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Evaluation of Inter-facility Medical Transport Journey Times in Southeastern British Columbia

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Masters thesis in Geographical Information Sciences,
30 credits

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Abstract

Very sick patients who need specialized health services often require transport from their community to a regional facility that is appropriately resourced to provide definitive care for their condition. This is particularly important for people living in rural and remote areas but can be challenging due to long distances, mountainous terrain and inclement weather.

The purpose of this research was to improve health service delivery to rural communities within the study area by identifying whether or not there were inter-facility medical transport routes within the study area with highly variable or unexpectedly long journey times. Select transport characteristics were examined to further inform decision making related to acute inter-facility transport within the study area.

The medical records of 418 high acuity patient transports within Southeastern British Columbia were reviewed in order to capture information about 'observed' transport times, locations, and other transport characteristics. A geographic network analysis of each route identified within the study dataset was conducted in order to estimate 'expected' transport times. These expected transport times, in addition to GoogleMap time estimates, were compared to observed transport times to determine areas of possible concern within the transport network. A multiple regression analysis was conducted to identify predictors of transport times.

Observed transport times in the study dataset were generally found to be within a statistically acceptable range of expected transport time estimates. The only transports with significantly longer than expected journey times were due to 'meets' in transport. Additional factors such as patients' clinical categories, mode of transport, and max elevation en-route were predictive of transport times within the study context.

Keywords: Geography, GIS, network analysis, inter-facility transport, patient transport, medical transport, high acuity, road network, rural health, Emergency Medical Services

Contents

Abbreviations

ALS	Advanced Life Support
BLS	Basic Life Support
BC	British Columbia
CCT	Critical Care Team
CCP	Critical Care Paramedic
CDED	Canadian Digital Elevation Data
CTAS	Canadian Triage and Acuity Scale
DAD	Discharge Abstract Database
DEM	Digital Elevation Model
ED	Emergency Department
EKRH	East Kootenay Regional Hospital
ePCR	Electronic Patient Care Record
EMAS	Emergency Medical Ambulance Service
EMS	Emergency Medical Service
GIS	Geographic Information Systems
GP	General Practitioner
GPS	Global Positioning System
HART	High Acuity Response Team
HCCM	Heteroscedasticity-Corrected Covariance Matrices
HA	Health Authority
HSDA	Health Service Delivery Area
IH	Interior Health
IQR	Inter-Quartile Range
KGH	Kelowna General Hospital
KBRH	Kootenay Boundary Regional Hospital
LHA	Local Health Area
MAD	Median Absolute Deviation

MD	Medical Doctor
NTS	National Topographic System
PRH	Penticton Regional Hospital
QI	Quality Improvement
REB	Research Ethics Board
RIH	Royal Inland Hospital
RN	Registered Nurse
RRT	Registered Respiratory Therapist
SD	Standard Deviation
UBC	University of British Columbia

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1 Introduction

1.1 Motivation

In 1984, Canada adopted the 'Canada Health Act'—legislation that has set priorities for healthcare in this country over the last 30 years. This Act describes five pillars of health services delivery in Canada: Public administration, Comprehensiveness, Universality, Portability, and Accessibility (R.S.C., 1985). However, with the established trend towards the regionalization of health services, ensuring *accessible* healthcare for people living outside of urban centres has become ever more challenging (Lin et al., 2002; Schuurman et al., 2006).

Patient transport plays a vital role in providing accessible healthcare to a widely distributed population (Doumouras et al., 2012). Very sick patients who need specialized health services often require transport from their community to a regional facility that is appropriately resourced to provide definitive care for their condition (Grzybowski et al., 2011). Efficient and timely medical transportation services ensure that people in rural areas can access regionalized health services as quickly as possible (Schuurman et al., 2006).

In a rural context, this type of 'inter-facility' transport often involves long distances, mountainous terrain and inclement weather (Chanta et al., 2014). On top of the geographic challenges, the complexity of moving high acuity patients is compounded by the need to ensure that a clinician who has the skill level needed to safely monitor and maintain a patient's clinical stability throughout transport is available to accompany the patient (Brayman et al., 2012).

Time to definitive care has been used as a benchmark in the management of a number of emergency conditions such as sepsis and stroke (Wallace et al., 2014). Therefore, having an accurate understanding of how much time it takes to transport patients between different facilities, and what might influence these times, can assist in dispatch decision making and system planning (Shin et al., 2013; Sethi and Subramanian, 2014; Cone and Landman, 2014).

1.2 Study aim

The purpose of this project is to improve health service delivery to rural communities within the study area by identifying whether or not there are inter-facility medical transport routes within the study area with highly variable or unexpectedly long journey times. Once these geographic areas of possible concern have been identified within the transport network, associations between transport time and selected transport and route characteristics will be examined to further inform decision making related to acute inter-facility transport within the study area.

1.3 Research questions

This study was guided by the following research questions:

1. Which routes within the IH inter-facility transport network, if any, display longer or more variable journey times than expected?

2. Do longer transport distances result in greater variability of journey times?

3. What factors influence inter-facility transport times in the study context?

2 Background

2.1 Study area

Interior Health (IH) covers a 215,000km^2 area within the Southeastern corner of British Columbia (BC), Canada (Figure 2.1).[1] One of five geographically distinct Health Authorities within BC, IH is responsible for delivering health care services to approximately 731,000 people spread across 59 communities.

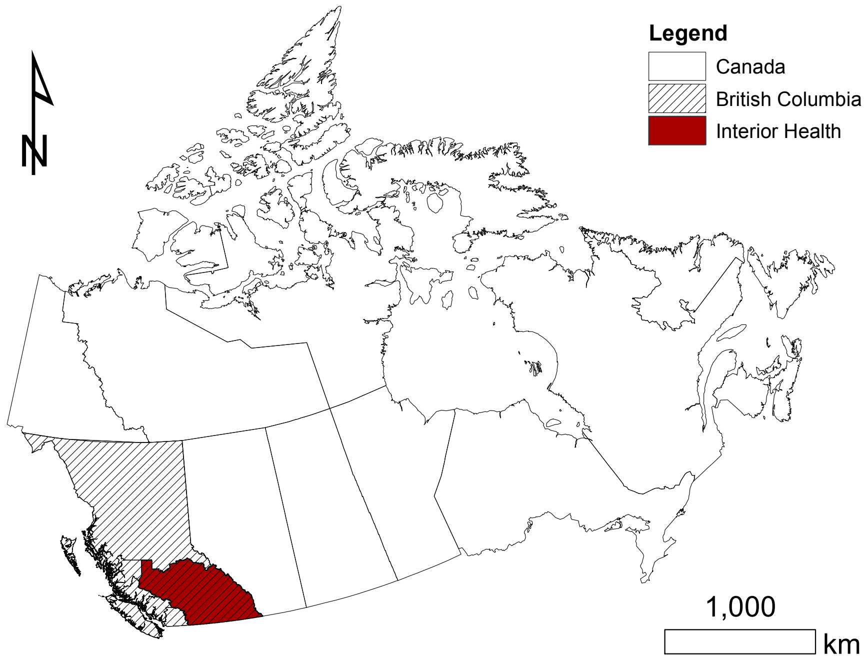
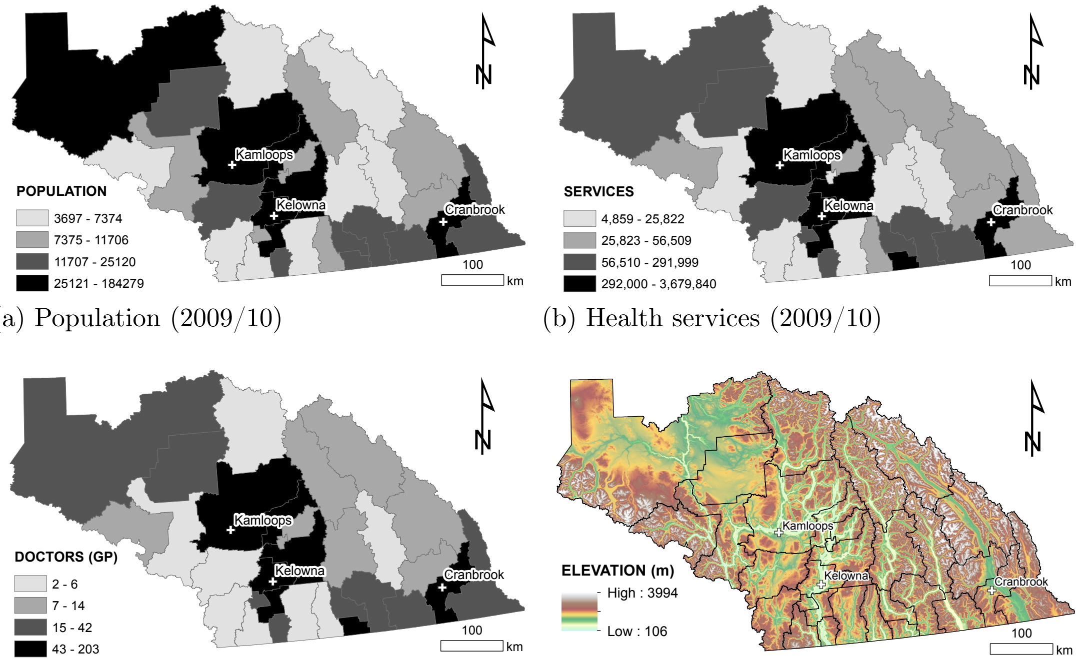


Figure 2.1: Interior Health, British Columbia, Canada

Health Authorities are further divided into 'Health Service Delivery Areas' (HSDA) and 'Local Health Areas' (LHA). These geographic units are used in the organization, administration and reporting of health services within the province. Figure

[1] All maps in this document use the 'NAD 1983 CSRS BC Environment Albers' projection.

