Pre-Disaster Identification of Evacuation Destinations to Support Provincial-Level Emergency Management Planning

by

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Abstract

The unpredictability of natural events like wildfires and earthquakes, and how they impact human settlements, often results in short- and no-notice evacuations, and can sometimes lead to evacuees being displaced for weeks if not months (and sometimes, years). One key issue of concern is where evacuees should go to reach safety, and access medical assistance, emergency supplies, and temporary shelter. The important decision of identifying these destinations is usually made operationally, either just before or when an evacuation order is called, due to the highly uncertain and rapidly changing nature of disasters like wildfires. Identification of these destinations is difficult across a large jurisdiction such as a state or province, where many communities within the jurisdiction may be under threat of wildfire, but it is entirely unknown if and where they will occur during the season. However, if potential destination communities can be identified prior to the wildfire season, in pre-disaster planning efforts that consider community suitability to host evacuees and community access to supplies from larger urban centres, evacuations can benefit from reduced decision burdens of local governments directing evacuations and the larger jurisdictions that support local governments in this work.

The main objective of this thesis is to develop knowledge around supporting emergency evacuation planning, specifically where and how to direct evacuees from (mainly smaller, rural) communities to safety in wildfire evacuations. Two sub-objectives support this main objective. The first is to identify a network of potential wildfire host communities across a large jurisdiction, as part of pre-wildfire season planning and preparation efforts – not knowing if, where, and when wildfires will occur within that region. The second is to identify capacity-restricted routes between potentially evacuating communities and pre-identified host communities.

For the first objective, a multi-objective facility location model is developed to identify potential wildfire evacuation host community locations across Alberta. A Pareto frontier of optimal solutions is identified, and clustering analysis is used to further understand the solution set. It is found that with 13 host communities, more than 90% of the wildfire-prone population (excluding those of one urbanized region) is "covered" by at least one of the 13 host communities. Options for the remaining "uncovered" communities are also explored.

For the second objective, two measures called *Escape Capacity Criticality* and *Max-flow Impact Index* are introduced. They are used to determine the contribution of roadway facilities to network bottleneck capacity between an evacuating community and a destination community. Results suggest that Level 2 Highways in the immediate vicinities of communities are most critical.

In the event of a short- and no-notice community evacuation, decision-makers make many important decisions in a short timespan. Identifying potential host communities before the annual wildfire season can help reduce decision burdens and ease coordination between emergency managers. It can support further decisions such as evacuation route identification, and centralized emergency logistics planning (plans for how supplies and other relief are distributed). With the frequencies and intensities of wildfires increasing in western Canada and other parts of the world, evacuation pre-planning and readiness continue to be of great concern in the protection of human safety.

Keywords: Pre-disaster emergency planning, short- and no-notice evacuation, multi-objective optimization, wildfire, evacuation host community identification, Province of Alberta.

Preface

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Published manuscripts:

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2. **Ohi, S.J.**, Kim, A.M., 2022. Identifying Alberta's Critical Road Segments in Supporting Wildfire Evacuees. In preparation for submission in August 2022. (CHAPTER 6).

Dedication

To my beloved husband, **Mahfuzul Hoque**

-For being there in good times and bad

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List of Acronyms

AADT	Annual Average Daily Traffic
AB	Alberta
ADA	Aggregated Dissemination Area
AEMA	Alberta Emergency Management Agency
AEP	Alberta Emergency Plan
AHS	Alberta Health Services
BILP	Binary Integer Linear Program
CD	Census Division
CRC	Canadian Red Cross
CSD	Census Subdivision
DA	Dissemination Area
DPL	Designated Places
EOC	Emergency Operations Centre
ESS	Emergency Social Services
FMM	Fort McMurray
GA	Genetic Algorithm
HCM	Highway Capacity Manual
HIRA	Hazard Identification and Risk Assessment
Hwy	Highway
MCMF	Min-Cut Max-Flow
MILP	Mixed-Integer Linear Program
MOO	Multi-Objective Optimization
NHS	National Highway System
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
OD	Origin-Destination (pair)
POC	Provincial Operations Centre
RCMP	Royal Canadian Mounted Police
SOLE	State of Local Emergency

List of Symbols

I	Set of origin community centroids
J	Set of potential host community centroids
S	Set of service centre centroids
G	Grid, set of cells
i	Index of origin community centroids; $i \in I$
j	Index of potential host community centroids; $j \in J$
s	Index of service centre centroids; $s \in S$
c	Square cell, $c \in G$
X_j	1 if j^{th} community is selected as the host community, 0 otherwise
Y_{ij}	1 if i^{th} community is served by j^{th} host community, 0 otherwise
Z_i	1 if i^{th} community is served by a host community within coverage radius, 0 otherwise
Cr_c	Escape Capacity Criticality of network facilities of grid cell c
MI_c	Max-flow Impact Index of cell c
N	Total OD pairs
HC	Number of host communities to be identified
P_i	Population of origin community, i
P_j	Population of the potential host community, j
P_s	Population of the service centre, s
RI_i	Remoteness Index (normalized) of the origin communities, i
AI_i	Accessibility Index (normalized) of the origin communities, i
BCI_j	Betweenness-Centrality Index (normalized) of the potential host community, j
F_{ij}	Bottleneck capacity from origin i to destination j on the existing network (before disruption).
F_{ijc}	Bottleneck capacity from i to j on the residual network (after disrupting cell c)
n_{is}^{j}	1 if the shortest path from community i to service centre s passes through potential host community j, and 0 otherwise
w_{ij}	Weight between nodes i and j
n_{is}	1 if community i and service centre s are connected; 0 otherwise
ω_j	Percent of raster cells with landscape fire exposure more than 80% within a 10 km radius of potential host community j
Ω	The upper limit of the total patch of landscape fire exposure
η	Maximum host community assigned to each evacuating community
σ	Minimum evacuating communities to be served by a host community
N_i	Eligible host community centroid for community $i = \{j \mid R_L \leq d_{ij} \leq R_U\}$

R_L	The lower limit of coverage radius (km)
R_U	The upper limit of coverage radius (km)
D	The maximum distance among all communities and host communities
d_{ij}	Travel distance between origin community i and host community j (km)
d_{is}	Travel distance between origin community i and service centre s (km)
$\overline{d_{s\forall\iota}}$	Average distance between all evacuating communities ($\forall i$) and service centre s
tc_{ij}	Travel cost between origin community i and host community j
T	Trip distributed between i and j
δ_{ij}	Matrix for coverage radius check; 1 if $R_L \leq d_{ij} \leq R_U$, 0 otherwise
θ_{ij}	1 if $F \neq F_{\mathrm{ij_c}}$, 0 otherwise
y_{ij}	Matrix for allocation check; 1 if $X_j * Z_i = 1$, 0 otherwise

CHAPTER 1. INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Evacuation often becomes necessary to remove people from the severe consequences of a disaster. Depending on the disaster characteristics, evacuation orders can be issued with long-, short- or no-notice (Bayram, 2016). A short- or no-notice evacuation often results because of a disaster being unpredictable (Insani et al., 2022) and fast-occurring; affected people must leave immediately, and pre-planning for these evacuations can be difficult. For example, evacuation orders for wildfires are often issued with little time to prepare. Weather factors like humidity, wind speed, and wind direction can change quickly; in addition to fuel accumulation, they influence wildfire occurrence and progression (Demange et al., 2020).

The frequencies and intensities of wildfires are increasing globally due to climate change (Zhao et al., 2021). Canada experiences wildfires annually (Bush and Lemmen, 2019; MNP LLP, 2017), and depending on a wildfire's intensity, perimeter, proximity to communities, and firefighting resource availability, evacuations may be necessary. In fact, they occur nearly every wildfire season. Although the 2016 Fort McMurray wildfire, resulting in the evacuation of nearly 90,000 people (Woo et al., 2017) was a very rare and extreme occurrence, about 178 evacuations of much smaller Alberta communities occurred from 1980-2018 due to wildfire (Beverly and Bothwell, 2011; Natural Resources Canada, 2020a). A wildfire's propagation depends on available fuels and wind direction, and thus a wildfire can quickly breach the wildland-urban interface (WUI), resulting in a community evacuation order issued with no or short notice.

Short- and no-notice evacuations are challenging because critical decisions must be made quickly, and confusion can take over (McGee et al., 2021). Communities at risk benefit from having pre-disaster plans in place. An important decision that needs to be made by, and sometimes for, evacuees is where they will go, and how they will reach these destinations. Evacuees have been known to travel long distances, upwards of 12 hrs in some extreme cases (McGee et al., 2021). During the 2011 Utikuma Complex Fires in Alberta, most evacuees from Whitefish Lake First Nation 459 (Atikameg) were unable to secure accommodations 92 km away in High Prairie, and instead, were required to travel 200-300 km to either Valleyview or Grande Prairie (McGee et al., 2021). In the summer of 2021, evacuees from Logan Lake, British Columbia were directed about 400 km away to Chilliwack, as closer communities like Ashcroft and Merritt were unable to accommodate them (Judd, 2021). Also, in the 2016 Fort McMurray fire, an alternate route (Hwy 881) was found to be underutilized due to a number of reasons (Woo et al., 2017).

Thus, although some evacuees will evacuate earlier than directed, towards destinations of their own choosing, it is important for emergency managers to provide direction in short- and no-notice evacuations, particularly for those that do not know where to go and/or need specific supports. However, given that emergency management planning is done at the local level, some without resources to even develop emergency plans, there is a lack of coordination between communities. Evacuation destinations are not typically identified in advance of evacuation, which can exacerbate the complexities identified (McGee et al., 2021; Shahparvari et al., 2016b). In the province of Alberta, Canada, according to provincial emergency management guidelines, the responsibility of preparing evacuation plans falls upon local authorities (Alberta Emergency Management Agency, 2022). Although community evacuation planning is mainly done by local authorities, provincially- and federally-managed resources may be required (Alberta Emergency Management Agency, 2022). For example, local authorities can draft mutual aid agreements with potential host communities, with the assistance of Alberta Emergency Social Services (ESS) and/or Alberta

Emergency Management Agency (AEMA) (Alberta Emergency Management Agency, 2022). Local and provincial emergency managers coordinating to pre-identify potential evacuation destination locations can support emergency managers towards making further critical decisions, both in advanced planning and during emergencies.

Destination communities, herein referred to as "host communities," are designated communities with sufficient supplies and resources to capably accommodate evacuees. The local authority managing a community's evacuation must form relationships and establish agreements with these potential host communities in advance (Emergency Management BC, 2022). Having potential host communities identified before a disaster – host communities that have been provided with supplies and resources in advance, or have a plan for doing so in the event of evacuation – can help facilitate greater efficiencies, reduced confusion, and overall better evacuee experiences during an emergency event. However, an approach to guide the location of such places across a large jurisdiction (i.e., a province), to support short- and no-notice evacuation movements, has not specifically been addressed in the literature. The existing literature on wildfire evacuation planning largely focuses on evacuee behaviours and egress movements (by simulation or survey) in specific wildfire scenarios (Cova et al., 2009; Cova and Johnson, 2002; Dombroski et al., 2006; McGee et al., 2015; McGee, 2019; Toledo et al., 2018; Wong et al., 2022, 2020b).

Given the uncertain, unpredictable nature of wildfires, and their prevalence across large swaths of western Canada, the western US, and other parts of the world, both coordination between jurisdictions (neighbouring, and different levels) as well as pre-disaster evacuation planning can benefit those that are directly impacted by these natural disasters. This thesis explores the issue of identifying evacuation destinations across a large jurisdiction in pre-disaster planning, to support local and provincial emergency managers in short- and no-notice evacuations.

1.2 RESEARCH QUESTION AND OBJECTIVES

The above leads to the following **research question**: How do we identify key potential evacuation destinations across a large jurisdiction, as part of pre-disaster emergency management planning, in which many mainly small, rural communities are threatened by short- or no-notice evacuation? This thesis has two objectives towards addressing the above research question.

Objective 1: Develop a framework to identify potential evacuation host communities across a large jurisdiction – i.e., *where* evacuees should be directed for safety and shelter.

- ⇨ A multi-objective optimization model will be developed to provide a set of optimal locations for the potential host communities in pre-wildfire season (Ch 5).

Objective 2: Develop a simple network scanning process to identify road segments that contribute to maximum evacuation capacity, towards supporting *how* evacuees might be routed through the provincial roadway network to destinations.

- ⇨ New measures, together with network scanning, are proposed to quantify the importance of road segments between evacuating and host communities (Ch 4).

The results from Objectives 1 (Ch 5) and 2 (Ch 4) are combined to investigate the features of routes between potentially evacuating communities and their host (destination) communities (Ch 6). The objectives are studied within the geographic context of Alberta, a province in western Canada prone to wildfires that have breached WUIs and impacted communities.

1.3 THESIS ORGANIZATION AND APPROACH

Figure 1.1 shows the thesis objectives, the tasks to achieve the objectives, how the objectives tie into one another, and how objectives and tasks are organized within the thesis chapters.

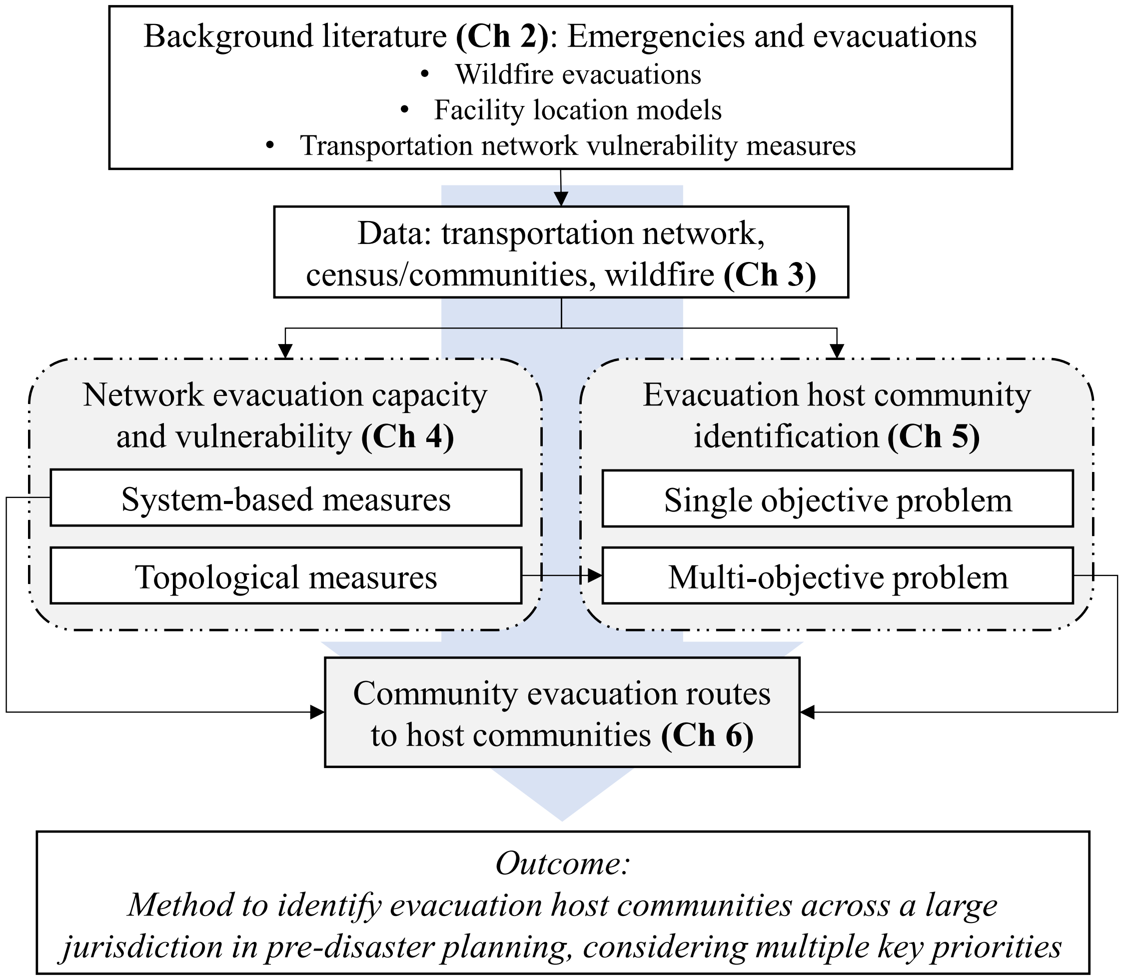

Figure 1.1: Thesis overview

CHAPTER 2 provides a review of the supporting literature (Section 2.1) as well as an overview of the study context and background (Section 2.2). Data sources are introduced and described in CHAPTER 3, which include transportation network data and community data used to build models of Alberta's transportation network and wildfire exposure data. In CHAPTER 4, the two network measures (Objective 2) are introduced. CHAPTER 5 introduces the facility location models used to identify evacuation host communities (Objective 1). In CHAPTER 6, the network measures (from Ch 4) are applied to identify evacuation-critical road segments of one Pareto solution (from Ch 5), and also options for evacuating communities not covered by the selected solution are discussed. The thesis concludes with CHAPTER 7, which provides a summary and synthesis of the work presented, highlights the main contributions, and discusses research limitations and paths for future study.

CHAPTER 2. LITERATURE REVIEW & STUDY CONTEXT

This chapter will first provide a review of the literature on three components: evacuations – specifically, wildfire evacuation and the various important components to be understood about them, facility location models applied within emergency management contexts, and transportation network analysis – specifically around the concept of vulnerability in evacuations. Then, the thesis study context and background will be discussed.

2.1 LITERATURE REVIEW

Evacuation planning is a key component of disaster management and can play a vital role in saving lives (Bayram, 2016; Boonmee et al., 2017; Thompson et al., 2017). Studies on evacuation planning often use survey data to gain insights about potential evacuees' characteristics and prior experiences, and then use this for inputs to evacuation optimization and simulation for evacuation destination identification, route selection, and traffic assignment, amongst other purposes (Abdelgawad and Abdulhai, 2009; Boonmee et al., 2017; Thompson et al., 2017). According to Lim et al. (2013), depending on the disaster, an evacuation order could be issued with ample warning or little to no warning, and planning must be done accordingly. Wildfires result in either short- or no-notice evacuation, as the occurrence and spread of fire cannot be easily predicted (Insani et al., 2022). This makes planning for wildfire evacuation challenging.

2.1.1 Wildfire Evacuation

Wildfires play a vital role in ecosystem renewal. However, when they start to grow uncontrollably and approach communities and infrastructure, they pose threats to public safety. Shelter-in-place, shelter-in-refuge, and evacuation are the common approaches for protecting people when a wildfire breaches the wildland-urban interface (WUI) into a community (Cova et al., 2011, 2009; Li et al., 2015; Shahparvari et al., 2016b; Taylor and Freeman, 2010). Shelter-in-place is ordered when there is insufficient time to escape, or escape routes are compromised due to encroaching fire (Li et al., 2015). Shelter-in-refuge is when people travel a short distance to a designated refuge centre within the threat area (Cova et al., 2011). Evacuation out of the community entirely is a common outcome when a fire breaches the WUI, as it results in a higher likelihood of safety for residents (Cova et al., 2009; Li et al., 2015). When developing an evacuation plan, consideration of departure time, evacuation travel modes and route selection, congestion/bottleneck locations, evacuee behaviour and compliance, and other factors can improve evacuation efficiency by reducing evacuation times and, ultimately, casualties (Wong et al., 2022a; Zhao and Wong, 2021). Centralized wildfire evacuation planning across a large jurisdiction with multiple communities at risk of wildfire is difficult, as it is unknown in advance where wildfires will originate, how they will move and grow (and often very quickly), and which and how many communities will need to be evacuated. Thus, there are fewer wildfire evacuation planning studies whose geographic scopes encompass multiple regions and communities, compared to those that focus on smaller regions or single communities, and are scenario-based (Henry et al., 2017; Li et al., 2015; Shahparvari et al., 2016a; Toledo et al., 2018).

In terms of the instructions given once an evacuation order has been made, the literature primarily focuses on three major aspects: i) *When* people should start evacuating, ii) *Mode choice and routes* for evacuees, and iii) *Where* evacuees should go to seek safety, supplies, and/or shelter. A fourth major area of research focuses on the factors driving peoples' decision-making on the above, in the face of encroaching danger. Post-disaster survey data and GPS data have been used to study evacuee risk perception and awareness, and model evacuee decision-making processes (Grajdura et al., 2021; Kuligowski et al., 2022; Wong et al., 2022b; Zhao et al., 2022). Zhao et al. (2022) used GPS data from mobile devices to study the responses of evacuees, including their decision to evacuate and their departure times. Kuligowski et al. (2022) used survey data and regression analysis to study the factors influencing the decision to evacuate in California's 2019 Kincaid Fire. Wong et al. (2022b) used survey data from California evacuees to develop discrete choice models towards understanding how evacuation decisions like departure time, destination, mode of transportation are impacted by the choices available to evacuees.

2.1.1.1 When to Evacuate

Evacuation orders are generally given if and when a wildfire crosses a designated perimeter around a community, known as a trigger buffer (Li et al., 2019). These perimeters could be set by selecting existing geographic features like rivers and ridges, or by performing trigger modeling using wildfire spread rate, wildfire intensity, etc. (Li et al., 2019). Cova et al. (2005) applied fire spread modelling using land topology, fuel accumulation and moisture, and wind direction and speed, to determine a fire's rate of spread. The rate of spread coupled with an estimated evacuation time yields the trigger buffer. Li e al. (2019) built on this work by using traffic simulation to determine evacuation time and fire spread rate to define the trigger buffer. Dennison et al. (2006) proposed the use of historical wind data in 16 wind directions to identify the trigger buffer and cut-off evacuation routes to develop a guideline for issuing evacuation orders. Li et al. (2015) applied a trigger buffer and fire spread rate to calculate the available evacuation lead time for households, and develop a staged evacuation warning method. Trigger buffers have also been used in microscopic simulations of evacuee flow in networks (Beloglazov et al., 2016; Li et al., 2019; Wahlqvist et al., 2021).

2.1.1.2 Evacuation Route Selection

Evacuation routing, using traffic models, has been explored (Intini et al., 2019; Murray-Tuite and Wolshon, 2013). Evacuation route selection and assignment have been studied using simulation (Beloglazov et al., 2016; Wolshon and Marchive, 2007) and optimization (Shahparvari et al., 2016a) models. Studies have also focused on identifying vulnerable or critical infrastructures that are important to community egress capacity during wildfire evacuation (Cova et al., 2013). Implementation of contraflow (i.e., switching traffic flow to the opposite direction for a temporary period, to increase egress capacity) has also been investigated by researchers (Zhao and Wong, 2021).

The factors involved in evacuees' selection of evacuation routes have also been investigated through survey or choice modelling (Brachman et al., 2019; McGee, 2018, 2019; McGee et al., 2019; Toledo et al., 2018; Wong et al., 2020a). In an investigation of evacuee behavior and decision-making during a wildfire in Haifa, Israel, Toledo et al. (2018) observed that evacuees make intermediate stops to gather family members, and select routes accordingly. Wong et al. (2022b) concluded that evacuation orders played a key role in evacuees' route selection during the Southern California Wildfire, as mandatory evacuation orders led evacuees towards highways.

2.1.1.3 Evacuation Destinations

There are a very limited number of studies on how destinations are identified and/or selected for wildfire evacuation, despite that the literature on evacuation destinations for other types of disasters and emergencies abound (see Section 2.1.2). While developing microscopic traffic simulation models for wildfire evacuation, Belogzalov et al. (2016) and Steer et al. (2017) determined evacuation destinations for simulation input using a basic facility location model. They proposed stepwise guidelines to study and support wildfire evacuation, starting with wildfire simulation, moving to trigger point and departure time modelling, then destination modelling, followed by traffic simulation as a final step. Demange et al. (2020) proposed a minimax shelter location model for small, localized wildfires with an objective that considers the uncertainties of fire outbreaks, applying their model to a theoretical test network. While reviewing the policy and practices of wildfire evacuation in Australia, Taylor and Freeman (2010) found that last-minute decision-making can lead to an increase in evacuation time.

2.1.2 Emergency Facility Location Models

2.1.2.1 Overview of Models

Facility location models, also called location-allocation models, involve methods to find optimal sites for facilities across a transportation network. The definition of what is optimal depends on the problem and stated objectives. One of the first models applied for optimizing facility locations is the minisum model. It was first proposed by Hakimi (1964) to locate a fixed number of police stations by minimizing the total travel distance to a police station. Another widely used facility location model is the coverage model. Coverage models assist with the placement of facilities within a specific distance of demand points. These coverage models can either cover all demand points (set coverage model by Church and ReVelle (1974)) or maximize the coverage of demand points with a fixed number of facilities (maximal coverage by Toregas et al. (1971)). Another facility location model heavily explored in literature is the minimax model (Hakimi, 1964). This model differs from the previous models as it focuses on minimizing the maximum distance between origins and destination facilities. These models comprise the basic types of single-objective facility location models, and there has been extensive research building on the above within different applications. In their review, Şahin and Süral (2007) identified case-specific facility groups as health-care facilities, waste management facilities, telecommunication facilities, production-distribution facilities, and emergency response facilities. Budget constraints (Dessouky et al., 2013; Salman and Yücel, 2015), capacity constraints (Barzinpour and Esmaeili, 2014; Ghasemi et al., 2019; Mete and Zabinsky, 2010), commodity availability constraints (Abounacer et al., 2014; Das and Hanaoka, 2013; Fereiduni and Shahanaghi, 2017; Setiawan et al., 2019), etc., are imposed within different applications.

Emergency response facilities include emergency service stations (e.g., police stations, fire stations, hospitals, ambulance dispatching stations, etc.) and emergency humanitarian logistics centres. In the last two decades, there has been extensive research in facility location models for emergency and disaster management, to locate facilities like shelters (Bayram et al., 2015; Kongsomsaksakul et al., 2005; Liu et al., 2011; Ozbay et al., 2019), relief distribution centres (Horner and Downs, 2010; Lin et al., 2012; Maharjan and Hanaoka, 2017; Ransikarbum and Mason, 2016; Rawls and Turnquist, 2010) and medical centres (Dessouky et al., 2013; Jabbarzadeh et al., 2014; Jia et al., 2007). Mete and Zabinsky (2010) used the minisum model on the upper level of their bi-level model to locate warehouses for medical supplies across Seattle, while the supplies are allocated to hospitals in the lower level. Ye et al. (2015) extended the minimax model by adding warehouse survival risk as a model constraint, to identify the emergency warehouses that should be opened from existing warehouses in China. Facility location models are also developed to find the optimal locations for relief distribution centres during an emergency. Balcik and Beamon (2008) identified worldwide relief distribution centres of various emergency supply items, using a stochastic maximal coverage model. To locate medical supply distribution centers across Los Angeles County, Jia et al. (2007) modified the maximal coverage model by introducing an ‘importance weighting factor’ for assigning a minimum number of facilities within a certain distance of demand points. Murli et al. (2012) addressed demand uncertainty by introducing objectives for the probability of demand satisfaction in their maximal coverage model. The minisum model was used to account for the resulting disparities in travel time and accessibility of those over 65 years old versus those under 65, in locating relief distribution facilities in Florida (Marcelin et al., 2016).

2.1.2.2 Facility Location Models for Shelters

A small subset of the literature on emergency facility location models involves evacuation shelter location. Kongsomsaksakul et al. (2005) designed their multi-objective flood shelter location model by developing a bi-level problem in which shelter locations are identified by decision-makers in the upper level, and evacuees choose shelters and routes in the lower level. Chanta and Sangsawang (2012) combined the objectives of the maximal coverage model and minisum model to assign flood shelters to the maximum number of evacuees while minimizing total travel distance. Khalilpourazari and Pasandideh (2021) introduced a penalty to address the worst-case scenario of associated costs during a tsunami evacuation in their bi-objective, capacity-constrained model. Na Ayudhya (2022) identified key temporary shelter locations in Thailand for evacuees escaping floods. Li et al. (2012) developed a stochastic model to consider unmet shelter demand and travel time under different hurricane scenarios. Since hurricane evacuation orders are usually made well in advance of the event, Apivatanagul et al. (2012) introduced a penalty cost for early evacuation while minimizing risk and travel costs. In their earthquake shelter location model for Tehran, Ghasemi et al. (2019) minimized transportation costs between demand origins and destination facilities, construction costs of the facilities, and unmet demand. Researchers have also looked at minimizing the number of shelters with the aim of reducing costs (Hu et al., 2014; Xu et al., 2018). The challenges of evacuation decision-making under uncertainties of demand and travel costs are addressed using a minimax model by Zhang et al. (2021).

Table 2-1 provides a summary of this review of emergency facility location models, organized primarily by problem formulation, and highlighting key differences in study objectives, scopes, and purposes.

Table 2-1: Facility Location Models for Emergency Facilities

Authors, Year	*Problem Formulation*	*Model Formulation*	*Objective*	*Facility Type*
(Hakimi, 1964)	Minisum, Minimax	Deterministic	Single objective	Police station/hospital
(Toregas et al., 1971)	Set coverage	Deterministic	Single objective	Fire station
(Church and ReVelle, 1974)	Maximal coverage	Deterministic	Single objective	Fire station/ ambulance dispatching stations
(Hale and Moberg, 2005)	Set coverage	Deterministic	Single objective	Emergency relief
(Ye et al., 2015)	Minimax	Deterministic	Single objective	Warehouse
(Abounacer et al., 2014)	Minisum, Set coverage	-	Multi-objective	Relief distribution
(Balcik and Beamon, 2008)	Maximal coverage	Stochastic	Single objective	Relief distribution centres during an earthquake
(Das and Hanaoka, 2013)	Minisum	Stochastic	Multi-objective, Multi/bi-level	Relief distribution centres for earthquake victims
(Barzinpour and Esmaeili, 2014)	Minisum, Maximal coverage	-	Multi-objective	Relief distribution centres for earthquake victims
(Jia et al., 2007)	Maximal coverage	Deterministic	Single objective	Medical supply and distribution centres during an epidemic
(Dessouky et al., 2013)	Minisum	Deterministic	Single objective	Medical supply and distribution during an Anthrax attack
(Murali et al., 2012)	Maximal Coverage	Deterministic	Single objective	Medical supply and distribution during an Anthrax attack
(Berger et al., 2007)	Minisum	-	Multi-objective	Medical supply
(Marcelin et al., 2016)	Minisum	-	Single objective	Hurricane relief distribution

Authors, Year	*Problem Formulation*	*Model Formulation*	*Objective*	*Facility Type*
(Rawls and Turnquist, 2010)	Minisum	Stochastic	Multi-objective, Multi/bi-level	Relief warehouse for hurricane victims
(Görmez et al., 2011)	Minisum	-	Multi-objective	Warehouse for earthquake
(Mete and Zabinsky, 2010)	Minisum	Stochastic	Multi/bi-level	Warehouse for medical supplies during an earthquake
(Sheu and Pan, 2014)	Minisum	-	Multi-objective, Multi/bi-level	Typhoon shelter, medical centre, and relief distribution
(Chen et al., 2013)	Minisum	-	Multi-objective	Shelter
(Kongsomsaksakul et al., 2005)	Minisum	Deterministic	Multi/bi-level	Flood shelter
(Chanta and Sangsawang, 2012)	Minisum	Deterministic	Multi-objective, Multi/bi-level	Flood shelter
(Khalilpourazari and Pasandideh, 2021)	Minisum, Maximal coverage	Stochastic	Multi-objective	Tsunami shelter
(Na Ayudhya, 2021)	Minimax	Deterministic	Single objective	Flood shelter
(Li et al., 2012)	Minisum	Stochastic	Multi-objective, Multi/bi-level	Hurricane shelter
(Ghasemi et al., 2019)	Minisum	Stochastic	Multi-objective	Earthquake shelter and medical centre
(Xu et al., 2018)	Minisum	-	Multi-objective	Earthquake shelter
(Hu et al., 2014)	Minisum, Set coverage	-	Multi-objective	Earthquake shelter
(Salman and Yücel, 2015)	Maximal coverage	Stochastic	Single objective	Earthquake shelter
(Alçada-Almeida et al., 2009)	Minisum	-	Multi-objective	Shelter for residential fire
(Shahparvari et al., 2016b)	Maximal coverage	Deterministic	Multi-objective	Wildfire shelter
(Zhang et al., 2021)	Minimax	-	Single objective	Emergency response
(Demange et al., 2020)	Minimax	Stochastic	Single objective	Wildfire shelter

Table 2-1 shows that most emergency facility location studies have focused on disasters like floods and earthquakes. Very few studies (only two identified in the table) focus on shelters for wildfire evacuations. Demange et al. (2020) proposed a minimax shelter location model wildfire evacuation with the objective of considering the uncertainty of fire outbreaks. They considered different scenarios based on the location of fire outbreak, within a theoretical test network. Shahparvari et al. (2016b) explored long-distance wildfire evacuation planning to support emergency management agencies in Australia in making decisions like shelter and route selection. The existing literature on wildfire-specific facility location is primarily scenario-based, for specific wildfire scenarios affecting a specific community.

2.1.2.3 Transportation Network in Facility Location Models

Considering the transportation network is critical when developing facility location models. To this end, in some studies, facility location has also been combined with evacuation routing. Ukkusuri and Yushimito (2008) developed a stochastic facility location model for prepositioning emergency relief with budget constraints that address the failure uncertainty of both links and nodes during natural disasters. In addition to transportation costs, they used route reliability as an input to determine facility locations and preferable routes to these facilities. Alçada-Almeida et al. (2009) developed a multi-objective model that considers transportation cost, route reliability as well as facility survival probability to locate capacitated shelters during residential fires in neighborhoods. They divided the study area into residential zones to assign primary shelters and identify evacuation paths for each zone. Furthermore, they identified secondary shelters and evacuation paths as a backup should the primary shelter and path become unusable during the fire. They assumed each path’s reliability is independent of another. But for large-scale disasters like wildfires, routes within close proximity may be inaccessible. This idea was explored by Salman and Yücel (2015), who applied the tabu search algorithm on a stochastic maximal location model assuming that when a link fails during a disaster, all weaker links within a certain vicinity will also fail. Li et al. (2012) formulated a bi-level problem, applying an evacuation traffic assignment model for the evacuating traffic (lower level problem) after locating shelters in the upper level problem by minimizing unmet demand. Shahparvari et al. (2015) considered access to the disrupted road network while routing wildfire evacuees to the optimally located shelters.

2.1.3 Transportation Network Vulnerability

Transportation network vulnerability has been defined in many ways in the literature, with one heavily-cited definition being: "Vulnerability in the road transportation system is a susceptibility to incidents that can result in considerable reductions in road network serviceability" (Berdica, 2002, p. 119). Holmgren and Molin (2006) defined vulnerability as: "… the collection of properties of an infrastructure system that may weaken or limit its ability to maintain its intended function, or provide its intended services, when exposed to threats and hazards that originate both within and outside of the boundaries of the system." (Holmgren and Molin, 2006, p. 243). In this thesis, network vulnerability is defined as the impact of road segment degradation or disruption on network performance (measured by bottleneck capacity between OD pairs.). Identifying vulnerable elements of the network can help in congestion mitigation, maintenance prioritization, and disaster management (Jenelius et al., 2006; Taylor, 2017). This can be carried out for the network pre-disaster, as well as its performance under deterioration and disruption (Erath et al., 2009). Taylor (2017) categorized transportation network vulnerability analysis into four types: i) risk-based, ii) topology-based, iii) serviceability-based, and iv) accessibility-based. *Risk-based analysis* focuses on structural soundness throughout the network, *topology-based analysis* focuses on the arrangement and connectivity of nodes and links in the network, *serviceability-based* *methods* focus on operational performance of the network (e.g., travel cost, capacity), and *accessibility-based methods* measure how well-connected the network is after a disastrous event in serving travel demand. Mattsson and Jenelius (2015) broadly classified transportation network vulnerability into two categories: *topological vulnerability* and *system-based vulnerability*, which are further discussed.

