as humans (e.g., loss of life, lost wages, or mental health effects), infrastructure, ecosystem, or habitat. The equation for wildland fire risk can now be expressed as:

$$Risk = \sum_{i}^{n} \sum_{j}^{n} p(F_i)[B_{ij} - L_{ij}] \tag{2}$$

where Equation 1 is changed by inserting the impact of the jth value under consideration, summed over n values being considered (Chalkin, 2010). Figure ***2-4*** is a flowchart representation of the equation.

The likelihood of occurrence is the probability that a wildland fire will occur based on two categorical inputs: the occurrence probability and fire's behaviour (ith fire behaviour). Temporal and spatial extents must be considered when modeling its probability. Effects are the consequences of the fire event as quantified by the difference between B_{ij} and L_{ij} from Equation 2. This can be viewed as the change in the valuation of the valued object(s) based on their susceptibility and the exposure to the fire. The values included in a risk assessment are often referred to as values at risk but can alternately be referred to as highly valued resources and assets (Thompson, 2016). Finally, exposure is the spatial union between a valued asset and the behaviour of the wildland fire. It also represents the extent to which the valued asset may be subjected to a fire.

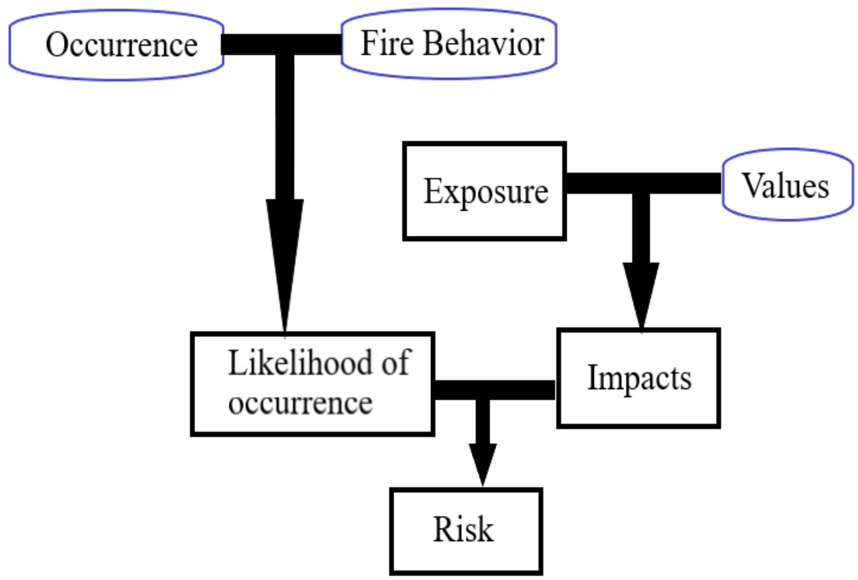


Figure 2-4 Wildland fire risk with primary components (rectangles) in their categories of inputs (capsules) (adopted from Johnston, 2020).

2.4.2. Fire-Risk Management

Assessments of fire risk can help guide management decisions to reduce the negative effects and promote the positive effects of fire (Sakellariou, 2019; Johnston, 2020). Some of the negative effects resulting from any wildland fire can be summarized as losing lives, valued assets, and injuries (Beverly, 2011). Even though the focus is usually given to the negative effects of a fire event, there are also several positive effects from fire events. For instance, fire is considered a major stand-renewing agent for the Canadian boreal zone and ecosystem by regulating the spread and effects of insects and diseases, and by influencing a species' age structure, composition, and biodiversity (Brandt, 2013). Fires can trigger regeneration and create habitat heterogeneity across the Canadian boreal forest and grassland ecosystems (Weber, 1997; Shroder, 2014). Also, wildland fires have an indirect positive impact on communities by encouraging the implementation of high standards and regulations in building codes, land-use zoning, and municipal planning to reduce the fire risk (Christianson, 2015). Furthermore, Christianson (2015) notes that fire has long been used as an effective tool by First Nations and Metis people, making it important culturally.

Fire-risk management can manifest in a variety of ways, such as using fuel management (Vojtek, 2007) to reduce extreme fire spread behaviour, preventing unwanted anthropogenic fires, and enforcing fire suppression programs to slow or prevent the spread of fires (Finney, 2005; Wotton, 2017; Johnston, 2020). Negative effects can be lessened through evacuation and emergency plans (Beverly, 2011; Sakellariou, 2019) along with enhanced building and zoning regulations to protect social and health vulnerable groups (Christianson, 2015). There is no single effective solution since different mitigating circumstances can make each situation unique. That being said, evacuations are the primary way to safeguard human lives in wildfires. No other method has come close in terms of effectiveness (Wong, 2020).

Multiple solutions can work together, and not all solutions are appropriate for every area (Beverly, 2010). Evacuations are almost always preferred for wildfires. Some nuance here, though, could be helpful. One situation where evacuations may not be most effective is if there exist suitable shelter (as a last resort) and there is no time to evacuate (Wong, 2020). A resilient ecosystem may have lessened risk because of how fast it can recover or adapt to a post-fire state based on its fire management regulations, actions, and policies (Keane, 2018). This highlights the importance of re-evaluating all the strategies and actions available related to mitigation, emergency response, evacuation plans, and recovery. A fire-risk management answer may include the use of FireSmart principles and guidelines to lessen the vulnerability of structure ignition (Johnston, 2020). FireSmart is a Canadian program that provides suggested guidelines for land managers and homeowners to enhance public safety activities by proposing over 40 projects which involve activities related to planning, public education, and fuel mitigation efforts (Summers, 2014; FireSmart Canada, 2020). The concerned areas are where humans, communities, and infrastructure impinge with or are interspersed within wildland fuel in the WUI (USDA and USDI 2001). FireSmart principles implemented for better wildland fire resistance may include community initiatives, large-scale collaboration and coordinated program promotion, governmental and insurance economic incentives, or building codes implementation and land development guidelines (FireSmart Canada, 2020; Johnston, 2020). Since the whole mitigation process starts with a well-educated community, the FireSmart Canada program regularly raises awareness to residents through online and printed resources (FireSmart Canada, 2020a). Further extensive research should be conducted on wildland fire-risk management to incorporate uncertainty and complex novel dynamics (Council of Canadian Academies, 2019).

2.4.3. Zoning & Building Regulations

Fire-risk models assist officials in identifying requirements for zoning and building regulations for city planning, emergency response, and evacuation process in case of any wildland fire occurrence. A fire can spread from one building to another based on the fire spreading parameters (Barnett, 1989; Carlsson, 1999; Heron, 2003; Hamins, 2012). For indirect fire spreading, there is both convective and radiative heat transfer, where the typical values of radiation for the spontaneous ignition of wood is 33.5 kW/m^2 (i.e., ignition in the absence of an ignition source), and 12.5 kW/m^2 for piloted ignition (i.e., ignition in the presence of an ignition source such as a spark or a brand) (Barnett, 1989; Carlsson, 1999).

Unfortunately, at the time of research, the current version of the National Building Code of Canada (NBCC) is not accessible to the public. Therefore, this subsection will reference other available literature and highlight only the most relevant information regarding building separation. The NBCC sets out tables of building separation based on the critically received radiation criterion of 12.5 kW/m^2, the same value used in England and Wales (Clarke, 1998). Canada uses higher values for emitted radiation and 1.2 m for flame projection distance from openings to prevent fire spread (Clarke, 1998; Carlsson, 1999; Himoto, 2003).

The Canadian code uses configuration factors of 0.07 for traditional buildings and 0.035 for buildings with combustible linings that are expected to burn more vigorously. These configuration factors are the same as those set out by McGuire (1965) and resulted in expected levels of radiation of 180 and 360 kW/m^2, respectively. The St. Lawrence Burns showed extraordinarily high levels of radiation after 16 minutes, much higher than what would be practical to use when determining building separation distances. The NBCC, therefore, requires that the separation distance should be doubled in areas where Fire Service intervention cannot be guaranteed within 10 minutes (Carlsson, 1999; Hamins, 2012).

Cities in the provinces of British Columbia and Alberta have set building guidelines and zoning regulations in their land use bylaw. In British Columbia, for instance, Prince George, Williams Lake, Squamish-Lillooet Regional District, Fernie, North Vancouver, and Kelowna, have the building and zoning regulations that must comply with the B.C. edition of FireSmart. In Alberta, Strathcona County, Hinton, Fort McMurray, Slave Lake, Canmore, and Banff have building codes and zoning regulations for land use developments that must comply with the Alberta edition of FireSmart. Rules for property holders in WUI apply in:

a) Priority Zones 1, defined within 10.0 m from structures, eliminate fuel, and alter vegetation to fire resistance species to create an environment that does not aid combustion, as shown in Figure ***2-5***.
b) Priority Zones 2, defined within 10.0 – 30.0 m from structures, expand fuel changed area by diminishing the flammable vegetation through thinning and pruning and produce an environment that will only aid low-intensity surface fires, as shown in Figure ***2-5***.
c) Priority Zones 3, defined within 30.0 – 100.0 m+ from structures, eradicate the potential for a high-intensity crown fire through thinning and pruning, consequently slowing the movement of a fire approach toward structures, as shown in Figure ***2-5***.
d) Fire resistant roofing materials (Class A or B) such as metal, clay tile, asphalt shingles and treated wooden shingles ought to be used on all buildings and structures.
e) Fire resistant exterior walls materials such as stucco, metal, brick, rock, and concrete ought to be used on all buildings and structures. Although logs and overwhelming timbers are less viable, they are also allowed.
f) Roof vents ought to be closed in and screened.
g) Decks, porches, and balconies ought to be secured with fire-resistant materials.
h) Chimneys ought to have affirmed spark arrestors; and
i) Vegetation ought to be cleared 3.0m back from power lines and propane tanks.

To mitigate the risk of fire hazards:

a) Integrate 'fire breaks' at standard interims across the roof, at the roof edge, and around all roof infiltrations.
b) Use fire retardant plants such as sedums, which have a high-water content; and
c) Use a sprinkler water system associated with a fire alarm (Canmore Revised Bylaw, 2020).

2.5. Future Fire Risk & Climate Change

The future may see a system with dramatic and variable fire activity, due to an increase in climatic extremes, the potential for unrestrained warming, and self-promoting carbon feedbacks (Price, 2013; Oris, 2014; Steffen, 2015; Johnston, 2020). The predicted changes are non-deterministic and vary across locations; however, the overall fire activity will diverge from the recent historical trends (Coogan, 2019). Since climate is a prevalent driver of fire activity in most areas of Canada, the effects of climate change will increase the variation and extremes in weather, such as increased temperatures, longer dry periods, and increased storm activities, thereby dramatically increasing future fire occurrences (Price, 2013; Wotton, 2017; Wang, 2017). These changes have already been recorded and recent studies conclude that dramatic fire weather and behaviour are 1.5 to 6 times more likely because of anthropogenic emissions (Coops, 2018; Hanes, 2019; Johnston, 2020). Climate change will increase the effects of wildfires relative to other natural disasters with the potential to impact physical infrastructure more rapidly and at a greater scale (Council of Canadian Academies, 2019).

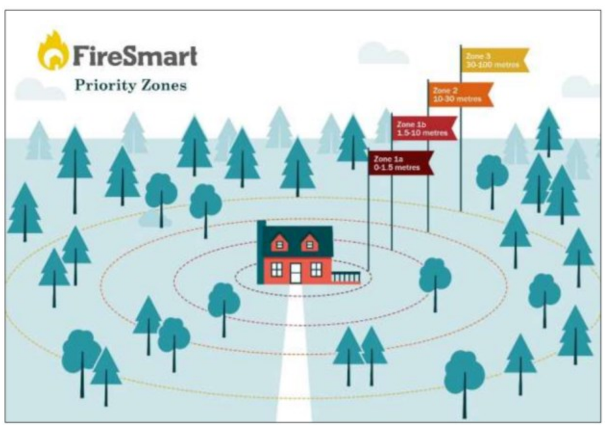


Figure 2-5 FireSmart Priority Zones (adopted from FireSmart Canada).

Human development and land use may change fuel characteristics in the future, resulting in changes in fire risk. Climate changes include species range shifts, changes in fuel consumption, loads, types, or arrangement (Hirsch, 2001; Wang, 2017). Pest outbreaks, along with climate changes, will be another factor determining future fire risk. Both will cause dramatic large buildups of dead fuels which influence fire occurrence (Price, 2013).

Wildfire impacts will also be affected by changing human population, building structures, and municipalities infrastructures. Canada's population is mainly growing in dense urban centers with more direct wildland fire risk (Statistics Canada, 2020). Urban sprawl and the development of municipalities increase the WUI, raising the fire risk for structures and populations (Johnston, 2020). In recent years, isolated communities and indigenous communities have experienced an escalated population growth, increasing the probability of fire-risk occurrences, in addition to already having higher risk because of their location (Johnston, 2020).

Because of climate-driven changes to fire, there will be an increase in fire-risk occurrences probability. An expanding body of evidence shows that besides proceeded rising costs, future climate-driven changes to fire action will surpass the current reaction capacity (Johnston, 2020). Contaminant capacity is especially susceptible to being overpowered when there are multiple different fires burning at once, causing huge, escaped fires (de Groot, 2013). Escaped fires are expected to extend up to 92% by the conclusion of the century in the province of Ontario, requiring an unlikely growth in the business capacity to keep pace (Hirsch, 2006).

Climate change will drive critical changes in annual burning rates within the boreal wildland. It is essential to determine accurately the climate change extent in the fire risk forecasting and modeling process. This can be done by integrating the data on long-term greenhouse climate changes obtained from an anthropogenic climate forcing scenario known as the Representative Concentration Pathway (RCP). The RCP attempts to capture future patterns such as whether humanity will continue to consume fossil fuels at an increasing pace or convert to renewable energy. They also forecast how greenhouse gas concentrations will vary in the atmosphere due to future human activity. Ultimately, the RCPs are used by scientists to model climate change and create impact scenarios for future planning. The RCPs' numbers (2.6, 4.5, 6.0, and 8.5) relate to concentrations in the year 2100. Figure ***2-6*** depicts future concentrations in the four RCPs, which vary from very high (RCP8.5) to very low (RCP2.6). RCP 8.5 results in substantially higher temperature increases, hence, larger impact and higher cost. Adapting to these changes will also be more expensive. Therefore, a balance between the cost of impacts and the cost of adaptation must be achieved (Moss, 2008; Weyant, 2009).

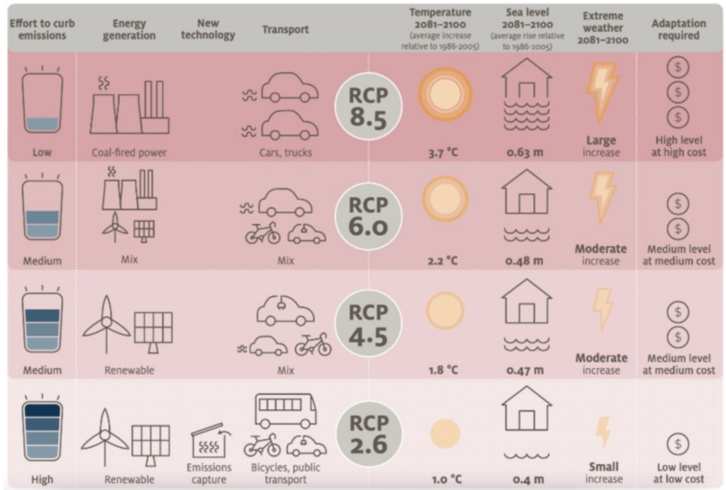


Figure 2-6 The four RCPs ranges future concentrations (adopted from Coastal climate change infographic series)

2.6. Summary

This chapter presented a thorough overview of fire-risk modeling, planning, management, and mitigation. Furthermore, a brief background on the importance of building a fire-risk model due to the increased risk of fire occurrences in Canada was also discussed. Finally, a set of actions and considerations were outlined for cities to build a reliable fire-risk model and management system.

There are a vast number of parameters that contribute to wildland fire occurrences, which could be grouped into 4 major categories: meteorological, topographical, biological, and anthropogenic. The development of a fire-risk model requires a substantial amount of data across many of the criteria discussed that is a logical problem solved using state-of-the-art datasets. The spatial scale of these parameters can be quite extensive; thus, any way to streamline the data collection while maintaining a high level of quality is of critical importance. One potential solution would be to use high-resolution LiDAR and satellite images, as they have been shown to provide high levels of detail while also being quick to get. Combining both types of datasets can provide an excellent source of topological, biological, and anthropogenic variables efficiently. Likewise, some meteorological variables can best be served by satellite images such as cloud cover and solar radiation. Another advantage of using these remotely sensed data is availability from an online database.

Research into fire-risk modeling has surged in recent years due to devastating fire events. To help mitigate their detrimental effects on living communities and environment, researchers have attempted to develop fire-risk prediction tools, forecasting models, and analysis techniques. Non-spatial models were the first ones to be developed because of its simplicity and ease of computations. Spatial models were then developed with computer hardware and software that can handle the more computationally intense calculations. From this advancement, spatial modeling has now become the dominant method of choice given the improvements in predictions and model accuracies over the non-spatial counterpart.