2.2 displays population and health service data[2] aggregated by LHA.[3] Data presented in Figure 2.2(a-c) are classified in quartiles with the lowest quartile represented with the lightest shaded LHAs and the highest quartile with the darkest. The largest population centers within the Interior are the communities of Kelowna and Kamloops (Figure 2.2(a)).



(a) Population (2009/10)

(b) Health services (2009/10)

(c) General practitioners (2009/10)

(d) Elevation

Figure 2.2: Interior Health demography and topography by Local Health Area

The distribution of physicians and health services generally follow population distribution; however, the higher number of health services in the Cranbrook (East Kootenays) area indicates that the regional hospital in that community provides services for the bulk of the population in the surrounding LHAs. Individuals living outside of the darkly shaded LHAs of 2.2(b) are often required to travel to larger urban centres to receive specialized health services. The majority of General Practitioners (e.g., physicians providing generalized services) are located in the darkly

[2] Health service and population data were obtained from DataBC's online Data Catalogue: https://catalogue.data.gov.bc.ca (downloaded Dec 14, 2015).

[3] Health boundaries were obtained from the BC Stats website: www.bcstats.gov.bc.ca (downloaded Nov 17, 2015).

shaded LHAs of Figure 2.2(c); individuals within the lightly shaded LHAs have limited access to family physicians.

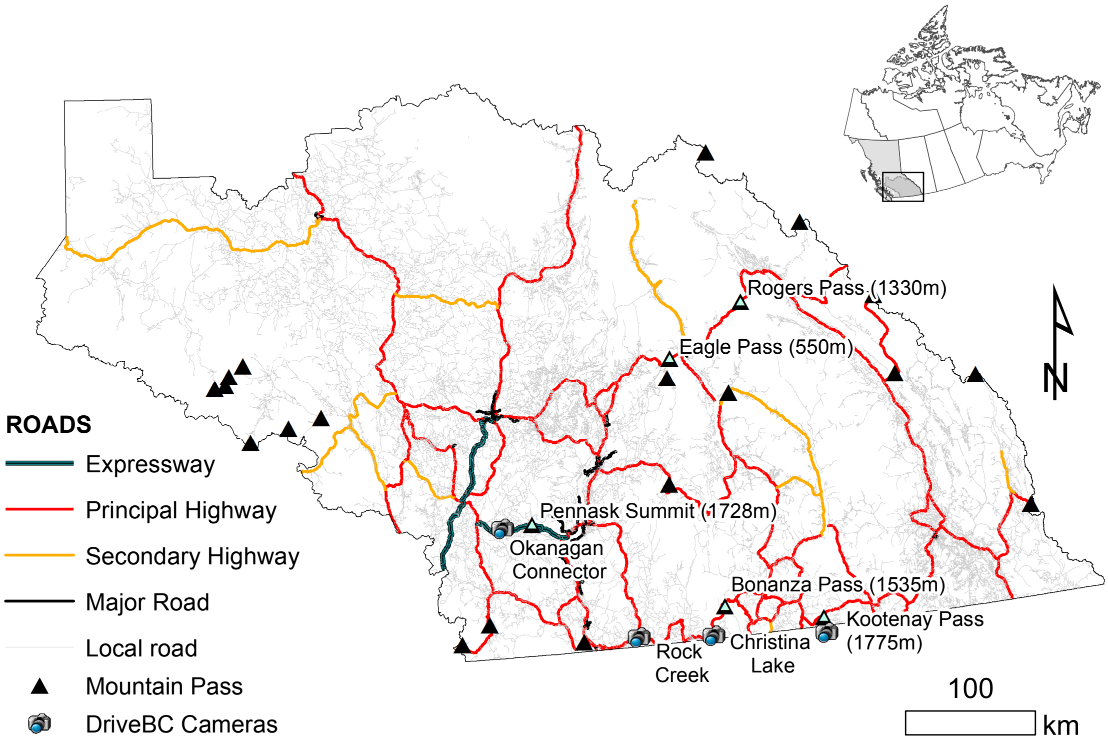


Figure 2.3: Road Network within Interior Health

Due to the Interior's vast and mountainous geography (Figure 2.2d), transportation between communities can be long and dangerous, particularly during winter months.[4] There are over 20 mountain passes within the region,[5] five of which are on regularly travelled inter-facility medical transport routes. Figure 2.3 shows the location of these passes along with the road system covering the study area.[6]

Road quality between communities varies from large three lane highways to poorly paved, winding single lane roads. Figure 2.4 shows examples of typical winter road

[4] Elevation data in Figure 2.2(d) is described in the Methodology section of this document (Section 3.2.2).

[5] Mountain passes shown in Figure 2.3 are listed on Wikipedia's Mountain passes of British Columbia website (accessed Nov 25, 2015) and are located within IH.

[6] Road network data in Figure 2.3 is described in the Methodology section of this document (Section 3.2.1).

conditions over some of the major roads within the Interior.[7]

(a) Okanagan Connector

(b) Christina Lake

(c) Rock Creek

(d) Kootenay Pass

Figure 2.4: BC Highway winter road conditions

2.2 Patient transport within Interior Health

In general, patient transport within BC is the jurisdiction of a provincial Emergency Medical Ambulance Service (EMAS). Each Health Authority, including IH, uses EMAS vehicles and paramedics (e.g., individuals with Basic Life Support (BLS) training) to transport their patients.

[7] These images were captured from the BC Highways website on Dec 20, 2015.

The provincial EMAS provides both pre-hospital transport (e.g., transport from site of a medical emergency to a hospital) and inter-facility transport (e.g., transport between two health care facilities). Pre-hospital transports generally take place within city limits and are less than 20 minutes (Patel et al., 2012). In contrast, inter-facility transport within the context of this study requires the movement of patients between communities. These transports can be upwards of three to four hours for patients residing in rural or remote areas.

An additional layer of complexity in inter-facility transport is faced when moving acutely ill patients. In these cases, patients require more than the BLS level of support provided by paramedics. Traditionally, a local physician (MD) or registered nurse (RN) would be required to escort the patient in the ambulance to ensure patient safety in transport, leaving their communities with diminished, or no, health services (Brayman et al., 2012). As most acute care services are located in urban areas of IH, a transport to definitive care could involves hours of driving through inclement weather and mountainous terrain. This trip is doubled for the escort who must make the return journey home. For the most time-sensitive cases, an air ambulance team of Critical Care Paramedics (CCPs) with Advanced Life Support (ALS) training is also available; however, this service is highly dependant on weather conditions and availability.

In 2010, IH transport program administrators proposed a new strategy to better deal with the challenge of high acuity inter-facility transport within IH: High Acuity Response Teams (HARTs). These teams are comprised of RNs and Registered Respiratory Therapists (RRTs) with advanced critical care transport training. Between 2010 and 2015, four HARTs were established across IH to support rural communities with the management and transport of high acuity patients. The full HART program model is further described by Brayman et al. (2012).

As of 2015, when a request for an IH high acuity inter-facility transport comes to the provincial dispatch centre, the dispatcher generally chooses from four available transport resources: Standard EMAS ambulance with two paramedics; RN/MD escort; HART escort; or a Critical Care Team (CCT) dispatched by air. The situation and context surrounding each transport is unique and dispatchers must make decisions using the best information available to them.

2.3 Theoretical framework

2.3.1 Transport time intervals

There are a number of critical time periods between an initial call to dispatch requesting a transport and the final transfer of patient care to healthcare providers at the receiving site (Fatahi et al., 2012; Cone et al., 2015; Giang, Donmez, Fatahi, Ahghari and MacDonald, 2014). These time periods are summarized in Figure 2.5.

In a UK-based study examining transfer time along the full continuum of transport intervals (e.g., call to dispatch – arrival at receiving site), Wong and Harris (2015) found that the correlation between transfer time and transport distance was weak, as was the correlation with several other environmental factors. They concluded that the delays might be largely attributable to organizational inefficiencies, likely resulting from the time intervals prior to the transport team's arrival to pick the patient up at the sending site (Wong and Harris, 2015).

As organizational factors influencing transport are beyond the scope of this study (i.e. data from these time intervals are unavailable), the following analysis will focus solely on the patient transport time interval (e.g., time between departure of sending site and arrival at receiving site). The red arrows of Figure 2.5 refer to these key time periods of interest.

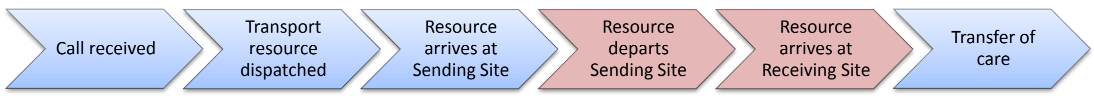


Figure 2.5: Major time intervals in inter-facility transport

2.3.2 Factors affecting transport time

Previous studies have examined a variety of factors that are hypothesized to influence observed transport time (e.g., the actual time it takes to transport a patient between sending and receiving sites). As journey time equals distance over speed and distance is generally assumed to remain constant (with the exception of route detours), it follows that most factors that influence transport time do so by influencing the speed of travel or are due to breaks in transport.