2.1.3.1 Topological Vulnerability

In studies of the topological vulnerability of a road network, Alpha, Beta, and Gamma indices are among the earliest developed measures of network connectivity (Ducruet and Rodrigue, 2017; Haggett and Chorley, 1969; Kansky, 1963; Scott et al., 2006; Sun et al., 2018). These measures evaluate the connectivity of the network by counting and comparing the number of nodes and links. Higher values of these indices indicate that nodes are better connected with each other. Other widely used measures of network connectivity are the Average Degree and Degree Centrality of nodes (Ducruet and Rodrigue, 2017; Holme et al., 2002). These measures determine the average number of links connected to a node and the total number of links connected to each node, respectively.

Topological measures also consider link lengths. For example, a measurement of network density may include the length of links per unit area (Berdica and Mattsson, 2007; Ducruet and Rodrigue, 2017). The characteristic path length measures a network's average shortest path length among all OD pairs (Latora and Marchiori, 2001). A node's Shimbel Index (also known as nodal accessibility) measures the average shortest distance between that node and all others (Ducruet and Rodrigue, 2017). Global Efficiency and Straightness Centrality compare the shortest network distance and the Euclidean distances between two nodes, respectively (Latora and Marchiori, 2001; Vragović et al., 2005). Centrality measures include Closeness Centrality and Betweenness-

Centrality. The Closeness Centrality of a node is measured by taking the inverse of the average shortest distance between the node and all other nodes. Betweenness Centrality calculates how many OD shortest paths pass through a node (node betweenness) or a link (link betweenness) (Ducruet and Rodrigue, 2017; Freeman, 1978, 1977).

The above topology-based measures only consider the spatial layout of nodes and links; they do not consider operational characteristics of the transportation network – for example, travel demand and serviceability (travel time, travel cost, capacity, etc.). The classic Hansen Integral Accessibility Index uses traffic demand and travel costs in measuring node accessibility (Hansen, 1959). Sarlas et al. (2020) proposed Betweenness-Accessibility, which considers travel demand between network nodes as weights on the betweenness measurement.

2.1.3.2 System-based Vulnerability

The purpose of system-based vulnerability analyses is to evaluate how the degradation or disruption of network elements impacts travel costs, travel times, and other operational characteristics of a transportation network. Link volume-to-capacity (V/C) ratios have been used widely, for over half a century, to measure changes in travel time or cost due to disruptions requiring reassignment of traffic volumes to other parts of the network (Transportation Research Board, 2016). Scott et al. (2006) proposed a system-based vulnerability measure called the Network Robustness Index (NRI). Travel demands and congestion effects on all links along travel paths are considered in measuring the total travel cost for the "base case" (all links operating at normal capacity) and the disrupted case (link closures, or 100% reduction of link capacity). NRI represents the difference in total travel cost between the disrupted and base scenario. However, NRI does not address the issue of the "isolating link," or the only connection between two OD pairs. Disrupting this link creates two subnetworks, and makes travel infeasible between affected

OD pairs. Various measures have been proposed to handle the isolating link problem. Instead of removing the link entirely, Sullivan et al. (2010) opted to reduce link capacity to various levels to calculate Network Trip Robustness (NTR). Other researchers took a different approach and provided two separate measures — one for cut-links (defined as a link removal disconnecting a node from the network) and the other for links with alternative routes (i.e., disruption of such link will cause a detour to reach the destination) — and combined them to calculate importance and exposure to failure (Jenelius et al., 2006; Jenelius and Mattsson, 2015, 2012). Cut-link importance is measured by counting the number of unsatisfied trips resulting from the removal of the cut-link. When alternate routes are available, link importance was quantified by measuring the additional travel time (using alternate routes) and/or wait time due to disruption over a certain period. Authors simulated both single link disruption (Jenelius et al., 2006) and removal of sets of links within predefined cells (Jenelius and Mattsson, 2015, 2012). However, the resulting link and cell importance measures ignore link capacity and consider only static demand (Jenelius et al., 2006; Jenelius and Mattsson, 2012). Their models assumed that all users would take the available shortest path instead of utilizing other paths to the destination.

Most studies measure network performance by travel times along shortest paths (Jenelius and Mattsson, 2015; Mahajan and Kim, 2020; Sullivan et al., 2010). Other measures such as community exit capacity and bottleneck capacity can also be used to measure network performance (Zhang and Alipour, 2020). Staes et al. (2021) used data collected from radar detectors to identify bottleneck locations and queue formation, to in turn assess evacuation flow characteristics in Florida. The min-cut max-flow (MCMF) theorem can be used to find the bottleneck capacity (or maximum allowable flow) and location, for an OD pair, over all possible routes within a network (Ford and Fulkerson, 1956). This theorem has been used to determine the capacity (and routes contributing to this limiting capacity) of en-route air sectors (Krozel et al., 2007; Namuduri and Soomro, 2017). This theorem has been applied to ground transportation networks to identify the bottleneck capacities/maximum flow between OD pairs across a network (Dong and Zhang, 2011; Kim et al., 2008; Qu et al., 2019; Yang et al., 2008), where infrastructure improvements can be made to reduce congestion (Abdullah and Kien Hua, 2017), and to estimate the earliest clearance times of, and arrival to, communities (Baumann and Skutella, 2009; Church and Cova, 2000; Zheng and Chiu, 2011). This theorem has been applied for evacuation planning: Yang et al. (2008) applied MCMF to assign evacuation flow by identifying bottleneck locations and their capacities on a network. Kim et al. (2008) applied MCMF in their study of evacuation due to power plant failure, proposing contraflow at the bottleneck section to increase egress capacity. These studies found that bottlenecks are usually located at or near egress points.

During a natural disaster, it is often the case that multiple links adjacent to each other, within an impacted area, are disrupted (Günneç and Salman, 2011). A grid-based approach, which assesses link segments within a grid together, can mirror an area-wide disruption following such disasters by disrupting multiple links in close proximity (Jenelius and Mattsson, 2012). Also, modelling the disruption of individual links one-by-one across a large network can be computationally expensive with a naïve network scanning method – computation times will be multiplied by the average number of links contained within cells. The cell size of a grid is chosen based on study scope, network scale, and computational capabilities. It is finer for studies over smaller geographic scales, with denser transportation networks (e.g., 20x20 m^2 for a small urban community (Helderop and Grubesic, 2019a, 2019b)) or coarser for larger regions (e.g., 25x25 km^2 for the Swedish road network (Jenelius and Mattsson, 2012)). A smaller cell size will emphasize road network characteristics and yield similar results to a single link failure analysis, while a larger cell size will shift focus to disruption characteristics (Jenelius and Mattsson, 2015, 2012). Jenelius and Mattsson (2015) quantified the importance of links and nodes when inaccessible for 12 hrs due to a disaster. Helderop and Grubesic (2019b) assigned different impedance values for various landcover surrounding roadways within grid cells, to measure road criticality in a flooding scenario. In another study, they used 20m×20m grid cells to identify alternate paths when the traditional road network is submerged due to flooding (Helderop and Grubesic, 2019a).

2.2 STUDY CONTEXT

This section introduces the background for this thesis, and application context for the concepts developed within its academic contributions.

2.2.1 Geographic Context and Wildfire Evacuations in Western Canada

The westernmost Canadian provinces of Alberta and British Columbia are prone to wildfires every year. They have experienced a number of devastating fires that breached wildland-urban interfaces (WUIs), causing damage and destruction to human settlements and infrastructure, and resulting in evacuations of entire communities and significant populations.

Alberta, Canada covers 660,000 km^2, with about 75% of its population of over four million concentrated in the major urban economic regions of Edmonton (the provincial capital) and Calgary (Statistics Canada, 2019). Asides from the Highway 2 corridor between Edmonton and Calgary, Alberta is generally sparsely populated. The largest urbanized areas in northern Alberta are Fort McMurray in the east and Grand Prairie in the west, with permanent populations of about 60-70,000 as of 2016.

Alberta had the second-highest 10-year average of wildfire occurrences (Natural Resources Canada, 2021) and total wildfire evacuations among all provinces and territories between 1980 and 2018 (Beverly and Bothwell, 2011; Natural Resources Canada, 2020a). On average, more than 1500 wildfires occur in Alberta each year and some of them are likely to encroach on WUIs, prompting evacuation (Alberta Wildfire, 2020). Boreal forests, which are more susceptible to wildfires compared with the forests of the Pacific Northwest (Natural Resources Canada, 2020b), cover nearly the entire northern half and 57% of the province in total (Alberta Wilderness Association, 2019; Tymstra et al., 2007). With an increasing number of extreme fire-weather days and decreasing soil moisture, an increasing trend in both frequency and intensity of wildfires is expected (Stralberg et al., 2018). Evacuating communities with limited road access/alternatives have faced several challenges, including but not limited to destination uncertainty, travelling for long periods of time before reaching safety, and requiring airlift due to entrapment (McGee, 2018, 2019; McGee et al., 2021).

Some of the largest wildfires experienced in Alberta, in total hectares, include the 1982 Keane, 2002 House River, 2011 Richardson, 2016 Horse River, 2019 McMillan, and 2019 Chuckegg Creek Fires (Alberta Wildfire, 2020). The Horse River Fire, also known as the Fort McMurray wildfire, was the costliest natural disaster in Canadian history (Insurance Bureau of Canada, 2016) and resulted in nearly 90,000 people evacuating over five days from the northeastern Wood Buffalo region of Alberta (Woo et al., 2017). The Chuckegg Creek Fire resulted in the evacuation of High Level and surrounding communities. Surrounded by boreal forest, High Level is the northernmost town in Alberta, experiencing multiple wildfires each year and holding the record for most Class E[1] wildfires in the province since 2006 (Alberta Wildfire, 2020). The town of Slave Lake was evacuated with the surrounding municipal district in 2011.

In a post-evacuation survey, McGee (2018) found that more than half of the evacuees from the Fort McMurray wildfire were not prepared to evacuate and experienced travel difficulties (traffic congestion, running out of fuel, etc.). Other studies report that only 25% of people had enough food and water during this evacuation, with many running out of food and fuel (Mamuji and Rozdilsky, 2019; McGee, 2019, 2018). Some evacuees were not certain of their destination, and many visited multiple communities in search of available shelter (McGee, 2019). In 2021, evacuees from the Logan Lake fire in British Columbia were instructed to travel almost 400 km to Chilliwack as nearer communities did not have the means to accommodate them (Judd, 2021). McGee (2021) identified destination uncertainty as one of the key issues residents in Alberta First Nations communities faced in evacuations.

2.2.2 Evacuation Planning in Alberta

Mitigation, preparedness, response and recovery are the four phases for disaster management (Boonmee et al., 2017; Coppola, 2011). A disaster management plan accounts for the needs in all phases. Alberta Emergency Management Agency (AEMA) acts as the coordinating organization and is responsible for preparing disaster management plans within Alberta. Following the Alberta Emergency Management Act, AEMA developed a framework that identifies stakeholders for disaster management (Alberta Emergency Management Agency, 2022).

According to the Act, the primary responsibility for planning and controlling the initial response to disasters like wildfires falls on local authorities (e.g., municipal council, settlement council for

[1] Wildfire classification defined for a final burned area exceeding 200 ha.

Metis settlement, etc.) (Government of Alberta, 2020). Local authorities are responsible for preparing an emergency plan that includes a hazard identification and risk assessment (HIRA) and having it reviewed by AEMA annually. Emergency plans for wildfire must include an inventory of firefighting resources, detailed evacuation protocol and list of critical infrastructures. The local authority is also expected to form a local/municipal emergency management agency and emergency advisory committee. As part of their disaster management plan, the local authority is also recommended to develop mutual aid agreements and establish partnerships with other communities (Alberta Emergency Management Agency, 2022).

During a wildfire, the local emergency management agency will assess and monitor the situation and its risks to their communities. Residents may be notified to prepare for evacuation should the situation severity increase. Upon the recommendation of fire management agency (e.g., Alberta Wildfire), the director of the local emergency management agency decides if the community is at high risk (Beverly and Bothwell, 2011; Government of Alberta, 2018). If the wildfire threat to a community becomes imminent (based on fire intensity, location, and spread rate), local elected officials/groups (i.e., councils and mayors of municipalities, First Nations chiefs) are authorized to declare a State of Local Emergency (SOLE) and issue an evacuation order (Alberta Emergency Management Agency, 2022; Government of Alberta, 2020). The Emergency Operations Centre (EOC) becomes active and the evacuation process is initiated according to the emergency plan; information and resources are coordinated among relevant authorities (KPMG LLP, 2012). Decisions like the area to be evacuated, the number of evacuees, available transportation resources, evacuation routes and destinations, and the weather forecast are considered and communicated among emergency response groups such as police, and paramedics.

Local authorities can also reach out to provincial authorities for support if and when needed (Alberta Emergency Management Agency, 2022; Beverly and Bothwell, 2011). Representatives from AEMA coordinate between the local/municipal EOC and the provincial operation centre (POC). Emergency Social Services (ESS), a provincial program led by AEMA to support local authorities with evacuation process, will also be involved should local authorities seek their support. ESS coordinates between communities and sets up reception centres where evacuees can register for, and receive, emergency services. Other local and provincial partners, like the Royal Canadian Mounted Police (RCMP), Alberta Health Services (AHS), Canadian Red Cross (CRC), local fire departments, Alberta Transportation, and other non-governmental organizations, are involved. For example, AHS supports the evacuation of healthcare centres, Alberta Transportation manages traffic on provincial roadway facilities by enforcing road closures or contraflow, and the RCMP provides support to local police in communicating evacuation orders and managing evacuation traffic flow (Government of Alberta, 2018). Local authorities lift the evacuation order once the threat has passed and initiate recovery with assistance from the Government of Alberta's Municipal Wildfire Assistance Program and Disaster Recovery Program (Alberta Emergency Management Agency, 2015; Government of Alberta, 2022).

2.3 SUMMARY AND RESEARCH GAPS

Wildfires present a unique challenge to developing evacuation plans, given uncertainties regarding where they will occur and how they will propagate. Due to these uncertainties, most of the abovementioned studies investigate smaller jurisdictions (neighbourhoods, communities, regions) using a scenario-based approach (i.e., a wildfire occurs and encroaches on a community in a specific manner). However, evacuation management is usually a joint effort between communities and the larger jurisdictions (regions and provinces, for example) in which they are located, with larger jurisdictions having more resources, emergency management authority, and oversight to help manage an evacuation. As many critical decisions must be made quickly in a short- or no-notice evacuation, it is critical that all jurisdictions have tools to support their evacuation planning efforts. Large jurisdictions that oversee a large geography and many population centres need tools to be prepared across the entire jurisdiction, or at least areas within the jurisdiction at risk. This is highly difficult when preparing for highly uncertain events like wildfires and wildfire-caused evacuations. However, with climate change increasing the frequency and intensity of wildfires (Bush and Lemmen, 2019; Hanes et al., 2019; Jain et al., 2017), it is becoming ever more important to prepare. As mentioned above, the existing literature does not focus on pre-disaster, short- and no-notice evacuation planning for large jurisdictions. This thesis addresses this gap, specifically towards a framework to identify potential wildfire evacuation host communities and critical road facilities (i.e., bottleneck locations, specifically, rather than other measures) across a large jurisdiction where wildfire occurrence and spread is difficult to predict.

CHAPTER 3. DATA DESCRIPTION AND NETWORK MODEL REPRESENTATION

This chapter introduces the data sources used to build a model of the Alberta highway network, communities, and wildfire exposure.

3.1 DATA DESCRIPTION

Data for the provincial highway network, community boundaries and populations, and 2019 wildfire exposure were gathered in shapefile format for use in this thesis research.

3.1.1 Provincial Highway

Alberta's provincial highway network is classified into four levels based on annual average daily traffic (AADT), and expected trip lengths, trip purposes, vehicle composition (i.e., % commercial trucks), and others (Stantec Consulting Limited, 2007).

i. *Level 1 or National Highway System (NHS):* Level 1 highways are the core facilities of the National Highway System, the highway network through major population centers across Canada, facilitating inter-provincial and international travel. Level 1 highways usually connect with other Level 1 or Level 2 highways, and are multilane divided highways constituting 18.4% of the provincial highway network.

ii. *Level 2 or Arterials:* Level 2 highways can be accessed via Level 1 or Level 3 highways and accommodate intra-provincial long-distance travel to connect communities with populations of 5,000 or more. These undivided highways account for 27.4% of the provincial highway network.

iii. *Level 3 or Collectors:* Level 3 highways are undivided two-lane highways that can be accessed via either Level 2 or Level 4 highways, and serve inter-regional and relatively shorter distance trips. 39.6% of highways fall under this category.

iv. *Level 4 or Locals:* Level 4 highways serve intra-regional trips such as commute trips within municipalities and constitute 13.3% of the network.

The raw roadway network shapefile is obtained from Alberta Transportation and contains roadway geospatial data of local road segments as well as the highway network (Figure 3.1.a).

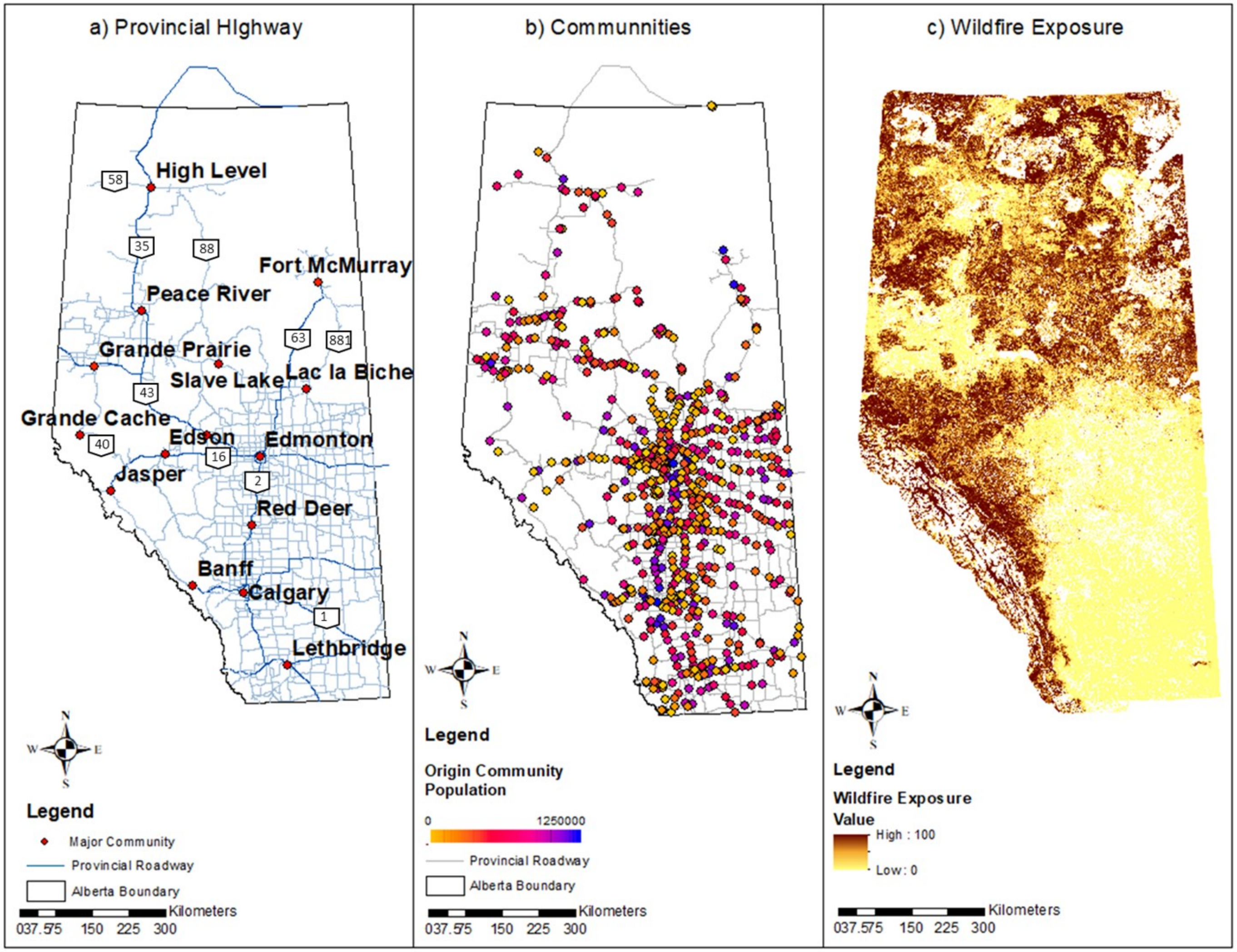

Figure 3.1: Data: a) Alberta provincial road network, b) Communities (CSD and DPL) in Alberta (Statistics Canada, 2019), and c) Landscape fire exposure map for 2019 (Beverly et al., 2021)

The data features attributes (i.e., route number, number of lanes, posted speed limit, presence of median) of each road segment. Additional attributes such as highway level, travel time for each link (calculated based on the posted speed limit and segment length), and capacity are available. Due to the lack of availability of infrastructure geometry details such as lane widths and shoulder widths, basic facility features such as the number of lanes, presence of a median, and highway level is used to calculate base capacities as per the Highway Capacity Manual method (Transportation Research Board, 2016). During the data cleaning process, various geoprocessing operations (e.g., merge, dissolve, intersect) were performed in ArcMap to obtain the road network, in which each polyline feature represents a road segment between two nodes. The resulting segment lengths are identified in kilometres (km) while roadway coordinates are generated at each endpoint using the 'Calculate Geometry' function of ArcMap. All polylines developed in this process are categorized as Category 1 links (discussed in Section 3.2.2) and the intersections between them are categorized as Category 1 nodes in the network representation (discussed in Section 3.2.1).

3.1.2 Communities

Data on populations of the census subdivisions and municipalities of Alberta are sourced from Statistics Canada and Alberta's Open Government data. As of the writing of this dissertation, the most up-to-date population data is from the 2016 Census (Statistics Canada, 2019). The data resolutions used are by census division (CD), census subdivision (CSD), aggregated dissemination area (ADA), and dissemination area (DA). The data also contains designated places (DPL) that include small rural communities (i.e., hamlets, Métis settlements, unincorporated places, dissolved municipalities) that do not meet the criteria to be listed as municipalities and sub-municipal areas (Statistics Canada, 2017a). Alberta has 19 CDs, 425 CSDs, 527 ADAs, 5803 DAs, and 304 DPLs in the 2016 Census (Statistics Canada, 2017b). After exploring each of the geographic subdivisions, populations at the census subdivision (CSD) level were chosen for use in this research. The primary justification for selecting this level of aggregation is that one CSD represents one municipality or equivalent area defined by its respective province/territory. The CSDs are used as the communities for which critical road segments during evacuation are identified (Section 4.3), and as origin (evacuating) communities towards identifying host community locations (Section 5.2.1). However, for the multi-objective host community identification problem (Section 5.3.2), the community dataset is enriched by also considering DPLs that include small sub-municipalities and other small places of importance. Therefore, the final dataset for analysis in Section 5.3.2 consists of a total of 729 communities including reserves and Métis settlements (Figure 3.1.b). Reserves[2] are lands set aside by the federal government for First Nation people, and Métis settlements are lands transferred to the Métis people of Alberta.

The shapefiles of the CSD and DPL boundaries are obtained from Statistics Canada, while the population centre location and census data for each community are obtained using the 2016 *GeoSuite* (Statistics Canada, 2017c), a Statistics Canada tool. Statistics Canada provides both web-based and downloadable versions of *GeoSuite* 2016 (Statistics Canada, 2017d). Using *GeoSuite*, census data for Alberta at the CSD and DPL levels are collected in "*.csv" format and converted into point features using ArcMap 10.6.1. Each point represents an Alberta community (425 CSD and 304 DPL), and contains community name, population count for 2016 and 2011, total and usual dwelling, area, and representative centroid coordinates.

[2] The Indian Act (https://laws-lois.justice.gc.ca/eng/acts/i-5/), passed by the federal government in 1876, is the primary law that the Canadian government uses to this day in all matters pertaining to Indian status, First Nations governments, and reserve lands. Please visit the following to learn more about this problematic and complex legislation: https://indigenousfoundations.arts.ubc.ca/the_indian_act/. Another recommended (and exceptional) reference is (Vowel, 2016); for information about reserves we refer specifically to pgs. 32-33 and Ch 9 (pgs. 260-267).

3.1.3 Wildfire

Forest fires pose serious threats to communities in and around the forest protection area (an area designated by the Forest and Prairie Protection Act to protect Alberta forests from fire (Government of Alberta, 2022)). Grass fires display fundamentally different characteristics than forest fires. Grass fires have lower intensity, transmit across a smaller area and are usually contained more quickly compared to forest fires (Collins et al., 2018). This thesis focuses on evacuation planning due to forest fires, and grass fires in the Prairie region in Western Canada are not considered in this study. A landscape fire exposure raster map for 2019 was obtained from Beverly et.al (2021). The authors used Alberta Wildfire Management Branch's thematic land cover raster with $100x100m^2$ resolution to identify the non-fuel and flammable fuel coverage of Alberta (Figure 3.1.c). They classified fuel as hazardous if it is transmissible for 500m, and determined exposure to hazardous fuel for each raster cell by performing neighbourhood analysis with the Focal Statistics tool in ArcGIS. Note that landscape fire exposure does not indicate the likelihood of wildfire breaches into a community; rather, it indicates whether there is a potential for fire transmission to the community (Beverly et al., 2021).

3.2 NETWORK BUILDING IN GIS

Polylines, points, and polygons are used in ArcMap to represent the highways, community centroids, and wildfire perimeters.

3.2.1 Nodes

In the GIS model of the Alberta highway network and communities, nodes are categorized into three types.

1. *Link End Nodes, EN (Category 1):* Highway intersections, beginnings, and ends are represented using link end nodes. These nodes are obtained by performing the ‘intersect’ geoprocessing operation followed by the ‘new network dataset’ operation on the highway shapefile in ArcMap.

2. *Community Centroid Nodes, C (Category 2):* The community centroid node represents the geographic center of each census subdivision (CSD) and designated place (DPL). Node coordinates are obtained from *GeoSuite* 2016.

3. *Community Connecting Nodes, CCN (Category 3):* A community centroid node is connected to the nearest road using the community connecting node. Located at one end of the community connector, this node has a community centroid at the other end. These nodes are obtained by drawing centroid connector links (CCL) from communities to their nearest road segment link (L) and then intersecting the highways and centroid connectors. When a community is located directly on a highway segment, the community centroid and the centroid connecting nodes are represented by the same point.

3.2.2 Links

Links are categorized into two types.

1. *Road Segment Link, L (Category 1):* The highway segment link is a representation of the highway network. Each polyline feature of this category connects a) two intersection nodes, b) two community centroid connector nodes, or c) one intersection node and one community centroid connector node.

2. *Centroid Connector Link, CCL (Category 2):* Centroid connector links are “dummy” links that connect community centroids with the nearest network link representing a road

segment. It is assumed that the entire population of the community represented by the community centroid node accesses the nearest link through its centroid connector links.

3.2.3 Area Grid

Natural disasters like wildfires and earthquakes are likely to disrupt multiple links in close proximity (Günneç and Salman, 2011). A grid-based approach, whereby link segments within a grid are grouped together, can represent area-wide disruptions that arise following such disasters (Jenelius and Mattsson, 2012). The cell size of a grid is chosen based on study scope, network scale, and computational capabilities (see section 2.1.3.2 for the review). A study of wildfire evacuations focuses on areas within a 10 km radius of target locations (and thus, 20 km diameter) (Beverly and Bothwell, 2011). Considering the size of the study area, a grid of 20x20 km^2 square cells is chosen, such that 70 rows and 44 columns are overlaid across the province. Alberta's highway network appears in 920 of the 3,080 resulting cells. Furthermore, links (both L and CCL) are intersected at cell boundaries, such that no link occupies more than one cell.

3.3 NETWORK GRAPH IN MATLAB

The GIS network (polyline, point, and polygon shapefiles) is transferred to MATLAB and directed graphs (G_dist and G_cap) with 'EdgeTable' and 'NodeTable' are built (Figure 3.2). Two separate edges are created between a node pair to represent two-way highway or road segments.

a) EdgeTable

EdgeTable

13203x6 table

	1 EndNodes		2 Weight	3 Time	4 Capacity	5 Type	6 ID
1	3395	3396	0.0367	0.0220	2300	1	1
2	3396	3395	0.0367	0.0220	2300	1	2
3	3396	3397	0.1351	0.0810	4600	1	3
4	3397	3396	0.1351	0.0810	4600	1	4
5	3397	3442	3.9636	2.3782	2300	1	5
6	3442	3397	3.9636	2.3782	2300	1	6
7	4905	4904	0.6339	0.7606	4500	1	7
8	4904	4905	0.6339	0.7606	4500	1	8
9	3706	3722	0.5675	0.3405	2300	1	9
10	3722	3706	0.5675	0.3405	2300	1	10

b) NodeTable

NodeTable

5988x4 table

	1 X1	2 Y1	3 Type	4 ID
1	-3.1761e+05	6.1324e+06	1	1
2	-3.1582e+05	6.1572e+06	1	2
3	-3.1344e+05	6.1901e+06	1	3
4	-3.1264e+05	6.1321e+06	1	4
5	-3.1013e+05	6.2358e+06	1	5
6	-3.0911e+05	6.2501e+06	1	6
7	-3.0860e+05	6.1383e+06	1	7
8	-3.0288e+05	6.1314e+06	1	8
9	-3.0243e+05	6.1379e+06	1	9
10	-3.0210e+05	6.1958e+06	1	10

Figure 3.2: Snippets of a) ‘EdgeTable’ and b) ‘NodeTable’ in MATLAB

‘EdgeTable’ defines edges by their end nodes and edge weights. Attributes such as edge length/travel time and capacity (calculated using the Highway Capacity Manual (Transportation Research Board, 2016)) are used as weights for determining the shortest path and maximum flow between Origin-Destination (OD) pairs, respectively. ‘NodeTable’ contains the node coordinates as well as node type, and the shapefiles of nodes and links are used as inputs for ‘NodeTable’ and ‘EdgeTable’ respectively.

CHAPTER 4. CAPACITY IMPACT DUE TO AREA-WIDE DISRUPTION

This chapter presents a quick scanning process for measuring the importance of transportation network facilities, in terms of their contribution to egress movement capacity for an evacuating community.

4.1 BACKGROUND

Whether for long-notice or short/no-notice evacuations, pre-disaster planning is important for agencies that must allocate limited emergency planning resources across several communities and provide evacuation plans (Kalafatas and Peeta, 2006). Wildfires lead to short- or no-notice evacuations (i.e., evacuations that must occur within minutes to hours of notice) as the occurrence, intensity, progression, and propagation rates of wildfires vary depending on a range of factors like fuel accumulation, wind speed, wind direction, and humidity (Demange et al., 2020). Due to this immediacy and uncertainty, wildfire evacuation studies have focused on simulating movement out of individual communities and/or small geographic regions (Cova and Johnson, 2002; Yerushalmi et al., 2021). However, for agencies covering large regions with many urbanized areas (different sizes, etc.) potentially under wildfire threat, it is difficult, if not infeasible, to conduct these detailed studies for each individual community. Thus, simple tools to measure and compare risk levels are necessary for allocating more resources toward detailed assessments of communities at higher risk versus those at lower (to no) risk. This method is one such tool to quickly identify capacity-critical roadway elements for communities potentially under evacuation threat. The maximum flow or bottleneck capacity between an origin (evacuating community) and destination (host community) is identified using the min-cut max-flow (MCMF) theorem (Ford and Fulkerson, 1956) and a grid-based scanning system. The grid-based approach – grouping link segments within a grid cell to quantify characteristics – allows us to capture the areawide impact of a wildfire while balancing the need for road network details against computational speed. Using this approach, the study identifies where the most capacity-critical roadway elements are located on a network for the origin evacuating community, by developing and applying metrics that reflect these roadway elements' contributions to OD bottleneck capacity.

4.2 METHODOLOGY

The importance of the contributions of network links to the bottleneck capacity between an evacuating community (origin) and its host community (destination) is assessed using the min-cut max-flow (MCMF) theorem combined with grid cell disruption. MCMF can be applied to find the maximum capacity flow (some volume per unit time, often vehicles per hour, passengers per hour, etc.) using all available routes in a network. Observing how the removal of a set of links within a grid impacts this maximum flow between an origin and destination can help in measuring the importance of these links in a community evacuation. These methods are discussed here.

4.2.1 Min-cut Max-flow

The MCMF theorem calculates the maximum flow achieved through the use of all possible routes between an OD pair (Elias et al., 1956; Ford and Fulkerson, 1956).

A cut is a set of links that, if removed, would separate the network into two sub-networks. The capacity of the cut is the sum of the removed links' individual capacities. A min-cut identifies the network bottleneck (or max flow) between two points. The min-cut may not be unique. In this study, the bottleneck capacity is used to develop performance measures for assessing network vulnerability.

In Figure 4.1.a, graph $G(N, L)$represents a road network with nodes $N\{O, 1, 2, 3, 4, 5, 6, D\}$and links $L\{a, b, c, d, e, f, g, h, i, j, k\}$. In the figure, the values in the parentheses are link capacities. Node O is the origin and D is the destination. Removing links b (with capacity of 10 units) and c (capacity 10 unit) divides the network into two, separating O and D. The cut capacity is 20 (=10+10). Similarly, $\{a\}$, $\{c, d, e, f\}$, and $\{e, f, g\}$ are other examples of cut links separating the network in two. Of all cuts, the lowest cut capacity is 15 units per unit time for cut $\{e, f, g\}$ (Figure 4.1.b). Thus, link set $\{e, f, g\}$ is the min-cut for this network with a maximum flow of 15 units per unit time (Figure 4.1.c).

Note that, regardless of the demand between an OD pair, the bottleneck capacity remains the same. Although a maximum flow of 99 units can leave O, the bottleneck capacity between O and D is 15 units per unit time such that any flow more than this capacity value will create congestion in the network starting at this bottleneck. Overall, MCMF can be used to locate which link or set of links within an area (i.e., a grid cell) sets the bottleneck capacity of an OD pair, and how this bottleneck capacity changes (reduces) when links are removed from the network.