Parametric and non-parametric modeling techniques were implemented with some success. It has been shown that the parametric methods performed well, if not slightly better, with the added advantage of its being able to see the entire model development process. Hybrid non-parametric (i.e., Hybrid-AI) techniques are a recent addition to the fire modeling and have shown to produce highly accurate fire-occurrence predictions; however, validation of these hybrid models required the use of another hybrid non-parametric model whereby making it a less preferable method. The parametric techniques provide transparent means of developing and implementing models to delineate wildfire-prone areas.

When applying the modeling techniques covered above, it is essential to realize that urban risk models differ significantly from rural risk models. The behaviour of the fire, the risk to human life, the risks to valued assets, and other confounding factors vary significantly between the two environments. Thus, it is imperative to define what risk model will be researched, as it will affect the choice of parameters chosen and modeling techniques applied. While there are few similarities in terms of how risk is assessed in both environments, the biggest differences lie in how the fire spreads, propagates, and is assessed in the two different settings. Hence, it is crucial to identify the scope of this project with a focus on developing a framework to model wildfire risk only. The risks explored will take into account the presence (i.e., in terms of magnitude and severity) of the aforementioned factors; however, the propagation and eventual consequence of this fire in terms of how it will spread over time is not part of the scope of the project. It is worth mentioning that the proposed model is not based on the risk quantification and the probability generation. It will solely be based on the AHP multi-criteria technique.

Fire incidents are considered a risk due to their probability of occurrence as well as the impact associated with it. This risk should be taken into consideration in the evacuation and emergency response plan by city planners and officials and governed by a robust fire-risk management system. Fire-risk assessment is an essential step in fire-risk management, and it must consider both the negative and positive effects of fire occurrences. Overall, fire-risk management plays a vital role in zoning and building codes and regulations to maintain the resiliency of the city before, during, and after a fire occurrence. This is the ultimate goal of every city that wishes to become a climate resilient metropolis.

Climate changes over the past decades have shown to have a tremendous impact on fire-risk assessment and modeling. Hence, it is essential to take climate changes into account in future fire-risk projections and modeling. Climate changes have been observed in extended dry periods, the increase in temperature and greenhouse effects, and the increase in thunderstorms and thunders. Also, climate changes affect the fuels and manipulate their structure and characterization. Alongside human development and land use shifts, climate change will increase wildland and urban fire risk.

Evacuations are a primary method for protecting human life in severe disasters. For example, hurricanes have forced millions of people to flee their homes in the United States (US) over the last five years (Wong, 2020). And, over the course of 11 California wildfires between 2017 and 2019, approximately 1.1 million people were ordered to evacuate with no advance notice (Wong, 2020). This foregrounds the importance of planning and developing transportation services and operations for effective evacuation in a wildland fire outbreak since moving large numbers of people quickly is paramount.

3. Data Sources & Feature Extraction

In terms of the four recommended criteria: climatic biological, topographic, and anthropogenic, there are a variety of resources available to obtain current and historical datasets.

Climatic data for the province can be obtained from Alberta's Department of Agriculture and Forestry, which provides current and historical weather station data. Climatic data for the country can be obtained from Environment Canada's online database and Canada Wildland Fire Information System. NASA's Daymet online databases also provide an extensive repository of daily meteorological observations for North America from 1980 onwards.

Biological data can be obtained from multiple sources, including the CoE's Digital Elevation Model (DEM) (Jaafari, 2018; Sánchez, 2018), or aerial LiDAR data (Erdody, 2010; Sánchez, 2018). Similarly, vegetation types and densities can be determined via satellite imagery (Hong, 2019). Using the data obtained from both methods, a clear picture of the biological criterion for an area can be established quickly.

Topographic factors can be obtained from the CoE's Digital Elevation Model (DEM) or aerial LiDAR data. Likewise, satellite imagery can also provide insight into the topographical characteristics of the regions under investigation (Scott, 2013; Kelly, 2015; Wang, 2017; Thach, 2018; Hong, 2019; Jaafari, 2019).

Anthropogenic data can be obtained from the LiDAR dataset, satellite images, or multiple other sources using the CoE's open data portal.

In this thesis, a comprehensive geo-database for developing the fire risk-model was first constructed from datasets procured from the CoE, the Faculty of Geography and Environmental Studies in the University of Regina, and other available online datasets. Each dataset was converted into a raster format using ArcGIS 10.7. A list of all the 12 variables used is this study along with their sources is shown in Table 1.

Table 1 All parameters used in the fire-risk modeling.

Parameters	Dataset	Source
Elevation	LiDAR data	CoE local authorities
Slope		
Aspect		
NDVI	Landsat 8 satellite images	USGS EarthExplorer
Forest type	uPLVI data	CoE local authorities
Land use	Land use dataset	CoE Open Data Portal
Proximity to water surface	LiDAR data	CoE local authorities
Proximity to roads		
Annual/Seasonal temperature	Road Weather Information System (RWIS) stations.	RCP4.5 – Alberta Climate Information Service and CoE local authorities. RCP8.5 – University of Regina.
Annual/Seasonal precipitation		
Annual/Seasonal humidity		
Annual/Seasonal wind speed		

3.1. Light Detection and Ranging (LiDAR)

LiDAR dataset was obtained from CoE, as depicted in Figure ***3-1***. The vertical accuracy of the LiDAR expressed in root-mean-square (RMS) is 2.4 cm or better. The two-sigma accuracy (95%) for a normal distribution was computed by multiplying the RMSE by 1.96. In order to appreciate the effort to build and compile this massive dataset, it is worth mentioning that the vertical accuracy, at the 95% confidence level, is approximately 4.7 cm. The calculated horizontal accuracies were determined to be 16 cm. This LiDAR dataset was collected in 2019, and it is 3.7 TB in size, with over 1400 files averaging 30 million points per file; it covers the entire city with a 200-meter buffer. Using ArcGIS 10.7, elevation, aspect, slope, proximity to roads, and proximity to water variables were all extracted from the LiDAR dataset and utilized in the fire-risk model (to be discussed in detail in Chapter 4) (ArcGIS Desktop, 2011).

Python (Van Rossum, 2009) is a highly adaptable and powerful scripting language that can be used in ArcGIS allowing users to perform computationally extensive geospatial operations. In this thesis, the "arcpy" library was built to perform all the geospatial operations. For each LiDAR file, only the ground and road files were imported into arcpy, followed by the spatial elevation operations as shown in Figure ***3-2***(a).

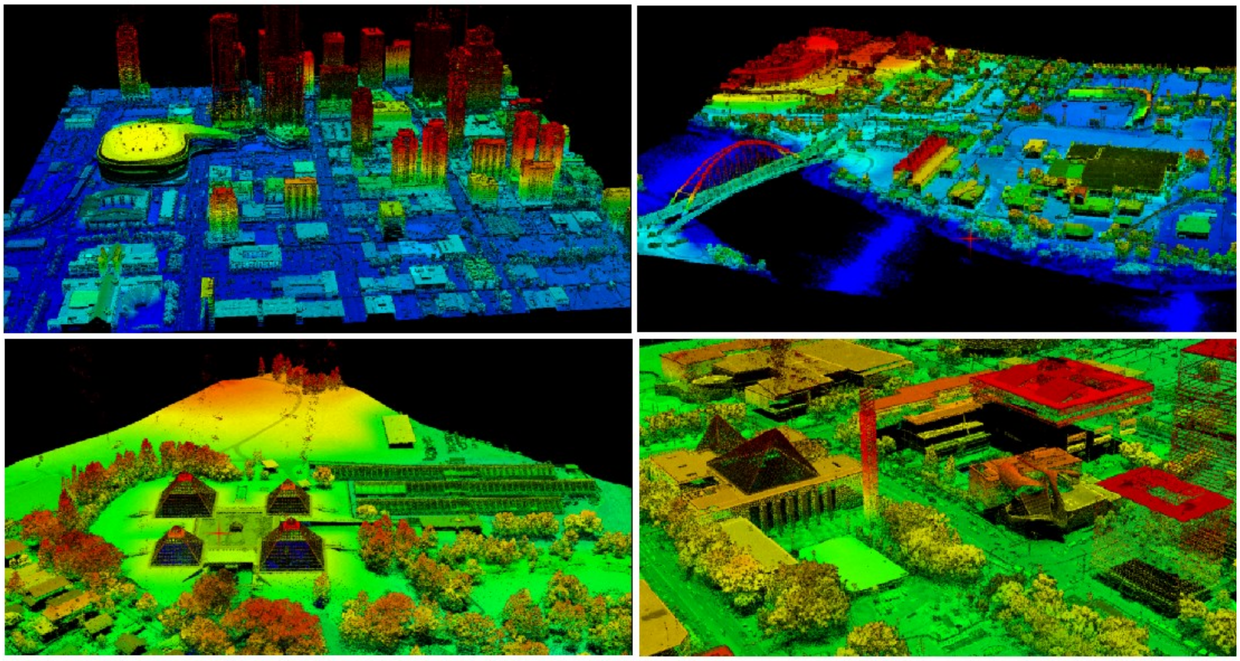


Figure 3-1 A snapshot of the LiDAR data procured from the CoE.

Afterward, all the elevation files were merged using a mosaic function into one file that represents the elevation of the CoE, as shown in Figure ***3-2***(b). Having the elevation map of CoE at hand, the slope function was then used to compute the slope map for the CoE. Finally, the aspect map was also computed from the elevation map using the aspect calculation function in the arcpy library. The Python script used can be found in Appendix A.

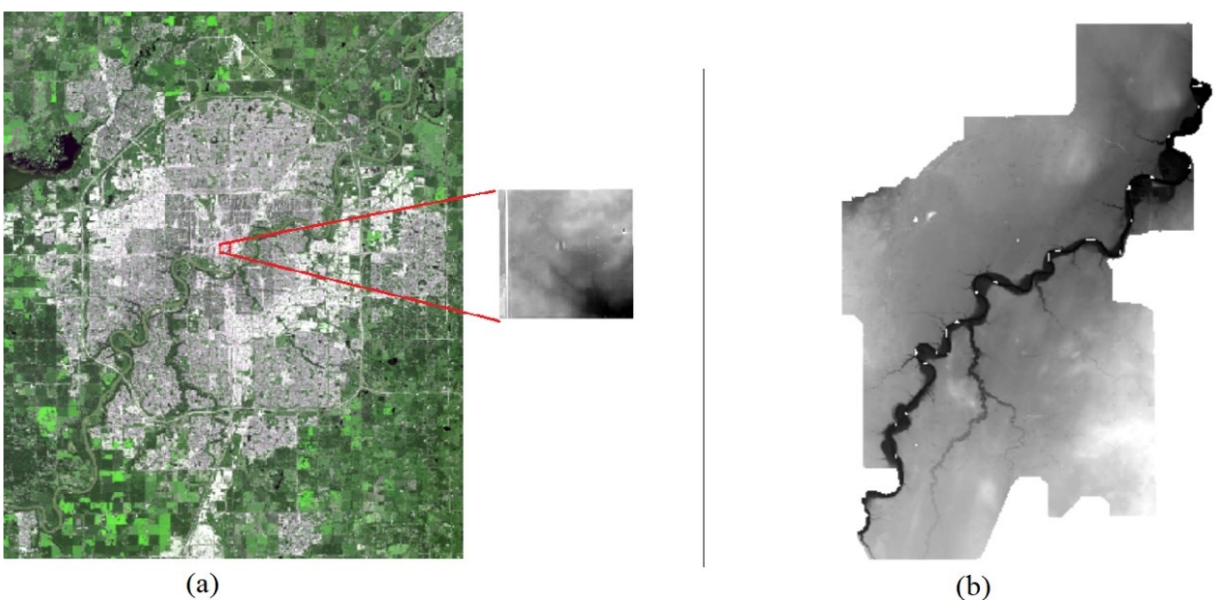


Figure 3-2 (a) The LiDAR file proportion to the map, (b) The mosaic elevation file of CoE.

3.2. Landsat Satellite Images

Landsat 8 satellite images were procured by the CoE in 2018 during the dry season. From April to September, the normalized difference vegetation index (NDVI) was computed from Landsat 8 OLI satellite images. The satellite images were obtained from USGS Earth-Explorer (https://earthexplorer.usgs.gov/). Equation 3 calculates the NDVI from the downloaded files using the mathematical, spatial calculator found in ArcGIS as shown in Figure ***3-3***.

$$NDVI = (NIR - RED) / (NIR + RED) \tag{3}$$

where NIR and RED bands are the near-infrared and the red bands, respectively.

3.3. urban Primary Land and Vegetation Inventory (uPLVI)

Biological variables for all the vegetation areas found in the CoE were extracted from the urban Primary Land, and Vegetation Inventory (uPLVI) data, collected in 2018. The data is composed of hierarchical polygons with a minimum area of 1 hectare. The polygon classifies each area into a vegetated or non-vegetated Primary Land class, with each having a more detailed secondary class called Land class that defines the natural state of the polygon. Below the Land class is the Stand type, the canopy stratification found in Edmonton's Urban Ecological Field Guide. A sample of the features and parameters mentioned above are listed in a table format, as illustrated in Figure ***3-4*** (sample only).

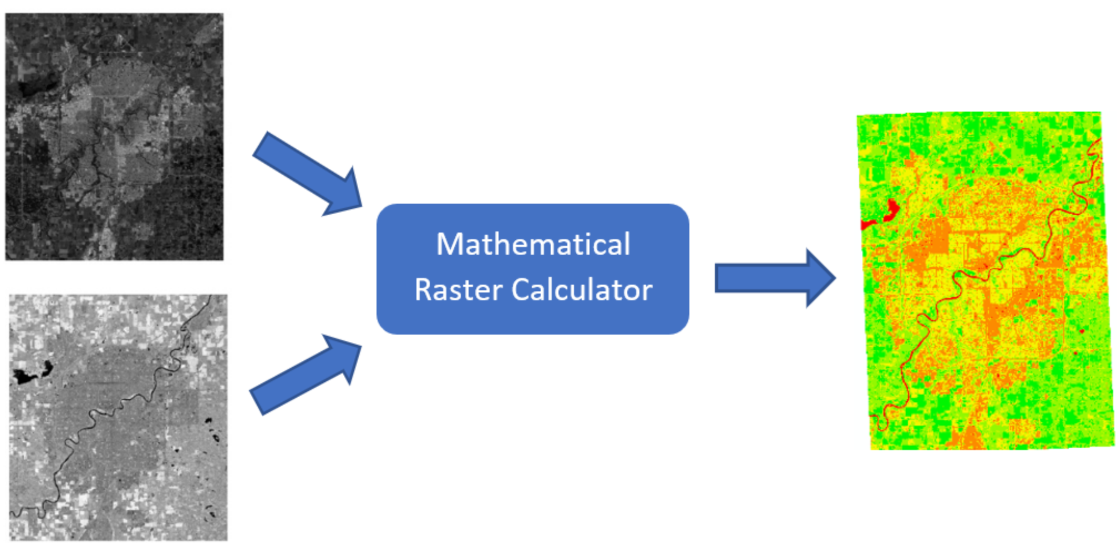


Figure 3-3 The procedures for the NDVI map generation.

Table

COE_2018_uPLVI_RES_UPDATE_DRAFTv1

FID	Shape *	POLY_NUM	AREAHA	NSR	PRIMECLAS1	LANDCLAS1	STYPE1	STYPEPER1	MOISTURE1	NUTRIENT1	ECOUNIT1	ECC
0	Polygon	1	0.3936	CP	NVE	DEV	ECS	10	0		Z	ANTH
1	Polygon	2	0.088	CP	VEG	MOD	NG	9	0		Z	ANTH
2	Polygon	3	0.1115	CP	VEG	MOD	NG	6	0		Z	ANTH
3	Polygon	4	0.2268	CP	VEG	MOD	NG	6	0		Z	ANTH
4	Polygon	5	0.502	CP	VEG	MOD	CA	10	5	C	C	MOD
5	Polygon	6	0.894	CP	VEG	NAW	FT	10	5	D	D	RICH
6	Polygon	7	1.9981	CP	NVE	DEV	OG	10	0		Z	ANTH
7	Polygon	8	0.5533	CP	VEG	MOD	AS	10	0		Z	ANTH
8	Polygon	9	0.7109	CP	VEG	MOD	MG	10	0		Z	ANTH
9	Polygon	10	1.765	CP	VEG	MOD	FS	8	0		Z	ANTH
10	Polygon	11	0.988	CP	VEG	MOD	NG	10	0		Z	ANTH
11	Polygon	12	0.6844	CP	VEG	NAW	FT	10	5	D	D	RICH
12	Polygon	13	6.7963	CP	VEG	WET	GF	10	7	D	G	RIPAI

1 (0 out of 17032 Selected)

COE_2018_uPLVI_RES_UPDATE_DRAFTv1

Figure 3-4 Features and parameters for the procured uPLVI data.

The forest type variable for the dominant and co-dominant species was extracted from this dataset. Detailed steps for the feature extraction process can be further investigated in Appendix B.