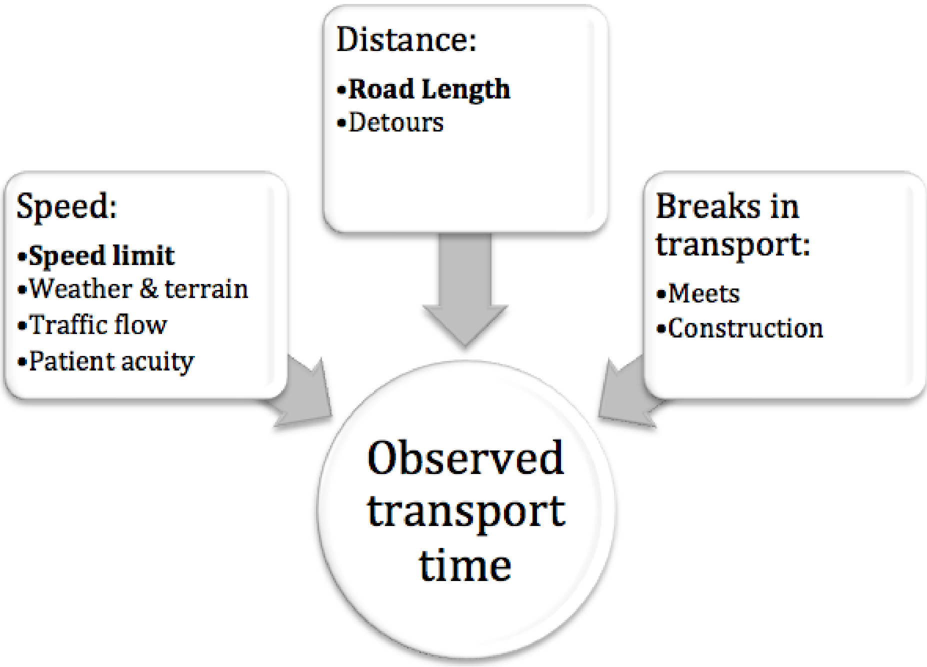


Figure 2.6: Theoretical framework of factors influencing observed transport time

General factors hypothesized to influence journey time through speed, distance, or breaks in transport respectively are presented in Figure 2.6. Road length and speed limit are highlighted in this figure as they are the principle road network attributes from which 'expected' transport times are calculated in this study. As this network analysis is based on retrospective data it is not feasible to accurately account for route detours or construction. However, this study will further investigate the impact of environmental factors, rush hour traffic, patient acuity and breaks in transport (e.g., meets) on observed transport times.

Road network

A road network describes key attributes (e.g., speed limit, length) for each road segment in an area of interest and can be used to calculate transport times and distances for routes of interest between two or more points. The use of GIS for calculating expected transport times in ArcGIS Network Analyst as well as in Google Maps is well established (Doumouras et al., 2012; McMeekin et al., 2014; Fleischman et al., 2013; Wallace et al., 2014; Patel et al., 2012).

In 2012, Doumouras et al. compared 'routing' (i.e. calculation of distances using road networks) to 'as-the-crow-flies' (i.e. straight line distance) methodology estimates of ground transport journey times in Ontario, Canada. These were the only two methodologies used to calculate Emergency Medical Service (EMS) access to critical care resources used in the literature to that point (Doumouras et al., 2012). The authors concluded that future methodologies for calculating EMS ground transport access should make use of routing methodology using valid routes calculated from road network datasets (Doumouras et al., 2012). In 2006, Shuurman et al. compared hospital catchment areas derived from as-the-crow-flies methodology with results derived from road network analysis within the Interior Health region of BC (Schuurman et al., 2006). As-the-crow-flies methodology resulted in an over-estimation of the population calculated to be within one hour of a hospital when compared to the results of the network analysis. The authors noted that using network analysis resulted in more accurate estimates of geographic access to health services (Schuurman et al., 2006).

A study published by McMeekin et al. in 2014 explored the use of a generic Geographic Information System in the comparison of actual versus predicted EMS transport times in northeast England (McMeekin et al., 2014). In this study, the authors used a basic road network analysis to determine the quickest route based on average speed limits for each road type. The authors found that this type of analysis was valid for transport predictions; however, it was noted that longer rural transport journeys, very short urban journeys, winter travel and travel in peak traffic hours were generally under-predicted and would need to be considered if using this methodology for resource allocation planning (McMeekin et al., 2014). This study suggests that road network analysis incorporating adjustments for additional environmental factors would be appropriate for modelling journey times.

The validity of using routing methodology along established road network datasets to calculate transport times was further confirmed by Fleischman et al. (2013) in a study exploring the ability of a Google Map, Global Positioning System (GPS) based web application to predict ambulance transport times in Multnomah County, Oregon. The authors of this study used street network speed limits in ArcGIS Network Analyst to estimate transport times. Adjustments to their model were made based on the results of a linear regression model incorporating patient characteristics, use of lights and sirens, weather, daylight, and rush-hour time intervals. Transport times were found to be shorter with the use of lights and sirens, and longer during daylight and rush-hour time intervals. Wet weather conditions and patient characteristics such as age and trauma status did not have a significant impact on transport and were ultimately excluded in the final model (Fleischman et al., 2013).

In a large study of nearly 30,000 pre-hospital transports in King County, Washington and southwestern Pennsylvania, Wallace et al. (2014) compared three methods of estimating transport times: Google Map *traveltime*[8], linear arc distance (e.g., straight line or as-the-crow-flies distance), and ArcGIS Network Analyst. The authors found that transport time estimates were within five minutes of observed transport time for 86.6% of Google Maps estimates, 79% of linear arc estimates, and 81.3% of ArcGIS estimates.

[8] '*traveltime*' is a Google plug-in for the Stata statistical software package (StataCorp, College Station, TX).

Environmental factors

Environmental factors that influence travel times include terrain characteristics (Miwa et al., 2006; Haynes et al., 2006) and weather conditions (Fleischman et al., 2013; Giang, Donmez, Ahghari and Macdonald, 2014; Giang, Donmez, Fatahi, Ahghari and MacDonald, 2014; Lam et al., 2015).

Roads built through mountainous terrain often have increases in curvature, slope and elevation to accommodate the underlying topography. These roads are also subject to extremes in weather, particularly during the winter months. Additional hazards such as rockslides, avalanches, and wildlife on the road increase the vulnerability of these roads. There have been limited studies looking at the impact of mountainous terrain on medical transport times; however, mountainous topography is frequently cited as rationale for accessing a community by air rather than by ground transport (Shaw et al., 2015).

In a recent study conducted in Ontario, Canada, Giang et al. reported an association between precipitation and observed transport times (Giang, Donmez, Ahghari and Macdonald, 2014). The nature of this association was different for intercity versus intracity transports. For intercity transports, rain caused delays of 1.7 minutes, 8.6% longer compared with no precipitation, and only marginal effects were seen with snow. Intracity transport (with 48 km median distance) saw delays of approximately 9.1% (3.1 minutes) with snow, while rain produced delays of 8.4% (2.9 minutes). The authors concluded that precipitation increased transport times for inter-facility transfers by eight to ten percent. Snow was associated with the longest transfer delays between cities but rain was associated with the longest transfer delays within a city. Similarly, in a study of factors affecting ambulance response times in Singapore, the authors found that weather (e.g., heavy rainfall), contributed to delays in response times (Lam et al., 2015)

Traffic flow

Two proxies of traffic flow commonly used in retrospective studies include time of travel (e.g., rush hours versus non-rush hours) and daytime versus overnight travel (Fleischman et al., 2013; Wallace et al., 2014). In 2013, Fleishchman et al. found that daylight, defined as sunrise to sunset, and rush-hour time intervals, defined as (07:00–09:00) and (16:00–18:30), were both predictive of ambulance transport times within their study context (Fleischman et al., 2013).

Similarly, Wallace et al. included seasons and time of day in their comparison of predictive models of transport times. In this case, seasons were grouped into Spring (March-May), Summer (June-August), Fall (September to November), and Winter (December to February). Time of day was grouped into four categories considered to have distinct traffic patterns: morning (06:01–10:00), mid-day (10:01–15:00), afternoon (15:01–20:00), and nighttime (20:01–06:00) (Wallace et al., 2014). The authors found that the inclusion of these factors slightly improved the sensitivity of their models; the greatest differences were found when comparing transport times on weekday mornings versus weekend mornings.

Although the above studies in Oregon, Washington, and Pennsylvania, USA found season and time of day to have a significant effect in their models of transport times, Fatahi et al. (2012) found that month and time a day were not statistically significant in their study of transport times in Ontario, Canada.

Patient acuity

It is hypothesized that high patient acuity and the related urgency for transport will result in reduced transport times where possible. In some cases the use of ‘lights and sirens’ reflects this urgency. For example, Fleischman et al. (2013) found that lights and sirens saved an average of 3.1 minutes for transports under 8.8 minutes and 5.3 minutes for longer transports. Although the median pre-hospital transport time of 15 minutes reported by Fleischman et al. was much lower than typical inter-facility transport times seen in the current study, it is reasonable to assume that a similar trend towards faster transport times for high acuity patients would be seen. Although data on the use of lights and sirens were unavailable for this study, there are several other proxies for urgency in transport that can be used such as stroke or myocardial infarction (HSF, 2015).

Breaks in transport

Long distance medical transports involve more complicated resource planning than most. For example, if dispatch receives a request for a patient transport that is estimated to be two hours from the sending site, the time required for the sending site crew would be over 4 hours (time to sending site, time for patient handover, and time to return home). If the request comes late in the afternoon, dispatchers must consider shift changes of the EMAS crew as well as the length of time a transport resource will be away from their assigned catchment area and unavailable to provide pre-hospital emergency transport.

In some cases, a 'meet' will be coordinated between a transport team based at the sending community and a team from the receiving community. This will reduce the amount of time the sending site crew needs to be away from their assigned catchment area as well as lessen the financial (e.g., overtime payments) and safety (e.g., sleep deprivation and overwork) related impacts of the transport. Meets may take place at an ambulance station, hospital, or side of the road near the mid-point of the transport route. The time it takes for a meet to occur may depend on a variety of factors such as the complexity of the patient (e.g., longer patient handover time) and the time it takes for both vehicles to reach the meet location (e.g., if the receiving site team is delayed, the sending site team may have to wait with the patient until they arrive).

2.4 Application of GIS

This study makes use of GIS as an integral part of evaluating observed transport times. Network analysis tools allowed for the identification of most likely routes between sending and receiving sites. Journey time estimates could then be calculated using speed limit and distance attributes. Raster analysis and interpolation functions were also performed to calculate maximum elevation on each route.