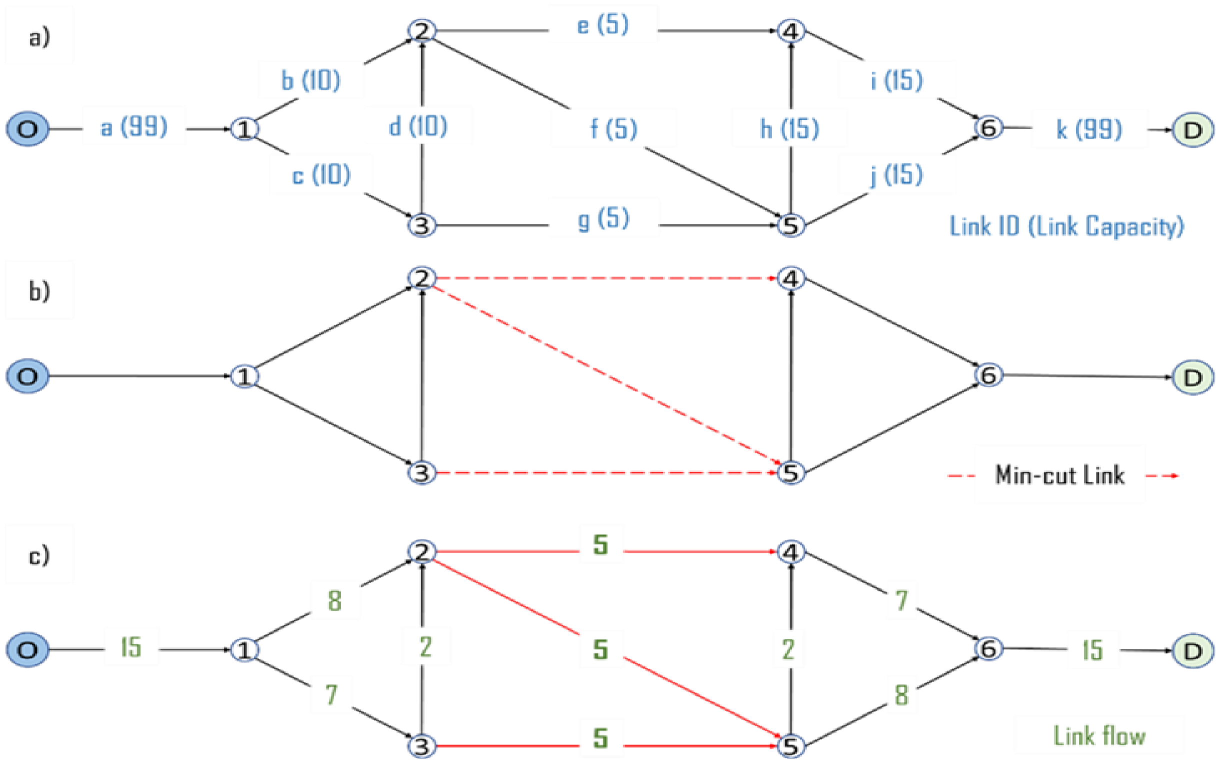

Figure 4.1: Min-cut max-flow example: a) Network, b) Min-cut between O and D, and c) Max-flow between O and D

4.2.2 Grid Disruption

As mentioned earlier, multiple links in an area may be disrupted during natural disasters that impact that area (Günneç and Salman, 2011). The impact of disrupting network elements like links, with full or partial degradation of their capabilities, can be assessed by the ensuing network performance degradation (using common metrics such as travel time increase and capacity decrease). To capture the area-wide impact of wildfire, multiple links within a certain distance are disrupted. As discussed in Section 3.2.3, this study follows previous research (Günneç and Salman, 2011; Helderop and Grubesic, 2019b, 2019a; Jenelius and Mattsson, 2015, 2012) to overlay a grid of 20x20 km^2 cells over the study network.

When a grid cell is disrupted, all links within the cell boundary are removed, leaving a residual network. Then, the base and residual network performances are compared to determine whether the removal or deterioration of the links in question degrade network performance. A residual network's degraded performance indicates that the disrupted cell was critical to the network. The measure of criticality is defined in the following section.

4.2.3 Escape Capacity Criticality and Max-flow Impact Index

This section presents metrics to quantify the contributions of network links to the bottleneck capacity between an evacuating community and the destination host community. The purpose is to identify where the facilities contributing significantly to the bottleneck capacity are located, in reference to the evacuating and destination communities.

Escape Capacity Criticality (Cr_c) measures the contribution of network elements within a grid cell c to the bottleneck capacity between an evacuating community and a destination. First, the bottleneck capacity between ODs (i, j) is determined on an existing network, F_{ij}. Disrupting grid cell c, i.e., removing all links within the cell, leaves a residual network. Next, the bottleneck capacity between i and j is recalculated for this residual network with disrupted cell c, F_{ijc}. Then, F_{ij} and F_{ijc} are compared to calculate Cr_c.

$$Cr_c = \begin{cases} \dfrac{\sum_i \sum_{j \neq i} \frac{F_{ij} - F_{ijc}}{F_{ij}}}{\sum_i \sum_{j \neq i} \theta_{ijc}}, & if \ \sum_i \sum_{j \neq i} \theta_{ijc} > 0 \\ 0 & , if \ \sum_i \sum_{j \neq i} \theta_{ijc} = 0 \end{cases}, Cr_c \in [0,1] \tag{4.1}$$

Where:

Cr_c = Escape Capacity Criticality of network facilities of grid cell c

F_{ij} = Bottleneck capacity from origin i to destination j on the existing network (before disruption)

F_{ijc} = Bottleneck capacity from i to j on the residual network (after disrupting cell c)

$$\theta_{ijc} = \begin{cases} 1 \ , if\ F_{ij} \neq F_{ijc} \\ 0 \ , otherwise \end{cases}$$

Higher Cr_c values indicate that the network facilities in c contribute more to the network bottleneck capacity of an OD pair. A Cr_c of 1 means the disruption of links within disrupted cell c will completely disconnect all OD pairs. A Cr_c of 0 means that no OD pairs are affected by c's disruption, i.e., $F_{ij} = F_{ijc}$ for all i and j.

The Cr_c measure considers all OD pairs to be of equal importance. However, because communities differ in population, potential for wildfire disruption, and economic and administrative roles, the ability to consider these differences in a metric like Cr_c may be useful. Thus, to define another metric called *Max-flow Impact Index* (MI_c), a weight w_{ij} is assigned to the bottleneck capacity reduction between each OD pair. One could use community population size, natural disaster, evacuation likelihood, or combinations of these and others to determine weights. When disruption of cell c occurs, the impact to bottleneck capacity is calculated by taking the average of the weighted change of the bottleneck capacity reciprocal across all OD pairs:

$$MI_c = \frac{\sum_i \sum_j M_{ijc}}{N} \tag{4.2}$$

Where:

MI_c = Max-flow Impact Index of cell c

$$\Delta M_{ijc} \;=\begin{cases} w_{ij}\left(\frac{1}{F_{ijc}}-\frac{1}{F_{ij}}\right), & if F_{ijc} > 0 \\ w_{ij} & ,Otherwise \end{cases}$$

w_{ij} = Weight for i, j

N = Total OD pairs = $\begin{cases} I \ * (I-1), & if\ I \ = \ J \\ I \ * J & ,if\ J \notin I \end{cases}$

4.2.4 Analysis and Illustrative Example

The Boykov-Kolmogorov algorithm (Boykov and Kolmogorov, 2004) is used to apply MCMF in MATLAB. Figure 4.2 illustrates the analysis approach.

The process starts with a cell, c, and origin i. The min-cut capacity, F_{ij}, is determined using the existing (undisrupted) network from i to predetermined destinations j. The OD demand is used as the weight (Eq. 4.2), obtained using the production-constrained gravity model $\left(w_{ij} = T_{ij} = \frac{P_i P_j d_{ij}^{-2}}{\sum_j P_j d_{ij}^{-2}}\right)$. P_i and P_j are the populations of origin and destination communities and d_{ij} is the shortest distance for the OD pairs as per the Dijkstra shortest path algorithm (Dijkstra, 1959). When only one destination is considered, the origin population is used as the weight: $w_{ij} = P_i$.

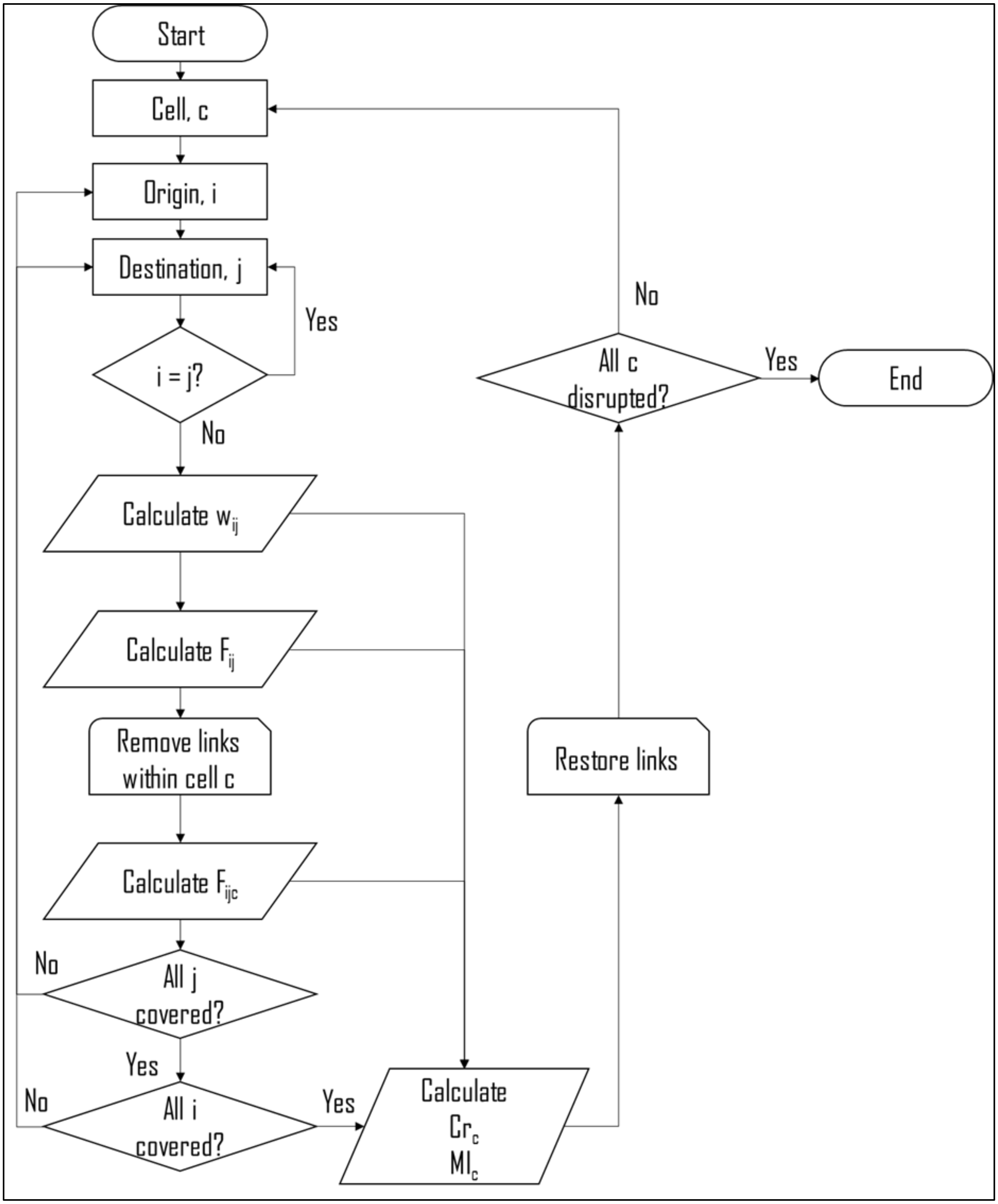

Figure 4.2: Analysis approach

Then, all links within cell c are removed to obtain the residual network and re-calculate the min-cut capacity after disruption, F_{ijc}. This process is repeated for all OD pairs, with Eqs. 4.1-4.2 used to calculate Cr_c and MI_c. The links of cell c are then restored, and the process is repeated on the next cell until all cells have been analysed.

Recall the example network (Figure 4.1.a), where the bottleneck capacity for OD was 15 units. Another community node Q has been added to the network from node 5 (Figure 4.3). The bottleneck capacity for QD is 20 units. Cells are disrupted one-by-one and Cr and MI for the elements within each disrupted cell is calculated. A Cr value of 0 indicates the cell elements are not vulnerable. As Cr increases towards 1 (upper limit), vulnerability increases (i.e., network performance or the bottleneck capacity decreases).

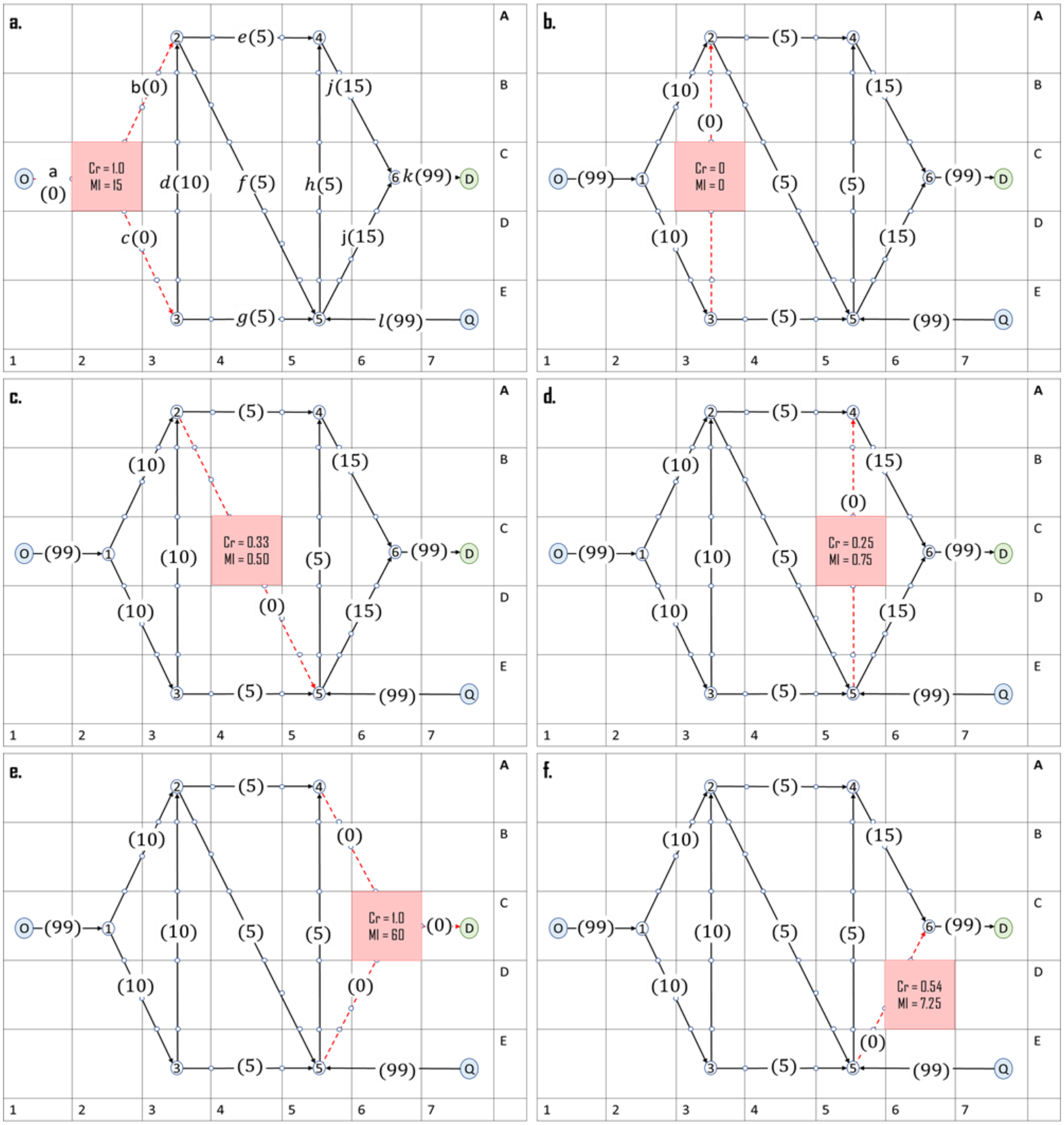

Figure 4.3: Impacts of cell disruptions: a. Cell C2, b. Cell C3, c. Cell C5, d. Cell C5, e. Cell C6, and f. Cell D6. (Values in brackets indicate link capacity)

When cell $C2$ is disrupted (Figure 4.3.a), links a, b, and c are disrupted and origin O is disconnected from destination D. Hence, demand from O to D is unsatisfied. This disruption, however, does not affect the bottleneck capacity for QD. Applying Eq. 3.1, $Cr_{C2} = 1$, which indicates complete disruption and inability to accommodate any flow. However, $Cr_{C3} = 0$ indicates that cell $C3$ has no impact on the minimum capacity flow between O and D as well as Q and D (Figure 4.3.b). Cells $C4$ (Figure 4.3.c) and $C5$ (Figure 4.3.d) reduce bottleneck capacity for OD ($F_{ODc4} = 10$) and QD ($F_{QDc4} = 15$), respectively. Note that in both scenarios the capacity of the disrupted links within the cell is the same (5 units), but due to network topology, the min-cut capacities for the residual networks are different. Thus, despite the disruption of the same number of links with the same capacity, the *Escape Capacity Criticalities* for these cells are different at 0.33 for $C4$ and 0.25 for $C5$. Network performance degrades more with the disruption of $C4$ compared with $C5$. Disruption of cells $C6$ and $D6$ impact the min-cut capacity for both OD and QD. Disruption of $C6$ will disconnect destination node D from both origin nodes (Figure 4.3.e) such that $Cr_{C6} = 1$. However, although disruption of cell $D6$ does not disconnect the origin nodes from the destination, it provides a lower bottleneck capacity for both OD and QD pairs such that $Cr_{D6} = 0.54$ (Figure 4.3.f).

Say the weights on OD and QD trips are equal to the origin populations ($w_{OD} = 30$ and $w_{QD} = 90$). Applying Eq. 3.2, the max-flow impact index for cell D6 will be $MI_{D6} = 7.25$. Similarly, MI_x for cells $x =$ $C2$, $C3$, $C4$, $C5$, and $C6$ are 15, 0, 0.50, 0.75, and 60, respectively. Note that MI_{C4} is lower than MI_{C5} despite that $Cr_{C4} > Cr_{C5}$. This implies that although cell $C5$ is not as important as $C4$ in providing higher min-cut capacity, more population is impacted by the disruption of $C5$. Similarly, although both $C2$ and $C6$ have equal Cr values, $MI_{C6} > MI_{C2}$.

4.3 CASE STUDY AND RESULTS

The province of Alberta is assessed for area-covering disruptions (Figure 4.4). Given its history of, and future outlook for, wildfires (discussed in Section 2.2.1), the aim is to determine the locations and capacities of bottlenecks on the Alberta Highway network with respect to remote and/or potentially fire-prone communities (Figure 4.4). These communities either have experienced wildfire evacuations in the past or are judged to be more likely than others to undergo evacuation in the future due to wildfire exposure. Alberta's evacuation guidelines state that a host community can accommodate evacuees that number up to 10% of the host community's population (Government of Alberta, 2018). Therefore, the nearest major economic centres, with the necessary capacity to provide evacuees with shelter, services, and supplies, are selected as host communities. It is assumed that all evacuees will travel to their nearest economic centres.

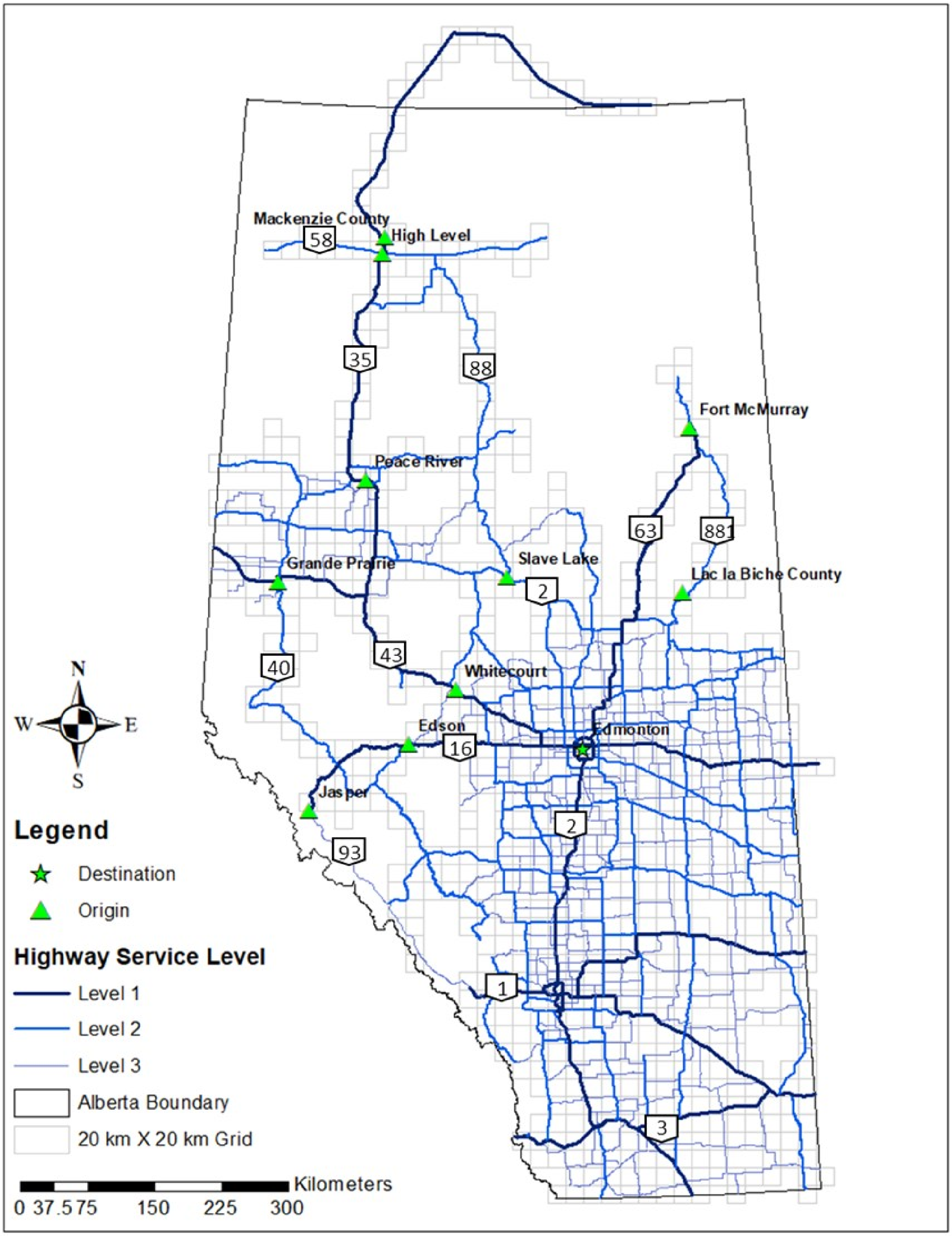

Figure 4.4: Selected origin and destination communities for bottleneck capacity analysis

As expected, the highway facilities contributing most to OD bottleneck capacity are adjacent to evacuating communities[3]. In addition, it is found that, depending on network topology and connectivity, a highway with a relatively low capacity located in a more remote part of the province may contribute a higher share to an evacuating community's bottleneck capacity, compared with a similarly low-capacity highway in a denser part of the province.

4.3.1 Edson to Edmonton and Grande Prairie

The Town of Edson had a population of 8,414 as of 2016. The multilane Hwy 16 runs east-west through town, Hwy 748 serves as a collector highway at Edson's northern periphery, and Hwy 47 runs south just west of the town boundary. For travel from Edson to Edmonton and Grande Prairie, roadway facility importance is shown in Figure 4.5.

Cells east of Edson have high Cr values, indicating that the multilane Hwy 16-eastbound is important to facilitating short-notice evacuation out of Edson. Disruption of these cells will divert evacuees to the two-lane highways, Hwys 748 and 47, at a reduced total bottleneck capacity. The cell immediately west of Edson has a Cr value of 0.25. Disrupting this cell will only allow eastbound evacuation via Hwy 16 and collector Hwy 748, at a 25% decrease in bottleneck capacity. The Escape Capacity Criticality of the cells further west on Hwy 16 is 0.02. Links within these cells contribute very little to the bottleneck capacity and disruption of these cells will result in only a 2% decrease in bottleneck capacity as evacuees have alternative routes (Hwys 47 and 748) to escape.

[3] This has been found to be true in all cases whether or not Level 4 facilities are included.

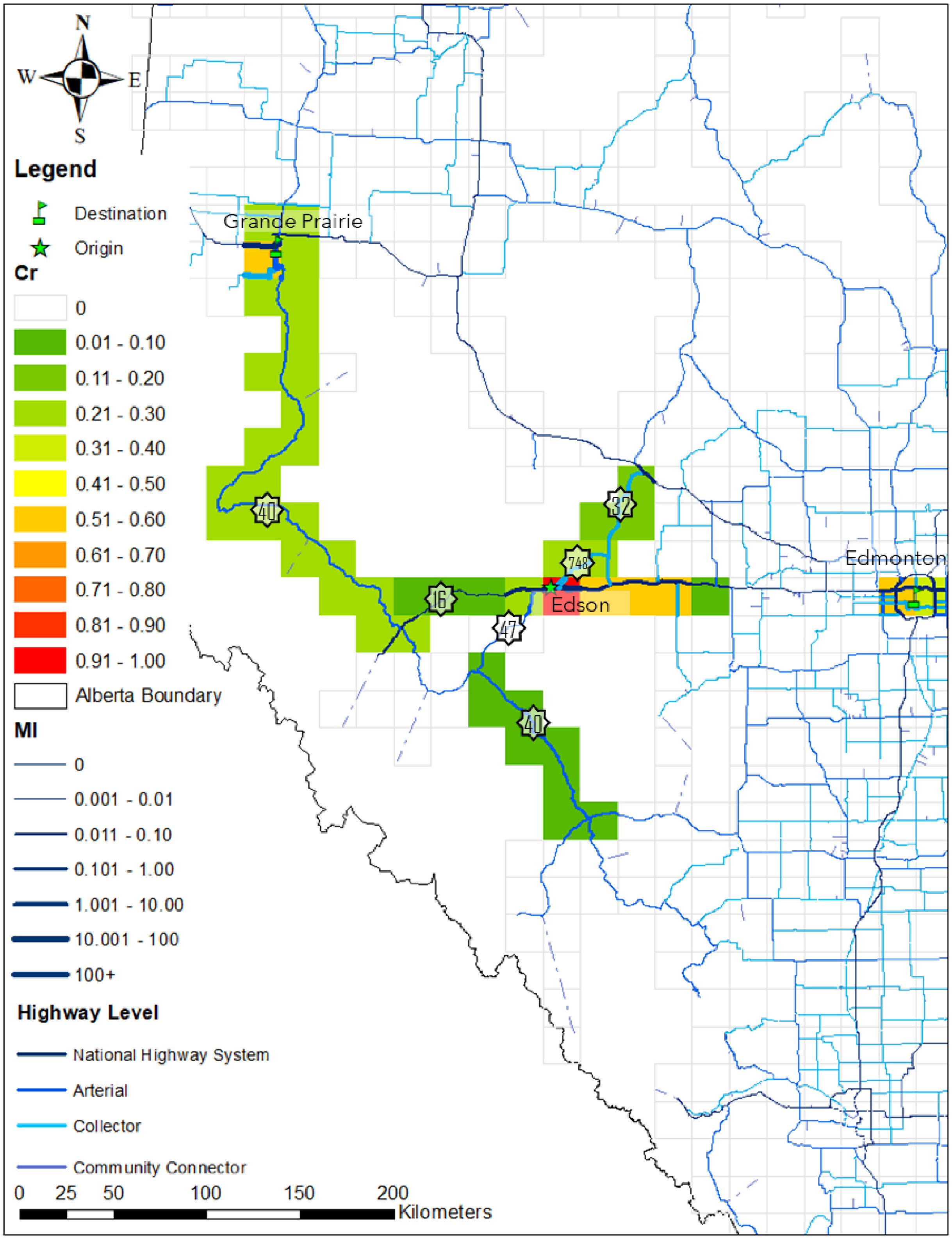

Figure 4.5: *Cr* and *MI* for evacuating from Edson to Edmonton and Grande Prairie

Hwy 40-north is one of two Level 1 highways connecting Edson and Grand Prairie, with a Cr value of 0.27. Theoretically, Hwy 40 can also be used to reach Edmonton, but it is a much longer route. Wong et al. (2020a) found a negative correlation between evacuees' route choice and route distance suggesting that evacuees prefer shorter routes to get to safety. Although it has been shown that people are more likely to use familiar routes in an evacuation (Sadri et al., 2014), Hwy 40 provides an alternative egress for emergency managers to direct evacuees as needed. The low Cr values for cells along Hwy 40 suggest that it has a very low contribution to the bottleneck capacity and other highways (primarily Hwy 16) are more important in this regard. Although Hwy 40-north and Hwy 40-south have equal contributions to bottleneck capacity between Edson and Edmonton, Hwy 40-north contributes more to the bottleneck capacity between Edson and Grande Prairie than that of Hwy 40-south. As a result, the combined effect shows a higher Cr value for Hwy 40-north. Furthermore, Edmonton, being a closer and larger service centre than Grande Prairie, will attract more evacuees. Therefore, routes to Edmonton (i.e., Hwys 16 and 40-south) have higher MI values.

4.3.2 Whitecourt to Edmonton

Whitecourt is a town of approximately 10,000 located 180 km north-west of Edmonton, at the juncture of Hwy 43 (running roughly east-west) and Hwy 32 (north-south) (Figure 4.6). To leave Whitecourt using provincial highway facilities, evacuees must take Hwy 43 (both eastbound and westbound) or Hwy 32 (southbound). Hwy 43 is a multilane highway and thus has a higher capacity than that of the two-lane Hwy 32. Evacuees can either travel northbound on Hwy 32 after travelling west for 7 km on Hwy 43 or continue on Hwy 43. Figure 4.6 shows the results of applying the two metrics Cr and MI.

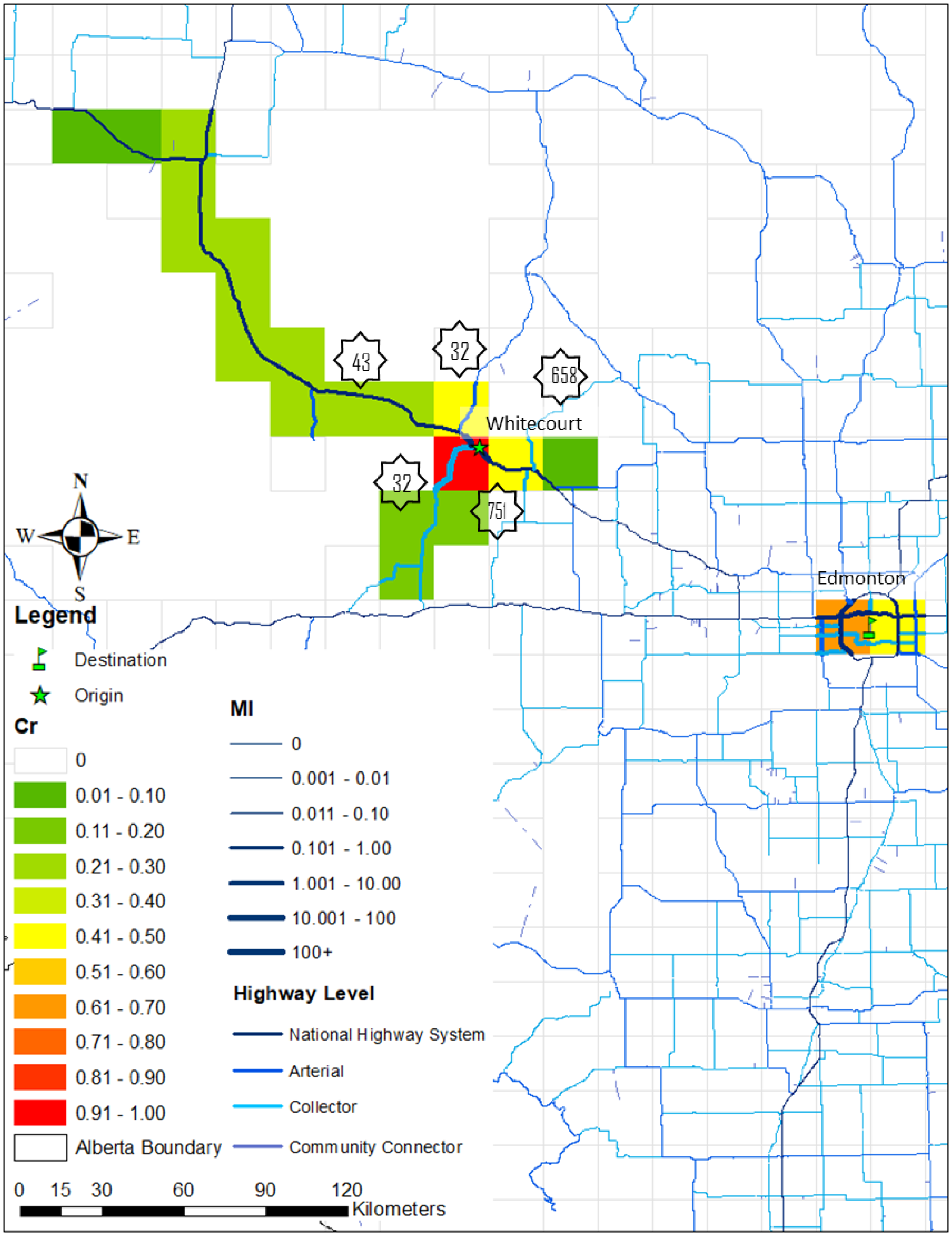

Figure 4.6: Cr and MI for evacuating from Whitecourt to Edmonton

A Cr value of 0.42 indicates that Hwy 43 (eastbound) in the immediate vicinity provides 42% of the bottleneck capacity. The same highway facility in the adjacent cell directly east has a lower Cr (= 0.11), because when this segment of Hwy 43 is not operational, 89% of the bottleneck capacity can be provided when evacuees use Hwy 658 and Hwy 751. The high Cr value of the cell immediately north of Whitecourt and low Cr values for the westbound segments of Hwy 43 are observed in a similar fashion. If the wildfire grows north of Whitecourt, egress routes using Hwy 32 (northbound) and Hwy 43 (westbound) may be inaccessible. For cells containing Hwy 32 (southbound from Whitecourt), Cr = 0.2 – lower than that of the westbound segment of Hwy 43. Emergency managers may want to consider prioritizing fire suppression and encroachment away from facilities with the highest Cr values, and consider investments to maintain facility infrastructures, in order to preserve higher community evacuation capacities (and thus, potential community evacuation speed).

4.3.3 Fort McMurray to Edmonton

Fort McMurray (FMM) is a city within Alberta's oilsands industry. It is connected to the rest of the province via a single multilane, divided provincial highway facility, Hwy 63 (Figure 4.7). Further south, it splits into Hwy 63-south and Hwy 881 (the latter a two-lane undivided facility). Therefore, Hwy 63 north of this intersection is critical with Cr = 1.0. South of the intersection, Hwy 63 has a higher Cr value than that of Hwy 881, due to differing directional capacities and thus, contributions to the bottleneck capacity from Fort McMurray to Edmonton. Disrupting either Hwy 63-south or Hwy 881 (over the "loop") reduces bottleneck capacities by 58% and 41%, respectively. Although Hwy 881 is not typically used for regular travel between the two cities (it is not as direct and has lower speeds than Hwy 63), it provides an important contribution to the overall travel capacity necessary in an evacuation.