The output biologic forest type map is shown in Figure ***3-5***. During the mapping process, any excluded pixels are assigned the value NULL. If these Null values left untouched when all maps are added altogether, the NULL pixels mask out overlapping pixels. Therefore, the null values must be converted into something else. Fortunately, ArcGIS provides a few methods for converting NULL values to other constants, such as zero. To convert NULL values, one alternative is to use the Con operation in combination with the IsNull operation from the Spatial Analyst toolbox. Hence, this formula was applied to the forest_type raster: Con(IsNull("forest_type"),0,"forest_type").

Understanding the category of each zone in the municipality is an important factor to consider as it makes it possible to determine the category of each vegetation area. CoE Open Data Portal (https://data.edmonton.ca/) has a detailed dataset for the land use for the city. This dataset is composed of 327 categories. The model only considered the essential categories that match the CoE's urban settings (Recreation areas, parks, open green areas, etc.). Another data source for land use was the uPLVI that, as mentioned earlier, had a field in the table to identify the land class as either open green areas, anthropogenic parks, or forests. Hence, all the land use categories could be identified with high accuracy, as shown in Figure ***3-6***. Finally, the risk field was added to the table of the land use to identify the risk associated for each land use category using the same procedures as mentioned earlier.

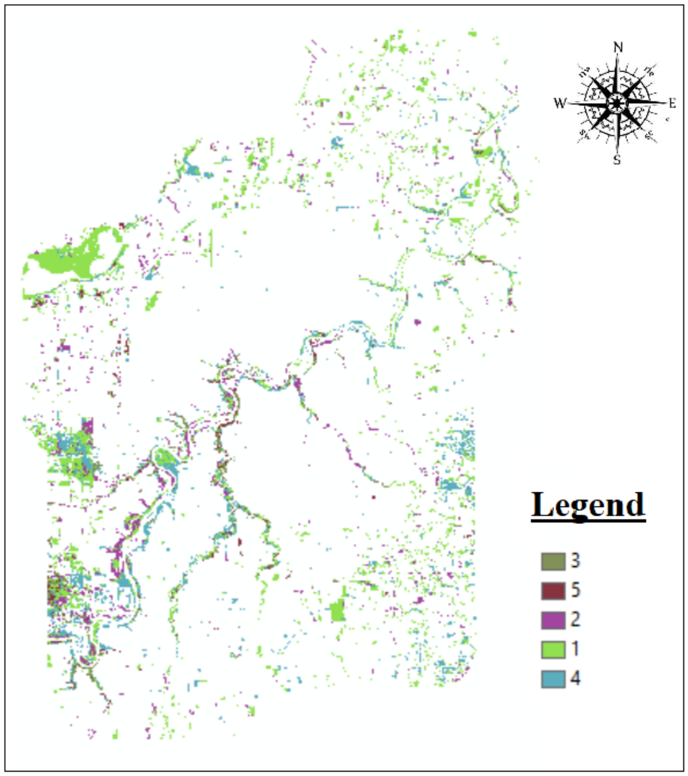


Figure 3-5 The forest type map generated from the uPLVI.

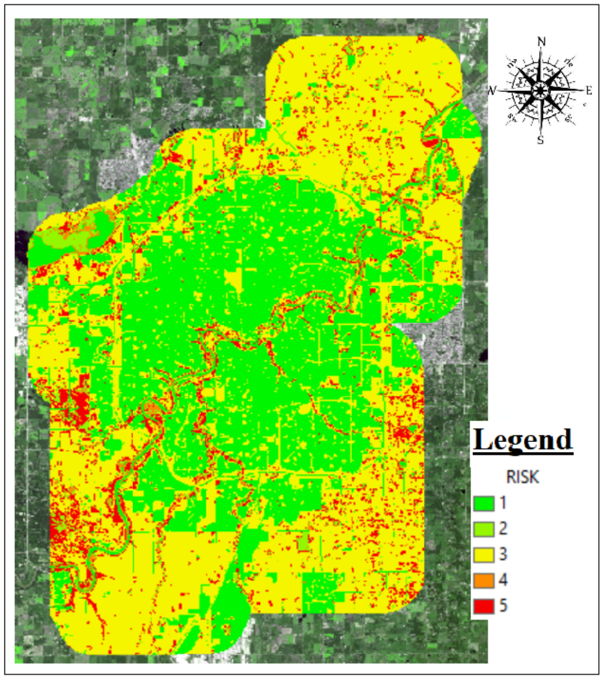


Figure 3-6 The land use risk class identification raster map.

3.4. Road Weather Information Systems (RWIS)

A major factor that influences the fire is the climate, such that higher temperatures with lower humidity and precipitation can stimulate fire ignition, and fire spread can be determined through wind speed. Meteorological data for the construction of climate maps were extracted by analyzing 23 Road Weather Information System (RWIS) stations surrounding CoE from Alberta Climate Information Service (https://acis.alberta.ca/), as shown in Figure ***3-7***. Climate variables that can result in a higher likelihood for a fire to ignite, are temperature, wind speed, precipitation, and humidity (Scott, 2013; Chang, 2013; Thach, 2018; Tien Bui, 2018; Hong, 2019; Kumari, 2020). Since these climate variables are point measurements, a spatial interpolation method was used to interpolate these variables over the entire study area. Kriging is a geostatistical process that creates an estimated surface from the scattering of z-valued points. Ordinary kriging is considered the default kriging method and has become the most common and frequently used variant (Oliver, 1990). Using the ordinary kriging interpolation technique available within ArcGIS 10.7 Geostatistical Analyst tool, a raster climatic map could be generated for each variable. However, the raster maps lacked both accuracy and high resolution to keep up with the other detailed, high-resolution raster maps.

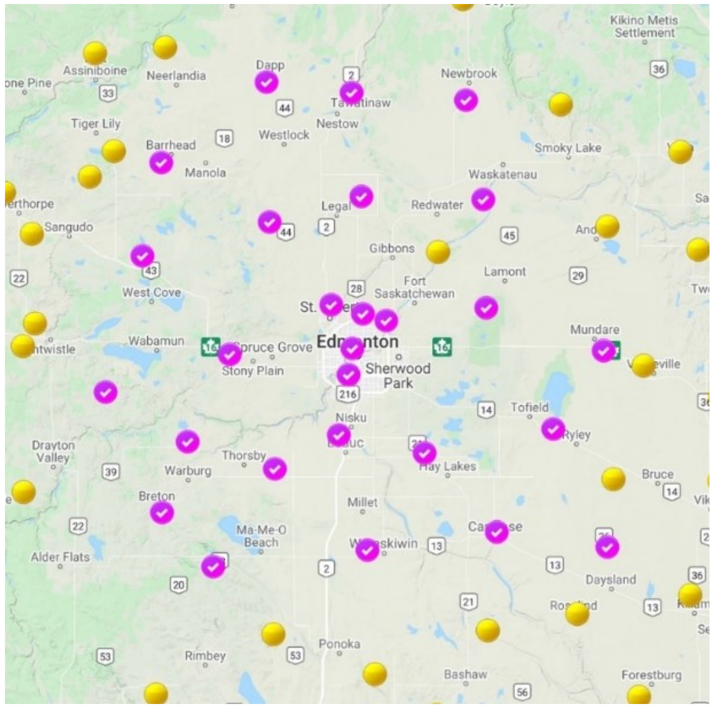


Figure 3-7 All selected RWIS stations surrounding the CoE

Both RCP4.5 and RCP8.5 climatic datasets were provided by the CoE local authorities and were integrated to create a single annual climatic value for each year. This was a major limitation in identifying and forecasting meteorological high risks and vulnerable specific places in the CoE because all other variables and criteria were in spatial representation, which were easily imported into and analyzed in ArcGIS. The spatial representation of the RCP8.5 climatic data, obtained from the University of Regina, was vital in generating the raster maps for the climatic variables for actual and correct assessment. One interesting fact in this dataset is its accuracy. The data is comprised of 120x66 grid points centered over CoE with a 30m x 30m grid area, as depicted in Figure ***3-8***.

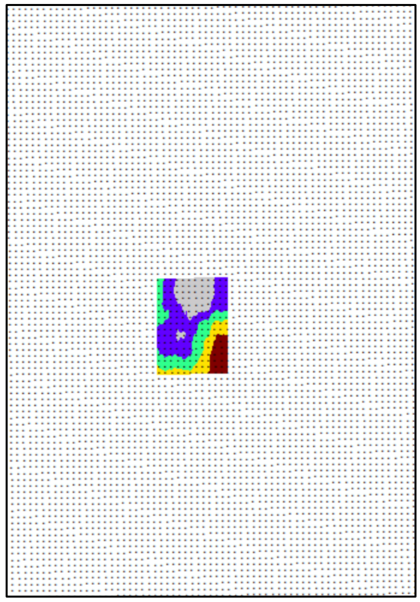


Figure 3-8 The RCP8.5 120x66 gridded points covering the CoE for estimating the climate variables.

The climate in Edmonton has high meteorological variance between seasons, and its low bias makes building an accurate model challenging. Extracting the fire season climate data was a crucial step to building an accurate fire-risk assessment model. Given that the fire season in CoE lies between May and October, the data have gone through extensive feature engineering to include both annual and seasonal climatic projections for those months. Climate change could alter this fire season to start earlier and end later. High winds and dry fuel can cause massive destruction even if temperatures are low (Wong, 2020).

As mentioned earlier, raster maps were generated for each climatic variable that became more accurate when integrated with the ordinary kriging interpolation technique. The following steps were done in ArcGIS to generate the climate maps. More detailed steps for the kriging interpolation and generation can be found in Appendix C.

a) Select the appropriate independent variable from the dataset.
b) The semivariogram from the Kriging interpolation window will clarify the surface trend as derived from the data, as shown in Figure ***3-9***.
c) The kriging prediction map should be generated from ArcGIS. Sample output is shown in Figure ***3-10***.

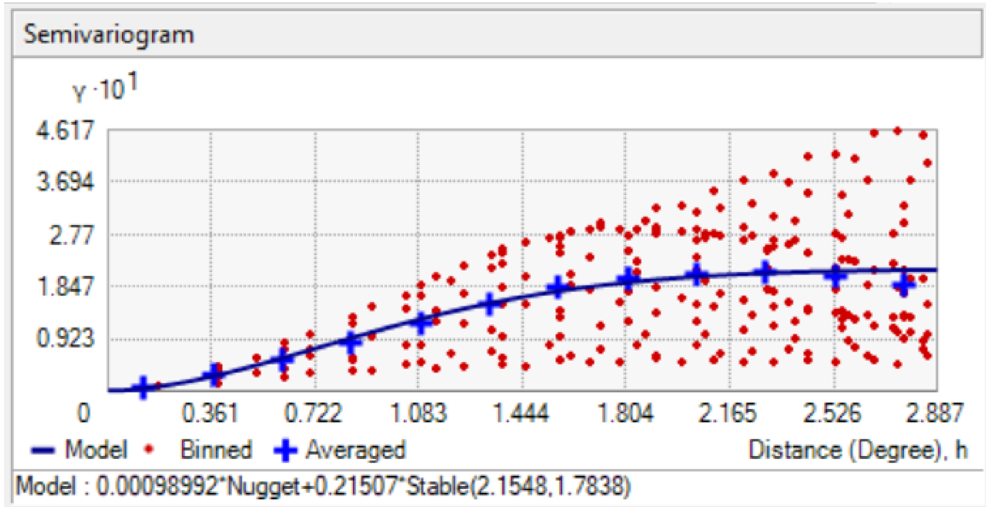


Figure 3-9 The semivariogram showing surface trend shown in the dataset.

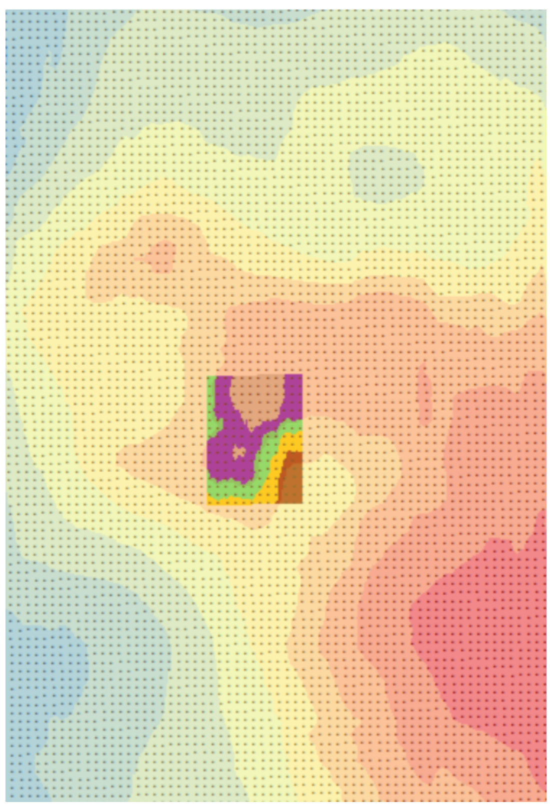


Figure 3-10 The Kriging prediction map generated from the Events file in ArcGIS.

As illustrated in Figure ***3-10***, the generated kriging prediction map goes beyond the CoE boundary limits, thus requiring it to be trimmed down to match the city's extents. Hence, the map needs to be trimmed to the exact extent of CoE. To execute this spatial operation, clip tool from the data management toolbox was used. The following procedures were followed:

a) The kriging prediction map was converted to raster.
b) The clip tool was used, with the limits of CoE selected and input raster selected as the exported raster kriging map.
c) The generated clipped map is the map that represents the climate variable for CoE, which can then be further processed into continuous, discrete, classified or stretched map.

Further data exploration can be done by changing the combination of different kriging properties to generate climate maps. The selected properties mentioned above were chosen based on the literature and data exploration.

Two major issues were encountered during data processing and feature engineering. First, the variables had different projections. This can be fixed in ArcGIS by using the same coordinate system. To project the data correctly using latitude and longitude, the projection of the coordinate system was set to "GCS_North_American_1983", which was the initial coordinate system chosen from the LiDAR dataset.

Second, all the RCP8.5 files were supplied in an NC file format to be converted to a CSV file to integrate with the ArcGIS model. To do this, Python was used to execute the file conversion; the script used is referenced in Appendix B. However, while processing the netCDF files, an infinite loop was encountered when converting the precipitation dataset. Upon investigation, the infinite loop was caused by a data type problem. To further elaborate, field variables in the precipitation dataset was of 2D type, whereas the netCDF file climate variables were of Geo2D type. This data mismatch is shown in Figure ***3-11***. To solve this problem, PanoplyWin software was used to slice and plot "generic" 2D arrays from larger multidimensional variables. Overall, to resolve the second issue, the following steps were followed:

a) Python script was used to convert all variables except Type 2D.

b) The netCDF file was exported using PanoplyWin software to CSV file format.

Once both issues were resolved, files were compiled using ArcGIS to produce raster maps.

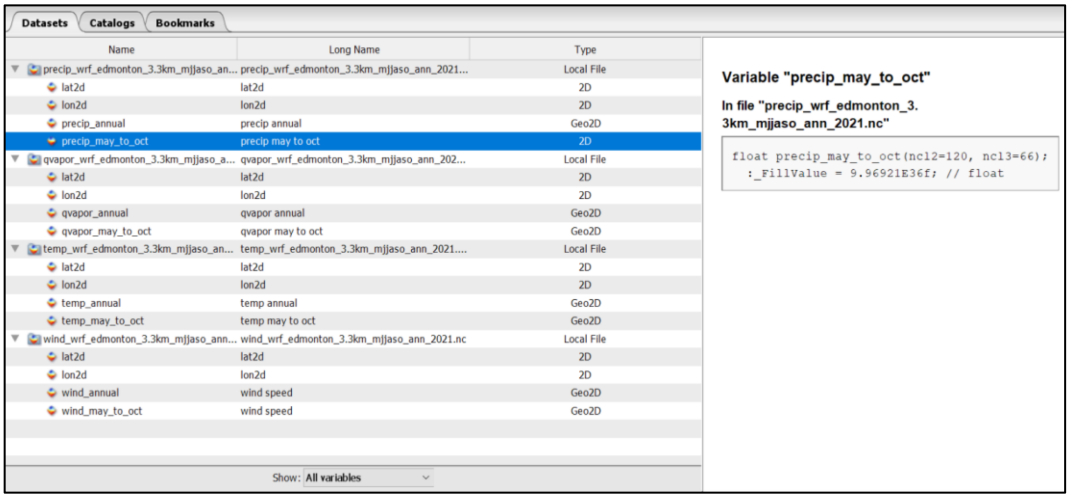


Figure 3-11 The data mismatch in the climate variable in the RCP8.5 data elaborated using PanoplyWin software.

4. Methodology

The overall workflow is shown in Figure ***4-1*** and it includes (1) compiling the independent/explanatory variables, (2) constructing the AHP matrix and assigning the weights to corresponding variables, (3) producing the fire risk assessment map, (4) generating forecasted fire risk maps, (5) generating the ecological vulnerability classification map, and finally (6) identifying the high-risk zones. According to the literature, combining the fire-risk assessment raster map with the vulnerability classification raster map provides an in-depth understanding of high-risk zones. This helps municipal authorities and decision-makers to better understand fire risk in specific zones, allowing them to plan and execute effective fire risk management strategic plans in the event of a fire outbreak.

