The influence of winter weather on high-crash days in Southern Ontario

by

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A thesis

presented to the University of Waterloo

in fulfillment of the

thesis requirement for the degree of

Master of Arts

in

Geography

Waterloo, Ontario, Canada, 2013

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Traffic crashes tend to occur at relatively greater frequencies at particular locations, at particular time periods, and for particular subsets of drivers and vehicles. It is well recognized among the road safety community that crash-risk is highly elevated when inclement weather conditions occur in the winter. To present, most of the road safety studies focus on event-based analysis or seasonal analysis and give little attention to explore high-risk conditions at the daily temporal scale. The purpose of the study is to advance our understanding of high-risk crash conditions at the daily level and their occurrences in Southern Ontario, Canada. The study explores different definitions of high-crash days, and quantifies the influences of weather conditions, risk exposure, months and timing of precipitation on the likelihood of a high-crash day occurring using binary logistic regression model. Additionally, an approach for estimating the relative risk exposure using available traffic count data has also been developed. The results of the study show a small proportion of high-crash days are responsible for a considerable amount of traffic crashes during the winter. The risk of traffic crash is twice as high on high-crash days in comparison to non-high-crash days. The modeling approach well-fits the data and shows that winter weather conditions have significant influence on high-crash days with results being mostly consistent across the four study areas, Toronto, the Area Surrounding Toronto, London and the Area Surrounding London. Low temperature, heavy snowfalls, high wind speeds, high traffic volumes, early winter months, occurrence of precipitation in both morning and evening increase the odds of high-crash days to a large extent. The results of study could help to pre-schedule traffic operation and enforcement, to effectively distribute road safety resources and personnel, and to create situational awareness among road users and other stakeholders.

Acknowledgements

First of all, I convey my gratefulness to God for giving me the ability to complete the thesis.

I would like to express my sincere gratitude to my supervisor, Dr. Jean Andrey, for her continued support, knowledge and flexibility through my graduate studies. Her love of the subject matter, natural teaching ability, and dedication have touched many students' lives, and I am lucky to be one.

I would like to acknowledge MITACS Accelerate, Institute of Catastrophic Loss Reduction, State Farm Insurance, and University of Waterloo for financial supports. I would also like to thank Transport Canada, Environment Canada, Ontario Ministry of Transport, Transport Department of the City of London, Dr. Liping Fu, Dr. Taimur Usman, Brain Mills, and Derrick Hambly for data support.

Finally, I would like to give special thanks to my family and friends, especially my husband Rubayet and my daughters, Samreen and Mehreen.

Dedication

This thesis is lovingly dedicated to my mother.

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List of Abbreviations

ABS	Anti-lock braking system
ASL	Area Surrounding London
AST	Area Surrounding Toronto
CMA	Census Metropolitan Area
ESC	Electronic Stability Control
GTA	Greater Toronto Area
MTO	Ministry of Transport, Ontario
NCDB	National Collision Database
PDCS	Permanent Data Count Station
PDO	Property-Damage-Only
RWIS	Road Weather Information System

Chapter 1

Introduction

1.1 Background

Located in the northern temperate zone and affected by arctic and polar air masses, Canada experiences extended periods of below-freezing and/or snowy weather conditions. Winter weather conditions affect virtually all transportation modes and operations. For road transportation, winter weather has notable effects on traffic volumes and collision rates (Dalta & Sharma, 2010; Hanbali & Kuemmel, 1992; Maze et al., 2006). Indeed, inclement weather events are sometimes associated with an exceptionally high number of crashes, with these weather events becoming the headlines of electronic media or newspapers, e.g., "Winter blast paralyses Hwy 402 traffic" and "Police report dozens of crashes due to winter blast" were the lead stories of the *Chatham Daily News* on December 15, 2010 and *The City News Channel* on January 13, 2012, respectively. Both the magnitude and timing of such events influence the crash frequency on a given winter day. For instance, a day is more likely to have more crashes if a winter storm occurs on a weekday, when there is more traffic movement. The focus of this study is those winter days that have an anomalously high number of traffic crashes. The study mainly explores the effects of winter weather and time variables on the occurrence of a high-crash day.

Driving is often more challenging during the winter than in the summer. Inclement weather conditions, including snowfalls, wind, fog, and freezing rain, all of which occur in Southern Ontario during the winter, affects driver behaviour, road conditions, and vehicle handling. Winter weather creates risky driving conditions by impairing visibility and limiting the sight distance of drivers. Moreover, snow accumulation on the roadways can hide the roadway markings and create physical obstructions to driving, if de-icing or snow-ploughing programs are not able to mitigate the effects of a storm. The reduced friction between tires and road surfaces due to wet, icy and snowy road surfaces as well as high winds, which make vehicle handling more challenging, are well recognized risk factors. One study reveals that under the same exposure (vehicle miles travelled), a driver's crash-risk doubles during the winter relative to the summer (Nilsson & Obrenovic, 1998). The literature widely implicates winter weather conditions in these higher crash events during this time of the year.

Numerous studies have tried to measure the frequency and severity of traffic crashes during various precipitation events (Andrey et al., 2003; Andrey & Knapper, 2003; Delta & Sharma, 2008; Eisenberg, 2004; Eisenberg & Warner, 2005; Strong et al., 2010). All of them agree that any form of precipitation elevates crash risk. Moreover, if the intensity of precipitation increases, the crash risk also increases (Brijs et al., 2008). Although they debate how much the crash risk increase during these precipitation events, they agree that snowfall has more impact on traffic crash risk than does rainfall (Qiu & Nixon, 2008; Andrey, 2010). Some of the studies also identify that timing of the precipitation events could have differential effects on crash rate and crash severity (Eisenberg, 2004, Eisenberg & Warner, 2005; Keay & Simmonds, 2006). For example, precipitations after dry spells and the first snowfall of the season increase crash rates.

1.2 Problem Statement

Traffic crashes are statistically random events that occur over time and space. Indeed, many geographers recognise traffic collisions as "time-space events that are embedded in human activity patterns" (Andrey, 2000:379). When it comes to spatial locations, some problematic sites such as intersections (Aust et al., 2012; Chen et al., 2012; Abdel-Aty & Killer, 2005; Britman et al., 2007), roundabouts (Persuad et al., 2002; Elvik, 2003), and particular road networks (Lovegrove & Sayed, 2006; Dumbaugh & Li, 2010) or road segments (Cheng & Wasington, 2008; Chung et al., 2011, Elvik, 2008), are identified as hot spots or black spots, because they are characterized by disproportionately higher crash risk than the average.

Similarly, certain times have elevated crash risk for certain groups of drivers (Doherty et al., 1998; Farmer & Williams, 2005; Martin, 2002; Anowar et al., 2013). Young drivers tend to be involved in more crashes during the weekends and at night time (Doherty et al., 1998). Again, holidays have more fatal crashes than non-holidays (Anowar et al., 2013). Targeting and taking appropriate interventions for those problematic times or sites can reduce the number of traffic crashes and casualties.

In the field of road safety research, one established approach is to focus on problem areas, whether these are sites, situations, or human factors. One stream of safety research concentrates on high-crash sites, commonly known as hot spots. Many studies have prioritised these spots and suggested appropriate roadway measures to reduce crashes in these locations (Cheng & Wasington, 2008; Chung et al., 2011, Elvik, 2008). Some literature also investigates the effectiveness of safety interventions at these sites (Candappa et al., 2007; Persaud et al., 2002). Another stream of safety research investigates accident-prone people like young drivers (Doherty et al., 1998; Dissanayake & Lu, 2002; William, 2003), old drivers (Hakamies-Blomqvist, 1993, Mayhew et al., 2006; McKnight & McKnight, 2003; Rakotonirainy et al., 2012), pedestrians (Kong & Yang, 2010; Morency & Cloutier, 2006), or impaired drivers (Hingson et al., 2002; Evan, 2004; Vanlaar, et al., 2012). Some studies focus on repeat offenders who commit multiple infractions. Many researchers have tried to explore safety measures to reduce traffic crashes among the various driving sub-populations or to restrict their road use through special safety measures, for example graduated licensing (Shope, 2007; Simpson, 2003).

Another stream of safety research is focused on high-crash situations. Much of this type of literature examines the effects of inclement weather events on traffic crashes and suggests appropriate safety interventions, including vehicular, roadways and driver programs, for these periods (Andrey, 2010; Carson & Mannering, 2001; Delta & Sharma, 2008; Eisenberg, 2004; Eisenberg & Warner, 2005; Qiu, & Nixon, 2008). However, little research has been done in the academic world to identify appropriate safety interventions for the high-risk time periods. In this less recognized area of road safety research, so far attention has been paid only to event-based or seasonal road safety analysis of high-risk time periods. None of the studies has focused on those days that have an unusually high crash frequency. This raises questions as to whether weather conditions, an exposure variable, months and timing of precipitation events can explain the likelihood of the high-crash day occurrence. The road safety benefits of targeting the high-crash days are also unknown.

In contrast to the academic field, some work is being done in the professional road safety field to identify high-crash days and to take appropriate safety measures for problematic road sites and problematic drivers groups on such days. In particular, the City of Edmonton is targeting high-crash days to improve the safety of their road system (Chen et al., 2013). However, this type of initiative is very limited and is being done at the local level as a piecemeal solution to solve the local problem. The results of these initiatives are not publicly accessible yet.

1.3 Objectives of the study

The purpose of the study is to advance our understanding of high-risk crash conditions at the daily level and their occurrences in Southern Ontario, Canada. The temporal unit of analysis is the daily level. The study will try to explain whether different situational risk factors can determine the likelihood of a high-crash occurrence. The study has the following four specific objectives:

1. To examine the safety implications of different definitions of a high-crash day.
2. To develop a surrogate traffic exposure variable to replace traffic volume given the absence of continuous, system-wide traffic count data.
3. To quantify the effects of weather conditions, traffic exposure, and time variables on the likelihood of high-crash day occurrence.
4. To reflect on the value of logistic regression for understanding the occurrence of high-crash days.

1.4 Research questions

1. What are appropriate operational definitions of high-crash days? How frequently do these days occur?
2. Why should we target high-crash days? What percentage of crashes and casualties occurs on these days? Are there any differences in the collision patterns between the main urban areas and their surrounding areas?
3. Is it possible to develop a winter traffic exposure adjustment variable that suitably acts as a surrogate for traffic volume?

4. How do weather, traffic exposure and temporal risk factors influence the occurrence of high-crash days? Do the effects vary between the main urban areas and their surrounding areas?
5. Can a statistical model, using situational risk factors as explanatory variables, detect high-crash days? Do such models give similar results if there is a variation in the definition of high-crash days?

1.5 Scope of the study

Winter road safety is an important issue in all northern countries. It connects with different sub-fields of research, such as winter road maintenance, driver behaviour, and applied meteorology. This study focuses specifically on the explanation of high crash counts at the daily level, based on weather conditions, months and timing of precipitation. The results of the study are applicable to the half of the year (November to April) when winter weather, especially snowfalls, are observed in Southern Ontario. The study findings are mainly relevant to winter conditions in four study areas in the Southern Ontario: Toronto, Area Surrounding Toronto (AST), London, and Area Surrounding London (ASL). Since the crash-risk may vary spatially and seasonally, the findings of this study may be slightly different than those of the other studies conducted elsewhere and for summer season or for all the year round crash-analysis.

1.6 Organization of the study

The study is divided into six chapters. Chapter 1 introduces the study topic, the study objectives and the research questions. This chapter is followed by Chapter 2, which provides a review of research on three main themes: extreme conditions, road safety theories, and traffic risk factors. Then, Chapter 3 shows the current situation of road safety in Canada and in the study areas. It also describes the study areas and their weather conditions. This chapter is followed by Chapter 4, which outlines data sources used for the study and the analytical methodology of the study. Next, Chapter 5 presents the winter traffic exposure adjustment factors and the empirical results of the study. Finally, Chapter 6 concludes the study by providing a discussion of the study results, recommendations and conclusions.

Chapter 2

Literature Review

This chapter, a review of important literature related to this study, consists of three sections. The first section examines existing empirical knowledge to explore why targeting extreme conditions is beneficial for road safety improvements. The second section not only describes the evolution of accident causation theories over time but also positions the study in light of these theories. In addition, it also reviews some theoretical perspectives related to drivers' behavioural adjustments to avoid accidents. Then, the third section briefly reviews the current knowledge about the contributing factors to traffic crashes.

2.1 Extreme or outlier conditions

This section explains the benefits of targeting extreme conditions and describes common practices within the road safety community to target these conditions. After that, it describes risk exposure to extreme conditions in light of weather conditions, which are major variables used in the modeling exercise.

2.1.1 Targeting extreme conditions

One effective way to advance road safety is to focus on the extremes or the outliers, which are uncommon but have significant consequences. The current study also follows this approach by modeling days that have a proportionally higher number of crashes in comparison to normal days. In the field safety research, this approach provides several benefits. First, by targeting extreme cases or outlier events, it may be possible to achieve safety improvements that are larger than what would occur with less focused approaches. Second, if we target extreme conditions and outlier events, safety improvements may be achieved in a more cost-effective way, ensuring the optimal utilization of limited resources available in the road safety field.

At present, numerous road safety studies follow this common approach of targeting extremes conditions or outlier cases. They can mainly be divided into four categories, based on road users, spatial locations, temporal scales, and weather conditions. In each case, it is possible to focus on those factors or conditions associated with high-crash rates or on those subsets of people, locations or times associated with multiple collisions.

The human factors approach to road safety focuses on driver errors and risk-taking propensity. Multiple studies suggest that driver age and driver condition are strongly correlated with collision involvement. Some drivers are more prone to accidents, such as older drivers (Hakamies-Blomqvist, 1993), young drivers (Dissanayake & Lu, 2002; Doherty et al., 1998; McKnight & McKnight, 2003), and impaired drivers (Evan, 2004; Hingson et al., 2002). The safety literature reveals that the relationship between driver age and crash risk is like U-shaped given the similar amount of exposure (Evan, 2000; Mayhew et al., 2003). Both young and older drivers have higher crash risks than the middle aged drivers. When considering fatal crashes, the older drivers are the most vulnerable (William, 2003). They are more prone to intersection crashes than the younger drivers because of their failure to yield the right-of-way, disobeying traffic controls or involvement in other traffic offenses, resulting from their reduced psychological and physical driving abilities, such as “inattention, perceptual lapses, misjudgement and illness” (Mayhew et al., 2003:121). Recently road safety researchers have given considerable attention to the older drivers’ problem because of their rising proportion in western countries.

