A geospatial analysis of severe injury, socio-economic status, and access to trauma centre care in Canada

by

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Abstract

Injuries are a major public health issue in Canada and around the world. In response, several strategies have been developed for reducing the burden of injury on populations. Some strategies focus on preventing the injury event from occurring, while others concentrate on improving the care of patients following the injury event. The two research papers presented in this thesis provide information that will support the development of both these approaches. The first explores the relationship between severe injury and neighbourhood socio-economic status in Greater Vancouver and thus, provides insight into the etiology of severe injury. The second evaluates the spatial accessibility of trauma care centres in Canada and identifies specific regions where spatial access to care could be improved. Both papers utilize a variety of geospatial methods and therefore, examine the burden of severe injury from a uniquely spatial perspective.

**Keywords:** Geographic Information System (GIS); spatial analysis; severe injury; trauma; socio-economic status; spatial access
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1. Introduction

1.1. Overview

The personal and economic costs of injuries in Canada are enormous. In 2004, for example, injuries resulted in 3,134,025 emergency department visits, 211,768 hospitalizations, and 13,667 deaths (SMARTRisk, 2009). Even for those individuals lucky enough to survive an injury, many are left with a life-altering disability. The total economic burden of injury, which in the same year was estimated to be 19.8 billion dollars, is just as staggering (SMARTRisk, 2009). This figure includes the direct costs to the Canadian health care system as well as the indirect costs to the Canadian economy in lost productivity. Although the injury-related mortality rates in Canada are declining, injury remains the leading cause of death during the first four decades of life. Further reducing the burden of injury is entirely possible because almost all of injuries are preventable. Alleviating even some of this burden would lessen the demands on the health care system, improve economic productivity, and most importantly, save lives.

Several approaches have been developed for reducing the burden of injury on populations. A common conceptual framework used in injury epidemiology, which captures the large breadth of these strategies, is the Haddon Matrix (Haddon, 1980a). Since it was first used by Haddon to gain a better understanding of the causes and potential countermeasures of motor vehicle collisions (Haddon, 1970, 1980b), this model has been successfully applied to a variety of other injury types (Conroy & Fowler, 2000; Peck et al., 2008). In this matrix, the rows refer to the “pre-event”, “event”, and “post-event” phases of an injury, whereas the columns refer to the host (e.g., the person who is injured), the agent (e.g., the vehicle or vector responsible for the transfer of energy that causes the injury), and the physical and social environments in which the injury occurs (Runyan, 2003).
Table 1-1 shows where the two papers presented in this thesis are located within this conceptual framework. Paper 1, which explores how the socio-economic status (SES) of a person’s residential neighbourhood influences their risk of severe injury, falls in the upper right-hand quadrant of the Haddon matrix because its underlying purpose is to identify qualities of the social environment that, if altered, may prevent an injury event from occurring. Paper 2, on the other hand, is located in the “post-event” row under the “physical environment” column because its main objective is to evaluate the location of trauma centres in Canada in relation to the spatial distribution of severely injured patients. Thus, the underlying purpose of paper 2 is to reduce the burden of severe injury by improving the care patients receive following an injury event.

Table 1-1. The Haddon matrix: the conceptual link between the two papers presented in this thesis

<table>
<thead>
<tr>
<th></th>
<th>host</th>
<th>agent</th>
<th>physical environment</th>
<th>social environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>pre-event</td>
<td></td>
<td></td>
<td></td>
<td>Paper 1</td>
</tr>
<tr>
<td>event</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>post-event</td>
<td></td>
<td></td>
<td></td>
<td>Paper 2</td>
</tr>
</tbody>
</table>

Using the Haddon matrix to frame the two studies presented in this thesis is useful because it highlights their similarities. For example, both are focused on understanding how the characteristics of the contextual environments, rather than the aspects of the individual or agent, influence the burden of severe injury. This reflects the ecological nature of both studies and their areal units of analysis. Likewise, both studies investigate how these contextual environments vary over space, which relates to the geospatial methods utilized in both studies. In other words, both focus on inequalities of the social and physical environments in which people live. Paper 1 highlights socio-economic inequalities of residential neighbourhoods, whereas paper 2 examines geographic inequalities in potential spatial access to trauma centre care. The Haddon matrix also highlights the key difference between the two studies, which is that they target different phases of the injury event. Paper 1 is focused on preventing an injury event from occurring, while paper 2 is aimed at improving the treatment of severely injured patients after an injury event has occurred.
1.2. Research Objectives

The overall objective of this thesis was to gain a better understanding of the physical and social environments thought to influence the burden of severe injury in Canada. The aim of the first study, presented in section 2, was to explore the relationship between the rates of all-cause, unintentional, and intentional adult severe injury and neighbourhood SES. In addition to determining the strength and direction of these relationships, this study also sought to explore whether they were spatially consistent or varied from one region to another. The goal of the second study, presented in section 3, was to evaluate the potential spatial accessibility of trauma centres in Canada in relation to the spatial distribution of severely injured patients. More specifically, this study sought to determine what proportion of severely injured patients and spatial clusters of severe injury were located within one hour drive time of the closest trauma centre. The overarching purpose of both papers was to inform future research, policy, and practice aimed at reducing the personal and economic costs of severe injury in Canada.

1.3. Background

This section provides background information relevant to both the papers presented in this thesis. It begins with an overview of the conceptualization and measurement of SES, as well as what is already known about its relationship with injuries. Then, the concept of spatial accessibility is discussed and the methods used to measure it are briefly reviewed. Next, a short description of the hypothesized relationship between injury mortality and spatial accessibility to trauma centre care is given, followed by a brief discussion of trauma systems and their current status in Canada. This section ends with a description of the benefits of using geographic information systems (GIS) in health and injury research.

1.3.1. Conceptualizing Socio-economic Status

SES and its conceptual relatives such as socio-economic position, social deprivation, and social class are very common measures in health research. The exact
term used to describe this complicated concept varies from study to study depending on the theoretical perspective and disciplinary roots of the authors. They all, however, share a common theme, which is the stratification of society into different population groups based on social and economic differences.

The concept of SES has a long history. In fact, many of the measures used to approximate SES in the health literature today are based on the work of early social theorists, such as Karl Marx and Max Weber (Galobardes, Lynch, & Smith, 2007; Liberatos, Link, & Kelsey, 1988). Marx viewed individuals as belonging to certain ‘social classes’, which reflected their role in a capitalist society (Galobardes, et al., 2007). In his conceptualization of social class, a person was either an exploiting owner who had power over the means of production or an exploited worker (Galobardes, et al., 2007). Weber’s notions of social class, on the other hand, were much broader. He identified three dimensions, class, status, and power, which describe an individual’s class position among society (Liberatos, et al., 1988). The class domain is related to a person’s access to and use of material resources, whereas the status domain is related to the ‘life chances’ that are afforded to an individual based on their social and cultural connections (Liberatos, et al., 1988). In contrast, the power domain is associated with an individual’s political context (Liberatos, et al., 1988). Unlike the mainly income-related indicators drawn from the Marxist ideas of social class, the three domains conceived by Weber expanded the measurement of SES to include occupation and education related indicators (Galobardes, et al., 2007).

In contrast to these Marxist and Weberian conceptualizations of social class, which broadly focus on an individual’s access to and control over material resources, more recently developed constructs of SES emphasize the consequences of or conditions resulting from these class divisions (Salmond, Crampton, King, & Waldegrave, 2006). For example, the idea of socio-economic deprivation, which was first described by Peter Townsend (Townsend, 1987), focuses on the living standards and social conditions experienced by an individual relative to their broader community (Salmond, et al., 2006). Developed in the mid-1980s, Peter Townsend’s concept of deprivation is comprised of two dimensions. The first, material deprivation, includes a person’s relative access to resources, goods, and services such as housing, food, recreational facilities, and health care services (Salmond, et al., 2006). The second
dimension, social deprivation, deals with the relative differences in social interactions stemming from social stratification and is associated with other social theories such as social capital, social fragmentation, and social isolation (R. Pampalon, Hamel, Gamache, & Raymond, 2009). Townsend believed these two components of deprivation differ from the concept of poverty because they deal with the conditions experienced by an individual that are the result of their socio-economic position, rather than their relative socio-economic standing alone (Salmond, et al., 2006).

1.3.2. Measuring Socio-economic Status

Due to the complex and multidimensional nature of the concept, a wide variety of indicators have been developed to measure SES in health research. The choice of SES indicator is based on a number of factors, including the purpose of the study and the anticipated causal pathway (Galobardes, Shaw, Lawlor, Lynch, & Davey Smith, 2006a). Whether SES is viewed as a potential confounder or the dependent variable of interest in a study will also dictate the choice of indicator (Galobardes, et al., 2006a). Thus, there is no single measure that can be applied universally to answer all research questions (Galobardes, et al., 2006a; Salmond, et al., 2006). Nonetheless, the choice of indicator is an important one because the manner in which the results are interpreted will depend on the theoretical origins of the indicator and thus, the causal mechanism through which SES is thought to influence health (Galobardes, et al., 2006a).

The most common measures of SES describe aspects of a person’s income or wealth (e.g., household income), education (e.g., total number of years of education), occupation (e.g., manual or non-manual occupation), or housing (e.g., owner or renter) (Galobardes, et al., 2006a). All of these indicators relate to Marxist and Weberian ideas of social class and Peter Townsend’s notion of material deprivation, and largely ignore the social conditions experienced by individuals within different social strata. These types of measures, related to Townsend’s idea of social deprivation, are rarely used in the health literature despite their plausible links with health and wellbeing. However, they may become more common as researchers continue to call for more comprehensive measures of SES (Cubbin & Smith, 2002).
Since SES has the potential to change over time, there has also been a push to measure it at different points throughout a person’s life (Galobardes, et al., 2007). This can be helpful for identifying critical time periods when experiencing low SES has the greatest impact on developing a particular disease (Galobardes, et al., 2007). For example, low SES during childhood has been shown to have a strong association with the development of stomach cancer later in life (Galobardes, Lynch, & Davey Smith, 2004). Using a life course approach to measure SES can also be helpful for elucidating whether or not the risks associated with lower SES accumulate over time (Galobardes, et al., 2007). For instance, research suggests that mortality from coronary heart disease is related to both childhood and adulthood SES (Galobardes, et al., 2004). Despite these benefits, however, most studies only measure SES at a single point in time.

While some studies simply use one indicator to approximate SES, others consider multiple measures, either together or separately (Robert, 1999). Another common approach is to amalgamate multiple indicators into a single SES index (Bell, Schuurman, Oliver, & Hayes, 2007; Carstairs & Morris, 1989; Robert Pampalon & Raymond, 2000). Each approach has its own set of benefits and limitations. For example, using a single measure may eliminate issues of multicollinearity and simplify the interpretation of the findings, but is prone to residual confounding by SES. In contrast, examining multiple indicators separately can provide important information about the relative strength of their associations with health, but will likely have problems due to multicollinearity (Robert, 1999). Using a single composite measure of SES, on the other hand, provides a better understanding of how the contextual characteristics of the SES environment work together to influence health while avoiding issues of multicollinearity (Robert, 1999). Still, SES indices do not allow the researcher to elucidate anything about the relative strength of the association between health and the indicators from which it is constructed. Thus, a combination of these different approaches may be the optimal strategy for examining the complex relationship between SES and health.

SES can also be measured at different levels. In fact, many authors argue that SES should be measured at the individual, household, and neighbourhood levels in order to capture the full influence of SES on health (Krieger, Williams, & Moss, 1997; Williams & Collins, 1995). The reason for this is that each level may play a unique role
in determining what a person is exposed to and therefore, may each have an independent effect on a person’s health (Krieger, et al., 1997). For example, an individual level measure of SES may capture environmental hazards at work (e.g., asbestos), whereas a household level measure may capture environmental exposures at home (e.g., mould), and a neighbourhood measure may capture environmental exposures within the broader community (e.g., air pollution). Only measuring SES at one level can also lead to misclassification. For example, a low-earning person may be misclassified as socio-economically deprived if the additional household income contributed by his or her spouse is not taken into account. In other words, a person’s SES measured at one level could be very different from their SES measured at a different level. Even when SES is measured at all three levels, it is important to remember that residual confounding may still exist.

Due to the recent growth in GIS technology and the difficulty of obtaining individual level socio-economic data, area-based indicators of SES are becoming more common. These measures are either used to proxy individual level SES or are used to explicitly examine the relationship between neighbourhood SES and health. In either case, these indicators differ substantially from their individual and household level counterparts, because they attempt to capture the socio-economic conditions of an area (Galobardes, Shaw, Lawlor, Lynch, & Davey Smith, 2006b). An important choice for these ecological studies is the unit of analysis (e.g., postal code, health service area, census tract). Smaller units of analysis are almost always preferable because they are more likely to represent homogeneous socio-economic environments (Robert Pampalon & Raymond, 2000). Census areas, such as census tracts or dissemination areas are usually preferable to other units of analysis because their boundaries were designed to mimic the geographic distribution of populations with similar social and economic characteristics (Krieger, et al., 1997). In contrast, postal codes cover large areas of land and were designed to assist in the delivery of mail and therefore, are more likely to contain both socio-economically deprived as well as socio-economically privileged neighbourhoods (Krieger, et al., 1997).
1.3.3. **Socio-economic Status and Injuries**

For centuries, researchers have documented a strong relationship between SES and health outcomes (Krieger, et al., 1997). This phenomenon is not unique to Canada, but has been identified within and between various countries, states, regions, and cities (Williams & Collins, 1995). No matter where the study is conducted or what population group is studied, poorer socio-economic conditions are almost always associated with poorer health outcomes. For example, researchers have identified a relationship between SES and all-cause mortality (R. Pampalon, et al., 2009), self-rated health (Bell, et al., 2007), cardiovascular disease (Singh & Siahpush, 2002), coronary heart disease (Huff & Gray, 2001), cancer (Ward et al., 2004), low birth weight (English et al., 2003), and obesity (Greves Grow et al., 2010). Unfortunately, research suggests that socio-economic inequalities in health are increasing as the gap between the rich and the poor continues to grow in many industrialized countries around the world, including Canada (Huff & Gray, 2001; Krieger, et al., 1997).