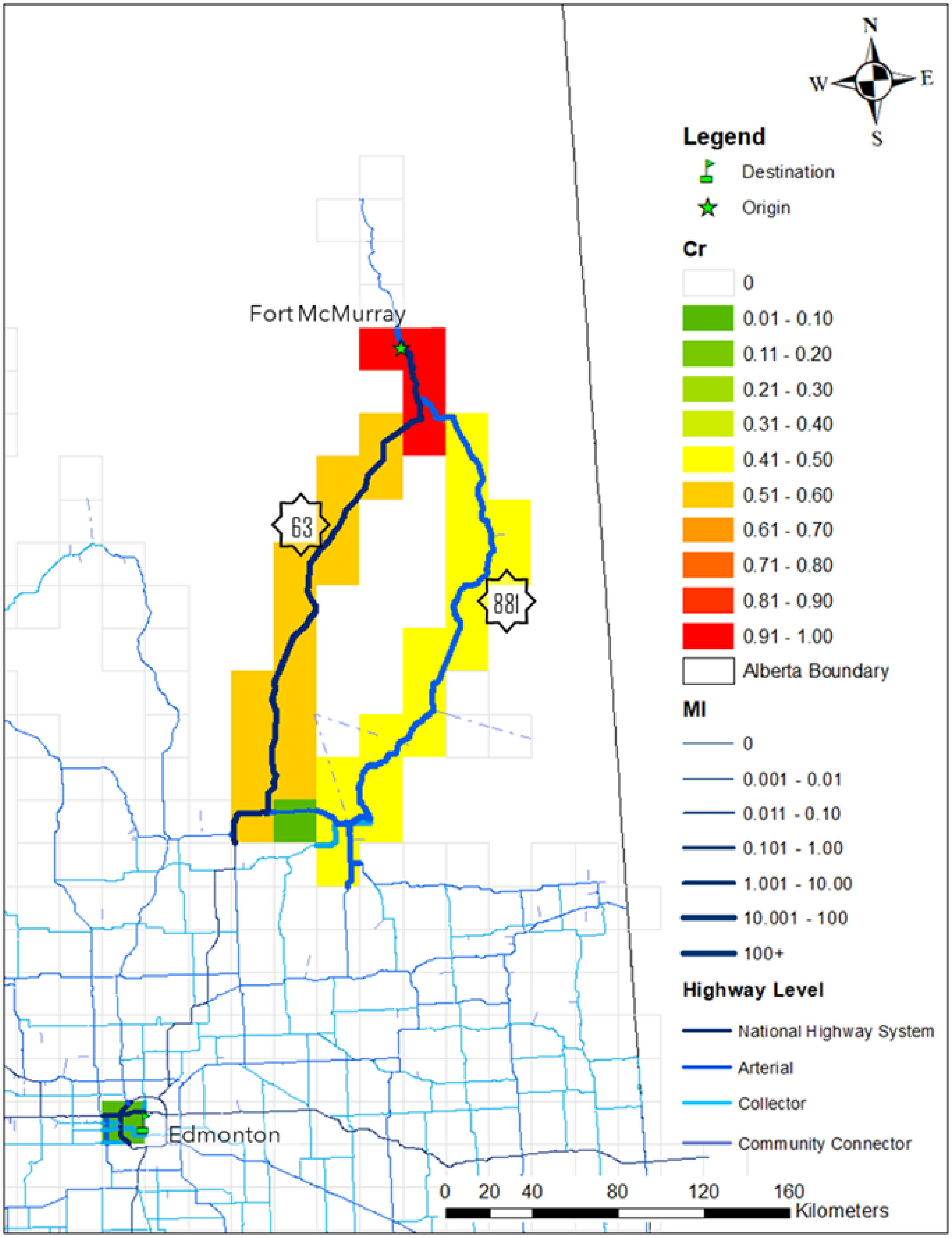

Figure 4.7: Cr and MI for evacuating from Fort McMurray to Edmonton

During the 2016 Horse River Fire, due to traffic management (or lack thereof), Hwy 63 experienced significant congestion while Hwy 881 was largely underutilized (Woo et al., 2017). Overall, given the lack of facilities directly southbound out of Fort McMurray, contraflow operations at least to the intersection of 63/881 should be considered as part of the emergency management plan, if only to facilitate more capacity and easy left-turn access onto Hwy 881 (Woo et al., 2017). The provincial government has considered an additional roadway southbound from Fort McMurray, given its concentrated population within the boreal forest (Wong, 2016).

4.3.4 High Level to Peace River

Hwy 58 runs east-west and Hwy 35 runs north-south through High Level, the northernmost town in Alberta. There are only two direct access highways – Hwys 35 and 58 – to evacuate south towards Peace River, the nearest economic centre (Figure 4.8). With approximately the same capacity, Hwys 35, 58, and 88 contribute to the bottleneck capacity equally, and disruption of any of these highways will obviously reduce the bottleneck capacity to half due to a lack of alternatives.

Therefore, Cr values are 0.5 for these highways. However, Cr = 0 for Hwy 986 because in the event of it not being accessible, evacuees can travel further south on Hwy 88 and take a detour to Peace River (or another host community).

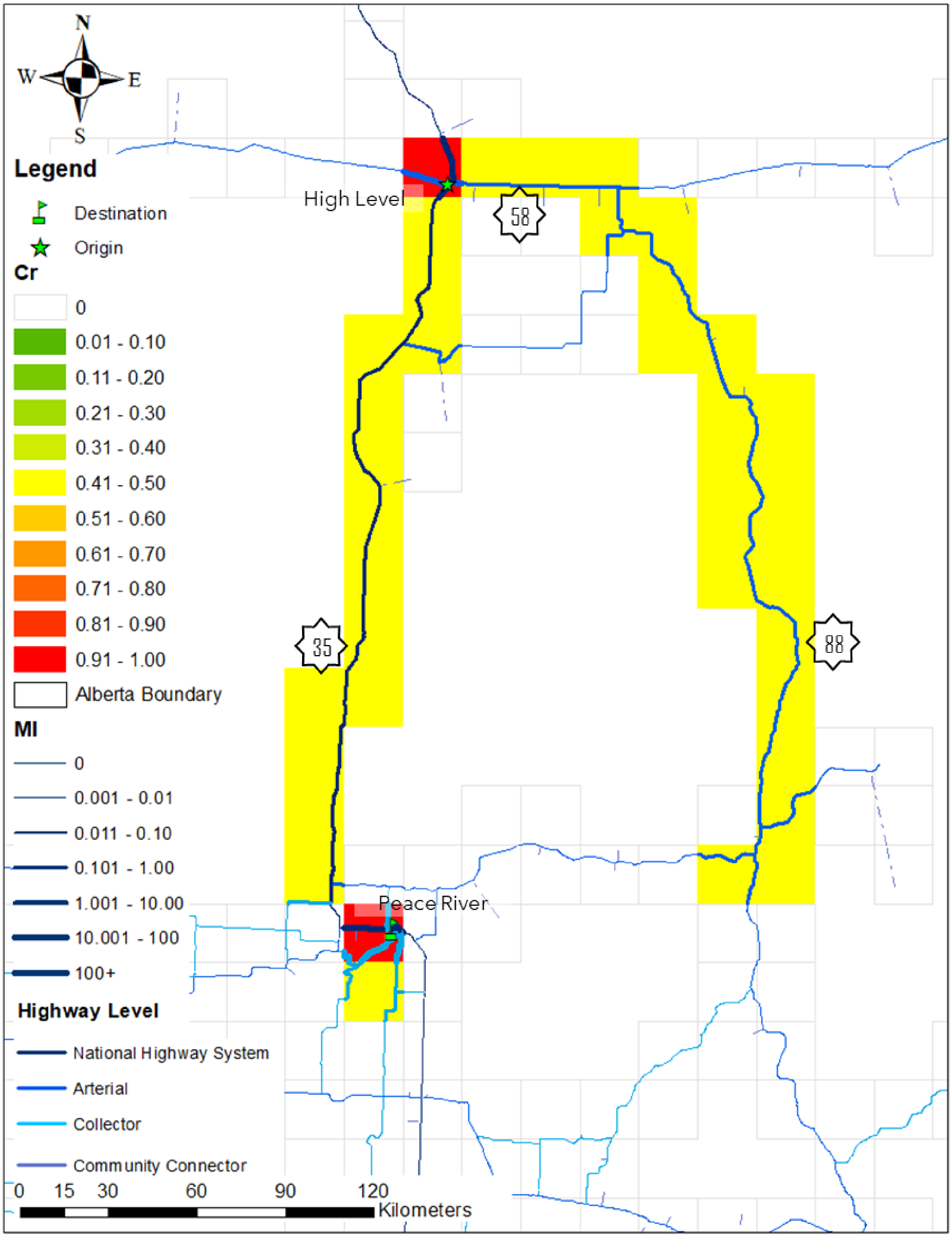

Figure 4.8: *Cr* and *MI* for evacuating from High Level to Peace River

4.3.5 Slave Lake to Edmonton

Slave Lake, a town of 6,651 residents as of the 2016 census, is located west of the intersection of Hwys 2 and 88, two-lane Level 2 highways with directional capacities of 2000 vph. Unlike Edson or Whitecourt, there are three main travel routes of equal capacity out of Slave Lake: northbound on Hwy 88, eastbound on Hwy 2, and westbound on Hwy 2. As per Figure 4.9, all three routes contribute equally to the bottleneck capacity between Slave Lake and Edmonton. Once westbound travellers are past the intersection of Hwy 2 and Hwy 33, or eastbound travellers past Hwy 2 and Hwy 44, they have more alternatives to reach Edmonton and thus Cr values beyond these points are zero.

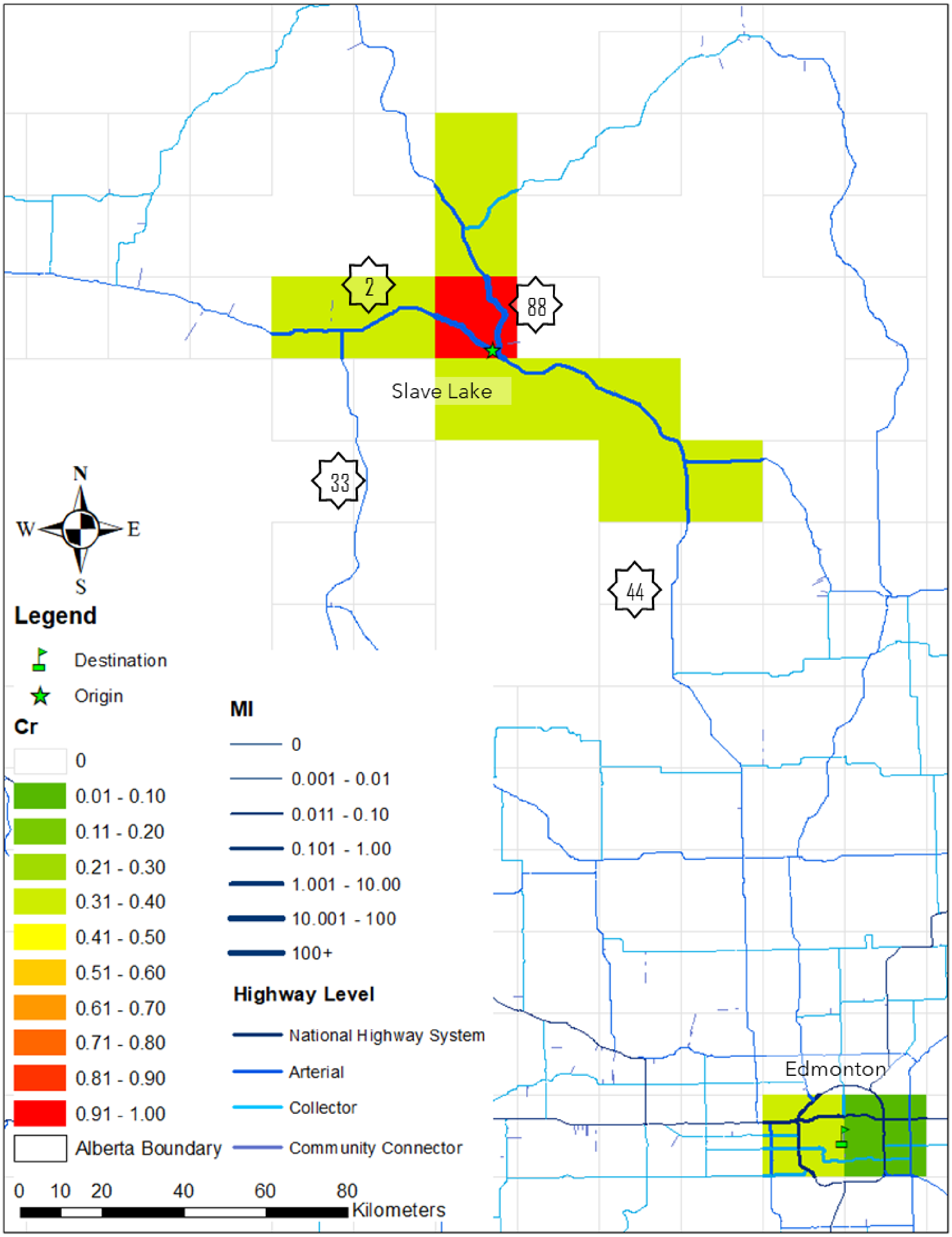

Figure 4.9: Cr and MI for evacuating from Slave Lake to Edmonton

4.3.6 Multiple Communities to Edmonton

Figure 4.10 illustrates the average Escape Capacity Criticality Cr and Max-flow Impact Index MI for ten wildfire-prone communities destined for Edmonton. The communities are not assumed to be evacuating all at once. Rather, the aim is to identify the segments that, on average, contribute more to community bottleneck capacities, and have higher community evacuation demands.

As shown earlier, cells immediately adjacent to origin communities are most critical, reinforcing the importance of community-level evacuation studies and municipal evacuation plans (Cova et al., 2013). As expected, cells covering denser parts of the network (and thus, with more routing alternatives) are of lower criticality compared with those covering sparser parts. Hwy 63 directly south of Fort McMurray, Hwy 35 directly south of High Level, Hwy 16 directly east of Edson, and Hwys 16 and 93 adjacent to Jasper are among the most critical. Disrupting these facilities will reduce bottleneck capacity by 50% or more. Despite that Hwys 43 and 16 have a higher capacity than that of Hwy 881, cells along Hwy 881 have Cr values higher than Hwy 16 (westbound of Edson) and the same as Hwy 43 due to lack of alternative routes. This suggests that solely referencing capacity for prioritizing highway investments in light of emergency evacuation needs can be misleading, because depending on network topology and connectivity, a highway with low capacity may contribute a higher share to the bottleneck capacity around a community. Cells on Hwys 986, 754, 813, and 33 add very little to bottleneck capacity as several alternative routes are available and hence can be assigned a lower priority.

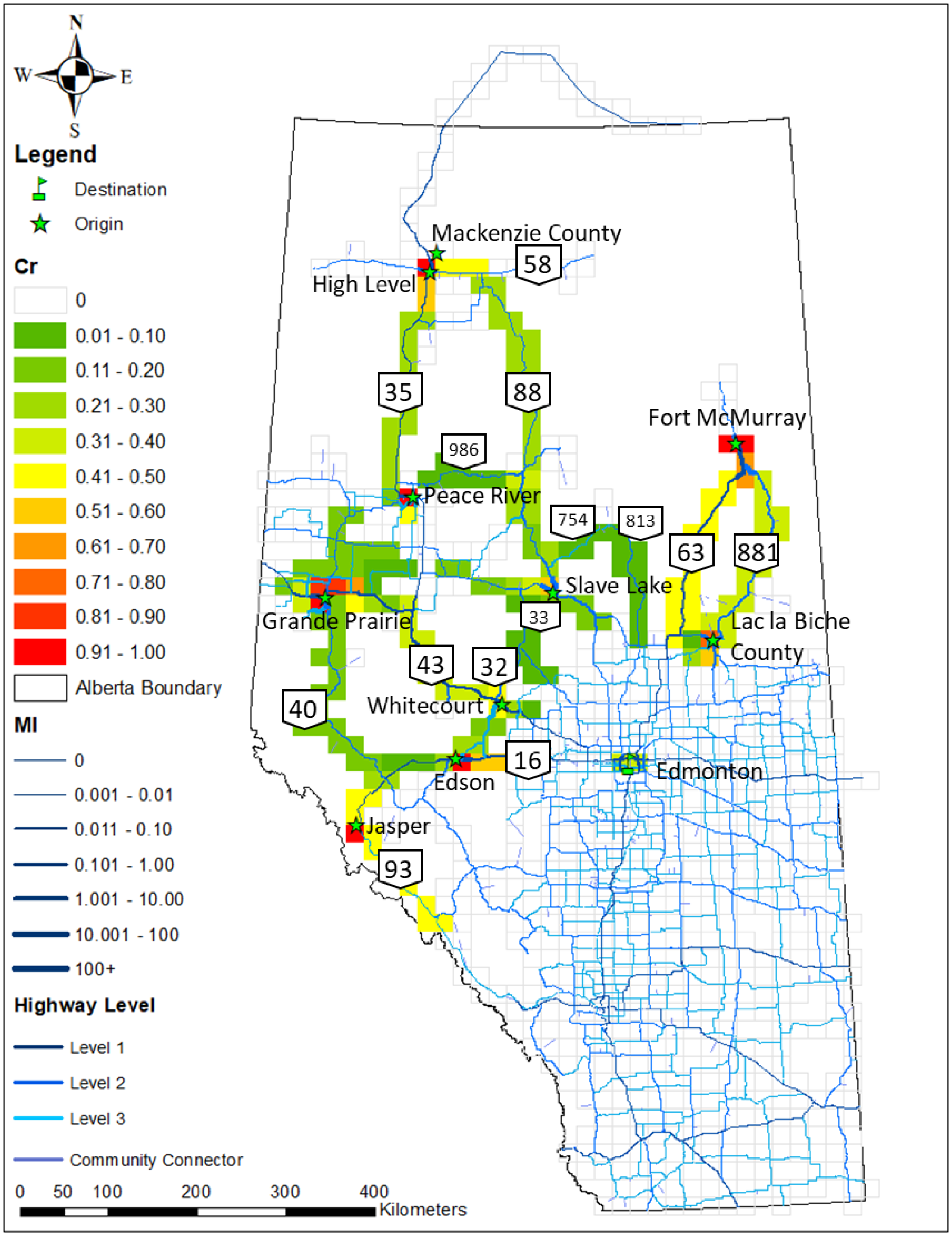

Figure 4.10: Cr and MI for evacuating from 10 communities to Edmonton

Hwys 63-south (west on the "loop" with 881), 93, and 58 have similar Cr values, but the MI value for Hwy 63 is higher than those of Hwys 93 and 58. These facilities serve communities where the transportation network is sparse. However, Fort McMurray has a larger population, and thus, disrupting Hwy 63 will have a much greater impact than disruptions on facilities serving the much smaller communities of High Level or Jasper.

4.4 SUMMARY

This chapter quantifies network vulnerability for evacuation, introducing two measures that consider bottleneck capacity between an evacuating community and an identified destination. Applications of these measures using MCMF and grid-cell disruption are demonstrated on individual evacuating communities, which can support community emergency management planning, as well as on multiple communities, which can support provincial-level planning. The result confirms that, based on the provincial highway network topology, all critical links are located in the vicinity of communities, affirming the importance of community wildfire evacuation operations studies focusing on the immediate vicinity of communities. Higher roadway link Cr values are observed where the network is sparse, and communities have few egress alternatives. In such cases, roads with low capacities and/or less-travelled roads (e.g., lower AADT) may be critical to accommodating evacuating traffic, yielding higher Cr values than roads with similar capacities in a denser part of the network. This simple method can be integrated as an analysis tool in an (say, provincial) agency's evacuation planning activities. One use may be to guide the allocation of limited emergency planning resources to communities across its jurisdiction – resources that can be directed towards communities found to be at higher risk for evacuation capacity issues.

The proposed method has shortcomings to improve upon. First, it is assumed that all grid cells have equal weight regardless of the length or density of the road network within them. The network density or length within each cell could be computed for use in cell weights. Second, this method only considers evacuating traffic, and does not consider existing background traffic on the network, which, if significant, can impact results. Third, network vulnerability was measured assuming evacuating communities will travel to their nearest service centres (which may not be able to accommodate, or be appropriate for accommodating, evacuees) rather than designated host communities. Thus, host community locations are identified in CHAPTER 5 and a case study of the results combining the work of CHAPTERS 4 and 5 are presented in CHAPTER 6.

CHAPTER 5. FACILITY LOCATION MODELS

This chapter presents facility location models that are used to identify a network of host communities across a large geographic area/jurisdiction, where evacuees can seek safety, shelter, and relief, when it is entirely unknown where and when natural disasters will occur and cause community evacuations. First, single-objective optimization models are developed to identify evacuee host communities across Alberta. Building on the insights gained, a multi-objective facility location model that considers wildfire exposure and road network topology is then proposed and results examined. Figure 5.1 illustrates the organization of this chapter.

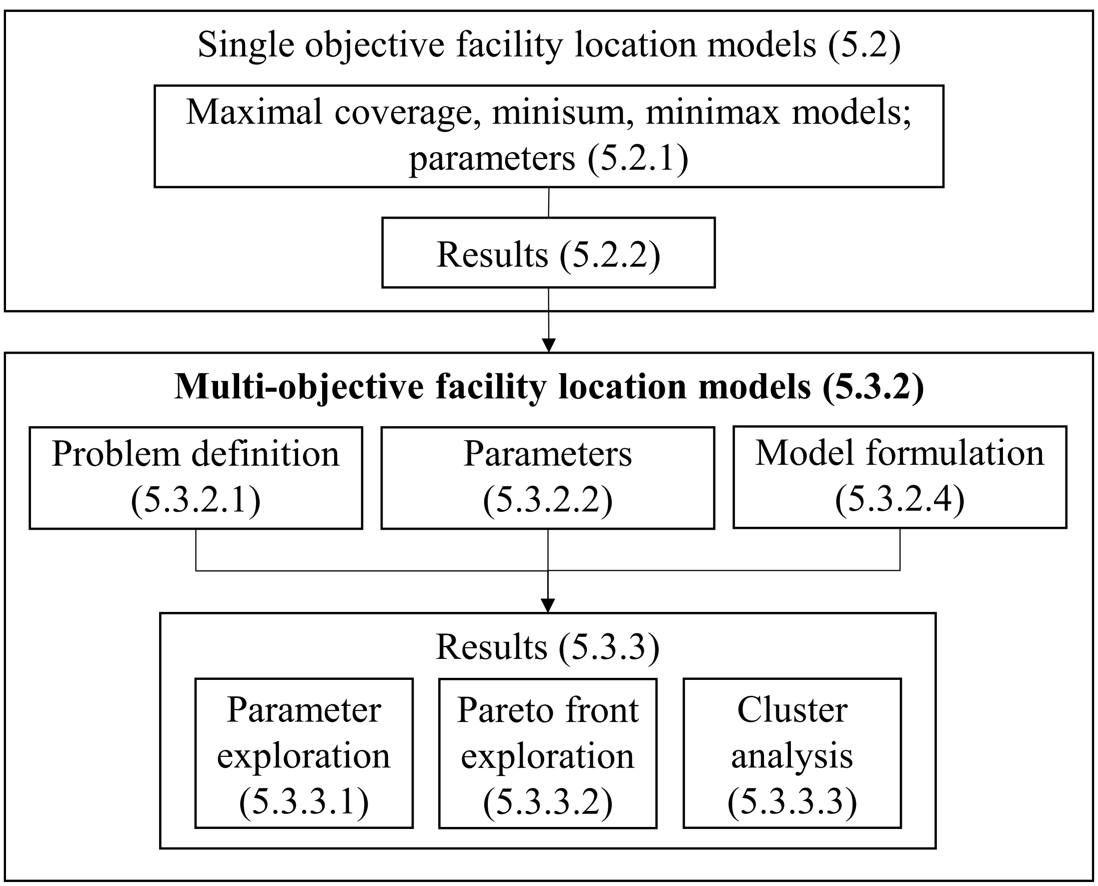

Figure 5.1: Chapter 5 facility location models overview

5.1 BACKGROUND

A pre-disaster community evacuation plan should identify potential destinations should an evacuation occur, for evacuees to access supplies such as food and fuel, medical services, and accommodations. For natural disasters such as wildfires and earthquakes that are difficult to predict and occur rapidly, short- and no-notice evacuation orders are often issued (Insani et al., 2022). Although it is unknown whether and how many communities will be impacted by wildfire in any given season (some may never require evacuation within the planning horizon), should a short- or no-notice evacuation be required, critical decisions must be made very quickly (McGee et al., 2021). Thus, having some knowledge of where evacuees can be safely and appropriately directed (to destination, or “host,” communities that are willing and capable to accommodate evacuees), in the event of an emergency evacuation, can reduce the decision-making burden of emergency managers during an emergency event, which in turn may lead to more timely and decisive instructions.

The question then becomes, how do we identify host communities that match with communities at risk of wildfire evacuation? To do so, characteristics like travel time/distance between the evacuating and host communities, and host communities to major service centres, may be important. As shown previously in Figure 3.1.a and Figure 3.1.c, road network density is low in northern Alberta, but landscape fire exposure is very high. Thus, communities in northern Alberta are more likely to experience wildfire than those elsewhere, but have fewer routes available that connect to the provincial road network. Without defined destinations, confusion may rise and increase egress times, putting people at risk.

5.2 SINGLE OBJECTIVE MODELS

The results of three single objective models (the maximal coverage model minisum model, and minimax model) are applied to understand how their results compare in distributing evacuation host communities and inform the setup of the multi-objective model in 5.3.

5.2.1 Facility Location Model Formulations

5.2.1.1 Maximal Coverage Model

The maximal coverage model aims to serve the maximum number of evacuating communities within a pre-determined distance, by locating a total of HC host communities (Toregas et al., 1971). The original model does not consider a lower limit for coverage distance. However, in wildfire evacuations, evacuees are directed to host communities that are judged to be a safe distance away from the wildfire and where it may potentially move (often quickly and possibly in a number of directions). Therefore, a lower coverage limit is introduced. In this model, community size is used as a weight.

Maximize $\sum_i P_i Z_i$ (5.1)

Subject to $\sum_{j \in N_i} X_j \geq Z_i, \quad \forall i$ (5.2)

$\sum_{j \in N_i} X_j = HC,$ (5.3)

$X_j,\ Z_i \in \{0,1\}, \quad \forall\, i, \forall\, j$ (5.4)

Sets:

I = Set of origin community centroids; $i \in I;\ I = \{1, 2, \dots, i\}$

J = Set of potential host community centroids; $j \in J;\ J = \{1, 2, \dots, j\}$

Decision variables:

X_j = 1 if the j^{th} community is selected as the host community, 0 otherwise

Z_i = 1 if the i^{th} community is served by a host community within the coverage radius, 0 otherwise

Parameters:

P_i = Population of origin community i

HC = Number of host communities to be identified

N_i = Eligible host community centroid for community i = $\{j|R_L \leq d_{ij} \leq R_U\}$

d_{ij} = Travel distance between i and j (km)

R_L = Lower limit of coverage radius (km)

R_U = Upper limit of coverage radius (km)

The objective function (Eq. 5.1) maximizes the coverage of the population in the study area. Constraints ensure that 1) community i is assigned to at least one host community within the coverage radius (Eq. 5.2), 2) a total of HC host communities are located (Eq. 5.3) and 3) decision variables are binary (Eq. 5.4). Thus, the model is a binary integer linear program (BILP), solved using the '*cplexbilp*' toolbox in MATLAB and CPLEX.

5.2.1.2 Minisum Model

The minisum model is the earliest formulation for the facility location problem (Hakimi, 1964). This model minimizes the total weighted cost with respect to travel distance or time, to locate HC

facilities. The original minisum model weights travel distance by community size, and below, travel distances are weighted using evacuating community population.

$$\text{Minimize} \quad \sum_i \sum_j P_i d_{ij} Y_{ij}, \tag{5.5}$$

$$\text{Subject to} \quad \sum_j Y_{ij} \geq 1, \qquad \forall i \tag{5.6}$$

$$\sum_j X_j = HC \tag{5.7}$$

$$Y_{ij} \leq X_j, \qquad \forall\, i, \forall\, j \tag{5.8}$$

$$X_j,\ Y_{ij} \in \{0,1\}, \qquad \forall\, i, \forall\, j \tag{5.9}$$

Where decision variable Y_{ij} = 1 if the i^{th} community is served by j^{th} host community; 0 otherwise. Other notation was introduced previously in Section 5.2.1.1.

The objective function (Eq. 5.5) minimizes the sum of the weighted distance between evacuating communities and host communities. The constraints ensure that 1) all communities in the set I are assigned to at least one host community in set J (Eq. 5.6), 2) a total of HC host communities are located (Eq. 5.7), 3) evacuating communities are allocated to host communities only (Eq. 5.8), and 4) decision variables are binary (Eq. 5.9). The model is again a binary integer linear program (BILP).

5.2.1.3 Minimax Model

The minimax model minimizes the maximum distance between evacuating communities and host communities (Boonmee et al., 2017; Hakimi, 1964):

$$\text{Minimize} \quad D \tag{5.10}$$

Subject to $\sum_j Y_{ij} = 1, \quad \forall i$ (5.11)

$$\sum_j X_j = HC\,, \tag{5.12}$$

$$Y_{ij} \le X_j\,, \quad \forall\, i, \forall\, j \tag{5.13}$$

$$D \ge \sum_j d_{ij} Y_{ij}, \quad \forall i \tag{5.14}$$

$$X_j,\ Y_{ij} \in \{0,1\}, \quad \forall\, i, \forall\, j \tag{5.15}$$

Where decision variable D = maximum distance between all communities and host communities (km), and other notation is as introduced previously in Section 5.2.1.1.

The objective function (Eq. 5.10) minimizes the maximum distance between a community and its designated host community. The constraints ensure that 1) all communities in the set I are assigned to only one host community in set J (Eq. 5.11), 2) a total of HC host communities are located (Eq. 5.12), 3) communities are allocated to the host community nodes only (Eq. 5.13), 4) the decision variable D is the maximum distance between the communities and the host communities (Eq. 5.14), and 5) decision variables X_j and Y_{ij} are binary (Eq. 5.15). This model is a mixed-integer linear program (MILP), solved using the '*cplexmilp*' toolbox in MATLAB and CPLEX.

5.2.2 Results

The three single objective models are solved to identify host communities throughout Alberta. First, the maximal coverage model is solved. The upper radius is varied from 60 km to 250 km after observing the area burned by historical wildfires.

Next, different numbers of host communities and their coverage radius are explored. With a higher upper coverage radius limit (>200 km), four host communities can cover 90% of the study area

(Figure 5.2). However, traveling 200 or more km may be difficult and cause additional distress due to needs for food, medical service, fuel, and/or rest. Also, community coverage increases with an increasing number of host communities; after 10 host communities, the rate of increase in coverage is reduced.

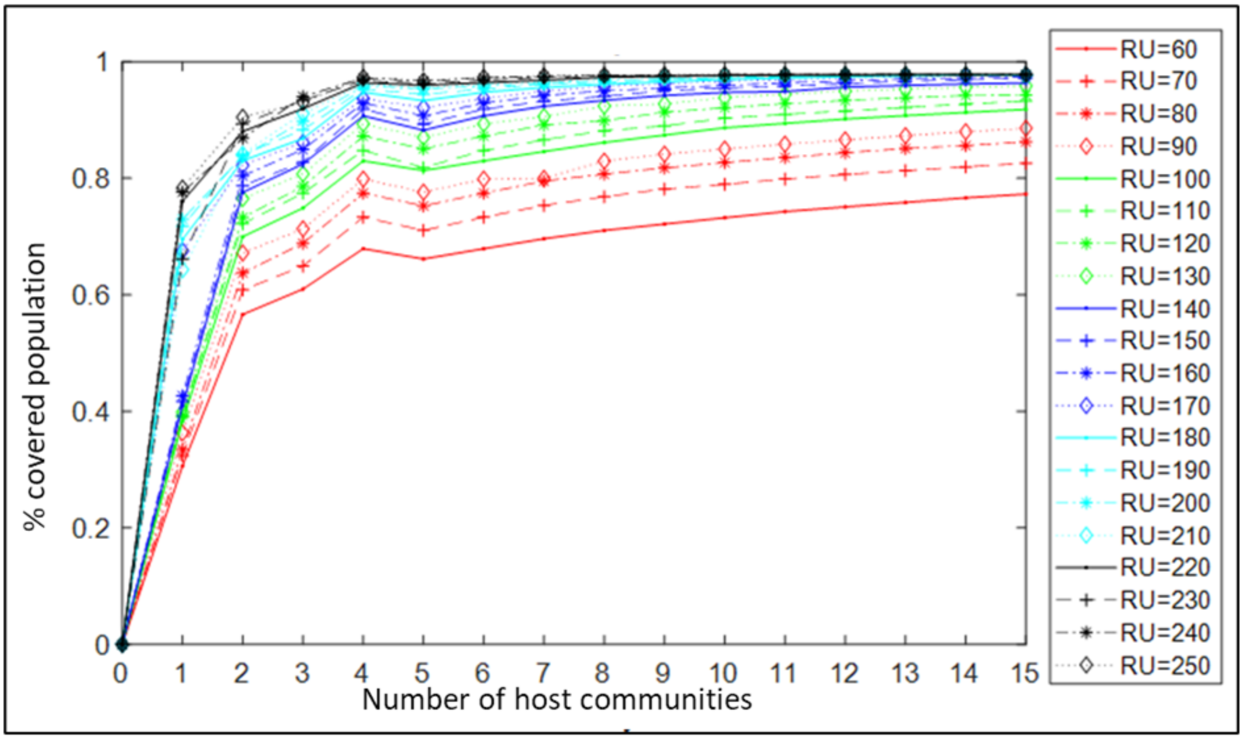

Figure 5.2: Community coverage by number of host communities

The maximum coverage radius is also varied (Figure 5.3). The results indicate that at R_U = 60 km, only 25% of the study area population has a host community within 60 km travel distance, and the average distance to the nearest host community (for both covered and not covered populations) is 116 km. 95% of the population (including those who are not covered within the coverage threshold) is covered when the threshold of maximum coverage radius, R_U, is set to 150 km. At this threshold, the lower and upper 25th percentile for travel distances are 63 km and 136 km, respectively. Thus, the analysis to identify 10 host communities is continued setting 150 km as the maximum coverage radius.

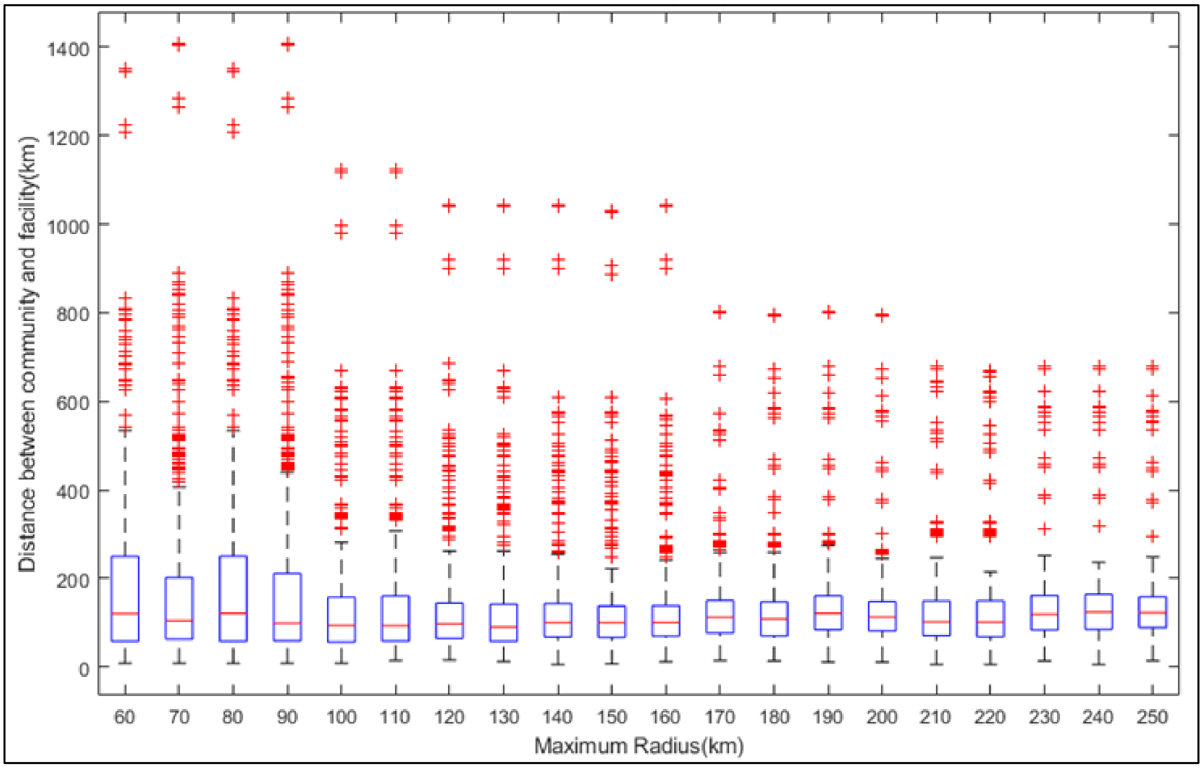

Figure 5.3: Travel distances between potential evacuating communities and their nearest host communities, as a function of coverage radius

The maximal coverage model (with HC = 10 and R_U= 150 km) populated southern Alberta with more host communities, which is intuitive as it is more densely populated than northern Alberta. A higher number of host communities are clustered along Level 1 provincial highways, especially Hwy 2, a major north-south corridor between Calgary and Edmonton that also extends just north of Edmonton. The absence of host communities in northern Alberta leaves 5% of the population without a designated host community within the chosen maximum distance. This is a small number, but they are also located in small remote communities with limited transportation access.