Network analysis

The Network Analyst toolbox in ArcGIS 10.2 can perform a variety of analytic functions on transportation networks such as route, service area, closest facility, and location-allocation analyses (Figure 2.7). Network datasets that model transportation networks can also be created and maintained using this tool (Mitchell, 1999). The primary function of Network Analyst used in this project was route analysis.

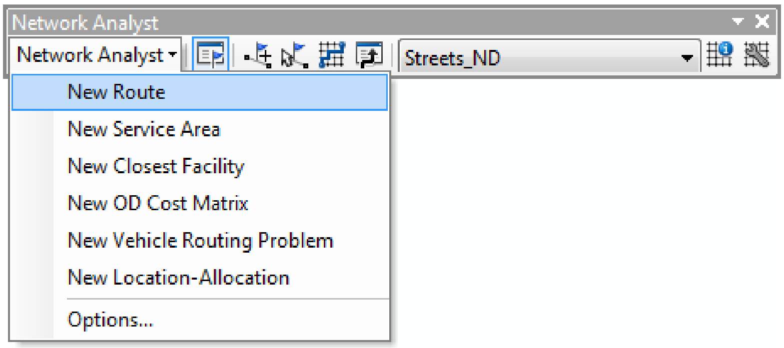


Figure 2.7: Analysis functions in ArcGIS Network Analyst

In order to perform analyses within the Network Analyst, a network dataset (e.g., a model of the road system) must be created or obtained. A shape file of a road network can be used to build a network dataset. The dataset will contain the same attribute information for each road segment, such as speed limit and distance; however, additional information such as road connectivity is built into the dataset to allow for more complicated analyses. The network dataset can be augmented to include a variety of additional information such as road hierarchy (e.g., gives more weight to road segments of certain road types), directionality (e.g., ensures correct use of one-way road segments), construction and traffic flow.

Once the network dataset has been created, a route analysis can be used to de-

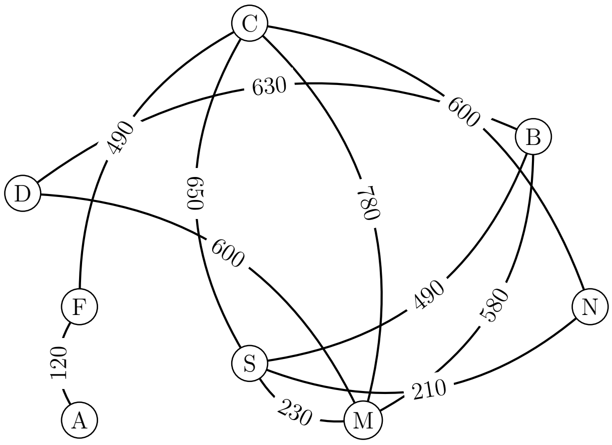


Figure 2.8: Network example

termine the 'best' route between two or more points on the network. What is considered the best route depends on the requirements and related impedance settings of the user (e.g., quickest, shortest, most scenic); any valid cost attribute of the road network can be used as an impedance value (e.g., speed limit or distance).

Route analysis calculations are based on Dijkstra's algorithm, a well know algorithm in the field of graph theory used for finding shortest paths (Derekenaris et al., 2001). As an example, when Dijkstra's algorithm is applied to a network such as that of Figure 2.8, a network analysis would consider the value (i.e. cost attribute) along each edge to determine the shortest path. For example, using this algorithm to determine the shortest path between N and D in Figure 2.8 would result in a path from **N** → S → M → **D** at a total cost of 1040.

Raster data

A 'raster' is a data structure represented by a grid (e.g., matrix of cells) where each cell is assigned a value (Mitchell, 1999). Rasters generally store information relating to a single attribute such as temperature or elevation. This is in contrast to 'vector' data, which stores information within the discrete boundaries of points, lines, or polygons (Mitchell, 1999). The raster data of interest in this project represents elevation over the study area and is also known as a Digital Elevation Model (DEM).

Canada releases a variety of geographic information based on the National Topographic System (NTS).[9] NTS maps are produced at a scale of 1:250 000 and 1:50 000, with the 1:50 000 scale maps covering an area of approximately 1000km^2. NTS 1:50 000 scale elevation data was obtained for this project.

In order to work with multiple raster tiles at a time, it is often necessary to combine them. ArcGIS has several functions to solve this problem within 'Data Management Tools → Raster' including the creation of a Mosaic Dataset, a Raster Dataset, or a Raster Catalog. Each of these options brings raster datasets together; however, they differ in how they store the data. The Mosaic Dataset provides the most flexible option for bringing together large numbers of raster datasets while minimizing storage requirements (Xu et al., 2013). Once a Mosaic Dataset has been created it can easily be converted into a single Raster Dataset.

Interpolation is a procedure that predicts the value of an area based on the values surrounding that area. This has many applications in GIS, where continuous data (e.g., raster data) is often created by interpolating values across a continuous surface based on information from a number of strategically selected sample points. This technique is also used when calculating z-values for a vector feature based on geographically related elevation data, converting a 2D feature to a 3D feature. Interpolation methods such as 'linear' and 'nearest neighbours' are available for use within this function.

Stack profiles are another way of examining raster data values over a line feature. This tool provides both a table of elevation values for every line segment and an associated graph. When using this tool to calculate elevation over a transport route, it is possible to identify min and max elevation as well as related information such as maximum slope and the number and size of hills along the route.

Each of the above functions were used to inform this project and are further described in the Methodology section below (3.2.2 Raster analysis).

[9] Visit www.nrcan.gc.ca for more information on the NTS system.

3 Methods

Administrative and geographic data were used to evaluate medical transport times and associated predictive factors for this project. The methods described in this study are grouped into three sections below: Data collection, geographic analysis, and statistical analysis.

This study was reviewed and approved by the University of British Columbia (UBC) Behavioural Research Ethics Board (REB) in harmonization with the Interior Health REB (H15-03038).

3.1 Data collection

A medical chart, also know as a medical record, contains all of the documentation relating to a patient's stay within the hospital. Some information may be documented and stored electronically (i.e. as an 'Electronic Medical Record' (EMR)), other information may be documented on paper. All of the paper documentation relating to a patient visit is bound together in a 'chart'. When the patient is discharged from the hospital their paper chart is then stored in the medical records department of that facility. Information required for this study was primarily within emergency department records, patient transport records, and nursing notes – all of which were paper-based within Interior Health during the time period of this study.

A retrospective chart review of high acuity inter-facility patient transports was conducted in order to collect information about transport times and other patient transport characteristics. After identifying high acuity patient transports that took place between Apr 1, 2011–Mar 31, 2015 and met all other selection criteria outlined within Table 3.1, the corresponding paper charts were pulled and reviewed. The author travelled to each of the five study sites (i.e. Kelowna, Kamloops, Cranbrook, Trail, and Penticton) to review and abstract data from these charts in person.

3.1.1 Sample selection

This study was focused on inter-facility transports. Only transports of those patients who had been admitted to an Emergency Department and then transferred to a higher level of care (e.g., the Emergency Department of another hospital) were selected for review. Patient acuity was determined using the Canadian Triage Assessment Scale (CTAS). This scale is used to inform triage decision-making in Canadian Emergency Departments – a CTAS score of 1 is assigned to the most acute patients (e.g., Patients need to be seen by a physician immediately 98% of the time) and 5 is assigned to the least acute patients (e.g., Patients need to be seen by a physician within 120 minutes 80% of the time).[1] Only patients who had been assigned a CTAS score of 1 or 2 were selected for this study (see Table 3.1).

Several electronic databases were used to identify patient transports meeting the sample selection criteria presented in Table 3.1. A random selection of 200 HART patient transports that met the selection criteria were identified by the systems analyst responsible for HART data systems. Information from the HART electronic Patient Care Record (ePCR) was joined with that of the Digital Abstract Database (DAD) using a unique identifier. The resulting sample reflected the relative transport volume to each of the base sites of interest. The earliest transport date cut-off (i.e. Apr 1, 2011) was selected as the start of the first fiscal year in which HART was fully established. An additional 218 transports that met selection criteria but were not in the HART ePCR (e.g., assumed to be non-HART transports) were also selected for inclusion in the study sample. These transports were case matched to reflect the distribution across clinical categories and base sites in the HART sample (i.e. A roughly equivalent number of non-HART trans-

[1] More information regarding CTAS scores and implementation guidelines can be found by visiting www.caep.ca.

Table 3.1: Selection Criteria

Inclusion Criteria	Exclusion Criteria
• Inter-facility transports • Adult transports (ages 16–65) • Admitted directly to ED • CTAS 1 and 2 • Transported Apr 1, 2011–Mar 31, 2014 • Clinical category: neurological, cardiac, respiratory, sepsis, and trauma	• Non-acute/scheduled transports • Pediatric transports • Pre-hospital transports • CTAS ≥ 3

ports from each of the base sites and in each of the clinical categories were selected for this study). In total, 418 patient transports were selected for review.

3.1.2 Tool development

The data abstraction tool used for this study was developed in consultation with HART clinicians and administrators within IH. Data elements included relevant transport time stamps, locations (e.g., sending site and receiving site), physiological parameters (e.g., patient vitals) and medical intervention information. The tool was piloted on 20 charts and subsequently revised for brevity and clarity. The primary revisions included a reduction in the amount of detail collected about medical interventions as well as decreasing the time period of interest at the receiving site. Revisions to the data collection tool reduced the time required to abstract data for a single transport from approximately one hour to fifteen minutes. A summary of the data elements collected within the final data abstraction tool is presented in Appendix A.

3.1.3 Data abstraction

Chart reviews took place at each of the five receiving sites of interest from Oct 2014–May 2015. Data were input into a password protected Excel spreadsheet and stored on a protected network. All data entry was done by the author; however, HART clinicians assisted in reviewing and interpreting the clinical aspects of the medical records. A HART clinician was available to assist at all sites except one. If clinical questions arose and a HART clinician was unavailable, the issue was documented and flagged for further follow-up. Documentation missing from the receiving site charts were requested from sending sites in follow-up to the main data collection process.