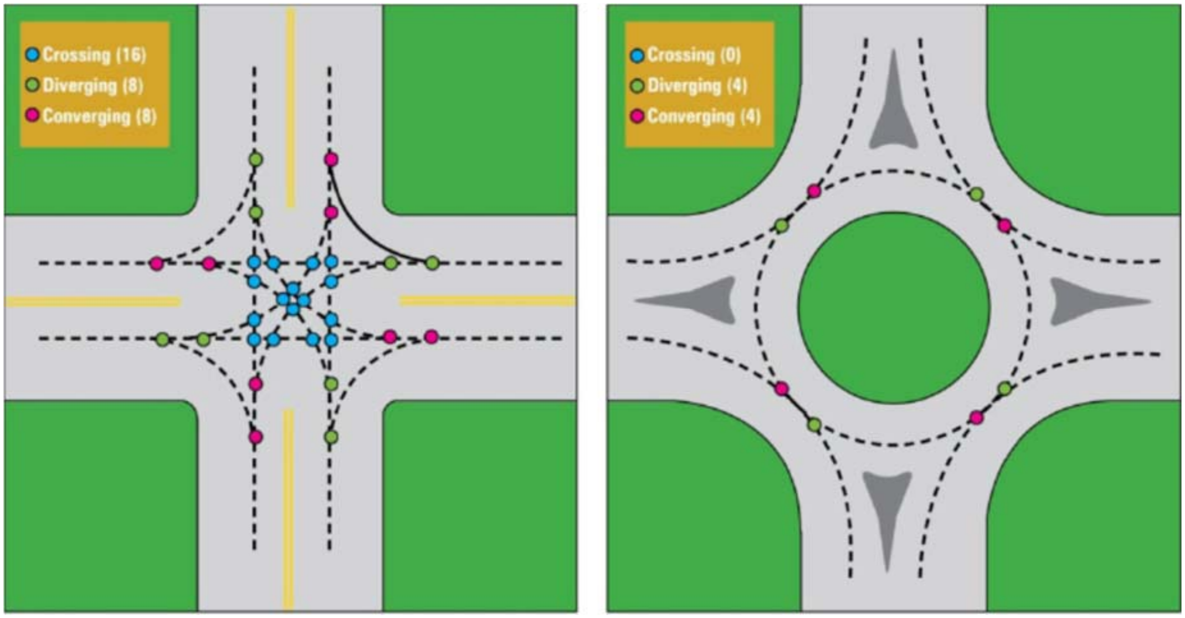
In a similar way, young drivers, 16-24 years old, are also a problematic group since their fatal crash rate both per licensed drivers and per distance driven are the highest among all age groups of drivers. They are over-represented in at-fault crashes relative to other age groups on weekends, at night times and with passengers (Doherty et al., 1998). Teenage drivers commit non-fatal traffic crashes 10 times more than the adult drivers due to their inexperience, aggressive driving attitude, overestimation of their driving ability and risk-taking driving behaviours, resulting from immaturity (McKnight & Mcknight, 2003). Young drivers are more involved in speeding and alcohol-related crashes than the older drivers. The involvement of young drivers in motor vehicle crashes in Canada have reduced over the past several years, in association with the adoption of graduated driver licensing (Programs beginning in the 1990's). Graduated driver licensing has been found to reduce traffic crashes from 4% to over 60% depending on the specific age group and the measure used (Simpson, 2003). In case of Canada, this reduction rate has been 15-30% (Transport Canada, 2011a).

An attempt has also been made in the literature to identify high-risk drivers who are mainly young drivers, impaired drivers, drivers refusing to take a breath test or repeat offenders of traffic infractions. In Canada, they comprise about 3-4% of drivers and are involved in 12% of deaths and 8% of injuries that occur from road crashes (CCMATA, 2009). Impaired driving (alcohol, other drugs, and fatigue) increases both crash risk and crash severity. The legal limit of blood alcohol is 0.08 g/dl for a criminal offense, which poses twice the crash risk than 0.05 g/dl and 75% higher risk of fatality than zero alcohol level (Evan, 2004; Peden et al., 2004). Impaired drivers are responsible for 20% of serious injuries occurring due to single-vehicle night-time collisions (Transport Canada, 2011a). If caught, impaired drivers are immediately suspended from the roadways. A study showed that about 57% of suspended driver continued to drive in Moncton and they prefer night time to day time for driving (Malenfant et al., 2002).

The second approach of targeting extreme crash conditions focuses on problematic sites where there is a tendency of traffic crashes to cluster. These sites are commonly known as black spots. The risk of fatal crashes increases when driving on undivided rural roads, at curve or crossing any intersections (Barua et al., 2010). In Canada, intersection-related crashes account for 30% of fatalities and 40% of serious injuries (Transport Canada, 2008). About 40% of these crash occur at undivided rural highways with a speed limit of 80 km/h or higher (Transport Canada, 2008). The most common crashes types are left-turn crashes and red-light running crashes at signalized intersections and right-angle crashes at un-signalized intersection (Aust et al., 2003; Chen et al., 2012). Among the risk factors, driver age and gender, speed zone, traffic control type, time of day, crash type and seatbelt usage are significantly related to the severity of intersection crashes (Chen et al., 2012). Many studies suggest replacing an intersection with a roundabout to reduce crash frequency and crash severity (Elvik, 2003; Persuad et al., 2002). As a roundabout has fewer conflicting points than a four-way intersections (Fig. 2-1), a roundabout reduces injury crashes by 30-50% and fatal crashes by 50-70% (Elvik, 2003). Moreover, three-way intersections have lower crash rates than the four-way intersections (Lovegrove & Sayed, 2006).

In the same way, the researchers investigate the influences of high-risk time periods on traffic crashes, such as weekends (Farmer & Williams, 2005) and holidays (Anowar et al., 2013). Finally, high-risk situations related to different weather conditions interest many road safety researchers (Andrey, 2010; Dalta & Sharma, 2008; Eisenberg, 2004; Eisenberg & Warner, 2005). The finding from the studies that investigate high-risk time periods and high-risk weather conditions are discussed in detailed in the third section of this chapter.

Fig. 2-1: Illustration of conflict points for a signalized intersection and roundabout



Source: Gross et al., 2013, p. 235

2.1.2 Risk of exposure to extreme conditions

Collision risk depends, in part, on traffic volumes, which provide an indication of risk exposure. Traffic volume refers to the number of vehicles using a road per unit of time. Traffic engineers frequently use this factor for planning, designing and managing highways. Based on the presence of various factors, traffic movements on a particular road may vary. For example, traffic volume varies by location, road type, level of service, behaviour of road users, day of week, and weather conditions (Dalta & Sharma, 2010; Hanabali & Kuemmel, 1993).

Road safety researchers unanimously agree that weather conditions greatly influence traffic conditions of any area. However, despite their awareness of a relationship between traffic volume and weather conditions, only a few studies have investigated this relationship empirically, mainly due to lack of adequate and reliable traffic count data. Weather impacts on traffic volume can vary based on numerous factors. Some safety literature reveals that the actual influence of adverse weather conditions on traffic movement is to some extent counterbalanced by drivers' behavioural adjustments. Some drivers either shift their modes or cancel their trips during extreme weather conditions (Brodsky & Hakkert, 1988; Kilpeläinen & Summala, 2007). Weather impacts on traffic volume has been found to vary according to the trip types on a particular road, time of day, and day of week. For example, traffic volume reduction due to inclement weather during peak hours or weekdays is smaller than during off-peak hours or on weekends (Hanabali & Kuemmel, 1993, Knapp, et al., 2000). This finding suggests that weather conditions affect discretionary trips more easily than commuter trips.

Past studies also investigated how different parameters of winter weather reduce traffic movement. The reported reduction in traffic volume varies from 1% to 80%, depending on parameters considered in the study and study location. Dalta and Sharma (2010) investigated the effects of Canadian winter weather on traffic movement on the provincial highways in Alberta, Canada. Considering snowfall and temperature in their study, they claimed that each centimeter of snowfall is responsible for a 1% to 2% reduction in traffic volume when temperature is above 0^0C. Hanbali and Kuemmel (1992) identified that winter storms are responsible for a traffic volume reduction of 7% to 56% on the major rural highways in the US, based on the snowfall intensity. Similarly, Knapp, et al. (2000) estimated an average of 16% to 47% reductions in traffic volume on the interstate highways in Iowa, USA during severe winter storms (at least 4 hour duration and snowfall 0.51cm/hr). Maze et al. (2006) included two additional winter weather parameters – visibility and wind speed – in their study. They reported that on a snowy day, Iowa rural highways have 20% less traffic if visibility is good and wind speed is low. However, traffic volume reduces up to 80% if a winter storm is coupled with poor visibility (1/4 mile ≈ 0.4 km) and high wind speed (more than 40 mph or 64 km/h). An additional 0.5% to 3% reduction in traffic volume occurs during severe cold temperature. Road safety literature also reveals that rainfalls have more minor effects on traffic volume reduction than do snowfalls during the winter. During this season, rainfalls reduce traffic volume by only 1.35% on urban roads in Melbourne, Australia, where the winter is less severe than Canada (Keay and Simmonds, 2005). Table 2-1 summarizes the findings of the above studies:

Table 2-1: Effects of winter weather condition on traffic volume

Study	Country	Winter Weather parameter	Reduction in traffic volume
Dalta & Sharma (2010)	Canada	Snowfall and temperature	1% to 2% when temperature > 0^0C. An additional 0.5% to 3% during severe cold temperature
Hanbali & Kuemmel (1992)	USA	Snowfalls	7%-56%
Keay & Simmonds study (2005)	Australia	Rainfalls and other weather variables	1.35%
Knapp et al. (2000)	USA	Severe snowfalls (0.51cm/hr)	16- 47%
Maze et al. (2006)	USA	Snowfalls, visibility and wind speed	80%

All the above studies consider either urban or rural roads. None of the study findings are applicable to both types of roadways. Similarly, they did not differentiated the roads between main urban areas and their surrounding regions. In addition, since traffic volume is study-area specific, the climate of the study area could also influence the results.

2.2 Road safety theories

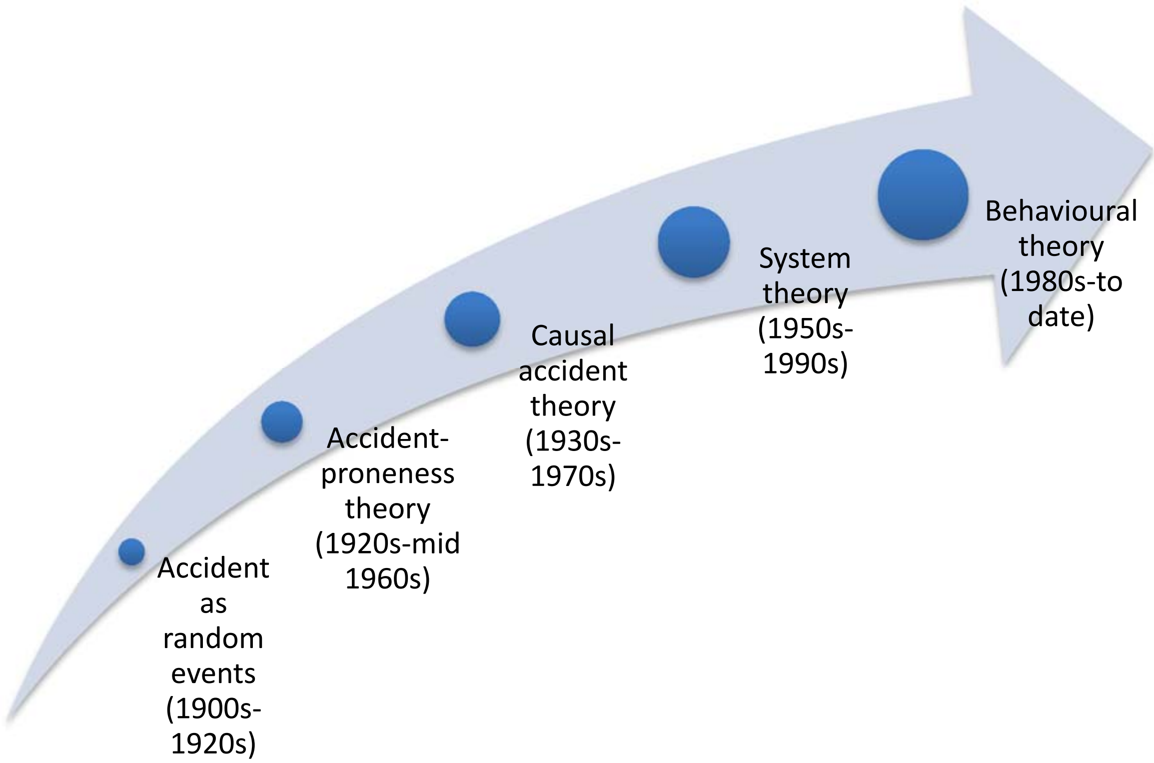
2.2.1 Accident-causation theoruwies

Since the advent of automobiles more than a century ago, several accident-causation theories have been articulated. Among them, five theories have received the most attention within the safety research community (Fig.2-2). Elvik and Vaa (2004) provided a comprehensive review of these five theories in their renowned work *The Handbook of Road Safety Measures*.

The first, accident-causation theory, which provides the basis for those which evolved later, considers traffic crashes as random events that occur while drivers are traveling from one place to another. The second theory explains that some people tend to be more involved in traffic collisions than others because of their personal characteristics. The third theory recognizes traffic crashes as multi-causal events occurring as a result of the combined effects of various risk factors that are commonly divided into three main categories: human, vehicular, and environmental. Even though it is very difficult to single out one factor as the sole reason for traffic crashes, human errors are often accused as the dominant factor. The fourth theory tries to explain the reasons for drivers' errors. It identifies that inadequate system designs or situational risk factors lead to these errors. Finally, since 1980, considerable safety research has focused on different behavioural theories, which reveal that human risk assessment and human risk acceptance play vital roles in determining the frequency of traffic crashes.

Although several theories of accident-causation have evolved over times, these still do not provide a general theory of accident causation. Some of these theories are narrowly focused and testable, whereas others provide only a conceptual framework. Furthermore, the evolution of accident-causation theory does not mean that a newer paradigm eliminates the prior accident-causation theories. Rather, they sometimes complement each other, providing partial insight about accident causation.

Fig. 2-2: Evolution of accident-causation theories



Source: Adapted from Elvik, & Vaa (2004)

At present, all these accident-causation theories are used to varying degrees in the field of road safety. Since road safety is a multi-disciplinary field, the popularity of different accident causation theories varies among different professionals. For example, systems theory is more popular among civil engineers, whereas behavioural theories are more commonly used by psychologists. The current study focuses on extreme conditions, which are of interest to meteorologists and geographers and which map onto accident proneness theory. That said, this study also deals with different situational risk factors that are relevant to system theories, and some results of the study are explained in light of the driver behavioural theories.

2.2.2 Driver behaviour

Whether a driver will be involved in a traffic crash is affected by the driver's risk perceptions and behavioural adaptations. However, there is no commonly accepted single theory for explaining driver behaviour, although many behavioural theories have been partially successful in illuminating drivers' complex behaviour. Most of these theories are illustrated by using three different types of risk: objective risk, subjective risk, and acceptable risk (Wang et al., 2002; Fuller, 2005). Objective risk, also known as statistical risk, refers to the statistical probability of a traffic crash, whereas subjective risk refers to a driver's attitude towards traffic risk and his own risk perception. Lastly, acceptable risk is the quantity of risk that a driver is willing to tolerate while driving from one place to another (Wang et al., 2002, Fuller, 2005). An example may help to clarify these risks in the context of winter road safety. The statistical probability of collision posed by a snow storm event is an objective risk, a driver's perception of the associated crash-risk is a subjective risk, and a driver's willingness to driving in a certain way during this snow storm is an accepted risk.

