DIVERTING RISK: SUPPORTING CLIMATE RESILIENCE THROUGH FIRE-RISK MODELING WITHIN THE CITY OF EDMONTON

Final Report

Mohamed M. Elshabrawy, M.Sc.

Graduate Research & Teaching Assistant
Department of Civil & Environmental Engineering
University of Alberta
Edmonton, AB, Canada, T6G 2W2
Tel: +1(780) 655-4461
Email: elshabra@ualberta.ca

Karim El-Basyouny, Ph.D., P.Eng.

Associate Professor
City of Edmonton's Urban Traffic Safety Research Chair
Department of Civil and Environmental Engineering
University of Alberta
Edmonton, AB, Canada, T6G 2W2
Tel: +1(780) 492-9564
Email: basyouny@ualberta.ca

Tae J. Kwon, Ph.D., P.Eng.

Assistant Professor
Department of Civil and Environmental Engineering
University of Alberta
Edmonton, AB, Canada, T6G 2W2
Tel: +1(780) 492-6121
Email: tjkwon@ualberta.ca

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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
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

Executive Summary

As more recent fire outbreaks have become infamous for their magnitude and ferocity, research into fire-risk modelling has garnered the attention of both researchers and government officials. Researchers have worked to develop fire-risk prediction tools, forecasting models, and analytic approaches to help lessen their negative impact on our communities and environment. For example, the Edmonton River valley, which flows straight through the City, is one of North America's largest urban parkland. It garners a lot of usage by the locals and outside visitors but leads to the potential danger of human-caused fires that could rage out of control because of elevated temperatures and reduced precipitation levels. When combined with the river valley's proximity to both residential and commercial districts, the need for fire-risk modeling and a robust emergency management plan is critical to ensuring Edmonton is a climate resilient region. As a result, it is critical to provide an accurate understanding of the green spaces as well as which areas pose the greatest risk of fire depending on the ignition sources in that area. City officials may use this information to create an appropriate emergency response and evacuation plan that provides information about transit services and their accessibility.

To accomplish these goals, this report has three main tasks with the first being the development of a fire risk assessment model. It is important to remember that urban risk models differ greatly from rural risk models when using modelling methodologies. The fire behaviour, the risk to human life, the risk to valuable objects, and other complicating factors differ dramatically between the two situations. As a result, it is critical to decide which risk model will be investigated, as this will influence the parameters used and the modelling methodologies used. While there are some parallels in how danger is assessed in both contexts, the most significant variations are in how fire spreads, propagates, and is assessed. Hence, it is critical to define the project's scope, which will focus on developing a framework for modelling wildfire risk. The report will begin with a thorough review of literature and background information for fire risk modeling and of past research efforts. Using data centered on the City of Edmonton (CoE), the fire risk assessment model development will include information about anthropogenic, biologic, topographic, and climatic features to be able to determine areas with a high risk of wildfire. This is combined with data obtained from satellite and aerial LiDAR photographs of the landscape, which will be layered

and mapped using advanced tools such as ArcGIS and Python scripting language. To develop the fire risk-model with the obtained state-of-the-art datasets, 4 different criteria with 12 critical variables that match the urban context and surroundings of the CoE were chosen with respect to the literature, as shown in Figure 0-1. Obtaining high-resolution information and rigorous data analysis are the building blocks for generating the fire-risk model, which ends up providing a high-resolution fire risk map. Fire risk assessment maps are subsequently generated by combining all the acquired datasets using the analytical hierarchy process (AHP) technique in weight assignment to build the fire risk model, which is then used to precisely determine the highest fire-risk zones within Edmonton. It is worth noting that the proposed model does not include risk quantification or probability generation. It is, however, based on the AHP multi-criteria methodology that is heavily reliant on the judgement matrix, which is influenced by the opinions and beliefs of city subject matter experts and decision-makers, resulting in an efficient multi-criteria decision analysis (MCDA). Results show that the northeast and southwest areas are at high risk of wildfires due to their high vegetation levels with prominent human activities. The river valley also showed an increased risk due to steep slopes and a high concentration of highly flammable trees.

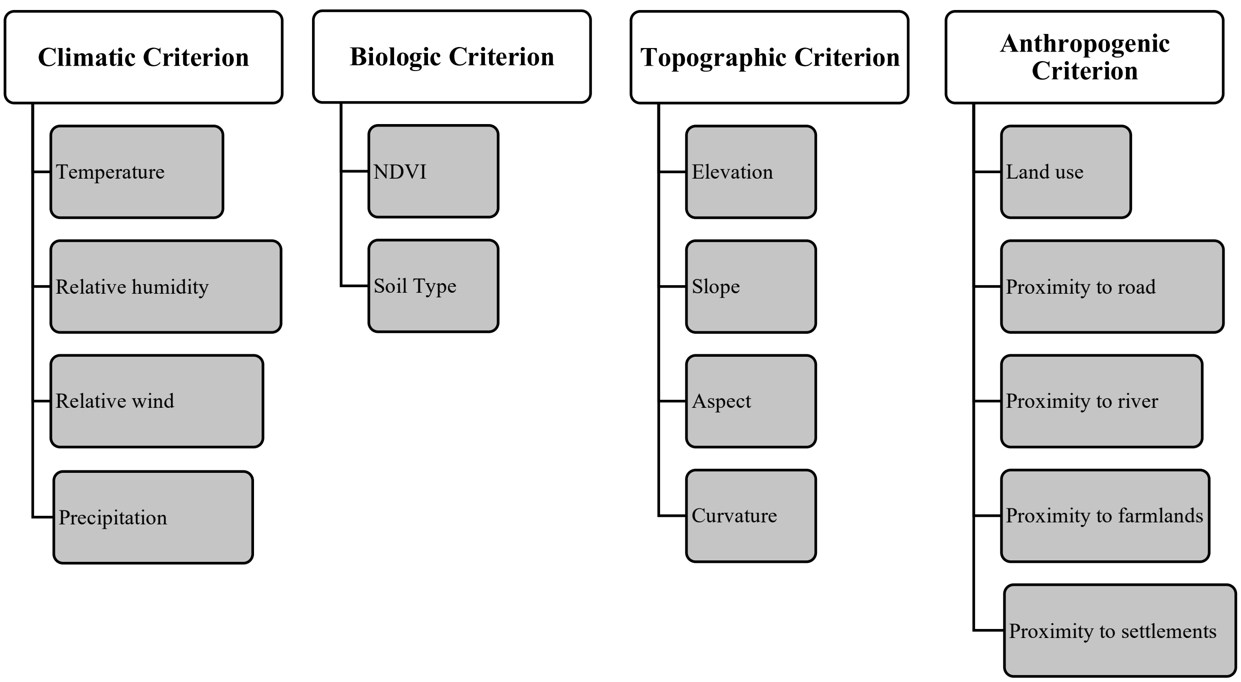


Figure 0-1 Summary of criteria and factors influencing wildland fire

Secondly, the intensity and frequency of fires are influenced by climate. As a result, major municipalities would benefit from having a comprehensive and detailed database. This report will explore the forecasting of wildland fire risk for 2050 and 2080 given the climatic IPCC RCP4.5 and RCP8.5 datasets combined with other available datasets. This will give the City officials and authorities a better understanding of the forecasted climate change by integrating a multitude of data sources including temperatures, precipitation, wind speed, and humidity levels that have a huge impact on the resiliency of the City of Edmonton. These analytical findings would provide city officials with the comprehensive details they need to create an emergency response and evacuation plan by ensuring the City's readiness with an unchecked wildfire in Edmonton's natural areas given respective future climate change scenarios. Conservatively, results indicate that from 2021 to 2050, the fire risk can increase by almost 20%. Furthermore, the risk will increase by another 11% from 2050 to 2080, as shown in Figure 0-2.

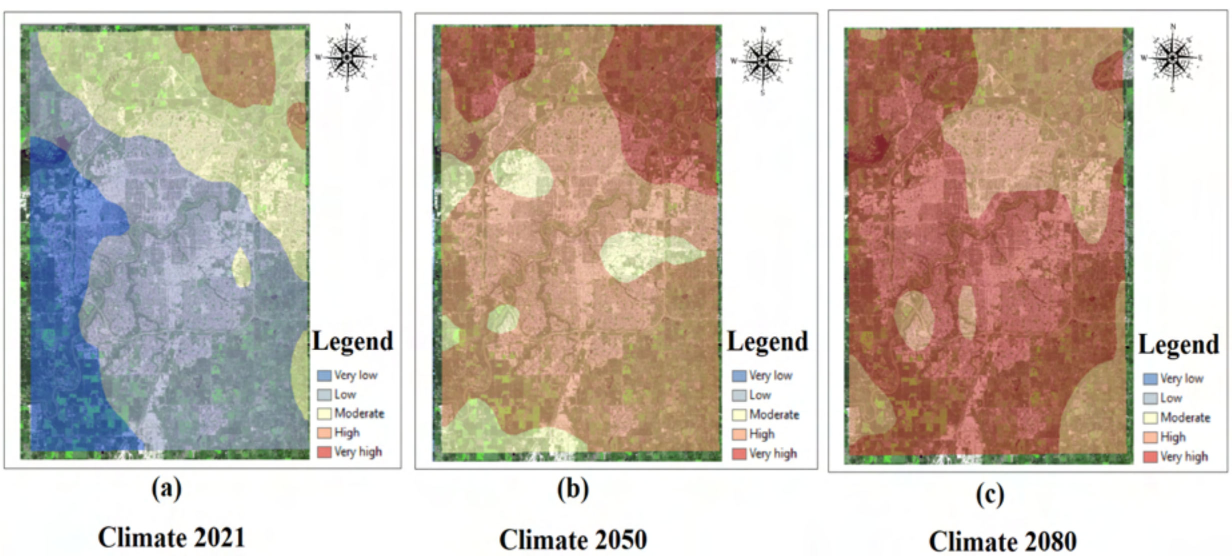
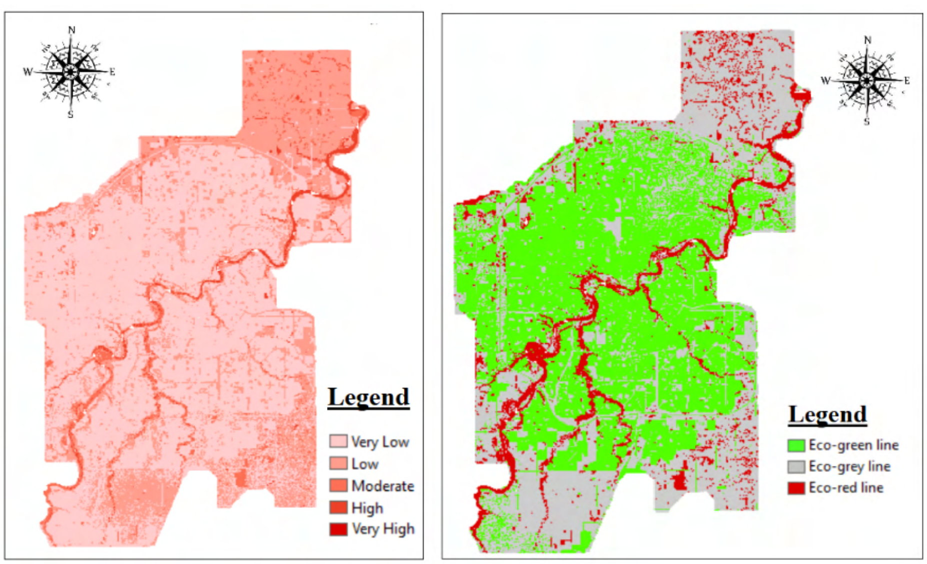


Figure 0-2 The wildfire risk in relation to climate projections for the CoE.

Finally, a comprehensive discussion follows that illustrates all the findings of the fire risk maps, current and forecasted, by which high risk areas were identified and highlighted. The output map of the fire risk assessment model was a map that depicts all of the City of Edmonton's risk areas, which was divided into five categories ranging from very low to very high, as depicted in Figure 0-3(a). The very high-risk locations were designated as priority locations for fire-risk management, and city officials and decision-makers should focus on implementing a fire-risk mitigation and preventive strategy in these regions. To provide the City officials with more information and data to support their decision-making process, an ecological vulnerability classification map was constructed for the City of Edmonton. The ecological vulnerability classification further classified the five fire-risk categories into three ecological categories, green, grey and red line areas, to identify the areas which are ecologically conserved or expandable in the municipality, as shown in Figure 0-3(b). Combining the fire-risk assessment raster map with the vulnerability categorization raster map, according to the literature, will provide a more in-depth and better knowledge of the resolution of high-risk locations. Subsequently, fire-risk management prioritises understanding responsibilities and sharing essential actions across stakeholders. Every stakeholder must have a solid knowledge of what they need and how it would be fulfilled. The government and homeowners share some obligations in fire-risk mitigation and prevention in order to obtain an ideal level of fire-risk mitigation and prevention. As a result, it was critical to define and clarify these obligations in terms of the literature in high-risk areas/zones.

Ultimately, this research will serve as a foundation for a climate-resilient city, allowing for greater fire mitigation as well as the prevention of losses. As a result, this research has focused on four key cornerstones that, if implemented, would help the City achieve greater climate resiliency. This is not a comprehensive guide on climate resiliency, but it can assist with evacuation responses and emergency preparedness decisions.



(a) **(b)**

Figure 0-3 (a) The fire-risk map for 2021, and (b) The ecological lines of City of Edmonton

1. Introduction

1.1. Background and Motivation

In recent years, municipalities in Canada have been expanding their limits. As cities grow bigger, so does their wildland-urban interface (WUI), which increases their risk of wildfires potentially encroaching upon and/or entering urban centers. Given the vast wilderness and expansive rural areas across the country, Canada has its fair share of wildfires (or wildland fires) occurring annually, which results in millions of hectares of burned areas and thousands of people requiring evacuation (Coops et al. 2018; Hanes et al. 2019).