Since the model is weighted by population, these communities are left without a host community nearby. Members of these communities must travel as far as 1,031 km to reach a host community.

Next, the minisum model is applied. It is observed that, unlike the coverage model, the minisum model locates host communities in Alberta's northeast and northwest (Figure 5.4), reducing travel distances/times for those in the more remote communities of these areas. This reflects in the reduced value of the maximum travel distance to the nearest host community in Table 5-1.

Medicine Hat in southeastern Alberta is identified as a host community. However, it is located in a part of the province that has not experienced as much wildfire; it is unlikely that evacuees from northern Alberta would be directed to Medicine Hat (evacuees may ultimately travel to Medicine Hat as their final destination, to be with friends or family, but this model concerns centrally-identified emergency evacuee host communities). Also, Wood Buffalo is identified as a host community, but this may be problematic as there is only one ground egress route out of Fort McMurray (McGee, 2019; Woo et al., 2017). With population weights, the minisum model will identify host communities closer to large communities to reduce the total weighted travel cost. As a result, small, northern, and wildfire-prone communities must travel longer distances to reach designated host communities. To address these issues, a wildfire-specific parameter – landscape fire exposure – was included in the multi-objective optimization model.

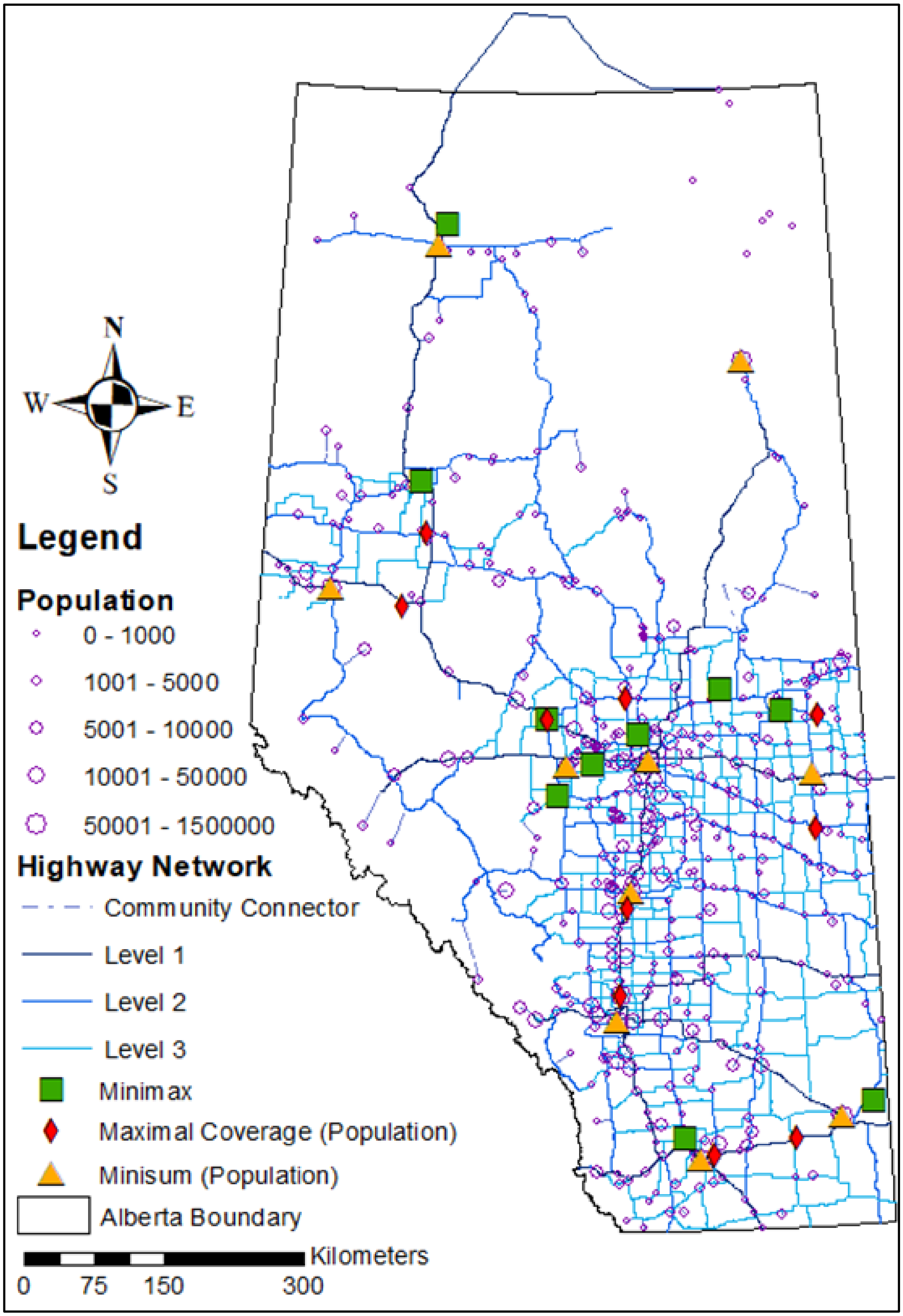

Figure 5.4: Host communities identified by different single objective facility location models

The minimax model only considers the distance between origin and host communities (Eqs. 5.10-5.15). When applied, a cluster of host communities is located in central Alberta because the province's population is heavily concentrated there (Figure 5.4). Mackenzie County and Peace River are the only host communities in the northern part of the province. Potential evacuees from northern communities will have to travel higher-than-average distances to reach host communities, which is undesirable given that communities in the northern half of the province are generally under greater wildfire threat.

Table 5-1: Comparing Three Model Results

	Maximal Coverage	*Minisum*	*Minimax*
Host community	Falher	Grande Prairie	Peace River
	Coaldale	High Level	St. Paul
	Westlock	Wood Buffalo	Mayerthorpe
	Mayerthorpe	Edmonton	Drayton Valley
	Sturgeon Lake 154	Parkland County	Mackenzie County
	Wainwright	Vermilion	Wabamun 133A
	Airdrie	Red Deer	Morinville
	St. Paul County No. 19	Calgary	Smoky Lake County
	Bow Island	Lethbridge	Nobleford
	Penhold	Medicine Hat	Cypress County
Objective value	-3881991	1.13E+08	6.71E+02
% Covered	95.37	NA	NA
Max distance to nearest host community (km)	1031.60	678.12	670.92
Computation time (sec)	0.95	53.28	24.19

From Table 5-1, it is observed that only Mayerthorpe has been identified as a host community in more than one model. The rest of the host communities are identified in only one of the models, suggesting that host community location/selection strongly depends on the objective functions. Also, some small communities (typically located in the north of the province) must travel 700 km or more to reach their nearest host communities. The maximum distance an origin community must travel to reach its nearest host community is 50% longer for the maximal coverage model compared to the others because the maximal coverage model objective prioritizes population coverage over travel distance. This may be addressed by introducing parameters for wildfire exposure of the communities to the maximal coverage model to ensure communities with high exposure are covered within the predefined coverage radius.

In summary, the purpose of exploring these single objective models was to gain insights into how different objectives and model structures lead to different spatial distributions of host communities across a large jurisdiction, in this case, Alberta. Each of the single objective models has inherent limitations. The models are biased against small communities, some of which are isolated due to highly limited transportation network access, as well as prone to wildfire. The results are used to inform a multi-objective facility location model in the next section.

5.3 MULTI-OBJECTIVE MODELS

5.3.1 Multi-objective Optimization

5.3.1.1 Overview

Multi-objective optimization (MOO) models consider more than one objective towards finding optimal solutions. Objectives are maximized or minimized simultaneously, with the general form as follows:

Min/Max	$f_k(\boldsymbol{x})$,	$k = 1, 2, \dots, K$	(5.16)
Subject to	$g_m(\boldsymbol{x}) \leq 0$,	$m = 1, 2, \dots, M$	(5.17)

$$h_n(\boldsymbol{x}) = 0, \qquad n = 1, 2, \dots, N \tag{5.18}$$

$$x_i^L \le x_i \le x_i^U, \qquad i = 1, 2, \dots, I \tag{5.19}$$

Eq. 5.16 indicates that K objective functions, $f_k(\boldsymbol{x})$, are maximized or minimized simultaneously, with decision variables vector $\boldsymbol{x} = x_1, x_2, \dots, x_I$. Eqs. 5.17 and 5.18 are inequality and equality constraints, respectively, while x_i^L and x_i^U are lower and upper bounds imposed on the decision variables (Eq. 5.19).

5.3.1.2 Dominance and Pareto Front

The objectives in a multi-objective optimization model will often conflict with one another; when one objective improves, one or more of the others may deteriorate. A multi-objective optimization model generates a set of optimal solutions, and the concept of dominance is used to evaluate the fitness of the solutions. Say there is a bi-objective optimization problem ($K = 2$) with two decision variables ($i = 1,2$). Solution x^{2^*} is dominated by solution x^{1^*} if x^{1^*} is no worse than solution x^{2^*} in all objectives and is found to be strictly better than x^{2^*} in at least one objective. If neither solution dominates, then both are non-dominated solutions. Figure 5.5 illustrates the Pareto fronts of four bi-objective optimization problems. Figure 5.5.a shows five solutions to a bi-objective MOO problem where both objectives $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$ are to be minimized. All four solutions dominate Solution 1. Solution 3 dominates Solution 2, but is dominated by Solutions 4 and 5. Solutions 4 and 5 are the non-dominated or Pareto-optimal solutions; one solution is not strictly better than the other.

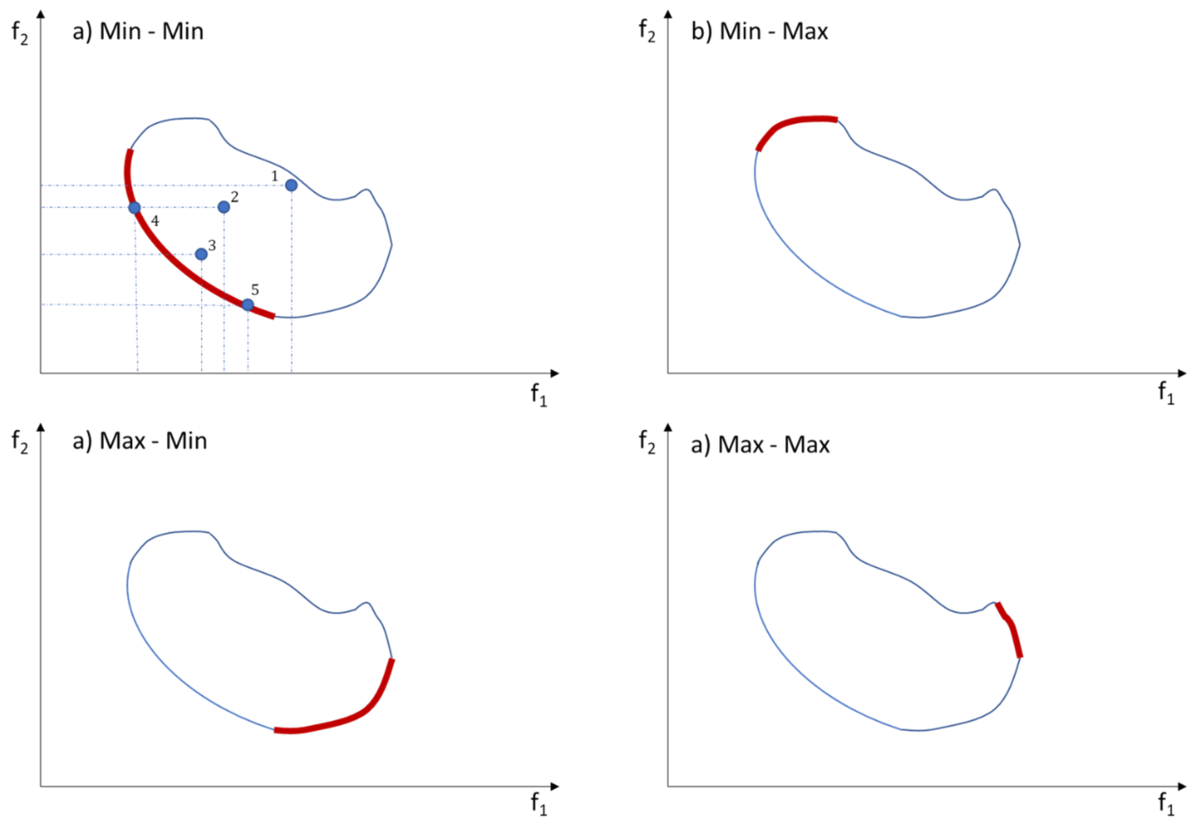

Figure 5.5: Pareto fronts of four bi-objective optimization problems: a) Min-min, b) Min-max, c) Max-min, and d) Max-max (Figure adapted from (Deb, 2001))

The set of non-dominated solutions defines the Pareto front. One wants to find solutions on the Pareto front, or at least solutions as close as possible to it. By selecting one Pareto solution over another, we make a trade-off between the objectives. In this case, Solution 5 is better than Solution 4 with respect to f_1, but the opposite is true for f_2. By choosing either Solution 4 or 5 one is expressing a preference for f_1 or f_2.

5.3.1.3 MOO Solution Methods

Four commonly used approaches to solve a MOO are as follows:

1. **Weighted Sum Method**: This is the simplest approach to solving a MOO problem (Miettinen, 1998). Objectives are converted to a single objective (Eq. 5.20) by introducing weights on each. The constraints remain the same (Eqs. 5.17-5.19):

$$\text{Min/Max} \qquad \sum_k w_k\, f_k(\boldsymbol{x}), \qquad k = 1, 2, \ldots, K \tag{5.20}$$

2. **$\boldsymbol{\varepsilon}$-constraint Method:** In this method, only one objective is optimized (Eq. 5.21) while remaining objectives are converted to constraints by imposing limiting values on them (Eq. 5.22) (Miettinen, 1998). The original constraints remain the same (Eqs. 5.17-5.19). The solutions obtained from this method are dependent on the upper/lower bounds applied to the converted constraints.

$$\text{Min/Max} \qquad f_\tau(\boldsymbol{x}), \tag{5.21}$$

$$\text{Subject to} \qquad f_k(\boldsymbol{x}) \leq \varepsilon_k, \qquad k = 1, 2, \ldots, K, \text{ and } k \neq \tau \tag{5.22}$$

3. **Goal Programming**: The minimum allowable deviation from the exact solution of each objective is determined a-priori. An acceptable target is set for each objective, and when solutions do not meet goals by either under- or over-achieving the expectation, deviation penalties or rewards are introduced (Miettinen, 1998). Instead of optimizing multiple objectives, the sum of deviations (as a single objective) is minimized. The solution depends on the expectation level as well as the deviation penalty/reward specified.

4. **Genetic Algorithm (GA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II):** Genetic algorithm is based on Darwin's survival of the fittest theory. A generic GA flowchart is shown in Figure 5.6. Each solution to the problem is called a chromosome containing an array of genes (Figure 5.6.i). The algorithm starts with an initial set of solutions (i.e., assembly

of chromosomes) forming a population of fixed size (population size is 4 in Figure 5.6.ii). This population can be initialized with a defined heuristic or at random. By evaluating the fitness/objective value of each chromosome, the fittest are selected as parents for offspring generation (Figure 5.6.iii). These parent chromosomes undergo crossover where a portion of their genes are interchanged to create new offspring (Figure 5.6.iv). Next, mutation is performed to maintain diversity in the offspring population, by changing some of the genes of the offspring (Figure 5.6.v). This process continues until the termination criteria for the optimization are met.

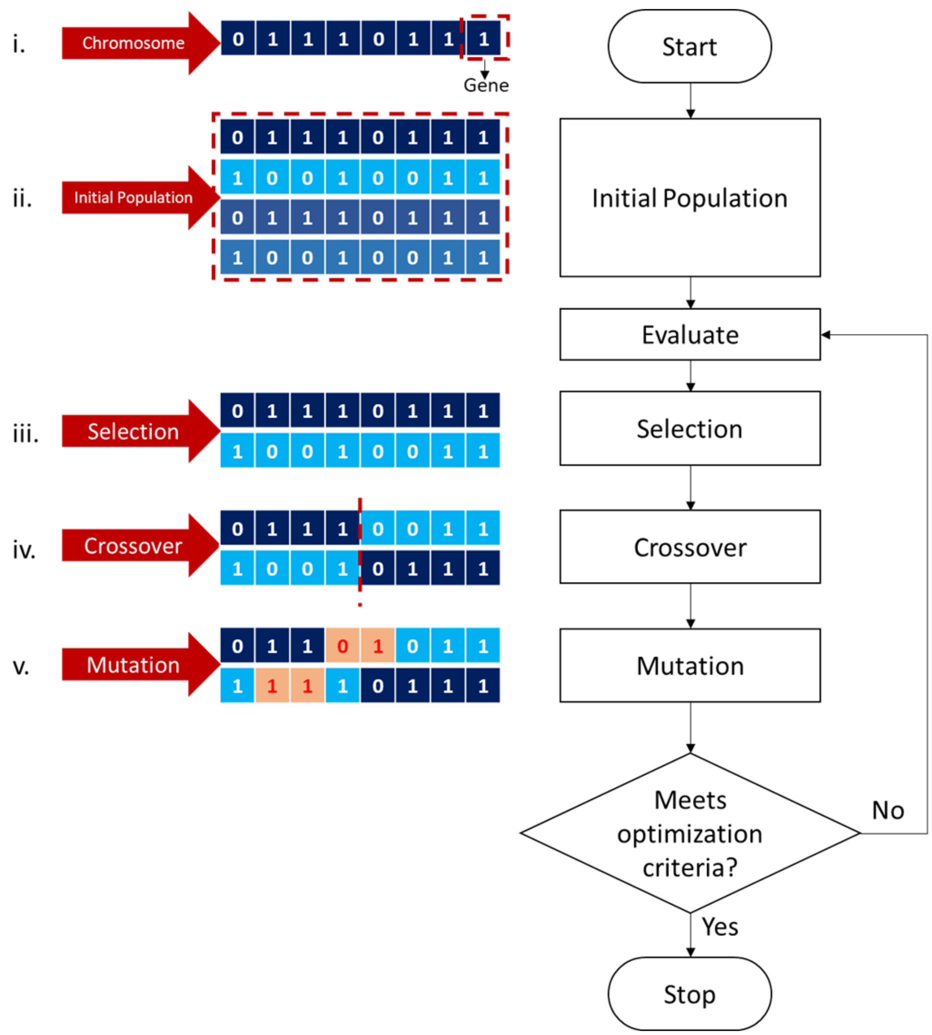

Figure 5.6: Genetic algorithm flowchart; image adapted from (Sakawa, 2002)

Srinivas and Deb (1994) proposed a Non-dominated Sorting Genetic Algorithm (NSGA) to eliminate solution bias toward specific regions in the simple genetic algorithm. Deb et al. (2002) proposed NSGA-II, a modified version of NSGA that has an updated parent selection and mating criteria for reproducing offspring. In NSGA-II, the fittest individuals are selected in the subsequent generation to reduce solution time. NSGA-II has been widely applied to solve MOO problems (Gang et al., 2005; Onan et al., 2015; Yeh, 2019).

5.3.2 Multi-objective Facility Location Model

A multi-objective model is proposed to locate host communities across Alberta, that can accommodate potential evacuees if and when wildfires breach their communities.

5.3.2.1 Problem Definition

Several objectives are considered for the multi-objective model. The first is to maximize coverage of the wildfire-exposed population. However, as mentioned earlier, many communities with high landscape fire exposures are in the remote boreal forest area and have very small populations. Only considering population will neglect those fire-prone communities, and thus, community populations are weighted with community Remoteness Indices. The Remoteness Index, RI, determines how far the communities are from service centres (e.g., population centres, cities) (Alasia et al., 2017). The second objective encourages host communities to be located at central locations between the demand points (i.e., origin communities) and supply locations (i.e., service centres). The combined Betweenness-Centrality Index, BCI (Freeman, 1977), of selected host communities is maximized to achieve the second objective. The third objective is to minimize the number of host communities to be selected.

Constraints are considered. One is to ensure that the travel distance between origin communities and their corresponding host community (or communities) is within an acceptable range. If host communities are too far (i.e., > R_U), evacuees are more likely to run out of fuel and other supplies. On the other hand, if host communities are too close (i.e., < R_L), the likelihood that the same fire impacts these communities is greater. Since it is difficult to predict how large a fire would grow, the shape and size of historical fire burnt area are used in this study to determine the value of R_L. The constraint on travel distance is meant to address these concerns. Also specified is the maximum number of host communities available to origin communities, η. Having multiple potential host communities can lead to confusion among evacuees (McGee et al., 2021). A constraint is also set on the minimum number of origin communities to be served, σ, by a host community. Finally, the set of host communities identified are ensured to have a low total cumulative value of % raster cells with landscape fire exposure of 80% or more, Ω, within 10 km buffer radii. Lower landscape fire exposure of each host community j (ω_j) is also desired.

5.3.2.2 Model Parameters

Wildfire exposure

Using the landscape fire exposure map introduced in CHAPTER 3, Forbes (2021) performed a landscape patch analysis to quantify the landscape fire exposure of each community. A circular buffer of 10 km radius is drawn around each community, and geospatial analysis was performed in ArcGIS to determine the percentage of the community buffer having landscape fire exposure of 80% or more (Beverly et al., 2021; Forbes, 2021). More than half of the ecological units studied by Beverly et al. (2021) contained burned areas with a pre-fire exposure of 80%. Figure 5.7 showed that the southeastern communities of Alberta have no raster cells with landscape fire exposure of

80% or more within their 10 km buffers, and hence are unlikely to experience a forest fire (distinguished from a grass fire, in CHAPTER 2).

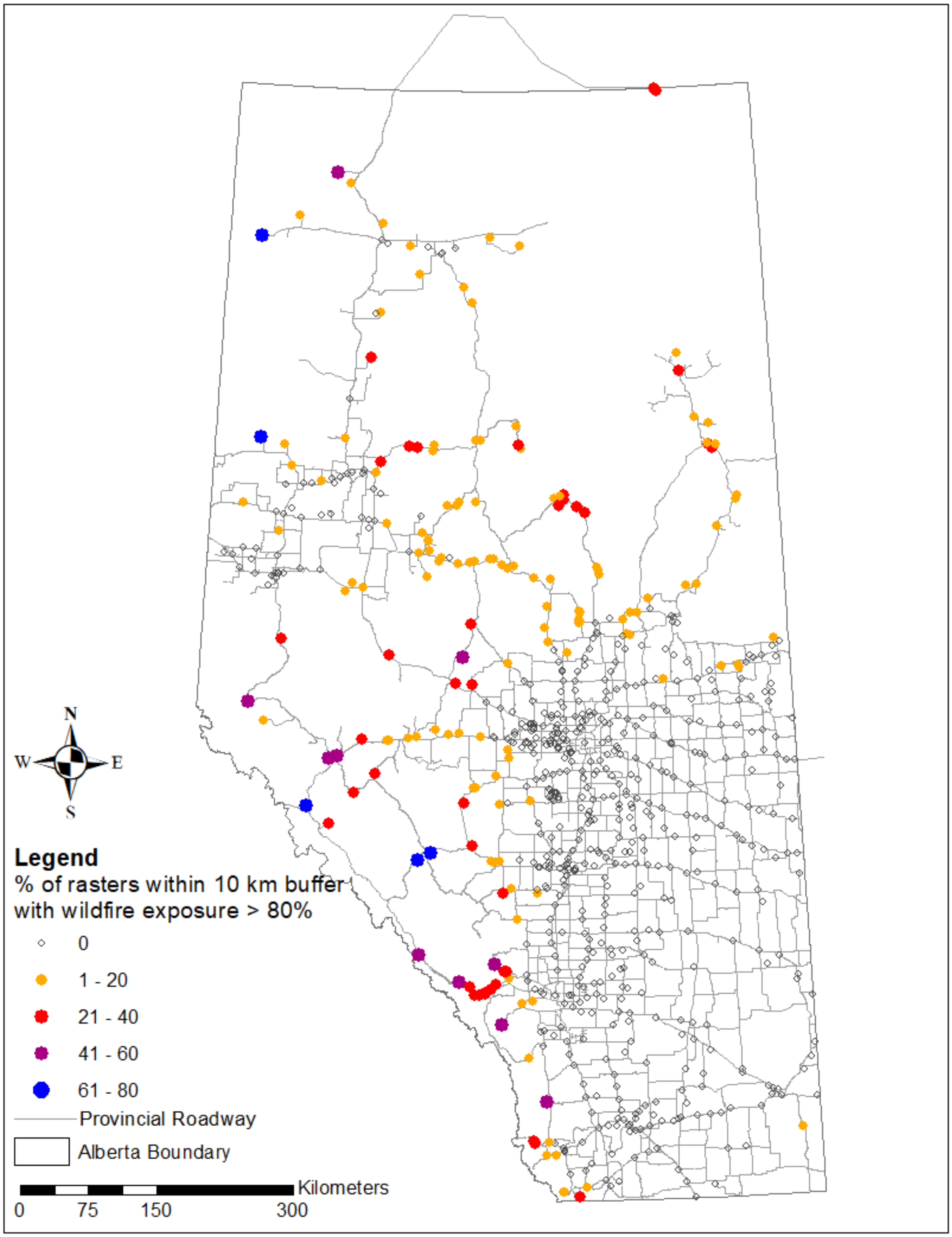

Figure 5.7: Landscape fire exposure around 10 km buffer for 729 communities

These results are used to identify communities with high fire exposure values (i.e., communities with at least one raster cell of 100x100 m^2 with ≥80% exposure) (Figure 5.7) and include them in the origin community dataset (Figure 5.8.a). The landscape fire exposure is also applied as a model constraint to choose destination host communities that have lower landscape fire exposure. The rationale is that host communities should have a low potential for disruption in terms of their own wildfire vulnerability, as they must be available to accommodate evacuees from other communities during wildfire season. Evacuation of a host community could lead to several negative consequences. Evacuees from both the host community itself, and other evacuating communities seeking refuge at the host communities, may not have a host community within a reasonable distance to seek shelter. Also, supplies/infrastructure designated for emergencies may be damaged and unusable.

Origins, destinations, and service centres

A total of 729 communities are represented in the dataset, described in CHAPTER 3. These include designated places (including Hamlets, Métis settlements) in addition to census subdivisions (including cities, Reserves, and towns). Different parameters were used to identify service centres, origin (i.e., potentially evacuating) communities, and destination (i.e., potential host) communities (Figure 5.8) for model inputs.

Origin (evacuating) communities: The raster cell percentage within a 10 km radial buffer of a community is used to filter for origin community selection. Communities with at least one raster cell with landscape fire exposure of 80% or more are selected as the origin communities. Of the 729 communities, 175 communities are selected as origin (i.e., evacuating) communities for the analysis (Figure 5.8.a, Table A-1).

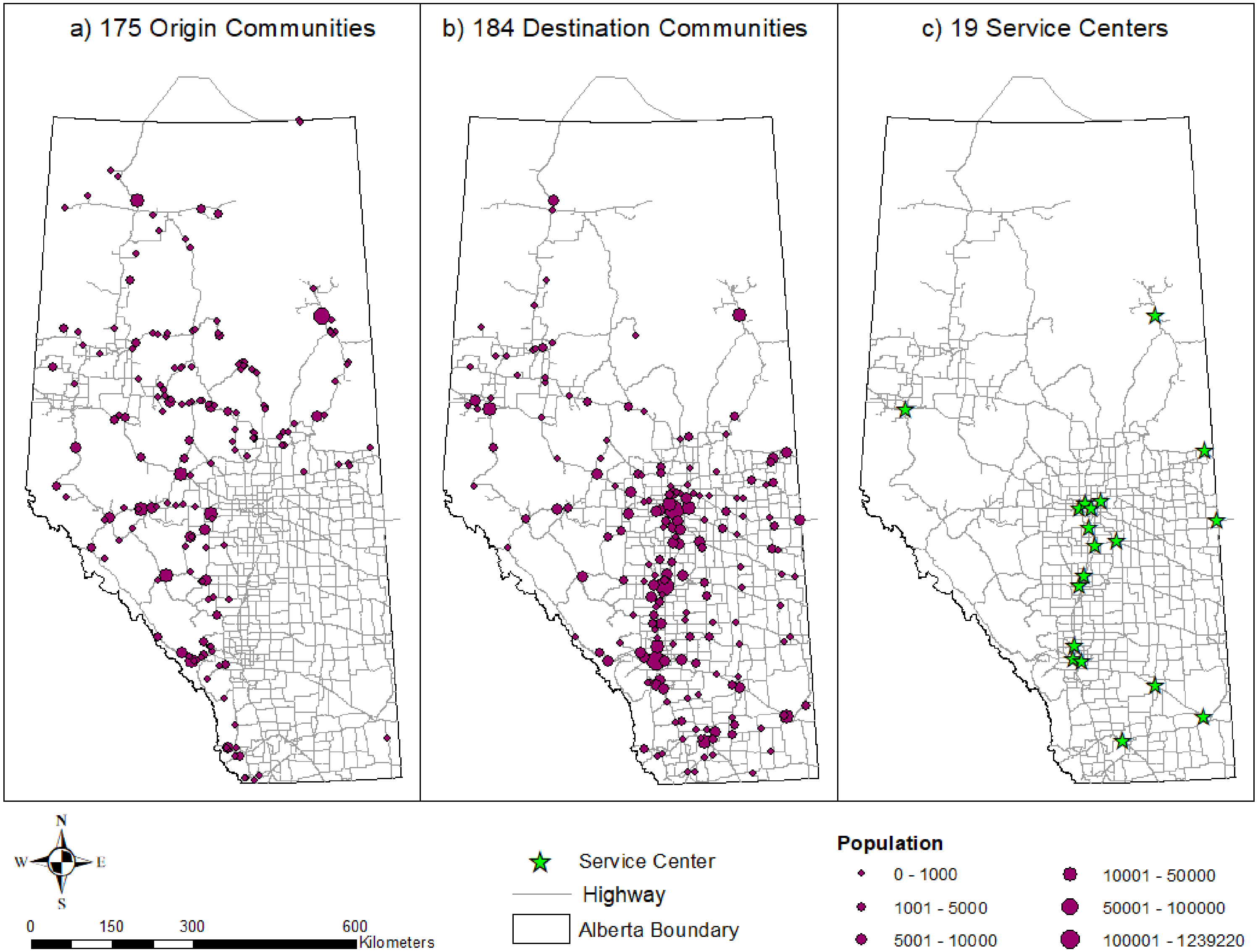

Figure 5.8: Identified communities: a) Origins (evacuating), b) Hosts (destination), and c) Service centres

- **Destination (host) communities**: Alberta's evacuation guidelines state that a host community can accommodate evacuees that number up to 10% of the community's population without reducing service levels to its own population (Government of Alberta, 2018). Of the identified origin communities, 75% have populations less than 3,000. Moreover, without knowing which community will evacuate, wildfire-prone origin communities are assigned a set of potential hosts J with populations of 1,000 or more. Reserves and Métis settlements are also excluded as potential host communities. Finally, 184 candidate host communities ($J = 184$) are identified (Figure 5.8.b, Table A-2).

- **Service centres**: It is assumed that service centres are major urban centres that can provide emergency supplies and services to both evacuating and host communities. For this study, it is assumed that census subdivisions classified as cities can be designated service centres, in addition to Fort McMurray in northeast Alberta (actually designated an Urban Service Area provincially). Figure 5.8.c shows the 19 service centres for the study area, most of which are clustered along Hwy 2 in the centre of the province (where wildfire risk is also low). Also, several cities within the Edmonton and Calgary Capital regions are designated, such that there are actually 13 geographically-distributed service centres. Most origin communities (Figure 5.8.a) are to the north and east of Hwy 2, so they are likely to be assigned to host communities along Hwy 2.

Network topology

Three topological measures – Accessibility Index (AI), Remoteness Index (RI), and Betweenness-Centrality Index (BCI) – consider the relative locations of community nodes in identifying their topological vulnerabilities (Figure 5.9).

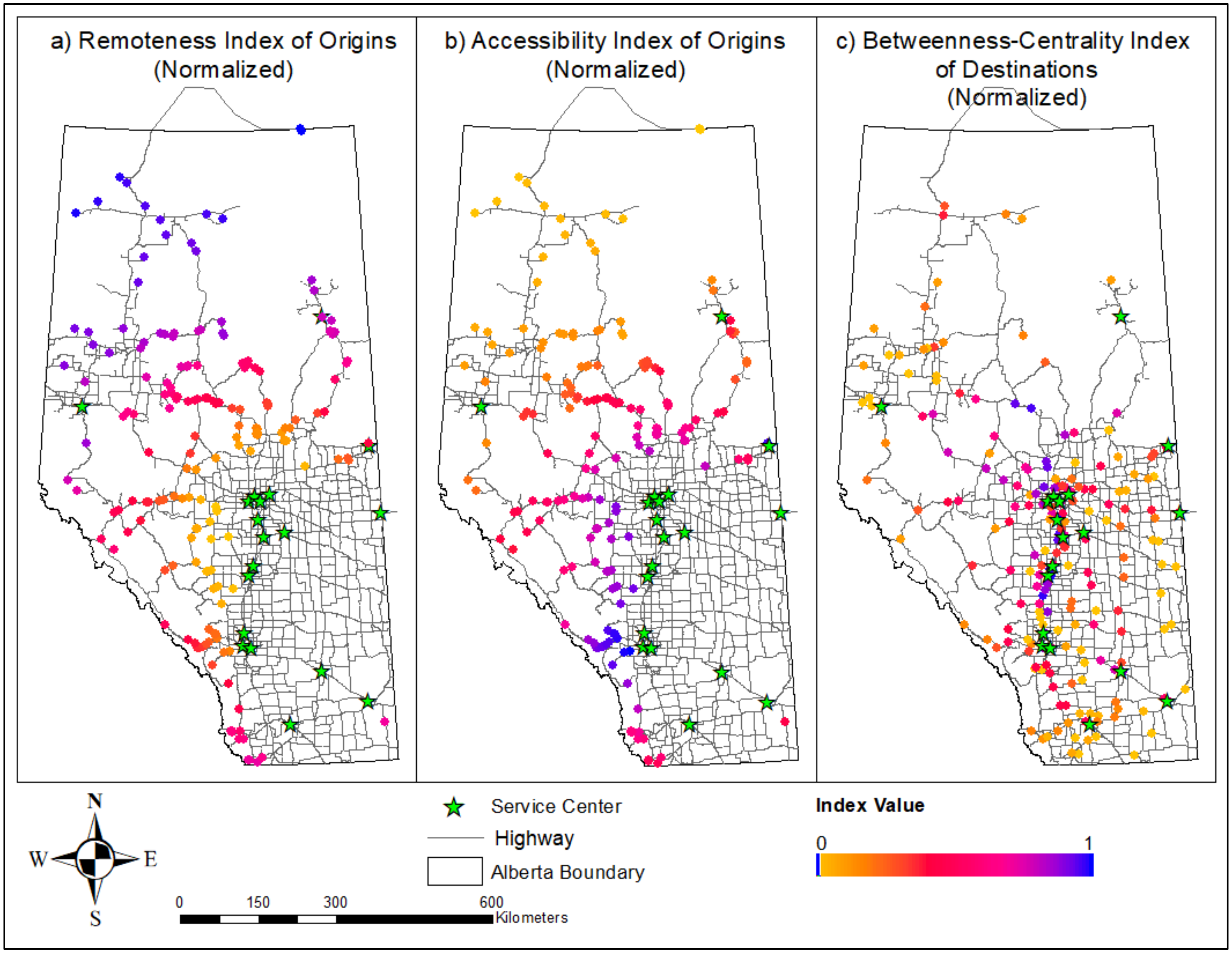

Figure 5.9: Topological measures: a) Accessibility Index of origin communities, b) Remoteness Index of origin communities, and c) Betweenness-Centrality Index of destination communities

Remoteness Index (RI): Taylor and Susilawati (2012) proposed the Accessibility/Remoteness Index of Australia (ARIA) to measure how isolated a community is from the service centres in Australia. Mahajan and Kim (2020) modified ARIA and proposed a Remoteness Index, RI, for Alberta.

$$RI_i = \sum_{s=1}^{S} \frac{d_{is}}{\overline{d_{s\forall\iota}}} \tag{5.23}$$

Here, d_{is} is the travel distance between origin community i and service centre s and $\overline{d_{s\forall\iota}}$ is the average distance between all evacuating communities and service centre s. A high RI indicates that a community is comparatively distant from service centres (and thus supplies and shelter), and is therefore vulnerable during emergencies like wildfires.