To provide comprehensive and informative recommendations to fire risk management and climate resiliency planning, three critical items were investigated. First, an ecological vulnerability classification map was constructed to define three different levels of vulnerability; namely, areas labelled as ecological green line, grey line, or red line. According to the literature, ecological green line areas are replete with residential buildings, natural resources, and recreational areas, which can be extensively developed and upgraded to meet climate resiliency requirements. Ecological grey line areas can serve as an ecological buffer zone, aiding the municipality in sprawling development or shrinkage protections. Ecological red line areas have rich natural and vegetation resources that cannot be developed and must be preserved (Zhang, 2015). Second, it is essential to define the responsibility of all stakeholders and their role in fire prevention and mitigation efforts. Wildfires burn indiscriminately across both private and public property, and hence everyone has a responsibility in wildfire prevention. Finally, by integrating all the above information, four cornerstones of strategic planning and action are proposed for each of the high-risk area/zone. These cornerstones will support the efforts to build a climate resilient city and serve as catalysts for climate adaption. The four cornerstones are separated into two categories: long-term insurability risk management, as well as the resiliency benefits communication of the zone to attract investments.

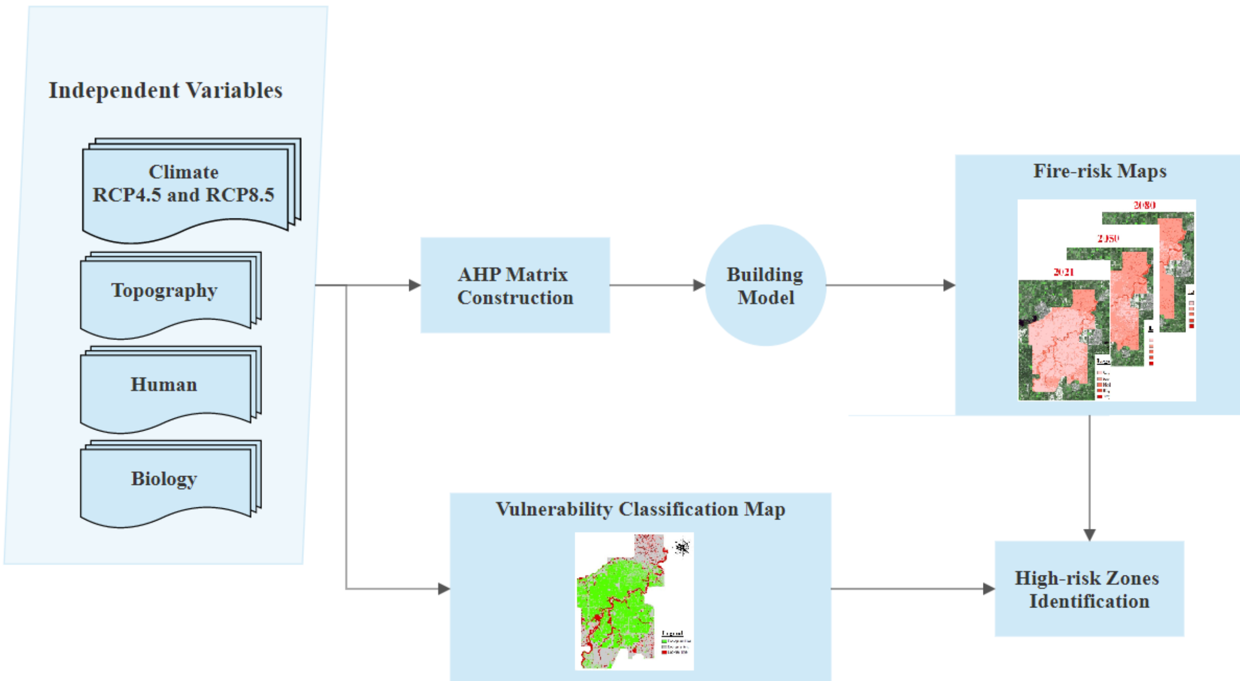


Figure 4-1 The overall workflow of the adopted methodology.

4.1. Analytical Hierarchy Process & Weight Assignment

Analytical Hierarchy Process (AHP) method (Saaty, 1977) is a comprehensive hierarchical weight assignment method used for an efficient multi-criteria decision analysis (MCDA). For each factor pair, an expert decisionmaker defines the extent one factor is more important than another. This then defines the relative position of one factor compared to all other factors. Quantitative weights can be assigned to each factor using the eigenvalue matrix technique so that distinct elements can be weighted with a homogeneous measurement scale. The weight assigned to each factor will reflect its priority compared to all other factors. Weights assigned are verified by calculating the consistency ratio for each Eigen matrix (Eskandari, 2017). Figure ***4-2*** depicts a simple AHP hierarchy with only one level of criteria that contributes to choosing an alternative.

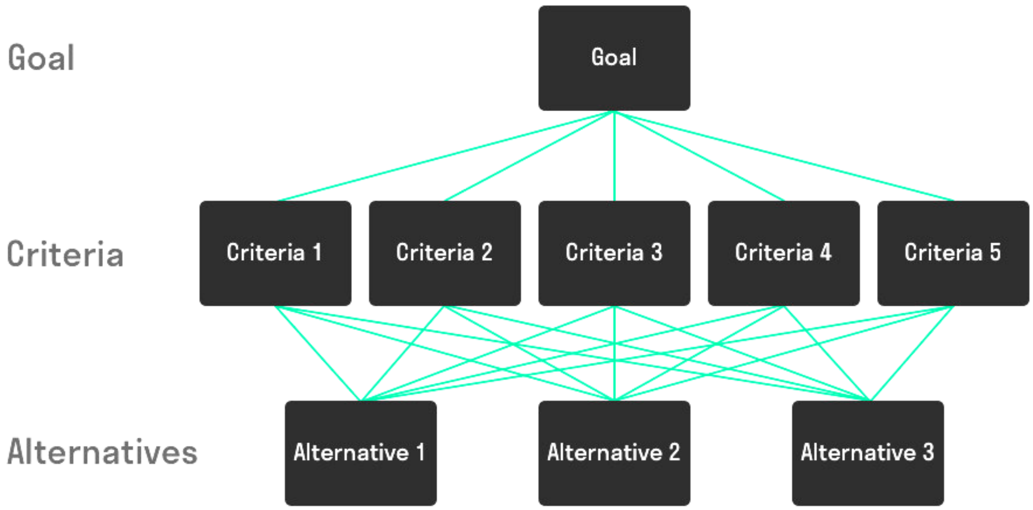


Figure 4-2 A simple AHP hierarchy, (adopted from Saaty, 2008).

AHP gains its advantages through its simplicity and transparency; however, its biggest advantage lies in the hierarchical framework that allows users to consider and measure the relative importance of indicators. To build hierarchical importance, a preliminary weight must be assigned to each variable in the matrix based on its relative impact on fire ignition and the associated ramifications. Since each weight significantly affects the influence variables have on the outcome, weight assignment is crucial in building the fire-risk model. Experts from the Urban Planning and Economy Department from the City of Edmonton were consulted to tailor the weights to the specific urban settings of the CoE. As already mentioned, high weights were assigned to climatic and human variables, while low weights were assigned to biologic and topographic variables. Finally, the consistency ratio was estimated for each matrix.

In this thesis, the fire risk model was developed using five pair-wise comparison matrices: (1) Topographic variables Eigen matrix; (2) Biologic variables Eigen matrix; (3) Meteorologic variables Eigen matrix; (4) Anthropogenic variables Eigen matrix; and (5) Fire-risk criteria Eigen matrix, as shown in Table 2 and Table 3.

Table 2 The calculated weights for each variable in each given criterion.

Criterion	Variable	Associated AHP Weight
Topographic	Slope	0.56
	Aspect	0.32
	Elevation	0.12
Meteorologic	Seasonal Temperature	0.42
	Seasonal Precipitation	0.37
	Seasonal Wind Speed	0.15
	Seasonal Humidity	0.07
Anthropogenic	Land Use	0.7158
	Proximity to Water	0.2841
	Proximity to Road	0.00002
Biologic	Forest Type	0.75
	NDVI	0.25

Table 3 The calculated weights for each criterion.

Criterion	Associated AHP Weight
Meteorologic	0.53
Anthropogenic	0.31
Topographic	0.08
Biologic	0.08

4.2. Fire-Risk Model Development & Analysis

The fire-risk model in this thesis is evaluated based on four different criteria, each with a unique set of variables. In total, there are twelve variables that are considered major factors for fire ignition in an urban setting. To briefly go over each criterion: first is the climatic criterion, considered a major fire trigger. This criterion includes temperature and precipitation variables that play a significant role in fire ignition, especially when high temperature is combined with dry weather. It also holds wind speed and humidity variables that influence fire behaviour and its ramifications. The second criterion is anthropogenic, affecting fire ignition. It contains the land use variable, proximity to water, and proximity to roads. Proximity to water is considered a fire mitigation variable. This is because water surfaces tend to increase soil moisture of surrounding areas, thereby subsequently reducing fire risk. Proximity to roads might be a fire mitigation variable; however, roads are not sufficient to stop massive wildfire spread in most cases. For instance, the Tubbs Fire in Santa Rosa, California, destroyed the city in 2017. Because of fire intensity and wind force, embers jumped six lanes of the 101 Freeway (Link-Herrera, 2019). Land use fire risk can be activity-based. An example of this is camping over vegetation as a fire hazard. The third and fourth criteria are topographic and biologic that are considered to have lower risk of fire ignition. The topographic criterion contains three variables: slope, elevation, and aspect. Slope relates directly to fire behaviour, while elevation and aspect relate manly to the fire ramifications. The biologic criterion contains two variables: forest type and NDVI.

The climatic, anthropogenic, topographic, and biologic risk maps were calculated based on Equations 4 - 7, respectively. The fire-risk model was developed using Equation 8, based on the weights obtained from AHP.

$$\textit{Climatic Risk (CR)} = 0.42*TMP + 0.37*PCP + 0.15*WS + 0.07*VAP \qquad (4)$$

$$\textit{Anthropogenic Risk (HR)} = 0.72*LU + 0.27*PRXW + 0.01*PRXR \qquad (5)$$

$$\textit{Topographic Risk (TR)} = 0.56*SLP + 0.32*ASP + 0.12*ELE \qquad (6)$$

$$\textit{Biologic Risk (BR)} = 0.75*FT + 0.25*NDVI \qquad (7)$$

$$\textit{Fire Risk} = 0.53*CR + 0.31*HR + 0.08*TR + 0.08*BR \qquad (8)$$

where TMP is temperature, PCP is precipitation, WS is wind speed, VAP is humidity, LU is land use, PRXW is proximity to water, PRXR is proximity to roads, SLP is slope, ASP is aspect, ELE is elevation, FT is forest type, and NDVI is the normalized difference vegetation index.

All variables and criteria were classified into five risk classes: Very low, Low, Moderate, High, and Very High. Classes and ratings are presented in Table 4 and a holistic conceptual model is shown in Figure ***4-3***. Elevation and slope were classified using the natural breaks (jenks) found in the city's data characteristics, where it is observed that lower elevations have higher fire frequencies (Calviño-Cancela, 2017). Aspect was classified according to the literature, where lower risk is associated to northern aspects (Eugenio, 2016; Hong, 2018; Busico, 2019). Land use was classified based on types and density of flora present as well as whether there is a body of water. The climatic factor was classified using equal intervals in accordance with the well-accepted notion that lower risk is associated with lower temperatures, higher precipitation, low wind speed and low humidity. It is worthwhile noting that the classification of data presented in this thesis was conducted based on the literature and can be adjusted differently using ArcGIS. Different classification methods, such as quantile and geometrical interval, can also be further explored to fit specific requirements.

Table 4 Model variables with classes and ratings for the assessment and mapping of fire risk for CoE.

Assessment Level	**Slope (°)**	**Aspect**	**Elevation (m)**	**Temperature (°C)**	**Humidity ($g.m^{-3}$)**	**Wind Speed (kph)**
1 Very low	0 - 4	North & Northeast	710 - 754	11.3296 - 11.3954	0.005943499 - 0.005988009	5.37884235 - 5.43728366
2 Low	4 - 10	Northwest	687 - 710	11.3954 - 11.4581	0.005912342 - 0.005943499	5.43728366 - 5.49351964
3 Medium	10 - 20	Southeast & East	668 - 687	11.4581 - 11.5026	0.005883093 - 0.005912342	5.49351964 - 5.53983163
4 High	20 - 36	Southwest & West	640 - 668	11.5026 - 11.5420	0.005857023 - 0.005883093	5.53983163 - 5.59165694
5 Very high	36 - 89	South	598 - 640	11.5420 - 11.5876	0.005825866 - 0.005857023	5.59165695 - 5.66002225

Assessment Level	**Precipitation (mm)**	**Land use**	**Distance from river (m)**	**Distance from roads (m)**	**Forest Type**	**NDVI**
1 Very low	405.7283386 - 465.4987183	Developed & Naturally Non-Vegetated	0 - 1000	0 - 0.179748	Mixed deciduous	-1-0
2 Low	372.4276985 - 405.7283385	Wetland	1000 - 2770	0.179748 - 1.047223	Balsam poplar	0.66-1
3 Medium	339.9809209 - 372.4276984	Modified	2770 - 4965	1.047223 - 5.23372	Deciduous mixedwood & White spruce	0.33-0.66
4 High	304.9725556 - 339.9809208	Naturally non-wooded	4965 - 7944	5.23372 - 25.438054	Trembling aspen	0.15-0.33
5 Very high	247.7637634 - 304.9725555	Naturally wooded	7944 - 13275	25.43805 - 122.945614	Coniferous mixedwood & Black spruce	0-0.15

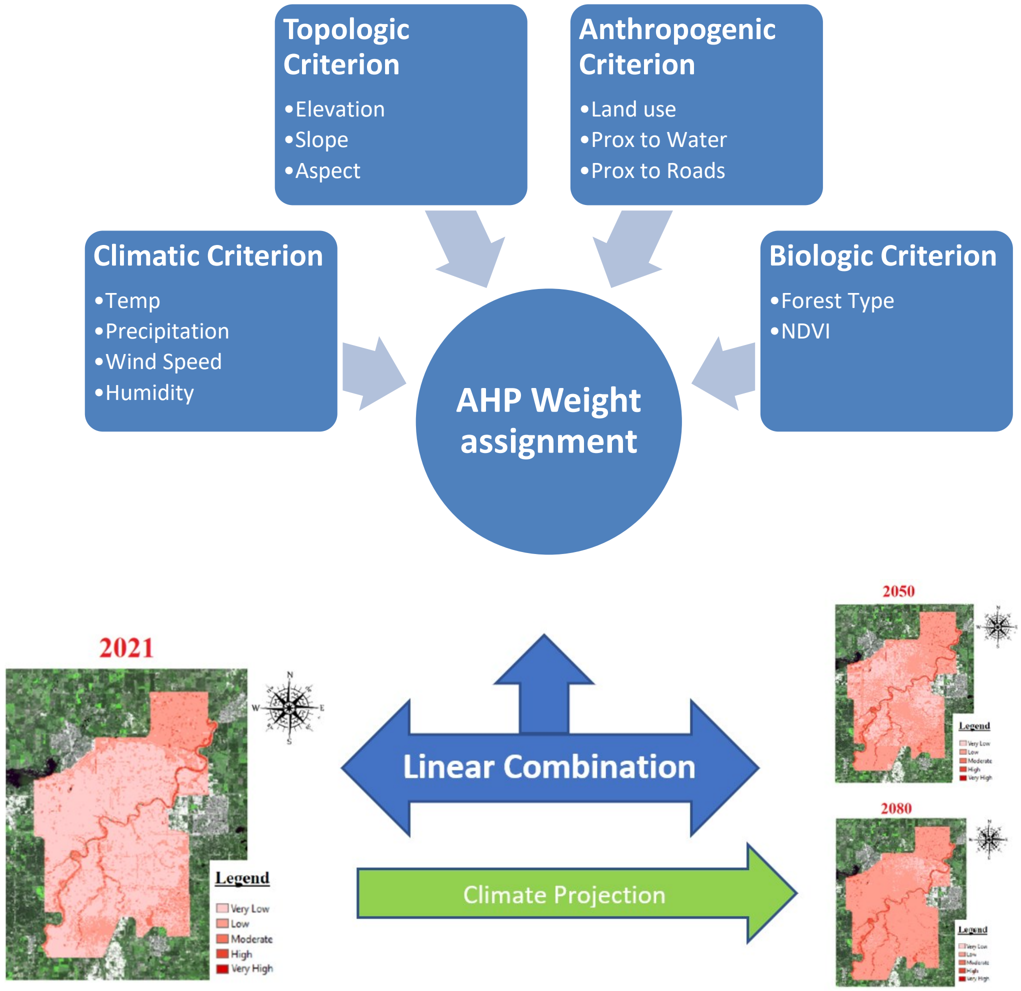


Figure 4-3 Conceptual model of fire-risk assessment model building.