Figure 1-1 depicts every wildland fire occurrence in Canada between 1980 and 2018. Wildfire events are one of the costliest natural hazards in Canada, especially after Alberta's 2016 Fort McMurray wildfire. This particular incident resulted in approximately $3.8 billion in insured losses—the highest-ever loss for a single year (Insurance Bureau of Canada 2020). Due to rapid climate changes, it is likely that wildfires will not only continue to occur, but 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).

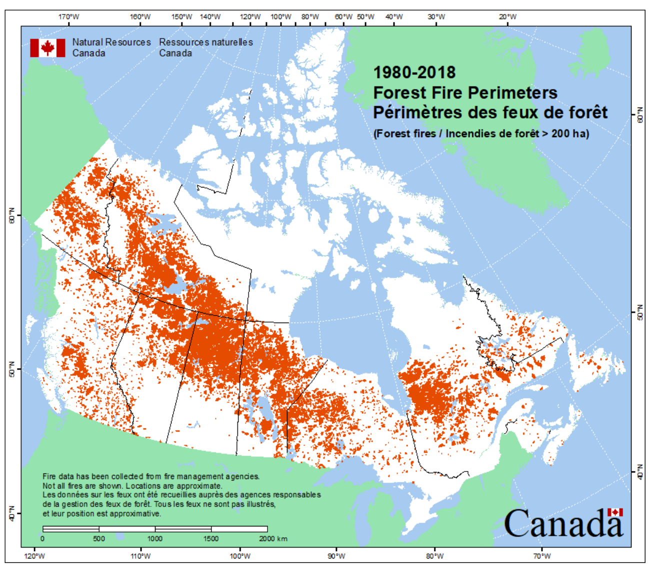


Figure 1-1: All wildland fire occurrences in Canada between 1980 and 2018 (adopted from the Canadian National Fire Database, CNFDB)

The City of Edmonton (CoE) is known for being one of North America's greenest cities due to having the longest connected stretch of urban parkland while also being the northernmost metropolis with a population of at least 1 million residents (CALDO 2020). Although these parklands are a sight to behold, they also come with increased risk for wildfire events. This is why the protection and preservation of Edmonton's green spaces and neighboring urban infrastructure have recently become a significant concern for the City. Since 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). However, there exists a significant gap in knowledge in developing a unified yet transferrable methodological framework that can identify high-risk zones in urban metropolitan areas.

1.2. Problem Statement

The environment, both natural and anthropogenic, has a significant effect on the behavior of fires as they burn and spread. Climate change effects must also be accounted for, as changes in factors such as higher winds, more prolonged droughts, and rising temperatures (Linder, 2010) would affect fire intensity, frequency, and movement. Hence, it is in the best interest of any municipality to have a comprehensive and detailed database including, but not limited to, vegetation, topography, climate, land use, roads, zoning, and population statistics.

Wildland fires are naturally occurring ecological and abiotic event that behaves as though it were alive with its features being dictated by the surrounding ecosystem. It is a globally important process that significantly and dynamically affects the ecosystems and many species have developed a response around it (Pausas, 2019). Lightning is the primary natural cause for many wildfires, but increasingly forest fires have become the result of anthropogenic 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). 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 to maximize its impact, it is of paramount importance to identify high fire-risk locations that require intervention.

A detailed evaluation of the countermeasures implemented and their effect on reducing the risk of complications with forest fires is best supported with an accurate fire risk map (Syphard, 2014). To develop effective and efficient 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.

Catastrophic losses owing to increased incidences of extreme climate trends and occurrences are on the upswing. In North America, increased climate risk is noticeable. 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.

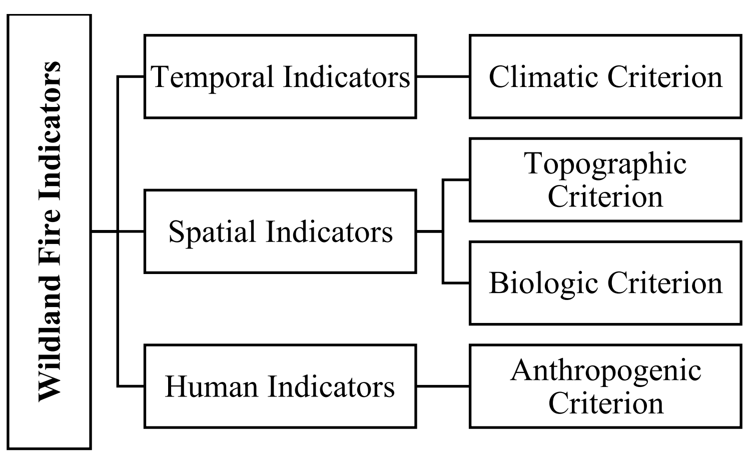


Figure 1-2 Summary of the three common wildland fire indicators

Based on the increasing frequency of extreme climate events observed, there are two paths forward for government agencies. Do nothing and continue to risk their investments, or alternatively, they can develop innovative mitigation strategy for at-risk areas to strengthen their resilience to climate events and preserve or even enhance insurability in those places (Brugmann, 2012). Shedding light on one of the highest-growing Canadian municipalities, Edmonton currently faces the tough decision of which path to follow. Edmonton has warmed up at one of the quickest rates of any city on the planet over the last 50 years. While Edmonton has only had one day each year above +30 degrees Celsius in the past, this might increase to more than 15 days by the 2040s, and more than 33 days by the 2070s. Edmonton may also see unprecedented temperature highs that have never been observed before (Martin, 2012; Roszko, 2020). Based on all these factors, it is therefore critical to consider fire risk management in the context of climate resiliency.

1.3. Research Objectives

Highlighting the importance of modeling fire risk hazards for major municipalities, the primary research question that will be addressed is:

"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 report looks to answer the above question via 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 adapt their proposed zoning and building regulations in accordance with how wildfire risk has increased due to climate change.

This report uses ArcGIS, which is one of the most widely used geographic information systems (GIS) software, to integrate multiple datasets and map their outcomes. Additionally, a weight assignment method; namely, the analytic hierarchy process (AHP) is introduced where factor weights are assigned to 12 variables, which 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 report, therefore, serves as a building block for future research on improving evacuation plans and emergency responses in the event of a fire outbreak. 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 preparedness (i.e., mobility) in the case of a citywide wildfire.

1.4. Report Outline

This report is divided into five sections that cover all the aforementioned objectives. Section 2 presents an extensive literature review aimed at identifying and exploring the variables that affect fire risks; look at fire-risk models with fire-risk definition and their associated unit of analysis; compare urban and rural fire models; present fire-risk management and policies, as well as zoning and building regulations due to fire risk; and, finally, investigate the impact of climate change on fire risk. Section 3 describes the datasets used, their sources, and preprocessing requirements. Section 4 provides the methodological framework used for building the fire-risk assessment model by going through the data and feature engineering process upon all the data sources, e.g., 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. Section 5 presents the results obtained from the fire-risk modelling and highlights the discussion regarding the output such as classifying the vulnerable areas, identifying the responsibility of fire-risk mitigation, and proposing fire-risk management cornerstones to climate resiliency. Finally, Section 6 concludes the entire report and provides future recommendations.

2. Literature Review

2.1. Factors Affecting Fire Risk

Wildfire risk modeling highly depends on a selection of factors and variables, which makes it one of the most critical steps. As introduced earlier in Figure 1-2, the three indicators can be further divided into four sub-criteria, which are climatic, biologic, topographic, and anthropogenic. Each of these criteria has been shown to influence and contribute to the fire season, 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). On the other hand, 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 section summarizes the variables used in wildland fire modeling, as shown in Figure 2-1.

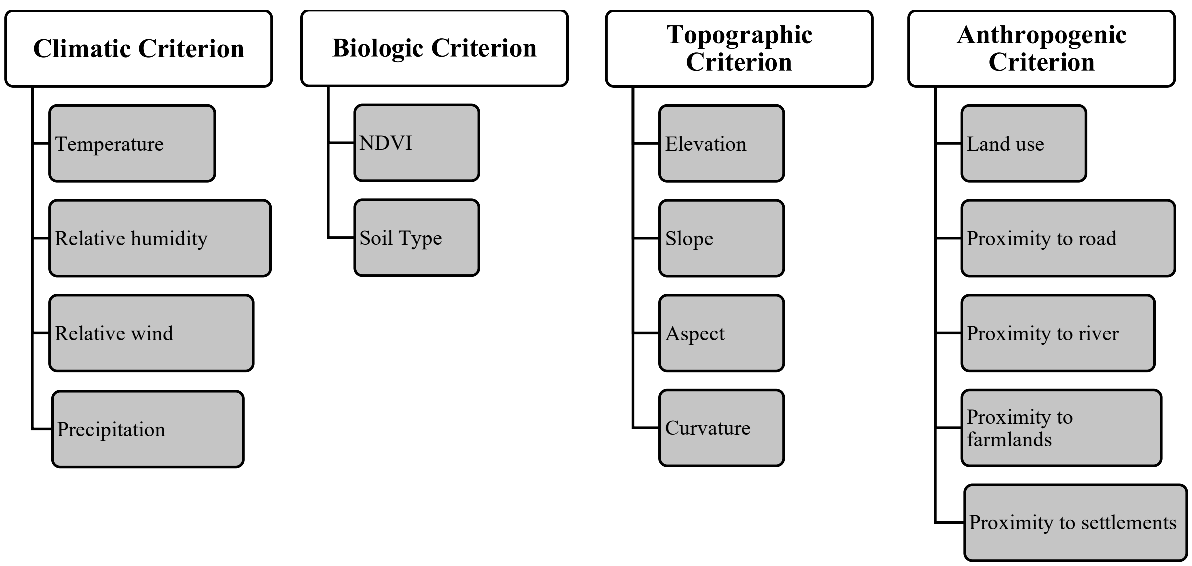


Figure 2-1 Summary of criteria and factors influencing wildland fire

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 as it has been found that 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 factor of interest due to its being a significant contributor to increasing the risk of forest fire (Eskandari, 2015). Often, precipitation is high in winter but then it significantly drops in spring and summer, leading to dry conditions (Jaafari, 2018).

2.1.2. Biologic 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, which can be represented by vegetation type and density, leaf litter depth, and moisture and soil characteristics (Eskandari, 2017; Bright, 2017; Hong, 2019; Jaafari, 2019; Jaafari 2019a). Previous studies showed that LiDAR data could capture structural information related to quantitative canopy fuel characteristics (Scott, 2013; Kelly, 2015; Yavari, 2018). The Normalized Differential Vegetation Index (NDVI) is not only an important variable that represents the biologic criterion, but it has also been proven to be the most dominant factor, which 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 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 behavior. Elevation influences solar radiation, temperature, and evapotranspiration of the terrain which are indirectly related 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 and has been proven to be an essential factor as 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 an 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 infrastructures. 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. Additionally, unintended vegetation contact and ignition with the power lines are rare, but may cause fires should the conditions be right, and often involve tall vegetation that has not been cut back to maintain a safe vegetation clearance zone as per industry best practices. With this in mind, any risk preparedness plan must, therefore, include electrical utility companies, especially if they have exposed infrastructure, but is beyond the scope of this report.

The main variables to be considered in this criterion are distances or proximities to roads, and types of land use (Thach, 2018; Tien Bui, 2018; Hong, 2019; Jaafari 2019). Other variables that displayed some influence over the extent of fire spread, such as distances from settlements or farmlands were also introduced (Ward, 2017). The distances from rivers were also used as it has been shown to affect the extent of fire spread (Wang, 2017).

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 to provide clear differentiation between each of them and to identify which method has shown to provide the best resolution and greatest accuracy for fire-risk modeling.

2.2.1. Non-Spatial Models

Non-spatial models are used to attribute the effects of independent variables to a dependant 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). Its simplicity and transparency are advantages that characterize AHP; however, its primary advantage is the hierarchical framework which 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), 13 second-level indicators (i.e., risk of fire accidents in the past, potential fire risk, meteorological factors, features of the City, evacuation protocols, the safety of buildings, etc.), and 48 third-level indicators (i.e., number of fires per 10 thousand persons, fire deaths per 10 thousand persons, relative humidity, rainfall, wind speed, population density, etc.). The Gray Correlation Degree method gives equal weight to each evaluation indicator so as to enable researchers to select these indicators objectively. This was also applied to set up the weights 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. The association of uncertainty and subjectivity to all available information is another limitation, which requires a researcher with extensive experience in wildfire risk modeling.

Another nonspatial fire study used two simulation methods, the Canadian Fire Behavior Prediction (FBP) and the U.S. BEHAVE systems. The Canadian FBP is an empirical model developed based on wildfire and prescribed burning data, which is then used to determine the behavior of surface and crown fires. 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 behavior 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 behavior. In contrast, the FBP system was deemed to be an efficient fire behavior prediction system for the boreal ecosystem.

2.2.2. Spatial Models

Spatial models consider the spatial aspect 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 themselves. Data that have an inherent correlation with themselves based on the distance between data points are said to be auto-correlated, 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 and 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, with the support of the Geospatial Information Systems (GIS), temporal and spatial differences of fire behavior and spread (Rothermel, 1972). FARSITE simulation can determine fire spread, fire intensity, as well as fuel consumption rate for different seasons (Kanga, 2014).

GIS can be integrated with a fuzzy AHP in a decision-making algorithm that can model wildland fire areas and identify their associated risk factor. Hence, the model was constructed in two phases. First, analyzing the importance of the major criteria in wildland fire risk, hence, obtaining the fuzzy weights for each criterion. Second, the spatial data of the 17 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 for 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 research by Nuthammachot (2019) concluded that research should continue to investigate the potential of the AHP technique in this domain as very few studies combined AHP with GIS for fire risk assessment.

With 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). One of the major limitations in using only 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, the 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 a huge amount 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 both LiDAR and satellite datasets can improve both 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 very promising prediction and analysis results.

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 1x1km 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 evacuation (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).

In another study by Guo (2016), logistic regression was compared to geographically weighted logistic regression (GWLR), an expansion of the standard logistic regression where it incorporates geographical location data, thus 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 1x1km grid, the author found GWLR had more insights into the parameters weight assignment and provided better predictions for wildland fire occurrences.