The Remoteness Index for each of the 175 origin communities is calculated (Figure 5.9.a). Communities in central Alberta have low RI, as they have multiple service centres within a relatively shorter distance. Moving north, the RI index of each community generally increases.

Accessibility Index (AI): The Accessibility Index is a measure of a community's accessibility to basic defined services. Alasia et al. (2017) defined AI as the logarithmic sum of the ratio of total revenue of the service centres and travel time from an origin community i to service centres.

$$AI_i = \ln\left(\sum_{s=1}^{S} \frac{P_s}{d_{is}}\right) \tag{5.24}$$

Here, d_{is} is the travel distance between origin community i and service centre s, and P_s is the population of s.

A community located closer to a service centre will have a higher Accessibility Index than one located farther away. The general assumption behind the measures introduced above is that a service centre with a higher population likely has more services that are also available to evacuating community members. Therefore, when two communities are located at the same distance to service centres of different sizes (i.e., population), the community located by the larger service centre will have a higher AI.

The accessibility measure by Mahajan and Kim (2020) was applied to the 175 origin communities to determine their accessibility to 19 service centres (Figure 5.9.b). because 16 of 19 service centres are located south of Edmonton, northern communities have very low AI. Communities with high AI are clustered around Edmonton and Calgary, as well as along Hwy 2.

Betweenness-Centrality Index (BCI): Betweenness-Centrality is a widely used measure in network graph theory. Freeman (1977) first introduced the centrality concept and developed the index. Since then, it has been applied to many network analyses (Goremyko et al., 2018; Mahajan and Kim, 2020; Zhang et al., 2011; Zhou et al., 2021). The Betweenness-Centrality Index, BCI, measures how many times a node (in this case, centroid connector node of a host community, j) fall on the shortest path between evacuating communities and service centres.

$$BCI_j = \frac{\sum_{i=1}^{I} \sum_{s=1}^{S} n_{is}^{j}}{\sum_{i=1}^{I} \sum_{s=1}^{S} n_{is}}, j \neq i; i \in I, j \in J, s \in S \tag{5.25}$$

Here n_{is}^{j} = 1 if the shortest path from community i to service centre s passes through potential host community j, and 0 otherwise; and n_{is} = 1 if community i and service centre s are connected, and 0 otherwise. The BCI values for 184 potential host communities are determined, and it is observed how centrally they are located between the evacuating communities and service centres. Figure 5.9.c shows that communities with the highest BCI values are along Hwys 2 and 43, such that these two highways are along many shortest paths between communities and service centres.

After considering all the measures introduced, RI and BCI were chosen for inclusion as model objectives. Consideration of RI, by weighting evacuating community populations with it, will help prioritize the smaller wildfire-prone communities in the north with higher RI values. The inclusion of BCI will lead to host communities being located centrally between the 175 potential evacuating communities and 19 service centres.

5.3.2.3 Notation

Sets:

I	Set of origin community centroids; $i \in I;\ I = \{1, 2, \dots, i\}$
J	Set of Potential host community centroids; $j \in J;\ J = \{1, 2, \dots, j\}$

Decision variables:

X_j	1 if the j^{th} community is selected as the host community, 0 otherwise
Z_i	1 if the i^{th} community is served by a host community within coverage radius, 0 otherwise

Parameters:

P_i	Population of origin community i
RI_i	Remoteness Index (normalized) of the origin community$i$
BCI_j	Betweenness-Centrality Index (normalized) of the potential host community j
ω_j	Percent (%) of raster cells with landscape fire exposure more than 80% within a 10 km radius of potential host community j

Ω	Cumulative landscape fire exposure of selected host communities
η	Maximum number of host communities assigned to each evacuating community
σ	Minimum number of evacuating communities to be served by a host community
δ_{ij}	Coverage radius check: 1 if $R_L \leq d_{ij} \leq R_U$, 0 otherwise
R_L	Lower limit of coverage radius of host communities (km)
R_U	Upper limit of coverage radius of host communities (km)
d_{ij}	Travel distance between origin community i and host community j (km)
y_{ij}	Matrix for allocation check; 1 if $X_j * Z_i = 1$, 0 otherwise

5.3.2.4 Model Formulation

The following multi-objective model is defined to locate host communities:

$$\text{Max } f_1 \qquad \sum_{i=1}^{I} P_i RI_i Z_i \tag{5.26}$$

$$\text{Max } f_2 \qquad \sum_{j=1}^{J} BCI_j X_j \tag{5.27}$$

$$\text{Min } f_3 \qquad \sum_{j=1}^{J} X_j \tag{5.28}$$

$$\text{Subject to} \qquad \sum_{j=1}^{J} \delta_{ij} X_j \geq Z_i, \qquad \forall i \tag{5.29}$$

$$\sum_{i=1}^{I} \delta_{ij} X_j \geq \sigma X_j, \qquad \forall j \tag{5.30}$$

$$\sum_{j=1}^{J} \delta_{ij}\, y_{\mathrm{ij}} \leq \eta, \qquad \forall i \tag{5.31}$$

$$\sum_{j=1}^{J} \omega_j X_j \leq \Omega \tag{5.32}$$

$$X_j,\ Z_i \in \{0,1\}, \qquad \forall i,\ \forall j \tag{5.33}$$

The first objective (Eq. 5.26) maximizes the total population (weighted by RI) of the potential evacuating communities covered by host communities. The second objective (Eq. 5.27) maximizes the total BCI of the selected host communities, to locate them on the highway network between potential evacuating communities and service centres as centrally as possible. The third objective (Eq. 5.28) minimizes the number of host communities. This is minimized in lieu of setting an upper constraint for two reasons. First, identification of a community as a potential host does not necessarily mean new infrastructure is required, but rather, that existing infrastructure is utilized towards evacuee hosting. Second, fewer hosts would cost less to administer (including coordination between the evacuating communities, host communities, and service centres) and reduce the decision space in emergencies.

The constraints are as follows. Eq. 5.29 ensures that evacuating community i is assigned to at least one host community j within the coverage radius. Eq. 5.30 ensures that each host community is matched to a minimum of σ evacuating communities. Eq. 5.31 stipulates that an evacuating community is assigned to no more than η eligible host communities because McGee et al. (2021) found that assigning evacuees to a greater number of host communities is more likely to lead to confusion. Embedded within these three constraints is the requirement that the travel distances between an evacuating community and their identified host communities are within an acceptable range. The longer evacuees must travel, the more likely they are to run out of fuel and other supplies. On the other hand, destinations too close to the origin could end up under threat from the same wildfire (a threat which is exacerbated by the fact that wildfires can grow quickly and unpredictably depending on winds and other factors). The above is accounted for by ensuring distances d_{ij} are within lower R_U and upper R_L bounds.

Eq. 5.32 ensures that the cumulative number of exposure patches (with landscape fire exposure of 80% or more, as discussed in 0) for selected host communities within their 10 km buffer radii is limited to a predefined value, Ω. This is meant to lower the likelihood of host communities themselves being vulnerable to wildfire, such that any stored supplies remain safe, and services are available to host evacuees from other communities i. Finally, Eq. 5.33 defines decision variables to be binary, thus making the model a binary integer linear program (BILP).

The NSGA-II algorithm has been shown to generate a diverse solution set close to true Pareto optimal (OuYang et al., 2008), and it is used to solve the above model. The model is executed using the *pymoo 0.5.0* framework in Python 3.8.8 (Blank and Deb, 2020). For this problem, each chromosome has two parts; the first represents the origin communities' coverage status, Z_i, and the last represents the potential host communities' selection status, X_j. Recall that both Z_i and X_j are binary variables.

The initial population (i.e., set of chromosomes of NSGA-II model) is selected by random sampling of the binary decision variables. The genetic crossover is achieved through half-uniform binary crossover, which evaluates the different indices between parents and selects half the differences to form offspring. Since the genes of the chromosomes are binary in the BILP model, the bit of the gene is flipped (0 to 1 or 1 to 0) to achieve mutation. With iterations, the generated new offspring (solutions) get higher fitness values – closer to true Pareto solutions. The termination criteria are set such that the offspring generation ends after 10,000 iterations as the change in the objective values of the solutions gets minimal after 10,000 iterations in this experiment. 10,000 iterations of the model are completed in about 550 seconds on a PC with Intel® Core (TM) i7-10700KF CPU @ 3.80GHz processor and 32GB RAM.

5.3.3 Results

The model is first tested with different parameter values, to explore their effects on the results. This informed parameter choices for further model runs, from which a Pareto front of solutions is generated. Then the Pareto solutions are explored using cluster analysis. The idea is to help decision-makers narrow down the solution space by first choosing cluster(s) that align with their current (and possibly shifting) priorities, and then further investigating solutions within the cluster before selecting one.

5.3.3.1 Parameter Exploration

Explorations of parameters R_U (upper coverage radius limit), η (maximum number of assigned host communities per origin community), σ (number of covered communities by a host community), and Ω (cumulative % of raster cells of landscape fire exposure around host communities), as well as the rationale for choosing values are presented.

The lower limit of coverage radius, R_L, is set at 30 km based on the average wildfire perimeter since 1990 (Alberta Agriculture and Forestry, 2019). An R_U of 100 km is increased at 10 km intervals up to 200 km. Figure 5.2 and Figure 5.3 showed that the population coverage and travel distance do not change significantly beyond $R_U = 200$ km. Values of both η and σ between 1 to 6 are explored. Ω values between 0.1 to 1, at 0.1 increments, are also explored. The rationale for choosing these bounds is that objective function values do not appear to change significantly beyond them. The results of these tests are shown in Figure 5.10.

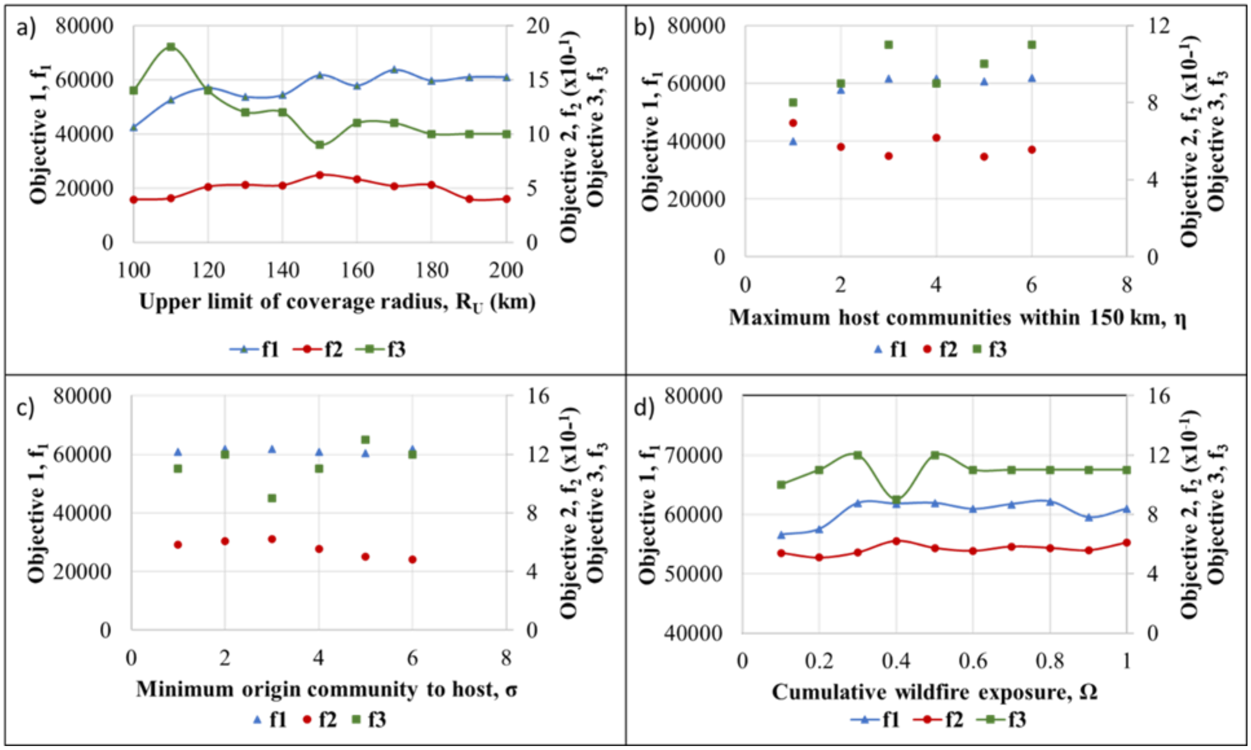

Figure 5.10: Objective sensitivity with parameter variation; a) R_U, b) η, c) σ, and d) Ω

The left-side y-axes in the plots of Figure 5.10 measure Objective 1 (f_1), the results which are represented by blue triangles for the values of each parameter. The red circles and green squares represent Objectives 2 (f_2) and 3 (f_3), respectively, with values measured on the right-side y-axes. Figure 5.10.a shows that f_1 generally increases and f_3 generally decreases with increasing R_U (upper limit of coverage radius). Objective f_2 increases to a maximum of 150 km, after which it decreases. Beyond $R_U = 180$ km, values for the three objectives do not change. This is due to the violation of the constraint of Eq. 5.31 because after 180 km the origin communities have more than η host communities available to them. Increasing η expands the feasible region, such that a resulting increase in f_1 is observed. Figure 5.10.b confirms that at a fixed upper radius (e.g., R_U=150 km), f_1 increases as η increases. Also, beyond $\sigma = 3$ (Figure 5.10.c), a decrease in f_2 is observed with increasing σ due to the constraint that a community needs to serve more evacuating communities to be eligible as a host (Eq. 5.30). As Ω increases (Figure 5.10.d), more communities (including northern communities with higher landscape fire exposure) become eligible as host communities. However, this also allows for more communities in the north to be covered, as seen by an increasing f_1.

From Figure 5.10.a, it is observed that one can achieve desired higher values for f_1 and f_2, and lower value for f_3, at an upper coverage radius of 150 km. Next, it is seen that with a smaller number of host communities (f_3), one can achieve higher coverage (f_1) with $\eta = 4$, $\sigma = 3$, and $\Omega = 0.4$. Therefore, the author proceeds with these parameters to obtain Pareto solutions.

5.3.3.2 Pareto Solutions Exploration

The model is solved with different seed values to plot the Pareto front of Figure 5.11 (Mazza et al., 2016). Figure 5.11 shows 1,200 non-dominated Pareto solutions with the abovementioned parameter values. The solutions cover a wide range. Objective 1 (f_1, total weighted population) covers 55-72% of the population within wildfire-prone communities. Objective 3 (f_3, total host communities) ranges from 9 to 66. With a low f_3, a high value of Objective 2 (f_2, total host community BCI) can be obtained only if the selected host communities have high BCI values (i.e., are centrally located). Conversely, with high f_3, low BCIs from a larger number of host communities cumulatively increase the value of f_2.

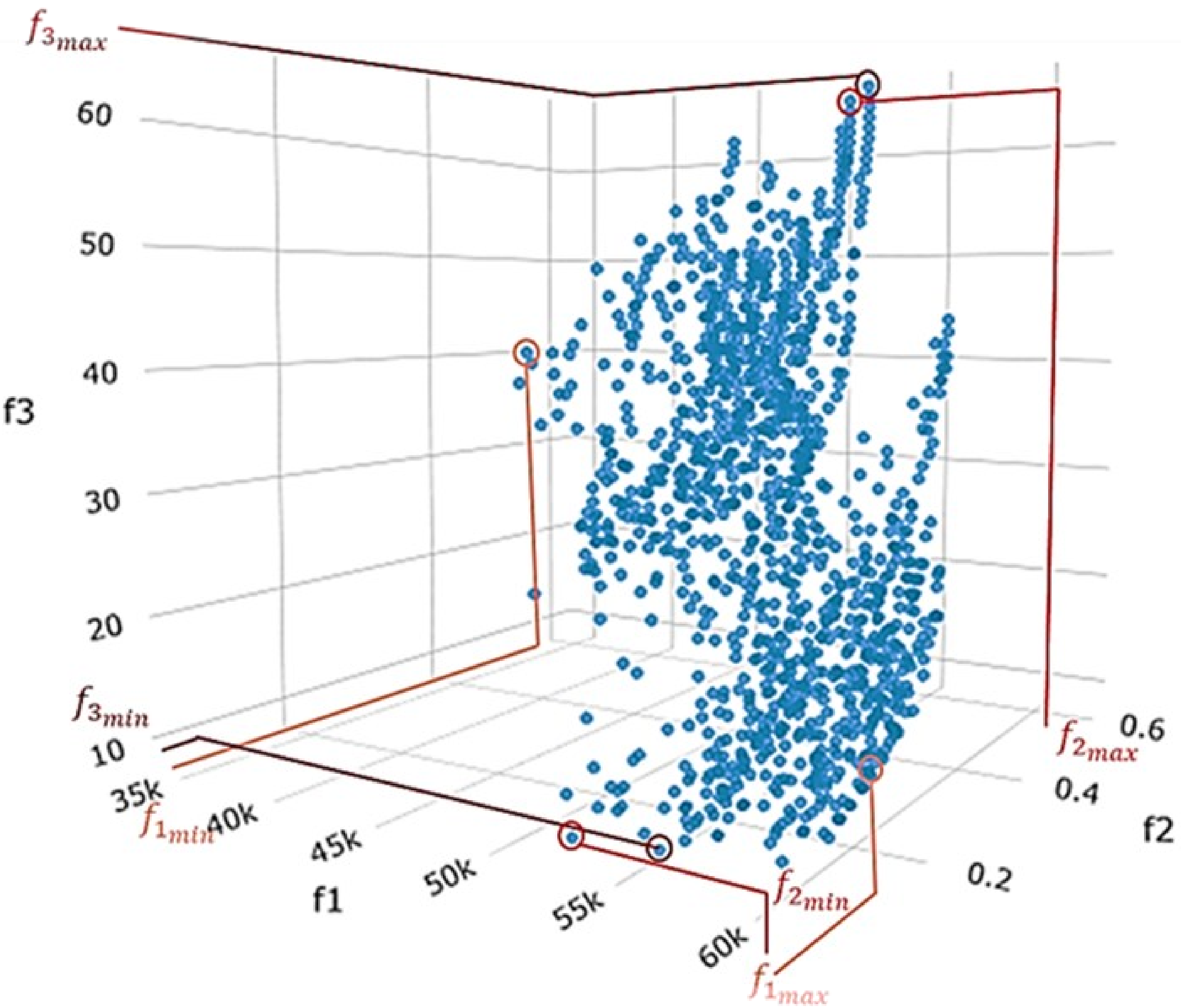

Figure 5.11: Pareto front of solutions

Each Pareto solution identifies different combinations and numbers of host and origin communities. Figure 5.12 shows how frequently a community is covered by a host community and Figure 5.13 shows how frequently a host community is selected, within the 1,200 Pareto solutions.

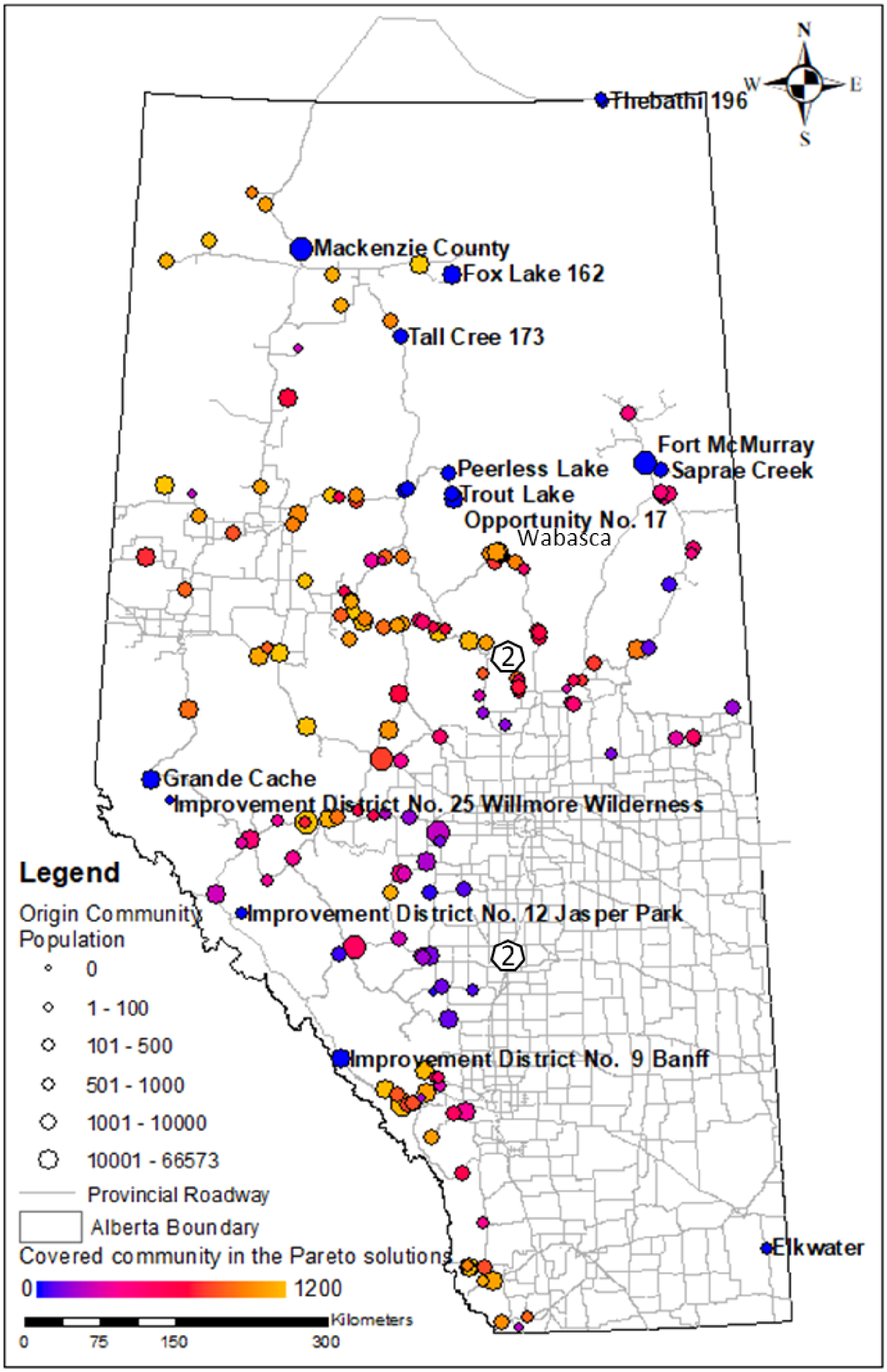

Figure 5.12: Frequency of origin community coverage within 1,200 Pareto solutions

Figure 5.12 shows that 17 origin communities have never been covered by a host community in any of the Pareto solutions with the given parameter values. Five of these communities (Thebathi 196, Thebacha Náre 196A, Improvement District No. 12 Jasper Park, Improvement District No. 25 Willmore Wilderness, and Elkwater) have populations of less than 100, while six (Fort McMurray, Grande Cache, Opportunity No. 17, Mackenzie County, Fox Lake 162, and Improvement District No. 9 Banff) have populations of 1,000 or more. With a population of 66,573, Fort McMurray constitutes more than 20% of the total population of wildfire-prone communities. However, it is unique insofar as it is highly remote for having such a large population, and thus does not have any potential host communities among the 184 destinations within the 150 km coverage radius. The closest potential host community for Fort McMurray is Lac la Biche County located 237 km away, although the latter would be entirely unable to accommodate the population of the former. With such a large population, Fort McMurray cannot be covered by a single community. Edmonton and Calgary are the only viable hosts for Fort McMurray; during the 2016 Fort McMurray evacuation, evacuees were eventually directed to Edmonton for shelter and assistance (McGee, 2019). The model is limited in its ability to handle this special case of Fort McMurray and thus will be further investigated.

Figure 5.13 illustrates how frequently a community is selected as a host. Sixteen host communities are identified in 75% of the Pareto solutions, with 9 of 16 along Hwy 2. These host communities not only have larger populations, making them good candidates to accommodate more evacuees, but they are located on the most significant highway corridor in the province and thus have high BCI values. Table 5-2 lists the 16 communities most frequently selected as host communities.

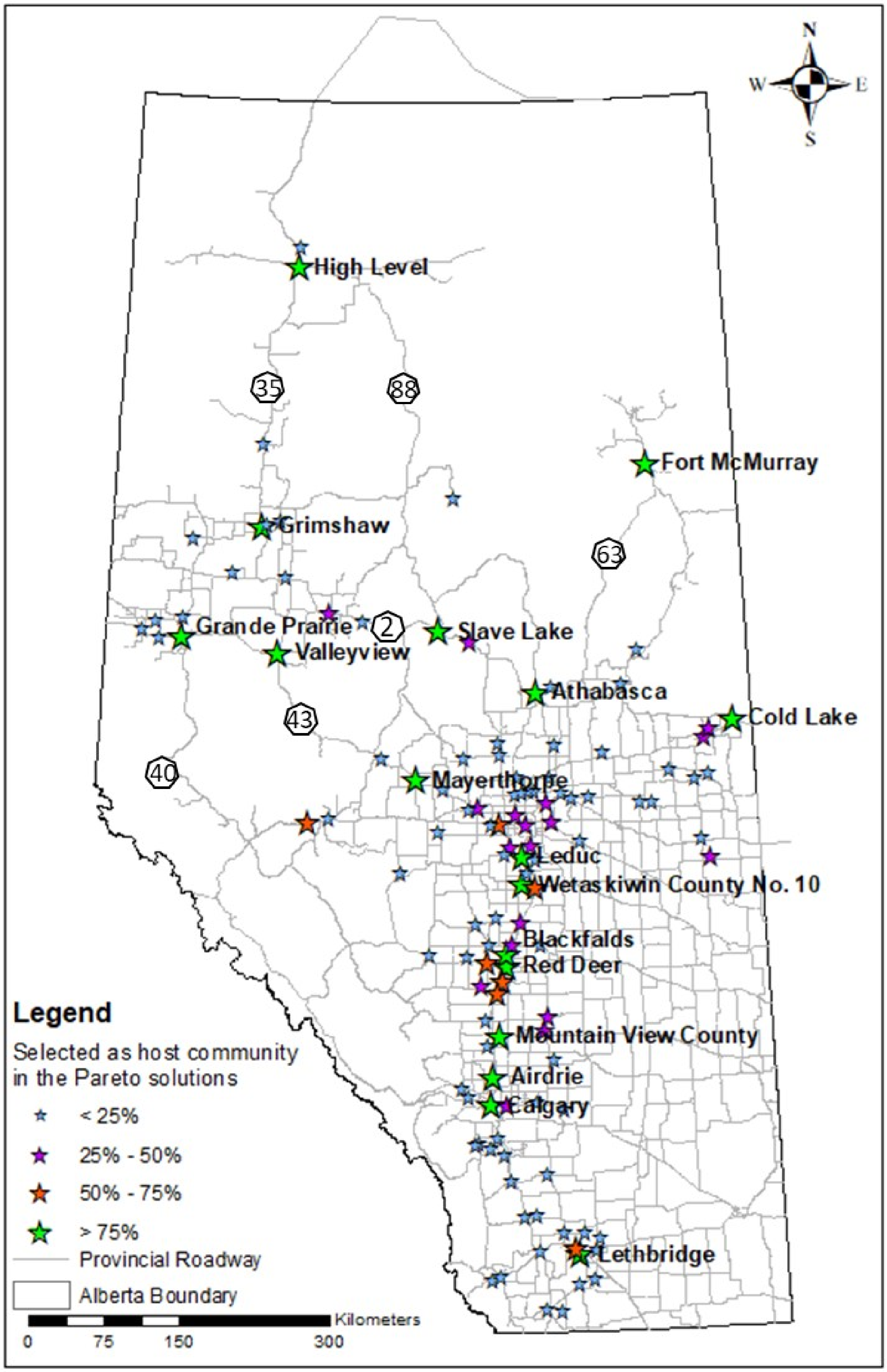

Figure 5.13: From Pareto solutions, the frequency of host community being selected

Table 5-2: Host Communities Identified in 75% of Pareto Solutions

Sl. No.	*Community Name*	*Frequently of selection in Pareto solutions*	*2016 Census Population* (Statistics Canada, 2017e)
1.	Slave Lake	1200	6,651
2.	High Level	1200	3,159
3.	Mayerthorpe	1198	1,320
4.	Lethbridge	1195	92,729
5.	Airdrie (Calgary Metropolitan Region)	1194	61,581
6.	Grande Prairie	1155	63,166
7.	Red Deer	1134	100,418
8.	Leduc (Alberta Capital Region)	1102	29,993
9.	Grimshaw	1043	2,718
10.	Blackfalds	1037	9,328
11.	Athabasca	986	2,965
12.	Valleyview	978	1,863
13.	Wetaskiwin County No. 10	968	11,181
14.	Mountain View County	958	13,074
15.	Cold Lake	951	14,961
16.	Calgary	932	1,239,220

As shown in Table 5-2, High Level and Slave Lake are selected as host communities in every Pareto solution. Airdrie, Red Deer, Lethbridge, Leduc, and Blackfalds are chosen in 1,000 or more solutions and are located along Hwy 2. Hwy 2 is a major highway connecting Edmonton and Calgary in the centre of Alberta and falls on the shortest path of many origin communities. Communities along this highway have a high BCI value, and thus, host communities are clustered in this corridor. Additionally, Edmonton and Calgary are selected in 516 and 932 of the solutions, respectively. Edmonton, the provincial capital of Alberta, falls within the coverage radius of 150 km for eight communities only. However, neighbouring communities that are part of the Alberta Capital Region, such as Leduc, Fort Saskatchewan, or Strathcona County, are within the set radius of many potential evacuating communities. This explains the lower number of Pareto solutions in which Edmonton is selected as a host. However, anytime a city within the Alberta Capital Region is selected as a host, it can be considered that the Edmonton area is selected; as such, the Edmonton area is identified as a host in every Pareto solution. Similarly, Calgary and neighbouring cities like Airdrie and Strathmore comprise the Calgary Metropolitan Region and are similarly identified in every Pareto solution.

5.3.3.3 Clustering Analysis of Solutions

Clustering analysis can help understand the structure of the Pareto front, by reducing the dimension of the solution set and facilitate organizing, comparing, and ultimately choosing a solution. Clustering analysis partitions data points into sub-classes or clusters that are as homogeneous as possible within a chosen feature. Because clustering analysis reduces the dimension of the solution set to facilitate decision-making, information can be lost in the process. Also, clusters may mask (or at least not highlight) the unique characteristics of specific solutions that would be of interest. It is important to note that clustering analysis is only one method of several to assess and organize results.

K-means clustering is chosen as it is one of the simplest and most widely used methods. K-means clustering groups and distributes data points of similar characteristics into k predefined clusters, based on the Euclidean distances between data points and cluster centres. The Elbow method is used to determine k, which involves calculating and plotting the sum of the average Euclidean distance of datapoints and cluster centres for varying k values (Marutho et al., 2018). The optimal k, or elbow, is identified where an increase in k leads to a diminishing increase in the percent of variance explained. Since Euclidean distance is used across all attributes (i.e., the objectives f_1, f_2, f_3) for clustering, the Pareto solutions' objective values are normalized (Kumari et al., 2016).

The Elbow method in *RStudio* was used to determine that $k = 4$ (Figure 5.14.a). Then, using the *factoextra* package, the Pareto solutions are distributed into four clusters (Kassambara and Mundt, 2017) (Figure 5.14.b-d). The idea is that a decision-maker can first identify the cluster that best aligns with their priorities and policies, to reduce their decision space in selecting a final solution from the cluster.

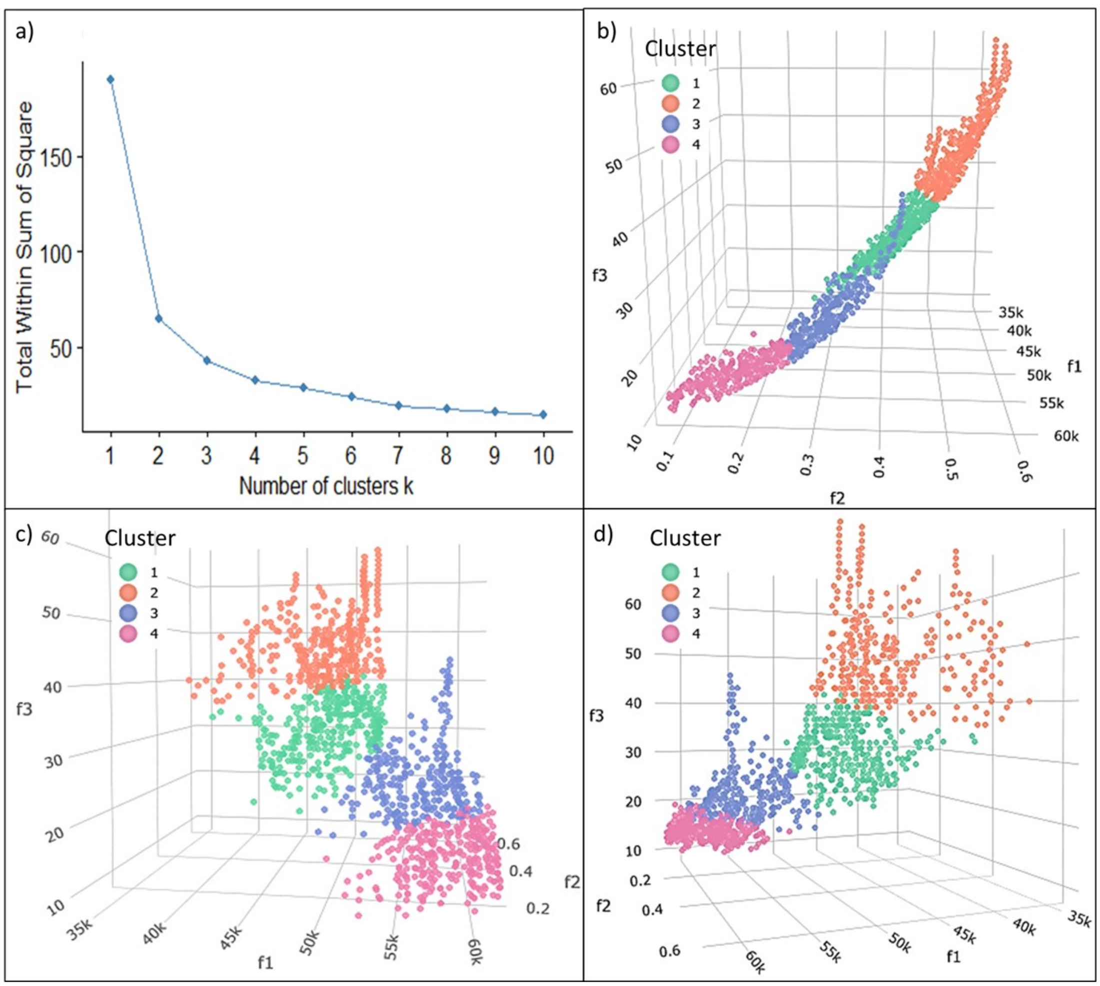

Figure 5.14: Result of clustering analysis. a) Optimum k-means cluster, b) Pareto front view 1, c) Pareto front view 2, d) Pareto front view 3

Figure 5.14.b-d show the Pareto front with non-dominated solutions clustered into four groups, from different angles. Cluster 2 solutions have large sets of host communities, totalling a high

overall Betweenness-Centrality (BCI). Host communities identified in the solutions of Cluster 4 yield the highest values for Objective 1 (f_1), and cover 65% to 72% of the population with a lower number (i.e., 9 to 21) of host communities. One reason Cluster 2 has a lower value of Objective 1 can be explained by the constraint of Eq. 5.31. An origin community is considered covered by a host community if and only if 1-4 (i.e., $\eta = 4$) host communities are within the defined radius. This constraint is used because Objective 2 (f_2) increases when additional host communities are assigned to an evacuating community that is already covered by one or more hosts. Thus, the constraint ensures that additional host communities are not identified only to increase the value of Objective 2, and with > 4 host communities, an evacuating community is not considered covered. The number of host communities is high in Cluster 2; therefore, many origin communities have more than four host communities within their search radius. The value of the covered population during post-processing is adjusted by introducing a binary variable to origin communities, to check if there is a host community available within the coverage radius. If the origin community has one or more host communities, the community population is considered covered. Thus, the coverage of Cluster 2 solutions is updated and found to be increased to 70% or more. Cluster 1 has a high value for f_2 with fewer host communities (i.e., low f_3), but achieves a lower value of f_1 (Figure 5.14.c). Cluster 3 can cover 67% of the population with fewer centrally located (i.e., high f_2) host communities. Also, solutions in Cluster 4 have lower f_3 and therefore, it is likely that evacuating communities will have access to fewer host communities than that of Cluster 2.