3.2 Geographic analysis

A number of geographic analyses were conducted in ArcGIS 10.2 to derive route characteristics such as accumulated journey time and distance as well as elevation profiles and maximum elevation.

3.2.1 Road network analysis

Network analysis was conducted using ArcGIS 10.2 Network Analyst. Accumulated transport times along all routes of interest were calculated based on route distance and speed attributes. The DMTI CanMap Route Logistics 2014 road network file, produced by DMTI Spatial Inc., was first converted into a network dataset with travel time added as a cost attribute for the network dataset. All hospital locations present in the study dataset were geocoded for use as network locations. A route analysis was then conducted for each of the 38 unique routes identified within the chart review (Figure 3.1).

Expected transport times

Fastest routes and associated accumulated travel time and distance for each route were calculated using travel time as the primary impedance attribute within Network Analyst. Travel time and distance estimates were also calculated in Google Maps for comparison. Each route derived from the Network Analyst was reviewed

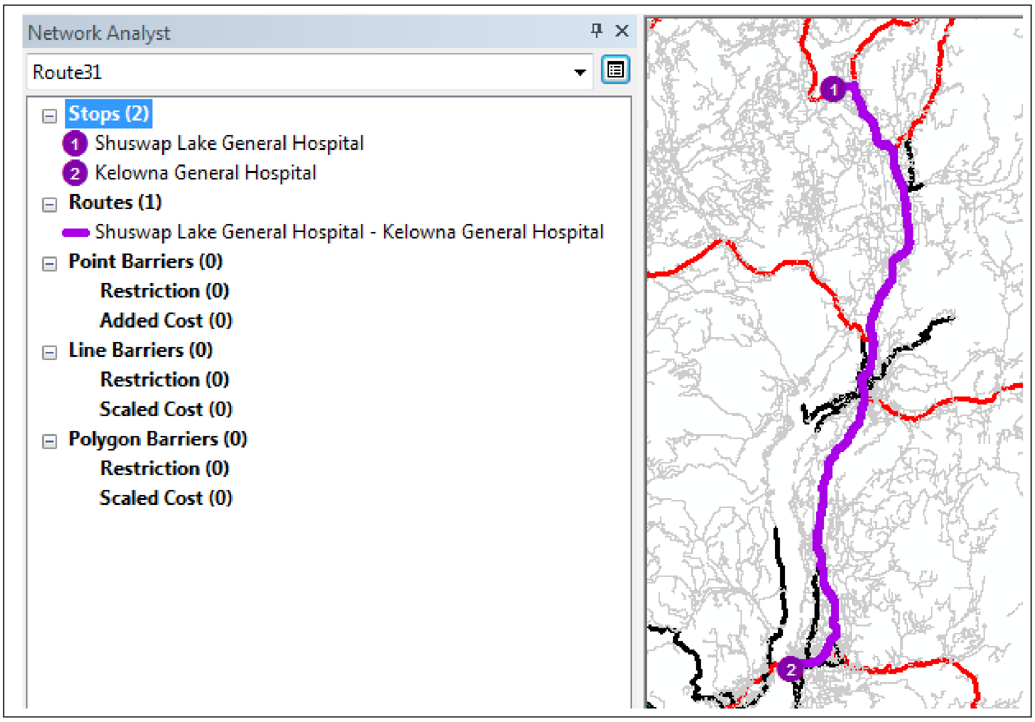


Figure 3.1: Route analysis example: Salmon Arm to Kelowna

using Google Maps results and personal knowledge of regional transport routes to confirm the route solver was returning valid solutions.

3.2.2 Raster analysis

Canadian Digital Elevation Data (CDED) covering the study area were downloaded from GeoBase in November 2015 (GeoBase, 2007; Natural Resources Canada, 2015). Figure 3.2 shows the NTS grid structure for the study area where each red box represents a 1:250 000 tile comprised of 32 green boxes, each representing a 1:50 000 tile. In total, 642 composite tiles were mosaicked together using the *Raster* function in ArcGIS Data Management Tools and clipped to cover the full study area.

The resulting DEM was used to create contour maps of the study area using the *Contour* function in 3D Analyst, Raster Surface Tools. It was also used to create

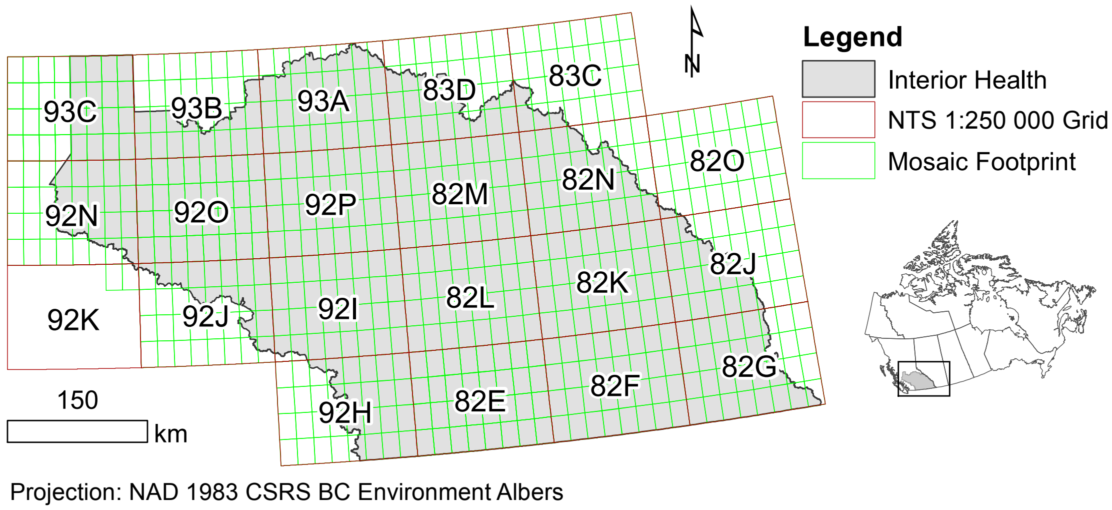


Figure 3.2: Mosaic of DEM tiles over study area

elevation profiles for all unique routes in the study dataset, first by using the *Interpolate Shape* function on the road network and the *Stack Profile* function in 3D Analyst, Functional Surface Tools for each route. These profiles were reviewed to identify the maximum elevation of each route. Figure 3.3 presents several views of the route between Trail and Kelowna as well as a display of elevation change in meters.

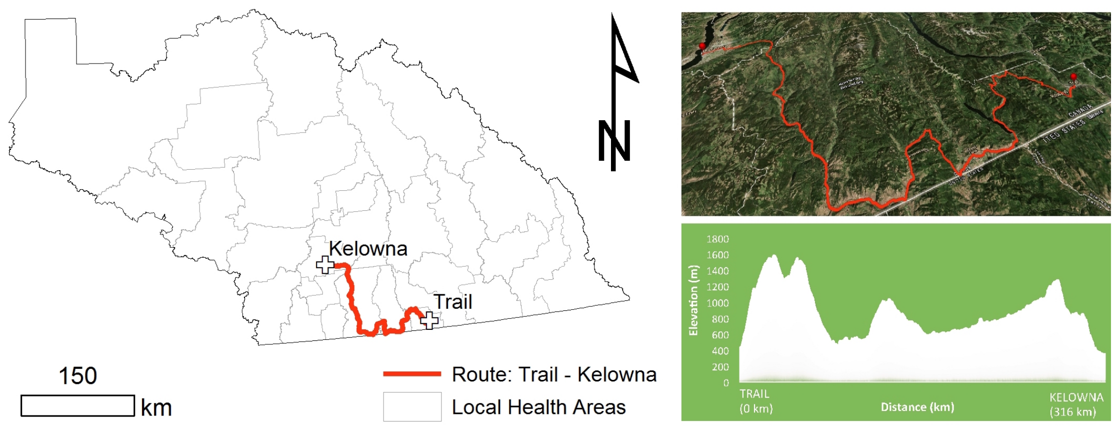


Figure 3.3: Elevation profile example: Trail to Kelowna

3.3 Statistical analysis

In order to answer each of the research questions in this study, information from the previous sections were collected or calculated and compiled into a complete dataset. The data were further examined using the statistical methods described within this section.

3.3.1 Descriptive statistics

Of the 418 charts reviewed in this study, 69 were excluded from the analysis due to ineligible mode of transport (i.e. air transports) or incomplete time-stamp data. The final dataset consisted of 349 transports.

Observed transport times were calculated using the difference between the 'depart sending' and 'arrive receiving' time-stamps identified in the chart review for each transport. Each route represented in the study dataset was assigned a unique route ID. The Median, Median Absolute Deviation (MAD), Inter Quartile Range (IQR) and other measures of variance of observed transport time were calculated for each route represented in the study sample. Observed transport times were evaluated against expected times for each route with more than ten cases using the Wilcox Signed-Rank Test (*wilcox.test*, stats package (R Core Team, 2015)) and the Sign Test (*signTest*, EnvStats package (Millard, 2013)) in **R** (R Core Team, 2015).

3.3.2 Heteroscedasticity

Heteroscedasticity is a measure of unequal variance of residuals over the range of a variable of interest. In this case, a measure of the variance of residuals of observed transport time by distance was used to determine whether or not the variance of observed transport times increased with distance travelled. Two tests were used to determine whether or not residuals were heteroscedastic: White's test (*whites.htest*, het.test package (Andersson, 2013)) and the modified Breusch-Pagan test (*bptest*, lmtest package (Zeileis and Hothorn, 2002)). Both were calculated in this study to ensure results were robust to the method used.