There is also ample evidence to suggest that injuries disproportionately affect population groups with lower SES (Laflamme, Burrows, & Hasselberg, 2009). However, the results of these studies have varied depending on the level of analysis (i.e., individual, ecological, multilevel), the cause and severity of the injuries that are examined, as well as the region and population that are studied (Cubbin & Smith, 2002). For example, stronger associations have been documented in studies that focus strictly on serious injuries, such as those resulting in death or hospitalization (Cubbin & Smith, 2002). In fact, when only fatal injuries are taken into account, strong associations have been identified between SES and a wide variety of injury types, including those resulting from motor vehicle collisions, self-inflicted and interpersonal violence, poisoning, and burns (Laflamme, et al., 2009). Although the empirical evidence of a relationship between non-fatal severe injuries and SES is less consistent, many studies have also identified substantial differences in the rates of various non-fatal injury types across different socio-economic populations (Laflamme, et al., 2009).

In addition to identifying a relationship between individual level SES and injury, numerous ecological studies have found a relationship between area-level SES and individual injury risk. There have also been a few multilevel studies, which have
observed this relationship even after controlling for individual level SES, suggesting that the socio-economic context in which an individual lives makes an independent contribution to their risk of injury (Borrell et al., 2002; Burrows, Auger, Gamache, & Hamel, 2012; Cubbin, LeClere, & Smith, 2000; Ferrando, Rodriguez-Sanz, Borrell, Martinez, & Plasencia, 2005; Reading, Langford, Haynes, & Lovett, 1999; Simpson, Janssen, Craig, & Pickett, 2005). Although the specific mechanisms underlying these relationships remain unclear, research suggests that SES plays an important role in determining the risk of injury at the individual and neighbourhood level.

1.3.4. Conceptualizing Spatial Accessibility

Access is a complex and multidimensional concept that can be defined in many different ways. In the context of health care services, access is most often defined as a patient’s ability to obtain required services (Khan & Bhardwaj, 1994). However, more precise definitions of this complex concept are often required to develop operational measures of access that can be used in research. Thus, authors often unpack the concept into more tangible and explicit sub-concepts. For example, studies of financial or economic access are strictly concerned with a patient’s ability to pay for a service and exclude other dimensions of access, such as a patient’s ability to travel to and from a service. The usefulness of a particular conceptualization is directly related to the health care service being studied (Khan & Bhardwaj, 1994). For instance, economic barriers may only be of interest when the cost of the health care service is not covered by a population’s public health insurance.

An increasingly common conceptualization of access divides the concept into four categories based on whether they examine potential or realized access, as well as whether they focus on spatial or aspatial barriers or facilitators to access (Guagliardo, 2004; Khan & Bhardwaj, 1994). While potential access is defined as the ability of a patient to obtain a service, realized access refers to the successful utilization of a service (Khan & Bhardwaj, 1994). Spatial access is determined by comparing the geographic distribution of services in relation to their potential users and often includes some sort of impedance measure related to distance (Schuurman, Berube, & Crooks, 2010). Studies focusing on aspatial access, on the other hand, explore the psychosocial and economic
factors that affect a patient’s ability to obtain a service, such as age, gender, income, or spoken language (Khan & Bhardwaj, 1994).

The conceptual framework upon which paper 2 is based is the model of access and healthcare utilization developed by Aday and Andersen (Aday & Andersen, 1974; Andersen & Aday, 1978). This model uses a systems perspective to integrate a range of environmental and population characteristics (e.g., predisposing characteristics, enabling resources, and need) that are associated with a patient’s ability to obtain care. The adapted framework, shown in Figure 1-1 below, only includes the aspects of Aday and Andersen’s (1974) model that are relevant to paper 2. For instance, factors related to a patient’s decision to seek care are excluded due to the incapacitation associated with a severe injury. As shown by the arrows in Figure 1-1, health care policy and planning is thought to influence both the characteristics of the trauma system as well as the characteristics of the population at risk. However, as with Aday and Anderson’s original framework, it is recognized that there are some immutable properties of the population at risk (e.g., age and gender), which cannot be altered by health care policy and planning (Aday & Andersen, 1974).

![Figure 1-1. Conceptual framework for paper 2](image)

### 1.3.5. Measuring Spatial Accessibility

Previous geographic research has utilized several methods for measuring spatial accessibility to health care services. Perhaps the most basic method employed involves
calculating simple ratios between the number of facilities within a bordered area, such as a census tract, and the underlying population (Christie, Morgan, Heaven, Sandifer, & van Woerden, 2005; Guagliardo, 2004). Such approaches have serious limitations: they ignore the fact that populations have the ability to cross these often arbitrary borders; they mask differences in accessibility within the defined units of analysis; and they exclude impedance measures related to distance (Guagliardo, 2004; Hewko, Smoyer-Tomic, & Hodgson, 2002). Because the results of these types of studies can vary greatly depending on the unit of analysis that is chosen, they also suffer from the modifiable areal unit problem (Guagliardo, 2004; Smoyer-Tomic, Hewko, & Hodgson, 2004).

With the advent of GIS, more nuanced and computationally complex measures of spatial access are being employed by geographers (Schuurman, Crooks, & Amram, 2010). In these studies, various distance metrics (e.g., Euclidean or ‘as the bird flies’ distance, travel distance along a network, or travel time along a network) are used to measure access. For example, several studies have calculated the distance from the geometric centroid of a bordered area to the nearest service provider location (Gimpel & Schuknecht, 2003; Sharkey & Horel, 2008). Although these methods may create an accurate depiction of spatial accessibility in rural areas, they are argued to be inappropriate for use in the urban context where users may not choose to visit the facility that is closest to them (Guagliardo, 2004). Similarly, other studies use the average travel impedance to all available facilities to estimate spatial access (Guagliardo, 2004). These measures of spatial accessibility are criticized for over-estimating the impact of facilities located on the periphery of the area of interest and do not account for people traversing boundaries (Guagliardo, 2004).

More recently, researchers have been experimenting with methods that include travel-times along a road network to more accurately estimate spatial accessibility (Branas et al., 2005; Brual et al., 2010; Christie, et al., 2005; Schuurman, Crooks, et al., 2010). For example, Schuurman et al. (2006) generated hospital catchments and then calculated the proportion of the underlying population residing within those catchments to estimate spatial accessibility to hospital-based healthcare in a rural region of British Columbia. Hospital catchments, or service areas, highlight the road segments within a certain drive time of a facility location and are very useful for both visualizing and
measuring potential spatial access (see Figure 1-2). Paper 2 uses a very similar drive time catchment method, except instead of calculating the proportion of the general population with access, paper 2 estimates spatial accessibility by the target population (i.e., severely injured patients).

![Figure 1-2. An example of hospital catchment areas](image)

**1.3.6. Injury Mortality and Spatial Access to Trauma Centre Care**

Half of all injury-related deaths occur immediately or within a very short period of time after the injury event itself, meaning the other half are potentially preventable by providing prompt access to appropriate medical care (Meislin et al., 1997; Rogers et al., 2005). Research has shown that the appropriate medical care for a severely injured patient is care at a designated trauma centre (Liberman, Mulder, Jurkovich, & Sampalis, 2005; MacKenzie et al., 2006). That is because care in this environment is associated with a 25% reduction in the mortality of severe injured patients (MacKenzie, et al., 2006). Research has also shown that the time to treatment can greatly impact a severely injured patient’s chances of survival (Peleg & Pliskin, 2004; Raghavan & Marik, 2006;
Sampalis et al., 1999). In fact, one hour is viewed by many as the optimal timeframe within which a patient should receive care after a serious injury (Crews & Holbrock, 2005; Raghavan & Marik, 2006). Thus, ensuring that access needs are met through the strategic distribution of trauma centres may be a critical method for reducing injury-related mortality (Committee on Trauma, 2006).

### 1.3.7. Trauma Systems

An organized system of trauma care can play a significant role in improving access. Regional or provincial trauma systems aim to integrate Emergency Medical Services (EMS) and acute care facilities, such that patients have timely access to centres with adequate resources to serve their needs. In highly developed systems, prevention programs and rehabilitation services are also encompassed (Ball et al., 2008). Trauma systems can either be exclusive, meaning only a few high level centres participate, or inclusive, meaning that all centres participate to the extent that their resources allow (Utter et al., 2006). Previous research has shown that trauma systems, particularly inclusive systems, are associated with a lower rate of injury-related mortality, and might be an important solution to addressing access limitations in rural regions (A. B. Nathens, Jurkovich, Cummings, Rivara, & Maier, 2000; A. B. Nathens, Jurkovich, Rivara, & Maier, 2000; Utter, et al., 2006).

### 1.3.8. Trauma Systems in Canada

Trauma system development in Canada is in its early stages. Of the 32 level I and level II trauma centres currently providing definitive trauma care in Canada, only 18 (56%) have been accredited or verified by an external agency, such as the Trauma Association of Canada (Hameed et al., 2010). In addition, some provincial trauma systems are missing essential components, such as pre-hospital air transportation (Hameed, et al., 2010). Furthermore, because trauma centres are located in urban areas, many people who sustain severe injuries in rural parts of the country may not have timely access to the resources, skills, and experience found in trauma centres. In this context, health outcomes from a severe injury are dependent on the delivery of optimal preliminary care, rapid triage, and transfer to a trauma centre. Transfer to a trauma centre is almost always necessary given that providers in rural environments
have limited experience and resources to care for the severely injured patient (Rogers, Shackford, Osler, Vane, & Davis, 1999). These and a miscellany of other factors operating at the system level are potential barriers that may be keeping some Canadians from receiving trauma centre care within the “golden hour” felt to be critical to patient survival (Lerner & Moscati, 2001; Tallon, 2002).

1.3.9. **GIS in Health and Injury Research**

There are several benefits to using GIS methods in health research. First, they are very good at integrating data from different sources, even if they are collected at different levels (e.g., individual, household, neighbourhood) (Schuurman, Hameed, Fiedler, Bell, & Simons, 2008). This drastically increases the number of research questions that can be investigated and provides a structural framework for multilevel studies, which can be used to compare the relative importance of individual and area-level factors that influence health. Another beneficial characteristic of GIS is its ability to visually display data and information using maps. This is particularly useful when communicating the results of a study to decision-makers, who may be better equipped to interpret a map than a table of data or list of statistics. The ability to map information is also valuable for the researcher as it can reveal important spatial patterns that may otherwise be left unnoticed. For example, exploratory spatial data analysis methods are extremely useful for developing hypotheses about the underlying causes of a disease with an unknown etiology.

Despite the many benefits of studying the spatial aspects of health and disease through the use of GIS, this technology and all the spatial analytical tools that come with it have only been applied relatively recently in health research. In fact, compared with other fields of study, such as biology and geology, health researchers have been very slow to adopt GIS, which was developed in the early 1980s. Since then, much has been written about the benefits of using GIS to address both health care and public health issues (Green, 2012; McLafferty, 2003; Rushton, 2003).

Similarly, GIS methods have only been applied to injury research in the past decade or so. Much of this research can be separated into two categories. The first includes studies that identify factors that influence the risk of injury and thus, are focused
on informing the development of injury prevention policies and programs (Schuurman, et al., 2008). The second group of studies involve the assessment of the spatial distribution and spatial accessibility of trauma care resources (Schuurman, et al., 2008). In the future, GIS methods may also be useful for evaluating the effectiveness of injury prevention efforts by mapping rates of injury over time (Linda S. Edelman, 2007). One thing is for sure, as the breadth and sophistication of the tools available in commercial GIS programs continues to grow, so too will the potential applications of GIS in health and injury research.

1.4. Thesis Outline

This thesis has four sections. The first section introduced the core concepts (i.e., SES and spatial accessibility) relevant to this thesis. Methods used to measure these complex concepts and their known and suspected associations with injuries were also discussed, laying the groundwork for the research papers presented in sections 2 and 3. This background section also discussed the benefits of using GIS in health and injury research.

Sections 2 and 3 are two research papers that have been submitted for publication in two different peer-reviewed journals. They both contain a description of how they improve upon earlier work and additional background information pertinent to this thesis. As previously mentioned, the aim of both papers was to gain a better understanding of the contextual factors that influence the burden of severe injury in Canada. A second, overarching goal of these papers was to inform future policies, programs, and services that strive to reduce the burden of severe injury.

The research paper presented in section 2 uses information contained within the BC Trauma Registry and BC Coroner’s service records to identify unique cases of adult severe injury within Greater Vancouver and map them by their residential neighbourhood (i.e., census dissemination area). A variety of exploratory spatial data analysis methods as well as ordinary least squares and geographically weighted regression are then used to explore the relationship between the rates of all-cause, unintentional, and intentional severe injury and two measures of neighbourhood level SES.
The study reported on in section 3 uses national vital statistics and hospitalization datasets to identify and map severely injured patients by their home residence postal codes. Then, using road network tools in a GIS, the proportion of severely injured patients within one hour drive time of a trauma centre is calculated. Spatial clusters of severely injured patients are also identified and using a simple overlay method, the proportion of those clusters within one hour drive time of a trauma centre is determined.

Section 4 summarizes the key findings of the research papers presented in section 2 and 3, and describes the significant research contributions of this thesis. Suggestions for future work are also provided in section 4.
2. A geospatial analysis of the relationship between neighbourhood socio-economic status and adult severe injury in Greater Vancouver

2.1. Abstract

2.1.1. Background

Every year, injuries cost the Canadian health care system billions of dollars and result in thousands of emergency room visits, hospitalizations, and deaths. The purpose of this study was to explore the relationship between neighbourhood socio-economic status (NSES) and the rates of all-cause, unintentional, and intentional severe injury in Greater Vancouver adults. A second objective was to determine whether the identified associations were spatially consistent or non-stationary.

2.1.2. Methods

Severe injury cases occurring between April 2001 and March 2006 were identified using the BC Coroner's Service records and the BC Trauma Registry, and mapped by census dissemination areas using a geographic information system (GIS). A variety of descriptive statistics and exploratory spatial data analysis methods were then used to gain a better understanding of the datasets and to explore the relationship between the rates of severe injury and two measures of NSES (social and material deprivation). Next, ordinary least squares (OLS) and geographically weighted regression (GWR) were used to model these relationships at the global and local levels. Results of the GWR analysis were mapped to highlight specific neighbourhoods where injury prevention policies and programs should be targeted.
2.1.3. Results

Inverse relationships were identified between both measures of NSES and the rates of severe injury. However, these relationships varied over space, with the strongest associations located in Greater Vancouver’s most socio-economically deprived neighbourhoods. Social deprivation was found to have a slightly stronger relationship with the rates of severe injury than material deprivation.