Depending on drivers' risk perception, drivers take decisions at three hierarchical levels (strategic, tactical and operational) to adjust to crash-risks (Fuller, 2005). First, drivers make decisions at the strategic level; these are typically off- road decisions. Examples of decisions at this level include route change, trip-timing change, travel mode alteration, and trip cancelation or rerouting. When on the road in high-risk conditions, drivers take tactical decisions related to manoeuvering, or operational decisions, like headway increments or speed adjustments. Adverse weather conditions are reported to affect driver attentiveness and control behaviour (Andrey and Olley, 1990).

Over the last four decades, many behavioural theories have tried to explain driver behaviour. One of the earlier theories in this category, Näätänen and Summala's Zero Risk theory (developed in the 1970s) states that in order to avoid traffic crashes, drivers adapt to risk situations according to their subjective perception of zero-risk (Summala, 1996). Later on, Wilde's theory of risk homeostasis (1982, 2002) became popular among road safety researchers. The main premise of this theory is that road safety improvement is possible only by reducing driver's target level of risks. This theory has received considerable criticism because this theory cannot be empirically proven wrong, and is therefore criticized for its vagueness (Evan, 1985; Elvik & Vaa, 2004; O'Neill & Williams 1998). However, this theory and other elaborations of risk compensation raise questions about the effectiveness of engineering measures, widely accepted among the road safety community as a mean of reducing traffic crashes.

2.3 Risk factors

According to accident causation theory, the risk factors that influence the probability of crash occurrence and affect the severity of traffic crashes can be classified into three main categories: drivers, vehicles and environment (Elvik & Vaa, 2004). However, these multiple risk factors work together in creating unsafe outcomes. Fig.2-3 summarizes some risk factors according to these main categories. The focus of this study is on environmental risk factors which include weather and temporal risk factors. The rest of this section will discuss these two themes in detail.

Among the environmental risk factors, road engineering and design have received the attention of many of the researchers who followed a system theory approach in investigating the contributing factors of traffic crashes. However, current road safety researchers mainly focus on driver behaviour theories which focus on drivers' awareness, perceptions, and behavioural reactions to different driving circumstances. They also examine the influence of environmental risk factors on crash frequency and crash severity.

Fig. 2-3: Risk factor classification

Driver

- Driver Characteristics (Age, sex, skills)
- Driver behaviour (Unsafe manoeuvres, disobeying traffic control or road ruls, distracted or inattentive)
- Driver conditions (Fatigue, impairement, sudden illness)

Vehicle

- Vehicle characteristics (type, size, colour)
- Vehicle engineering and design (seatbelts, airbags, blindspots, electronic stability control)

Environment

- Road engineering & design (Traffic controls, intersection design, road surface materials, median)
- Weather factors (fog, blowing snow, glare, rain, snow, ice, wind, temperature, light condition)
- Temporal factors (season, time of day, day of week)
- Situational factors (Road Location, tarffic volume, traffic rules and regulations, animal or obstruction in roadways, Road surface conditions)

Source: Elvik & Vaa, 2004; Evans, 2004; Peden et al., 2004

2.3.1 Weather Risk factors

Weather-related traffic crashes, which occur in the presence of inclement weather and/or slick pavement, comprise about 30% and 24%% of the total traffic crashes in the UK and the USA, respectively (Andrew & Bared, 1998; FHWA, 2010). In Canada, such crashes account for approximately 20% of the total crashes (Andrey 2013). One Canadian study estimates that the annual cost of weather-related traffic crashes in Canada is about $1 billion Canadian dollars (Andrey et al., 2001). In contrast to Canada, the financial burden of such crashes in the US is approximately $42 billion US dollars (USDOC, 2002), although the methods used to arrive at the two estimates appear to be quite different. Andrey (2013) provides other useful contextual information, noting that, while only 5% of collisions in Canada have weather noted as a "contributing factor" on the collision reporting form, 6% to 7% would like not have occurred had it not been for inclement weather conditions, and a full 20% occur during inclement weather conditions like rain, freezing rain, snow, fog, and strong wind.

Weather-related traffic crashes also depend on exposure to inclement weather (rain, snow, fog, and strong wind). Maze et al. (2006) found the exposure of US drivers to inclement weather conditions to be approximately 25% of a year. In Canada, this exposure varies between 9% and 38% of the time, with an average of 23% of the time, depending on location and year (Andrey et al., 2005). Here precipitation events like rainfalls, snowfalls, and mixed precipitation events occur 10-20% of time (Andrey et al., 2005).

Table 2-2 summarizes the effects of different inclement weather events on roads, traffic flows and drivers/vehicles. Among all these weather conditions, rain and snow have received the most attention from road safety researchers. Numerous studies that focused on these two types of events confirming that crash risk elevates by 50% to 100% during rain and snow (Andrey et al., 2003; Andrey, 2010; Qui & Nixon, 2008) and crash characteristics vary by weather conditions.

The estimated effects of rainfall on traffic crashes vary from study to study. A meta-analysis of 34 studies showed that rainfalls increase crash rate by 75% and injury rate by 49% (Qui & Nixon, 2008). Andrey (2010) also provided a similar estimate in Canada, demonstrating that crash risk elevate by 72% during rainfalls. The crash risk tends to be the highest at night, indicating an interactive effect of darkness/driver fatigue (Andrey, 2010; Keay & Simmonds, 2006). The most common rain-induced collisions are rear-end collisions. The injury crash risk is 3 times higher in wet roads in compare to dry roads (Brodsky & Hakkert, 1988). However, a recent trend analysis of relative crash-risk in Canada estimates that casualty risk during rainfalls has decreased significant by 60% over the last two decades (1984-2002), indicating an enhancement in vehicle and road design, and driver skills and training (Andrey, 2010).

Table 2-2: Weather impacts on road, traffic flow and driver/vehicle

Weather variables	Road Impacts	Traffic Flow Impacts	Driver/Vehicle impacts
Rain	• Visibility obstruction • Road friction • Road obstruction	• Road capacity • Traffic speed • Speed variance • Time delay • Crash risk	• Vehicle performance (e.g. traction) • Driver capabilities • Driver behaviour
Snow	• Visibility obstruction • Road friction • Road obstruction	• Traffic speed • Traffic delay • Crash risk	• Vehicle performance (e.g., traction) • Driver capabilities • Driver behaviour
Wind speed	• Visibility obstruction (due to blowing dust & debris) • Lane obstruction	• Traffic speed • Time delay • Crash risk	• Vehicle performance (e.g., traction) • Driver capabilities • Driver behaviour
Visibility obstruction (Fog/smoke/smog)	• Visibility obstruction	• Traffic speed • Speed variance • Crash risk	• Vehicle performance (e.g., traction) • Driver capabilities • Driver behaviour
Temperature	• Road surface softening & rutting • Road surface bucking	• Traffic speed • Speed variance • Time delay • Crash risk	• Vehicle performance (e.g., traction) • Driver capabilities • Driver behaviour

Source: Rowland et al., 2007, p. 4

Empirical evidence suggests that as the intensity of rainfall increases, the crash rate increases (Brijs et al., 2008; Andrey 2010). Moreover, the duration of rain is also an issue in safety analysis (Brodsky & Hakkert, 1988; Brijis et al., 2008). Crash risk is the highest when the rain is falling on the ground and it return to normal level as soon as the rain ends (Andrey & Yagar, 1993). Although rainfalls increase all types of crashes, the increase is the highest for property-damage-only crashes (Andrey et al., 2003; Eisenberg, 2004). This finding indicates that drivers adjust their behaviour to reduce their crash-risk during rainfalls. The literature also reports that a dry spell increases crash risk in the following rainfall event (Brodsky & Hakkert, 1988; Eisenberg, 2004; Keay & Simmonds, 2006). In comparison to a two-day dry spell, a dry spell of more than 20 days has 2-3 times greater impacts on crash risk (Eisenberg, 2004). Most probably, the accumulated oil on the roads during dry spells intensifies the rain-related crash risk after a dry spell.

Among all forms of winter weather precipitation, freezing rain is sometimes purported to be the most hazardous event as it is associated with black ice on the road surface, which not only reduces friction but also is hard to notice. One Canadian study showed that crash risk is perceived as being highest for freezing rain (Andrey et al., 2003). However, a study on snow storms in Wisconsin contradicts this finding in regards to crash risk (Qin et al., 2006). According to this study, the effect of freezing rain on the winter crash rate (3.85 crashes/event) was to reduce it to below the crash rate during snowstorm (5 crashes/event). However, freezing rains cause more casualties per crash than the other precipitation events (Qin et al., 2006). The lower crash rate during the freezing rain suggests that the good and precautionary winter road maintenance effects or increasing public awareness or caution works in such inclement weather conditions.

It is widely recognized among road safety researchers that snowfall has a greater impact on crash risk than does rainfall (Andrey et al., 2003; Andrey, 2010; Qui & Nixon, 2008). Table 2-3 compiles the main findings from some key winter road safety studies. On average, the crash rate increase 100% during snowfall relative to normal winter conditions. The safety literature reports that crash risk is often highest during the first snowfalls of the winter seasons and especially for elderly drivers (Fridstrøm et al., 1995; Eisenberg & Warner, 2005; Andrey 1989). Also, crash risk increases more from low-intensity snowfalls to moderate-intensity snowfalls but is similar from moderate-intensity snowfalls to high-intensity snowfalls, probably indicating traffic volume reduction and driver adjustments during severe snowstorms/ blizzards (Andrey, 2010).

Road safety researchers often debate about the extent to which snowfalls affect crash rates, both overall and by crash severity. Studies show that snowfalls increase property-damage-only crashes the most with less effect on injury crashes and sometimes reductions in fatality crashes (Eisenberg, 2005; Evans, 2004). This finding would suggest reduced vehicle speeds resulting from driver adjustment to snowfalls. After adjusting crash risk with the traffic exposure variable (traffic volume), Eisenberg and Warner (2005) found that the risks of fatality, injury and property-damage-only crashes were increased by 18%, 74% and 150%, respectively, during snowfalls in comparison to normal conditions. In contrast to rainfall-induced casualty risk trend, snowfall-induced casualty risk has not changed significantly over the period of 1984-2002 in Canada (Andrey, 2010). The reason for this finding is unknown and requires further investigations.

Also, crash risk varies by locations and by vehicle types. Snow-related crash risk has been found to be higher on local roads than on highways (Qin et al., 2006). Tractor trailers have been found to be more involved in snow-related crashes than other types of vehicles (Braver et al., 1997). Head-on crashes also are overrepresented on snowy roads (Hagiwara et al., 2005).

Table 2-3: The main findings of some prominent winter road safety studies

Author	Study Location	Weather risk factor	Main findings
Andrey et al. (2003)	Six Canadian City 1995-1998	Precipitation amount and storm duration	Crash risk increases by 94-153% during snow falls.
Knapp et al. (2000)	Iowa (USA)	Million vehicle miles Strom duration Snowfall intensity Maximum wind speed	Crash rate increases by 1300% during severe snow storm events and 250% with 1 in/h of snow
Suggett (2003)	Regina, Saskatchewan (Canada)	Precipitation amount Strom duration	Crash risk increases by 111% during snowstorms.
Andrey (2010)	Canada 1984-2002	Rainfall Snowfall	Crash risk increases by 72% during rainfalls and 87% during snowfalls
Eisenberg & Warner (2005)	48 states in USA 1975-200	Precipitation Snowfall Snowfall intensity	Snow days had fewer crashes than dry days but more injury crashes and property damage crashes. First snow fall is the most dangerous than other snow days.
Fu et al. (2006)	London, Ontario (Canada)	Snowfall Road maintenance activities	Crash risk increases 8-13% for 1 cm of snowfall (water equivalent) per hour
Qui & Nixon (2008)	Meta-analysis of 34 studies 1967-2005	Rainfall Snowfall	Rain increases crash rate by 71% and injury rate by 49%. Snow increase crash rate by 84% and injury rate by 75%.

Limited studies focus on the safety effects of severe winter storms, but individual storms have been associated with increases that are orders of magnitude greater than normal (Kanpp et al., 2000; Suggett, 2003). Crash risk tends to be the highest at the beginning of snowstorms and it reduces as the snowstorms progresses, resulting from the reduced traffic volume and/or extensive road maintenance activities (Qin et al., 2006). The crash severity during these events is a debatable issues in safety research as systematic studies of driver adjustment to these events are very limited.

The crash risk of temperature is complex and debateable due to seasonal variation in the relationship. The early studies could not establish a discernible relationship between temperature and crash rate. Later, considering the seasonal variation pattern, Andreescu and Frost (1998) established a relationship between temperature and traffic crashes, stating that the relationship is positive during the summer and negative during the winter. They concluded that temperature is not the main crash risk factor but is confounded by precipitation amount and type. A recent study claims that "the relationship between the absolute temperature and the number of crashes is negative, highly significant and nonlinear. Indeed, relative to the base category (temperatures above 20), lower temperatures result in more crashes, with temperatures below zero being the most significant" (Brijs et al., 2008:15); however, this study did not control for precipitation and snowfall.

Hours of sunlight also can affect the probability of crashes (Brijs et al., 2008; Fridstrøm et al., 1995; Hermans et al. 2006). As the hours of sunlight increase, the crash risk decreases due to better visibility. An extra hour of sunlight can reduce traffic crashes by 4% (Fridstrøm et al., 1995). Safety literature has also revealed that darkness raises the risk of an injury crash by 30% in urban areas and by 50% in rural areas (Johansson et al., 2009).

Atmospheric visibility plays a role in accident causation. Although blowing snow, fog and smoke limit drivers' visibility, only few studies have investigated their influence on traffic crashes. A review of these studies provides evidence that fog in the winter morning is particularly hazardous time for driving (Abdel-Aty et al., 2011). Fog-induced crashes cause multi-vehicle traffic crashes and they are generally head-on or rear-end crashes. Moreover, fog-related crashes often occur at night and result in more severe injuries than the clear weather conditions (Abdel-Aty et al., 2011). Fog increases the crash risk by 12% on unlit roads (Wanvik, 2009). Across Canada, fog, mist or smog are observed 7% of the time; some of these occurrences reduce atmospheric visibility in ways that would affect drivers (Andrey et al., 2003). In comparison to experienced drivers, novice drivers are more prone to collisions on foggy conditions due to their longer hazard response times and greater variability in driving skills (Muellers & Trick, 2012)

High winds can overturn vehicles, make steering difficult, and blow obstacles such as snow, sand or debris onto the roadway. Studies reveal that wind speed is positively correlated with the traffic crash rates (Hermans et al., 2006; Knapp et al., 2000; Maze et al., 2006; Baker and Reynolds, 1992). Large vehicles such as buses and commercial trucks are at risk for the wind-induced collisions. In England only 4% of the total crashes occur from wind hazards but the presence of high wind (>20 knots ≈ 37.04 km/h) significantly increases collision risk (Edwards, 1994). High wind during a snowstorm can result in devastating effects on road safety conditions as found in some studies (Knapp et al., 2000; Maze et al., 2006; Baker and Reynolds, 1992). Snow storms with high wind (>32 km/h) and low visibility (≤1/4 mi ≈ ≤0.4 km) have been found to elevate crash risk by up to 25 times relative to normal conditions (Maze et al., 2006).