In another comparison 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 to each other 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 of using them is the fact that they do not require any distributional assumptions on the fire records. The benefits associated with non-parametric models are flexibility in fitting many functional forms without having to gain any prior knowledge and greater performance 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 more 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 obtained 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 resources as smaller municipalities have fewer resources, having 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). This study intended to compare these 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. Summary

While the earlier fire-risk models developed were non-spatial due to the limitation in computational powers in software and hardware, 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 our 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 very 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, as is 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). Moreover, 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 the combination of spatial and parametric modeling approaches be used for developing 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, 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 behavior 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 egress 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, as 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 from one structure can spread 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 is the most common fire spread method between non-contiguous buildings, by which fire spread by radiated heat. Radiation heat spread can occur if there is a straight line from 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 basically 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).

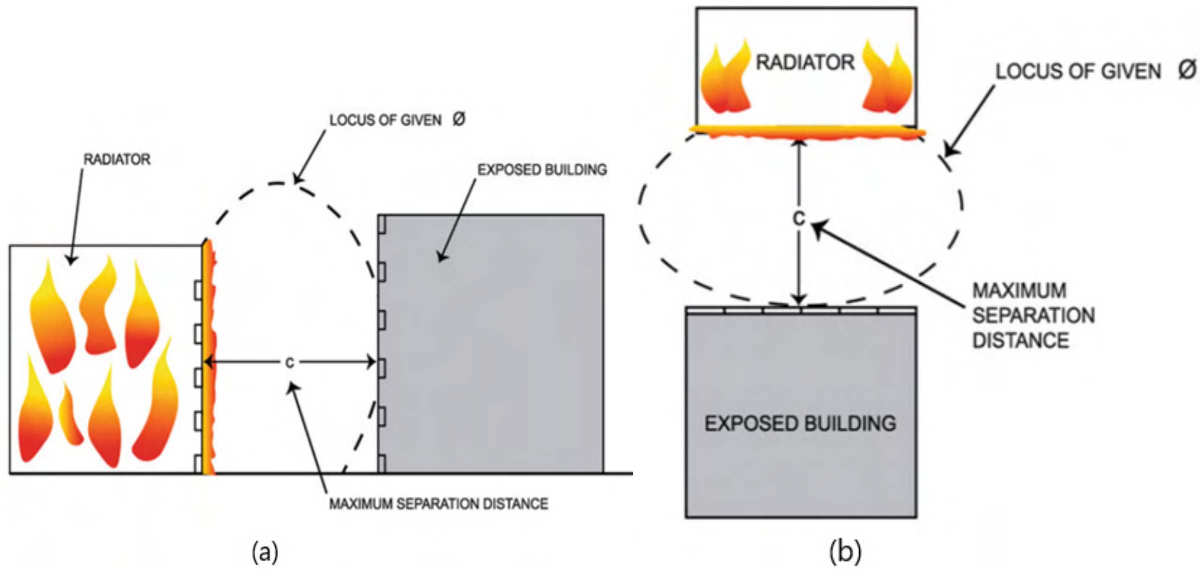


Figure 2-2 Generalized concept of critical separation. (a) Vertical section. (b) Horizontal section, (adopted from O'Connor, 2016).

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).

In determining the safe separation distances between buildings, the predicted fire temperature in the compartment, and the levels of emitted radiation are essential parameters to use (Carlsson, 1999). An urban fire model is developed using two sub-models. One model predicts the building fire behavior under the exposure of the heating 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, whether the heat source is from within or from another building nearby, exceeds a specific heat flux, 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).

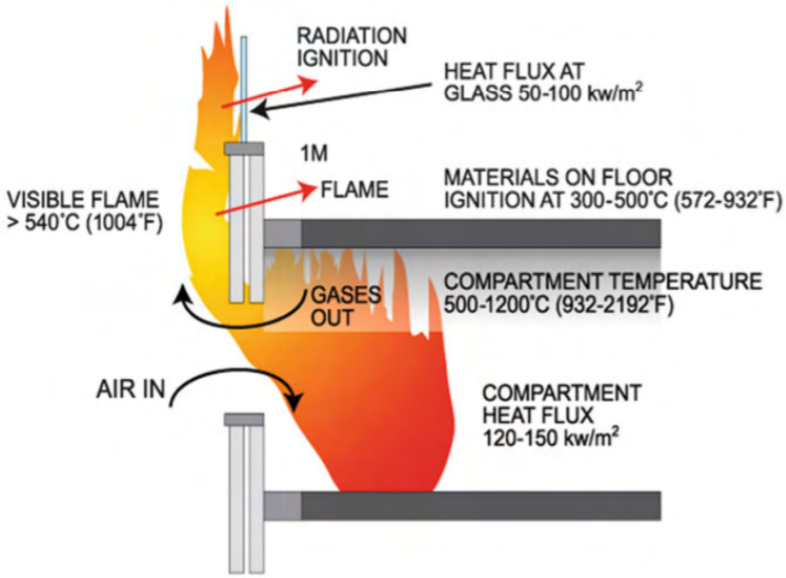


Figure 2-3 Difference between intact and broken window, (adopted from O'Connor, 2016).

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).

2.4. Fire Risk Management and Building Regulations

Risk can be defined in a variety of ways based on context. The Oxford dictionary defines risk as the chance or possibility of danger, loss, injury, etc. (Simpson, 1989). 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 section 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 will also be covered in this section.

2.4.1. Wildland Fire Risk Definition

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). 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). When accounting for the likelihood of a fire and its potential affects, it is critical to managing the risk and the trade-off qualitatively and effectively. 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 behavior $p(F_i)$, 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 "ad" 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 j^{th} value under consideration, summed over n values being considered (Chalkin, 2010). Figure 2-4 is a flowchart representation of the equation.

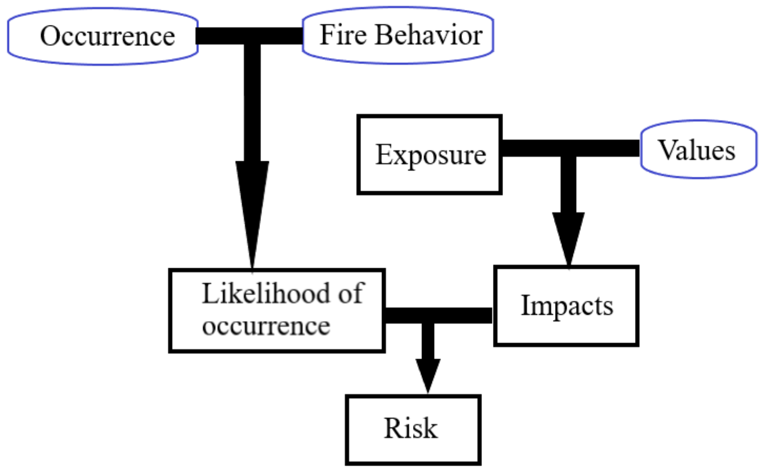


Figure 2-4 Wildland fire risk with primary components (rectangles) in their categories of inputs (capsules), (adopted from Johnston, 2020).

The likelihood of occurrence is the probability that a wildland fire will occur based on two categorical inputs: the occurrence probability and fire's behavior (i^{th} fire behavior). 'Temporal and spatial extents must be considered when modeling its probability. Affects 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 behavior of the wildland fire. It also represents the extent to which the valued asset may be subjected to a fire.

2.4.2. Fire-Risk Management

Assessments of fire risk can 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).

Fire-risk management can manifest in a variety of ways, such as using fuel management (Vojtek, 2007) to reduce extreme fire spread behavior, 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) and enhanced building and zoning regulations to protect social and health vulnerable groups (Christianson, 2015). There is no single effective solution as there are lots of other mitigation options available, with each being unique to a specific situation.

Multiple solutions can work together, and not all solutions are appropriate for every area (Beverly, 2010). 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, which is called the wildland–urban interface (WUI; USDA and USDI 2001). Implementations of FireSmart principles 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 processes 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 convective heat transfer, 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 section 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, which is like the values used in England and Wales, (Clarke, 1998). Canada uses higher values of emitted radiation and a flame projection distance from openings at 1.2 m to prevent fire spread through radiation and openings (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, which is 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, for instance, 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 intervals 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).

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

2.5. Future Fire Risk and Climate Change

Future fire activities may see a transition to a system with dramatic variable fire activity, considering the increasing occurrence of 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 variable across locations; however, the overall fire activity will diverge from the recent historical trends (Coogan, 2019). Since climate is more prevalent as a driver of fire activity in most areas of Canada, the effects of climate change will promote an increase in the variation and extremes in weather, such as increased temperatures, longer dry periods, and increased storm activities, which will dramatically increase future fire occurrences within Canada (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).

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).

Effects on human population, building structures, and municipal infrastructures will encounter future changes as well. Canada's population is growing mostly in dense urban centres with less direct wildland fire risk (Statistics Canada, 2020). Urban sprawl and recreational centres development increase the Wildland-Urban Interface (WUI), raising the fire risk on structures and populations (Johnston, 2020). Nowadays, isolated communities and indigenous communities have experienced an escalated population growth, which increases the probability of fire-risk occurrences, as these communities are already at risk because of their location (Johnston, 2020).

Future changes to fire risk will have significant effects on fire management in Canada. Current research focused on the shifting or increasing of fire occurrences will affect expenditures of fire management. 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 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, which can cause huge, escaped fires (de Groot, 2013). Escaped fires are expected to extend up to 92% by the end of the century in the province of Ontario, which will greatly outpace resources necessary to manage these fires (Hirsch, 2006). Climate change effects also suggest that there will be more extraordinary fire weather.

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 long-term greenhouse climate changes which are 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 in the atmosphere will vary in the future due to human activity. Ultimately, the RCPs are used by scientists to model climate change and create impact scenarios for future planning. The RCPs' numerical 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).

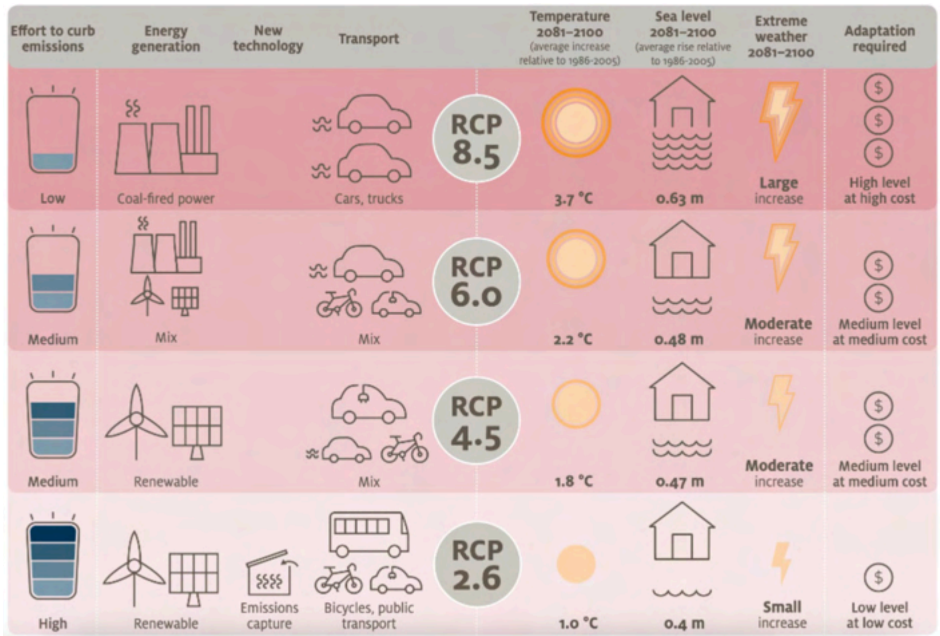


Figure 2-6 The four RCPs ranges future concentrations, (adopted from Coastal climate change infographic series)

2.6. Summary

Presented in this section is 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. This is a logical problem that can be 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 a high level of details 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 its 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 behavior 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, which will focus on developing a framework to model wildfire risk only. The risks because of the presence (i.e., in terms of magnitude and severity) of the aforementioned factors will be explored; 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's 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, as well as human development and land use shifts, leading to an increase in wildland and urban fire risk.

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 can be obtained from Alberta's Department of Agriculture and Forestry which provides current and historical Alberta weather station data. Climatic data for Canada 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 quickly established.

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 report, 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 the 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 with an average of 30 million points per file and covers the entire city with a 200m buffer. Elevation, aspect, slope, proximity to roads, and proximity to water variables were used in the fire-risk model (to be discussed in detail in Section 4) from this given LiDAR dataset using ArcGIS 10.7 (ArcGIS Desktop, 2011).