4.3. Climate Predictions

Given the increased probability of wildfire events developing in Western Canada, protecting municipalities' green spaces and urban infrastructure has become a pressing concern. Significant efforts have been exerted by major municipalities in North America to tackle climate change and by doing so create a climate resilient city, one of which is the City of Edmonton (CoE). In 2018, the CoE joined 4,500 cities around the world in a shared commitment to obstruct global mean temperature rise from surpassing 1.5°C.

Climate predictions were accounted for in the proposed model via RCPs. RCP8.5 assumes that the global emissions will follow current trajectory (i.e., "business as usual" scenario). RCP4.5 assumes there to be climate mitigation actions taken to limit global temperature rise to less than 2°C (i.e., "strong mitigation" scenario). RCP8.5 is the most conservative as it represents the worst-case scenario. In collaboration with the University of Regina, the procured RCP8.5 data have temperature, precipitation, wind speed, and humidity variables with a reference period between 2021 and 2080. The data were engineered to represent the fire season average for each variable. Fire season in CoE is from May to October, where all the climate variables have the highest potential for fire ignition. The data comprised 120x66 grid points centered over CoE with a 30m x 30m grid area. The projections of the climatic variables were calculated for 2021, 2050, and 2080, as depicted in Figure ***4-4***. The classification method used for each climate variable projection uses natural breaks (Jenks), effectively grouping similar values together while maximizing the differences between the classes.

It may strike the reader that an assumption was made for these climate projections that all the other criteria and variables maps show either no or only slight change over the next few decades. CoE's topographic and anthropogenic criteria are assumed to remain constant over time. The biologic criterion is also assumed to be constant since almost all the vegetated areas are natural preservations protected by law (Zoning Bylaw Renewal Initiative, 2020).

Before discussing variable projections any further, it is worth mentioning that the RCP4.5 data project only annual temperature and precipitation variables, while the RCP8.5 data project data all the climate variables. First, regarding the annual projections, the RCP4.5 climate projections for 2050 predict that annual temperature will increase by 40.5% and annual precipitation will decrease by 3.2%. On the other hand, RCP8.5 predict that the annual temperature will increase by 28.7% and annual precipitation will increase by 10.0%. Regarding the RCP4.5 climate projections from 2050 to 2080, the annual temperature will increase by 18.0% and annual precipitation will further decrease by 3.3%. With respect to RCP8.5, annual temperature and precipitation will increase by 54.3% and 4.6%, respectively.

Altogether, these results make intuitive sense as the RCP8.5 values showed a higher overall percentage of change than the RCP4.5 values. When comparing both current and 2080 scenarios, the percent of change in temperature for RCP4.5 and RCP8.5 was found to increase by 65.9% and 98.7%, while precipitation amounts were predicted to decrease by 6.3% and increase by 15.0%, respectively. Table 5 summarizes the projected RCP4.5 and RCP8.5 values for annual temperature and precipitation.

Table 5 The annual temperature and annual precipitation variables projection for RCP4.5 and RCP8.5 (source: CoE local authorities).

Year	Annual Temperature (°C)		Annual Precipitation (mm)	
	RCP4.5	**RCP8.5**	**RCP4.5**	**RCP8.5**
2021	3.346	3.618	549.329	504.840
2050	4.703	4.654	531.949	555.195
2080	5.55	7.188	514.637	580.8

Using RCP8.5, variable projections for seasonal temperature, precipitation, wind speed, and humidity were also calculated. By the year 2050, it is predicted that the precipitation average will decrease by 42.5%, temperature average will increase by 33.7%, humidity average will increase by 17.0%, and wind speed will decrease by 15.3%. Between 2050 and 2080, seasonal precipitation average will increase by 11.7%, seasonal temperature average will increase by an additional 8.5%, seasonal humidity average will increase by another 5%, and seasonal wind speed average will increase by 7.9%. Table 6 shows the seasonal temperature, precipitation, wind speed and humidity values for RCP8.5.

Table 6 The seasonal temperature, precipitation, wind speed and humidity variables projection for RCP8.5 (source: University of Regina).

Year	Precipitation (mm)	Temperature (°C)	Humidity ($g.kg^{-1}$)	Wind speed (mph)
2021	319.927	11.108	0.0059	5.282
2050	183.941	14.857	0.0069	4.476
2080	205.431	16.12	0.0072	4.828

Climate projections for 2050 and 2080 were calculated using Equation 4 and are depicted in Figure ***4-5***. These climate changes will play a significant role in increasing fire ignition, hence, will drastically increase overall fire risk. The class classification of the climate raster maps has equal intervals for all risk factors. For instance, Very Low is defined between 0.546 and 0.5847, Low is between 0.585 and 0.623, Moderate is between 0.623 and 0.66, High is between 0.66 and 0. 699, and Very High is between 0.699 and 0.74. Each class above has an interval of 0.038.

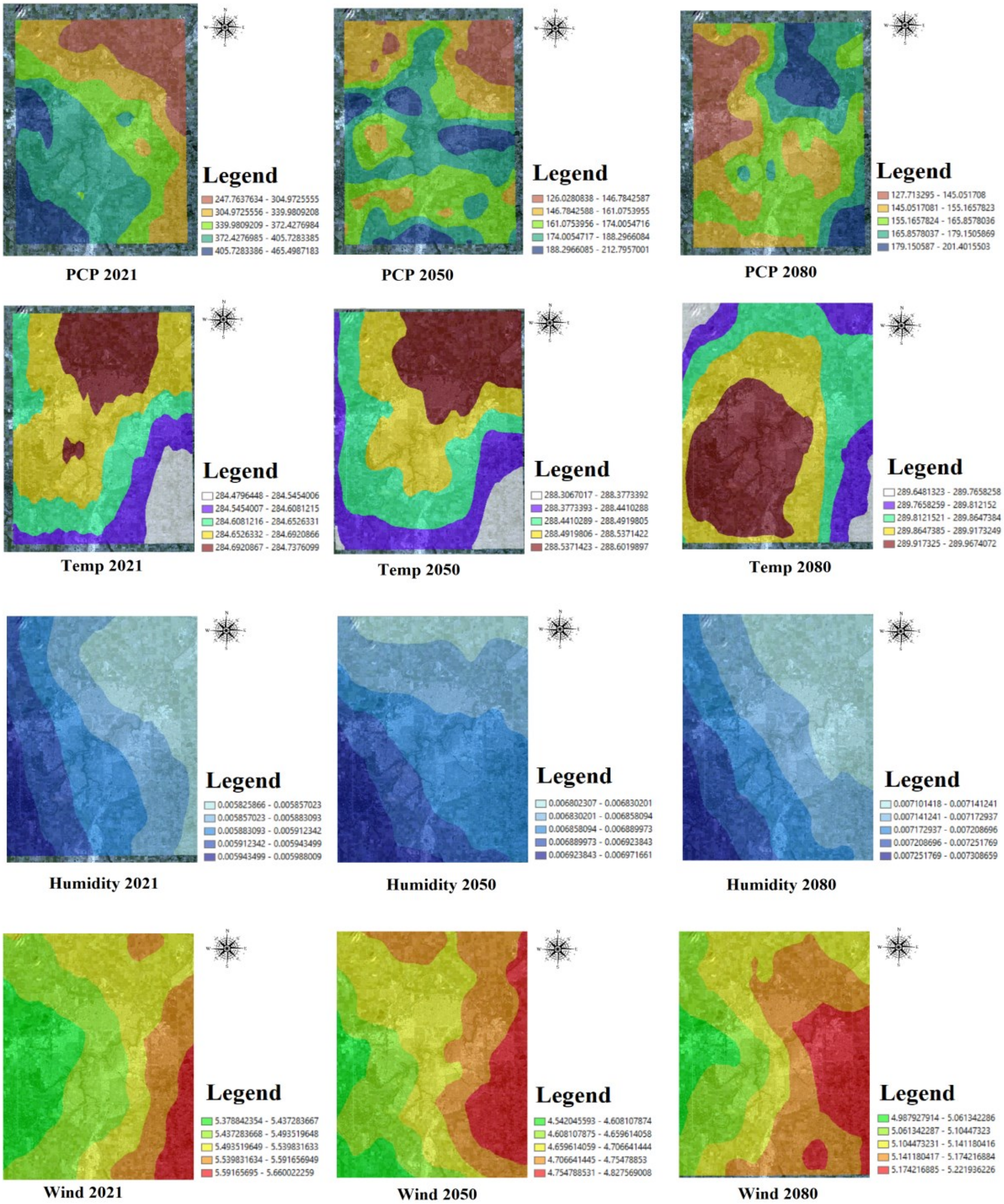
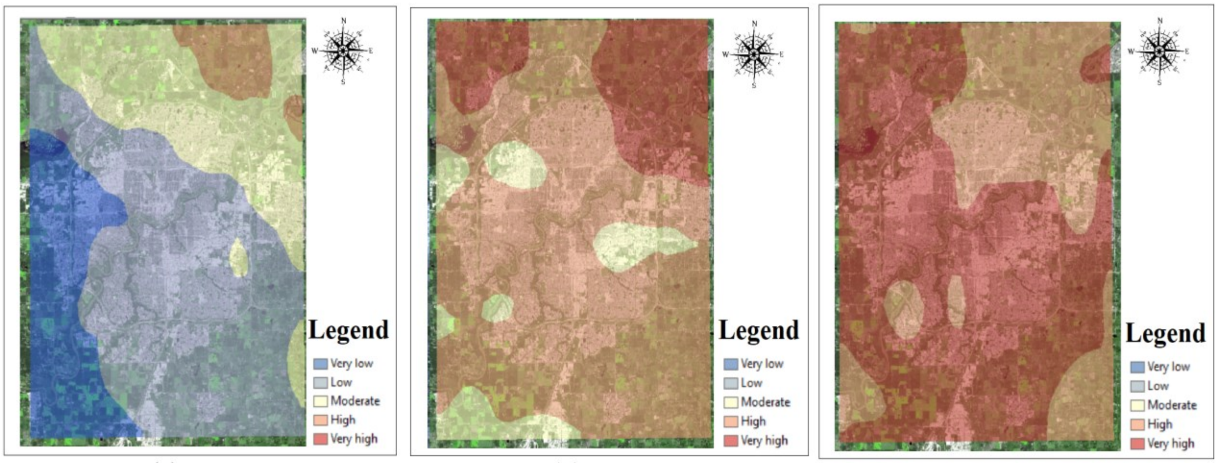


Figure 4-4 Climate variables for 2021 and predictions for 2050 and 2080 based on RCP8.5 data.



(a) Climate 2021 (b) Climate 2050 (c) Climate 2080

Figure 4-5 The climate criterion of fire season maps using RCP8.5 for CoE calculated using Equation 4 for (a) 2021, (b) 2050 and (c) 2080.

4.4. Summary

A reliable fire risk model requires abundant and accurate data. However, integrating an overabundance of data into a single model can cause it to be overly complex. Hence, one should only select the most effective variables and/or factors that contribute to the model assessment. In this thesis, the fire risk model is constructed based on four criteria containing a total of twelve variables that represent the urban setting and the environment of the CoE. The model building process consisted of procuring all the high-resolution datasets, feature engineering, and thorough data analysis. The result was a high-resolution fire risk map. Once the fire risk map had been constructed, weight assignments were performed in accordance with AHP such that expert opinions could be incorporated in the suggested weights.

Climate predictions and forecasts were based on two climate datasets, RCP4.5 and RCP8.5 datasets, for three different years, 2021, 2050, and 2080. The two datasets were then integrated to forecast climatic conditions that are expected to change drastically and cause an increase in risk of wildfire in the city as time progresses. Along with high risks associated with climate, it should be noted that grassland fires could also pose a threat to Edmonton, especially in suburbs on the edge of the urbanized area.

5. Results & Discussion

Chapter 5 focuses on the fire-risk assessment maps generated via the fire-risk assessment model. There are six subsections in this chapter. The first subsection discusses the 2021 fire risk assessment map in light of transportation development expansion and evacuation planning. The second subsection discusses and compares forecasted fire risk assessment maps for 2050 and 2080 that were generated using the RCP8.5 dataset. The third subsection explains the ecological vulnerability classification method along with its contributions to this research. The fourth subsection outlines the shared responsibilities between stakeholders for fire prevention and mitigation, whereas the fifth subsection highlights the key pillars of strategic planning and action to zone resiliency. The final subsection provides a summary of the important points discussed in this chapter.

5.1. The Fire-Risk Map For 2021

The 2021 fire-risk map was classified into five categories with equal intervals that range from 0.300 to 0.723: Very low, Low, Moderate, High, and Very High. Risks maps were first generated for each of the 12 variables, and then combined to form the final risk map. These maps are shown in Figure ***5-1*** and Figure ***5-2***, respectively. In terms of the different risk levels, the very high-risk class is observed to contain mostly coniferous and black spruce trees, species known to have the highest flammability in Edmonton. Furthermore, this category also contains the river valley area, mainly because of its low elevation and high slope angle around its edges, both of which are factors known to increase fire risk. Very high risk also encompasses the center, north, and north-east parts of Edmonton because of temperature and precipitation as shown in Figure ***5-1***.

During the fire season, these open-vegetation areas in Edmonton are exposed to higher levels of human activity, such as camping, that can result in unintentional fires. Although these areas are close to a waterbody, their proximity to water had no impact in attenuating fire risk. This is because during most of the fire season, other variables have much larger weights, effectively nullifying the proximity to water factor. The next highest risk category is high-risk. This category is characterized by the forest type trembling aspen trees. One thing to note is that in both very high-risk and high-risk are green areas and parks where human activities are most likely to occur, leading to higher probability of fire ignition and ramification. The next category representing moderate-risk contains white spruce, the balsam poplar, and various other deciduous trees, all regarded as less-flammable species. The second lowest risk class, the low-risk category contains agricultural area south-west of Edmonton. And finally, the very low-risk category holds majority of the buildings and residential areas. It is important to make clear that lower risk areas do not necessarily imply low consequence. While the probability of a fire ignition in a low-risk area could be very low, the consequence and propagation could be massive and destructive.

To review the fire risk assessment map for 2021 from the transportation perspective, we have overlayed the roads network of the CoE. The generated map is shown in **Figure 5-3 The transportation infrastructure overlayed with the fire risk map for the CoE.**Figure ***5-3***, and a few critical points can be interpolated from this map. Most importantly, this can aid in evacuation planning and transportation development expansion. An important factor to consider for a thorough evacuation plan is the supply and demand calculation of a given vulnerable neighborhood, should there be a fire outbreak. Supply can be represented as the roads and transportation means, determined through the given map and/or other datasets. Demand can be represented as the people living in the neighborhood that need evacuating, determined through the census dataset. Traffic and network analysis could be simulated for vulnerable neighborhoods to gain insight prior to future development. Vulnerable neighborhoods should have the highest priority in the evacuation process in fire breakout. These neighborhoods typically have school zones, hospitals, and recreational and shopping areas.

An important marker of successful evacuation planning is the total evacuation time. The total evacuation time is measured from the beginning of the evacuation (when the evacuation alert is issued) to the last vehicle reaching the destination egress in the road network (Li, 2019). Another important marker is the geographical and cultural context for directing evacuation resources. (Wong, 2020). Significant variables that may impact those decisions could include age, family members, household income, number of children in households, transportation availability, and evacuation route of choice, to name few (Wong, 2020).