3.3.3 Regression

A regression analysis is a process that estimates the relationships between a response variable and one or more independent variables of interest. There are many techniques available for conducting a regression analysis. This project makes use of a (backwards) stepwise selection strategy to identify which independent variables are statistically significant predictors of the response variable. This multiple regression analysis was performed in **R** using both adjusted R^2 and P-values to determine if the result was robust to the statistical parameter used to evaluate the model. Each of the variables considered for use within the full model are outlined below:

(1) Expected time: Expected transfer times were calculated for each route within the study. These times were calculated using accumulated distance and speed based on road segment length and speed limit in ArcMap. Expected travel times were also calculated in Google Maps for comparison.

(2) Elevation: Elevation data (in meters) for each route were calculated by interpolating elevation values from a DEM raster. Maximum elevation for each route was identified and used in this analysis. Elevation cut-offs points were also examined but were not used as part of the full regression model due to known limitations of dichotomized quantitative variables (MacCallum et al., 2002).

(3) Mountain passes: A mountain pass is a route over a ridge or mountain range. This boolean variable was used as a proxy of mountain driving conditions within the regression analysis.

(4) Time of day: Time of departure from the sending site was coded to capture the following driving intervals: morning rush (07:01–10:00), daytime (10:01–15:30), afternoon rush (15:31–18:30), and nighttime (18:31–0:700). Rush hours in this study are slightly smaller (3 hours with peaks at 08:30 and 17:00) than what may be assigned in a larger urban centre as traffic volume is lower within IH than in more heavily populated areas.

(5) Season: The date of departure from the sending site was coded into four seasons: Spring (March-May), Summer (June-August), Fall (September to November), and Winter (December to February).

(6) Meet: This boolean variable captures whether or not two transport teams met and transferred patient care in transport. Separate regressions were also run on a subset of data that excluded transports involving a meet to ensure that high leverage residuals (due to meets) were not influencing the final variables and related coefficients included in the best fit model.

(7) Transport resource: Transport resource refers to the make-up of the transport teams who were dispatched on each transport. Three transport resource options were included within this analysis: EMAS alone, EMAS with HART and EMAS with a MD/RN escort.

(8) Clinical category: A proxy for patient acuity, the clinical categories included in this study were respiratory, neurological, cardiac, trauma and sepsis.

(9) Stroke: Another proxy for patient acuity, stroke or suspected stroke cases are particularly time sensitive. This boolean variable was coded yes or no for suspected stroke.

(10) Intubation: Intubation is a common intervention to assist in airway management. Although intubation can be seen as another proxy for patient acuity, this boolean variable likely behaves differently with respect to transport time than the other measures in this study. Whereas a fast transport time is considered to *be* the intervention for a stroke patient, an intubated patient may be associated with longer transport times due to the added clinical complexity of managing intubation in transport.

Hourly climate data, including temperature and weather conditions, were available for approximately 13% of the dataset at the sending site and 72% at the receiving site from Environment Canada's Historic Climate Data website. This variable was excluded from the regression analysis due to the large amount of missing data and the low occurrence of rain or snow within the available data.

Dummy coding was applied to all categorical variables within R. Upon examination of the model residuals, transports involving a meet were also removed from the dataset in a secondary analysis due to the high leverage of corresponding residuals.

A number of regression diagnostics were performed to ensure that the basic assumptions of a linear regression such as linearity, normality, and homoscedasticity were met (Mitchell, 2005). As the assumption of homoscedasticity was already hypothesized to be violated, model inference was made using heteroscedasticity-corrected covariance matrices (HCCM).

4 Results

4.1 Evaluation of transport times

Network analysis identified most likely routes between each sending and receiving site within the study dataset based on distance and speed limits. These routes are presented in Figure 4.1.

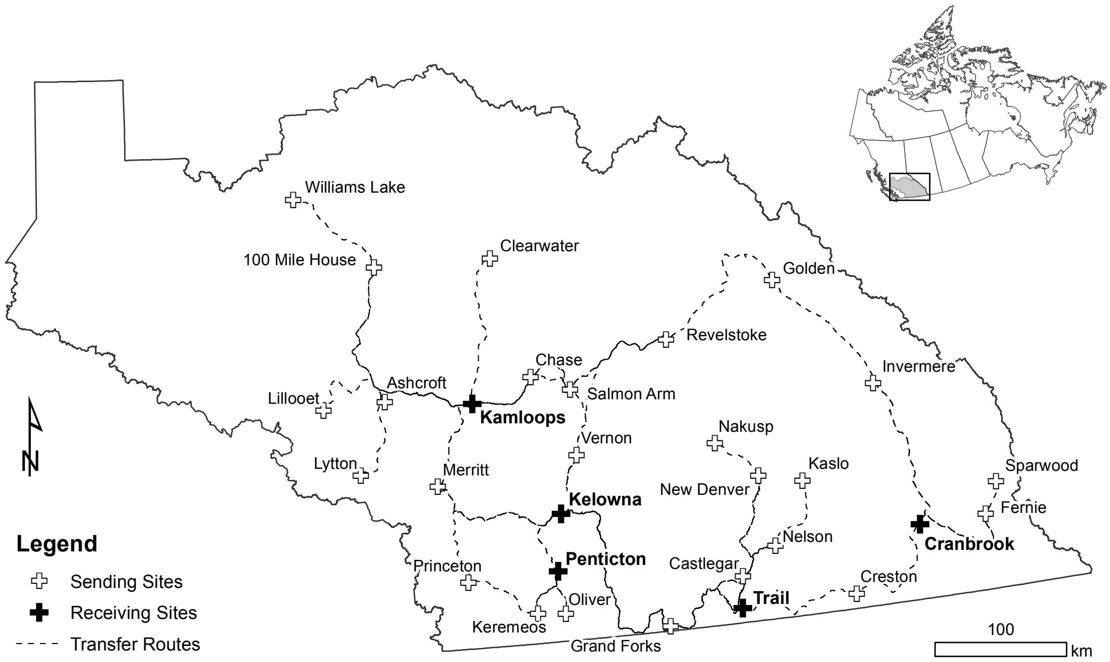


Figure 4.1: Transport routes within the study dataset

Journey times, both expected and observed, were calculated for all 38 unique routes found within the dataset. The number of cases along each route varied between 1 and 25.

A comparison of expected transport times calculated using Google Maps versus those calculated using ArcMap showed that both estimates were similar and highly correlated to observed transport times. A summary table displaying transport time percentiles is presented in Table 4.1.

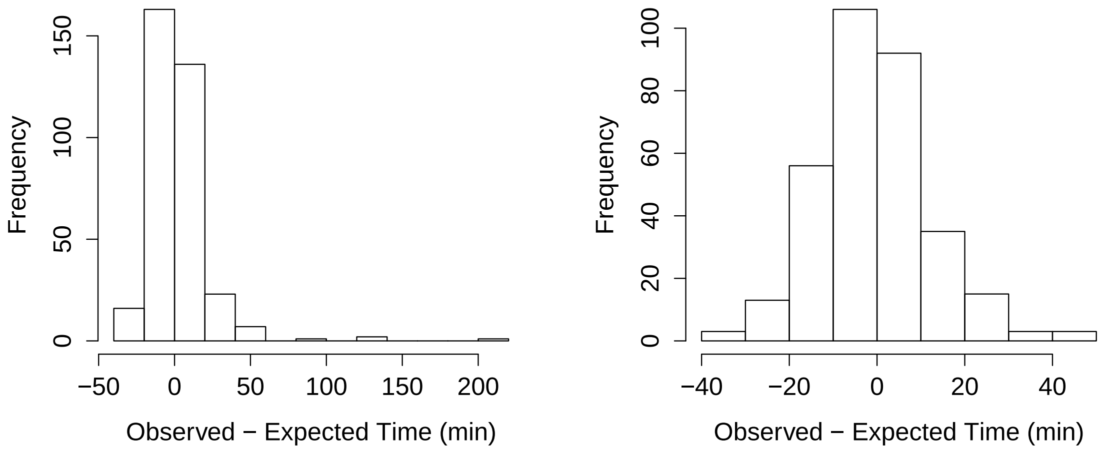
Table 4.1: Transport times by percentile

Statistic	Min	Pctl(25)	Median	Pctl(75)	Max
Observed Time	18	54	75	108	461
Expected Time (ArcMap)	24.5	45.0	83.7	102.7	276.4
Expected Time (GoogleMap)	29	50	78	104	284

Google Maps estimates had a slightly higher correlation with observed transport times in the full dataset than the ArcMap analysis (R^2 of 0.893 versus 0.872). This is consistent with previous findings comparing the results of a generic network analysis with that of Google Maps (Wallace et al., 2014). This may be partly due to the amount of traffic flow data that is available to Google that has allowed for improvements in their time estimate algorithms. Both Google Maps and ArcMap time estimates were used to evaluate observed transport times.

Measures of variance including Median Absolute Deviation (MAD) and Standard Deviation (SD) of the difference between observed and expected transport (ArcMap) time were calculated in **R** using the stats package (R Core Team, 2015). The MAD represents the extent to which data deviates from the median, irrespective of the direction of the deviation. In contrast to SD, MAD is a measure of variance that is robust to outliers. For example, Figure 4.2a presents data for all 349 transports, including 23 transports where a meet took place. The inclusion of meets in transport resulted in greater differences between observed and expected transport times and a right skewed distribution of observed transport times. The MAD and SD of the complete dataset were 12.01 and 21.43 minutes respectively; however, when 'meets' were excluded from the dataset (Figure 4.2b, the associated MAD and SD were 11.42 and 12.69 minutes respectively.

Although MAD is a robust measure of variance, sample sizes equal to or smaller than ten are found to be unreliable and overestimated (Harding et al., 2014). Therefore, only the 15 routes with more than ten cases in the study dataset



(a) Meets included n=349

(b) Meets excluded n=326

Figure 4.2: Distribution of difference between observed and expected transport times

are presented in Table 4.2 below (23 routes with fewer than ten cases were excluded).