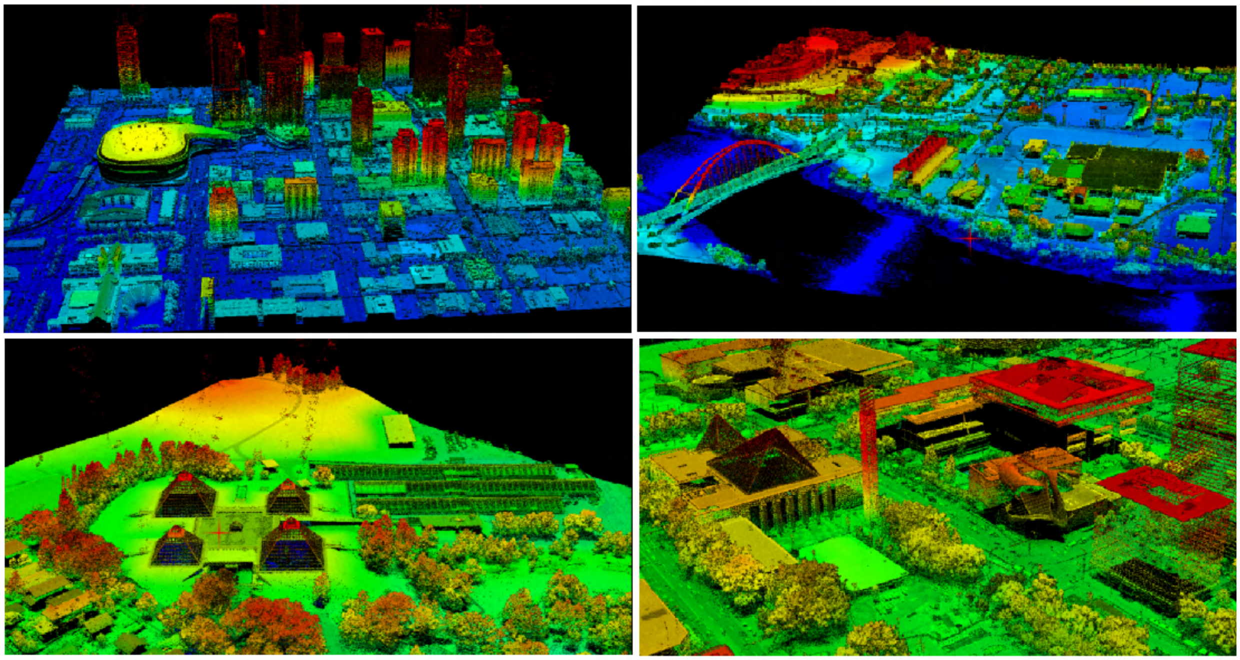
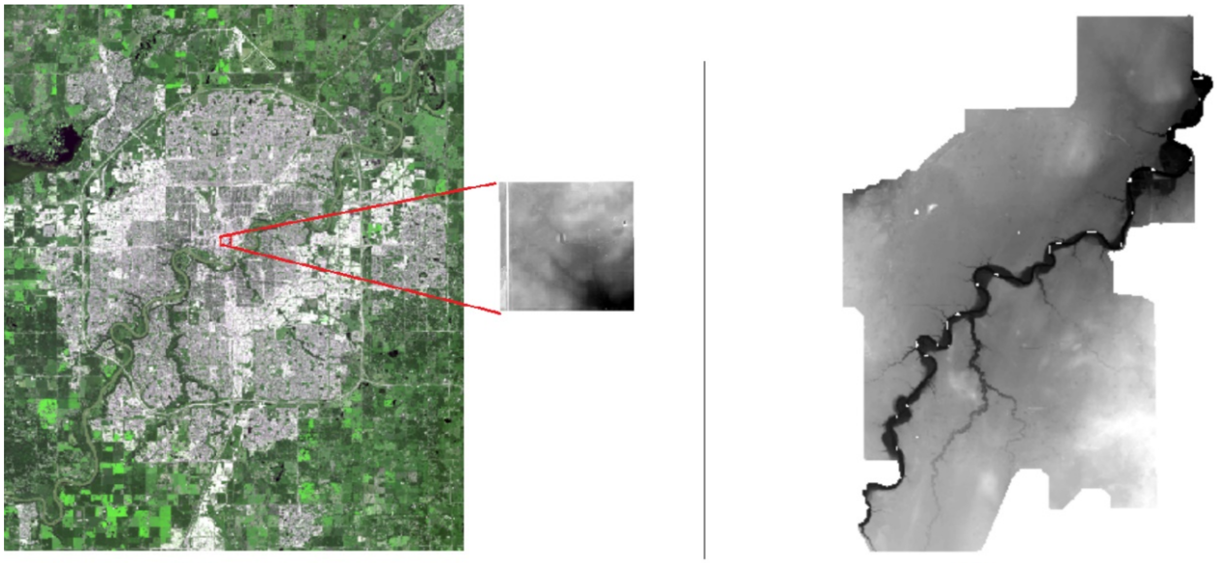


Figure 3-1 A snapshot of the LiDAR data procured from the CoE.

Python (Van Rossum, 2009) is a highly adaptable and powerful scripting language that is used in ArcGIS which is so powerful to perform computationally extensive geo-operations. The “arcpy” library was built to perform all the geospatial operations which were performed from the user-interface but in the scripting terminal. For each LiDAR file, only the ground and roads file were imported into arcpy, and then the spatial elevation operation was executed, as shown in Figure 3-2(a). Afterward, all the elevation files were imported in a mosaic function to merge them into one file that represents the elevation of the CoE, as shown in Figure 3-2(b). Having the elevation map of the CoE in hand, the slope function was then called 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.



(a) (b)

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

3.2. Landsat Satellite Images

Landsat 8 satellite images were procured for the CoE in 2018 for 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 in ArcGIS, as shown in Figure 3-3.

$$NDVI = (NIR - RED) / (NIR + RED) \quad (3)$$

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

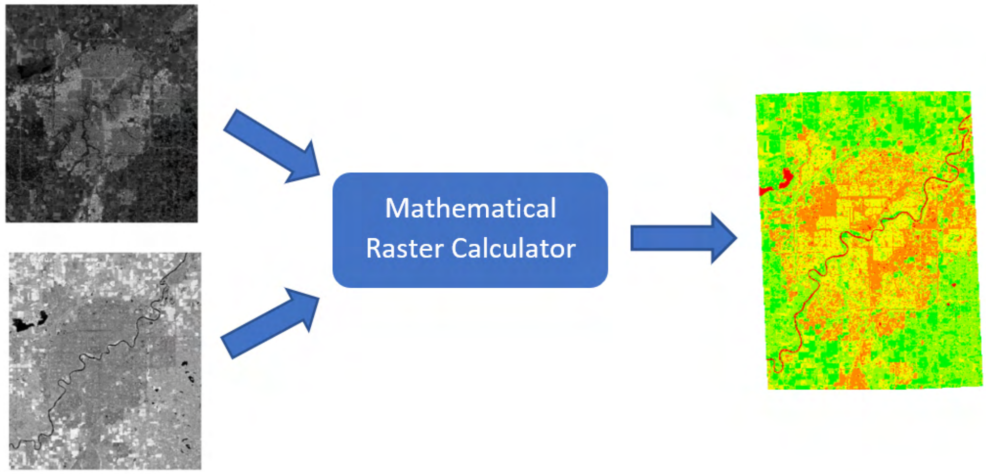
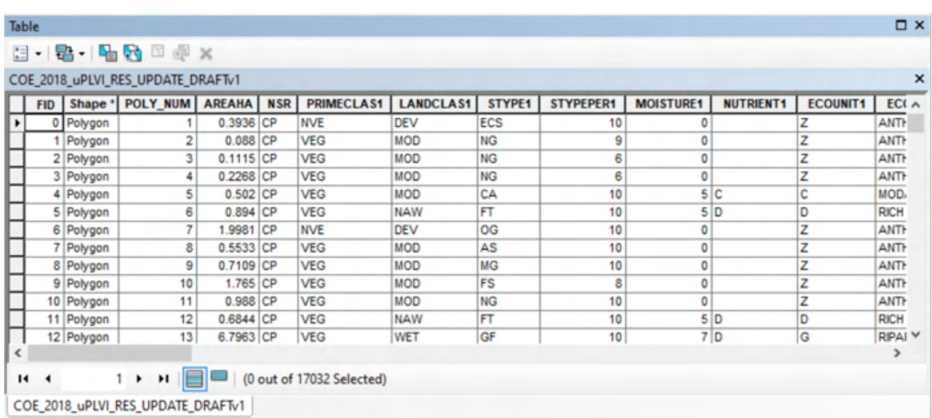


Figure 3-3 The procedures for the NDVI map generation.

3.3. urban Primary Land and Vegetation Inventory (uPLVI)

Regarding the biological variables extraction for all the vegetation areas in the CoE, urban Primary Land, and Vegetation Inventory (uPLVI) data, collected in 2018, were obtained from the CoE. The data is made up of hierarchical polygons with a minimum area of 1 hectare. The polygon classifies each area into a vegetated or non-vegetated Primary Land class. The Primary Land class has a more-detailed level called Land class, which defines the natural state of the polygon. Below the Land class is the Stand type is the canopy stratification found in Edmonton's Urban Ecological Field Guide. The data contained the aforementioned hierarchy for primary, secondary, and tertiary features. All the features and parameters were listed in a table format, as shown in Figure 3-4 (sample only).



Table

COE_2018_uPLVI_RES_UPDATE_DRAFTv1

FID	Shape *	POLY_NUM	AREAHA	NSR	PRIMECLAS1	LANDCLAS1	STYPE1	STYPEPER1	MOISTURE1	NUTRIENT1	ECOUNIT1	EC
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	RIPA

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 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) Export the features file to 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 unique values many fields.
e) Select 'Edit table attribute' to enable editing the table.
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.

The output biologic forest type map is shown in Figure 3-5. Since the excluded pixels are NULL, it is essential to include a value for these given pixels because when all the maps are added together, the NULL pixels mask out the overlapping pixels in other raster files. ArcGIS provides a few options 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, we applied this formula to the forest_type raster: Con(IsNull(“forest_type”),0,”forest_type”).

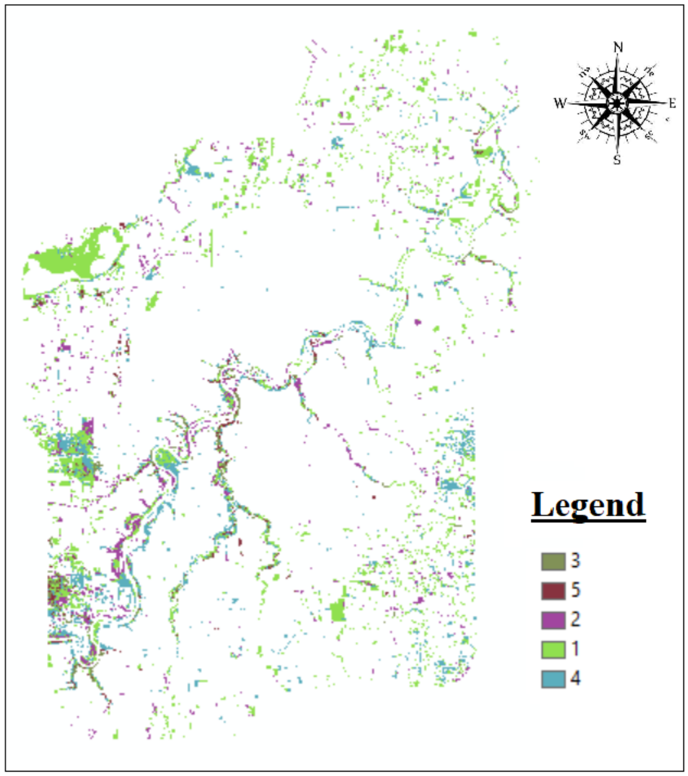


Figure 3-5 The forest type map generated from the uPLVI.

Understanding the category of each zone in the CoE is an important factor to consider as it makes it possible to determine the category of each vegetation area. The CoE's Open Data Portal (https://data.edmonton.ca/) has a detailed dataset for the land use in 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 which, as mentioned earlier, had a field in the table to identify the land class, as either open green areas, anthropogenic parks, or forests. Hence, we could identify all the land use categories 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 wildfire risk associated for each land use category using the same procedures as mentioned in earlier.

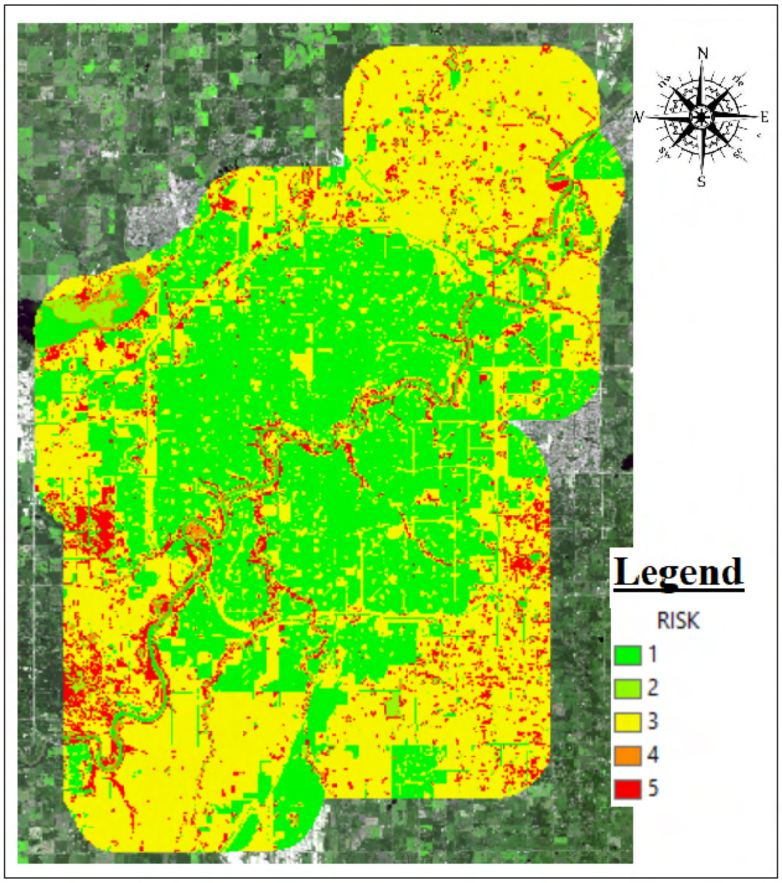


Figure 3-6 The land use risk class identification raster map.

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 the CoE from Alberta Climate Information Service (https://acis.alberta.ca/), as shown in Figure 3-7. Climate variables, which 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 is used to interpolate these variables over the entire study area. Kriging is a geostatistical process that creates an estimated surface from a scattering of z-valued points. The default kriging method is ordinary kriging, which is the most common and frequently used of the kriging methods (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 other detailed, high-resolution raster maps.