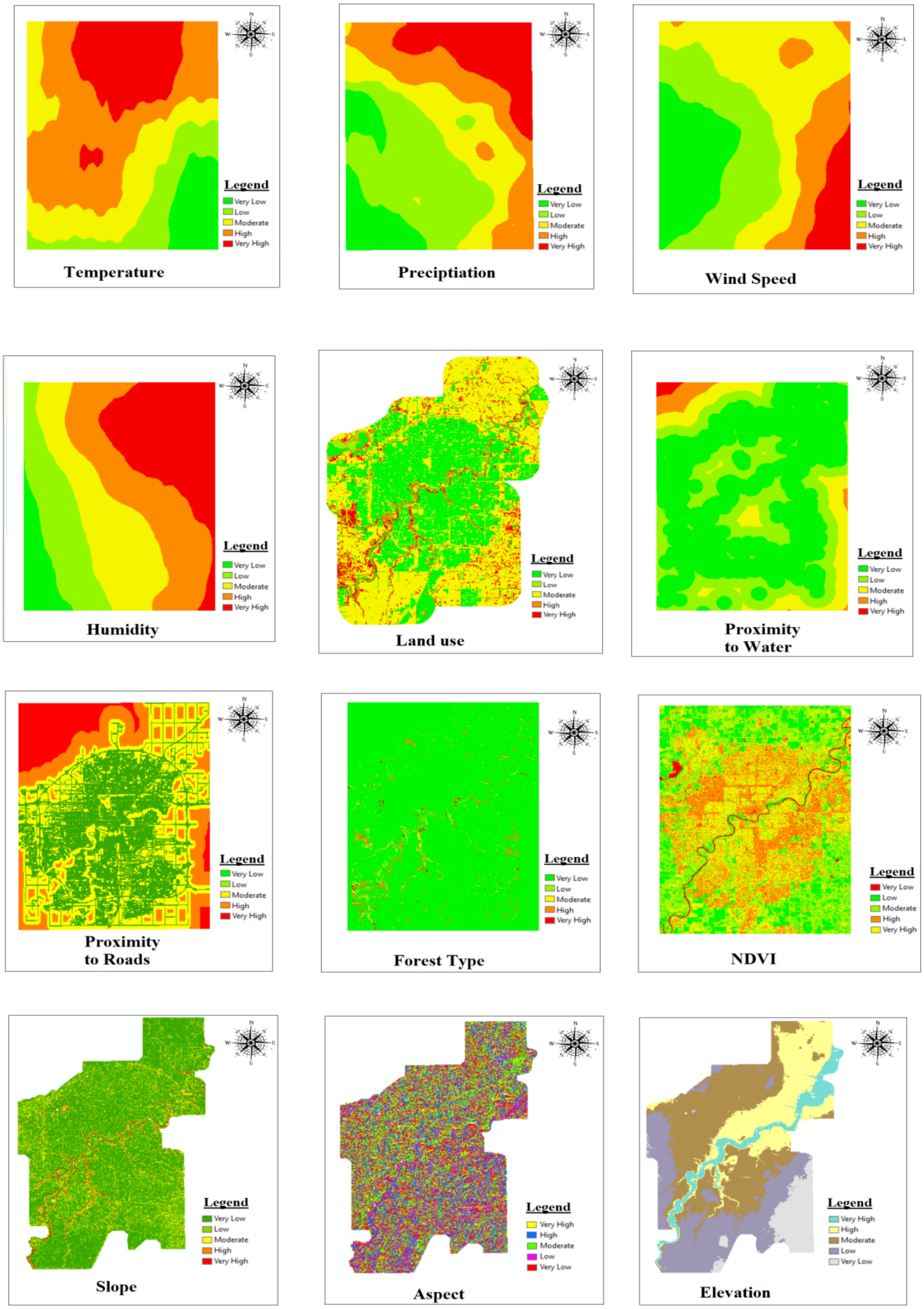


Figure 5-1 Risk map for all the 12 variables used for fire-risk assessment.

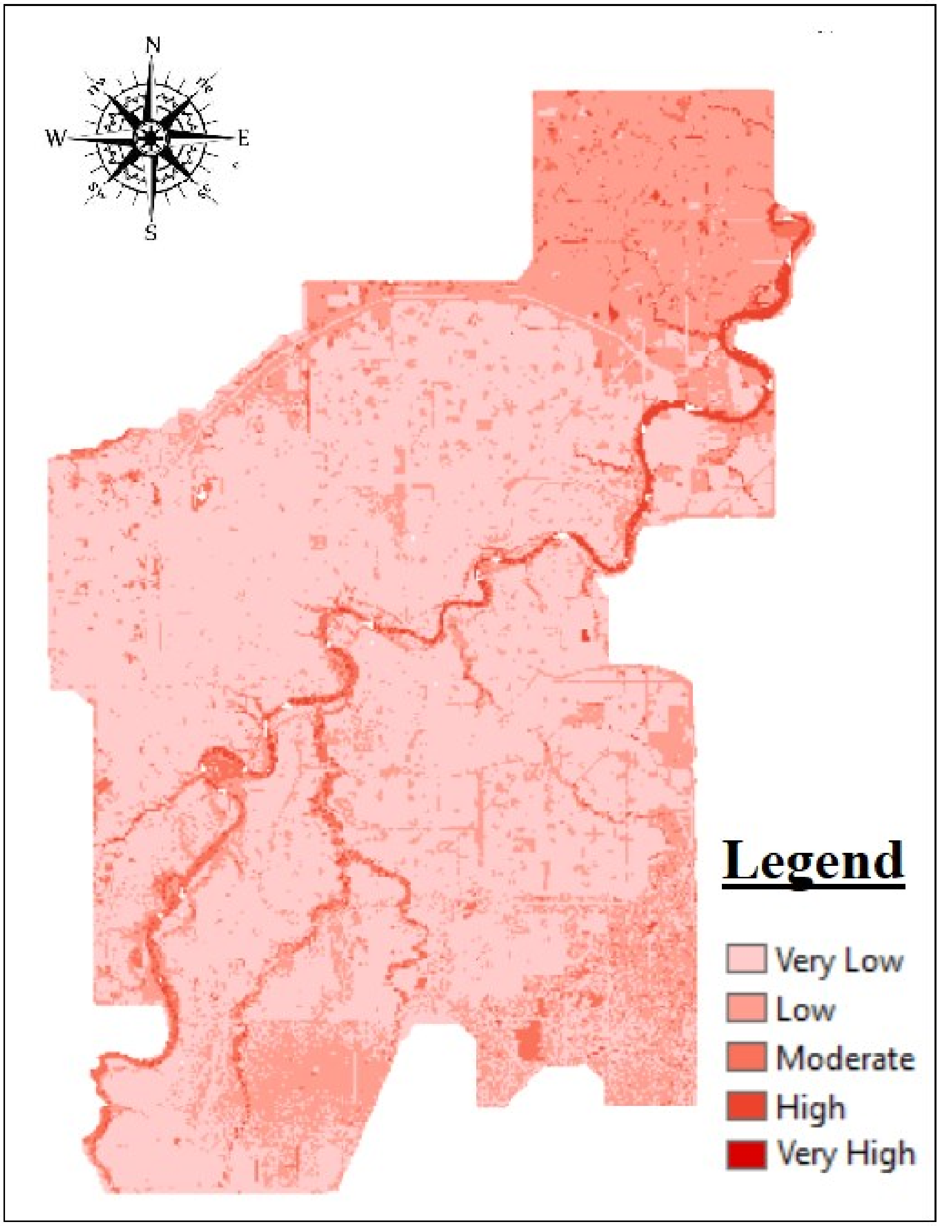


Figure 5-2 The fire-risk map for 2021.

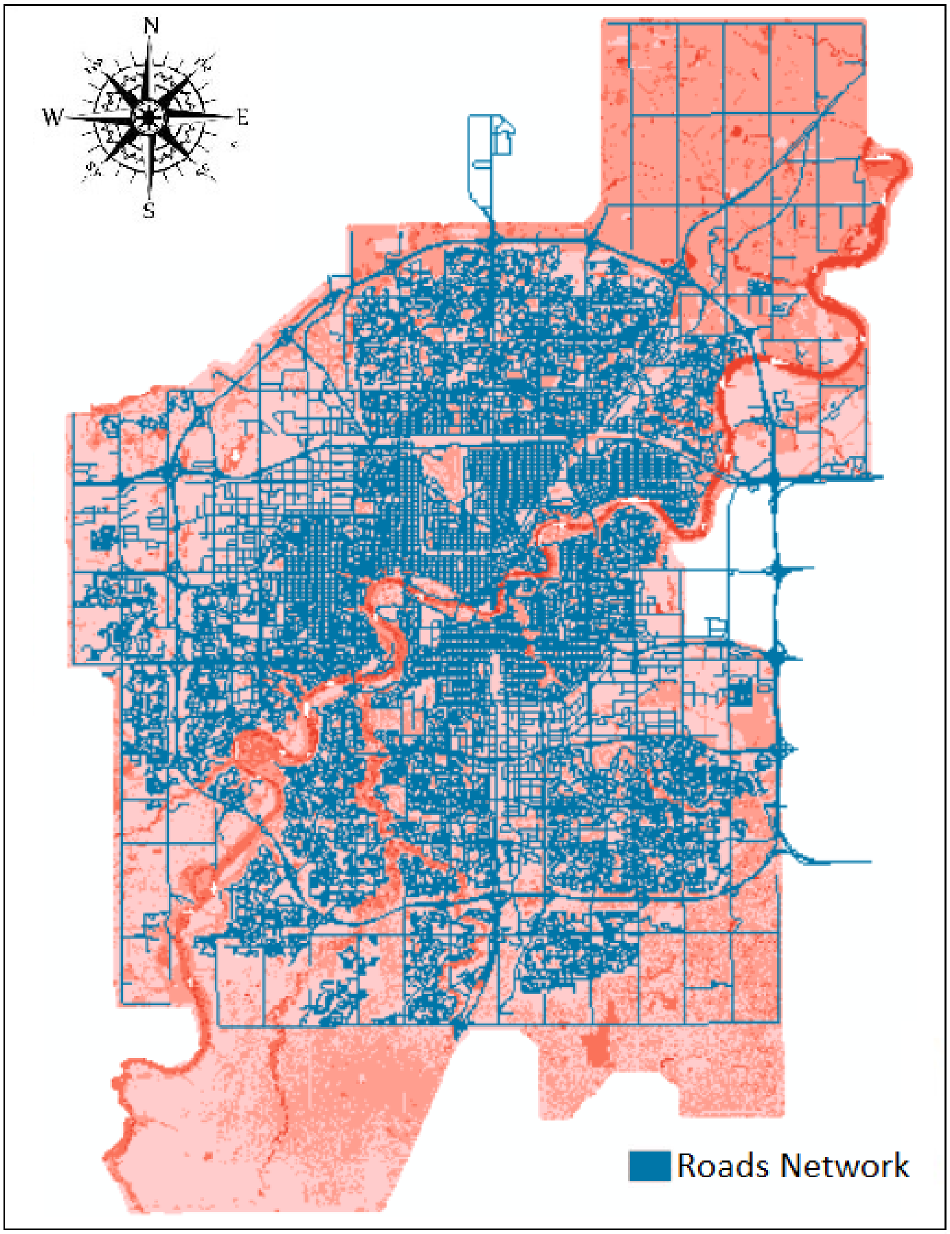
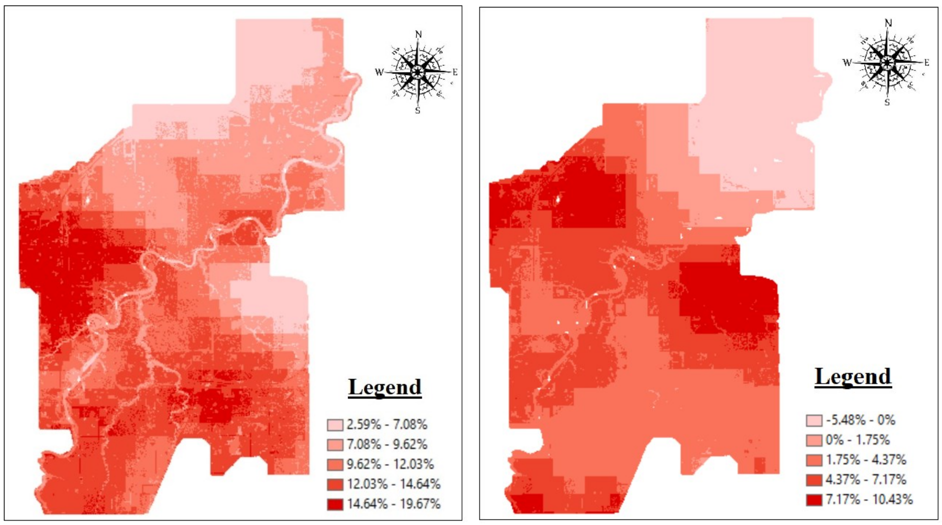


Figure 5-3 The transportation infrastructure overlayed with the fire risk map for the CoE.

5.2. The Fire-Risk Maps for 2050 and 2080

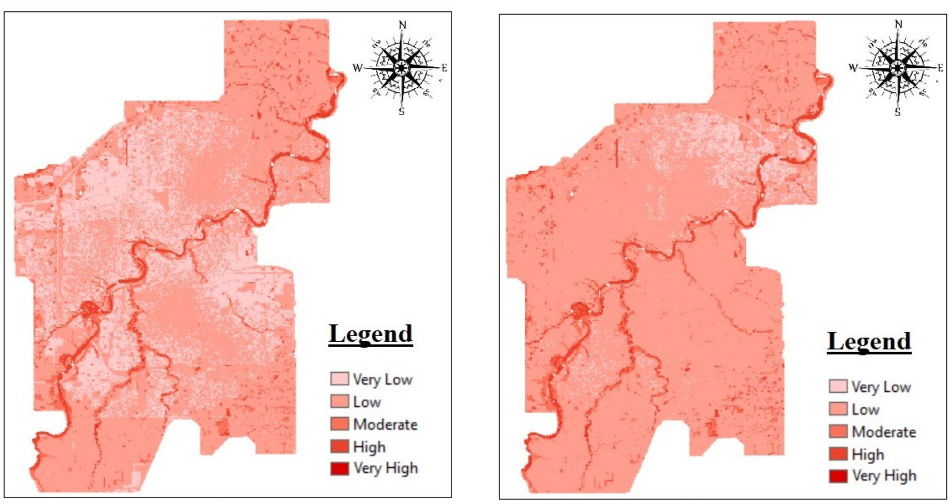
By projecting fire-risk into horizon years, it is possible to determine which zones are the most impacted by climate change. And thus, climate projections were made for 2050 and 2080 using the climatic RCP8.5 data as depicted in Figure ***5-4***. Figure ***5-4***(a) illustrates that by 2050, west and south regions' fire risk will increase by 14-19.7%. Within the central regions, risk will increase by 12-14.4%. Figure ***5-4***((b) also suggests that by 2080, the northwest and east zones will increase their fire potential by 7.2-10.4%, and southern regions will experience a moderate fire risk increase of 1.7-4.3%. Contrary to the above two zones, the northeast zones will have a lower fire risk. Their fire potential is forecasted to decrease by up to 5.48% due to the projected climate changes.

The forecasted fire-risk maps for 2050 and for 2080 using the climate RCP8.5 data are shown in Figure ***5-5***(a) and in Figure ***5-5***(b), respectively. The climate projection maps indicate a higher level of risk, with Very low and Low risk areas becoming Moderate and High-risk areas.



(a) **(b)**

Figure 5-4 Risk rate of changes on the CoE (a) from 2021 to 2050, and (b) from 2050 to 2080.



(a) **(b)**

Figure 5-5 Forecasted fire-risk map for CoE for (a) 2050, and (b) 2080 using climate RCP8.5 data.

5.3. Vulnerability Classification

The five risk categories shown earlier in Figure ***5-2*** can be grouped into three types of regulatory zones: ecological green line, grey line, and red line areas (Zhang, 2015), as depicted in Figure ***5-6***. It is worthwhile noting that the generated ecological lines are not fixed but can easily be adjusted to other classification ranges within ArcGIS, thereby increasing the model transferability potential.

The ecological green line areas include the very-low- and low-risk areas in CoE. From the perspective of sustainable development and zoning regulations, the ecological green line areas are abundant in residential buildings, natural resources, and recreational areas, making these regions the most livable for residents (Zhang, 2015). Most of the green areas in the CoE are urban developed and residential areas located near city center. The ecological grey line areas comprise of moderate-risk regions found between the red and the green line areas. The grey line area can aid various ways in city development. For instance, if a city pursues sprawling development, grey line can offer adequate space as back-up for urban development; whereas if a city desires a shrinkage protection strategy, grey area can act as the ecological safeguard zone to protect the environment from forthcoming urban development (Zhang, 2015). In terms of CoE, grey line areas are often developed agricultural areas, found mainly in the south-east and south-west areas just outside the city. The ecological red line areas comprise of high- and very-high-risk areas with rich natural and vegetation resources. These areas are ecologically preserved and cannot be used for urban development or industrialization purposes. These areas serve to promote sustainable development and natural heritage (Zhang, 2015). Within CoE, all forested and natural lake areas are red line areas.

Importantly, the ecological green line areas replete with residential buildings and people should be highlighted since there is a strong connection between urban sprawl and increasing greenhouse gas (GHG) emissions. High levels of urban sparsity within vast distances from the city centre, in particular, are linked to higher per capita emissions (Dubeux, 2007; Baur, 2015). Hence, the ecological grey-line areas could aid city experts and planners with climate resiliency and transportation development and expansion. GHG emissions reduction and evacuation planning need to be prioritized.

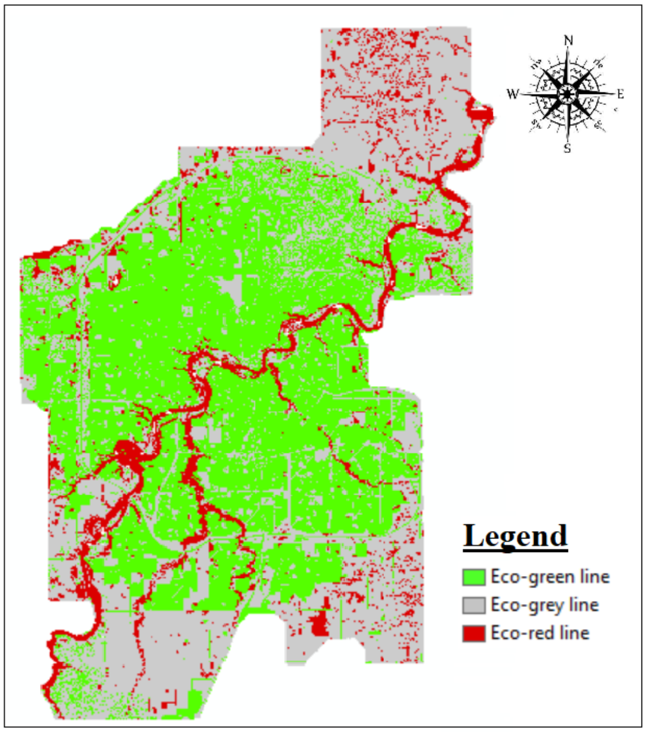


Figure 5-6 The regulatory zone of ecological lines of City of Edmonton.