2.1.4. Conclusions

The results of this study suggest that policies and programs aimed at reducing the burden of severe injury in Greater Vancouver should take into account both social and material deprivation, and should target the most socio-economically deprived neighbourhoods in Greater Vancouver.

2.2. Background

Injury is a serious public health issue in Canada. In addition to being the leading cause of death in the first four decades of life, injuries are estimated to cost the Canadian health care system $10.7 billion in direct health care costs and the Canadian economy $9.1 billion in indirect costs resulting from hospitalization, disability and premature death (SMARTRISK, 2009). Every year, injuries result in approximately 13,677 deaths, 211,000 hospitalizations, and 3 million emergency room visits (SMARTRISK, 2009). What sets injuries apart from the other leading causes of death in Canada is that they are almost always preventable.

The aim of this study was to explore the relationship between neighbourhood socio-economic status (NSES) and the rate of adult severe injury in Greater Vancouver using a variety of descriptive statistics and exploratory spatial data analysis (ESDA) methods. More specifically, this study sought to determine whether there was a statistically significant relationship between NSES and the rate of all-cause, unintentional, and intentional adult severe injury in Greater Vancouver. If so, the second objective of this study was to determine whether this relationship was spatially consistent or varied from one region to another. Understanding the factors that influence a
person’s risk for severe injury can help public health organizations develop effective injury prevention programs and policies. Likewise, knowing what population groups are at greatest risk of severe injury can inform where these programs and other health care services (e.g., trauma centres) should be located. Investigating the degree of spatial heterogeneity in the NSES-injury relationship can help to further target these resources by identifying places where the relationship is strongest and thus, where modifying the socio-economic environment would potentially result in the largest reduction of severe injury (Sridharan, Koschinsky, & Walker, 2011).

Individual level socio-economic status (SES) is widely accepted as a fundamental determinant of health (K. E. Pickett & Pearl, 2001; Robert, 1999; Yen & Syme, 1999). There is also a growing amount of evidence to suggest that NSES plays an important role in determining an individual’s health. For example, lower NSES has been associated with an increase in all-cause mortality, coronary heart disease, childhood obesity, and cancer (Greves Grow, et al., 2010; Huff & Gray, 2001; Singh & Siahpush, 2002; Sridharan, et al., 2011; Ward, et al., 2004). In fact, a few studies have found a relationship between area-level SES and injury even after adjusting for individual socio-economic standing (Burrows, et al., 2012; Cubbin, et al., 2000; Reading, et al., 1999). In other words, they found that an individual with high socio-economic status living in a socio-economically deprived neighbourhood is likely to have poorer health outcomes than one living in a socio-economically privileged neighbourhood.

Compared with other health outcomes, the relationship between NSES and injury seems especially plausible given that the cause is external to the individual and thus, is likely to be closely correlated with the individual’s contextual surroundings (Cubbin, et al., 2000). For example, the built environment of a socio-economically privileged neighbourhood may have features that reduce the risk of injury (e.g., slower speed limits, sidewalks, well-marked crosswalks, etc.), whereas the built environment of a socio-economically deprived neighbourhood may include hazardous features that increase the risk of injury (e.g., high volume roads and intersections, substandard housing, alcohol outlets, etc.). Differences between the social environments, such as the rate of crime and the tolerance of deviant behaviour, may also explain the higher rates of injury found in areas with low SES (Cubbin & Smith, 2002). Furthermore, socio-economically deprived neighbourhoods are likely to have smaller municipal budgets and
thus, fewer emergency response resources such as police and fire stations, which may worsen the health outcomes of injured persons (Cubbin & Smith, 2002).

Many studies investigating the association between SES and health have utilized traditional regression methods such as ordinary least squares (OLS). Despite their popularity, these methods have some important limitations when applied to spatial data. First, they are based on the assumption that the observations and residuals are independent, which conflicts with Tobler’s first law of Geography that states “everything is related to everything else, but near things are more related than distant things” (Gilbert & Chakraborty, 2011; Tobler, 1970, p. 236). Similarly, they assume that the relationship under study is spatially consistent. In other words, they assume that the strength and direction of the relationship is the same regardless of the local social and economic environments. Violating these assumptions can lead to erroneous model and coefficient estimates, or in some cases even change the direction of the identified relationship (Ali, Partridge, & Olfert, 2007; Gilbert & Chakraborty, 2011). Nonetheless, these assumptions are rarely justified or tested in the published literature (Sridharan, et al., 2011). Thus, one of the key aims of this article was to explicitly test the validity of these assumptions for the NSES-injury relationship in Greater Vancouver.

Previous studies examining the relationship between SES and injury, of which there are relatively few, have been criticized for their inadequate measurement of SES (Cubbin & Smith, 2002). For instance, many studies have used one-dimensional measures (e.g., proportion of the population living below the poverty line) to approximate SES when in actuality it is a complex concept with multiple components (Faelker, Pickett, & Brison, 2000; Zarzaur, Croce, Fabian, Fischer, & Magnotti, 2010). In addition to using more comprehensive measures of SES, it has also been argued that researchers should conduct their analyses using multiple measures of SES instead of choosing just one (Cubbin & Smith, 2002). Furthermore, the SES measures used in previous research are often binary (e.g., with or without private health insurance), making it impossible to discern whether an SES gradient exists (King & Palmisano, 1992). Our study improves upon this earlier work by using two deprivation indices representing Peter Townsend’s notions of material and social deprivation, which are each comprised of multiple census variables (Robert Pampalon & Raymond, 2000; Townsend, 1987).
Much of the existing literature investigating the underlying causes of severe injury has focused on specific ages groups (e.g., children, adolescents, or the elderly), or specific types of severe injury (e.g., traumatic brain injury, burn injury) (Bruns & Hauser, 2003; Linda S. Edelman, 2007; Faelker, et al., 2000; Potter et al., 2005; Yiannakoulias et al., 2003). Also, the majority of the studies examining the link between injury and SES have used measures related to material deprivation, leaving the possible link between social deprivation and SES relatively unexplored. Our study is thus unique in that it sought to examine the relationship between all-cause severe injury rates in adults, and social as well as material deprivation. In addition, many of the studies examining the relationship between injury and SES have only used hospitalization data to identify injury cases and in doing so, excluded injuries that resulted in death prior to hospital admission (Faelker, et al., 2000; Laupland, Kortbeek, Findlay, & Hameed, 2005; Zarzaur, et al., 2010). Given that half of all injury-related deaths occur at the scene of the injury, this is a significant limitation (Meislin, et al., 1997; Rogers, et al., 2005). So in order to capture the entire population of severely injured people, we used both hospitalization and vital statistics data to identify all severe injury cases within a five year period.

2.3. Methods

2.3.1. Study Region

For the purposes of this study, Greater Vancouver was defined as the Vancouver and Abbotsford census metropolitan areas (CMA) (Figure 2-1). This is a largely urban region located within south-western British Columbia, Canada and is home to approximately 2.4 million people (Statistics Canada). Greater Vancouver was chosen for this analysis because it is comprised of a socio-economically diverse collection of communities. In fact, this region contains some of the most socio-economically privileged as well as some of the most socio-economically deprived neighbourhoods in Canada. Many residents of Vancouver’s Downtown Eastside (DTES), for example, suffer from extreme levels of poverty, homelessness, mental illness, and drug addiction (Milner, 2009).
2.3.2. Data

2.3.2.1. Rates of Severe Injury

British Columbia’s Coroner’s Service records and the BC Trauma Registry (BCTR) were used to identify all adults that had sustained a severe injury between April 1, 2001 and March 31, 2006. A severe injury was defined as an injury that results in death prior to hospital admission or one that is treated at one of BC’s eight trauma centres and given an injury severity score (ISS) greater than 12. An adult was considered to be someone 20 years of age or older so that the injury data aligned with the denominator census population groupings used to calculate the rates. Duplicate cases, which were identified using the date of death, age, sex, and cause of death fields
present in both datasets, were removed following a case-by-case inspection of the severe injuries that resulted in death.

Once identified, the severe injury cases were aggregated by the 2006 census dissemination areas (DA) using their home residence postal codes and Statistics Canada’s Postal Code Conversion File. DAs are about the size of a neighbourhood block and have a population of 400 to 700 people (Statistics Canada, 2010). Next, the crude annual incidence rates of all-cause, unintentional, and intentional severe injury per 100,000 person-years was calculated for all 3,591 DAs within our study region. The denominator used for these incidence rate calculations was the population of people aged 20 years of age and older, which was obtained from the 2006 census, multiplied by five years.

2.3.2.2. Neighbourhood SES

NSSES was measured at the DA level using area-based indices of material and social deprivation based on the conceptualization of deprivation proposed by Peter Townsend (Townsend, 1987). Although these indices were originally developed in the province of Quebec, they have since been expanded to include the entire country (R. Pampalon, et al., 2009; Robert Pampalon & Raymond, 2000). One of the key strengths of these indices is that they were constructed using a principal component analysis, which was then validated in numerous locations across the country, including Vancouver’s CMA (R. Pampalon, et al., 2009). The social deprivation index is comprised of the following 2006 census variables: the proportion of individuals living alone; the proportion of individuals who are separated, divorced or widowed; and the proportion of single-parent families. The material deprivation index, on the other hand, includes: the proportion of people with no high school diploma; the employment/population ratio; and the average income of adults. We used the composite scores of these indices in our regression models and the quintile ranks in our descriptive analyses. The deprivation quintiles were population weighted so that each quintile contains approximately 20% of the study region’s population. Figure 2-2 illustrates the dramatic spatial variation in social and material deprivation across our study area.
Figure 2-2. Maps of social (a), material (b), and both social and material (c) deprivation in Greater Vancouver

Note. These maps show the spatial distribution of social, material, and both social and material deprivation across Greater Vancouver. Each census dissemination area is symbolized based on their quintile rank, with dark green depicting neighbourhoods in the least deprived quintile (Q1) and red depicting neighbourhoods in the most deprived quintile (Q5). In Figure 2-2c, only the neighbourhoods that are in the least deprived quintile of both indices (Q1-Q1) and in the most deprived quintile of both indices (Q5-Q5) are highlighted. As shown, there is very little overlap between the spatial distribution of social and material deprivation in Greater Vancouver.
We selected these two area-based indicators to measure NSES for several reasons. First, given their significant conceptual differences, we wanted to examine the relationship between severe injury and social and material deprivation separately as well as together. In other words, we wanted to discern which of these components plays a larger role in determining the rates of severe injury in Greater Vancouver. By doing so, we thought our results would be more informative for injury prevention program and policy makers. Furthermore, given the consistent statistical independence that was found between these two indices, we did not have to worry about multicollinearity issues when modelling the NSES-injury relationship, which may well have been an issue if we studied these components using individual census variables.

2.3.2.3. Covariates

To account for the influence of the age and gender structure of neighbourhoods on the rates of severe injury, we included two control variables in our regression analyses. We used the proportion of the population that was male (%MALE) to control for differences in the gender split between neighbourhoods, and the proportion of the population that was 85 years of age or older (%85+) to account for differences in the age structure of the neighbourhoods. We chose to control for this age group because it had the highest age-specific severe injury incidence rate and because it had been identified previously as an age group with a significantly higher risk of severe injury in Canada (Laupland, et al., 2005). We also considered controlling for the proportion of young adults (i.e., 20-24 years) in each neighbourhood, but surprisingly, this population had the same rate of severe injury as the overall sample (76.0 per 100,000 person-years) and a very weak negative correlation with the rates of severe injury (Table 2-1).
Table 2-1. Pearson correlations between potential covariates and the rates of severe injury

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Explanatory Variable</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>All-cause rate</td>
<td>%MALE</td>
<td>0.277*</td>
</tr>
<tr>
<td></td>
<td>%85+</td>
<td>0.050*</td>
</tr>
<tr>
<td></td>
<td>%20-24</td>
<td>-0.098*</td>
</tr>
<tr>
<td>Intentional rate</td>
<td>%MALE</td>
<td>0.230*</td>
</tr>
<tr>
<td></td>
<td>%85+</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>%20-24</td>
<td>-0.067*</td>
</tr>
<tr>
<td>Unintentional rate</td>
<td>%MALE</td>
<td>0.259*</td>
</tr>
<tr>
<td></td>
<td>%85+</td>
<td>0.060*</td>
</tr>
<tr>
<td></td>
<td>%20-24</td>
<td>-0.104*</td>
</tr>
</tbody>
</table>

*Significant correlation at the 0.01 level

2.3.3. Calculating Smoothed Rates

Due to the instability of rates calculated for small geographic units, we utilized a spatial rate smoother (Kafadar, 1996), as implemented in OpenGeoDa version 1.0.1 (Anselin, Syabri, & Kho, 2006), to adjust our crude rates. This method replaces the raw rate with a spatial window average rate (Anselin, Kim, & Syabri, 2004). In other words, for each unit of analysis (e.g., DA), a smoothed rate is calculated using the numerator (e.g., number of severe injury cases) and denominator (e.g., population aged 20 years of age and older) information from that unit as well as its neighbours (Anselin, et al., 2004). We chose to use a local rather than a global smoothing technique because the crude rates exhibited statistically significant positive spatial autocorrelation (Figure 2-3) and thus, it would have been inappropriate to smooth the crude rates using the average rate for the entire study region (Anselin, et al., 2004).

As with other local smoothing techniques, the larger the bandwidth or window used to select the neighbouring units, the more the data is smoothed. Since we opted to use the population-weighted centroids of the DA’s instead of the polygons, we used the nearest neighbour approach to select which units were used in each local rate calculation. To determine the appropriate number of neighbours to use, we measured the degree of spatial autocorrelation present in the crude rates at multiple scales and
plotted the results (Figure 2-3). Because we wanted to retain as much of the local variation in the rates as possible, we chose the number of neighbours associated with the first peak in this *spatial correlogram*. In other words, we chose to use 10 nearest neighbours as our bandwidth in order to mimic the inherent spatial scale of clustering present in the crude rates. To examine the impact of our choice of local smoothing technique and bandwidth size on our results, we conducted two sensitivity analyses. Both showed that these choices did not significantly alter our findings.

![Graph showing spatial autocorrelation](image)

**Figure 2-3. Spatial autocorrelation present in the crude all-cause severe injury rates at multiple spatial scales**

*Note.* This graph shows how the degree of spatial autocorrelation present in the crude all-cause severe injury rates increases as the bandwidth increases. The graph first peaks at 10 nearest neighbours. This is the bandwidth that was chosen to smooth the rates of severe injury because it mimics the inherent spatial scale of clustering present in the crude rates.