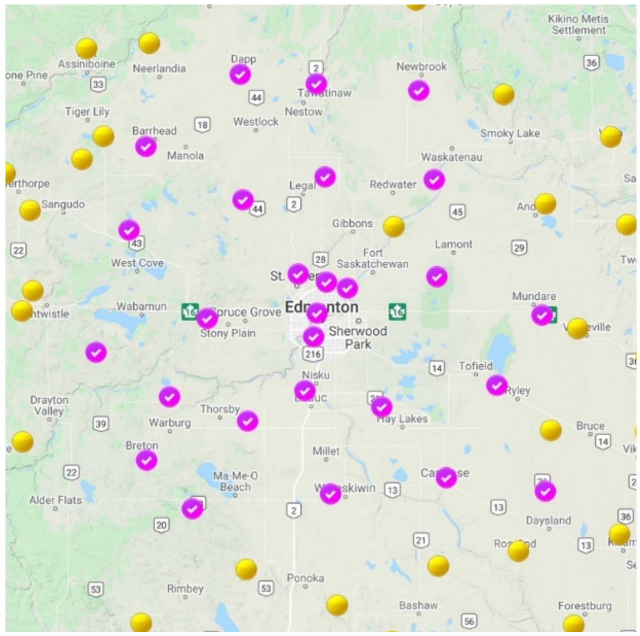


Figure 3-7 All selected RWIS stations surrounding the CoE

The CoE local authorities provided us with both RCP4.5 and RCP8.5 climate dataset. These datasets were used as one annual climatic point per year. However, this would be a huge limitation to identify high risks and vulnerable specific regions in the CoE, because we had all other variables and criteria in spatial representation which are easily integrated together into ArcGIS. However, regarding the RCP4.5 dataset, we needed to integrate it into our model to have an overview of the key differences in the climate change forecast between RCP4.5 and RCP8.5 and how they are going to affect the fire risk assessment.

On the other hand, we managed to find a spatial RCP8.5 dataset. For actual and accurate assessment, we used the RCP8.5 climatic data obtained from the University of Regina to generate the raster maps for the climatic variables. One interesting fact in this dataset is its accuracy. The data consists of 120x66 grid points centred over CoE with a 30m x 30m grid area, as depicted in Figure 3-8.

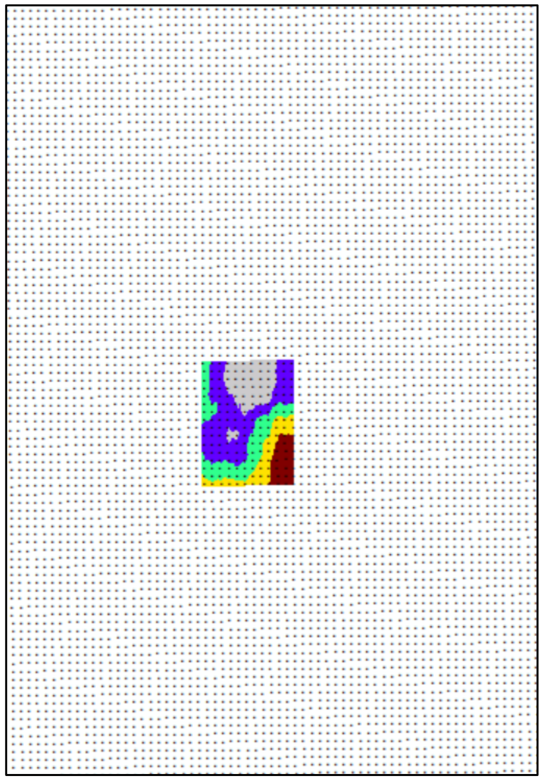


Figure 3-8 The RCP8.5 120x66 gridded points covering the CoE for estimating the climate variables.

The climate in Edmonton has a high meteorological variance between its seasons, and its low bias makes building an accurate model challenging. Extracting the fire season climate data was a crucial step to build an accurate fire-risk assessment model. According to city experts, the fire season in CoE lies between May and October. Therefore, the data have gone through extensive feature engineering to include both annual and seasonal climatic projections.

As mentioned earlier, we generated the raster maps for each climatic variable, which were more accurate using the ordinary kriging interpolation technique using ArcGIS 10.7 Geostatistical Analyst tool. The steps followed to generate the climate maps are:

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 our case, we selected the ordinary kriging type for a prediction output surface type, and we set the order of trend removal to first order. It is essential to remove the surface trend from the data. Then click 'Next'.

d) There are different models of semivariogram such as Gaussian, exponential, spherical, etc. The data's geographical autocorrelation and prior knowledge of the occurrence are used to determine which model of the semivariogram to use (Astraatmadja, 2016). In our case, the exponential model is used since 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 remove trend, the optimization of a semivariogram/covariance model could be performed assuming that just one semivariogram model is used, that it is isotropic, and that the default searching neighbourhood has four sectors (ArcGIS Desktop, 2021). Then click 'Next'.

f) Make sure the neighborhood type is set to standard. Then click 'Next'.

g) In the predictions error panel, we need to make sure 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, we will need to go back to choose different combinations in earlier stages of the model building. Otherwise, click 'Finish'. Then click 'OK' on the prompt model summary window.

h) The kriging prediction map generated in ArcGIS, the output from Figure 3-8 is shown in Figure 3-10.

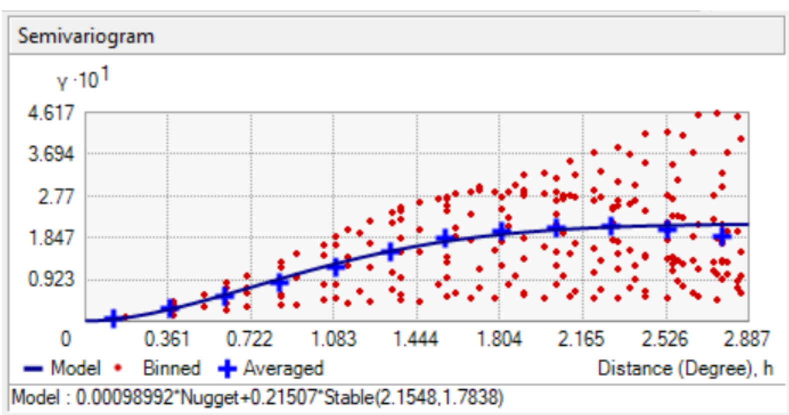


Figure 3-9 The semivariogram showing surface trend shown in the dataset.

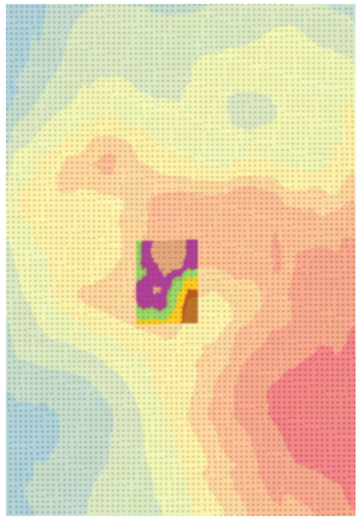


Figure 3-10 The Kriging prediction map generated from the Events file in ArcGIS.

As can been seen in Figure 3-11, the generated kriging prediction map is covering the CoE with an extensive extent. Hence, the map needs to be trimmed to the exact extent of CoE. To execute this spatial operation, the data management toolbox contains a clip tool. First, we need to export the kriging prediction map to raster to use the clip tool. Second, we should open the clip tool and select the input raster as the exported raster kriging map and select the extent of CoE. Finally, the generated clipped map is the map that represents the climate variable for CoE, which can then be further processed to be continuous or discrete, classified or stretched map.

There is a lot of room for further data exploration by changing the combination of different kriging properties to generate the climate present/prediction maps. The selected properties mentioned above were chosen with respect to the literature and data exploration. Statisticians and experts can further perform different kriging combinations to make the data represent the CoE variables as accurately as possible.

Two major issues were raised upon data processing and feature engineering. First, a major issue that we encountered during the raster maps generation for each variable was their different projections. ArcGIS has a tool that fixes the projections; hence, all the maps were layered appropriately in the same projection with the same coordinate system. We used the following steps to project the data correctly using the latitude and longitude:

a) Insert the CSV file into the Table of Contents.
b) Right click and select Display XY Data.

c) Set the Coordinate System to "GCS_North_American_1983", which was our initial coordinate system chosen from the LiDAR dataset.

Second, all the RCP8.5 files were supplied in an NC file format, which should be converted to a CSV file to be integrated with the ArcGIS model. Python scripting language was used to execute the file conversion. However, while processing the netCDF files, there has been an infinite loop in converting the precipitation dataset. Upon investigation, it was revealed that the reason for this infinite loop was that a field variable in the precipitation dataset was of 2D type whereas the netCDF file climate variable should be of Geo2D type. As shown in Figure 3-11, this data mismatch is elaborated using PanoplyWin software, which is a software that can slice and plot geo-referenced latitude-longitude, latitude-vertical, longitude-vertical, time-latitude or time-vertical arrays from larger multidimensional variables, and slice and plot "generic" 2D arrays from larger multidimensional variables. In order to resolve this issue, we followed these steps:

a) The conversion was done using the Python scripting code for all variables except of Type 2D.
b) The netCDF file was exported using PanoplyWin software to CSV file format.
c) The two files were precisely integrated to match the lat2d and lon2d variables with the other fields.

These files were then compiled using ArcGIS to produce the raster maps as mentioned earlier.

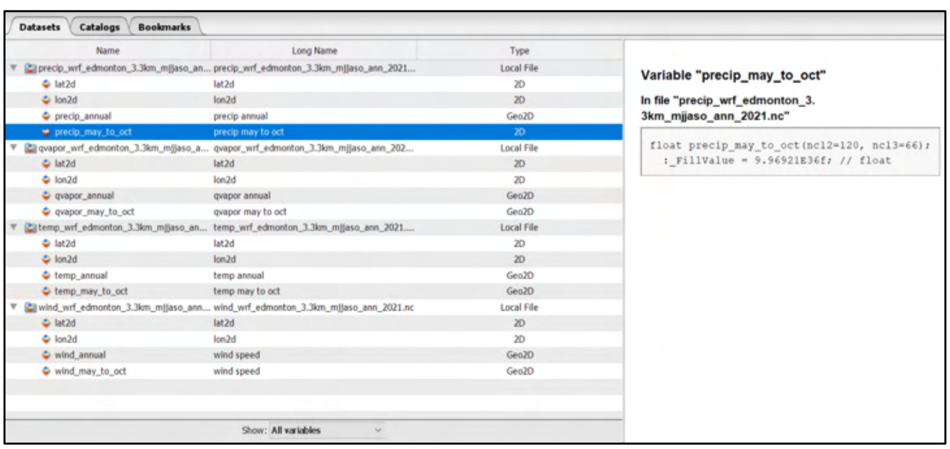


Figure 3-11 The data mismatch in the climate variable in the RCP8.5 data elaborated using PanoplyWin software.

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.

In an attempt to provide comprehensive and informative recommendations to fire risk management and climate resiliency planning, three critical items were investigated. First, ecological vulnerability classification map was constructed to define three different levels of vulnerability; namely, ecological green line, ecological grey line, and ecological red line. As per the literature, ecological green line areas can be extensively developed; ecological grey line areas can serve as an ecological buffer zone; and ecological red line areas 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: risk management and long-term insurability, as well as the ability of the zone to attract investments and communicate resilience benefits.

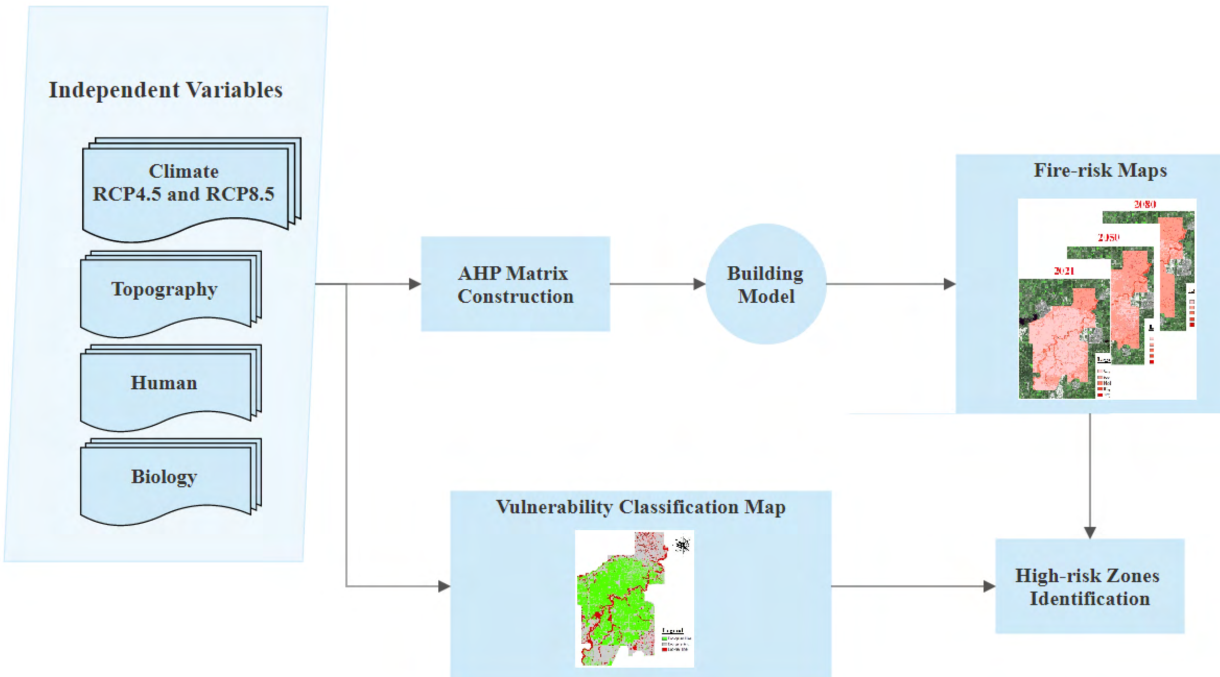


Figure 4-1 The overall workflow of the adopted methodology.

4.1. Analytical Hierarchy Process and 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 decision maker defines to what extent one factor is more important than the other. Hence, this 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 which contribute to choosing an alternative.