The Sign test and the Wilcoxon signed rank test were used to compare observed times with expected time estimates. When analyzed across the full dataset, neither test showed a statistically significant difference between these two variables.

The Sign test was also used to evaluate observed versus expected transport times for each of the routes presented in Table 4.2. This test is a non-parametric test of the null hypothesis that a median is equal to a user-specified value, in this case the expected transport time, and creates a confidence interval for the median. Of the 15 routes, the median observed transport time along three routes differed significantly from ArcMap estimates; however, these differences were not detected when comparing observed transport time to Google Map estimates. There were no routes that had a statistically significant difference between observed time and *both* ArcMap and Google Map calculated transport time estimates.

This finding reinforces the validity of using journey time estimates from route anal-

Table 4.2: Summary of observed journey times by route

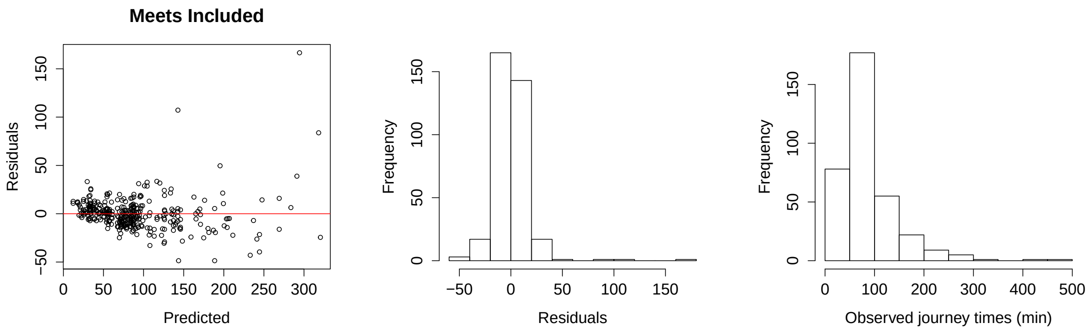
				Observed Time (minutes)			
Sending	Receiving	N	Dist (km)	Median	MAD	IQR	Range
Ashcroft	Kamloops	25	94	65	8.9	11	42
Merritt	Kamloops	23	85	54	8.9	9	35
Oliver	Penticton	23	40	39	10.4	13	35
Salmon Arm	Kamloops	22	111	79	9.6	12	40
100 Mile House	Kamloops	21	196	135	7.4	10	74
Keremeos	Penticton	20	46	41	5.2	8	37
Castlegar	Trail	17	29	29	5.9	6	22
Nelson	Trail	17	70	58	5.9	8	34
Creston	Cranbrook	16	107	75	8.9	14	34
Invermere	Cranbrook	14	135	91	8.9	13	50
Princeton	Penticton	14	115	86	12.6	15	41
Fernie	Cranbrook	13	97	66	5.9	9	35
Clearwater	Kamloops	12	125	93	18.5	18	44
Grand Forks	Trail	11	108	84	11.9	14	61
Lillooet	Kamloops	11	171	128	10.4	23	70

ysis; however, it is also important to note that this is an exploratory analysis of pilot data with sample size limitations (i.e., low numbers of transports along individual routes). Future data collection (or access) using an a priori determination of which routes to include within the study will be required to achieve appropriate statistical power.

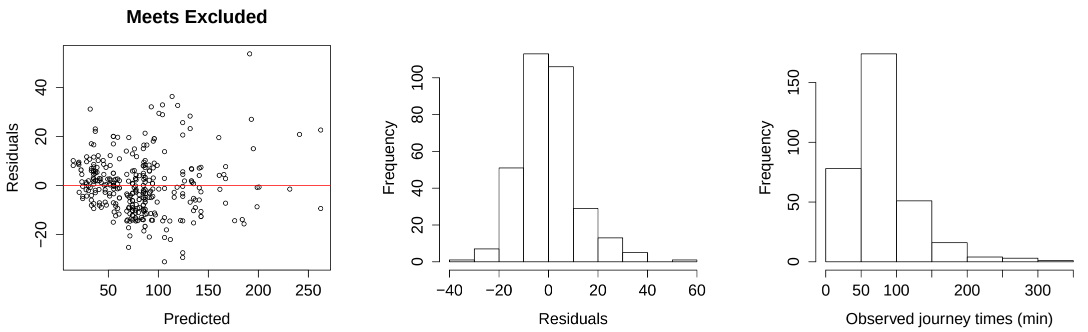
4.2 Variability of transport times

An examination of observed versus expected transport times showed increased heteroscedasticity with distance (Figure 4.3(a-c)). This finding was confirmed with a positive studentized Breusch-Pagan test (BP=56.96, $p < 0.01$).

Meets in transport introduced a high degree of uncertainty in transport times. Although meets had a relationship with distance (e.g., most commonly took place on longer transport routes), the resulting delays were not proportional to distance



(a) Residuals vs predicted (b) Frequency of residuals (c) Observed transport times



(d) Residuals vs predicted (e) Frequency of residuals (f) Observed transport times

Figure 4.3: Distribution of residuals of observed versus expected transport times

and ranged from minutes to hours. To ensure that the variability seen in the residual plot was not driven by delays due to meets in transport, these cases (n=23) were removed in a secondary analysis (Figure4.3 (d-f)); however, the studentized Breusch-Pagan test remained positive (BP=24.80, $p < 0.01$).

4.3 Factors influencing transport times

Regression analysis was conducted on the full dataset (1) as well as a subset of the data excluding meets (2). Variables with coefficients that were not statistically significant at the α=0.05 level were removed to create a best fit model. The most parsimonious model for the dataset without meets included the same four predictor variables as the the analysis of the full dataset. The presence of a meet was also a statistically significant predictor in the full dataset.

Tables 4.3 and 4.4 show the regression coefficients for both multiple regression analyses (i.e. analysis of full dataset and analysis of subset excluding meets). Statistically significant results are denoted by one or more asterisks depending on the level of significance. Standard error is presented in brackets to the right of each regression coefficient. Table 4.3 shows the results of these multiple regression analyses using ArcMap time estimates while table 4.4 uses Google Map time estimates.

Table 4.3: Regression results (ArcMap time estimates)

	Dependent variable:	
	Observed transport time (in minutes)	
	(1)	(2)
	Meets	No Meets
Intercept	-8.06^{**} (3.16)	-3.66^{*} (2.16)
Expected Time	0.98^{***} (0.02)	0.94^{***} (0.02)
Elevation (m)	0.01^{***} (0.00)	0.01^{***} (0.00)
Type: Neuro	-7.50^{**} (2.92)	-7.79^{***} (2.03)
Type: Resp	2.42 (2.73)	1.78 (1.84)
Type: Sepsis	4.13 (4.37)	3.67 (2.89)
Type: Trauma	3.27 (2.52)	1.69 (1.73)
Transport: Escort	−3.44 (3.76)	−3.56 (2.49)
Transport: HART	5.55^{***} (2.04)	5.65^{***} (1.40)
Meet	45.87^{***} (4.26)	
Observations	349	326
R^2	0.910	0.932
Adjusted R^2	0.908	0.930
Residual Std. Error	17.66 (df = 339)	11.65 (df = 317)
F Statistic	381.73^{***} (df = 9; 339)	540.14^{***} (df = 8; 317)
Note:		*p<0.1; **p<0.05; ***p<0.01

Although the previous finding of heteroscedasticity confirmed that variability in transport time increased with distance, it also violates a basic assumption of re-

Table 4.4: Regression results (GoogleMaps time estimates)

	Dependent variable:	
	Observed transport time (in minutes)	
	(1)	(2)
	Meet	No Meet
Intercept	-6.25^{***} (2.38)	-4.03^{**} (1.80)
Expected Time	1.07^{***} (0.02)	1.06^{***} (0.02)
Type: Neuro	-9.07^{***} (2.67)	-8.94^{***} (2.03)
Type: Resp	2.91 (2.49)	2.30 (1.83)
Type: Sepsis	4.49 (3.99)	3.675 (2.89)
Type: Trauma	3.43 (2.29)	1.48 (1.73)
Transport: Escort	−0.52 (3.42)	−1.16 (2.49)
Transport: HART	4.64^{**} (1.86)	5.54^{***} (1.40)
Meet	42.39^{***} (3.90)	
Mountain Pass		-9.94^{***} (2.48)
Observations	349	326
R^2	0.925	0.932
Adjusted R^2	0.923	0.930
Residual Std. Error	16.13 (df = 340)	11.63 (df = 317)
F Statistic	522.79^{***} (df = 8; 340)	541.90^{***} (df = 8; 32)
Note:		*p<0.1; **p<0.05; ***p<0.01

gression analysis: uniform variance. To correct for this, White's heteroscedasticity-corrected covariance matrices (HCCM) were used to make inferences in this analysis.

The explanatory variables within the model included expected (ArcMap) transport time, clinical type, elevation, and the mode of transport. The linear regression using the full dataset was able to explain 91.0% of the variance within observed transport times, whereas the linear regression using the dataset with meets excluded was able to explain 93.2%. In comparison, a single linear regression looking only at the response variable (observed transport time) as a function of distance was able to account for 85.0% and 90.6% of the variance in the full dataset and subset of data excluding meets respectively.

The Box Cox power transformation corrects non-normal data, allowing for statistical analysis tools to function under conventional assumptions. Lambda (λ), the suggested power transformation, was calculated for each regression model. Results indicated a square root transformation ($\lambda = 0.53$) of the dependent variable (observed transport time) for the regression with meets included and a two-thirds power transformation ($\lambda = 0.63$) for the regression with meets excluded. However, power transformation of the dependent variable (*BoxCox*, MASS package of R (Venables and Ripley, 2002)) did not effect significance of the explanatory variables selected in the best fit model.