### 2.3.4. Estimating Missing NSES Values

Census data is often suppressed at the DA level to ensure the confidentiality of individual responses. Since our NSES measures were both constructed using various census variables, there were some DA’s within our study region that were missing NSES values. In response to this, researchers can opt to conduct their analysis using a larger unit of analysis (e.g., census tracts), or simply remove these geographic units from their analysis. Unfortunately, both of these solutions have important limitations. Omitting the units with missing data could introduce unnecessary bias and performing the analysis at
a lower resolution could mask spatial relationships or patterns operating at smaller spatial scales. With these limitations in mind, we decided to estimate the missing NSES values using a simple interpolation method that would take advantage of the spatial structure (i.e., positive spatial autocorrelation) of the NSES data. In total, we only needed to estimate the NSES values for 107 of the 3,591 DA’s in our study region, but we thought this was worthwhile due to the fact that removing these DA’s from our analysis would have meant omitting 406 of the severe injury cases.

Once again, because we were using the population-weighted centroids of the DA’s, we used a point-based nearest neighbour method to estimate the missing NSES values. This method uses the known NSES values of neighbouring DA’s to estimate the missing NSES values, with closer neighbours having more influence on the estimate than more distant ones. In other words, we estimated the missing NSES values using the inverse distance weighted average NSES value of the five nearest DA’s (Antoniuk, 1997). For these calculations, distance was defined as the Euclidean distance between the population-weighted DA centroids.

2.3.5. Estimating Missing Census Population Values

Various population values from the 2006 census were needed to calculate the rates of severe injury and to create the age and gender control variables. For the 20 DA’s that were missing these data, we used a residual method, which takes advantage of the hierarchical and nested structure of census data, to estimate their values (Antoniuk, 1997). In our case, the known DA population values were subtracted from the parent census tract population value to estimate the unknown DA population value. When there was more than one DA within a census tract with a missing population value, the residual population count was divided equally between those DA’s. Although this method may not result in a perfect population estimate due to the random rounding of the census population figures, the amount of error introduced was assumed to be minimal (Antoniuk, 1997).

2.3.6. Descriptive Statistics and Exploratory Spatial Data Analysis

We began our analysis by using a variety of exploratory spatial data analysis methods and some basic descriptive statistics to gain a better understanding of our data.
First, we used the global Moran’s I statistic, as implemented in ArcGIS© Desktop version 10 (ESRI, 2010), to determine the degree of spatial autocorrelation (i.e., clustering) present in each dataset. Global Moran’s I is a global measure of spatial autocorrelation meaning it only describes the amount of clustering present in the dataset as a whole. Thus, to determine where in our study region the values of each variable were clustered, we used the Anselin Local Moran’s I statistic, a local measure of spatial autocorrelation also available in ArcGIS, to identify hotspots (i.e., regions where high values are found adjacent to high values) and coldspots (i.e., regions where low values are found adjacent to low values) within each dataset. Next, we calculated the Pearson correlations between the rates of severe injury and our explanatory variables to determine the direction and magnitude of their associations. Lastly, we calculated the crude annual incidence rates of severe injury per 100,000 person-years for each social and material deprivation quintile in Greater Vancouver.

2.3.7. Modelling the NSES-Injury Relationship

To begin our exploration of the relationship between NSES and the rates of severe injury in Greater Vancouver, we built numerous models using ordinary least squares (OLS) regression. For each dependent variable (e.g., all-cause severe injury rate, intentional severe injury rate, and unintentional severe injury rate), we sought to determine which combination of explanatory variables resulted in the optimal model. First, we built models with social deprivation (SOC), material deprivation (MAT) and both social and material deprivation as the only explanatory variables. Then, we added the proportion of the population that is male (%MALE) and the proportion of the population that is aged 85 years and older (%85+) to each model to control for the age and gender structures of the neighbourhoods. Once the optimal model for each dependent variable was identified, we tested the residuals for spatial autocorrelation using the global Moran’s I tool.

Next, we used geographically weighted regression (GWR) to explicitly test whether the NSES-injury relationship was spatially consistent or heterogeneous. Unlike traditional regression methods, GWR does not assume that the observations are spatially independent (Brunsdon, Fotheringham, & Charlton, 1998). Instead, GWR is based on the assumption that spatial autocorrelation does exist and enables the
researcher to objectively measure and visualize how a relationship varies over space (Schuurman, Peters, & Oliver, 2009). In other words, instead of producing one set of parameter estimates that explains the global or average relationship over the entire study region, GWR outputs local parameter estimates for every observation point that can be mapped to reveal informative spatial patterns or trends. For example, mapping the local $R^2$ values can indicate where the model performs the best and mapping the local model coefficients can show where the relationship between an independent variable and the dependent variable is the strongest. Mapping the local parameter estimates can also provide clues about what, if any, explanatory variables are missing from the model. In other words, GWR can provide a researcher with a lot of useful information about a modelled relationship, which cannot be ascertained from modelling the relationship at the global level (Ali, et al., 2007; Nakaya, Fotheringham, Brunsdon, & Charlton, 2005).

Important considerations for any GWR analysis are the choice of weighting scheme and bandwidth (Fotheringham S., Brunsdon C., & Charlton M., 2002). For our GWR analysis, we used a Gaussian rather than a Poisson kernel because our data was overly dispersed (i.e., the observed variance was much larger than the mean) (Berk & MacDonald, 2008). The choice of bandwidth (i.e., the number of nearest neighbours included in each regression calculation) was automated so that the bandwidth which produced the model with the smallest corrected Akaike’s Information Criterion (AICc) value was used. We chose an adaptive rather than a fixed distance bandwidth because of the large variation in the density of DA’s within our study region.

We chose to use GWR over other modelling techniques used to study the spatial consistency of multivariate relationships for several reasons. First, unlike with multilevel modelling or the creation of regional dummy variables, GWR does not require predefined groups or categories of spatial units (Nakaya, et al., 2005). Other methods (e.g., spatial expansion method, spatially adaptive filtering) are useful for elucidating broader spatial trends in a relationship, but can hide lower-level variations (Fotheringham S., et al., 2002). Spatial regression models would also be inappropriate because they only produce a single set of global parameter estimates and thus, can potentially obscure important local variations (Fotheringham S., et al., 2002).
In this study, we used the Adjusted R-Squared ($R^2_{adj}$) and AICc values to compare the relative performance of our regression models. Both are goodness-of-fit measures, but Adjusted $R^2$ is an absolute measure that always ranges from 0 to 1, whereas AICc is a relative measure that can take on any value (Fotheringham S., et al., 2002). The closer a model’s Adjusted $R^2$ value is to 1, the better the model fits with the observed data (Gao & Li, 2011). Adjusted $R^2$ is considered to be a more robust measure than $R^2$ because it includes an adjustment for the number of variables in the model (i.e., model complexity) (Gao & Li, 2011). AICc, unlike Adjusted $R^2$, can only be used to compare models with the same dependent variable (Fotheringham S., et al., 2002). If the AICc values of two models differ by more than 3, the model with the smaller value is assumed to perform better (Fotheringham S., et al., 2002).

2.4. Results

Initially, we identified 3849 adult severe injury cases within the BCTR and 3973 within the BC Coroner’s Service records that occurred between April 1, 2001 and March 31, 2006. However, after removing the 386 duplicate records from the BC Coroner’s Service dataset that were also present in the BCTR, and omitting the 800 records with insufficient home location information, we were left with 6636 unique severe injury cases for our analysis. Of these, 4742 (72%) were unintentional, 1704 (26%) were intentional, and 190 (3%) had an unknown intentionality.

2.4.1. Descriptive Statistics and Exploratory Spatial Data Analysis

Over our five year study period, the annual adult incidence rate of all-cause severe injury was 76 per 100,000 person-years. When broken down by intentionality, the rate of unintentional injuries (54 per 100,000 person-years) was more than double the rate of intentional severe injuries (19 per 100,000 person-years). The median age was 46 and the highest age-specific incidence rate (228 per 100,000 person-years) was observed in the very elderly (i.e., 85 years of age and older) population, which is consistent with the results of other injury surveillance research in Canada (Figure 2-4) (Laupland, et al., 2005; W. Pickett, Hartling, & Brison, 1997). There was also a significant gender gap in the rate of severe injury, with Greater Vancouver men having
an all-cause severe injury incidence rate (115 per 100,000 person-years) almost triple that of Greater Vancouver women (40 per 100,000 person-years). Interestingly, a gender gap in the incidence rate of all-cause severe injury was observed in every age category, not just the young (Figure 2-4).

![Age-specific annual incidence rates of all-cause severe injury in Greater Vancouver](image)

**Figure 2-4. Age-specific annual incidence rates of all-cause severe injury in Greater Vancouver**

Note. This graph depicts the age-specific annual incidence rates of all-cause severe injury in Greater Vancouver between April 2001 and March 2006. As shown, males have a higher incidence rate than females in every age category and the highest age-specific annual incidence rate for both sexes was observed in the population aged 85 years and older.

The crude all-cause severe injury incidence rates for each social and material deprivation quintile are shown in Figure 2-5. As shown, the rate of severe injury in the most socially deprived neighbourhoods (101 per 100,000 person-years) was much higher than in the least socially deprived neighbourhoods (60 per 100,000 person-years). Similarly, the neighbourhoods with the greatest material deprivation had a much higher rate of severe injury (96 per 100,000 person-years) than those with the least amount of material deprivation (65 per 100,000 person-years). When the NSES quintiles were considered together (i.e., Q1-Q1 versus Q5-Q5) the gap was even more pronounced, with the rate of severe injury almost 4 times higher in the most deprived neighbourhoods (205 per 100,000 person-years) compared with least deprived neighbourhoods (56 per 100,000 person-years).
Figure 2-5 also indicates that there is a socio-economic gradient in the rate of severe injury. In other words, the rate of severe injury increases with each incremental step down the NSES ladder, suggesting that NSES affects a person’s risk of severe injury regardless of where they are located along the socio-economic continuum. However, the largest jump in the crude rate of severe injury was observed between the fourth and fifth quintiles (i.e., the second most deprived neighbourhoods and the most deprived neighbourhoods). This suggests that NSES may play a larger role in influencing the rate of severe injury in the most deprived neighbourhoods than at other levels of NSES. When comparing the slopes of the graphs shown in Figure 2-5, it is also evident that social deprivation may have a slightly stronger relationship with the rate of severe injury than material deprivation.

![Figure 2-5. Crude annual incidence rates of all-cause severe injury by NSES quintiles](image)

**Note.** The crude annual incidence rate of all-cause severe injury is given for each social and material deprivation quintile. Neighbourhoods in the least deprived social and material deprivation quintiles (Q1-Q1) are also compared with the neighbourhoods in the most deprived social and material deprivation quintiles (Q5-Q5). The dark green bars correspond with the least deprived quintiles (Q1) and red bars correspond with the most deprived quintiles (Q5).
The Pearson correlations between the rates of severe injury and the explanatory variables used in our regression analyses are shown in Table 2-2. These were calculated using SPSS software version 19.0 (SPSS Inc., Chicago). The only insignificant association was between the rate of intentional severe injury and the proportion of the population aged 85 years or older (%85+). Thus, this variable was not included in any of the intentional severe injury regression models. Interestingly, social deprivation (SOC) had a stronger association with every rate of severe injury than material deprivation (MAT). Also, both social deprivation and material had a stronger correlation with the rate of intentional severe injury than with the rate of unintentional severe injury. It was also observed that the association between the rate of unintentional severe injury and the proportion of the population that is male (%MALE) was equally as strong as the correlation between the rate of unintentional injury and social deprivation.

### Table 2-2. Pearson correlations between the dependent and explanatory variables used in the regression analyses

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Explanatory Variable</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All-cause rate</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOC</td>
<td></td>
<td>0.308*</td>
</tr>
<tr>
<td>MAT</td>
<td></td>
<td>0.201*</td>
</tr>
<tr>
<td>%MALE</td>
<td></td>
<td>0.276*</td>
</tr>
<tr>
<td>%85+</td>
<td></td>
<td>0.047*</td>
</tr>
<tr>
<td><strong>Intentional rate</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOC</td>
<td></td>
<td>0.340*</td>
</tr>
<tr>
<td>MAT</td>
<td></td>
<td>0.229*</td>
</tr>
<tr>
<td>%MALE</td>
<td></td>
<td>0.228*</td>
</tr>
<tr>
<td>%85+</td>
<td></td>
<td>0.024</td>
</tr>
<tr>
<td><strong>Unintentional rate</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOC</td>
<td></td>
<td>0.261*</td>
</tr>
<tr>
<td>MAT</td>
<td></td>
<td>0.166*</td>
</tr>
<tr>
<td>%MALE</td>
<td></td>
<td>0.261*</td>
</tr>
<tr>
<td>%85+</td>
<td></td>
<td>0.056*</td>
</tr>
</tbody>
</table>

Note: The strongest association for each dependent variable is shown in bold text.

*Significant correlation at the 0.01 level

All of the explanatory and outcome variables exhibited statistically significant positive spatial autocorrelation at both the global and local level (Figure 2-6 and 2-7).
This was not surprising given the spatial patterns that were evident after initially mapping the datasets. Although one would expect the rates of severe injury to be spatially correlated since they were derived using a local smoothing technique, even the crude rates of severe injury exhibited statistically significant spatial autocorrelation (data not shown). These tests of spatial autocorrelation confirm that our observations are not independent and thus, the use of OLS to measure the relationship between our dependent and independent variables may be inappropriate (Holt & Lo, 2008).

As shown in Figure 2-6, there was a fair amount of overlap between the local clusters of unintentional and intentional severe injury rates in Greater Vancouver. For example, there were clusters of high unintentional and intentional severe injury rates (i.e., hotspots) in northern Surrey and the north-eastern Vancouver. In addition, low rates of both unintentional and intentional severe injury rates clustered in Anmore, Richmond, and north-western Coquitlam.