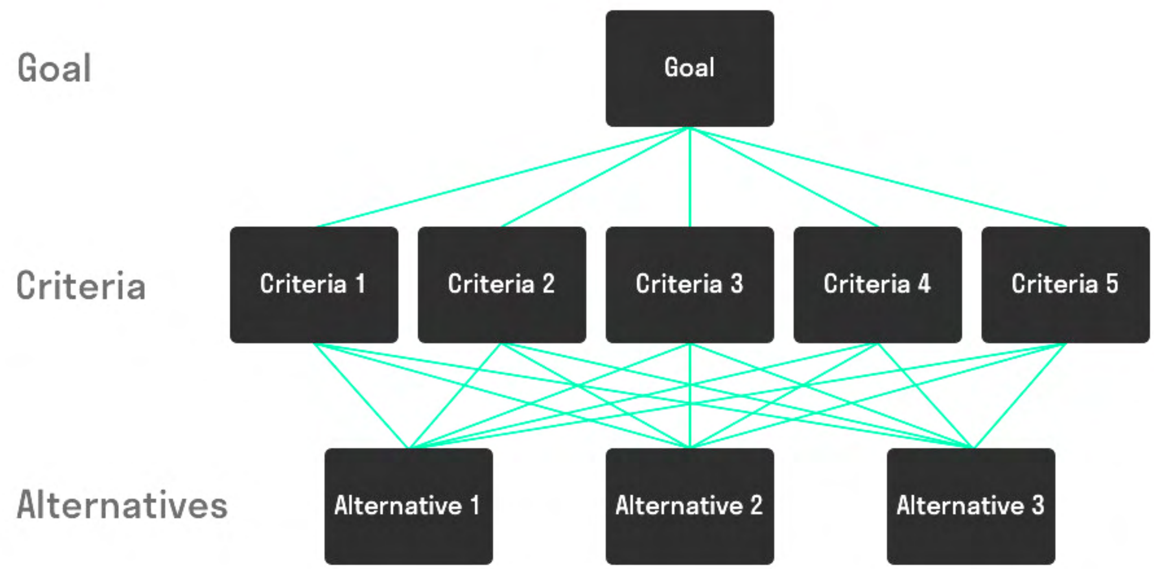


Figure 4-2 A simple AHP hierarchy, (adopted from Saaty, 2008).

Its simplicity and transparency are advantages that characterize AHP; however, its major advantage lies in the hierarchical framework which 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 a crucial step in building the fire-risk model. As mentioned earlier, high weights were assigned to climatic and human variables, while low weights were assigned to biologic and topographic variables. After building the initial matrices with the assigned weights, environmental experts were involved to review and to propose weights concerning the case study. Finally, the consistency ratio was estimated for each matrix to check for consistency.

In this report, 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 Analysis

The fire-risk model in this report is evaluated based on 4 different criteria, each with a unique set of variables. In total, there are 12 variables that are considered major factors for fire ignition in an urban setting. To briefly go over each criterion: first is the climatic criterion, which is considered a major fire trigger. Within this criterion are 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, which influence fire behavior and its ramifications. The second criterion is anthropogenic, which affects fire ignition. It contains land use variable, proximity to water, and proximity to roads. Proximity to water and road are considered fire mitigation variables. This is because water surfaces tend to increase soil moisture of surrounding areas, thereby subsequently reducing fire risk. Land use fire risk can be activity based. An example of this is camping over vegetation, which can be a fire hazard. The third and fourth criteria are topographic and biologic that are considered to have lower risk of fire ignition. Topographic criterion contains 3 variables: slope, elevation, and aspect. Slope relates directly to fire behavior, while elevation and aspect relate manly to the fire ramifications. Biologic criterion contains 2 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, which is based on the weights obtained from AHP.

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

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

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

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

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

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, it is revealed that 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 report 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 of fire risk for the 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

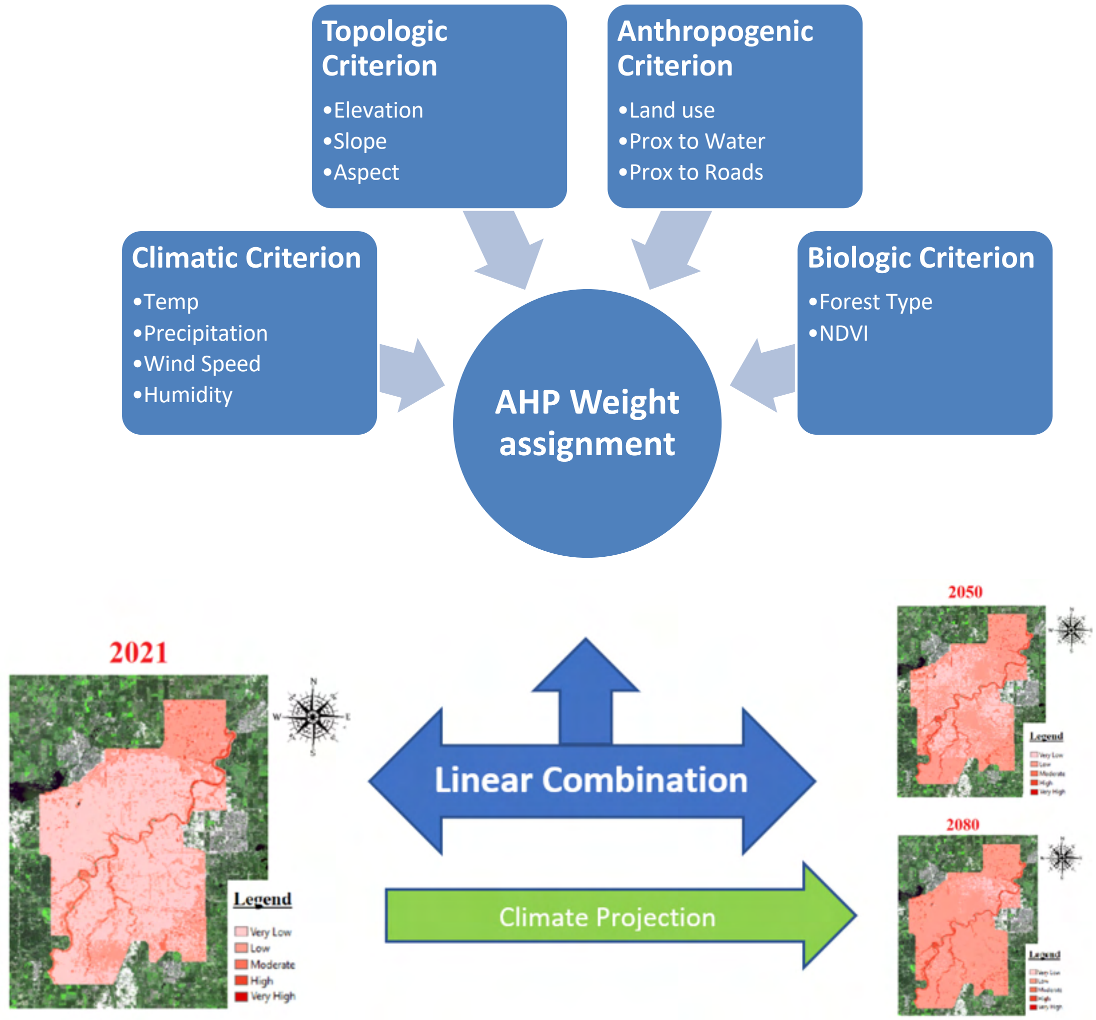


Figure 4-3 Conceptual model of fire-risk assessment model building.

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 significant 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 these major municipalities 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. To accomplish this, CoE has set a target to eradicate a maximum of 155 megatonnes of greenhouse gases within before 2100.

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 starts 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), which effectively groups similar values together while maximizing the differences between the classes.

Before discussing variable projections any further, it is worth mentioning that the RCP4.5 data project only annual temperature and annual 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 predicted that annual temperature will increase by 40.5% and annual precipitation will decrease by 3.2%. On the other hand, RCP8.5 predicted that the annual temperature will increase by 28.7% and annual precipitation will increase by 10.0%. With regard to 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 annual precipitation will increase by 54.3% and 4.6%, respectively.

Altogether, these results make intuitive sense as RCP8.5 values showed 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 were 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	3.3461	3.6177	549.3286	504.8401
2050	4.7025	4.6543	531.9492	555.1953
2080	5.5501	7.1875	514.6369	580.7997

Using RCP8.5, variable projection for seasonal temperature, precipitation, wind speed, and humidity were also calculated. In 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	319.9265	11.1082	0.00589	5.2817
2050	183.9414	14.8572	0.00689	4.4760
2080	205.4308	16.1197	0.00723	4.8283

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 0.5847 and 0.6229, Moderate is between 0.6229 and 0.661, High is between 0.6611 and 0. 6993, and Very High is between 0.6993 and 0.74; every single class above has an interval of 0.0382.

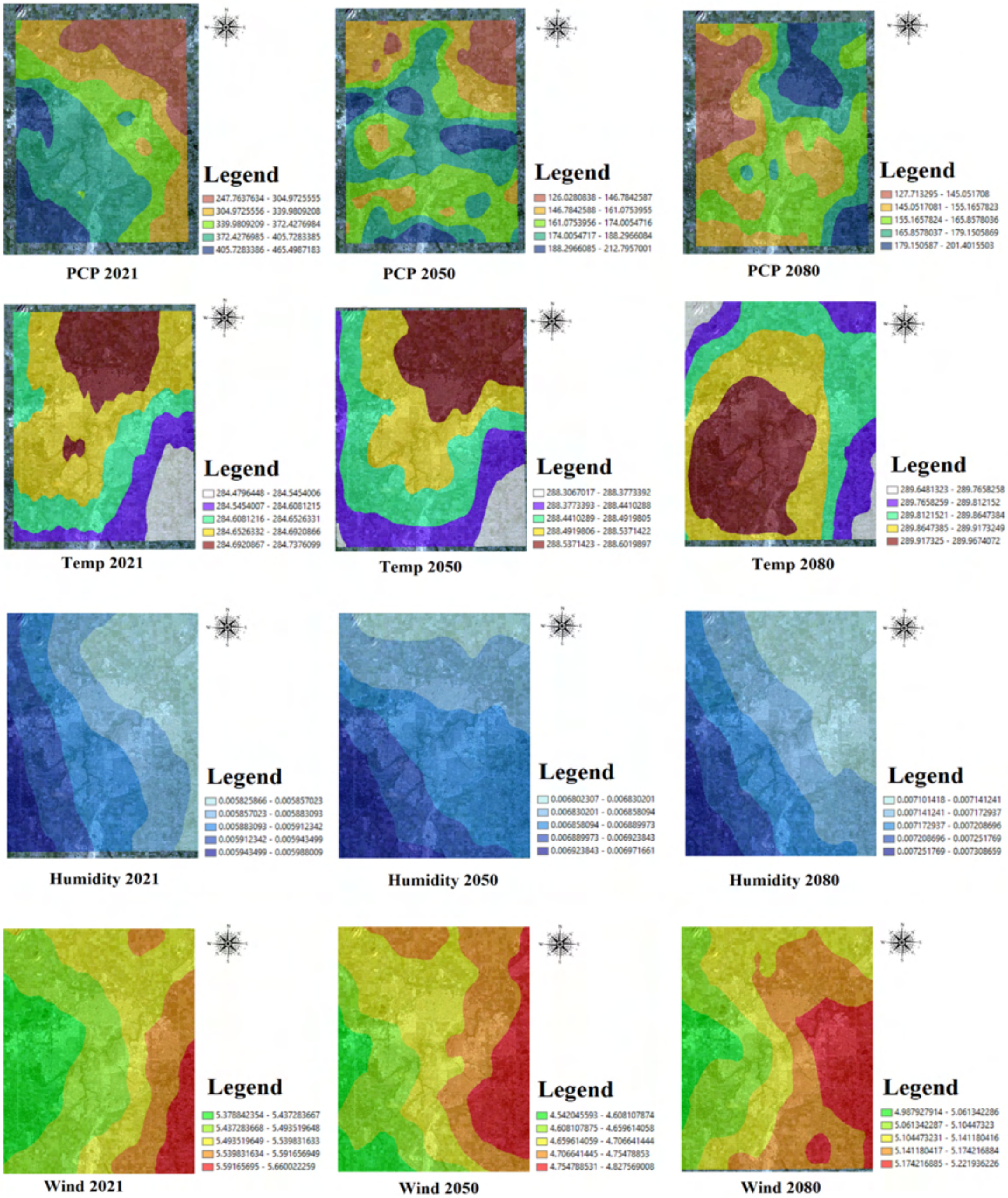


Figure 4-4 Climate variables for 2021 and predictions for 2050 and 2080 based on RCP8.5 data.

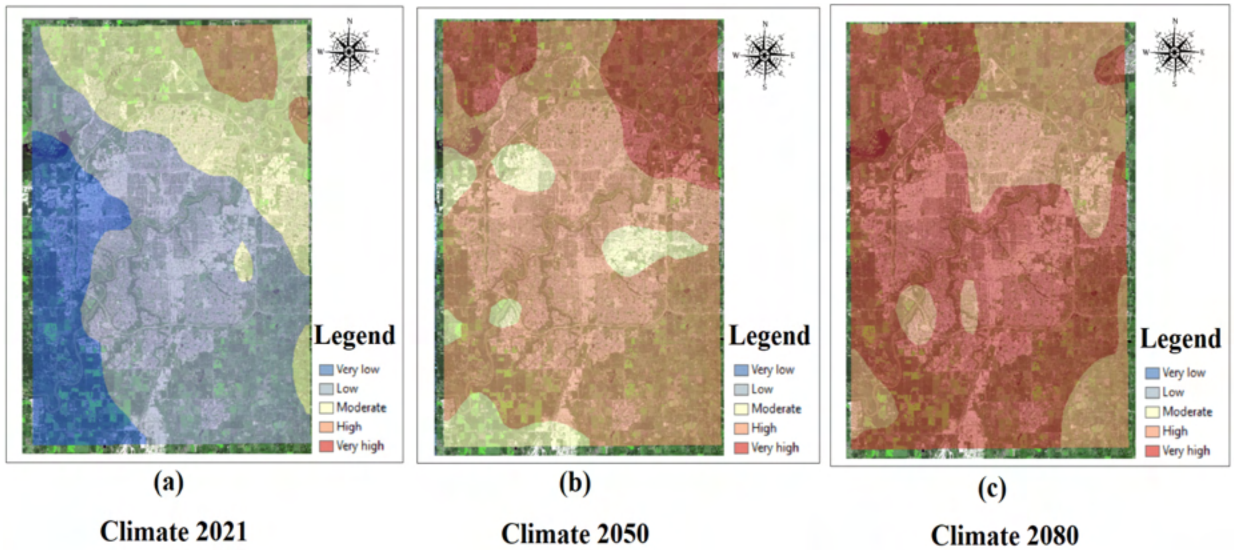


Figure 4-5 The wildfire risk in relation to climate projections for the CoE.