The majority of the studies that investigate the weather impacts on traffic crashes use a wide range of methodological approaches for crash-analysis. For example, empirical bayes methods (Dalta & Sharma, 2008), time series analysis (Brijs et al., 2008), matched-pair analysis (Andrey et al., 2013), the negative binomial model (Eisenberg & Warner, 2005; Qin et al., 2006; Usman et al., 2011), and poisson regression models (Knapp et al., 2000). These models are mainly single level and make estimates with aggregated data at the daily, monthly, seasonal or yearly scale (Usman et al., 2011). Among these modeling approaches, the statistical modeling approach is most widely used in the road safety studies. Currently, the negative binomial is more popular for accident frequency analysis and logistics regression model for accident severity analysis. The use of the logistic regression model in accident frequency analysis is mainly restricted by their need of a dichotomous dependent variable. Therefore, the value of logistic regression model in accident frequency analysis is not fully explored.

2.3.2 Temporal risk factors

Particular time periods also sometimes are associated with elevated risk levels. These include seasons, months, day of the week, time of the day and holidays. The summer is associated with greater exposure to crash risk (higher vehicle-km driven), but the winter is associated with higher crash rates (Andreescu & Frost, 1998; Nilsson & Obrenovic, 1998). The risk of fatal crashes increase more in the summer whereas the risk of PDO crashes increase more in the winter (Brown & Baass, 1997; Farmer & Williams, 2005; Ramage-Morin, 2008). Crash risk also varies throughout the winter season. The beginning of the winter has a 3.5 times greater crash risk than the end of the winter (cf. Pisano et al., 2008). Similarly, the first snowfall of the season has a greater crash risk than the later snowfalls (Eisenberg & Warner, 2005; Fridstrøm et al., 1995).

The fatal crash risk also varies by months and by time of the day. An investigation of 17-years of (1986-2002) fatal crashes in the USA showed that the summer and fall months (June to November) have the highest and January and February have the lowest number of fatalities from traffic collisions in the USA (Farmer & Williams, 2005). The average crash-fatality per day reaches a peak in August. Similar findings are found in a Canadian study (Ramage-Morin, 2008). However, when considering the exposure (billion vehicle miles traveled), October and December have the highest fatality rate per mile, whereas March has the lowest fatality rate per mile (Farmer & Williams, 2005). In terms of time of the day, the fatality-risk is the highest in afternoon and evening times (Farmer & Williams, 2005). Many studies identified that the risk of traffic crashes are higher at night-time than day-time (Dorhorty et al., 1998; Giuliano, 1989). A recent study refutes this finding stating that the number of crashes does not differ significantly between day-time and night-time in urban areas (Martin, 2002). However, the latter study does note that the severity of a crash increases at night time.

Day of the week has two opposing relationships with crash frequency and crash severity. Weekdays has more concentration of crashes than the weekends, but weekends crashes are more severe in nature (Andreescu & Frost, 1998; Brijs et al., 2008; Giuliano, 1989). The risk of a traffic crash is the highest on Friday and the lowest on Sunday. However, for certain group of drivers, such as young drivers and impaired drivers, the risk of a traffic crash is higher on weekends (Doherty et al., 1998; Transport Canada, 2011a).

Holidays has a detrimental effect on traffic crashes. A study showed that six out of the ten days with higher number of crash deaths occurred near the major American holidays: Independence Day, Christmas, New Year and Labor Day (Farmar & Williams, 2005). Casualty crashes also are over-represented during the holidays (Anowar et al., 2013). Despite the media coverage of traffic crashes during major holidays, studies investigating the risk factors of holiday crashes are comparatively limited. The review of these studies shows that increased discretionary travel, alcohol-impaired driving, and excessive speeding are associated with the higher number of fatality during the holidays (Anowar et al., 2013; Farmar & Willians, 2005).

Chapter 3

Study Context and Study Areas

This chapter introduces the study context and study areas. It is divided into two main sections. The first section presents an overview of the current road safety situations worldwide, and then for Canada and Ontario. The second section reports the population and spatial context of the study areas, followed by winter weather conditions and winter road safety conditions in these regions.

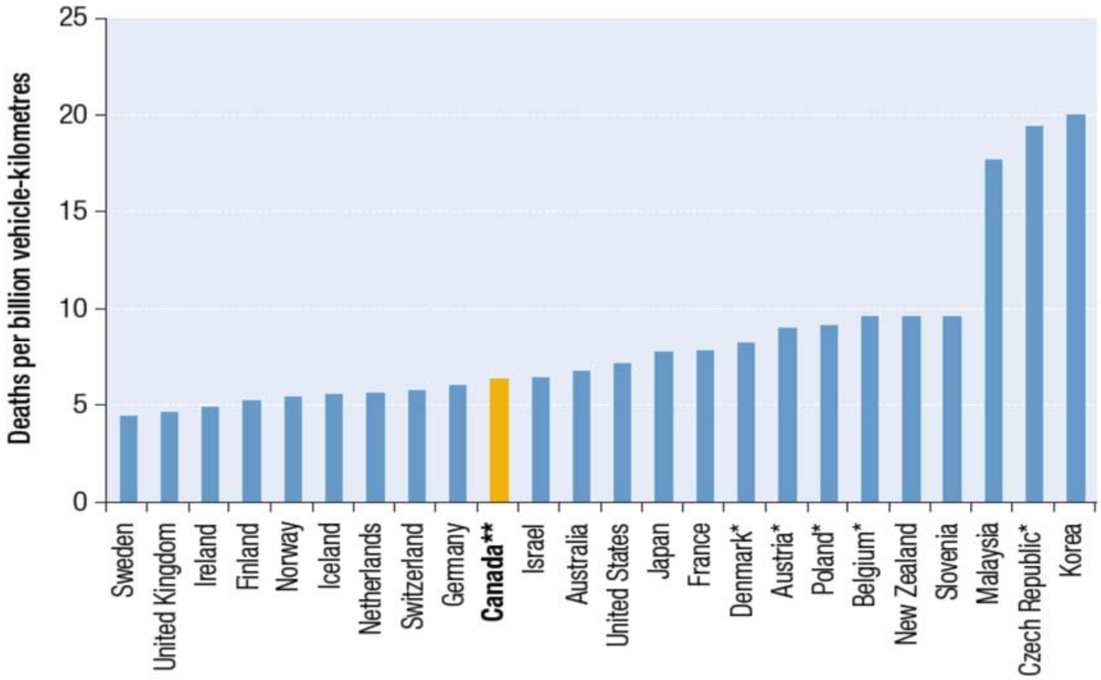
3.1 Road Safety Today

3.1.1 Worldwide and Canada

In transportation geography, traffic crashes are identified as a risk embedded in everyday mobility. Traffic crashes pose a threat to their properties and lives. They are considered one of World Health Organization's top ten causes of death globally (WHO, 2010). Every year on the world's roads, traffic crashes are account for approximately 1.3 million fatalities and 50 million injuries (WHO, 2010).

Fig. 3-1 presents road fatality counts in some top-ranking countries in the world in 2009. It shows that Sweden is the safest country in the world, followed by the United Kingdom and Ireland. The risk of traffic fatalities in these countries was lower than 5 deaths per billion vehicle-km. Having a risk of traffic fatalities of 6.6 deaths per billion vehicle-km, Canada ranked 10th among these countries.

Fig. 3-1: Deaths per billion vehicle-km in 2009, by country



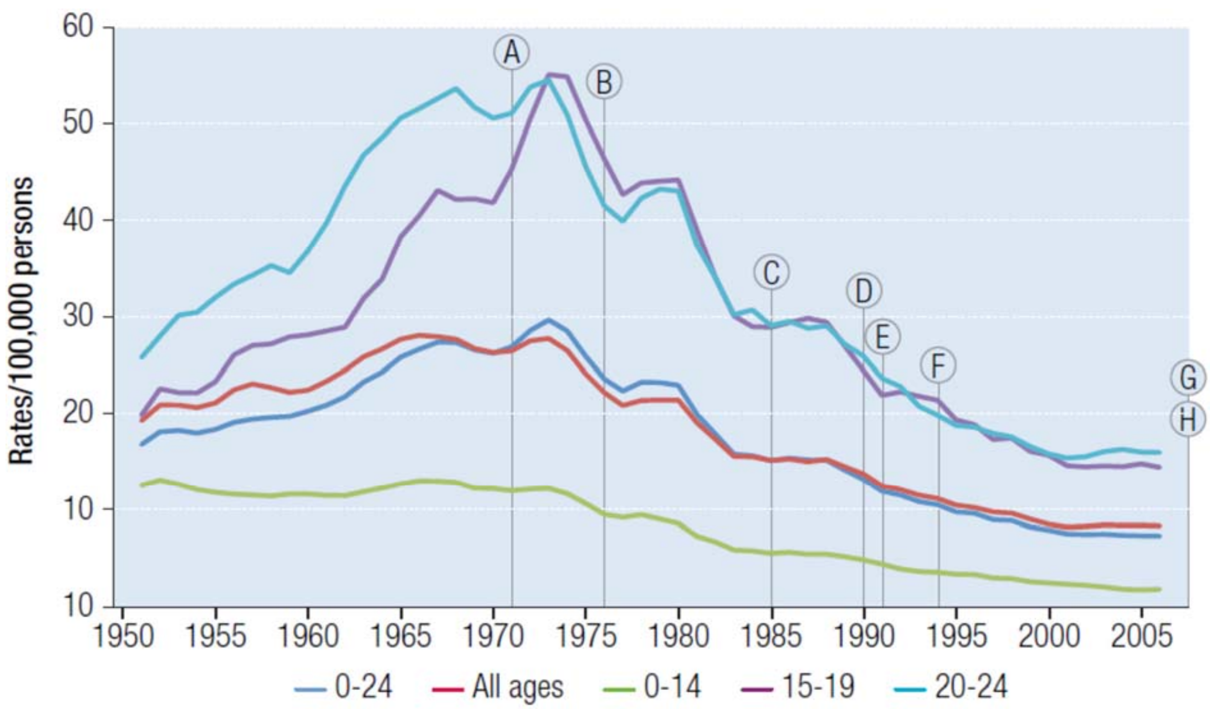
Source: Public Health Agency of Canada, 2012, p.12

Traffic crashes also take a substantial financial toll on society. According to the World Health Organization (WHO), the estimated economic cost of traffic crashes is approximately $US 500 billion (Peden et al., 2004). In 2010 , UN declared 2011-2020 as the UN Decade of Action for Road Safety with the goal to reduce the risk of traffic fatalities around the world by 2020 (WHO, 2010).

Traffic crashes lead to many casualties in Canada. Every day six Canadians die on the roads, on average (CCMTA, 2011). The Public Health Agency of Canada (2012) indicates that traffic crashes are the leading cause of death for young Canadian adults (15-24 years of age). In 2009, the country had approximately 125,000 traffic crashes, causing 2,209 deaths and 172,883 injuries (Transport Canada, 2011b). The traffic-fatality trend over the period of 1970-2009 shows a 58% decrease in number of fatalities mainly due to the initiation of various road safety measures in the country (IRTAD, 2011).

Fig. 3-2 demonstrates the traffic fatality rate in Canada between 1950 and 2007. It shows that the traffic fatality rate per 100,000 persons was the highest in the 1970s. Then the traffic fatality rate gradually declined over the past four decades. The implementation of various road safety initiatives, including legislation, played an important role in this downward trend. The major selected road safety legislations (listed in Table 3-1) are also marked in Fig. 3-2.

Fig. 3-2: Traffic fatality rate in Canada, 1950-2007, selected age groups



Source: Public Health Agency of Canada, 2012, p.20

Table 3-1: Benchmark of selected road safety legislations in Canada

Label	Year	Road safety legislation
A	1971	Seat belts required in all new vehicles
B	1976	Ontario is the first jurisdiction to pass the mandatory seat belt law
C	1985	Amendments to the Criminal Code resulted in tougher penalties for impaired drivers
D	1990	Canadian Motor Vehicle Safety Standard 108 (CMVSS 108) requires daytime running lights on all vehicles made or imported after January 1st, 1990
E	1991	Seat belt legislation enacted in all jurisdictions
F	1994-2005	Graduated licensing programs introduced in most Canadian jurisdictions
G	2008	New Criminal Code provisions on impaired driving give police better tools to detect and investigate alcohol- and drug-impaired driving.
H	2010	By 2010, hand-held cell phone use while driving banned in most Canadian jurisdiction. Canada Motor Vehicle Safety Standard 126 requires Electronic Stability Control on all passenger cars, multi-purpose vehicles, trucks and buses with a Gross Vehicle Weight Rating of 4536 kg or less, and manufactured on or after September 1st, 2011

Source: Public Health Agency of Canada, 2012, p. 20

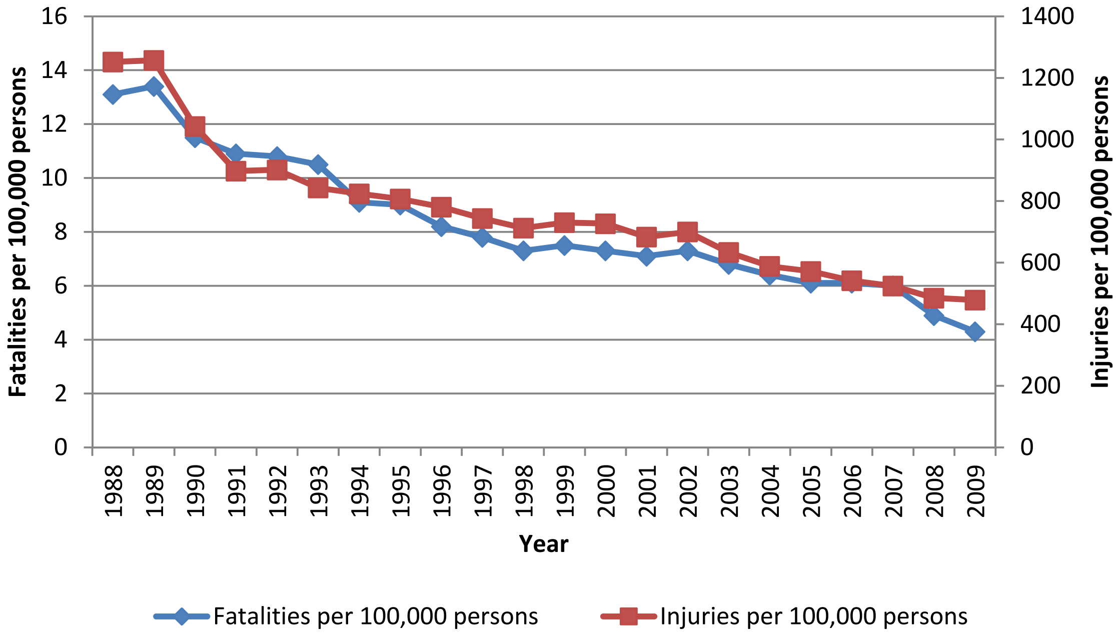
Canada's vision of road safety is to have the safest roads in the world (Transport Canada, 2011a). In realize this vision, Transport Canada launched Road Safety Vision 2001 and 2010, and Road Safety Strategy 2015. The main objectives Road Safety Strategy 2015 are to increase public awareness, enhance enforcement of traffic laws, increase communications, cooperation and collaboration among the partners and increase information in support of research and evaluation. The slogan of this strategy is "Rethink Road Safety", which requires actions from all road users. Transport Canada also declared 2011 as the National Year of Road safety to raise awareness about the road safety in Canada.