Local spatial clusters of our explanatory variables are shown in Figure 2-7. A clear spatial trend was evident in the distribution of material deprivation across Vancouver, with the west side having clusters of low values and the east side having clusters of high values. There was also a large hotspot of material deprivation in north-western Surrey and a few smaller ones in Mission, Abbotsford, and Richmond. In contrast, high values of social deprivation seemed to cluster in and around downtown Vancouver, North Vancouver, New Westminster, White Rock, the Township of Langley, and the north-western tip of Surrey.
Figure 2-6. Clusters of high (HH) and low (LL) rates of all-cause (a), unintentional (b), and intentional severe injury (c)

Note. These maps show spatial clusters of both high (HH) and low (LL) rates of all-cause, unintentional, and intentional severe injury in Greater Vancouver. The global Moran’s I statistic for each dataset is also given. Those statistics marked with an asterisk have a statistically significant p-value at the 0.01 level.
Figure 2-7. Clusters of high (HH) and low (LL) values of social deprivation (a), material deprivation (b), the proportion of the population that is male (c), and the proportion of the population aged 85 years and older (d)

Note. These maps show spatial clusters of both high (HH) and low (LL) values of social and material deprivation, the proportion of the population that is male and the proportion of the population that is aged 85 years and older. The global Moran’s I statistic for each dataset is also given. Those statistics marked with an asterisk have a statistically significant p-value at the 0.01 level.
2.4.2. **OLS Regression Results**

The results of our OLS regression analysis are shown in Table 2-3. Although each of our initial OLS models (Models 2-4, 6-8, 10-12) were statistically significant, they all had fairly low Adjusted R² values meaning they only explained a small proportion of the variation in the rates of severe injury. However, by examining maps of these models’ residuals (e.g., Figure 2-8), we discovered that each of our initial models greatly under-predicted the rates of severe injury in and around Vancouver’s DTES. Therefore, we created a dummy variable (DTES) to account for this regional variation and added it to the optimum model for each dependent variable. As shown in Table 2-5, the addition of this dummy variable significantly improved the Adjusted R² and AICc values in each of the models, suggesting the relationships between NSES and the rates of severe injury are indeed location dependent.

### Table 2-3. **OLS regression models**

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th># Explanatory Variables:</th>
<th>Adjusted R²</th>
<th>AICc</th>
<th>Global Moran’s I of Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All-cause rate</strong></td>
<td>1 SOC, MAT, %MALE, %85+, DTES</td>
<td>0.594*</td>
<td>-48204</td>
<td>0.191**</td>
</tr>
<tr>
<td></td>
<td>2 SOC, MAT, %MALE, %85+</td>
<td>0.287*</td>
<td>-46183</td>
<td>0.287**</td>
</tr>
<tr>
<td></td>
<td>3 SOC, %MALE, %85+</td>
<td>0.222*</td>
<td>-45869</td>
<td>0.307**</td>
</tr>
<tr>
<td></td>
<td>4 MAT, %MALE, %85+</td>
<td>0.139*</td>
<td>-45503</td>
<td>0.395**</td>
</tr>
<tr>
<td><strong>Intentional rate</strong></td>
<td>5 SOC, MAT, %MALE, DTES</td>
<td>0.500*</td>
<td>-55351</td>
<td>0.174**</td>
</tr>
<tr>
<td></td>
<td>6 SOC, MAT, %MALE</td>
<td>0.286*</td>
<td>-54074</td>
<td>0.245**</td>
</tr>
<tr>
<td></td>
<td>7 SOC, %MALE</td>
<td>0.194*</td>
<td>-53642</td>
<td>0.287**</td>
</tr>
<tr>
<td></td>
<td>8 MAT, %MALE</td>
<td>0.094*</td>
<td>-53220</td>
<td>0.377**</td>
</tr>
<tr>
<td><strong>Unintentional rate</strong></td>
<td>9 SOC, MAT, %MALE, %85+, DTES</td>
<td>0.504*</td>
<td>-50404</td>
<td>0.176**</td>
</tr>
<tr>
<td></td>
<td>10 SOC, MAT, %MALE, %85+</td>
<td>0.227*</td>
<td>-48813</td>
<td>0.259**</td>
</tr>
<tr>
<td></td>
<td>11 SOC, %MALE, %85+</td>
<td>0.184*</td>
<td>-48617</td>
<td>0.271**</td>
</tr>
<tr>
<td></td>
<td>12 MAT, %MALE, %85+</td>
<td>0.121*</td>
<td>-48352</td>
<td>0.337**</td>
</tr>
</tbody>
</table>

Note: The optimum model for each dependent variable is shown in bold text.
*Joint F-Statistic and Joint Wald Statistic with a significant p-value at the 0.01 level
**Statistically significant p-value at the 0.01 level
Although the inclusion of the age and gender variables (i.e., %MALE, %85+) improved the performance of our OLS models, both social and material deprivation explained more of the variation in the rates of severe injury than either of these control variables. Also, the coefficients for social deprivation were consistently larger than the coefficients for material deprivation in the models containing both measures. However, as shown in Table 2-3, the best performing OLS models for each dependent variable included both material and social deprivation as explanatory variables.

Figure 2-8. Map of the standardized residuals for OLS Model 2

Note. This map shows the spatial distribution of the standardized residuals from OLS Model 2. It also highlights the geographic extent of Vancouver’s DTES, where the model underpredicted the rates of severe injury. The global Moran’s I statistic for the dataset is also given, with the asterisk indicating a statistically significant p-value at the 0.01 level.

The coefficients of the explanatory variables in all the models shown in Table 2-3 were statistically significant and the Variance Inflation Factor (VIF) for each explanatory variable was less than 1.5, meaning there were no issues of multicollinearity (i.e., redundancy among the independent variables). However, as shown in Table 2-3 and Figure 2-8, the residuals for every OLS model exhibited statistically significant spatial
autocorrelation. This indicates that our OLS results may be unreliable because the assumption of residual independence has been violated.

2.4.3. **GWR Results**

Unlike with our OLS models, the inclusion of the age and gender variables (%MALE and %85+) in our GWR models resulted in significant local multicollinearity. Therefore, we created an interaction variable by multiplying the age and gender variables together. However, the inclusion of this interaction term did not improve the explanatory power of our GWR models and thus, the results of these models are not shown in Table 2-4. Also, because GWR allows the model parameters to vary over space, the inclusion of the DTES dummy variable was unnecessary.

The results of our GWR analysis are shown in Table 2-4. Interestingly, the GWR models that performed the best for each dependent variable had social deprivation as the only explanatory variable. Also, the GWR models with the rate of unintentional severe injury as the dependent variable performed slightly better than the models with the rate of intentional severe injury as the dependent variable. This was consistent with the results of our OLS analysis, but conflicted with our Pearson correlation results, which both measured the strength of these associations at the global level.

**Table 2-4. GWR models**

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>#</th>
<th>Explanatory Variables:</th>
<th>Adjusted R²</th>
<th>AICc</th>
<th>Global Moran’s I of Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>All-cause rate</td>
<td>1</td>
<td>SOC, MAT</td>
<td>0.919</td>
<td>-52288</td>
<td>0.003*</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>SOC</td>
<td>0.936</td>
<td>-53632</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>MAT</td>
<td>0.929</td>
<td>-53195</td>
<td>0.001</td>
</tr>
<tr>
<td>Intentional rate</td>
<td>4</td>
<td>SOC, MAT</td>
<td>0.869</td>
<td>-58797</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>SOC</td>
<td>0.893</td>
<td>-59786</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>MAT</td>
<td>0.891</td>
<td>-59660</td>
<td>0.000</td>
</tr>
<tr>
<td>Unintentional rate</td>
<td>7</td>
<td>SOC, MAT</td>
<td>0.897</td>
<td>-54337</td>
<td>0.005*</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>SOC</td>
<td>0.916</td>
<td>-55573</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>MAT</td>
<td>0.910</td>
<td>-55227</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Note: The optimum model for each dependent variable is shown in bold text.
*Significant at the 0.05 level
As shown by their higher Adjusted R² values and the lower AICc values, the GWR models provided a better fit with the observed data than the OLS models (Table 2-3 and 2-4). The residuals of the GWR models also exhibited very little or no spatial autocorrelation, meaning their parameter estimates are more reliable than their OLS counterparts (Table 2-4). Furthermore, the condition numbers for the GWR models including both social and material deprivation were all far less than 30, meaning there were no issues with local multicollinearity (Gao & Li, 2011).

Maps of the local R² values, social deprivation coefficients, and standardized residuals for GWR Model 2 are shown in Figure 2-9. Although the mean local R² value was 0.132, the performance of this model ranged from explaining a large proportion of the variation in the rate of severe injury in some regions (R²=0.806) to hardly any or none of the variation in the rates of severe injury in others (R²=0.000) (Figure 2-9a). The strength of the relationship between the rates of severe injury and social deprivation also varied over space, with some regions exhibiting a weak negative relationship and others exhibiting a strong positive relationship (Figure 2-9b).

To aid in the interpretation of the coefficient map (Figure 2-9b), we used the Anselin Local Moran’s I statistic to identify statistically significant clusters of high and low values. As shown in Figure 2-10, this revealed several distinct hotspots and coldspots. Although this map shows where the relationship between severe injury and social deprivation is the strongest, these regions may not be ideal targets for intervention because they may not have high rates of severe injury. Figure 2-11, on the other hand, highlights regions where there were both clusters of high rates of all-cause severe injury and clusters of high social deprivation coefficient values. In other words, it identifies specific neighbourhoods within Greater Vancouver where there were relatively high rates of severe injury and where the relationship between social deprivation and severe injury was the strongest. Figure 2-11, therefore, depicts regions where policies and programs aimed at reducing the rates of severe injury by augmenting the social environment would have the greatest benefit.
Figure 2-9. Spatial distribution of the local $R^2$ values (a), social deprivation coefficients (b), and standardized residuals (c) from GWR Model 2

Note. These maps show the spatial distribution of the local $R^2$ values, social deprivation coefficients, and standardized residuals from GWR Model 2. They illustrate the spatial variation in the modelled relationship.
Figure 2-10. Clusters of high (HH) and low (LL) social deprivation coefficient values for GWR Model 2

Note. This map shows spatial clusters of high (HH) and low (LL) social deprivation coefficient values for GWR Model 2. In other words, this map shows where the relationship between the incidence rate of all-cause severe injury and social deprivation is the strongest and the weakest. The global Moran’s I statistic for the dataset is also given, with the asterisk indicating a statistically significant p-value at the 0.01 level.
44

Figure 2-11. **Regions where high all-cause severe injury rates and social deprivation coefficient values cluster**

Note. This map identifies the neighbourhoods where there were clusters of high all-cause severe injury rates and social deprivation coefficient values. In other words, it depicts specific regions within our study area where policies and programs aimed at reducing the rates of all-cause severe injury by augmenting the social environment would have the greatest benefit.

2.5. Discussion

Our study identified a statistically significant inverse relationship between two measures of NSES and the rates of all-cause, unintentional, and intentional severe injury in Greater Vancouver. In other words, neighbourhoods (i.e., DA’s) with high social and material deprivation were associated with higher rates of severe injury. This supports the findings of a literature review on injury and SES conducted by Cubbin et al. (2002), which found that injuries resulting in a death or hospitalization had an inverse relationship with both individual and area level measures of SES. Interestingly, our results were mixed as to whether NSES had a stronger relationship with the rates of intentional or unintentional severe injuries. However, our analysis did find that social
deprivation explained slightly more of the variation in the rates of severe injury than material deprivation. This suggests that the sociocultural milieu of a neighbourhood plays at least an equally important role as material deprivation in determining the risk of severe injury in Greater Vancouver. Although much of the literature investigating the relationship between injury and SES has used material measures of SES, the few studies that have used measures related to the social components of SES, have also detected an inverse association (Reimers & Laflamme, 2005; Whitley, Gunnell, Dorling, & Smith, 1999).

In a recent study investigating the relationship between material deprivation and unintentional injury deaths across Canada, the authors found that area level SES only played a significant role in determining the risk of injury death in the most deprived neighbourhoods (Burrows, et al., 2012). Similarly, the results of our analysis suggest that the relationship between NSES and severe injury is the strongest in the most socio-economically deprived regions of Greater Vancouver. In fact, given the dramatic improvement in our OLS models after the addition of the dummy variable for Vancouver’s DTES, it is plausible that these strong local relationships are the driving force behind the identified relationships at the global level. This highlights the importance of explicitly testing whether or not an identified relationship is stationary, because if it is not, important local variations and local drivers could be overlooked (Ali, et al., 2007).

This study has several limitations. First, we had to omit 800 cases of severe injury from our analysis because they lacked sufficient home address information. However, because we utilized provincial datasets, not all of these cases would have resided within Greater Vancouver. Also, many of these cases were homeless individuals and thus, would likely also be missing from the denominator census population figures used to calculate the rates of severe injury. Nonetheless, the exclusion of these cases from our analysis may have influenced our results. Second, although we attempted to control for potential confounders such as the age and gender structure of the neighbourhoods, the results of our regression analyses may still suffer from omitted variable or residual confounding bias and thus, should be interpreted with caution. Similarly, because we did not control for individual level SES, we were unable to infer whether the observed relationship was due to mechanisms working at the
individual or neighbourhood level. Because of this, and due to the cross-sectional nature of the data used and the lack of temporal order between the explanatory and dependent variables, we were unable to infer causality. Lastly, it is important to note that our results may have been different if we had used another rate smoothing technique or unit of analysis. Likewise, results may have varied if we had used other measures of SES, if we had studied a different population or age group, if we had studied injuries with different outcome, or if we had studied a different type of severe injury (Cubbin & Smith, 2002).

The use of GWR also has important limitations. First, due to the problem of multiple significance testing, it should be viewed as an exploratory rather than an inferential method (Páez & Wheeler, 2009). Second, GWR models often have issues related to local collinearity, which can result in highly variable regression coefficients and therefore, misinterpretations of the regression relationships (Páez & Wheeler, 2009; D. Wheeler & Tiefelsdorf, 2005). Nonetheless, GWR is very useful for investigating whether or not a relationship identified at the global level varies locally, which was the main purpose of its use in this paper (Gilbert & Chakraborty, 2011).