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 overcomplex. Hence, one should only select the most effective variables and/or factors that contribute to the model assessment. In this report, the fire risk model is constructed based on 4 criteria containing a total of 12 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 3 separate years, 2021, 2050, and 2080. The two datasets were then integrated to forecast the climatic conditions, which are expected to drastically change and cause an increase in risk of wildfire in the City as time progresses.

5. Results & Discussion

Section 5 focuses on the fire-risk assessment maps generated via the fire-risk assessment model. There are 6 subsections in this section. The first subsection discusses the 2021 fire risk assessment map while 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 as well as 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 section.

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 as a result of temperature and precipitation as shown in Figure 5-1.

During the fire season, these open-vegetated 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, of which are 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.

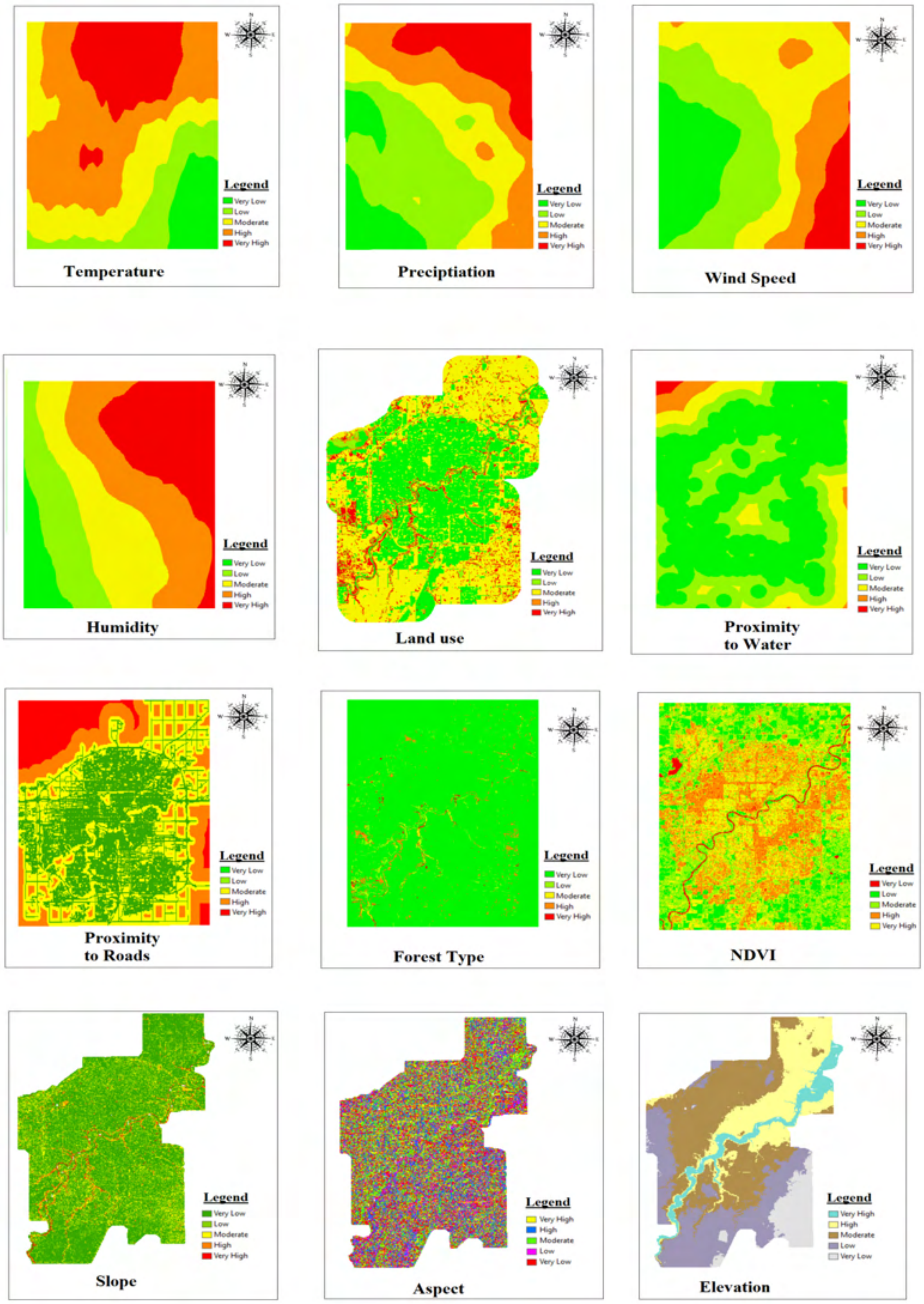


Figure 5-1 Risk map for all the 12 variables used for fire-risk assessment.

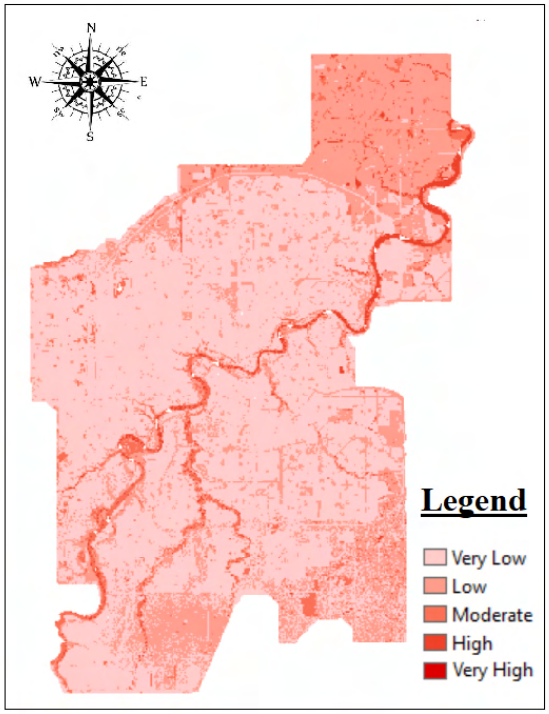


Figure 5-2 The fire-risk map for 2021.

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 done for 2050 and 2080 using the climatic RCP8.5 data as depicted in Figure 5-3. It can be observed in Figure 5-3(a) that by 2050, west and south regions' fire risk will increase by 14-19.7%. And within the central regions, risk will increase by 12-14.4%. Figure 5-3((b) also suggests that by 2080, the northwest and east zones will have their fire potential increase by 7.2-10.4%, and the south regions will experience moderate fire risk increase of 1.7-4.3%. Contrary to the above two mentioned zones, the northeast zones will actually have 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 5-4(a) and in Figure 5-4(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.

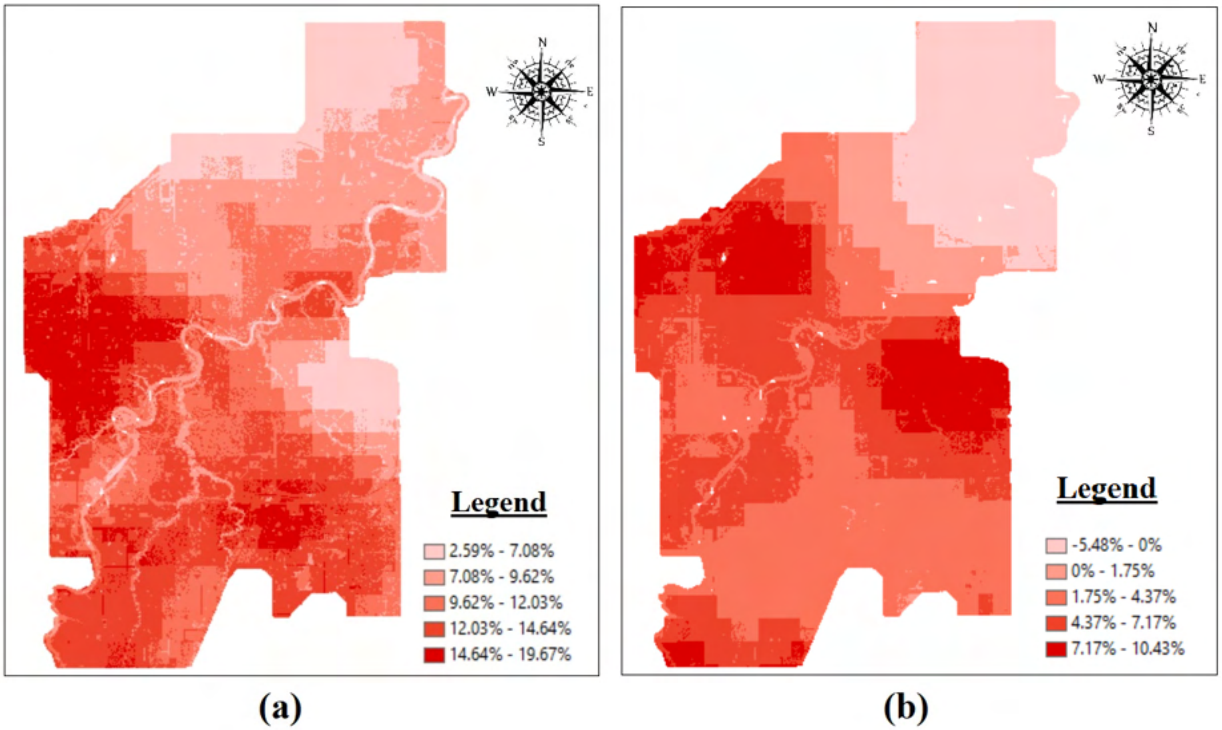


Figure 5-3 Risk rate of changes on the CoE (a) from 2021 to 2050, and (b) from 2050 to 2080.

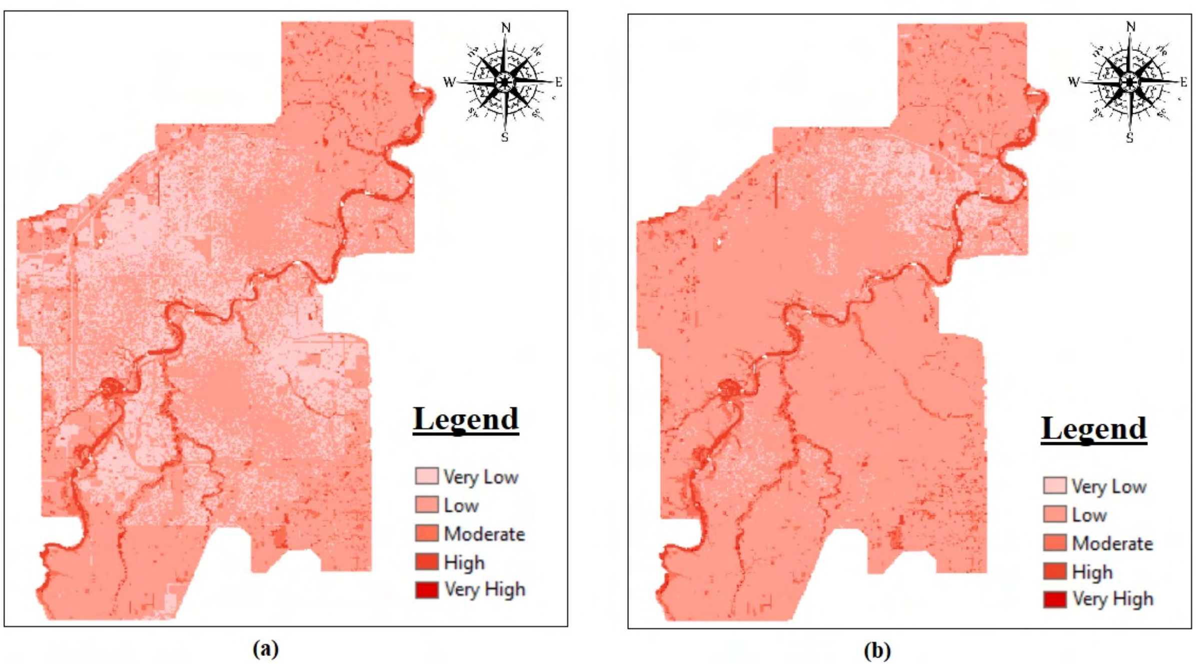


Figure 5-4 Forecasted fire-risk map for CoE for (a) 2050, and (b) 2080 using climate RCP8.5 data.

5.3. Vulnerability Classification

The five risk categories shown earlier in Figure 5-2 can be further grouped into three types of regulatory zones: ecological green line areas, ecological grey line areas and ecological red line areas (Zhang, 2015), as depicted in Figure 5-5.

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, which makes these regions the most livable for residents (Zhang, 2015). Most of the green areas in 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.

It is worthwhile noting that the above-mentioned ecological lines are not fixed but can easily be adjusted to other classification ranges within ArcGIS, thereby increasing the model transferability potential.