Decision-makers can decide on clusters and then determine which cluster's solutions best fit their current needs and policies. For example, if the priority is to identify and designate as few host communities as possible due to resource limitations, solutions in Cluster 4 may be of the highest interest for further investigation. However, if their aim is to consider all three objectives as equally as possible, solutions from Clusters 1 or 3 would be considered.

5.3.3.4 Model Limitations

First, the model does not include a capacity constraint for the host community. In the case of a large wildfire affecting multiple neighbouring communities, the designated host communities might have insufficient capacity to host all evacuees. However, the inclusion of a host community capacity constraint could have limited value, given that the number of communities that could be impacted by the same wildfire at the same time, requiring evacuation, is unknown. Furthermore, an example of an extreme situation is the evacuation of Wood Buffalo Region and Fort McMurray; with a population of over 66,000 in the last census (Statistics Canada, 2017f), no host community (or even set of communities) within the coverage radius threshold can accommodate this population should it need to evacuate (as it did in May 2016). The only viable hosts are Edmonton and Calgary (McGee, 2018), and many evacuees (approximately 50% of participants of a survey conducted by McGee (2019)) did go to Edmonton during the 2016 wildfire evacuation. Second, the model does not allow the evacuees of a community to be split amongst multiple hosts. Although it was discussed earlier that directing evacuees to multiple destinations could be confusing and also, difficult to broadcast (McGee et al., 2021), the flexibility to allow for this may be explored in the future. Third, the model also does not account for interprovincial evacuation, as it limits host communities to those located within the province. Evacuees from border communities may choose to travel to communities in neighbouring jurisdictions (Provinces of British Columbia and Saskatchewan; the Northwest Territories). Finally, the model does not account for the fact that some number of evacuees (possibly significant, depending on a number of factors) will travel significant distances to the larger cities and towards friends and family, instead of the host community to which they are directed.

5.4 SUMMARY

This chapter explores different single objective facility location models to locate host communities for wildfire evacuation across Alberta. Results from three models are biased toward large communities in central Alberta as the model objectives are weighted against community population. Thus, the northern small communities which encountered a high number of wildfires in the past and have limited access to the network for evacuation will have to travel long distance for reaching safety in the event of a wildfire breakout. Observing this limitation of the single objective optimization models, a multi-objective facility location model is proposed. The MOO model eliminated the biasedness against the remote communities by introducing RI and BCI as model parameters. The model also applies landscape fire exposure to account for wildfire exposure of the communities of Alberta. The model yielded a Pareto front of 1200 solutions that are grouped into four clusters to reduce the dimension of the solution. In the following chapter, solutions from different clusters are explored and one solution is selected to locate the host communities across Alberta.

CHAPTER 6. HOST COMMUNITIES AND NETWORK VULNERABILITY

This chapter presents a case study that brings together the analyses proposed in CHAPTER 4 and CHAPTER 5, in a post-processing exploration. First, it is determined which potential evacuating communities of the selected solution from CHAPTER 5 have coverage and which do not. Designated host communities are identified and matched to the covered evacuating communities. For potential evacuating communities not covered by the model, the nearest host communities are identified. Finally, for all community pairs identified, critical highway locations are found using the network scanning method of CHAPTER 4.

6.1 EXAMPLE SOLUTIONS

Depending on the final solution chosen from the optimal solutions of Figure 5.11, evacuating origin community coverage (and thus, the potential evacuating population) varies. For example, Calling Lake and its surrounding communities will be covered if the selected Pareto solution identifies Athabasca as a host community; Calling Lake cannot be covered otherwise. As discussed in CHAPTER 5, the purpose of the clustering analysis is to help understand the defining characteristics of the solutions on each cluster, how clusters compare against one another, and reduce the decision-space in choosing solutions that align with current policies, priorities, and resource availability. To explore how solutions from different clusters compare in terms of host community numbers/locations and evacuating community coverage, solutions near the centroids of Clusters 1 and 4 are selected and mapped in Figure 6.1.

Figure 6.1.a shows the 30 host communities identified by a Cluster 1 solution (with f_1=49,747, f_2=0.41, and f_3=30). Figure 6.1.b shows the 13 host communities from a Cluster 4 solution

(f_1=61,501, f_2=0.13, and f_3=13). Recall f_1 represents the total population of covered origin communities weighted by RI (maximized), f_2 is the total BCI of the selected host communities (maximized), and f_3 is the number of host communities (minimized). The sizes of the markers for the evacuating communities represent population, while the colours illustrate the number of host communities available to each evacuating community within 150 km travel distance.

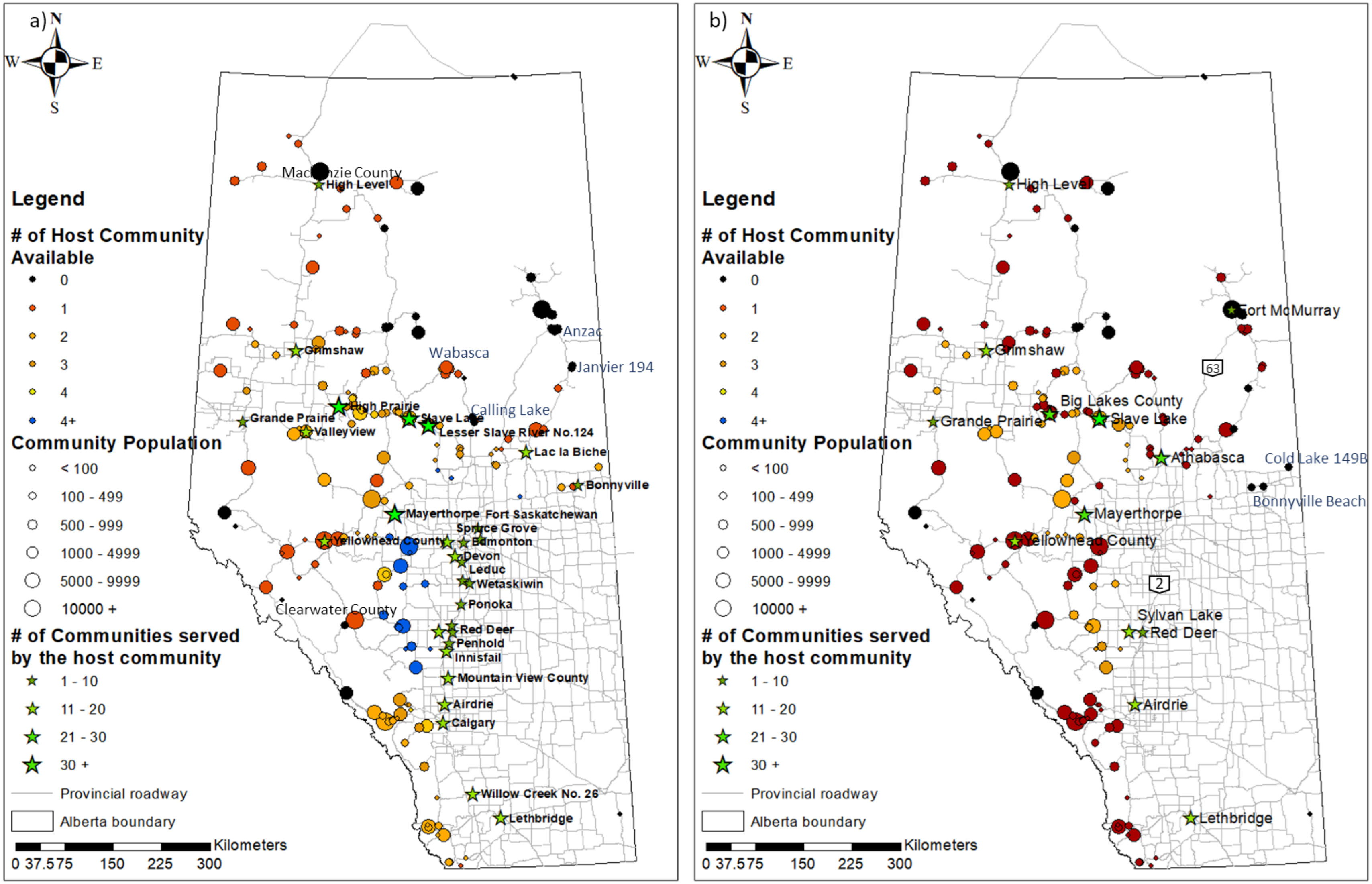

Figure 6.1: Community coverage and host community locations of Pareto solution in a) Cluster 1 (left side) and b) Cluster 4 (right side)

In the Cluster 1 solution, 19 of the 30 host communities are along Hwy 2 and thus have higher BCI values, which in turn contributes to high values for f_2 (the cumulative BCI of the selected host communities). The two solutions cover 70% and 71.5% of the potentially evacuating population (if excluding Fort McMurray, about 90% and 91.5%), respectively, indicating a higher number of host communities does not necessarily mean higher population coverage. Although communities around Bonnyville and Cold Lake are covered, some relatively larger communities like Anzac and Calling Lake are not covered in the selected solution from Cluster 1. These two origin communities are covered by Fort McMurray and Athabasca in the selected solution from Cluster 4 (Figure 6.1.b). On average, each origin community in the selected solution of Cluster 1 has more alternate host communities (more than four, in some cases) than those of Cluster 4. Moreover, the Pareto solution from Cluster 4 covers more of the population with a smaller number of host communities. This solution is selected for further investigation.

Table 6-1 lists some important characteristics of the 13 host communities identified, and Figure 6.2 shows the host community assignment to origin communities, both in the Cluster 4 solution.

Table 6-1: Host Communities (13) in Example Cluster 4 Pareto Solution

Host Community	*Total Origin Communities Served*	*% Raster Cells with High Landscape Fire Exposure, ω_j*	*Access Points at 10 km*
Lethbridge	11	0	7
Airdrie	20	0	6
Red Deer	10	0	10
Sylvan Lake	11	0	5
Fort McMurray	7	8	3
Mayerthorpe	21	0	5
Athabasca	21	0	5
Yellowhead County	13	11	2
Big Lakes County	22	7	2
Slave Lake	34	7	3
High Level	9	0	4
Grande Prairie	8	0	6
Grimshaw	14	0	6

Table 6-1 lists the number of origin communities serves by each host community (Figure 6.2), landscape fire exposure for the host community (Figure 6.3), and the number of access points to the host community at a 10 km radius buffer (Figure 6.3). Fort McMurray, Grande Prairie, and High Level serve less than 10 communities each, all of which are remotely located in the northern part of the province and/or are reserves with limited access to the road network. These three host communities serve as the sole host for the majority of the origin communities assigned to them. Slave Lake, Mayerthorpe, Big Lakes County, Athabasca, and Airdrie serve 20 or more origin communities each, and nearly all these origin communities have alternative hosts identified. It should also be noted that not all evacuees will necessarily seek shelter in (or even temporarily travel to) the host community to which they are directed. Some will travel to larger cities like Edmonton and Calgary, or elsewhere (including neighbouring provinces), possibly towards friends and family. Finally, nine of the 13 host communities have no raster cells with high landscape fire exposure surrounding them (i.e., $\omega_j = 0\%$), indicating that they are less likely to experience wildfire themselves.

The 13 host communities identified cover 71.5% of the population located within wildfire-prone communities of Alberta (again, closer to 91.5% of the population excluding that of Fort McMurray). Among the 151 covered communities, 43 communities have two or more hosts assigned to them. The remaining 108, as shown in Figure 6.1.b and Figure 6.2, are each assigned to only one host community within the coverage radius. Figure 6.3 shows the locations of the host communities, with the 10 km buffer radius and access points around each centroid indicated as well as landscape fire exposure.

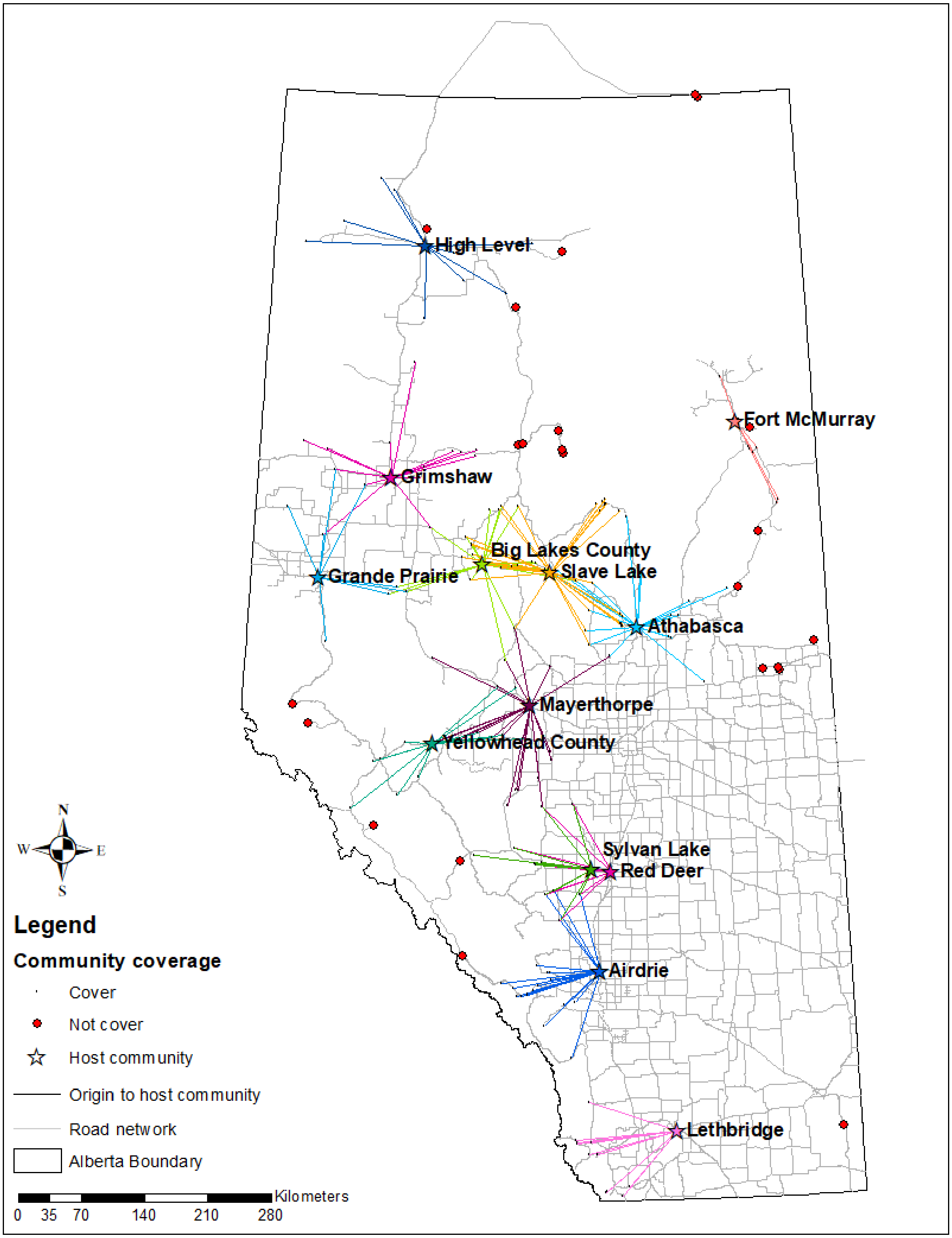

Figure 6.2: Designated host communities in example Cluster 4 Pareto solution

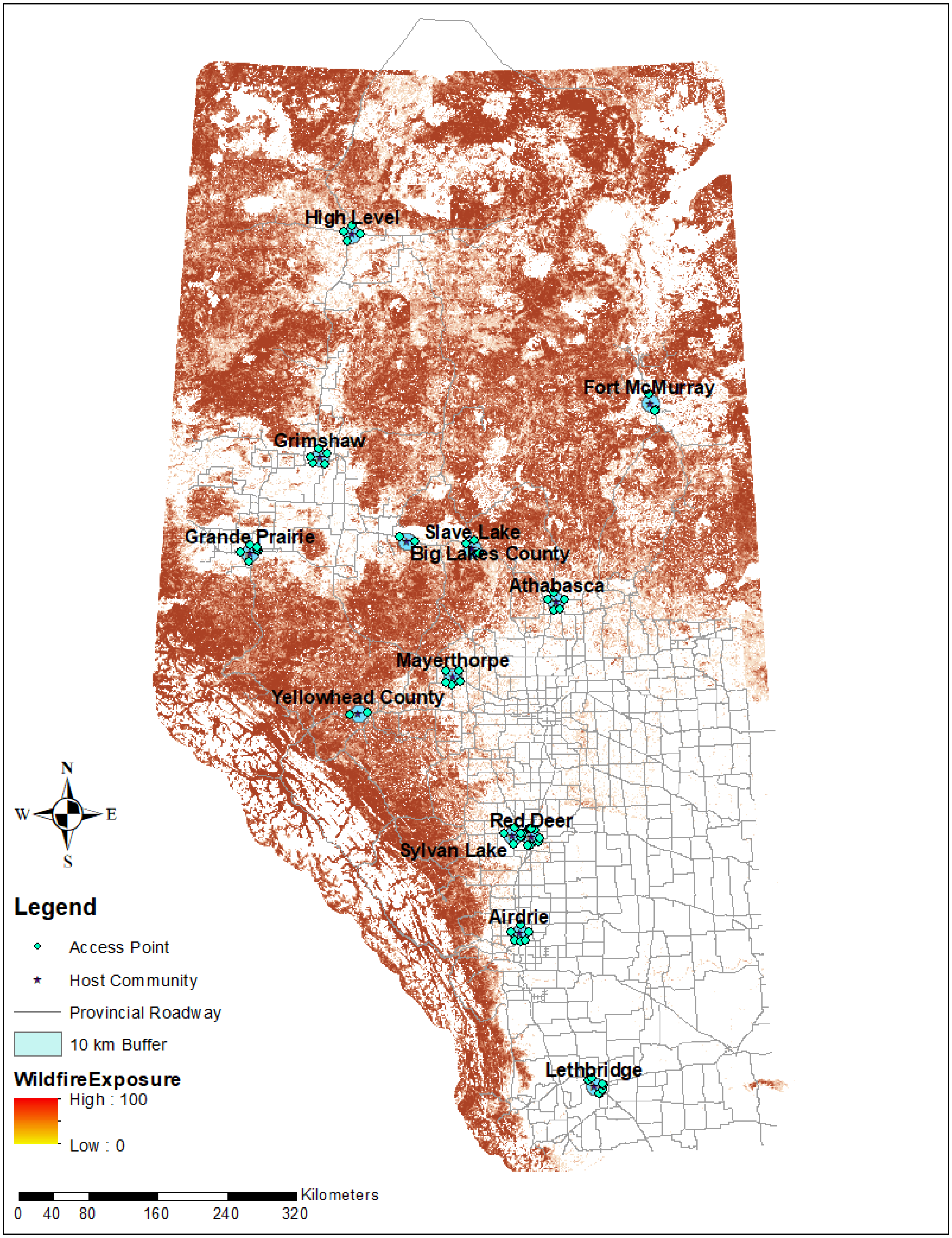

Figure 6.3: 10 km buffer radius and access points around each centroid of the host community and landscape fire exposure

All but four of the 13 host communities have a low potential for wildfire disruption, as per our landscape fire exposure definition from Section 5.3.2.2 (i.e., <80% within a 10 km buffer of the community centroid). There is little to no landscape fire exposure around Airdrie, Lethbridge, and Grande Prairie. A few discontinuous exposures around Red Deer, Sylvan Lake, Grimshaw, Mayerthorpe, Athabasca, and High Level are observed, but the values are less than 40% (a low fire transmissibility). 11% of the buffer area around the centroid of Yellowhead County has more than 80% landscape fire exposure (Table 6-1) and there are only two access points to this community (Figure 6.3). In our Cluster 4 solution, Yellowhead County is assigned 13 origin communities. Although populations can be spread out across large areas in counties lacking necessary resources in centralized urban areas, the study initially considered counties as potential hosts due to the lack of suitable host large communities in the north.

Fort McMurray has three provincial highway access points; the northern access (Hwy 63) leads to Fort Mackay and ends there. This indicates that evacuees could get trapped if the southern access points are blocked. During the 2016 Fort MacMurray wildfire, evacuees who initially took shelter at oilsands work camps north of the city had to be further evacuated south by road and (mainly) air due to encroaching fire (McGee, 2018). To avoid a similar entrapment situation, these communities with limited access should be reconsidered as potential hosts, in favor of larger, farther communities to the south.

Next, the distances evacuees would travel to reach host communities are examined. The box plots in Figure 6.4 show the distributions of network travel distances between each of the host communities and all origin communities they cover. The host communities are arranged by ascending number of assigned origins along the x-axis. Evacuees in origin communities must travel an average of 98 km to reach their designated host communities, as indicated by the red line in Figure 6.4.

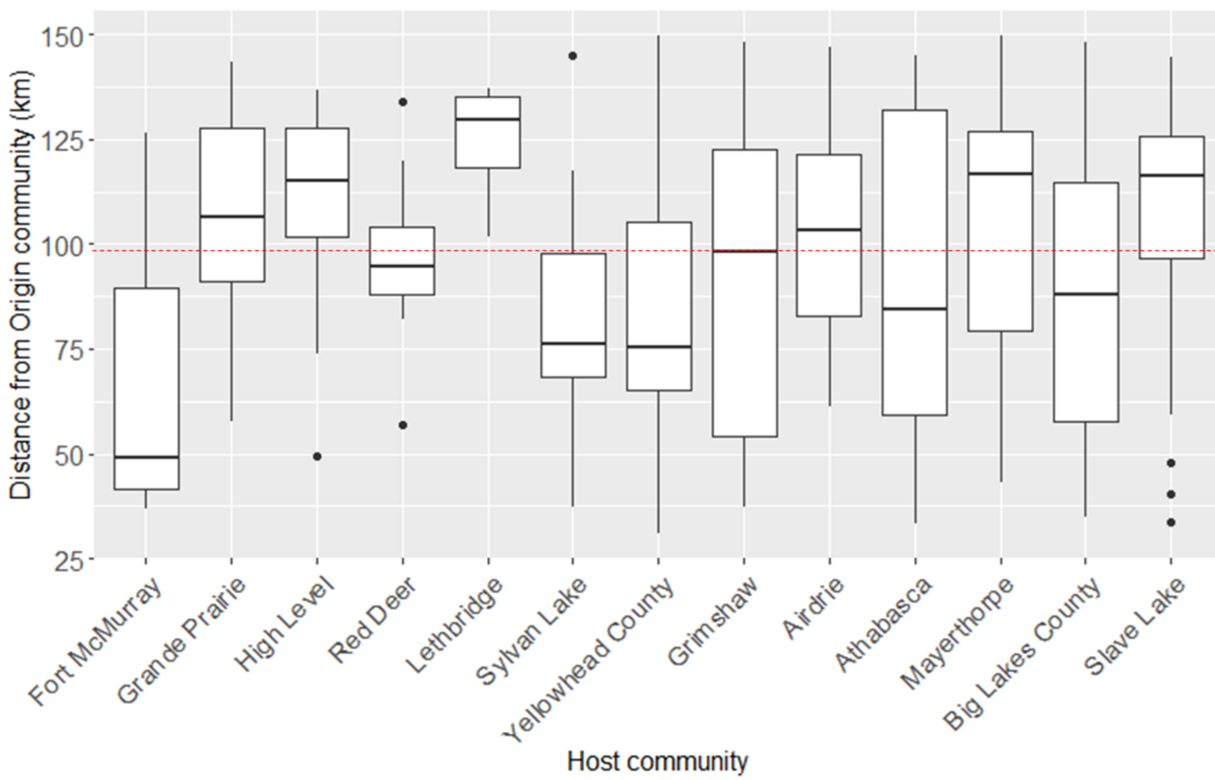

Figure 6.4: Distances between origin and host communities

Most communities served by Yellowhead County, Fort McMurray, Big Lake County, Red Deer and Sylvan Lake are located within 100 km. Communities assigned to Lethbridge must travel a longer distance compared to other communities (i.e., more than 125 km on average) to reach safety, given that Lethbridge is located in the southeast of the province, farther away from most identified origin communities.

6.2 ORIGIN COMMUNITIES NOT COVERED BY HOST COMMUNITIES

Figure 6.4 only includes communities that are covered within the distance thresholds used as constraints in the MOO model (i.e., R_L = 30 km and R_U = 150 km). As noted earlier, 24 of the 175 origin communities (or 28.5% of the study population; 8.5% not including Fort McMurray) could not be covered in this Cluster 4 model solution (Figure 6.1.b). Origin communities not covered by host communities in the model solution must travel on average of 241 km to reach their nearest host. 50% of these communities must travel 215 km or less and the upper 25th percentile must travel 259 km to reach their nearest host communities. Fort McMurray is the largest community that is not covered. Its nearly 70,000 residents are approximately 306 km away from Athabasca, the nearest identified host community (Figure 6.5). However, this is not a feasible solution as Athabasca cannot accommodate this population. The only feasible options for Fort McMurray residents are Calgary and Edmonton, the two largest population centres in Alberta (and the 4th and 5th largest in Canada). During the 2016 Fort McMurray wildfire evacuation, some evacuees initially took shelter north of Fort McMurray at Fort McKay, Long Lake and oilsands work camp sites. But as the fire moved north, they relocated to Lac la Biche and eventually headed further south to Edmonton (Mamuji and Rozdilsky, 2019). Some of these evacuees that initially evacuated to the north were taken by air to Edmonton and Calgary, facilitated by airstrips at the work camp sites (Woo et al., 2017).

Athabasca is also the nearest host community for seven of the 24 communities, with an average origin community travel distance of 185 km. Communities near the provincial borders (Saskatchewan to the east, British Columbia to the west, and the Northwest Territories to the north) may likely evacuate to communities in the adjacent province/territory. For example, Elkwater residents may evacuate to destinations in Saskatchewan instead of travelling to Lethbridge, while Thebathi 196 may be directed to Hay River in the Northwest Territories (particularly given the highway connection) (Figure 6.5).

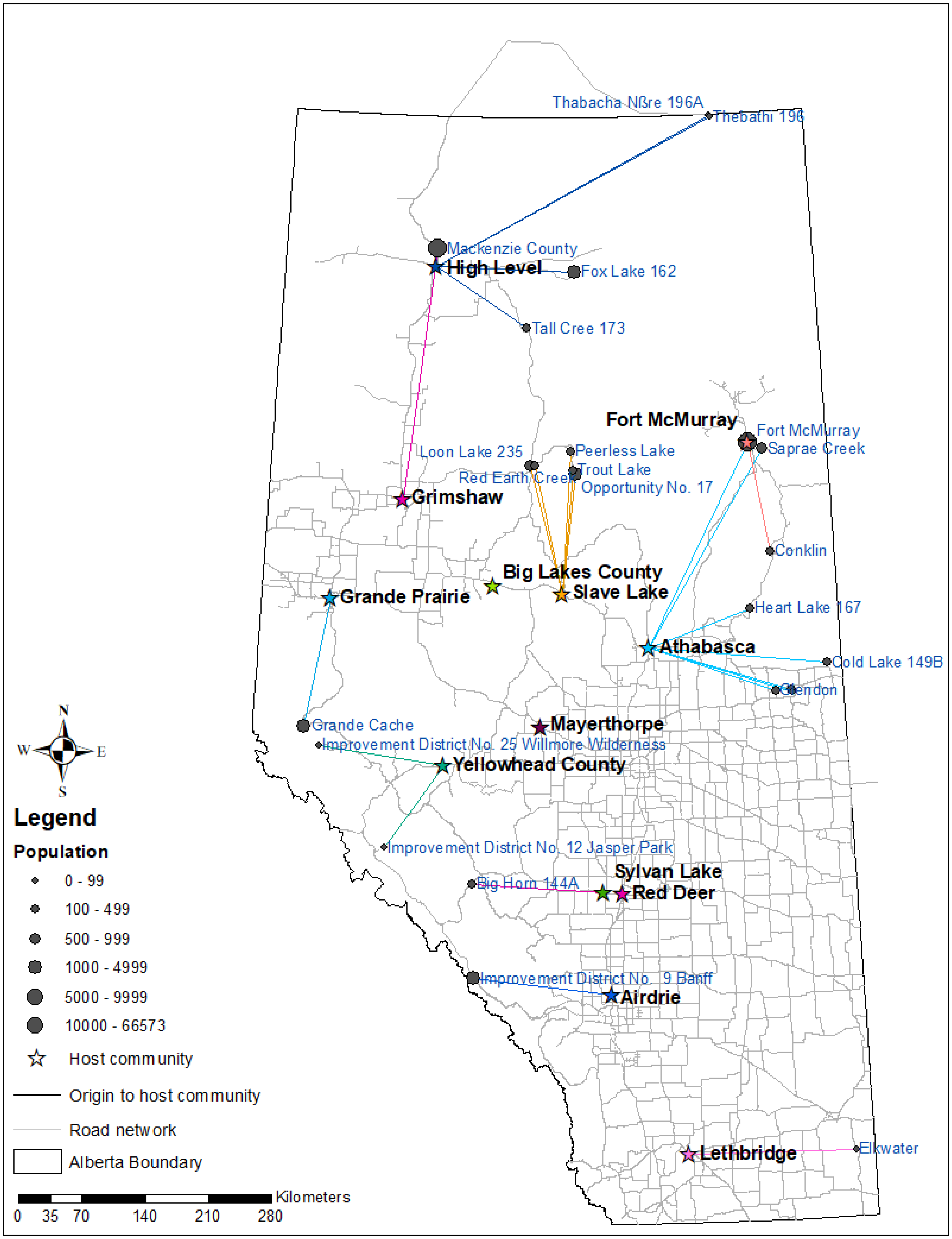

Figure 6.5: Nearest host communities for communities not covered

6.3 IDENTIFYING CRITICAL HIGHWAY LOCATIONS BETWEEN ORIGIN AND HOST COMMUNITIES

The topological and system-based vulnerability measures are applied to further assess the Cluster 4 solution investigated thus far. The BCI index (Eq. 5.25) is recalculated using the identified host communities (HC) instead of service centres(s) as the destination. For this link BCI calculation, it is assumed that the communities not covered will evacuate to the nearest host community identified in the solution. Figure 6.6 illustrates the BCI indices of the links.

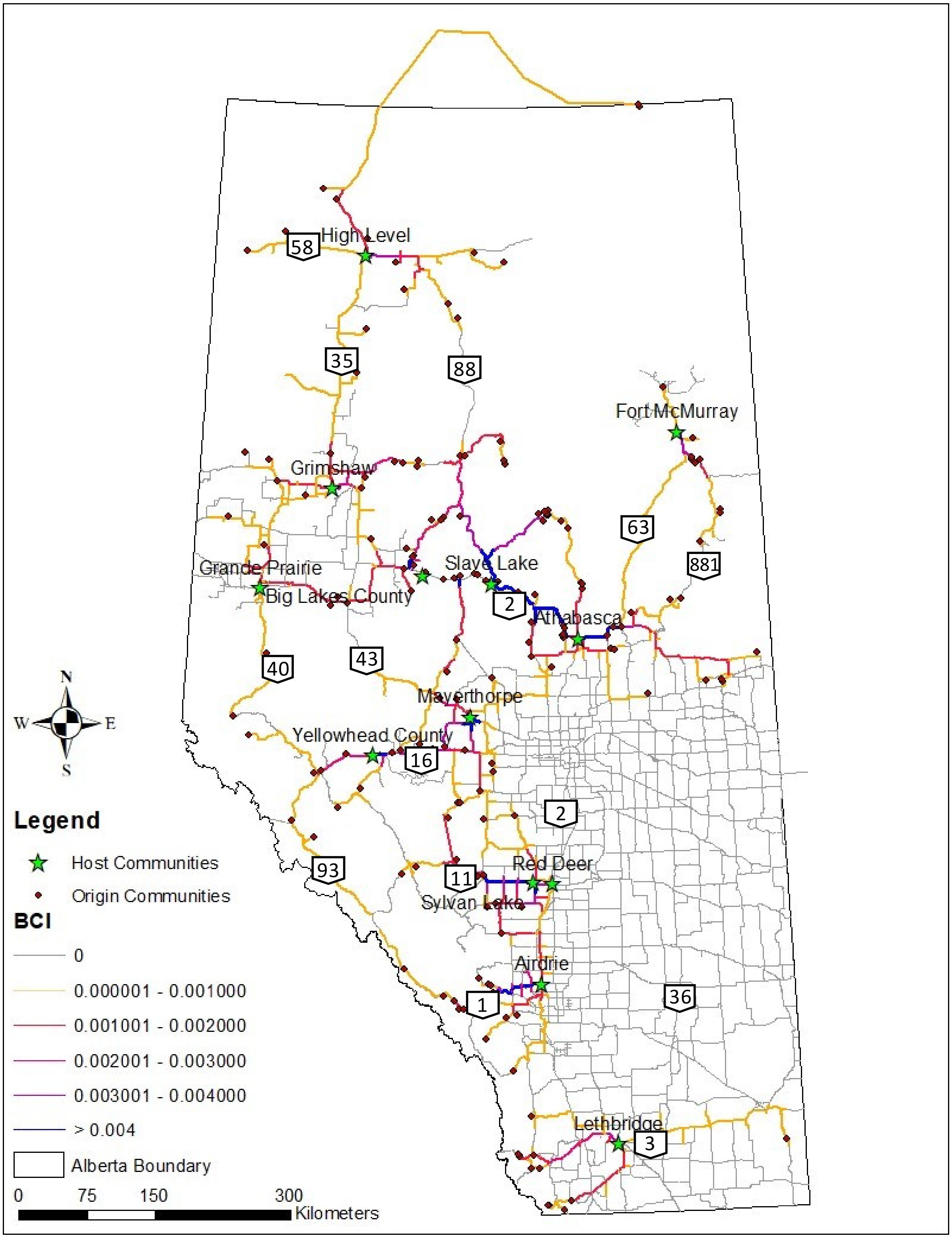

Figure 6.6: Betweenness-Centrality Index (*BCI*) of the road network with respect to host communities

Figure 6.6 indicates that Hwy 2 east of Slave Lake has the highest BCI value. As discussed in Section 6.1, Slave Lake is designated to host 34 origin communities, with most required to travel on Hwy 2 to reach it. There are three access points into Slave Lake, two of which are on Hwy 2. This part of Hwy 2 is also used by many origin communities to reach Athabasca. Therefore, this segment of Hwy 2 is an important facility connecting potentially evacuating communities to their designated hosts. Hwy 11 west of Red Deer has the second highest BCI value. It is on the shortest path for multiple communities evacuating to Red Deer and Sylvan Lake. If Hwy 11 becomes inaccessible during an evacuation, evacuees from some communities might have to drive an additional 40 to 120 km (depending on the location of disruption along Hwy 11) to reach safety. Many small communities located just east of Hwy 881 use it to access Fort McMurray, whereas only two communities (Fort McMurray and Saprae Creek) use Hwy 63 to reach Athabasca (Figure 6.5). Therefore, the northern part of Hwy 881 has a higher BCI value than Hwy 63. This suggests that fire mitigation or suppression measures should be considered for Hwy 881 to ensure it is operational, should evacuation orders be issued for communities along it.