2.6. Conclusions

This study found statistically significant global as well as local relationships between the rates of all-cause, unintentional, and intentional adult severe injury and two measures of NSES in Greater Vancouver. This suggests that a combination of region-wide and neighbourhood-specific injury prevention programs and policies may be warranted. However, the strength of the local relationships varied from place to place, with the strongest associations located in the most socio-economically deprived neighbourhoods of our study region, such as Vancouver’s DTES. This variation in the NSES-injury relationship may mean that injury prevention efforts would be more successful in some regions than in others. Because of the small scale of our analysis, we were able to highlight specific regions within our study area where policies and programs aimed at reducing the rates of severe injury through the modification of the social environment would have the greatest benefit (Figure 2-11). This study also found that social deprivation had a slightly stronger relationship with the rates of severe injury.
than material deprivation, which suggests that injury prevention programs and policies aimed at supporting single-parent families, persons living alone, and individuals who are separated, divorced or widowed (e.g., free day care, free counselling or psychological services) may have a greater impact than those solely focused on reducing material deprivation.

Further research is needed to illuminate the underlying causal mechanisms responsible for the identified relationships between NSES and severe injury. Given the strength of the relationship identified between social deprivation and the rates of both unintentional and intentional severe injury, future research should try to include measures of social deprivation in addition to the more commonly used material measures of SES.
3. Evaluating potential spatial access to trauma centre care by severely injured patients

3.1. Abstract

Injuries are a major public health problem around the world. Previous research has suggested that providing prompt access to specialized trauma centre care may greatly improve the health outcomes of trauma patients. In this paper, various geographic information system (GIS) methods are used to examine potential spatial access to trauma centres by individuals who were either hospitalized or died as a result of a major trauma. Overall, it was determined that 68.5% of individuals who suffered from a major trauma lived within one hour travel time of a level I or II trauma centre. In addition, major traumas resulting in death were found to have poorer potential spatial access to trauma centre care than those that were admitted to hospital.

3.2. Introduction

Injury is a significant source of premature mortality, hospitalizations, and health care expenditure around the world. Globally, 5.8 million people die every year as a result of an injury and millions more are hospitalized (World Health Organization, 2010). The burden of injury in Canada is just as staggering. Each year approximately 15,000 Canadians die and over 225,000 are hospitalized as a result of injury, and the total direct and indirect costs amount to an estimated $19.8 billion (Public Health Agency of Canada, 2010a, 2010b; SMARTRISK, 2009). Although injury prevention strategies play an important role in reducing the rate of injuries, the care patients receive after an injury has occurred can dramatically affect their chances of survival (Liberman, et al., 2005; MacKenzie, et al., 2006). Unfortunately, inequitable spatial access to trauma centre care may be leading to potentially preventable injury-related mortality and morbidity in Canada.
While previous research has focused on measuring spatial access to trauma centre care by the general population (Branas, et al., 2005; Hameed, et al., 2010), the work presented in this paper is unique in that it evaluates spatial access to trauma centre care by individuals who have sustained a major trauma. In other words, this approach acknowledges that the spatial distribution of injury may not parallel the spatial distribution of the general population, which is a reasonable assumption given that not all population groups have the same risk of severe injury (Charyk-Stewart et al., 2010; Cubbin & Smith, 2002; Laupland, et al., 2005; W. Pickett, et al., 1997).

In this paper we begin by outlining the rationale for trauma centre care and then provide a brief description of trauma services in Canada. Next, we use hospitalization and mortality data to identify major traumas and then use geographic information systems (GIS) to measure their potential spatial accessibility to trauma centre care. In addition, we combine the use of a spatial scan statistic and a drive time catchment method to identify specific regions of the country that would benefit from improved access to trauma centre care. Then we present the results, highlighting gaps in access where needs are high and resources are few, and conclude by discussing the implications of our findings.

3.3. Rationale for Trauma Centre Care

Although one half of all injury-related deaths occur at the site of the injury, the remaining 50% of deaths are potentially preventable through prompt access to appropriate medical care (Meislin, et al., 1997; Rogers, et al., 2005). Ideally, care of the severely injured should be provided in a designated trauma centre that has undergone accreditation or verification by an external agency (Committee on Trauma, 2006; Trauma Association of Canada, 2011). Designated trauma centres are acute care hospitals that have a trauma team immediately available to assess patients, and all the resources required to provide definitive care to severely injured patients (Committee on Trauma, 2006; Trauma Association of Canada, 2011). Access to a trauma centre is critically important for the severely injured patient, as care in this environment is associated with a 25% lower risk of death compared to care in non-designated centres (Liberman, et al., 2005; MacKenzie, et al., 2006).
3.4. Trauma Centre Care in Canada

Trauma system development in Canada is in its early stages. Although a few provinces have relatively mature trauma systems that optimize access to trauma centre care, many provincial trauma systems are still missing essential components. For example, the majority of provinces and territories (all except British Columbia, Alberta, Ontario, and Nova Scotia) have yet to implement pre-hospital air transportation programs (Hameed, et al., 2010). For a more detailed description of Canada’s provincial and territorial trauma systems please refer to Hameed et al., 2010.

3.5. Data

3.5.1. Trauma Centres

Since the majority of trauma centres in Canada have yet to be accredited or verified by an external agency, a national survey of trauma centre personnel was used to identify all level I and II trauma centres across Canada, regardless of their designation status. The survey used the Trauma Association of Canada’s Trauma System Accreditation Guidelines (2011) to categorize hospitals based on the resources they provide as well as other characteristics such as patient volume and training (Hameed, et al., 2010). Because the purpose of this study was to measure access to expert care within resource-rich facilities by patients with life threatening injuries, only level I and II trauma centres with full time neurosurgical capability were included. The neurosurgical requirement was used because traumatic brain injury (TBI) is the most common cause of traumatic mortality and because TBI patients who are transferred directly to a trauma centre capable of providing neurosurgical care have a much higher survival rate than those who are sent to centres without neurosurgical capacity (Hameed, et al., 2010; Härtl et al., 2006). Once these hospitals were identified, their street addresses were geocoded using road network data from DMTI (Desktop Mapping Technologies Inc.) Spatial Canada v.2009.3.
3.5.2. **Major Traumas**

Both Vital Statistics and Hospital Morbidity Database data were used to identify all major traumas that occurred between April 1, 2001 and March 31, 2006. A major trauma was defined as an injury that results in death prior to hospital admission or one that is assessed at a hospital and given an Injury Severity Score (ISS) greater than 15. ISS, the most frequently used method for quantifying injury severity, is derived from the Abbreviated Injury Scale, which provides an injury severity score ranging from one to six for each injury across all body regions (Association for the Advancement of Automotive Medicine, 1998; Baker, O'Neill, Haddon, & Long, 1974). Patients less than 16 years of age were excluded because severely injured children are often treated at pediatric trauma centres, which were not the focus of this study (Carr & Nance, 2010). Since cases were mapped using their full six digit postal codes and the province of Quebec only reports the forward sortation areas (i.e., the first three digits of the postal code) of patients who are hospitalized, Quebec was excluded from this study. All of the preliminary data preparation and extraction was conducted using SAS v.9.1 (SAS Institute, 2004).

3.5.2.1. **Major Traumas Resulting in Death prior to Hospitalization**

Major traumas that resulted in death outside of hospital were identified through Canada’s Vital Statistics Death Database using the cause of death field.

3.5.2.2. **Major Traumas Resulting in Hospitalization**

Major traumas that resulted in a hospitalization were identified through the Hospital Morbidity Database (HMBD), a national administrative discharge database containing demographic, administrative and clinical data on all inpatient hospitalizations in Canada. Health Person-Oriented Information (HPOI) was derived from the HMBD at Statistics Canada in order to link these records at the person level. HPOI includes information on the patient’s age, sex, medical diagnoses, admission/discharge dates, and postal code of home residence.

A recently developed and validated algorithm developed by Haas et al. (2009) was used to derive ISS from the International Classification of Diseases, 10th Revision (ICD-10) diagnoses codes (Rogers, et al., 2005). Since Canada’s provinces and
territories transitioned from the ICD-9 to the ICD-10 at different times, this study was only able to use a full five years (2001/2002-2005/2006) of data for British Columbia, Newfoundland, Prince Edward Island, Nova Scotia, and the Yukon. As for the remaining provinces and territories, four years of data (2002/2003-2005/2006) was used for Alberta, Ontario, Saskatchewan, and the North West Territories, three years (2003/2004-2005/2006) for New Brunswick and Nunavut, and two years (2004/2005-2005/2006) for Manitoba. For consistency, these same date ranges were used when extracting injuries from the Vital Statistics database. To eliminate the double counting of patients who were transferred from one hospital to another for the same major trauma event, an individual discharged and admitted on the same day was considered a transfer, and only the initial hospitalization record was retained for our analysis (Oliver & Kohen, 2009).

3.6. Methods

3.6.1. Mapping Major Traumas

Individuals who sustained a major trauma were mapped according to their six-digit postal code of home residence using the geographic coordinates provided in Statistics Canada’s Postal Code Conversion File (2009). We used the postal code of home residence instead of the location of the injury because the latter was not included in either of the datasets used in this study. Although the average postal code in Canada contains 19 households, the size of a postal code can vary dramatically from urban regions where one postal code may serve a single business (i.e., zero households), to rural and remote regions where a postal code may contain up to 10,000 households (Statistics Canada, 2007). Unless otherwise stated, all mapping and spatial analyzes were conducted using ArcGIS® Desktop version 10 (ESRI, 2010).

3.6.2. Calculating Travel Times

The Origin-Destination (OD) Cost Matrix tool available in ArcGIS’s Network Analyst toolbox was used to determine the proportion of major trauma cases within one hour travel time of a level I or level II trauma centre. Travel times were also calculated for two mutually exclusive subpopulations – major traumas resulting in death prior to hospital admission and major traumas resulting in a hospitalization - because of their
suspected differences in spatial access to trauma centre care. In the context of this study, “cost” refers to the time it takes an individual suffering from a major trauma to be transported by land from their home residence to a trauma centre. Using the home residences as “origins” and the trauma centres as “destinations”, this tool generates a table giving the total travel time in minutes from each home resident postal code to the nearest trauma centre. The GIS calculates these total travel times by summing the individual drive times associated with each road segment that make up the optimal (i.e., quickest) route between each trauma location (i.e., postal code) and a trauma centre.

The individual drive times associated with each road segment were derived from the posted speed limits and road segment lengths, which are stored as attribute values in the road network data. Using posted speed limits to model ambulance drive times is appropriate given that ambulances normally obey these limits when transporting patients to ensure patient safety and avoid causing secondary motor vehicle collisions (Amram, Schuurman, & Hameed, 2011). If a trauma postal code was farther than 2500 metres from the closest road segment, it was assumed to be farther than four hours from the nearest trauma centre. In order to account for the cross-border care of patients, trauma centres located in the neighbouring provinces were included as possible destinations in all drive time calculations. If there were fewer than 10 major trauma cases per provincial drive time category (e.g., within one hour or farther than one hour), these cases were suppressed to ensure patient confidentiality.

3.6.3. Identifying Significant Clusters of Severe Injury

The purpose of our next analysis was to identify specific regions, rather than individuals, within each province that would benefit from improved access to trauma centre care. The benefit of identifying spatial aggregations (i.e., clusters) of cases, rather than individuals, is that their needs can be considered together. Then, if the clusters are deemed large enough, additional resources can be provided in that geographic area, which meet their collective need for trauma centre care. In contrast, if cases are considered individually, these spatial patterns of need may be left unnoticed and opportunities for the efficient use of trauma care resources may be missed.
To conduct our cluster analysis, we first used SaTScan™ v. 9.1.1 software (2011), which implements Kulldorff’s spatial scan statistic, to identify statistically significant geographic clusters of major traumas (Martin Kulldorff, 1997; Martin Kulldorff & Nagarwalla, 1995). SaTScan creates circles of increasing size around each case and control up to a user set maximum cluster size. For every circle, SaTScan calculates a likelihood ratio by comparing the risk of major trauma inside versus outside the circle, returning the circle with the largest likelihood function as the “most likely cluster”; all other clusters are termed “secondary clusters”. In addition to the size (i.e., radius) and location (i.e., centroid latitude and longitude coordinates), SaTScan also returns a p-value for every cluster, which it derives from calculating the same likelihood ratios, but for 999 Monte Carlo randomizations of the case labels. The p-value is based on the rank order of the likelihood ratio of the cluster amongst all of the likelihood ratios produced by the 999 replications of the data set.

For our analysis, we used the Bernoulli model with the postal codes containing at least one major trauma as the cases and a random sample of postal codes as the controls. Due to computational memory constraints, we were unable to use all of the postal codes as controls. Fortunately, we were still able to attain a one to three ratio of cases to controls, which is the standard in epidemiological research (D. C. Wheeler, 2007). Initially, we used the default maximum cluster size (i.e., 50% of the population at risk), but this resulted in the detection of very large clusters containing areas of both high and low relative risk. SaTScan’s tendency to favor larger, heterogeneous clusters comprised of multiple smaller clusters of high risk as well as areas with relatively low risk is well documented (Chen, Roth, Naito, Lengerich, & MacEachren, 2008; Sugumaran, Larson, & DeGroote, 2009; Tango, 2007). We therefore decided to reduce our maximum cluster size to a 20km radius to ensure that the clusters we identified would be homogeneous regions of elevated risk of severe injury. After the significant (i.e., p-value less than 0.05) clusters of major trauma were identified, they were mapped using their centroid coordinates and radii provided in the SaTScan output files. Clusters with fewer than 10 major traumas were suppressed to ensure patient confidentiality.

The major benefit of using the Bernoulli method is that it does not require the spatial distribution of the underlying population to calculate risk, which would be inappropriate given that the risk of injury is not uniformly distributed across the general
population (Karmali et al., 2005; Newgard et al., 2011). Similarly, the Bernoulli model uses counts instead of rates, which was beneficial because denominator population data is unavailable at the postal code level and even so, rates calculated at such a fine spatial resolution would be subject to the small number problem (Burra, Jerrett, Burnett, & Anderson, 2002). Using the Bernoulli model was also reasonable given that it produces similar results as the Poisson model when analyzing rare health events, such as severe injury (Martin Kulldorff, 1997).

SaTScan’s spatial scan statistic was chosen over the other cluster detection techniques available because it does not require any a priori knowledge about the geographic extent of the underlying clustering process or processes, which was critical given that the etiology of major trauma is largely unknown (Root, Meyer, & Emch, 2009). Another advantage was that SaTScan returns an exact location, size, and significance value (p-value) for every cluster, allowing us to identify specific towns and cities with an elevated risk of severe injury that are located outside one hour travel time of the closest trauma centre. In addition, SaTScan can search for clusters using point data, which allowed us to maintain the fine resolution of our data set, minimizing the possibility of aggregation bias (Ozdenerol, Williams, Kang, & Magsumbol, 2005) and maximizing our ability to detect spatial clusters (Meliker, Jacquez, Goovaerts, Copeland, & Yassine, 2009; Ozonoff, Jeffery, Manjourides, White, & Pagano, 2007). Yet another benefit of using SaTScan is that, unlike some of the other cluster detection methods, the reported significance values are adjusted for the bias introduced by multiple testing (Lu, 2009).