5.4. Responsibility Identification

Residents, homeowners, fire departments, and the government share responsibility for developing a climate-resilient city. For instance, the government is responsible for firefighting and encouraging, directing homeowners, while homeowners should handle fire prevention to increase the city's preparedness.

The government has the duty to provide information about protection measures and the dangers associated with fire. Additionally, the government also has to develop a well thought out fire management plan by considering the risk of fire and its associated impacts. During the developmental process, it is essential to have a strong fire-risk management system as reference, as it plays an additional role in zoning and building codes that function as active preventions. The fire guidelines engrained in these codes to maintain city resiliency before, during, and after a fire occurrence. Becoming a climate-resilient city is a significant goal for any major municipality (Mell, 2010; Fire Smart, 2020).

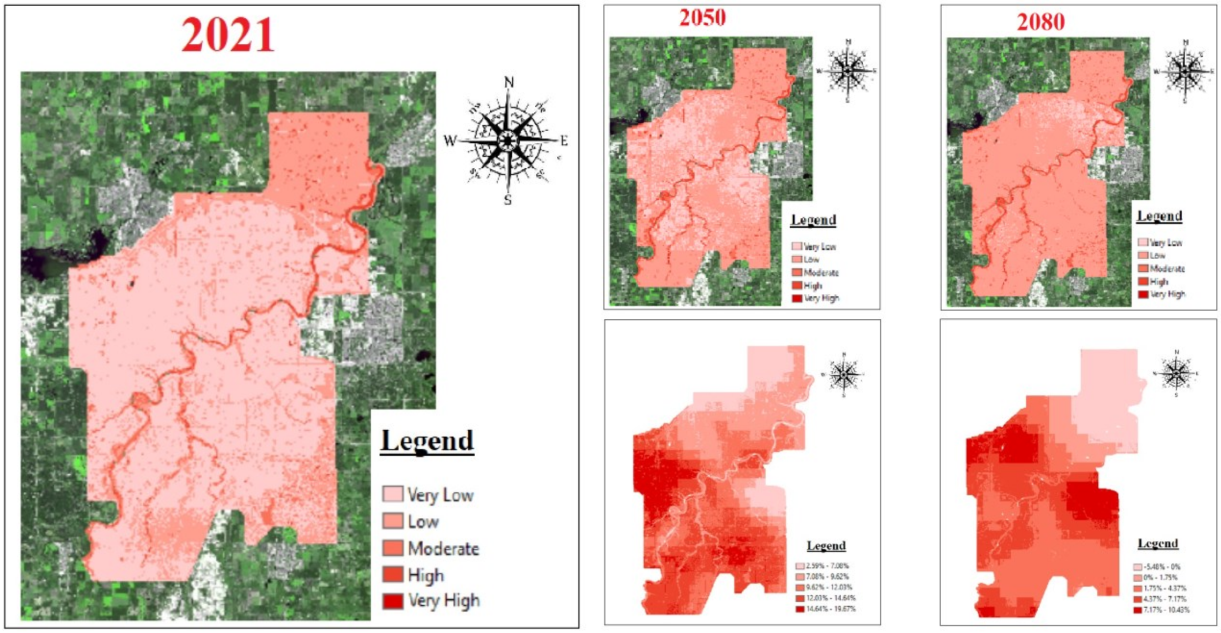
But for these roles to work, homeowners first need to be responsible and fire conscious. The government could reach this level of education by outlining two procedures. First, homeowners must be careful with fire in their private property. Secondly, they must educate themselves on and practice fire-risk prevention. This can be achieved when the government educates the homeowners, encouraging them to comply with fire mitigation and prevention guidelines and sometimes paying a portion of the materials and building cost (Mell, 2010; Fire Smart, 2020).

The vulnerability classification and the responsibility identification sections are intertwined to provide insights into urban (especially transportation department) development and climate resiliency. It can be interpreted from this section that the government has the responsibility to (1) Educate people and ensure compliance during development and upgrading, and (2) Undertake urban development considering fire risk management and evacuation planning in a climate resiliency context. The expected output from these is a reduction in GHG emissions while simultaneously considering the transportation development for effective evacuation in case of a fire outbreak.

5.5. Fire-Risk Management to Climate Resiliency

Three points can be concluded from the 2021, 2050, and 2080 fire-risk maps, obtained as outputs from the fire-risk model. First, there are currently high-risk areas in the north and south direction in CoE, as shown in Figure ***5-7***(a). Secondly, as demonstrated in Figure ***5-7***(b), there will eventually be a high-risk area in the east and west direction and a minor risk region in the south. Lastly, higher risk regions will be created in the west, east and south, as shown in Figure ***5-7***(c).

As mentioned, fire-risk raster maps can be further converted into regulatory zones. The green and grey ecological areas are considered the areas of focus for fire prevention, as depicted in Figure ***5-8***. Green areas could be sustainable when GHG emissions are reduced and grey areas are expandable. Findings therefore suggest that it is essential to consider more fire-risk management processes as well as zoning and building regulations to implement in the initial steps toward climate resiliency.



(a) (b) (c)

Figure 5-7 All fire-risk raster maps for 2021, 2050 and 2080, associated with the delta map for the corresponding forecasted year.

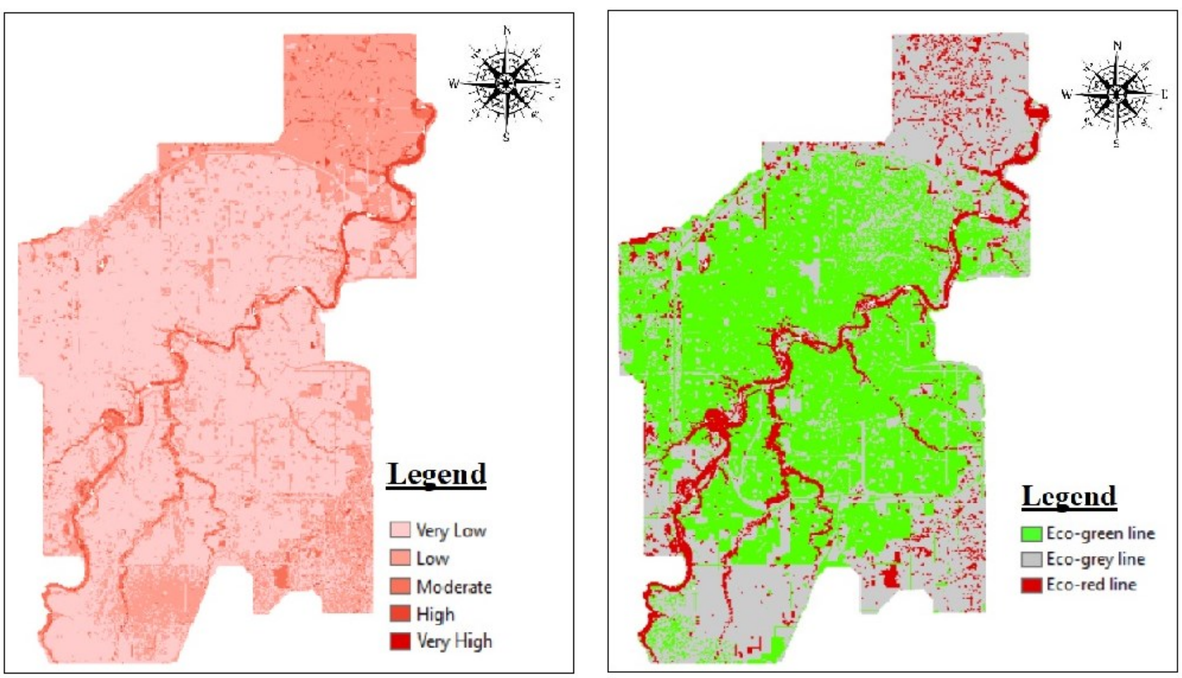


Figure 5-8 The fire-risk assessment raster map along with the vulnerability classification raster map for the CoE.

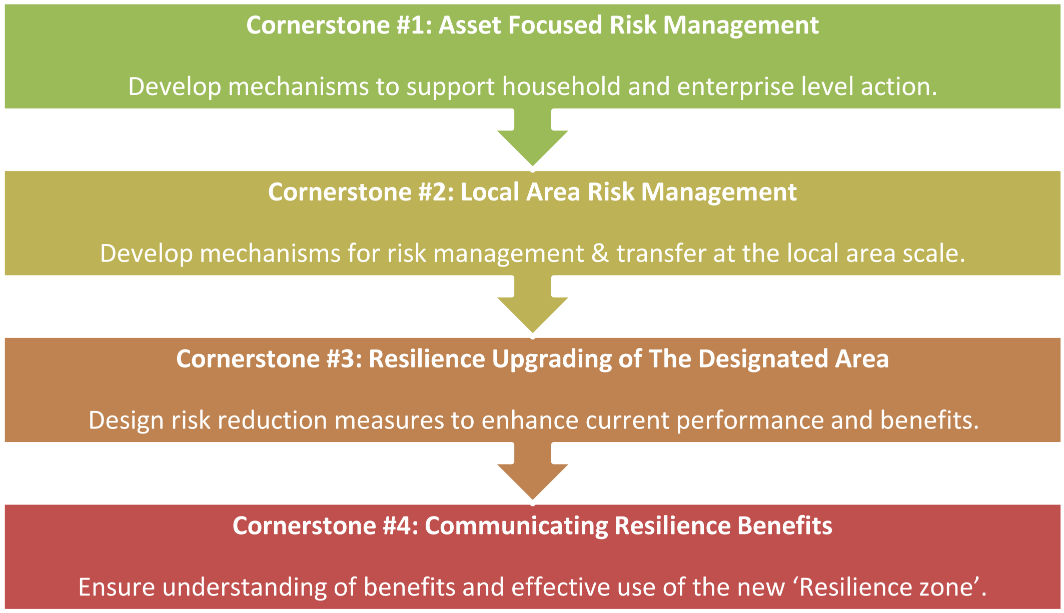


Figure 5-9 Four fundamental cornerstones for strategic planning and policy regulations, (adopted from Brugmann, 2014).

The Resilience Zone approach, shown in Figure ***5-9***, centers around strategic planning and the establishment of a market foundation for climate adaptation. Such approach comprises of four cornerstones. The first two cornerstones serve to reinforce risk management and sustained insurability. The successive two cornerstones aim at attracting investment and to communicate resilience benefits to preserve and enhance Resilient Zone value (Brugmann, 2014).

5.5.1. Cornerstone #1: Asset-Focused Risk Management

The first step in building a resilient city is defining the fire risk hazards present. For this reason, local stakeholders and their partners in government, insurance and utility companies, and other relevant industry sectors should work collaboratively to discover the dangers present. And through policies, building standards, and risk education, the discovered risks can be managed and mitigated (Brugmann, 2014). Hence, this cornerstone focuses on motivating and supporting homeowners and infrastructure providers to manage climate risks on their own.

The aim is to identify measures that altogether could establish market dynamics that better influence climate-related risks into the risk management of individual assets and businesses (Brugmann, 2014). One notable example of this is building codes. By integrating fire prevention method into building guidelines, property owners are effectively incorporated into the fire risk management process. For homeowners, they have to consider hardening of homes, reducing distance between homes and wildlands, and increasing brush clearance, thereby transitioning some of the responsibility from governmental agencies to homeowners. This cornerstone could be achieved through the development of and compliance with the FireSmart guidelines.

5.5.2. Cornerstone #2: Local Area Risk Management

The urban-setting risk management is confined to homeowners and assets, single organizations, and enterprises. Even if homeowners and businesses manage their business and asset risks efficiently, they are still exposed to higher scaled risks, like fire risks at a district, neighborhood, or corridor level. Residents and businesses may also not afford to bear with risks on that scale. Hence, asset owners and stakeholders in high climate vulnerability zones must create mechanisms for collaborative risk management specific to the area (Brugmann, 2014). One mechanism may be the establishment of an institution that is accountable for risk management at the local area level. This entity may collaborate with insurance providers to develop tailored risk transfer resolutions for its unique exposures.

Local Area Risk Management emphasizes risk management and vulnerability reduction to develop current primacies at a zonal level. It aims to clarify the separation between current risk management priorities regarding businesses and assets and the needed requirements for longer term climate resilience (Brugmann, 2014).

5.5.3. Cornerstone #3: Resilience Upgrading of the Designated Area

Improved safety is not risk managements' only benefits but it also has the potential to improve the attractiveness of the area and, by doing so, add value to the land and attract investments. For instance, the City of Curitiba, Brazil significantly reduced their flooding crises through voluntary home relocation by its residents, followed by a general system expansion and development of riverside parks, cycling trails, catchment ponds, and sports fields. These expansion and development efforts have made Curitiba one of the most livable and attractive residential and business locations on the continent (Brugmann, 2014).

With the support of creative design and business innovation, the adaptation process to climate change may theoretically be pursued as a redevelopment/investment opportunity that yields financial returns. Investments that create local resilience may result in a performance premium for homeowners and public entities from increased property values, rental, tax, and service revenues (Brugmann, 2014). This could extend to transportation development and expansion to reduce GHG emissions and support in planning effective evacuation procedures.

5.5.4. Cornerstone #4: Communicating Resilience Benefits.

Once risk in a vulnerable area has been reduced and transferred, and the development of the Resilience Zone underway, the advantages of the local area may be documented and communicated to create market demand, increasing the potential for a 'resilience premium'. Hence, there must be an effective communication strategy, possibly through benchmarking and key performance indicators (KPIs) that clearly demonstrate the benefits of a resilient area (Brugmann, 2014).

For instance, the evolution of "green building" practice advocates the value of such a method. 'Green building' was a new type of urban development performance that could have simply wound up as marketing. However, it became a conventional performance measure in the building industry because it was identifiable by a broadly acknowledged standard; LEED. The U.S. Green Building Council and LEED showed how market recognition of enhanced performance relies on communication measures. Good communication made LEED-rated structures recognizable for their efficient energy performance, successfully creating an interest in building project owners to make their own buildings LEED-rated. This has conveyed recognition, while at the same time, contributes to city resilience (Brugmann, 2014). Using green building as reference, cities that choose to lead the founding of market support for climate adaptation should therefore develop a communication strategy in a similar manner.

Communication should include encouraging neighborhoods to comply with climate resiliency development and fire-risk management, like the evacuation process. The benefit of evacuation has to be communicated consistently to residents within both high- and low-fire risk areas, so the community understands and complies with the processes and procedures in case of an emergency evacuation.

5.6. Summary

From the developed model, a series of wildfire risk maps were generated that separates CoE into different risk categories. The very high-risk areas were identified as the priority areas for fire-risk management. These regions should be the focus of fire-risk mitigation and prevention strategies. More importantly, a road map was overlayed with the fire-risk map to define the transportation infrastructure, safety, and operations for each area/neighborhood. This is crucial to aid in hazard risk assessment and identifying possible evacuation routes. Furthermore, forecasted fire-risk maps were generated to help city officials and decision makers make effective long-term fire-risk management plans.

The risk categories from the wildfire risk map were then converted into three ecological categories: green, grey, and red line areas. Green line regions represent development areas, grey line areas represent ecological buffer zones, and red line areas represent preservation areas. Combining the fire-risk assessment raster map with the vulnerability classification raster map can help municipal authorities and decision-makers fully understand the associated fire risk in a specific zone, allowing them to plan and execute effective fire risk management strategies in the event of a fire outbreak.

A priority for fire-risk management is to understand the duties involved and distribute them among the stakeholders. Every stakeholder must have a clear understanding of their responsibilities and how they can fulfill them. Certainly, the government and homeowners share responsibility for fire-risk mitigation and prevention and, as a result, it is crucial to identify and clarify the roles involved. Accordingly, a neighborhood map might be more helpful to both homeowners and decision-makers.

Ultimately, the goal of this thesis is to provide a foundation for building a climate resilient city. Hence, the last subsection focused on four strategic planning and action cornerstones for establishing a market framework for climate adaption. The first two cornerstones, asset-focused risk management and local area risk management, improve risk management and ensure insurability. The subsequent two cornerstones, resilience upgrading and communicating resilience benefits, help high-risk zones attract investment and convey resilience benefits as a means of maintaining and even increasing value in the resilient zones. These four cornerstones would combine to achieve higher levels of compliance to climate resiliency. This is not a full roadmap to climate resiliency, but it could be essential in terms of decision-making for evacuation response and emergency planning.

6. Conclusion & Future Work

The frequency of wildfire events has increased dramatically over the past decade in Western Canada, making cities like the city of Edmonton (CoE) with large stretches of green space more concerned over the possibility of wildfires occurring near its limits. To combat this growing concern, data from the CoE were used to construct a fire risk assessment model. The model proposed and developed herein is unique in that it adopts a multitude of large-scale and high-resolution geospatial and remotely-sensed data to assess both current and future fire-risk scenarios. The following sections summarize the key findings and contributions of this thesis along with limitations and recommendations for future research.