3.1.2 Ontario

In terms of road safety, Ontario is the safest jurisdiction with the lowest fatality rate in Canada (MTO, 2011). Like those of the entire country, Ontario's road safety conditions have gradually improved over time. In 2009, the traffic fatality rate of Ontario was 4.6 deaths per billion vehicle-km, well below the country's average traffic fatality rate of 6.6 deaths per billion vehicle-km (Transport Canada, 2011b). In that year, 564 persons died and 62,562 persons were injured in 216,315 traffic collisions on Ontario's roads. Between 2000 and 2009, both the number of fatalities and the number of injuries decreased by 33.6% and 26.4%, respectively (MTO, 2011). Fig. 3-3 presents the casualty trends in Ontario between 1988 and 2009. Both fatalities and injuries per 100,000 persons steadily declined over this period.

Despite this commendable progress in road safety, the social cost of traffic crashes in Ontario is very high, estimated at $17.9 billion in 2004, almost 28% of the national financial burden of traffic crashes and nearly 50% higher than in 1994 (Vodden et al., 2007).

Fig. 3-3: Casualty-severity trend in Ontario, 1988-2009



Source: MTO, 2011

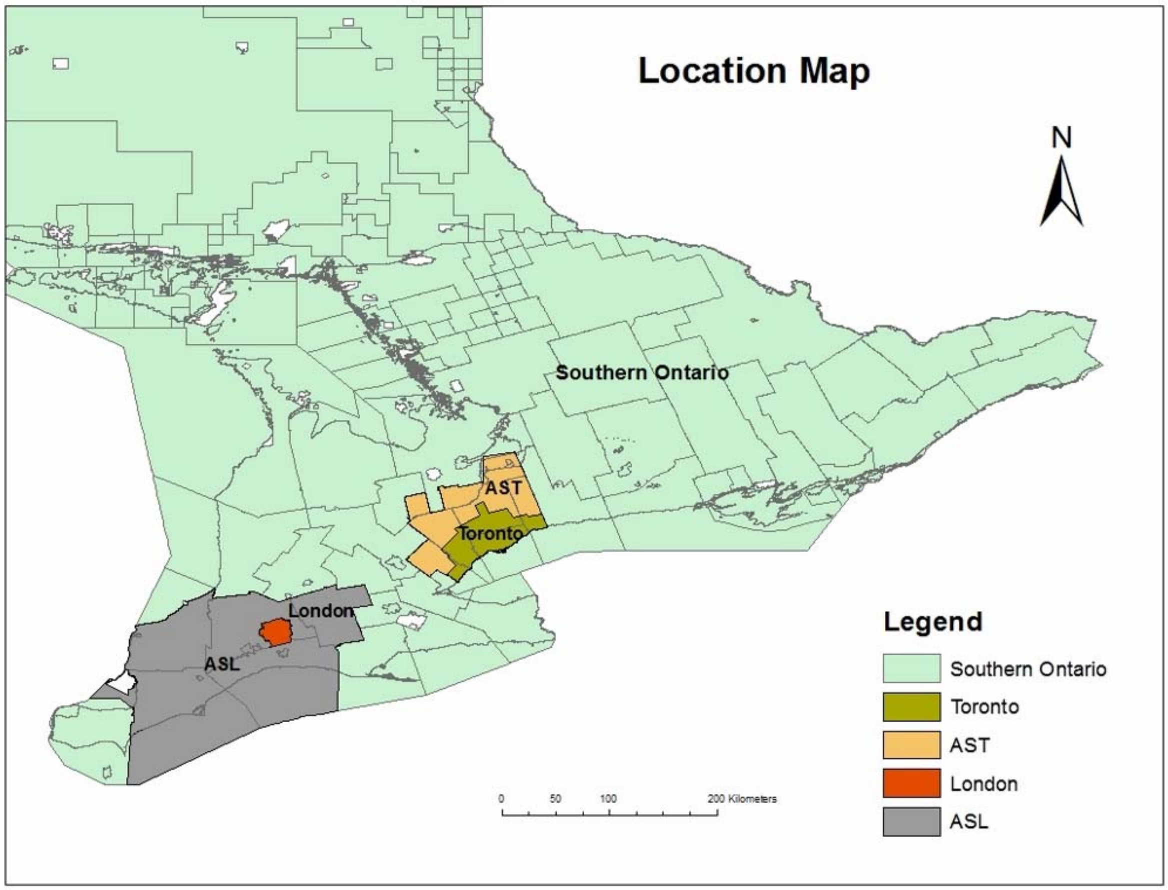
3.2 Study Areas

3.2.1 Populations and spatial extent

The focus of this study is Southern Ontario, which is the most densely populated part of the province. Most traffic collisions of the province occur in this region.

The study is based on four regions in Southern Ontario, named for the purpose of the study, Toronto, Area Surrounding Toronto (AST), London and Area Surrounding London (ASL) (Fig. 3-4, Table 3-2). Almost half of Ontario's population inhabits these four study areas and approximately half of Ontario's traffic crashes also occur here (Table 3-2).

Fig. 3-4: Location of the study areas



Toronto is located on the north shore of Lake Ontario. The study area includes the entire area of the City of Toronto, Ajax, Aurora, Brampton, Markham, Mississauga, Newmarket, Oakville, Pickering, Richmond Hill and Vaughan. It covers nearly 2,297 square km with a population of over 4.7 million people (38.9% of Ontario's provincial population) (Table 3-2). The density of this region is 2,067 people per square km, the highest density in Ontario. Despite having a good public transit system, approximately 70% of trips are made by cars. Toronto is well served by a number of 400-series highways and two municipal expressways (Queen Elizabeth highway and Gardiner expressway), as well as an extensive network of city streets.

The Area Surrounding Toronto (AST), which includes municipalities to the north of the Greater Toronto Area (GTA), is less densely developed with an approximately 0.38 million population living in 3,592 square km. Although this study area is almost 1.6 time larger than Toronto, it has a lower density of 105 people per square km, despite the inclusion of several towns and small cities: Bradford West Gwillimbury, Caledon, East Gwillimbury, Georgina, Halton Hills, King City, Milton, Mono Mills, New Tecumseth, Orangeville, Uxbridge, and Whitchurch-Stouffville. Being adjacent to Toronto, this area has a very well-developed road network, and the area is criss-crossed by several 400 series highways.

Table 3-2: Study area profile

Characteristics	Toronto	AST	London	ASL
Population	4,734,321	378,475	352,395	494,426
% of Ontario population	38.9%	3.1%	2.9%	4.1%
Land area (km^2)	2,297.40	3,591.70	420.6	12,276.60
% of Ontario land area	0.3%	0.4%	0.1%	1.4%
Total collisions, 2003-2009	622,517	53,237	51,633	46,422
% of Ontario collisions, 2003-2009	38.9%	3.3%	3.2%	2.9%

Source: Statistics Canada, 2007; Transport Canada, 2011c

London refers to the City of London, a mid-sized urban area in Ontario located at the junction of Highway 401 and 402. London is the smallest, both in size and population, among the four study areas, having approximately 0.35 million population in an area of just over 400 square km. The density of this study area is 838 people per square km. This study area covers 1.4% of the provincial land and only 3.2% of the provincial population lives here. Like other

Canadian mid-sized cities, the public transit system is not well used in London (only 7% of trips are made by transit). Rather residents rely on cars for most trips.

Finally, the Area Surrounding London (ASL) refers to Middlesex (excluding the City of London), Chatham-Kent, Oxford, Lambton, and Elgin counties located in southwestern Ontario. Although the region is mainly rural, it also includes three small cities (St. Thomas, Sarnia, and Woodstock) and other smaller communities. Altogether the area covers over 12,000 Square Km with a population of one-half million, but the density of the population is very low, only 40 people per square km. The area is crisscrossed by a number of different highways (Highway 401, 402, 403, 2, 3 4, 7, 14, 22), municipal rural roads (Middlesex county road 22, Oxford county road 55) and city/town streets.

These four study areas represent different mixes of road types and driving environments. As Canada's largest city, Toronto represents the most urbanized driving environment of the four. The area surrounding Toronto comprises both an extension of the Toronto urban field as well as open farmland. London is a mid-sized city located in the heart of southwestern Ontario that is sufficiently distant from Toronto so as to be outside the commuter shed of this metropolitan region, for the most part. The area surrounding London is the most rural of the four study areas, comprising mostly farmland, but does include three small cities that are part of the industrial fabric of southern Ontario.

In the field of road safety, urban-rural roadways are often differentiated based on speed limits; although clearly urban-rural differences in driving include other aspects as well including traffic density. Also, there are some differences in the collision characteristic of urban versus rural roads (Transport Canada, 2011a; CCMTA, 2008). In Canada, fatal crashes occurs more on undivided rural roads with a speed limits of 80 km/h or over (Barua et al., 2010; Transport Canada, 2011a). Again, single-vehicle crashes occur with greater frequency on rural roads (CCMTA, 2008). On the other hand, having more intersections, urban areas have a greater number of intersection crashes. Table 3-3 characterizes the four study areas based on available data in the National Collision database.

Table 3-3: Crash profile of the study areas, 2003-2009

Characteristics	Toronto	AST	London	ASL
Posted speed limit				
≤50 km/h	44%	30%	66%	49%
60-70 km/h	38%	24%	22%	5%
80-90 km/h	5%	33%	6%	35%
100 km/h	14%	14%	6%	11%
Total	100%	100%	100%	100%
Crash location				
Intersection	59%	47%	73%	49%
Non-intersection	41%	53%	26%	51%
Total	100%	100%	100%	100%
Number of vehicles Involved				
Single	12%	35%	13%	41%
Two	79%	59%	79%	55%
Multiple	9%	7%	8%	4%
Total	100%	100%	100%	100%
Sub-regions (Municipality and/or County)				
	Toronto – 62%	Mono Mills – 3%	The City of London – 100%	Elgin (excluding St. Thomas) – 8%
	Ajax – 1%	Orangeville – 4%		Chatham-Kent – 16%
	Pickering – 2%	Uxbridge – 4%		Lambton (excluding Sarnia) – 12%
	Oakville – 3%	Halton Hills – 10%		Middlesex (excluding London) – 17%
	Brampton – 7%	Milton – 19%		Oxford (excluding Woodstock) – 19%
	Mississauga – 12%	Caledon – 17%		St Thomas – 6%
	Aurora – 1%	Peel Region – 7%		Sarnia – 15%
	Markham – 4%	Bradford West Gwillimbury & New Tecumseth – 7%		Woodstock – 7%
	Newmarket – 1%	Georgina – 11%		
	Richmond Hill – 2%	East Gwillimbury – 5%		
	Vaughan – 5%	King city – 9%		
		Whitchurch-Stouffville – 5%		
Total	100%	100%	100%	100%

As shown Table 3-3, Toronto and London are mostly similar; as are two study areas surrounding these urban regions. Being more urbanized, Toronto and London have more intersection crashes and more two or multiple-vehicle crashes than AST and ASL. In contrast, AST and ASL have greater frequency of single-vehicle crashes and higher number of crashes on high speed roads (≥80 km/h) in comparison to Toronto and London.

3.1.2 Winter weather conditions

The weather conditions of the study areas are presented in Table 3-4 for the study period of November-April, 2003-2009. The decision to focus on the six-month period, November to April, ensures that all winter weather is considered. The table shows selected weather parameters, collected from the two prominent weather stations located within the study areas. The weather data of Toronto and AST were collected from the Lester B. Pearson International Airport. The weather data of London and ASL were collected from the London International Airport.

The table demonstrates that, although all study areas have similar winter temperatures, precipitation events vary between two study regions. Being located in the snowbelt area of the Southern Ontario, London and its surrounding area have the harsher winter in comparison to Toronto and its surrounding area. During November-April, 2003-2009, nearly 25% and 22% days were rain days and 28% and 37% days were snow days in Toronto and London, respectively. During the study period, the annual accumulation of snowfall was more than double in London than in Toronto (Table 3-4). The majority of snowfalls come from the lake-effect snow originating from Lake Huron (Wikipedia, 2013).

Table 3-4: Winter weather conditions in the study areas, November-April, 2003-2009

Selected weather condition	Toronto & AST	London & ASL
Annual rainfalls (mm)	279.4	357.6
Annual # rain days (≥ 0.4 mm rain)	45	51
Annual snowfalls (cm)	125.6	255.1
Annual # snow days (≥ 0.4 cm snow)	40	67
Daily average temperature	0	0
Annual # days with mean temperature ≤0^0c	88	93

Source: Environment Canada, 2012

3.1.3 Winter road safety conditions

The Ministry of Transportation, Ontario (MTO) and local municipalities are responsible for traffic safety programs in the four study areas. However, the provincial and municipal police enforce traffic laws; they also record the traffic crash information under their jurisdictions. This traffic crash information is then centrally maintained by the Transport Canada in their National Collision Database (NCDB). According to this database, 90,517 persons died or were injured in 321,875 crashes in Toronto during November-April, 2003-2009. The corresponding number for the other study areas are as follows: 7,505 persons died or were injured in 29,831 crashes in the Area Surrounding Toronto (AST), 7,631 persons died or were injured in 28,118 crashes in London, and 7,494 persons died or were injured in 26,148 crashes in the Area Surrounding London (ASL), respectively. However, these numbers of crashes are underreported, because NCDB contains only the information of the collisions that cost at least $1,000 CAD property damage and/or any casualty.

Table 3-5 summarizes the winter road safety conditions of the four study areas. Both the crash rate and the casualty (fatality plus injury) rate are calculated per 100,000 people for an easy comparison among the study areas. In terms of the per capita crash rate and casualty rate, the traffic safety situation is the best in ASL and the worst in London among the study areas.

However, through traffic on three 400 series highways in the Area Surroundings London (ASL) likely overstates the safety problem in this study area.

Table 3-5: Winter road safety conditions of the study areas, November-April, 2003-2009

Incident Types	Toronto	AST	London	ASL
Crashes per 100,000 people				
Fatal	8	31	9	30
Injury	1344	1328	1490	992
PDO	5447	6523	6481	4267
Total	6799	7882	7979	5289
Casualties per 100,000 people				
Injuries	1903	1949	2156	1483
Fatalities	9	34	10	33
Total	1912	1983	2165	1516

Source: Transport Canada, 2011c

If we consider only the fatality rate per 100,000 people, the traffic safety situation is the worst in the area surrounding Toronto (34 fatalities per 100,000 people) and the best in Toronto (8 fatalities per 100,000 people). The table also indicates that the per capita risk of fatalities appears to be more than three times greater in the areas surroundings Toronto and London than these two main cities in Southern Ontario—but this because many urban trips are short and therefore taken by residents whereas rural trips in the two surrounding study areas are typically longer and include disproportionately more through trips. Due to data limitation, the study results could not identify the influence of through traffic on the road safety conditions in the study areas.