The second step involved in identifying clusters farther than one hour travel time of a level I or II trauma centre, was the creation of drive time catchment or service areas for every level I and II trauma centre in the country using a well-established travel time catchment method developed by Schuurman et al. (2006). This method delineates catchments within a GIS by selecting all of the road segments within a certain road travel time of a point location, such as a trauma centre. These catchments were produced using the same road network dataset as the previous drive time calculations and then overlaid with the clusters to identify those that intersected with the one hour drive time catchment areas. In other words, to be considered within one hour drive time of a trauma centre, a cluster only had to partially overlap a catchment area.
3.7. Results

A total of 32 level I and II trauma centres capable of providing definitive trauma care were identified, all of which were located in urban centres near the southern border of the country. Although each of them had provincial designation, only 18 (56%) had been accredited or verified by an external agency, such as the TAC (Hameed, et al., 2010). Prince Edward Island, Canada’s smallest province, and Canada’s three northern territories (the Yukon, Northwest Territories, and Nunavut) did not contain any level I or II trauma centres. Thus, assuming all major traumas were treated at a trauma centre, 827 (1.3%) of the trauma cases identified in this study would have had to travel outside their resident province or territory to receive the recommended care.

During the study period, 65,004 major traumas were identified. Of these, 13,410 (20.6%) resulted in death prior to hospital admission and 51,594 (79.4%) resulted in a hospitalization. However, 1,866 cases (2.9% of the dataset) were excluded from our analysis because they did not have a corresponding postal code in Statistics Canada’s Postal Code Conversion file, they had to be suppressed to ensure patient confidentiality, or their postal code was not connected to a trauma centre by the road network (i.e., the postal code was located on an isolated portion of the road network such as an island, or a portion of the road network that was incompletely or incorrectly digitized). Once these cases were removed, we were left with 63,138 major traumas for our analysis, of which 13,103 (20.8%) resulted in death and 50,035 (79.2%) resulted in a hospitalization.

Overall, 68.5% of the population who suffered from a major trauma lived within one hour travel time of either a level I or II trauma centre. However, as shown in Table 3-1, spatial access to trauma centre care varied across the country, with some provinces having better access to trauma centre care than others. Ontario had the best coverage with 79.9% of the population who suffered from a major trauma living within one hour of either a level I or II trauma centre. Prince Edward Island and Canada’s three territories, which have no trauma centres of their own and fall outside the one hour catchment areas of their neighbouring provinces’ trauma centres, had the worst coverage, with no severe injuries occurring within one hour drive time of either a level I or II centre.
Table 3-1. The number and percent of major trauma cases living within one hour of a level I or II trauma centre, by health outcome and province.

<table>
<thead>
<tr>
<th>Province/Territory</th>
<th>Major traumas resulting in death outside a hospital</th>
<th>Major traumas resulting in a hospitalization</th>
<th>Total (all major traumas)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#</td>
<td>%</td>
<td>#</td>
</tr>
<tr>
<td>Alberta</td>
<td>1,089</td>
<td>52.9</td>
<td>5,702</td>
</tr>
<tr>
<td>British Columbia</td>
<td>2,327</td>
<td>67.3</td>
<td>8,776</td>
</tr>
<tr>
<td>Manitoba</td>
<td>177</td>
<td>52.5</td>
<td>796</td>
</tr>
<tr>
<td>New Brunswick</td>
<td>196</td>
<td>42.9</td>
<td>488</td>
</tr>
<tr>
<td>Newfoundland</td>
<td>97</td>
<td>29.0</td>
<td>260</td>
</tr>
<tr>
<td>Nova Scotia</td>
<td>259</td>
<td>39.3</td>
<td>838</td>
</tr>
<tr>
<td>Ontario</td>
<td>3,653</td>
<td>78.1</td>
<td>16,796</td>
</tr>
<tr>
<td>Saskatchewan</td>
<td>383</td>
<td>42.7</td>
<td>1,382</td>
</tr>
<tr>
<td>Canada</td>
<td>8,181</td>
<td>62.4</td>
<td>35,038</td>
</tr>
</tbody>
</table>

a Prince Edward Island and Canada’s northern territories are not shown because they have no trauma centres of their own and are farther than one hour drive time from their neighbouring provinces’ trauma centres. However, they were used to calculate the national estimates.

b The national figures exclude Quebec.

Major traumas that resulted in death prior to hospital admission had poorer (62.4%) potential spatial access to trauma centre care than the major trauma cases who survived to hospital admission (70.0%). As shown in Figure 1, this difference was consistent across all the provinces except in New Brunswick, where the estimates of spatial accessibility were almost identical (42.9% vs. 42.0%).
Figure 3-1. Percentage of major trauma cases that lived within one hour of a level I or II trauma centre, by health outcome and province.

Note. Prince Edward Island and Canada’s northern territories are not shown because they have no trauma centres of their own and are farther than one hour drive time from their neighbouring provinces’ trauma centres. However, they were used to calculate the national estimates. Also note that the national figures exclude Quebec.

Our cluster analysis identified 222 significant spatial clusters of major trauma that were outside one hour travel time of trauma centre. Of these clusters, 59 were comprised of a single postal code and 164 included two or more postal codes. British Columbia (43), Alberta (50), and Ontario (105) had the largest number of significant spatial clusters outside one hour, and the fewest were identified in Nunavut (1) and New Brunswick (0). Excluding the single cluster that had to be omitted from our results to ensure patient confidentiality, the average cluster contained 31 major traumas and had a radius of 10.8 km.
Table 3-2. Significant spatial clusters of major trauma outside one hour of a level I or II trauma centre, by province/territory.

<table>
<thead>
<tr>
<th>Province/Territory</th>
<th># of clusters</th>
<th># of major traumas within clusters</th>
<th>Localities within the most likely clustera</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alberta</td>
<td>50</td>
<td>1,563</td>
<td>St. Paul, Horseshoe Bay</td>
</tr>
<tr>
<td>British Columbia</td>
<td>43</td>
<td>1,557</td>
<td>Gibsons, Sechelt, Roberts Creek, Bowen Island</td>
</tr>
<tr>
<td>Manitoba</td>
<td>13</td>
<td>200</td>
<td>Shoal Lake</td>
</tr>
<tr>
<td>New Brunswick</td>
<td>0</td>
<td>0</td>
<td>N/A</td>
</tr>
<tr>
<td>Newfoundland</td>
<td>14</td>
<td>257</td>
<td>Cottlesville, Summerford, Twillingate, Birchy Bay, Baytona, Comfort Cove-Newstead</td>
</tr>
<tr>
<td>Northwest Territories</td>
<td>3</td>
<td>42</td>
<td>Aklavik</td>
</tr>
<tr>
<td>Nova Scotia</td>
<td>21</td>
<td>705</td>
<td>Kingston, Greenwood, Berwick, Middleton</td>
</tr>
<tr>
<td>Nunavut</td>
<td>1</td>
<td>23</td>
<td>Iqaluit</td>
</tr>
<tr>
<td>Ontario</td>
<td>36</td>
<td>1,491</td>
<td>Bridgenorth, Chemong Park, Bobcaygeon, Curve Lake First Nation 35</td>
</tr>
<tr>
<td>Prince Edward Island</td>
<td>7</td>
<td>240</td>
<td>Mount Stewart, Morell, Morell 2, Scotchfort 4</td>
</tr>
<tr>
<td>Saskatchewan</td>
<td>31</td>
<td>652</td>
<td>Hudson Bay</td>
</tr>
<tr>
<td>Yukon</td>
<td>3</td>
<td>42</td>
<td>Watson Lake</td>
</tr>
<tr>
<td>Canadaa,b</td>
<td>222</td>
<td>6,772</td>
<td></td>
</tr>
</tbody>
</table>

a The ‘most likely cluster’ is the cluster within each province/territory with the highest log likelihood value.
b One significant cluster was omitted to ensure patient confidentiality because it contained fewer than 10 cases.
c The national figures exclude Quebec.

Figure 2 shows the locations of the 222 significant spatial clusters of major trauma that did not intersect with the one hour travel time catchment areas. From this map you can clearly see that there are spatial clusters of need located outside the optimal drive time of the closest trauma centre in almost every province and territory. Table 3-2 lists the cities and towns located within the most likely cluster (i.e., the cluster with the highest log likelihood ratio) in each province and territory. During our study period, these are the locations where the likelihood of a severe injury event occurring was greatest when compared to the rest of the province or territory. If this spatial pattern of need remains the same in the future, these regions may benefit from improved access to trauma centre care.
Figure 3-2. **Significant spatial clusters of major trauma that are farther than one hour of a level I or II trauma centre.**

Note. The results of the cluster analysis are shown for every province and territory in Canada. Only clusters with a p-value less than 0.05 that are outside the one hour drive time catchment areas of the 32 level I or II trauma centres are shown. The clusters are coloured according to the number of major traumas they contain.

3.8. Limitations

This observational study has several recognized limitations. First, because the precise geographic coordinates of the actual sites of major trauma were not present in either of the datasets used in this study, the home residence postal codes were used as a proxy measure. This is reasonable given that most injuries occur within a relatively short distance (e.g., 5 to 10 miles) of the home (Boyle, Lampkin, Schulman, & Bucuvalas, 2007; Evans, Palmer, Jones, Jones, & Polacarz, 2005). However, it is
possible that the use of postal codes caused us to overestimate spatial accessibility to trauma centre care in Canada because severe injuries, such as those resulting from motor vehicle collisions, often occur in rural or remote regions of the country far from any residential neighbourhood (Muelleman, Wadman, Tran, Ullrich, & Anderson, 2007; Peek-Asa, Zwerling, & Stallones, 2004). It is also important to note that postal codes typically cover large geographic areas in rural regions of the country and thus, using postal code centroids as a proxy for home address is more accurate in urban versus rural settings.

A second limitation was our inability to accurately account for any additional travel time caused by traffic lights, stop signs, traffic congestion, road closures, or poor weather conditions. Because the datasets used in this study did not contain information about how the cases were transported to hospital, we were also unable to account for the time EMS personnel spend travelling to and at the scene of the trauma for instances when individuals are transported via air or ground ambulance. This too may have caused us to overestimate spatial accessibility of trauma services. However, when the estimated drive times were compared with a random sample of actual ambulance drive times from Metro Vancouver, British Columbia, the results were comparable. We were also unable to account for the availability of pre-hospital air transportation, which may have caused us to underestimate access to trauma centre care in the provinces where these programs exist. However, depending on the additional time required to prepare the air ambulance and the proximity of the closest helipad or landing zone to the scene of the trauma, air transport may not be faster than ground transportation (Hameed, et al., 2010; Lerner, Billittier, Sikora, & Moscati, 1999; Shepherd, Trethewy, Kennedy, & Davis, 2008).

Our study also has limitations related to the two datasets that were used. Because in-hospital deaths were recorded in both the hospitalization and Vital Statistics data, we had to exclude them from the Vital Statistics data in order to avoid the double counting of cases. This may have caused us to exclude traumas that resulted in an in-hospital death. For example, falls and gunshot wounds classified as not severe (i.e., ISS <16), but that resulted in an in-hospital death would have been excluded from our analysis. Since the Vital Statistics data often includes only one cause of death code, we may have also excluded trauma-related deaths where the primary cause was recorded as something other than a trauma. In addition, our method of using admission and
discharge by date to remove duplicate hospitalization records, which is standard practice with these data, may have resulted in the double counting of cases that took longer than one day to transfer.

Lastly, our methods and the interpretation of our results are based on the assumption that the future spatial distribution of need for trauma centre care will closely match that of the past. Although extrapolating past patterns into the future is risky, it is often the only option when planning the future allocation of resources and is common practice in the health care services literature (Branas, MacKenzie, & ReVelle, 2000; Foo, Ahghari, & MacDonald, 2010; Schuurman, Bell, L'Heureux, & Hameed, 2009). Nonetheless, caution should be taken when interpreting our results, especially for those provinces where only a few years of data were aggregated.

### 3.9. Discussion

The proportion of the major trauma patients that lived within one hour of the nearest trauma centre was highlighted in this paper because one hour, or the ‘golden hour’, is widely recognized as the time within which patients should receive emergency medical care at a hospital in order to minimize the risk of serious health outcomes (Crews & Holbrock, 2005; Raghavan & Marik, 2006). The principle of the golden hour was originally based on data collected during World War I, which showed that the time to treatment had a significant impact on the mortality rates of injured soldiers (Kane, MacCallum, & Friedrich, 2007). Although one hour travel time is frequently used by researchers when evaluating spatial accessibility to health services (Brabyn & Skelly, 2002; Schuurman, et al., 2006), it has also been criticized because of the inherent differences (e.g., type of injury, age, gender) between the soldiers who are injured in combat and the civilians who are injured on home soil (Lerner & Moscati, 2001). Nonetheless, there is ample evidence to suggest that the treatment patients receive during the first few hours, or the “golden hours”, following a major trauma is paramount to their survival (Raghavan & Marik, 2006; Sampalis, et al., 1999).

While need for trauma centre care has typically been estimated through an assessment of the number and distribution of severely injured patients admitted to
hospital, this information provides a biased evaluation (A. B. Nathens, Jurkovich, MacKenzie, & Rivara, 2004). Focusing on this cohort alone results in the exclusion of individuals who die in the field or the emergency department, whose location of death may well reflect an unmet need for trauma centre care. Others have focused on the relationship between the underlying population distribution and the location of trauma centres as a measure of access, but this too is a poor surrogate of need given that not all populations are at similar risk of major trauma (Branas, et al., 2005; Hameed, et al., 2010; Nance, Carr, & Branas, 2009). For example, Aboriginal Canadians are at much higher risk of major trauma than the general population (Karmali, et al., 2005).