Interestingly, running the same regression with expected transport times calculated in Google Maps (rather than ArcMap) did not find elevation as a continuous variable to be statistically significant. Rather, it selected the variable 'Mountain Pass' as significant predictor within the model (Table 4.4). The presence of a mountain pass was also found to have an opposite effect on transport time in this model (e.g., presence of a pass predicted faster transport times) than what was hypothesized and seen in the previous regression using ArcMap times.

5 Discussion

An examination of some of the most frequently used inter-facility transport routes within IH showed that, although variability of transport times increased with distance, no routes had significantly longer than expected transport times that could not reasonably be accounted for by the presence of a meet in transport. Regression analysis showed that a meet in transport increased transport time by an average of approximately 42 minutes in this study dataset (see Table 4.4). This finding, in addition to the fact that meets often already took place on longer distance transports, underscores the importance of ensuring that this process is as efficient as possible.

Statistically, transport times were found to have greater variability as distance increased (e.g., exhibited heteroscedasticity). This finding also displayed face validity as longer transport times were generally associated with greater measures of variability (e.g., MAD, IQR and range). For example, routes with distances greater than 100km generally had the highest IQRs (e.g., 10 minutes or higher). A notable exception was the transport route between Oliver and Penticton which, although it was only 40km, had a MAD of 10.4 minutes and an IQR of 13 minutes. In comparison, another route of a similar distance (between Keremeos and Penticton) had a MAD of 5.2, and IQR of 8. This may warrant further investigation of transport data from Oliver to Penticton to determine if there are any areas of improvement on this route. Conversely, the route between 100 Mile House and Kamloops provided a positive exception. Despite being a 196km, the associated MAD and IQR on this route were 7.4 minutes and 10 minutes respectively (see Table 4.2).

In this study, several proxies for mountain driving conditions were examined. Elevation was found to be the best proxy of the variables used within this analysis with each meter of elevation increasing the estimated transport time by 0.01 minutes (see Table 4.3). To provide another picture of how elevation influenced transport time estimates, elevation was also analyzed as a dichotomous variable (e.g., low elevation transports ($\leq$ 1250m) versus high elevation transports ($>$ 1250m)). High elevation transports were, on average, found to be 12.5 minutes slower. It is, however, also important to note that high elevation is associated with other characteristics relating to mountain travel in this study context (e.g., winding roads and poor road conditions). Although this finding supports the general assertion that mountain road conditions negatively impact transport times, it may not be generalizable to different study contexts where high elevation is not associated with the same characteristics.

When GoogleMap time estimates were used as a predictor of observed transport times (rather than ArcMap predictions), the significance of elevation in the final model disappeared (see Table 4.4). This is likely due to the fact that GoogleMap incorporates additional information such as traffic flow data on major transport routes to inform its time estimates. I hypothesize that this information already accounted for the changes in speed associated with mountain travel and the use of elevation as an additional parameter was made redundant. In this sense, the simplicity of the ArcMap road network, incorporating only speed limits and road lengths, may be of benefit when examining factors that influence travel speeds and overall transport times.

The variable for 'Clinical Type' was found to be the best predictor of patient acuity within the model. Neurological cases (e.g., including stroke and related disorders) were found to be an average of 7.5 minutes faster ($p=0.01$) than non-neurological cases as classified by this variable. Due to the correlation between 'Clinical Type' and 'Stroke' (a separate boolean variable), these two variables could not be used in the same model. However, when 'Clinical Type' was excluded from the model, the variable 'Stroke' showed similar results to that of the neurological cases of 'Clinical Type' (e.g., Stroke cases were an average of 7.8 minutes faster ($p=0.05$) than non-stroke cases). Other clinical types such as Sepsis and Respiratory cases were associated with slightly slower transport times; however, these coefficients were not found to be statistically significant.

HART transports were, on average, found to be 5.6 minutes slower than non-HART transports (p=0.00). However, this warrants further examination as it is unclear whether this finding reflects differences in documentation practices, clinical complexity, or other factors. When conducting chart reviews for this study, I found notable differences in documentation practices for each of the three transport resources. All transports are driven by EMAS paramedics and have a standard EMAS form associated with them; however, the degree of detail available in this documentation (and the availability of more detailed supplementary documentation) depended on whether or not there was also a HART or a RN/MD escort on the call.

Due to the fact that the HART program is unique to IH and specializes in high acuity transports, the program has a heavy focus on Quality Improvement (QI) processes and requires its clinicians to complete relatively detailed supplementary documentation for each transport. This focus on the importance of documentation and charting practices may have resulted in greater specificity when writing out times stamps (e.g., writing out actual times rather than rounding to the nearest five minutes or borrowing initial transport time and vitals from the sending site hospital charts).

In contrast, transports that were escorted by a RN or MD did not have the same standardized documentation and charting practices; there did not appear to be a standardized form available to RNs/MDs for the purposes of clinical charting in transport (at least not that was commonly used). It may also be that, due to the limited frequency with which rural RNs/MDs are called upon to escort patients, these clinicians have limited familiarity with transport documentation best practices.

The finding that neither season nor time of day were predictive of observed transport times may be a reflection of the differences between intra and inter city transport. While intra city transport is subject to higher population densities and associated traffic volume at peak hours, these patterns may not effect inter city transport to the same degree. This finding is in agreement with suggestions that time of day and season may not be representative of traffic conditions and weather respectively, particularly in the context of inter-facility transport (Fatahi et al., 2012).

5.1 Limitations

Data were obtained through chart reviews—a resource intensive and time consuming process. Although this methodology allowed for the collection of more detailed information than could be found in available electronic databases, it also placed practical restrictions on the study sample size. As such, this pilot study and associated exploratory analysis is primarily intended to inform further development of transport processes within IH and to guide future research.

Another limitation of this study was the inability to identify air transports or ground transports with RN/MD escorts using current electronic databases. This had further implications for the sample sizes available in each of the transport resource groups as it was only possible to identify whether a non-HART transport was associated with an Air transport or RN/MD escort by reviewing the paper chart. This made it difficult to obtain enough RN/MD escort cases to achieve an appropriate power for comparative analysis between transport groups.

The previously mentioned differences in documentation practices places additional limitations on the inference that can be made regarding how transport times differ between different transport groups. Further work to standardize documentation practices between these groups is recommended.

Finally, a methodological challenge in the comparison of retrospective data with transport time estimates on a single road network dataset is the inability to incorporate factors such as construction or road network changes that occurred over time. This challenge may have been partially mitigated by the fact that most transport routes in this study dataset relied on well established and heavily travelled segments of the road network.

6 Conclusion

The goal of this research was to promote the accessibility of healthcare services within Southeastern BC by examining medical transport times across the region—identifying areas for improvement as well as potential predictors of transport time within the study context.

The use of GIS provided critical information for this study. Transport time estimates derived from network analysis of inter-facility medical transports (in ArcMap) allowed for the evaluation of observed transport times. The results of this network analysis also provided a geographic reference that allowed for the interpolation of elevation values over each route.

Q1: Which routes within the IH inter-facility transport network, if any, display longer or more variable journey times than expected?

All transport routes that were formally evaluated against expected transport times were found to have a median time within a statistically acceptable range (when assessed against expected transport times calculated in ArcMap in addition to Google Maps).

Q2: Do longer transport distances result in greater variability of journey times?

Transport routes generally had greater measures of variance (e.g., MAD and range) as distances increased. This finding was consistent with a statistically significant level of heterscedasticity observed in the residuals of observed transport time with increasing distance.

Q3: What factors influence inter-facility transport times in the study context?

Several predictors of transport time within the study context (including proxies for patient acuity, route elevation, mode of transport, and the need for a 'meet' in transport) were identified and warrant further exploration to determine whether they have a similar influence on transport times in different contexts.

The majority of research relating to medical transport to date has been focused on pre-hospital transport in an urban context. This study contributes a rural perspective to current medical transport literature with a unique focus on inter-facility transport.

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Appendix A: Data Collection Tool

Patient ID:_______

SENDING SITE	
Admission Information	Sending Site:
	ER Admit Date:
	ER Admit Time:
	Arrival Mode:
	CTAS:
Advanced Interventions	Airway? (Y/N):
	Breathing? (Y/N):
	Circulation? (Y/N):
	Disability? (Y/N):
	Medication/Other? (Y/N):
Untoward Events	Untoward Events? (Y/N):
	Event Type:
Initial Vitals	Time:
	BP:
	HR:
	RR:
	Temp:
	SPO2:
	GCS:
Final Vitals	Time:
	BP:
	HR:
	RR:
	Temp:
	SPO2:
	GCS:
NOTES:	

RECEIVING SITE	
Admission Information	Receiving Site:
	ER Admit Date:
	ER Admit Time:
Interventions/ Untoward	Notable Events (30 min):
	Case Study? (Y/N), why?:
Initial Vitals	Time:
	BP:
	HR:
	RR:
	Temp:
	SPO2:
	GCS:
NOTES:	

TRANSPORT	
Transport Details	HART Transfer? (Y/N):
	HART Service Area / BCAS Location:
	Transfer Date:
	Mode:
	#RNs:
	#RTs:
	#BCAS EMTs:
	Other Escort? (Y/N), who?:
	AMPDS:
	CEDIS:
	Assisted Sending Site? (Y/N), how?:
Transport Times	(1) Time Paged:
	(3) BCAS Arrival:
	(4) En-route:
	(6) Care Assumed:
	(8) Depart to Sending:
	(9) At Destination:
	(10) Report Given:
	(12) Call Complete:
Advanced Interventions	Airway? (Y/N):
	Breathing? (Y/N):
	Circulation? (Y/N):
	Disability? (Y/N):
	Medication/Other? (Y/N):
Untoward Events	Untoward Events? (Y/N):
	Event Type:
Initial Vitals	Time:
	BP:
	HR:
	RR:
	Temp:
	SPO2:
	GCS:
Final Vitals	Time:
	BP:
	HR:
	RR:
	Temp:
	SPO2:
	GCS:
Additional Vitals	(every 15 min if available)
NOTES:	

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