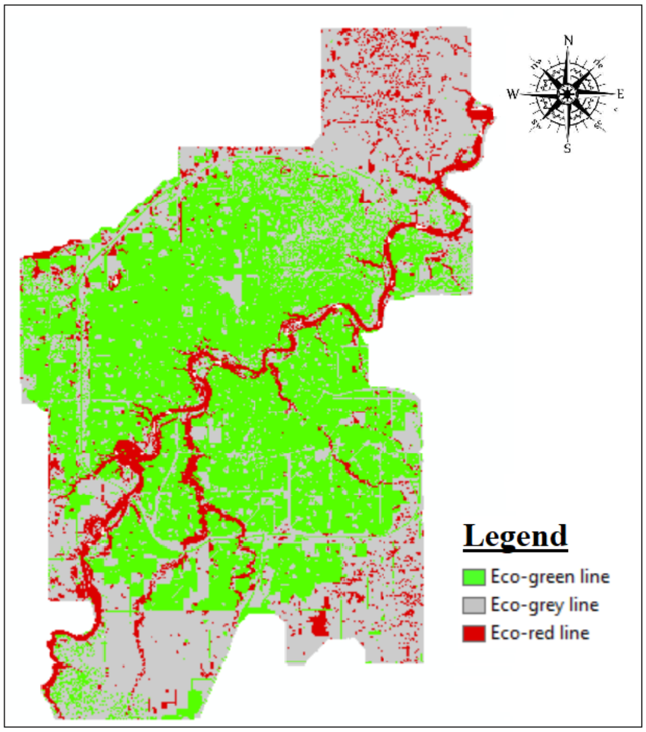


Figure 5-5 The regulatory zone of ecological lines of the City of Edmonton.

The classification of the ecological green line areas in the CoE was through grouping the very-low and low-risk areas, of the ecological grey line areas as the moderate-risk areas, and of the ecological red line areas through grouping the high- and very-high-risk areas. This classification approach was determined throughout the literature which followed the same approach. It is advisable that city planners and experts have the tools adjusted properly in ArcGIS to set the classification ranges and properties suitable to the situation regarding CoE.

5.4. Responsibility Identification

Residents, homeowners, fire departments, and the government all share responsibility in developing a climate-resilient city. For instance, the government is responsible for firefighting while homeowners handle fire prevention. Together they function as cogs in a machine, all indispensable, and if one cog fails to perform, the whole system fails.

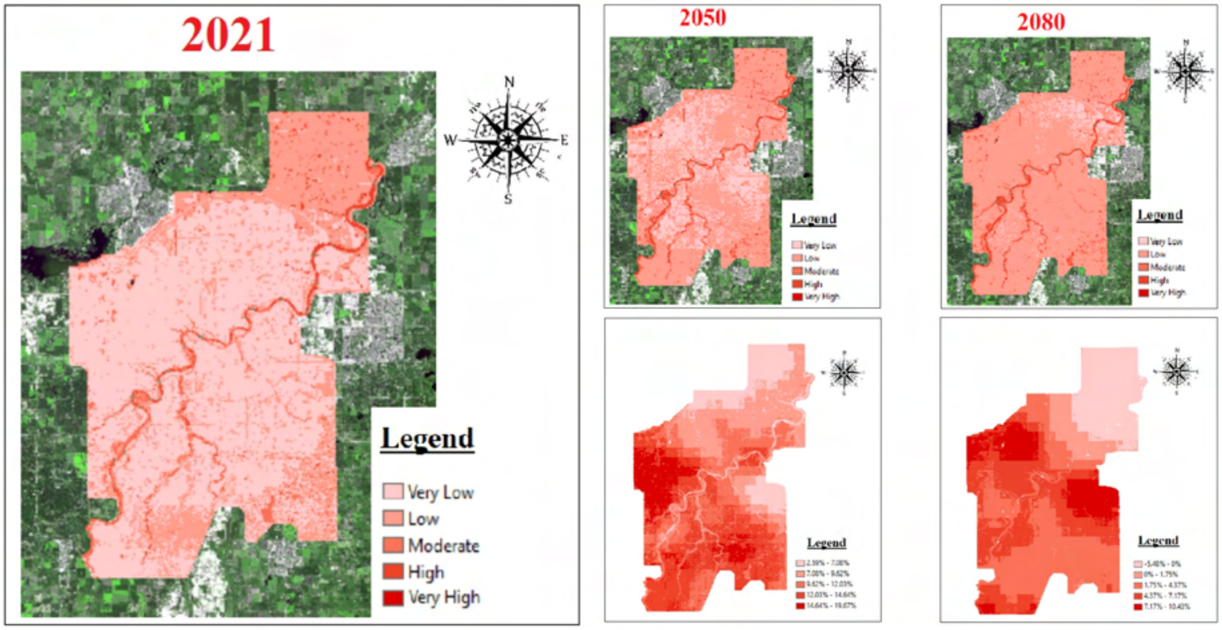
The government has the duty to provide information about protection measures and the dangers associated with fire. Additionally, the government also has to develop a well thought out fire management plan by considering the risk of fire and its associated impacts. During the developmental process, it 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. This is ultimately the goal of any major municipality to becoming a climate-resilient city.

But for these roles to work, homeowners first need to be responsible and fire conscious. The responsibility of homeowners can be summarized into: (1) being cautious with fire, and (2) protecting their private property from wildland fire damage. First, homeowners must be careful with fire in their private property. For instance, garbage present around the houses is one of the biggest culprits for grass fires, which may eventually result in a house fire that later becomes a neighborhood fire. Therefore, a homeowner must keep their property void of any easily flammable material. Secondly, they must educate themselves on and practice fire-risk prevention. These are things like spraying fire retardant and trimming flora around their property to reduce the probability of fire ignition occurrence.

5.5. Fire-Risk Management to Climate Resiliency

Three points can be concluded from the 2021, 2050, and 2080 fire-risk maps, of which were 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 5-6(a). Secondly, as demonstrated in Figure 5-6(b), there will eventually be a high-risk area in the east and west direction as well a minor risk region in the south. Lastly, higher risk regions will be created in the west, east and south directions, as shown in Figure 5-6(c).

As mentioned before, 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 5-7. Green areas are sustainable 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 5-6 All fire-risk raster maps for 2021, 2050 and 2080, associated with the delta map for the corresponding forecasted year.

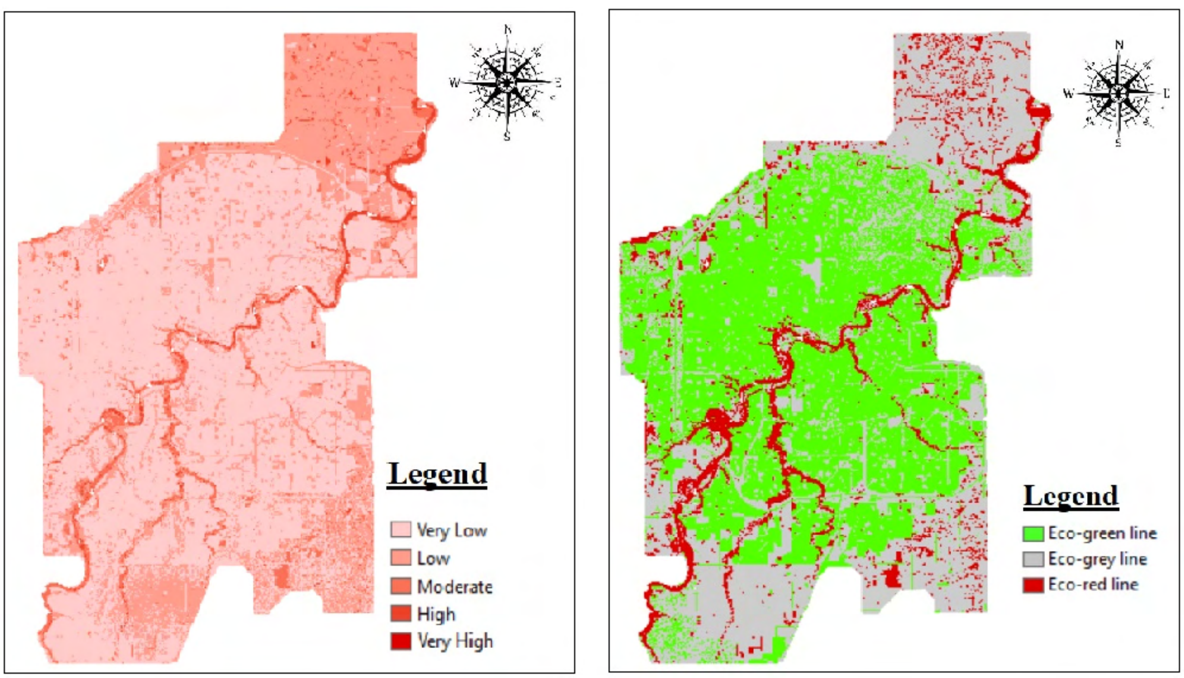


Figure 5-7 The fire-risk assessment raster map along with the vulnerability classification raster map for the CoE.

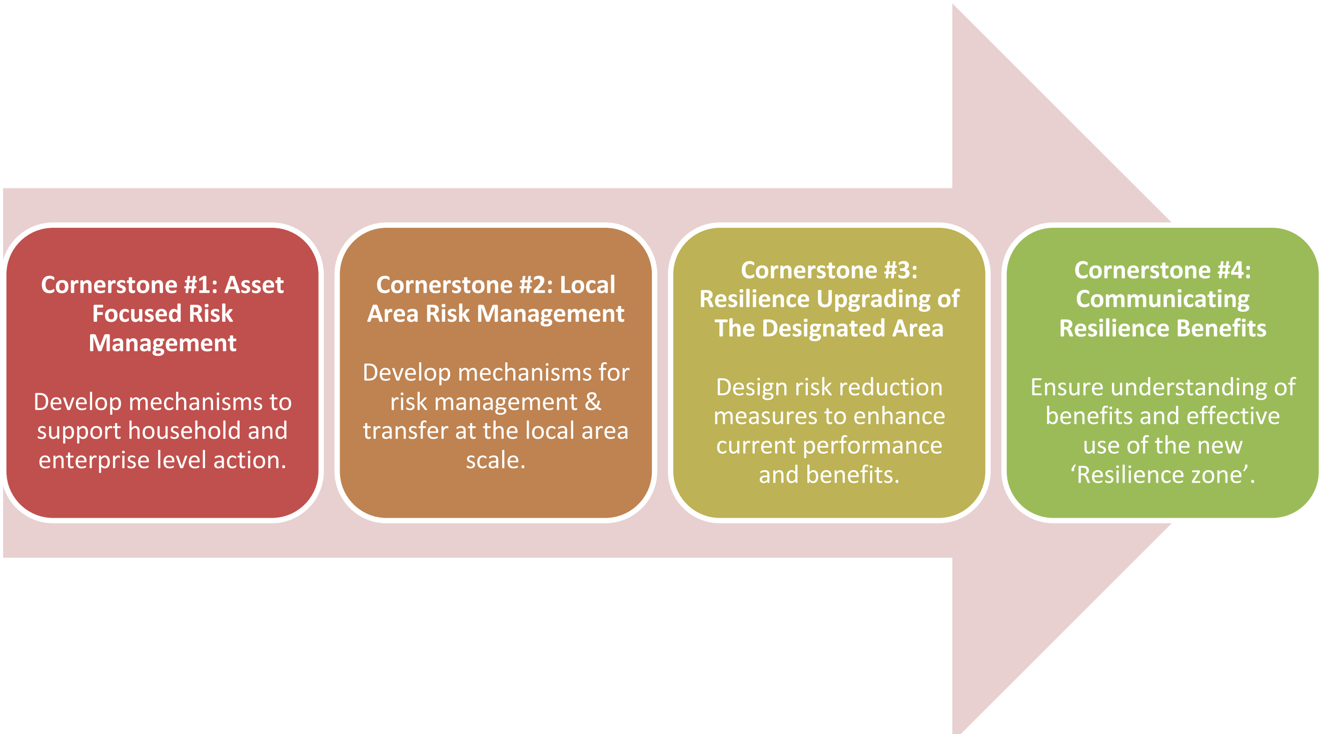


Figure 5-8 Four fundamental cornerstones for strategic planning and policy regulations, (adopted from Brugmann, 2014).

The Resilience Zone approach, shown in Figure 5-8, 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 great 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.

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 produce a performance premium for homeowners and public entities from increased property values, rental, tax, and service revenues (Brugmann, 2014).

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 rates. This has gained them 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.

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. 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. For example, 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.

Ultimately, the goal of this report 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, which are asset-focused risk management and local area risk management, improve risk management and ensure insurability. The subsequent two cornerstones, which are 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 whereby 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 report along with limitations and recommendations for future research. This report covered three major 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. In terms of modelling, a brief background was introduced to show the importance of building a city-specific fire-risk model as it will serve as a steppingstone 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 previous literature 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) how to adapt to increased wildfire risk and 2) how to achieve 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, whereas the remaining two cornerstones focus on how high-risk zones can be modified to attract investments, and how communicating resilience benefits can increase resilient zone value. It is anticipated that these four cornerstones would help achieve higher levels of climate resiliency compliance.

Two major future bodies of work should be considered so that it may contribute to this research and could potentially provide researchers a better understanding for their development of evacuation plans and emergency responses. First, traffic network analysis and street connectivity are major factors for the CoE to investigate to help simulate and set an evacuation plan in case of fire occurrences. Street connectivity measures the density of network links and the directness of paths. A well-connected street has many short links and intersections, with little to no culs-de-sacs. Travel distances decrease in a network with more capacity, shorter paths exist between each origin and destination, and more destinations become available within the allocated time budget. It also increases the feasibility of active transportation modes and decreases the time required for emergency responders to respond. Street connectivity is an essential characteristic of sustainable cities. People must be able to move safely and efficiently across the City. Such an ecosystem is created by a sustainable street network, which allows for a variety of transportation modes and routes. Connections between modes of transportation must be simple and convenient. Routes must be clear and secure in case of any emergency or evacuation (Zlatkovic, 2019).

Second, given the fire-risk map, high-risk zones and areas which need more attention can be easily identified. Combustibility analysis for the urban setting differs significantly from the rural setting. Hence, further building and zoning regulation and investigation can be compiled to increase resiliency and awareness. Other factors and variables would need to be explored in depth to decide how it is contributing to fire and if it is required to be included in the model. These variables might include, but not limited to, openings, collapsed buildings, flame brands, direct flame contact, emitted radiation through fuel, fire temperature and compartment properties, and radiative heat transfer. Also, some field work and ground truthing can be the next steps to verify the fire risk levels in the field given the high-risk areas. This further investigation point can be of an essential investigation in the future if there must be microanalysis for fire-risk assessment. This might also give insights to better zoning and building regulations in high-risk areas; hence, better fire-risk management and mitigation strategies will be implemented.

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