Our analysis improved upon this earlier work in two important ways. First, the use of multiple datasets, which account for both the major trauma cases that die before reaching a hospital as well as those admitted to hospital, eliminates the potential for survival bias. In fact, to the best of our knowledge, this is the first Canadian study that combined hospitalization and mortality data to examine the entire spectrum of major trauma cases. Second, the use of these datasets allowed us to evaluate potential spatial access to trauma centres in Canada by those individuals who had sustained a major trauma (i.e., the target population) instead of the general population. In other words, these improvements enabled us to provide better insight into how well Canada’s trauma care needs and resources are spatially aligned.

Our cluster analysis was particularly informative because it highlighted specific locations where the likelihood of a case occurring was significantly higher than surrounding areas. In other words, we identified areas where the number of cases was unexpectedly high given the spatial distribution of the control postal codes. Assuming the spatial distribution of major trauma stays the same, these are areas of the country that would potentially benefit from improved spatial access to trauma centre care.

Our analysis showed that major traumas resulting in death had poorer potential spatial access to trauma centre care than those that were admitted to hospital. However, because of our study design we are unable to determine whether this association is casual or whether it is due to a confounding factor. For instance, this result may simply indicate that traumas sustained by individuals who live farther from trauma centre care are due to a different, and perhaps more fatal mechanism. It may
also be due to the fact that postal codes have less positional accuracy in rural versus urban regions. Further research is therefore needed to determine whether spatial access to trauma centre care affects a severely injured patient’s chances of survival, as has been suggested in the trauma literature (Fatovich & Jacobs, 2009; Gomez et al., 2010; Kroneman, Verheij, Tacken, & van der Zee, 2010; Minei et al., 2010; Muelleman, et al., 2007; Peek-Asa, et al., 2004).

As shown in Figure 2, the results of this study are inconsistent with previous work by Hameed et al.(2010), who estimated potential spatial access to trauma centre care in Canada using a very similar drive time method. However, instead of using the spatial distribution of severely injured patients to estimate the need for trauma centre care, the authors of this paper based their analysis on census block populations. Although the inclusion of Quebec may explain their higher national estimate of spatial accessibility to trauma centre care, the conflicting provincial results suggest that the distribution of major trauma does not parallel that of the general population. These differing results, therefore, highlight the importance of using a target population that accurately reflects the spatial distribution of need when estimating potential spatial access to a particular health care or social service.
Figure 3-3. The comparison of two estimates of potential spatial access to trauma centre care in Canada, by province.

Note. The results of the present study are shown alongside the results of a previous study conducted by Hameed et al. (2010). Both give an estimate of proportion of the population within one hour of a level I or II trauma centre. However, the present study used the postal codes of severely injured patients to estimate the need for trauma centre care whereas the previously published findings were derived using 2006 census block population figures.

In comparison to the proportion of the United States’ population living within one hour of a level I or II trauma centre (84.1%) reported by Branas et al. (2005), the results of this study indicate that most of Canada’s provinces have poorer potential spatial access to trauma centre care than their American neighbours. However, their analysis accounted for the availability of helicopter as well as ground ambulance transportation of patients, which increased the overall level of access from only 56.4% to 84.1%. Thus, when only considering ground transportation of patients, our findings suggest that most of Canada’s provinces have better potential spatial access to trauma centre care than the US. In addition, because Branas et al. (2005) based their estimates on census block
group populations instead of the actual population of severely injured patients, they may also have overestimated access to trauma centre care.

According to the Canada Health Act, which includes the principles of ‘universality’ and ‘accessibility’, provinces are required to provide access to health services for all citizens (Canada Health Act, "Canada Health Act," 1985). This presents several challenges, particularly in the case of trauma services as care must be delivered within a very limited time span. First, Canada’s large landmass, coupled with its unevenly and often sparsely distributed population, makes equitable service provision inherently difficult, especially in its many rural and remote communities (Schuurman, Crooks, et al., 2010). Physical barriers, such as mountain ranges, rivers, and lakes, which make up the Canadian landscape, also impede access. These physical barriers often combine with severe weather conditions, including snow, rain, wind, and ice, to make transporting severely injured patients to trauma centres extremely dangerous or impossible, even where air transportation programs are available. Further, the declining population of many Canadian rural communities has made the equitable provision of health care services especially problematic and in some cases has led to the closure of rural hospitals (Liu, Hader, Brossart, White, & Lewis, 2001).

Because trauma system development in Canada is in its early stages, this study has a unique opportunity to guide future system development. By identifying regions of the country that have poor potential spatial access to trauma centre care and spatial clusters of major traumas, we have highlighted locations where there is an unmet need for trauma centre care. This is valuable information that could be used by provinces to prioritize the future allocation of trauma care resources. For example, health planners could use this information to inform decisions about the promotion of lower level acute care hospitals to designated trauma centres as well as the implementation or expansion of pre-hospital air transportation programs.

As demonstrated in this paper, GIS methods are well-suited to evaluate the spatial accessibility of health services because of their unique ability to effectively describe and illustrate the spatial relationships between the characteristics of the health care system and its potential users. In addition to estimating spatial access to trauma centre care (Gomez, et al., 2010; Hameed, et al., 2010), trauma researchers have used
GIS to identify the optimum location for trauma centres, aeromedical depots, and helipads (Branas, et al., 2000; Foo, et al., 2010; Kivell & Mason, 1999), and determine the best mode of transport for severely injured patients (Lerner, et al., 1999). Others have used GIS to identify clusters of injuries so that injury prevention programs can be targeted to the geographic locations and populations at greatest risk (Newgard, et al., 2011; Craig Warden, 2008; C. Warden, Sahni, & Newgard, 2010; Yiannakoulias, et al., 2003). Although these studies demonstrate the value of GIS as a decision support tool in health care planning, our results emphasize the importance of using accurate input data.

3.10. Conclusion

Despite major advances in injury prevention and control, trauma is still a significant public health problem in Canada and around the world (Bell & Schuurman, 2010; World Health Organization, 2010). Because of this, many researchers have begun to investigate trauma system structures and processes as another possible means for reducing injury-related morbidity and mortality (Branas, et al., 2005; Carr & Nance, 2010; Hameed, et al., 2010; Kivell & Mason, 1999; Liberman, et al., 2005; MacKenzie, et al., 2006; Nance, et al., 2009; Avery B. Nathens, Brunet, & Maier, 2004; A. B. Nathens, Jurkovich, Rivara, et al., 2000; Rogers et al., 1999; C. Warden, et al., 2010). This paper used various geospatial analytical methods to evaluate the spatial distribution of trauma centre care in relation to the spatial distribution of severely injured patients. Although the future spatial distribution of major trauma may differ, our results provide a useful baseline from which to measure the continuing development of trauma systems in Canada. Results demonstrated that 68.5% of Canadian major trauma cases residing outside Quebec lived within one hour travel time of a level I or II trauma centre. This study also identified numerous significant spatial clusters of major trauma that were outside one hour travel time of the closest trauma centre, suggesting there may be an unmet need for trauma centre care in some parts of the country. Finally, this paper also demonstrated how GIS can be a valuable decision support tool for health planners, but that the accuracy of results from geospatial analyzes are largely dependent upon the quality of the input data.
4. Conclusion

Several different strategies have been developed for reducing the burden of injury on populations. This thesis has provided important information that may guide the development of two different approaches, which target different stages of an injury event. The first paper, presented in section 2, will inform injury prevention strategies acting on the pre-event phase of an injury. The second paper, presented in section 3, will help to inform the future development of Canada’s trauma systems and thus, will inform strategies acting on the post-event phase of an injury.

The paper presented in section 2 had two closely related objectives. First, it sought to determine whether there was a statistically significant association between the rates of severe injury and neighbourhood SES in Greater Vancouver. The second objective of this study, however, was to find out whether or not this relationship varied over space. A variety of aspatial (e.g., Pearson correlations, ordinary least squares) and geospatial methods (e.g., cluster analyses, geographically weighted regression) were used to meet these objectives. Overall, the study found a relationship between both material and social deprivation and the rates of all-cause, unintentional, and intentional severe injury. However, this relationship was found to vary over space and was strongest in the most socio-economically deprived neighbourhoods in the study region. Social deprivation was also found to have a slightly stronger association with the rates of severe injury than material deprivation.

The aim of the second paper, presented in section 3, was to evaluate the spatial distribution of trauma centres in Canada in relation to the spatial distribution of severely injured patients. Two different geospatial methods were used to meet this objective. First, a network drive time method was used to determine the proportion of severely injured patients that lived within one hour of a trauma centre. Next, spatial clusters of severe injury were identified and the proportion of those clusters within one hour drive time of a trauma centre was calculated. Results indicated that spatial access to trauma
centre care varied from province to province, with some having much better potential spatial access than others. Interestingly, the levels of spatial accessibility to trauma centre care for each province were less than the estimates reported by a previous study. Also, severe injuries resulting in death were found to have poorer levels of spatial accessibility to trauma centre care than severe injuries resulting in a hospitalization.

4.1. Research Contributions

The research presented in this thesis has important implications for policies, programs, and services aimed at reducing the burden of severe injury in Canada. For example, the results of the first study showed that the relationship between SES and severe injury is strongest in the most socio-economically deprived neighbourhoods in Greater Vancouver and that some of these regions also had very high rates of severe injury. Thus, injury prevention programs and policies aimed at reducing the rates of severe injury in Greater Vancouver through the modification of the socio-economic environment are likely to be the most successful if they targeted these neighbourhoods.

Paper 1 also provided a great deal of new information about the complex relationship between NSES and severe injury. For example, the results indicated that the strength of the relationship varies over space, with some neighbourhoods having a very strong association and others exhibiting very little or no association. Paper 1 also found that social deprivation explained slightly more of the geographic variation in the rates of severe injury than material deprivation. This is an important contribution to the injury prevention literature, because social measures of SES are rarely used. In fact, this may explain why some studies find no association between SES and injury. For example, studies examining the relationship between SES and suicide have had mixed results, but most of them only included material measures of SES (Cubbin & Smith, 2002). Especially in the case of intentional injuries such as suicide, it seems plausible that social deprivation may play a larger role. However, more research is needed to empirically test this hypothesis.

Because trauma system development in Canada is in its infancy, the results of paper 2 could be used to guide as well as track future system development. By
comparing potential spatial access to trauma centres across Canada’s provinces, which have each implemented trauma care differently, this research may also inform decision-makers about what types of trauma systems or trauma system components are associated with better potential spatial access. For example, provinces such as Manitoba, which had several geographically disparate pockets of poor potential spatial access, may benefit from the implementation of pre-hospital air transportation programs. By identifying spatial clusters of severely injured patients with poor potential spatial access to trauma centres, this work also identified gaps in service provision. Therefore, this work could be used to identify locations where lower level centres should be promoted to designated trauma centres or incorporated into the existing trauma system.

Both papers presented in this thesis strengthen the argument for the use of GIS in public health and health care research. For example, the first paper demonstrated how GIS can uncover aspects of relationships (e.g., spatial non-stationarity) that cannot be observed or tested for when using more traditional statistical techniques, such as ordinary least squares regression. This paper also showed how GIS can be used to map how a relationship varies over space, which can be helpful for illuminating the underlying causal mechanisms of a disease or illness. Similarly, the second paper demonstrated the ability of GIS to effectively measure and visualize spatial relationships between health care services (e.g., trauma centres) and their target population (e.g., severely injured patients).

The spatial analytical methods used in this thesis are also transferable to future public health and health care accessibility studies. For example, the drive time calculations used to measure spatial accessibility in paper 2 could be applied to evaluate the spatial distribution of health care services that provide care to patients with other time sensitive illnesses, such as ischemic stroke. Geographically weighted regression and the other exploratory spatial data analysis methods used in paper 1, on the other hand, could be used to further explore the relationship between the health of populations and the unique physical and social environments in which they live. These spatial analytical methods could also be used to answer the same research questions, but in different settings or at different scales.
4.2. Future Work

In addition to having important implications for injury-related policies, programs and services, the work presented in this thesis also has the potential to guide future research on injuries. For example, a key finding of paper 1 was that social deprivation played at least an equally important role as material deprivation in determining the risk of severe injury in Greater Vancouver neighbourhoods. Future work investigating the complex relationship between SES and injuries should therefore take into account social as well as material measures of deprivation. This suggestion is in line with other calls for the use of more comprehensive measures of SES when studying its influence on injuries (Cubbin & Smith, 2002).

Another important finding of the study presented in section 2 was that the rates of severe injury were highest in the neighbourhoods with the lowest SES. However, more research is needed to determine exactly what about these neighbourhood environments increases the risk of severe injury. On the other hand, perhaps the difference in the rates of severe injury between neighbourhoods is due to protective elements present in high SES neighbourhoods that mitigate the risk of injury. Nonetheless, more studies that test individual causal pathways are required to elucidate exactly how the SES of a neighbourhood influences the risk of severe injury. These studies will need to be multilevel so that they can control for the influence of individual SES on the risk of injury. By identifying specific causal mechanisms, more effective interventions could be implemented to reduce the socio-economic inequalities of severe injury in Greater Vancouver.

In our second study, we assumed that emergency responders would by-pass any non-trauma centre hospitals and take the severely injured patients directly to the closest trauma centre. However, there is no empirical evidence to support or refute this assumption. Therefore, more research is necessary to discover how these decisions are being made in the field because they have the potential to dramatically affect the mortality rates of severely injured patients. Our second paper also assumed that patients were transported by ground ambulances, whereas in many provinces they may be transported either by helicopter or fixed wing airplanes. For example, Alberta has an extensive helicopter emergency medical system used to transport critically ill patients to
hospital (Hameed, et al., 2010). Thus, research that incorporates the possibility of air transportation of patients is required to get more accurate estimates of spatial accessibility to trauma centre care in these provinces.

Paper 2 also found that severe injuries resulting in death had poorer potential spatial access to trauma centre care than severe injuries resulting in a hospitalization. The reasons behind this association, however, were unclear because potential confounding factors, such as injury severity and patient age, were not taken into account. More research is therefore needed to infer whether or not spatial access to trauma centre care influences the mortality rates of severely injured patients in Canada. For instance, more research is needed to discern whether geographic inequalities in spatial access to trauma centre care are contributing to the 4-fold higher injury-related mortality rate observed among rural Canadians (Canadian Institute for Health Information, 2006).
References


Canada Health Act, c. C-6 (1985).


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Statistics Canada. Table 051-0046 - Estimates of population by census metropolitan area, sex and age group for July 1, based on the Standard Geographical Classification (SGC) 2006, annual (persons), CANSIM (database).