Chapter 4

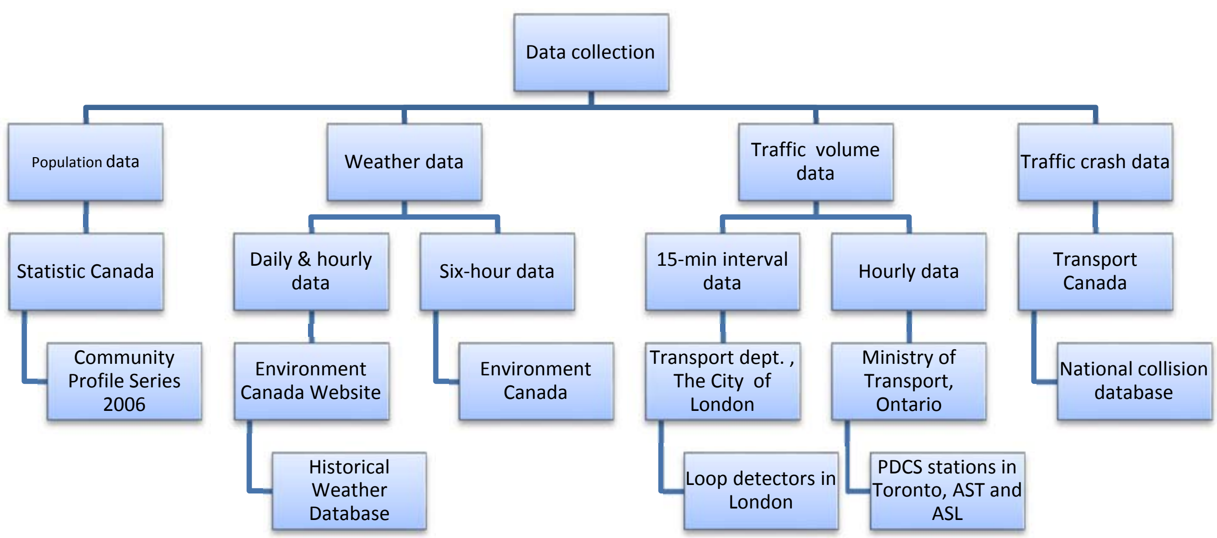
Data and Methods

This chapter summarizes the data and methods used in the study. It comprises four sections: the first section describes the data, data sources and data processing; the second section details methods used for developing a winter traffic exposure adjustment variable, the third section describes the methods used in defining high-crash days, and the fourth section provides information about the variables and logistic regression model used in the data analysis.

4.1 Study Data

The data used for this study can be categorized into four major types: population data, weather data, traffic volume data, and traffic crash data. Figure 4-1 summarizes the data collection process of the study.

Fig. 4-1: Data collection process



A detailed description of these four categories of data and their sources is given below.

4.1.1 Population data

The population data for the study were collected from Statistics Canada's Community Profile Series, 2006. Although the population data of the Community Profiles Series, 2011 was also available at the time of the study, the data for 2006 were considered more suitable for this study because 2006 remained at the middle of the study period 2003-2009.

4.1.2 Weather data

The study used daily, six-hourly and hourly weather information of different weather parameters – temperature, rainfall, snowfalls, freezing rain, visibility obstruction (fog, smoke, or blowing snow), and wind speed. The hourly and six-hourly weather data were aggregated to the daily level, which is the unit of analysis for this study. The daily and hourly weather data were collected from Environment Canada's website, which has a historical weather database considered as the most authentic source for atmospheric weather parameters. The two major weather stations used for this study are Toronto Lester B. Pearson International Airport (43°40'38" N, 79°37'50" W) and London International Airport (43°01'59" N, 81°09'04" W). In addition, this study used daily precipitation data recorded at Environment Canada weather stations located in proximity to Permanent Data Count Stations (PDCS) and Loop detectors along road segments, both of which are instrumented to provide traffic count data. These weather stations are as follows – Toronto Buttonville A (43°51'44" N, 79°22'12" W), Orangeville Ministry of Environment (MOE) (43°55'06" N, 80°05'11" W) , Thedford (43°10'32" N, 81°51'21" W), Delhi Count Station (CS) (42°52'00" N, 80°33'00" W) , Region of Waterloo International Airport (43°27'32" N, 80°22'39" W). Finally, the study used six-hour precipitation records collected from Environment Canada to identify the timing of precipitation- whether precipitation occurred during morning and/or afternoon.

4.1.3 Traffic volume data

Traffic volume data for the study areas were collected from two sources: Permanent Data Count Stations (PDCS) and Loop detectors. Traffic volume data were collected from Ministry of Transportation, Ontario's (MTO) nine PDCS stations located in Toronto, AST and ASL areas. There is not any PDCS station in London. In each study area in Toronto, AST and ASL, traffic data were collected from three PDCS stations, which provided traffic count data for the winter period of November to April, 2003-2009 on an hourly basis. After processing the data, hourly information was converted to daily traffic counts for each station. Then, the days with incomplete traffic count data were omitted from the database. Thus, only the days with complete traffic count data were used in this study. The precipitation information for those days was collected from nearby weather stations. The locations of these PDCS stations and their nearby weather station information are given in Table 4-1.

For London, the traffic count data were collected from the three loop detectors – Northbound Adelaide South of Oxford, Northbound left lane Adelaide South of Oxford and Southbound Adelaide South of Oxford – located at Adelaide at Oxford intersection in the City of London. The duration of the data was January to April, 2011 and November, 2011 to February 2012. The Transport Department of the City of London provided these data for this study. The original data were at 15-minute intervals. After adding the traffic count data from these three loop detectors, the data were then converted to the daily traffic count. Thereafter, the days with incomplete traffic count data were removed from the database. Therefore, the study used only complete traffic count data for this study area. The weather information for the loop detector data was collected from London CS station, which is located approximately 8.43Km away from the loop detectors.

Table 4-1: PDCS station and Weather station Information

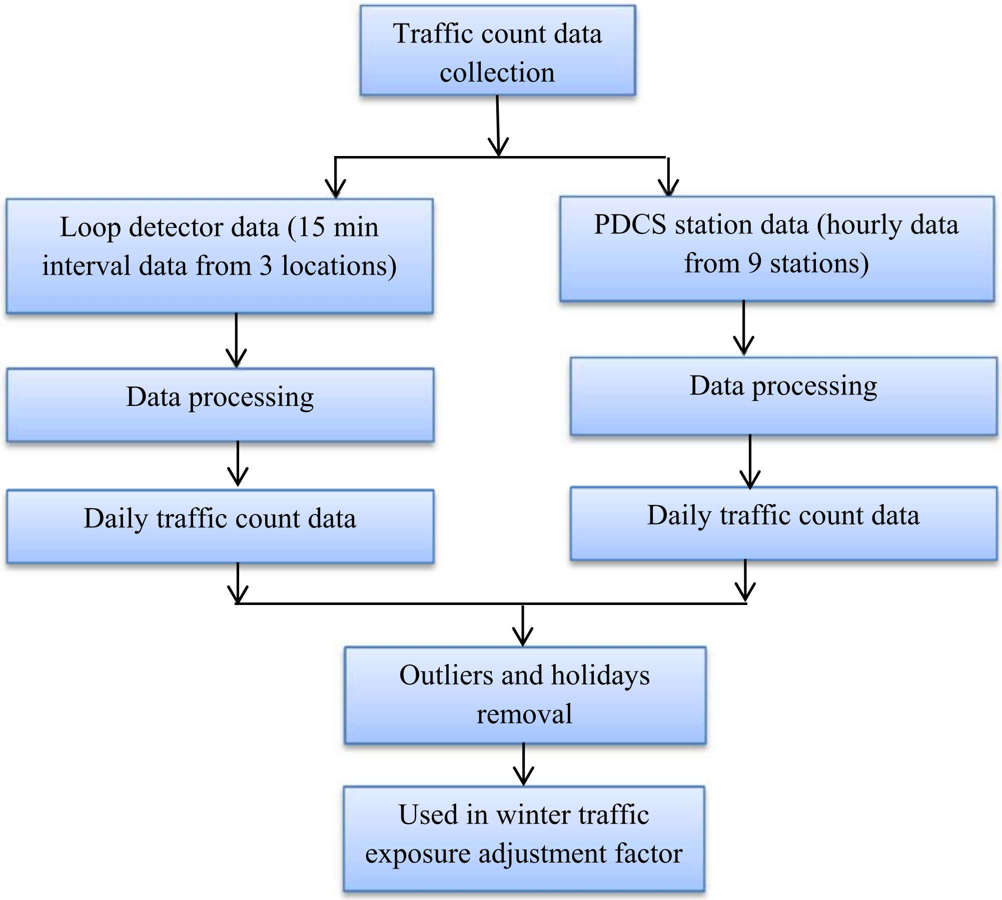
Latitude	Longitude	Name	Description	Study Area	Weather station	Distance[1] (Km)
N43° 36.226'	W079° 33.687'	Mississauga	QEW	Toronto	Toronto Lester B. Pearson Int'l A	10.58
N43° 37.456'	W79° 41.995'	Dixie	401	Toronto	Toronto Lester B. Pearson Int'l A	8.4
N43° 43.531'	W79° 28.058'	Keele	401	Toronto	Toronto Buttonville A	7.47
N43° 54.094'	W79° 33.698'	Maple	400	AST	Toronto Buttonville A	15.62
N43° 33.026’	W079° 51.180’	Milton	401	AST	Toronto Lester B. Pearson Int'l A	21.51
N43° 45.862'	W79° 51.979'	Snelgrove	10	AST	Orangeville Moe	19.93
N43° 14.556'	W81° 41.772'	Grand Bend	21	ASL	Thedford	27.01
N42° 49.441'	W80° 26.266'	Simcoe	3	ASL	Delhi CS	11.97
N43° 12.959'	W80° 36.352'	Woodstock (Drumbo)	401	ASL	Region of Waterloo Int'l Airport	17.09

Source: MTO, 2011, and Environment Canada, 2012

The traffic data from both sources were further screened for any outliers caused by any technological malfunction. Moreover, the major holidays during November to April were also excluded from the dataset, as traffic volumes on holidays are significantly different from other times, controlling for day of the week. These holidays were New Year’s, Family Day, Easter weekend, Remembrance Day, and Christmas. Figure 4-2 shows the schematic diagram of traffic data processing.

[1] The distance between the PDCS station and the weather station

Fig. 4-2: Traffic count data processing



4.1.3 Traffic crash data

The study analysis is based on the traffic crash data from Transport Canada's National Collision Database (NCDB). The NCDB data, based on collision reported by the respective provincial and municipal police agencies, provides detailed information about collisions, as well as persons and vehicles involved. Also included is information on the visible weather conditions at the time of the collisions. This database includes crashes that cause at least $1000 economic damage and/or any casualty (MTO, 2007). During 2003-2009, the total collisions and casualties that occurred in the four study areas are given in Table 4-2. According to this table, the average daily crash rate was 243 in Toronto, 21 in AST, 20 in London, and 18 in

ASL. The daily crash rate was more than 10 times higher in Toronto area than in the other three study areas, which is largely a reflection of traffic volume as the per capita rates are similar.

Table 4-2: Traffic crashes and casualties in the study areas

Incident Types	Toronto	AST	London	ASL
Crashes				
Fatal	849	248	81	329
Injury	133,366	10,136	10,851	10,055
PDO	488,302	42,853	40,701	36,038
Total	622,517	53,237	51,633	46,422
Casualties				
Injuries	191,085	15,174	15,476	15,159
Fatalities	912	281	88	364
Total	191,997	15,455	15,564	15,523

4.2 Method for developing the proxy exposure variable

The study considered a day with more than 0.4 cm total precipitation as a measureable precipitation day and coded it as 1. In contrast, days with no precipitation and days with less than 0.4 cm total precipitation were considered as good weather days and coded as 0. At the preliminary stage of analysis, daily traffic count data from each PDCS station were treated separately. However, the data from three loop detectors were later combined as they provided traffic count data for the same intersection. Thus, these traffic data are considered to represent one station. As a result, in total, 10 site-specific winter traffic exposure adjustment factors were developed for the study areas: one for London, and three for each of the other study areas. For each of the latter three study areas, the three adjustment factors were then averaged to develop a final winter traffic exposure adjustment factor for each study area.

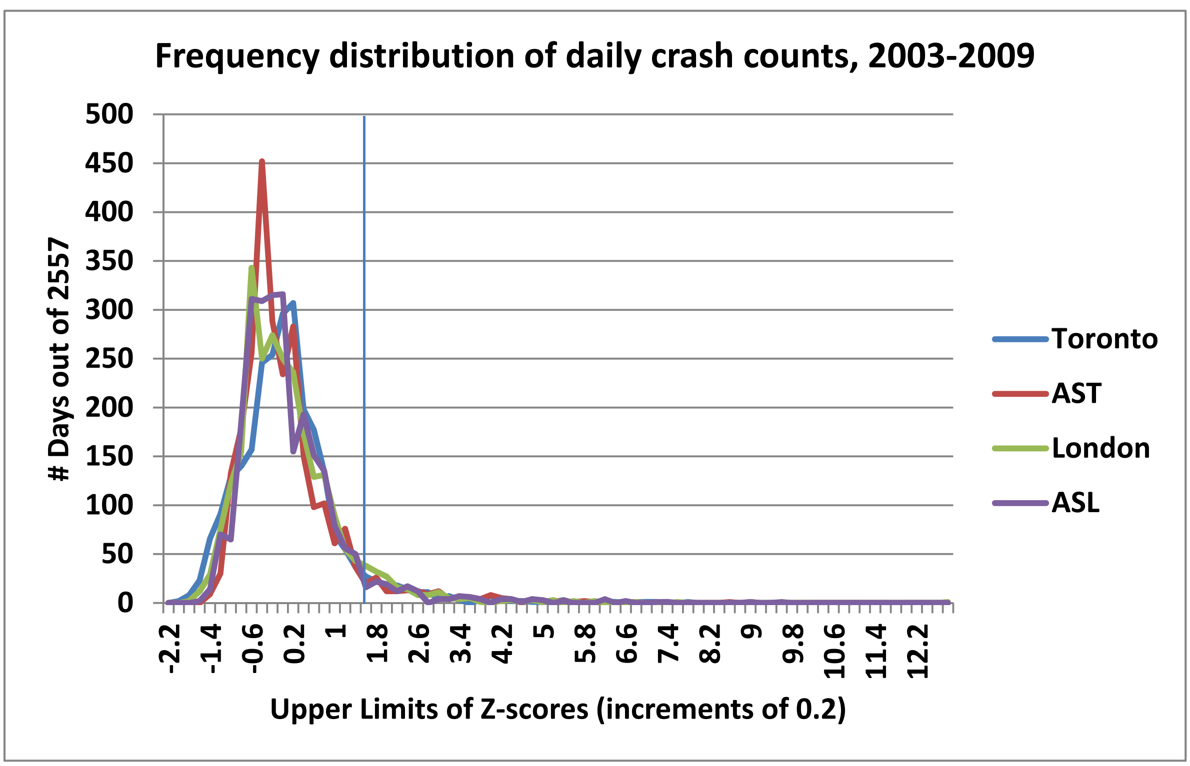
4.3 Methods used in defining high crash days

The main point of interest of this study is high-crash days which are somewhat neglected in road safety research. Nevertheless, many road safety studies investigate a similar concept by defining a high-risk day based on different weather variables (Eisenberg, 2004; Eisenberg & Warner, 2005; Jean et al., 2012; Knapp et al., 2000). A high-risk weather day has the potential to become a high-crash day, based in large part on event duration and/or weather intensity. The definition of high-risk days varies among the studies. For example Knapp et al. (2000) pointed out clearly that a snowy day having at least four hours of snow accumulation with a 0.51 cm per hour snowfall rate are significantly risky for traffic crashes, and therefore, they define these days as the high-risk days. Their definition of high-risk days is event-based. Other studies have defined high-risk days based on the daily precipitation amount alone. The cut-out point of this amount is highly contextual and varies among the study areas. In two related studies, Eisenberg (Eisenberg, 2004; Eisenberg & Warner, 2005) declared that crash risk elevated highly if the day has at least 0.5 cm snow, whereas Andrey et al. (2013) define an elevated risk day when the day has any amount of measurable precipitation.