The Escape Capacity Criticality (Cr) and Max-flow Impact Index (MI) are also assessed for the network grid cells for the 175 wildfire-prone origin communities travelling to their designated host communities (instead of the nearest large service centre as per CHAPTER 4) (Figure 6.7). It should be noted that we are not assuming 175 communities are evacuating all at once. Rather, the results are used to determine the contribution of the road segments to the bottleneck capacity between origin and destination communities. With limited emergency planning resources, the capacity-critical segments can be prioritized for fire suppression measures and investments can be allocated for infrastructure maintenance.

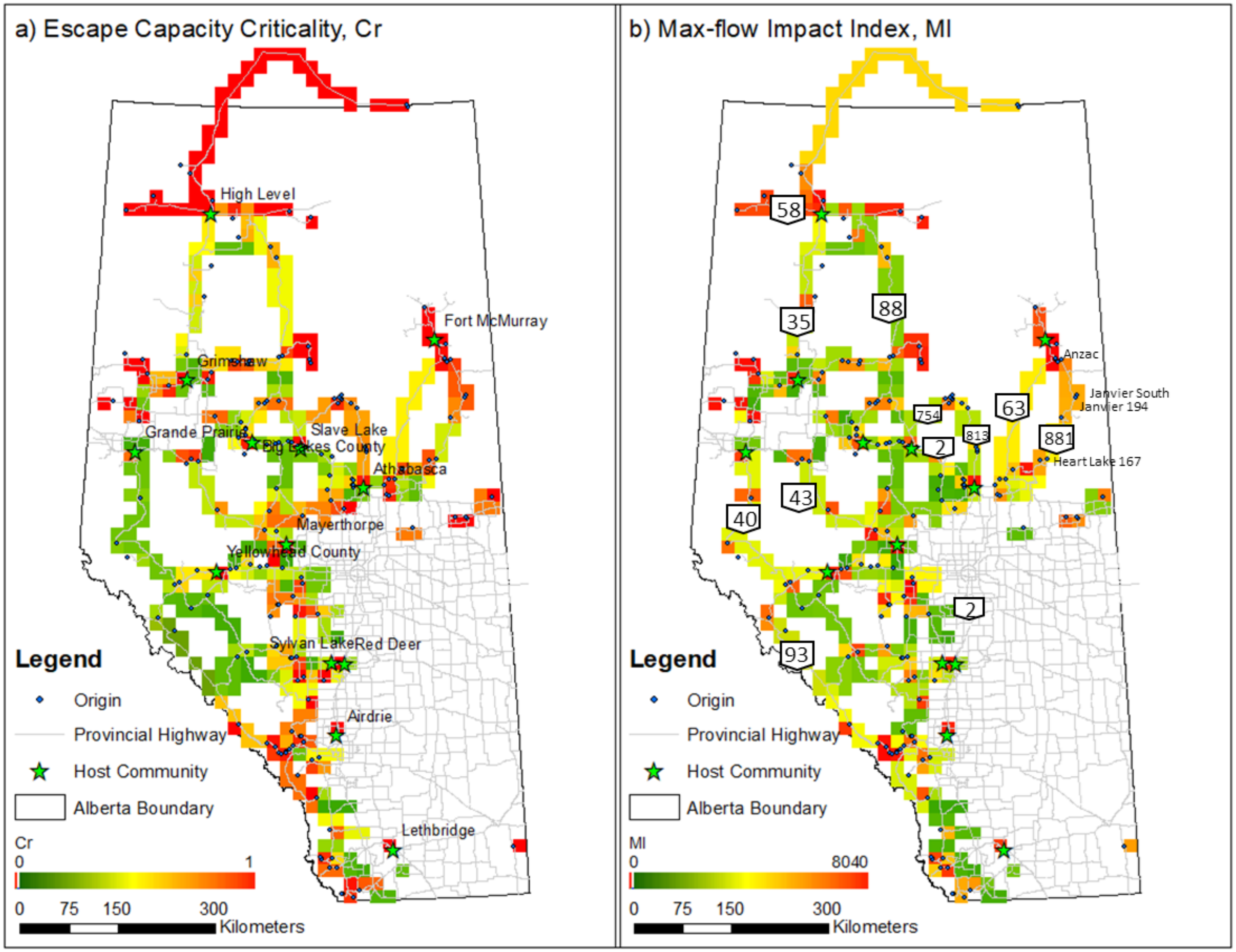

Figure 6.7: a) Cr and b) MI for evacuating 175 origin communities to the selected 13 host communities

As mentioned earlier, Hwy 2 has the highest BCI index as a higher number of communities would use it for evacuation. However, given the high network density and availability of alternative roads, Hwy 2 is less critical (i.e., low Cr and MI) in contributing to the bottleneck capacity between origin and host communities (Figure 6.7). Hwy 35, north of Hwy 58, is the only egress route available to the northernmost communities. Its absence would isolate Thebathi 196 from the rest of Alberta's road network. Therefore, as an isolating connection, the cells along this highway segment have the highest Cr value of 1 (Figure 6.7.a), as do Hwy 58 and the northern part of Hwy 63. Disruption of either Hwys 754 or 813 results in an almost 50% reduction in bottleneck capacity for Wabasca and its surrounding 11 communities, suggesting that these highways are essential for evacuating these communities to their designated hosts. As a result, a high Cr value is observed for cells along Hwys 754 and 813. Hwy 35 has lower Cr and higher MI values than Hwy 88. Hwy 88 connects many small Reserves to High Level or Slave Lake (Figure 6.2 and Figure 6.5) and thus a high number of communities are affected by its disruption (i.e., high Cr). Alternately, Hwy 35 connected fewer communities to Grimshaw or High Level, but the populations of the origin communities are higher than the Reserves served by Hwy 88. Therefore, disruption of Hwy 35 will impact a larger number of people resulting in a high MI (Figure 6.7.b). All the communities east of Hwy 63 can use Hwy 881 to reach their designated host community, Fort McMurray. Since Hwy 881 serves several small and remote communities (e.g., Heart Lake 167, Anzac, and Janvier 194) and is critical for egress should they need to evacuate, it has a higher Cr value than Hwy 63. However, disruption of Hwy 63 during an evacuation of Fort McMurray results in a high MI value, given the high population of Fort McMurray and a lack of alternate egress options. A list of the five most critical highway segments is provided in Table 6-2.

Table 6-2: Five Most Critical Highway Segments by Cr and MI

Rank	Cr	MI
1	Hwy 58	Hwy 58
2	Hwy 63 (north of the intersection of Hwy 63 and Hwy 881)	Hwy 63 (north of the intersection of Hwy 63 and Hwy881)
3	Hwy 35 (north of Hwy 58)	Hwy 881
4	Hwy 881	Hwy 35 (north of Hwy 58)
5	Hwy 813	Hwy 63 (south of the intersection of Hwy 63 and Hwy 881)

According to Table 6-2, Hwy 58 and Hwy 63 (north of the intersection of Hwy 63/Hwy 881) have the highest Cr and MI values. Although Hwy 813 is among five most critical routes by Cr, it does not qualify in the top five by MI as it serves relatively smaller communities. Hwy 63 (south of the intersection of Hwy 63/Hwy 881) is ranked fifth among the routes with the highest MI values, as its disruption impacts ~66,000 Fort McMurray residents.

6.4 SUMMARY

In this chapter, two solutions from the host community location model of CHAPTER 5 are explored, and one is selected for further investigation, with results showing that with 13 host communities, about 90% of potential evacuees (not including the residents of Fort McMurray) are matched to hosts. Further increases in the number of host communities leads to smaller increases in coverage, as the additional host communities are clustered around major highways increasing BCI value (objective 2). This chapter also investigates the features of origin communities not covered by hosts.

This chapter then applies the network scanning method of CHAPTER 4 to identify bottleneck locations between identified origin and host community pairs. Critical highway sections include those within the vicinity of potentially evacuating communities, and those in remote locations serving remote communities (with few connections to the rest of the provincial network). Identification of these critical segments can help in the development of detailed community evacuation plans. They can also guide infrastructure investments and potentially, vegetation management around critical roads, towards community protection.

CHAPTER 7. CONCLUSIONS

This chapter first provides an overview of the research objectives, approaches taken, and results. It then discusses both academic and practice-based contributions offered, and closes with a discussion of its limitations and directions for future work.

7.1 OVERVIEW AND FINDINGS

This thesis answers the research question raised in CHAPTER 1, "How do we identify key potential evacuation destinations across a large jurisdiction, as part of pre-disaster emergency management planning, in which many mainly small, rural communities are threatened by short- or no-notice evacuation?" by addressing two research objectives independently, as well as bringing the approaches made to address each objective together in a third outcome.

Research Objective 1: Develop a framework to identify potential evacuation host communities across a large jurisdiction – i.e., *where* evacuees should be directed for safety and shelter.

Summary of Work: Three single objective facility location models to identify wildfire host communities – minisum model, coverage model, and minimax model – were investigated. Based on insights gained, a multi-objective host community location model (CHAPTER 5) was proposed. The proposed model has three objectives – to maximize coverage of the (at-risk) population, maximize the cumulative Betweenness-Centrality Index BCI, of the host communities (i.e., to ensure they are located as centrally between origins and service centres as possible), and minimize the number of host communities.

Results: The multi-objective model generates a set (Pareto front) of optimal solutions, which differ from one another in the values of the three objective functions obtained. Clustering analysis is performed to facilitate organizing (along key characteristics), comparing, and ultimately choosing a solution that aligns with current policies, priorities, and resource availability. This resulted in four optimal clusters. A decision-maker can first identify the cluster of possible solutions that best aligns with their priorities and policies, to reduce their decision space towards selecting a final solution. For example, solutions in Cluster 4 identify a lower number of host communities than other clusters but provide high population coverage. Results also indicate that having a higher number of host communities does not necessarily lead to higher coverage.

Depending on the cluster and then final solution selected, evacuating origin community coverage (and thus, the potential evacuating population) varies. After exploring how solutions from different clusters compare in terms of host community numbers/locations and evacuating community coverage, one cluster is selected for further investigation. According to result of the selected solution from Cluster 4, 91% of the population at wildfire risk (excluding FMM) can be covered by 13 communities, and the average travel distance between host and covered origin communities is 98 km. Host communities located along the major highway in the centre of the province (Hwy 2) serve more origin communities than others. Furthermore, most remote communities in the northern, remote part of the province are covered by host communities. This is the result of using the remoteness index RI, in addition to population, in Objective 1. The 24 communities that could not be covered within the distance constraints of the MOO model were investigated, identifying their nearest host communities and determining travel distances to them.

Research Objective 2: Develop a simple network scanning process to identify road segments that contribute to maximum evacuation capacity, towards supporting *how* evacuees might be routed through the provincial roadway network to destinations.

Summary of Work: Two vulnerability measures, Cr and MI, that measure network bottleneck capacity between the OD pairs before and after link disruption, are proposed to identify capacity-critical road segments, important for contributing to evacuation capacity. The min-cut max-flow (MCMF) theorem is used to calculate the bottleneck capacity of the original and residual (i.e., post-disruption) network. A cell grid is used to disrupt multiple links in simulating area-wide disruption. The method is first applied to a few key individual communities and destinations (CHAPTER 4), and then applied to all wildfire-prone communities and identified host communities in Alberta (CHAPTER 6).

Results: All critical links are found to be located in the vicinity of evacuating communities, confirming the importance of focusing on traffic operations within and around these communities for wildfire evacuation operations studies. Higher Cr values for roadway links are observed where the network is sparse and communities have few egress alternatives. In such cases, roads with low capacity and/or less-travelled roads may be critical to accommodating evacuating traffic, yielding higher Cr values than roads with the same capacity in a denser part of the network. If a community has multiple alternatives with the same Cr values (e.g., Slave Lake, High Level, Jasper), emergency managers can look at other characteristics of the infrastructure, traffic operations, demand, and vegetation/land cover (and thus, fire exposure) to prioritize and develop evacuation routes. Evacuation demand alongside bottleneck capacity is also considered to determine the weighted importance of road segments. Roadways serving multiple and/or large communities will have higher MI values, despite offering the same contribution to bottleneck capacity (Cr). Major highways like Hwy 2 are found to be less critical (i.e., low Cr and MI) in contributing to the bottleneck capacity between origin and host communities if there are alternate routes available.

Highways located in the sparsest, most remote parts of the province have the highest Cr and MI values.

7.2 RESEARCH CONTRIBUTION

A pre-disaster plan for a community, which includes where evacuees will be directed (to destination, or "host," communities that are willing and capable to accommodate evacuees), can potentially lead to time savings and reduced confusion during an evacuation. This thesis addresses the need to identify host communities for short- and no-notice evacuations, within pre-disaster evacuation planning coordinated across a large jurisdiction, over which the location and occurrence of natural disasters prompting community evacuation are difficult to forecast. Wildfires are one such disaster, as wildfire occurrence and spread can occur quickly and are difficult to predict. With increases in the frequency and size of wildfires both observed and predicted in western Canada and other parts of the world, evacuation pre-planning and readiness continues to be of great concern. Identifying a network of communities that are able to provide emergency shelter and support (and that can receive emergency supplies from larger hubs), before an emergency situation occurs, can be instrumental in reducing decision burdens during an emergency event, increasing evacuation efficiencies and ultimately, reducing the trauma and burden of evacuation.

Because natural disasters like wildfires are difficult to predict in terms of when and/or where they occur, the literature is mainly focused on scenario-based planning and modelling of evacuations at the regional or community level for these short- and no-notice evacuations. It is a challenge for large jurisdictions like states and provinces, with many communities at risk, to do pre-disaster evacuation planning under such conditions. For these agencies covering many different urbanized areas potentially under wildfire threat (combined with limited transportation networks), the proposed multi-objective host community location model can be used to identify and pre-position these emergency facilities based on a set of key priorities, in pre-disaster planning, despite not knowing where and how disasters will occur. This research also contributes to the literature by developing a method to illuminate where and to what degree of importance network facilities have in providing transportation capacity between evacuating communities and their host communities. The network scanning method can quickly identify capacity-critical roadway locations in a community evacuation scenario.

Practitioners can use the results of the multi-objective facility location model in pre-disaster planning to identify host communities to shelter and support potential evacuees, investigating and selecting a solution(s) that best suits their and prevailing policies/priorities and needs. Thus, resources can be identified and potentially distributed to host communities in preparation for upcoming fire season(s). This also allows for potential evacuating communities and their matched hosts to establish relationships and direct communication channels, facilitated by provincial agencies.

Discussions with Alberta Emergency Management Agency (AEMA) and Provincial Emergency Social Services (ESS) revealed that identifying evacuation destinations before fire season can be instrumental towards improving wildfire evacuation preparedness and efficiency. With host communities benchmarked, decision-makers can further advise on evacuation routes, personnel, and supplies dispatch, etc. and reduce potential confusion and inefficiencies during evacuations. This can lead to reductions in evacuation time/distance, as well as facilitate timely dispatch and receipt of relief supplies at host communities.

Results of the network scanning tool can be used to support provincial and local municipal governments in deciding which communities require more detailed emergency evacuation studies, and better identify and communicate transportation network deficiencies to provincial and federal bodies that fund infrastructure investments toward community health and resilience.

7.3 LIMITATIONS AND FUTURE WORK

There are some key limitations to address in future work, in addition to future avenues of inquiry, that are identified.

Like many existing evacuation studies, the study did not consider background traffic when calculating the network metrics Cr and MI. Although background traffic on interurban highways, particularly in remote areas, can be small, a significant presence will reduce available evacuation capacity. Estimates of background traffic should be included in future studies of evacuation capacity and routing, particularly those that focus on smaller, more specific geographic areas around communities (where the results have shown to be of most concern).

The multi-objective host community location model flags an origin community as not covered when the number of host communities exceeds an upper bound of four. This constraint was introduced to ensure that the model does not identify more host communities to increase the value of Objective 2. An alternate approach could be to place bounds on the travel distances between host communities, which would also reduce clustering of host communities around central locations like the Hwy 2 corridor. Second, the model does not match origin and host communities' populations and capacities, despite the importance of ensuring that host communities are able to accommodate evacuee populations, and Alberta's guidelines that a host community can accommodate up to 10% of the host community's population (Government of Alberta, 2018).

Third, it does not consider evacuee compliance to instruction and/or the number of evacuees that would actually travel to the host communities. Fourth, the model does not distribute evacuees across multiple host communities, which could be necessary given the second limitation listed above (although for small communities, instructions to one host may be ideal to reduce confusion).

The line of inquiry pursued in this thesis would benefit from an interdisciplinary collaboration with wildland fire scientists. One idea is to develop other measures for the grid disruption that account for fire pathways and how they interact with the roadway network, such as the density of interactions within grid cells.

A final recommendation for a future study is to focus on the unique characteristics and needs of Reserves and Métis Settlements when identifying their host communities, and in doing so, work with First Nations and Metis communities, alongside the province and federal governments, to co-develop these plans. McGee et al. (2021) found that First Nations communities prefer to evacuate to other First Nations communities whenever possible, consideration which could be given through the use of a model objective (using a penalty for not matching) or constraint. Although First Nations Chiefs and band councils are in charge of emergency and evacuation planning, they will consult and work with federal (and sometimes provincial) agencies (McGee et al., 2021).

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APPENDIX

Table A-1: List of Origin Communities (175 considered)

Sl.	*Origin Community*	*Population*	*Remoteness Index (RI)*
1	Improvement District No. 4 Waterton	105	0.345372
2	Pincher Creek No. 9	2965	0.315332
3	Blood 148A	0	0.348618
4	Sundre	2729	0.178178
5	Eden Valley 216	596	0.25261
6	Tsuu T'ina Nation 145 (Sarcee 145)	1643	0.201743
7	Clearwater County	11947	0.227663
8	Burnstick Lake	0	0.180037
9	Caroline	512	0.175785
10	Rocky Mountain House	6635	0.171898
11	O'Chiese 203	789	0.194112
12	Sunchild 202	749	0.194283
13	Big Horn 144A	237	0.238176
14	Drayton Valley	7235	0.170655
15	Brazeau County	7771	0.190525
16	Parkland County	32097	0.162748
17	Bonnyville Beach	84	0.243228
18	Glendon	493	0.233592
19	Pelican Narrows	151	0.248824
20	Lac la Biche County	8330	0.261213
21	Cold Lake 149B	163	0.27998
22	Heart Lake 167	184	0.287263
23	Woodlands County	4754	0.254544
24	Whitecourt	10204	0.226254
25	Larkspur	44	0.200441
26	Mewatha Beach	90	0.212827
27	Sunset Beach	49	0.22049
28	Island Lake	228	0.228618
29	Island Lake South	61	0.226935
30	Bondiss	110	0.212955
31	South Baptiste	66	0.222068
32	West Baptiste	38	0.22483
33	Whispering Hills	142	0.223729
34	Yellowhead County	10995	0.257445
35	Hinton	9882	0.290095
36	Edson	8414	0.243277

Sl.	*Origin Community*	*Population*	*Remoteness Index (RI)*
37	Improvement District No. 25 Willmore Wilderness	0	0.370128
38	Crowsnest Pass	5589	0.311553
39	Kananaskis	221	0.23277
40	Bighorn No. 8	1334	0.220109
41	Canmore	13992	0.240931
42	Ghost Lake	82	0.207578
43	Waiparous	49	0.213607
44	Improvement District No. 9 Banff	1028	0.290325
45	Jasper	4590	0.314738
46	Banff	7851	0.259161
47	Improvement District No. 12 Jasper Park	53	0.323439
48	Ranchland No. 66	92	0.271976
49	Stoney 142, 143, 144	3713	0.219627
50	Janvier 194	414	0.368306
51	Gregoire Lake 176	191	0.396602
52	Gregoire Lake 176A	130	0.396127
53	Fort Mackay	742	0.446973
54	Thebathi 196	20	1
55	Thabacha Nßre 196A	28	1
56	Swan Hills	1301	0.25646
57	Northern Sunrise County	1891	0.437644
58	Big Lakes County	5672	0.340566
59	Slave Lake	6651	0.280183
60	Opportunity No. 17	3181	0.459366
61	Lesser Slave River No.124	2803	0.258626
62	Clear Hills	3023	0.510874
63	Hines Creek	346	0.483123
64	Northern Lights County	4200	0.544205
65	Mackenzie County	11171	0.626845
66	Rainbow Lake	795	0.711388
67	Jean Baptiste Gambler 183	253	0.260139
68	Wabasca 166	160	0.316447
69	Wabasca 166A	658	0.326813
70	Wabasca 166B	190	0.335303
71	Wabasca 166C	188	0.326657
72	Wabasca 166D	961	0.333073
73	Utikoomak Lake 155	723	0.37261
74	Clear Hills 152C	0	0.501016
75	Utikoomak Lake 155A	127	0.34613
76	Sucker Creek 150A	689	0.338573
77	Kapawe'no First Nation (Pakashan 150D)	5	0.367667

Sl.	Origin Community	Population	Remoteness Index (RI)
78	Swan River 150E	413	0.306837
79	Sawridge 150G	20	0.28793
80	Sawridge 150H	10	0.285571
81	Fox Lake 162	2032	0.667658
82	Kapawe'no First Nation (Freeman 150B)	154	0.354866
83	John d'Or Prairie 215	1196	0.630929
84	Tall Cree 173	250	0.51257
85	Tall Cree 173A	224	0.530738
86	Child Lake 164A	216	0.597486
87	Hay Lake 209	883	0.686503
88	Upper Hay River 212	294	0.665477
89	Little Buffalo	452	0.422891
90	Carcajou 187	0	0.58905
91	Desmarais	105	0.327599
92	Woodland Cree 226	723	0.440186
93	Woodland Cree 228	150	0.421898
94	Loon Lake 235	555	0.389492
95	Fox Creek	1971	0.27968
96	Grande Cache	3571	0.382485
97	Greenview No. 16	5583	0.44944
98	Valleyview	1863	0.336107
99	Sturgeon Lake 154	1447	0.347286
100	Sturgeon Lake 154A	53	0.342912
101	McLennan	701	0.38483
102	Saddle Hills County	2225	0.478331
103	Alder Flats	167	0.164147
104	Anzac	548	0.400365
105	Atmore	35	0.231783
106	Beaver Mines	82	0.312207
107	Benchlands	43	0.212757
108	Blue Ridge	244	0.214919
109	Bragg Creek	589	0.208526
110	Brule	31	0.295521
111	Cadomin	40	0.285242
112	Cadotte Lake	5	0.434252
113	Canyon Creek	284	0.302844
114	Centre Calling Lake	149	0.256912
115	Chisholm	25	0.233065
116	Conklin	185	0.336531
117	Pigeon Mountain	125	0.239707
118	Desmarais	74	0.327612

Sl.	Origin Community	Population	Remoteness Index (RI)
119	Dickson	58	0.158907
120	Dixonville	108	0.468283
121	Donatville	0	0.21789
122	Enilda	155	0.344986
123	Exshaw	412	0.231228
124	Faust	261	0.314042
125	Fawcett	69	0.206308
126	Ferrier Acres Trailer Court	395	0.17456
127	Flatbush	45	0.219674
128	Gift Lake part A	658	0.379205
129	Grassland	68	0.228032
130	Grouard Mission	255	0.35294
131	Harvie Heights	184	0.246647
132	Joussard	223	0.328449
133	La Crete	433	0.590659
134	Lac des Arcs	130	0.234634
135	Lodgepole	116	0.189546
136	Lundbreck	236	0.301506
137	Mackay	10	0.205509
138	Marlboro	90	0.259821
139	Martins Trailer Court	104	0.174421
140	Mountain View	90	0.328459
141	Niton Junction	38	0.217343
142	Calling Lake	299	0.256912
143	Obed	10	0.27337
144	Peers	98	0.226847
145	Sandy Lake	52	0.303753
146	Pine Shadows	155	0.239924
147	Red Earth Creek	294	0.396602
148	Robb	170	0.261342
149	Rossian	113	0.249023
150	Seebe	0	0.227348
151	Smith	148	0.254387
152	St Isidore	266	0.42474
153	Tomahawk	62	0.163397
154	Wabasca	1406	0.329046
155	Whitelaw	125	0.471332
156	Widewater	348	0.292033
157	Winfield	238	0.143248
158	Woking	102	0.433982
159	Zama City	74	0.690978

Sl.	Origin Community	Population	Remoteness Index (RI)
160	Trout Lake	349	0.459697
161	Peerless Lake	334	0.441167
162	Waterton Park	105	0.345372
163	Elkwater	84	0.344896
164	East Prairie	304	0.36446
165	Gregoire Lake Estates	165	0.395478
166	Saprae Creek	572	0
167	Janvier South	100	0.366388
168	Gift Lake part B	0	0.375543
169	Hillcrest Mines	394	0.312384
170	Frank	85	0.312819
171	Wildwood	273	0.189789
172	Kinuso	182	0.305265
173	Bellis	50	0.19013
174	Fort Assiniboine	176	0.215613
175	Fort McMurray	66573	0.407398

Table A-2: List of Potential Host Communities (184 considered)

Sl.	*Potential Host Community*	*Population*	*BCI*	*Raster Cells with Landscape Fire Exposure value of 80% or more, ω_j (%)*
1	Cypress County	7662	0.000875	0
2	Medicine Hat	63260	0.009572	0
3	Forty Mile County No. 8	3581	0.000222	0
4	Bow Island	1983	0.001084	0
5	Redcliff	5600	0.00903	0
6	Warner County No. 5	3847	0.000222	0
7	Raymond	3708	0.000222	0
8	Lethbridge County	10353	0.001589	0
9	Lethbridge	92729	0.010595	0
10	Coalhurst	2668	0.008735	0
11	Nobleford	1278	0.001183	0
12	Picture Butte	1810	0.000961	0
13	Coaldale	8215	0.003782	0
14	Taber	7098	0.003708	0
15	Taber	8428	0.004386	0
16	Vauxhall	1222	0.004891	0
17	Newell County	7524	0.017556	0
18	Brooks	14451	0.017519	0
19	Duchess	1085	0.003647	0
20	Bassano	1206	0.014882	0
21	Cardston County	4481	0.000222	0
22	Magrath	2374	0.000628	0
23	Cardston	3585	0.000628	0
24	Pincher Creek No. 9	2965	0.000283	0.03
25	Pincher Creek	3642	0.000394	0
26	Willow Creek No. 26	5179	0.006653	0
27	Fort Macleod	2967	0.001725	0
28	Claresholm	3780	0.006542	0
29	Nanton	2130	0.006985	0
30	Special Area No. 2	1905	0.006776	0
31	Hanna	2559	0.006973	0
32	Special Area No. 3	1042	0.000431	0
33	Oyen	1001	0.000973	0
34	Special Area No. 4	1237	0.000308	0
35	Vulcan County	3984	0.000776	0
36	Vulcan	1917	0.006443	0
37	Wheatland County	8788	0.00361	0
38	Strathmore	13756	0.003819	0

Sl.	Potential Host Community	Population	BCI	Raster Cells with Landscape Fire Exposure value of 80% or more, ω_j (%)
39	Drumheller	7982	0.014771	0
40	Starland County	2066	0.000875	0
41	Kneehill County	5001	0.004447	0
42	Three Hills	3212	0.006406	0
43	Trochu	1058	0.006517	0
44	Foothills No. 31	22766	0.000271	0
45	High River	13584	0.007232	0
46	Turner Valley	2559	0.000431	0
47	Black Diamond	2700	0.002316	0
48	Okotoks	28881	0.002513	0
49	Rocky View County	39407	0.000591	0
50	Calgary	1239220	0.016977	0
51	Chestermere	19887	0.009893	0
52	Cochrane	25853	0.000222	0
53	Airdrie	61581	0.023827	0
54	Irricana	1216	0.002341	0
55	Crossfield	2983	0.000222	0
56	Mountain View County	13074	0.02119	0
57	Carstairs	4077	0.000444	0
58	Didsbury	5268	0.000517	0
59	Olds	9184	0.003486	0
60	Sundre	2729	0.002033	0.02
61	Provost No. 52	2205	0.000616	0
62	Provost	1998	0.001207	0
63	Paintearth County No. 18	2102	0.004866	0
64	Stettler County No. 6	5322	0.012369	0
65	Stettler	5952	0.01317	0
66	Flagstaff County	3738	0.003807	0
67	Wainwright No. 61	4479	0.000813	0
68	Wainwright	6270	0.001491	0
69	Red Deer County	19541	0.008661	0
70	Bowden	1240	0	0
71	Innisfail	7847	0.016496	0
72	Penhold	3277	0.016151	0
73	Red Deer	100418	0.034791	0
74	Sylvan Lake	14816	0.008969	0
75	Lacombe County	10343	0.003191	0
76	Eckville	1125	0.000259	0
77	Bentley	1078	0.002563	0
78	Blackfalds	9328	0.028767	0

Sl.	Potential Host Community	Population	BCI	Raster Cells with Landscape Fire Exposure value of 80% or more, ω_j (%)
79	Lacombe	13057	0.00977	0
80	Ponoka County	9806	0.000222	0
81	Ponoka	7229	0.01062	0
82	Rimbey	2567	0.011507	0
83	Clearwater County	11947	0.001331	0.8
84	Rocky Mountain House	6635	0.002193	0.03
85	Camrose County	8458	0.013145	0
86	Camrose	18742	0.025059	0
87	Beaver County	5905	0.002156	0
88	Tofield	2081	0.002476	0
89	Viking	1083	0.006037	0
90	Minburn County No. 27	3188	0.004411	0
91	Vegreville	5708	0.005285	0
92	Vermilion River County	8267	0.005852	0
93	Lloydminster (Part)	19645	0.008747	0
94	Vermilion	4084	0.005716	0
95	Two Hills County No. 21	3322	0.002131	0
96	Two Hills	1352	0.002304	0
97	Lamont County	3899	0.003955	0
98	Lamont	1774	0.003955	0
99	Bruderheim	1308	0.002107	0
100	Wetaskiwin County No. 10	11181	0.023962	0
101	Wetaskiwin	12655	0.016164	0
102	Millet	1945	0.005174	0
103	Leduc County	13780	0.002094	0
104	Beaumont	17396	0.007232	0
105	Leduc	29993	0.03314	0
106	Devon	6578	0.014119	0
107	Calmar	2228	0.001676	0
108	Drayton Valley	7235	0.001589	0.02
109	Brazeau County	7771	0.000259	0.08
110	Parkland County	32097	0.007786	0.01
111	Stony Plain	17189	0.010977	0
112	Spruce Grove	34066	0.016533	0
113	Strathcona County	98044	0.008747	0
114	Fort Saskatchewan	24149	0.012073	0
115	Sturgeon County	20495	0.003942	0
116	Edmonton	932546	0.009622	0
117	St. Albert	65589	0.011445	0
118	Gibbons	3159	0.006086	0

Sl.	Potential Host Community	Population	BCI	Raster Cells with Landscape Fire Exposure value of 80% or more, ω_j (%)
119	Redwater	2053	0.001257	0
120	Bon Accord	1529	0.003265	0
121	Morinville	9848	0.007762	0
122	Legal	1345	0.000887	0
123	Cold Lake	14961	0.008821	0
124	Bonnyville No. 87	13575	0.007293	0
125	Bonnyville	5417	0.007478	0
126	St. Paul County No. 19	6036	0.000222	0
127	Elk Point	1452	0.00154	0
128	St. Paul	5827	0.000924	0
129	Smoky Lake County	4107	0	0
130	Lac la Biche County	8330	0.001441	0.03
131	Lac Ste. Anne County	10899	0.010373	0
132	Mayerthorpe	1320	0.016878	0
133	Alberta Beach	1018	0	0
134	Onoway	1029	0.014242	0
135	Barrhead County No. 11	6288	0	0
136	Barrhead	4579	0.004078	0
137	Westlock County	7220	0.008193	0
138	Woodlands County	4754	0.000234	0.45
139	Whitecourt	10204	0.017174	0.23
140	Westlock	5101	0.009338	0
141	Thorhild County	3254	0.000554	0
142	Athabasca County	7869	0.002242	0
143	Athabasca	2965	0.004928	0
144	Yellowhead County	10995	0.001343	0.11
145	Hinton	9882	0.00085	0.54
146	Edson	8414	0.001774	0.05
147	Crowsnest Pass	5589	0.000444	0.25
148	Bighorn No. 8	1334	0.001392	0.59
149	Canmore	13992	0.000899	0.3
150	Improvement District No. 9 Banff	1028	0.00037	0.57
151	Jasper	4590	0.000222	0.73
152	Banff	7851	0.000456	0.57
153	High Prairie	2564	0.002575	0
154	Swan Hills	1301	0.003142	0.37
155	Northern Sunrise County	1891	0.000357	0.39
156	Big Lakes County	5672	0.003831	0.07
157	Slave Lake	6651	0.009363	0.07
158	Opportunity No. 17	3181	0.000444	0.19

Sl.	*Potential Host Community*	*Population*	*BCI*	*Raster Cells with Landscape Fire Exposure value of 80% or more, ω_j (%)*
159	Lesser Slave River No.124	2803	0.00956	0.09
160	Clear Hills	3023	0.000222	0.71
161	Northern Lights County	4200	0.000222	0.33
162	Manning	1183	0.000862	0
163	High Level	3159	0.001602	0
164	Mackenzie County	11171	0.000887	0.05
165	Fox Creek	1971	0.016804	0.39
166	Grande Cache	3571	0.000542	0.46
167	Greenview No. 16	5583	0.000394	0.37
168	Valleyview	1863	0.016644	0.01
169	Grande Prairie County No. 1	22303	0.000641	0
170	Beaverlodge	2465	0.000246	0
171	Wembley	1516	0.000505	0
172	Grande Prairie	63166	0.00908	0
173	Sexsmith	2620	0.000222	0
174	Peace River	6842	0.002944	0
175	Smoky River No. 130	2023	0.00122	0
176	Falher	1047	0.001023	0
177	Birch Hills County	1553	0.000222	0
178	Saddle Hills County	2225	0.000222	0.06
179	Fairview No. 136	1604	0.000222	0
180	Fairview	2998	0.000554	0
181	Peace No. 135	1747	0.000222	0
182	Grimshaw	2718	0.001331	0
183	Lac la Biche	2314	0.000222	0
184	Fort McMurray	66573	0.000665	0.08