6.1. Summary

This thesis covered three major research objectives as summarized below.

First, an extensive and thorough literature review was completed to cover a wide range of topics on fire-risk modeling, planning, management, and mitigation. The extensive review revealed the differences between spatial and non-spatial, parametric and non-parametric modeling techniques, and urban and rural risk models. In addition, it was also found that fire-risk assessment was an essential step in fire-risk management that includes zoning and regulations to help maintain climate resiliency. A brief background was introduced to show the importance of building a city-specific fire-risk model. This model and research, with its focus on hazard identification and transportation infrastructure, safety and operations development and expansion, will serve as a stepping stone to assist city planners and managers with developing a comprehensive emergency response and evacuation plan.

Secondly, a novel fire-risk mapping method was proposed using a parametric linear combination of state-of-the-art datasets reinforced by an AHP application. When developing the model, only the most essential aspects were considered, such as meteorological, topographical, biological, and anthropogenic parameters. The proposed method divided risk areas into five classes, from very low to very high. Factors and variables were selected based on prior study findings. For the purposed of assigning weights to variables using AHP, experts from the CoE were consulted to tailor the weight for an urban setting. Moreover, projection fire-risk maps were produced for the years 2050 and 2080 using the climate projections datasets; more specifically, RCP4.5 and RCP8.5. Project risk maps showed fire risk increase in many regions from increase in average seasonal temperature and wind speed and decrease in average seasonal precipitation and humidity.

Finally, fire-risk assessment was further processed to identify methods of accomplishing two tasks: 1) adapting to increased wildfire risk and 2) achieving higher levels of compliance to climate resiliency. The ecological vulnerability classification map was then constructed to define three different levels of vulnerability: (1) green line areas that can be extensively developed, (2) grey line areas that can serve as an ecological buffer zone; and (3) red line areas that cannot be developed and must be preserved. In order to achieve city resilience, it is crucial to have a well thought out fire risk management plan, where each stakeholder has particular duties that, when combined, can lead to greater fire risk management and prevention. To guide the development of a proper fire risk management plan, four strategic planning and action cornerstones were proposed. This system works by highlighting policies and regulations required to attain better levels of climate resiliency. The first two cornerstones help with risk management and insurability, while the remaining two cornerstones focus on high-risk zone modification to attract investments and resilience benefit communication to increase resilient zone value. It is anticipated that these four cornerstones will help achieve higher levels of climate resiliency compliance.

6.2. Research Contributions

Several practical and intellectual contributions were demonstrated in this thesis. The findings stated herein will substantially aid municipal planners and managers in developing a complete emergency response and evacuation plan in the event of an uncontrolled wildfire, as well as achieve higher climate resiliency through strategic planning and action cornerstones. The following are a list of contributions made in this thesis:

- **Applied remote-sensing technology and data management techniques to process large-scale state-of-the-art datasets while ensuring data consolidation and integrity.** Unlike existing fire risk evaluations methods, this study included a wider variety of variables for each criterion with each variable showing a high levels of precision (spatial resolution of 30mx30m). This was accomplished by writing Python scripts to move data sets and execute spatial and mathematical computations, resulting in improved detection accuracy.

- **Performed suitability analysis on the engineered raster data using a multi-criteria evaluation approach to generate the fire risk assessment map.** AHP was chosen in this study to handle weight assignment subjectivity and to assign factor weights to the twelve different variables. The ultimate goal of this was to assess fire risk within a city using such variables that contribute to fire ignition.
- **Forecasted climate projections and implemented geostatistical interpolation techniques to perform the 2D change analysis over time and space.** To account for future climate changes, a fire risk assessment was created using climate forecasts from RCP4.5 and RCP8.5 datasets for years 2050 and 2080. This allows governmental agencies to preemptively plan methods of combatting growing wildfire risks in high-risk areas.
- **Constructed roadmap overlayed with the fire-risk map and ecological vulnerability classification map to define different risk areas and vulnerability levels.** This provides detailed information on the transportation infrastructure and the risk of wildfires on or near the network, improving preparedness for planning. In addition, an ecological vulnerability map will help provide more in-depth information about municipality development and housing decision-making. This will consequently improve the transportation operations and building and zoning laws to protect the public during emergency evacuation response planning.
- **Provided four strategic planning and action cornerstones for establishing a market framework for climate adaption and achieving zone resiliency.** These four cornerstones were presented to highlight the policies and legislation required for improving climate and zone resiliency and the need to improve the transportation infrastructure and operations, which will consequently improve the climate resiliency during the municipality development and planning.

6.3. Research Limitations & Future Work

Due to lack of data, this study did not include any microscopic variables such as housing combustibility and fire propagation between buildings. Instead, this study was focused on presenting a macroscopic view of high-risk zones. The RCP4.5 dataset lacked an efficient number of data points, which affected the accuracy of generating a climate map to represent the strong mitigation scenario. One important assumption here was that the fire season will remain between May and October, putting to one side that climate change could alter this fire season to start earlier and end later. Another limitation in this research is the assumption that the forecasted topologic, anthropogenic, and biologic criteria and their associated variables are constant. This assumption limits the accuracy of the forecasted fire-risk maps for 2050 and 2080.

Additionally, it was considered in the best interest of the research to highlight the fire risk using the appropriate variables and provided weights to tailor the model to the CoE due to the lack of historical data to verify the accuracy of the fire risk model. The high-risk areas imply being more fire-prone than the low-risk areas; however, the fire risk map prioritizes the areas/neighborhoods to start implementing; fire mitigation and evacuation plans, and transportation infrastructure and operations development. Low-risk areas also need to be considered and developed, bearing in mind that low-risk areas do not mean low consequence. Low-risk areas could contribute to disastrous consequences if not precisely considered.

There are three notable future extensions that should be considered. First and most important, traffic network analysis and street connectivity should be investigated to help simulate and setup a fire evacuation plan. Providing the road map overlayed with the fire-risk map could help with evacuation planning and transportation infrastructure, safety, and operations development. Transportation supply and demand datasets for each neighborhood will be required to identify the available modes and captive population to certain modes and plan for a multimodal evacuation strategy that synergizes the effect of multiple modes. Finally, it is essential to represent the background traffic or noncompliant evacuees accurately. Second, since combustibility analysis differs significantly between urban and rural settings, building and zoning regulations can be investigated more extensively and compiled to increase awareness and build city resilience. Third, there is a need to explore additional variables, such as openings, collapsed buildings, flame brands, direct flame contact, emitted radiation through fuel, fire temperature and compartment properties, and radiative heat transfer that contribute to fire risk and determine whether they can be incorporated into the model. Exploring these variables may also give insight into better zoning and building regulations in high-risk areas, resulting in better fire-risk management and mitigation strategies.

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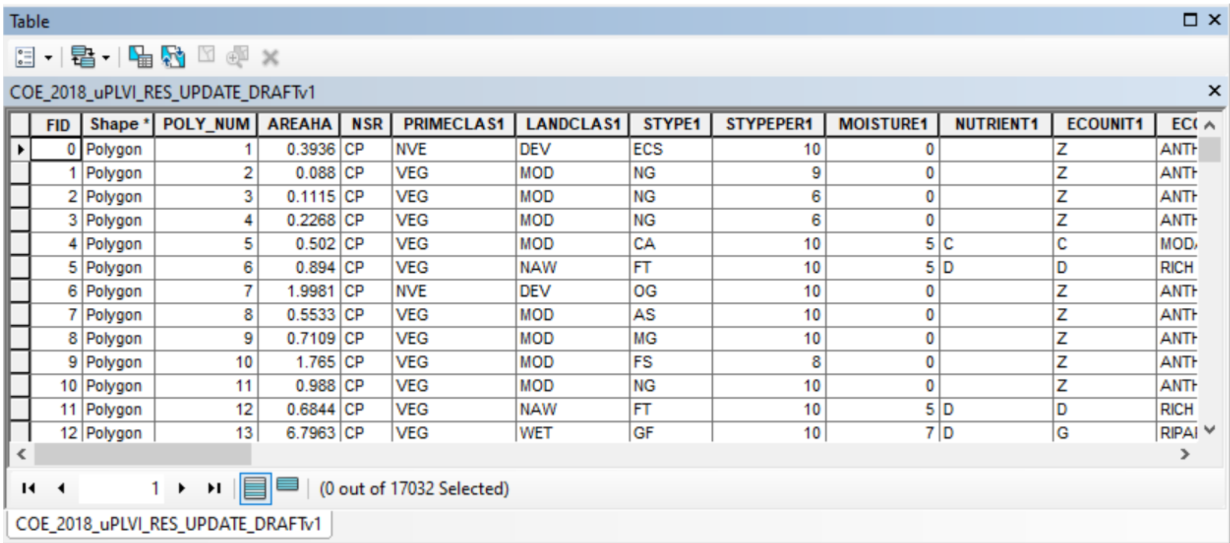
Appendix

Appendix A: The Python script to convert the LiDAR files into elevation raster maps, combine all the generated elevation files into a mosaic file, then calculate the slope and aspect.

```
from os import listdir, makedirs, path
from os.path import isfile, join, isdir, exists
from arcpy import env
import shutil
import os
import arcpy

# Setting all the environment variables
env.workspace = "E:\Lidar\Las_Point_Cloud_v1.4\All_Points"
env.overwriteOutput = True
env.outputCoordinateSystem = arcpy.SpatialReference("NAD 1983 3TM 114")
mypath = env.workspace

# Clean all the directories if found
for dir in ['Slope', 'Elevation', 'Mosaic', 'Aspect', 'Roads']:
    dirpath = os.path.join(mypath, dir)
    if os.path.exists(dirpath) and os.path.isdir(dirpath):
        shutil.rmtree(dirpath)

# Reading all the las files
onlyfiles = [f for f in listdir(mypath) if isfile(join(mypath, f))]
numFiles = len(onlyfiles)
print("number of LAS files = " + str(numFiles))

# Calculating the Elevation for all the files in "Elevation" folder
print("Calculating the Elevation for all the files in \"Elevation\" folder.")
makedirs(mypath+"\Elevation")
for i in range(numFiles):
    print(str(int(i*100/numFiles)) + "%")
    arcpy.LasDatasetToRaster_conversion(onlyfiles[i],'Elevation\elev'+str(i),"ELEVATION",
sampling_value=1)
print("100%")

# Merging the output files in Merged folder.
print("Merging the all elevation files in \"Mosaic\" folder.")
allElevFiles = ""
for i in range(numFiles):
    allElevFiles += "Elevation\elev"+str(i)+";"
allElevFiles = allElevFiles.rstrip(';')
makedirs(mypath+'\Mosaic')
arcpy.MosaicToNewRaster_management(allElevFiles,mypath+'\Mosaic',"mrgdscp",
"","32_BIT_FLOAT",number_of_bands=1)
print("Done")
```

```
# Compute the slope
# Check out the Spatial extension
arcpy.CheckOutExtension("Spatial")
print("Computing the slope")
makedirs(mypath+"\Slope")
try:
    arcpy.Slope_3d(mypath+"\Mosaic\mrgdscp", mypath+"\Slope\Slope", "DEGREE", 1,
"PLANAR", "METER")
    print("Done")
except:
    print("ERROR: The tool is not licensed to calculate the slope!")

# Compute the aspect
print("Computing the aspect")
arcpy.CheckOutExtension("Spatial")
makedirs(mypath+"\Aspect")
try:
    arcpy.Aspect_3d(mypath+"\Mosaic\mrgdscp", mypath+"\Aspect\Aspect", "PLANAR", "METER")
    print("Done")
except:
    print("ERROR: The tool is not licensed to calculate the aspect!")


# Extract all the road points from the las files
print("Extracting all the roads in CoE")
arcpy.CheckOutExtension("3D")
makedirs(mypath+"\Roads")
try:
    arcpy.LASToMultipoint_3d(mypath, mypath+"\Roads\Roads", 2, "11", "ANY_RETURNS", "",
"", "","","RECURSION")
    print("Done")
except:
    print("ERROR: The tool is not licensed to convert the las files to multipoint!")
```

Appendix B: Extracting the dominant and co-dominant forest species from uPLVI.



Table

COE_2018_uPLVI_RES_UPDATE_DRAFTv1

FID	Shape *	POLY_NUM	AREAHA	NSR	PRIMECLAS1	LANDCLAS1	STYPE1	STYPEPER1	MOISTURE1	NUTRIENT1	ECOUNIT1	ECO
0	Polygon	1	0.3936	CP	NVE	DEV	ECS	10	0		Z	ANTH
1	Polygon	2	0.088	CP	VEG	MOD	NG	9	0		Z	ANTH
2	Polygon	3	0.1115	CP	VEG	MOD	NG	6	0		Z	ANTH
3	Polygon	4	0.2268	CP	VEG	MOD	NG	6	0		Z	ANTH
4	Polygon	5	0.502	CP	VEG	MOD	CA	10	5	C	C	MODA
5	Polygon	6	0.894	CP	VEG	NAW	FT	10	5	D	D	RICH
6	Polygon	7	1.9981	CP	NVE	DEV	OG	10	0		Z	ANTH
7	Polygon	8	0.5533	CP	VEG	MOD	AS	10	0		Z	ANTH
8	Polygon	9	0.7109	CP	VEG	MOD	MG	10	0		Z	ANTH
9	Polygon	10	1.765	CP	VEG	MOD	FS	8	0		Z	ANTH
10	Polygon	11	0.988	CP	VEG	MOD	NG	10	0		Z	ANTH
11	Polygon	12	0.6844	CP	VEG	NAW	FT	10	5	D	D	RICH
12	Polygon	13	6.7963	CP	VEG	WET	GF	10	7	D	G	RIPAI

1 (0 out of 17032 Selected)

COE_2018_uPLVI_RES_UPDATE_DRAFTv1

Figure B-1 Features and parameters for the procured uPLVI data.

The forest type variable for only the dominant and co-dominant species was extracted from this dataset. Afterward, the steps below were followed to extract the vegetation areas from the uPLVI land class variable:

a) From the features file, apply the following selection criteria to the table (”PRIMECLAS1” = ‘VEG’ AND “LANDCLAS1” <> ‘WET’).
b) Convert features file into a shape file.
c) Right click on the shape file and select properties.
d) From the Symbology tab, select 'Categories' from the Show panel, then select unique values many fields.
e) Select 'Edit table attribute' to enable table editing.
f) From the data management toolbox, select the 'Add Feature' tool to add a *Risk* field in the table.
g) Assign *Rank* values into the *Risk* field.

Appendix C: The Spatial Interpolation for Climate Variables.

The following steps were done in ArcGIS to generate the climate raster maps using ordinary kriging interpolation technique:

a) In the Geostatistical Analyst tool, click on the geostatistical wizard.
b) From the methods panel, select the Kriging/Cokriging geostatistical method, and in the Input Data panel, select the Source Dataset, which is the events file, and select the Data Field as the seasonal climate variable, like temp_may_to_oct. Afterward, click 'Next'.
c) In this research, the ordinary kriging type was selected for a prediction output surface type, and the order of trend removal was set to first order. It is essential to remove the surface trend from the data. Then click 'Next'.
d) There are different semivariogram models such as Gaussian, exponential, spherical, etc. The data's geographical autocorrelation and prior knowledge of the occurrence are used to determine the most optimal semivariogram model (Astraatmadja, 2016). In this research, the exponential model was used because spatial autocorrelation decreases exponentially with increasing distance. Then click 'Next'.
e) The semivariogram will show if there is a surface trend in the data, as shown in Figure ***3-9***. To detrend, the optimization of a semivariogram/covariance model could be performed assuming that only one isotropic semivariogram model was used, and that the default searching neighborhood has four sectors (ArcGIS Desktop, 2021). Then click 'Next'.
f) Verify that the neighborhood type is set to standard. Then click 'Next'.
g) In the predictions error panel, it is prudent to ensure that: (1) the root-mean-square standardized has to be near 1, (2) RMSSE should be near to 1, and (3) ASE is close to RMSE. If the prediction error does not meet the above three criteria, try other combinations of detrending order and semivariogram model type. Otherwise, click 'Finish'. Then click 'OK' on the prompt model summary window.
h) The kriging prediction map should be generated from ArcGIS, example output is shown in Figure ***3-10***.

Appendix B: The Python script to convert the netCDF files into CSV files.

```
import xarray as xr
import pandas as pd
import os

folders = {"precip_ann"} ##os. listdir()
print(folders)

for folder in folders:
    if os.path.isfile(folder):
        continue
    output_folder = folder + '_csv'
    if not os.path.exists(output_folder):
        os.makedirs(output_folder)


    for file in os.listdir(folder):
        if ("2050.nc" in file) or ("2080.nc" in file):
            print("Converting ", file)
            data = xr.open_dataset(folder+'\\'+file)
            data_df = data.to_dataframe().reset_index()
 #In case of Precipitation folder converstion, use this line --> data_df =
data[['precip_annual', 'lat2d', 'lon2d']].to_dataframe().reset_index()
            data_df.to_csv(output_folder+'\\'+file.replace('.nc','.csv'))
```