The current study took a slightly different approach in defining high-risk days, focusing on daily traffic crash counts, rather than pre-defined risk variables, and then tried to analyse the influence of weather on these days. The calculation of high-crash was done separately for each study area. The study followed three different approaches to define high-crash days. For the first approach, all 2557 days between 2003 and 2009 were sorted on the basis of daily crash counts; and the 10% of days with the highest daily crash counts were considered high-crash days. The decision to select 10% of days was based in part on Hassan & Barker's study (1999) on the influence of extreme weather conditions on traffic activities. Because, in some cases, the crash count was the same for multiple days, the exact percentage of the 10% varies between 9% and 11%. For example, 5 days out of 2557 days in Toronto, had 147 crashes, the 10th highest number of daily total crashes in this study area; and all these five days were included as high-crash days.

Second, the study defined high-crash days based on the z-scores of daily crash counts. After converting daily crash count to a standard score (z-score), the frequency distribution was plotted for all study areas (Fig. 4-3). Fig. 4-3 shows that a small number of days have very high crash counts in comparison to the rest of the days. While there was no generally accepted definition of a high-crash day, the current study considered a day as a high-crash day if it had a z-score value ≥ 1.5, i.e., the crash count was at least 1.5 standard deviations greater than average. These days accounted for approximately 6% of 2557 days in each study areas.

Fig. 4-3: Frequency distribution of daily crash counts, 2003-2009



Third, the study considered 10% of the 2557 days as high-crash days, based on the largest positive differences between observed crash counts and expected crash counts. This approach considered that traffic crashes varied among years, months, and day of week; and time adjustment factors could explain all these variation in traffic crashes. The adjustment factor for a year was calculated by dividing average traffic crashes of that particular year by the average daily traffic crashes of the whole study period (Table 4-3). Likewise, adjustment factors for months and day of week were calculated (Table 4-4 and 4-5).

Table 4-3: Time adjustment factor for years

Year	Toronto	AST	London	ASL
2003	1.11	1.01	1.04	1.09
2004	1.00	1.04	0.97	1.00
2005	0.99	1.03	0.99	1.02
2006	0.91	0.94	0.99	1.00
2007	1.01	1.06	1.05	1.00
2008	1.01	1.02	1.01	0.99
2009	0.96	0.91	0.94	0.88

Table 4-4: Time adjustment factor for months

Months	Toronto	AST	London	ASL
Jan	1.22	1.41	1.23	1.22
Feb	1.11	1.22	1.24	1.26
Mar	0.86	0.81	0.89	0.92
Apr	0.87	0.78	0.87	0.86
Nov	1.09	1.28	1.18	1.28
Dec	1.10	1.27	1.18	1.28

After estimating adjustment factors for each year, month, and day of week between 2003 and 2009 for each study area, the daily expected crash count of a study area was calculated by multiplying these adjustment factors with the daily average count of the whole study period. Thus, a daily expected crash count followed the equation:

Daily expected crash count = average daily crash count over 7 years (2003-2009) × adjustment factor for year × adjustment factor for month × adjustment factor for day of week.

Table 4-5: Time adjustment factor for the day of week

Day of week	Toronto	AST	London	ASL
Sun	0.66	0.75	0.59	0.82
Mon	0.97	1.02	0.96	0.98
Tue	1.07	1.03	1.06	0.99
Wed	1.10	1.05	1.09	1.00
Thu	1.10	1.05	1.14	1.07
Fri	1.20	1.19	1.26	1.16
Sat	0.90	0.91	0.88	0.98

After calculating high-crash days according to the above methods, the study excluded the holidays from the high-crash day counts because holidays have slightly different traffic patterns than other days; and their traffic safety situations are also different. Inclusion of holidays in high-crash days may lead to anomalies in the study results. Table 4-6 to 4-11 shows the different statistics of high crash days.

Table 4-6: High-crash days according to the first approach and including holidays

High crash days	Toronto	AST	London	ASL
Day Count	256	283	287	257
Total crashes in the study period	110,181	13,100	11,686	9,778
Average daily crashes	430	46	41	38
StDev of daily crashes	109.5	15.5	12.7	12.9
Non high crash days				
Day Count	2,301	2,274	2,270	2,300
Total crashes in the study period	512,336	40,137	39,947	36,644
Average daily crashes	223	18	18	16
StDev of daily crashes	55.1	6.0	6.2	5.1
All days				
Day Count	2,557	2,557	2,557	2,557
Total crashes in the study period	622,517	53,237	51,633	46,422
Average daily crashes	243	21	20	18
StDev of daily crashes	88.4	11.8	10.3	9.2

Table 4-7: High-crash days according to the first approach and excluding holidays

High crash days	Toronto	AST	London	ASL
Day Count	253	275	286	247
Total crashes in the study period	108,835	12,777	11,642	9,443
Average daily crashes	430	46	41	38
StDev of daily crashes	109.6	15.6	12.7	13.1
Non high crash days				
Day Count	2,221	2,199	2,188	2,227
Total crashes in the study period	499,785	39,152	38,973	35,689
Average daily crashes	225	18	18	16
StDev of daily crashes	53.4	5.9	6.1	5.1
All days				
Day Count	2,474	2,474	2,474	2,474
Total crashes in the study period	608,620	51,929	50,615	45,132
Average daily crashes	246	21	20	18
StDev of daily crashes	87.4	11.8	10.3	9.2

Table 4-8: High-crash days according to the second approach and including holidays

High crash days	Toronto	AST	London	ASL
Day Count	156	160	169	151
Total crashes in the study period	75,150	8,792	7,822	6,664
Average daily crashes	482	55	46	44
StDev of daily crashes	113.4	15.8	14.0	13.9
Non high crash days				
Day Count	2,401	2,397	2,388	2,406
Total crashes in the study period	547,367	44,445	43,811	39,758
Average daily crashes	228	19	18	17
StDev of daily crashes	59.7	7.0	6.9	5.7
All days				
Day Count	2,557	2,557	2,557	2,557
Total crashes in the study period	622,517	53,237	51,633	46,422
Average daily crashes	243	21	20	18
StDev of daily crashes	88.4	11.8	10.3	9.2

Table 4-9: High-crash days according to the second approach and excluding holidays

High crash days	Toronto	AST	London	ASL
Day Count	154	157	168	146
Total crashes in the study period	74,156	8,639	7,778	6,476
Average daily crashes	482	55	46	44
StDev of daily crashes	113.7	15.9	14.1	14.0
Non high crash days				
Day Count	2,320	2,317	2,306	2,328
Total crashes in the study period	534,464	43,290	42,837	38,656
Average daily crashes	230	19	19	17
StDev of daily crashes	58.1	6.9	6.8	5.7
All days				
Day Count	2,474	2,474	2,474	2,474
Total crashes in the study period	608,620	51,929	50,615	45,132
Average daily crashes	246	21	20	18
StDev of daily crashes	87.4	11.8	10.3	9.2

Table 4-10: High-crash days according to the third approach and including holidays

High crash days	Toronto	AST	London	ASL
Day Count	256	262	292	259
Total crashes in the study period	106,205	11,926	11,361	9,536
Average daily crashes	415	46	39	37
StDev of daily crashes	123.0	17.2	13.8	13.8
Non high crash days				
Day Count	2,301	2,295	2,265	2,298
Total crashes in the study period	516,312	41,311	40,272	36,886
Average daily crashes	224	18	18	16
StDev of daily crashes	58.1	6.7	6.6	5.4
All days				
Day Count	2,557	2,557	2,557	2,557
Total crashes in the study period	622,517	53,237	51,633	464,22
Average daily crashes	243	21	20	18
StDev of daily crashes	88.4	11.8	10.3	9.2

Table 4-11: High-crash days according to the third approach and excluding holidays

High crash days	Toronto	AST	London	ASL
Day Count	251	256	290	254
Total crashes in the study period	104,321	11,670	11,292	9,349
Average daily crashes	416	46	39	37
StDev of daily crashes	123.0	17.3	13.9	13.9
Non high crash days				
Day Count	2,223	2,218	2,184	2,220
Total crashes in the study period	504,299	40,259	39,323	35,783
Average daily crashes	227	18	18	16
StDev of daily crashes	56.5	6.6	6.5	5.3
All days				
Day Count	2,474	2,474	2,474	2,474
Total crashes in the study period	608,620	51,929	50,615	45,132
Average daily crashes	246	21	20	18
StDev of daily crashes	87.4	11.8	10.3	9.2

4.4 Data Analysis

4.4.1 Logistic Regression Model

Logistic regression analysis is commonly used either to predict the membership of a group or to identify the relationship and strength among the variables. According to Bruns & Bruns (2008), the assumptions of the logistic regression are as follows:

- The relationship between dependent and independent variables is non-linear.
- The dependent variable is binary.
- The distribution of independent variables can take any form. They do not have to be normally distributed, linearly related or of equal variance within each group
- A case must belong to one of the categories, which are mutually exclusive and exhaustive.

The independent variables can be entered into the binary logistic regression model into three ways. If all variables are entered at a time, the method is then called the simultaneous regression. The hierarchical method includes first the control variables and then the predictor variables. Lastly, the stepwise method enters variables into several steps to maximise their contribution into the model. The current study applied the simultaneous method to include all independent variables into the binary logistic regression model in the *SPSS 21*.

Logistic regression requires a large sample size. According to one of the most widely used books for logistic regression, each independent variable needs at least 10 cases (Hosmer and Lemeshow, 2000). Peduzzi et al (1996) also claimed that no major problem occurs in a simultaneous analysis when case to variable ratio is 10 or greater. However, the preferable case to independent variable ratio is 20:1 for simultaneous and hierarchical logistic regression; and 50:1 for stepwise logistic regression.

Road safety researchers commonly use logistic regression models to estimate the influence of different risk factors on traffic crashes, when the dependent variable is a dichotomous or binary variable (Anowar et al., 2013; Al-Ghamdi, 2002; Chen et al., 2012; Kong & Yang, 2010, Tay et al., 2008; Yan et al., 2005). The current study also applies the binary logistic regression model to determine the likelihood of high-crash day occurrence using a set of independent variables. As the dependent variable high-crash days is discrete and dichotomous in nature (equation 4.1), the binary logistic regression model is appropriate for this study.

$$\text{High-crash days, Y} = \begin{cases} 1\ if\ a\ day\ belongs\ to\ high\ crash\ days \\ 0\ if\ a\ day\ does\ not\ belong\ to\ high\ crash\ days \end{cases} \quad \ldots\ldots\ldots\ldots (4.1)$$

The study followed the logistic regression methodology described by Tay et al. (2008). In this model, Logit (p) is the log (to base e) of the odd ratio or likelihood ratio that dependent variable is 1 (high-crash day), as oppose to 0 (non-high-crash day). In symbol form, the equation is as follows:

$$\text{logit}\ (\rho) = \log\left(\frac{\rho}{1-\rho}\right) = \ln\left(\frac{\rho}{1-\rho}\right) = \beta X$$

Where β is the vector of parameters to be estimated and X is the vector of independent variables. Moreover, the range of ρ is between 1 and 0; but logit (ρ) scale ranges from –α to +α, and is symmetrical around the logit of 0.5, which is 0 (Bruns & Bruns, 2008). Logits (log odds) are the slope b coefficient (slope values) of the regression equation.

Unlike Ordinary Least Square (OLS) regression, logistic regression does not estimate change in the dependent variable (high-crash days). Rather, it estimates change in the log odds of dependent variable. In the current study, the odds value measures the probability of high-crash days rather than probability of non-high-crash days (Bruns & Bruns, 2008).

The results of the study are based on interpretations of the odds ratio (OR). If all other factors remaining constant, one unit increase in an independent variable x_i increases the odds by a factor exp(β_i), which is called the odds ratio (OR). The odds ratio (OR) can vary from 0 to + α. The odds ratio (OR) indicates the relative amount by which the odds of a high-crash day increases (OR>1) or decreases (OR<1) when the value of the corresponding independent variable increases by one unit The odds ratio is the better way of communicating the risk of extreme weather events to people than deterministic or probabilistic statements (Leclerc & Jaslyn, 2012).

The present study used a set of nine risk factors divided into 29 independent weather and time variables described in the section 4.4.2. Here all the independent variables are categorical variables. The categories are mutually exclusive and exhaustive. Many of them are dichotomous in nature. Categorical and dichotomous variables help both the estimation and the interpretation of the odd ratios.

The study used *SPSS 21* and *MS Excel 2010* for developing the logistic regression models. For each study area, three logistic regression models were developed. Although the same set of independent variables was used in these three models, the definition of the dependent variable varied. Three different definitions of high-crash days were used (Section 4.3). Accordingly, three models were developed for each of the four study areas. In the calibrated models, each risk factor has more than one category. To measure the effects of a risk factor on high-crash days, the first category of a factor is considered as a reference in the estimation. Therefore, the effects of each independent variable are interpreted relative to the reference category. For example, for daily total snow, no snowfall was considered as the reference category and the estimate for a heavy snow (>5cm) situation is relative to a day with no snowfall (<0.4 cm)

4.4.2 Description of the independent variables

According to the literature review, the study used nine crash risk factors to identify their influence on high-crash days. They are then divided into 29 independent variables as shown in Table 4-12. The table also shows the frequency distribution of these independent variables. Due to lake-effect snowfall, London and ASL have almost double high-crash days with medium to heavy snowfalls than Toronto and AST. Moreover, London and ASL have a greater number of high-crash days with freezing rain and blowing snow (visibility obstructions) as demonstrated in the table.

Table 4-12: Description of independent variable used in the model

Description of variables	% days, Toronto & AST		% days, London & ASL	
(1) Daily mean temperature				
<-10^{0}C	8%		9%	
-10^{0}C to -3^{0}C	30%		31%	
-2^{0}C to +2^{0}C	26%		24%	
> +2^{0}C	37%		36%	
(2) Daily total rainfall				
No rainfall (<0.4mm)	76%		72%	
Low rainfall (0.4-2.0mm)	8%		10%	
Medium rainfall (2.1-5.0mm)	6%		6%	
Heavy rainfall (> 5.0mm)	10%		12%	
(3) Daily total snowfall				
No snowfall (< 0.4cm)	78%		62%	
Low snowfall (0.4-2.0cm)	12%		17%	
Medium snowfall (2.1-5.0cm)	6%		13%	
Heavy snowfall (> 5cm)	4%		8%	
(4) Freezing rain (freezing rains, ice-pellets)				
No	94%		90%	
Yes	6%		10%	
(5) Visibility obstruction (fog, smoke, or blowing snow)				
No	72%		54%	
Yes	28%		46%	
(6) Average hourly wind speed				
Low wind (< 16 km/h)	45%		53%	
Medium wind (16-32 km/h)	49%		45%	
Strong wind (> 32 km/h)	5%		2%	
(7) Winter traffic exposure adjustment factor	Toronto	AST	London	ASL
≤ 1.10	14%	19%	14%	20%
1.11-1.20	5%	9%	36%	15%
1.21-1.30	58%	27%	50%	44%
> 1.30	23%	46%	-	21%
(8) Months				
Nov-Dec	32%		32%	
Jan-Feb	34%		34%	
Mar-Apr	34%		34%	
(9) Timing of precipitation				
No precipitation	69%		62%	
Either morning or afternoon	19%		35%	
Both morning and afternoon	12%		13%	

Initially, four additional crash-risk factors were also considered – daily total precipitation, sunlight, holidays and day of the week. After correlation tests, precipitation was dropped from the models because precipitation had a strong correlation with two other risk factors, daily total rain and daily total snow. Appropriate sunlight data and winter traffic exposure values for the holidays were not available. Therefore, these two independent variables were also eliminated from the models. Finally, day of the week was also removed from the model because it had a strong correlation with the winter traffic exposure adjustment factor.

Section four of the literature review chapter describes how temperature, rainfall, snowfall, freezing rain, fog, smoke, blowing snow, and daylight affect traffic crashes. A winter traffic exposure adjustment factor was also developed and applied in order to normalize exposure based on whether or not precipitation occurred as well as day of the week. The models did not include holidays because of the unavailability of exposure adjustment data for long weekends and other holiday events that would alter travel patterns. Also, a time variable, months, was used to measure their influences on high-crash days. The descriptive data analysis showed that winter months November and December have similar daily average crash rate. Therefore, these two months were grouped together (Table 4-13). As winter traffic exposure factor was developed considering day of the week, another time variable, day of the week, was not used in modeling.

Table 4-13: Daily Average crash rate in different months in the study areas

Month	Toronto	AST	London	ASL
Nov	266	27	24	23
Dec	267	26	24	23
Jan	297	29	25	22
Feb	271	25	25	23
Mar	208	17	18	17
Apr	213	16	18	16
Average	243	21	20	18

The binary logistic regression model was developed on all days (except holidays) for six months (November to April) of seven years (2003-2009). Therefore, the total number of cases (days) was 1186. Considering 29 independent variables, the variable to case ratio was 1: 41, which is greater than preferable limit of simultaneous regression model, as developed here.

Chapter 5

Results of the study

This chapter presents the results of the study that are organized into three sections. The first section investigates high-crash days and their safety implications. The second section describes the winter traffic exposure adjustment factor that is used as a proxy variable instead of traffic volume. The third section summarizes the results of the logistic regression models, and justifies the application of logistic regression model in explaining the occurrence of high-crash days.

5.1 Safety implications of high-crash days

The study defined high-crash days in three ways in the previous chapter (section 4.3). There high-crash days were identified considering the entire year. This section focuses on winter months (November-April) for the study period, 2003-2009. The results showed that on average 83% of the total high-crash days, as defined according to the first approach, occurred in the winter months (November to April). The share of high-crash day occurrence varied among the definitions. According to the second and the third definitions, 92% and 70% of the total high-crash days were found in the winter periods. This finding indicates that the driving in the winter (November to April) is more risky than the summer. This finding confirms the finding of many road safety studies (Andreescu & Frost, 1998; Nilsson & Obrenovic, 1998). The winter may have some special features that contribute to frequent traffic crashes. Thus, the decision was taken to restrict the modeling exercise to the November to April period. It was expected that weather conditions during November to April contributed to the frequent occurrence of high-crash days during this time period of the year.

Drivers' crash risk was highly elevated on these outlier days. Figures 5-1 to 5-3 illustrate that the daily average crash rate was substantially different between high-crash and non-high-crash days in the study areas. The daily average crash rate was almost doubled on high-crash days relative to non-high crash days in all study areas except the Area Surrounding Toronto (AST), where the crash rate increased by two and half times. This finding was consistent across three definitions of high-cash days. On high-crash days, the increase in average daily crash rate was slightly more in the areas surrounding Toronto and London than in these two urban areas in Southern Ontario. This result is same as the finding of earlier study (Andrey et al., 2012).

Fig. 5-1: Crash differences during November-April according to the first definition

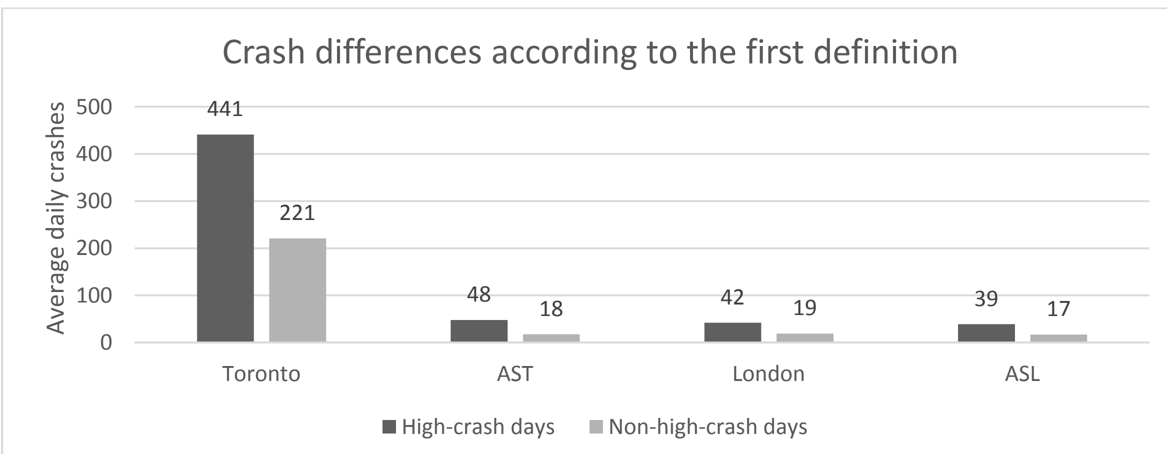


Fig. 5-2. Crash differences during November-April according to the second definition

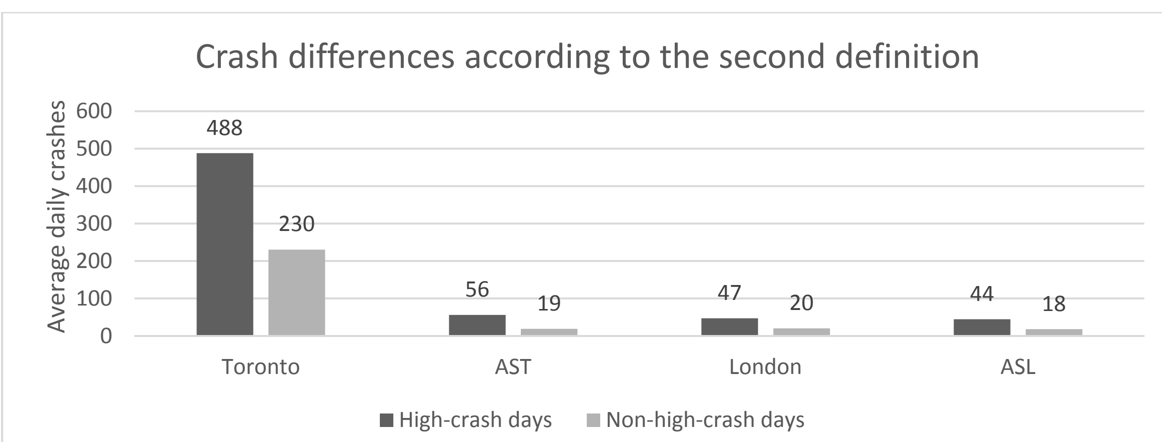
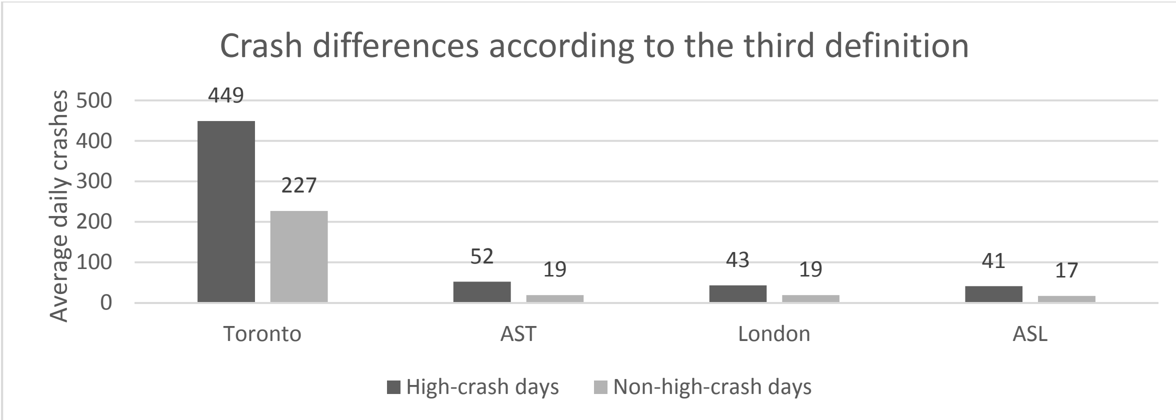


Fig. 5-3: Crash differences during November-April according to the third definition



The results of the study revealed that focusing on high-crash days was potentially a valuable approach to improve safety conditions in the study areas because a small proportion of high-crash days was responsible for a considerable share of traffic crashes and casualties during the winter (Table 5-1). The proportion of high crash days and their effects on traffic crashes and casualties varied across definitions. The table 5-1 shows that high-crash days occurred 12% to 19% of the winter days but they were accounted for 25% to 35% of the winter crashes and 23% to 32% of the winter casualties. In AST and ASL study areas, high-crash days had particularly elevated collision and casualty counts in comparison to Toronto and London.

By definition, high-crash days had a disproportionately higher number of crashes than the other winter days, but overall these crashes were less severe in nature, as summarized in Table 5-2. More than 80% of these crashes were property-damage-only crashes in each study area. This table also indicates that the severity profiles of crashes on high-crash days versus other days varied more in Toronto and London than in their surrounding areas. For example, according to the first definition, the proportion of property-damage-only crashes increased in all study areas, but the increase was by 2.70% to 2.90% in Toronto and London whereas by 0.50% to 0.90% in their surrounding areas, AST and ASL, respectively.

Table 5-1: Safety implications of high-crash days

1st definition			
Area	% of winter days	% of winter crashes	% of winter casualties
Toronto	18%	30%	25%
AST	20%	40%	37%
London	18%	33%	28%
ASL	19%	36%	36%
Average	19%	35%	32%
2nd definition			
Toronto	12%	22%	18%
AST	13%	29%	28%
London	12%	24%	20%
ASL	12%	26%	26%
Average	12%	25%	23%
3rd definition			
Toronto	15%	26%	21%
AST	15%	32%	30%
London	15%	29%	25%
ASL	15%	30%	29%
Average	15%	29%	26%

Table 5-2: The effects of high crash days on the severity of crashes

Crash Type	High-crash days				Normal winter days			
	Toronto	**AST**	**London**	**ASL**	**Toronto**	**AST**	**London**	**ASL**
1st definition								
Fatal	0.1%	0.3%	0.1%	0.4%	0.1%	0.4%	0.1%	0.6%
Injury	17.1%	16.0%	15.8%	18.4%	19.8%	16.8%	18.6%	18.8%
PDO	82.8%	83.7%	84.2%	81.1%	80.1%	82.8%	81.3%	80.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
2nd definition								
Fatal	0.1%	0.3%	0.0%	0.4%	0.1%	0.4%	0.1%	0.6%
Injury	16.6%	15.7%	15.1%	18.7%	19.8%	16.8%	18.6%	18.8%
PDO	83.3%	84.1%	84.8%	80.9%	80.1%	82.8%	81.3%	80.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
3rd definition								
Fatal	0.1%	0.3%	0.1%	0.3%	0.1%	0.4%	0.1%	0.6%
Injury	16.8%	15.6%	15.9%	18.2%	19.8%	16.8%	18.6%	18.8%
PDO	83.1%	84.1%	84.0%	81.4%	80.1%	82.8%	81.3%	80.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

5.2 Winter traffic exposure adjustment factors

Winter traffic exposure adjustment factors were developed to quantitatively estimate the extent to which traffic counts varied by day of the week and by measurable precipitation conditions (daily total precipitation > 0.4 mm). The first step in creating these adjustment factors was to calculate the average daily traffic count for each day of the week for both good and precipitation days (days with total precipitation > 0.4 mm) at ten locations in the four study areas as summarized in Tables 5-3 and 5-4. These two tables reveal that Sundays with measurable precipitation conditions typically have the lowest traffic counts, except for Grand Bend, which is a famous tourist spot located in the Area Surrounding London (ASL). The weekend traffic movement in Grand Bend is different than the other nine locations due to its large number of tourist activities on weekends.

Considering the traffic counts for Sundays with measurable precipitation conditions as the base, the study subsequently developed site-specific traffic exposure adjustment factors for both good and precipitation days in all ten locations (Table 5-4 and 5-5). Finally, the winter traffic exposure adjustment factors were estimated by averaging three raw traffic exposure adjustment factors for each of Toronto, AST and ASL (Table 5-7and 5-8). Due to unavailability of city-wide traffic count data, London had only one traffic exposure adjustment factor. The resulting values showed the relative exposure to travel risks considering the impacts of precipitation and day of the week. For example, the top left cell value of Table 5-7 is 1.09, which indicate that the traffic volume at Toronto is 9% higher on Sundays with good weather conditions than on Sundays with measurable precipitation conditions. Similarly, the cell value below it (1.24) specifies that the traffic volume at Toronto is 24% higher on Mondays with good weather conditions than on Sundays with measurable precipitation conditions.

Table 5-3: Daily average daily traffic count on good-weather days

Day of week	Toronto			AST			London	ASL		
	Dixie	Mississauga	Keele	Snelgrove	Milton	Maple	London	Woodstock	Simcoe	Grand Bend
Sun	139,399	120,988	215,999	14,612	97,712	78,095	21,567	37,728	4,655	3,523
Mon	160,506	128,915	258,983	17,835	115,997	91,188	25,820	40,116	6,066	3,331
Tue	165,932	136,449	260,296	17,887	117,194	93,385	26,337	41,249	6,490	3,417
Wed	165,665	142,171	264,074	18,301	118,311	96,624	25,446	42,287	6,631	3,443
Thu	169,080	144,252	274,235	18,717	124,963	99,551	25,598	43,970	6,768	3,616
Fri	175,237	151,177	272,183	19,693	132,012	105,183	26,357	48,867	7,191	4,018
Sat	155,519	138,221	244,581	15,844	104,483	84,748	24,996	35,858	5,653	3,633
Average	161,561	137,614	255,397	17,524	115,419	92,669	25,227	41,528	6,136	3,574

Table 5-4: Daily average traffic count on precipitation days

Day of week	Toronto			AST			London	ASL		
	Dixie	Mississauga	Keele	Snelgrove	Milton	Maple	London	Woodstock	Simcoe	Grand bend
Sun	132,046	104,715	203,069	13,967	90,183	69,520	21,128	34,506	4,196	3,279
Mon	149,251	136,573	240,198	17,249	111,405	89,849	25,049	38,326	6,098	3,203
Tue	152,212	144,270	246,160	17,874	117,721	90,230	24,568	40,034	6,256	3,183
Wed	157,245	137,227	249,556	18,178	114,631	90,157	25,763	41,844	6,184	3,244
Thu	160,549	138,349	253,989	18,139	120,044	93,839	25,576	42,935	6,502	3,361
Fri	169,834	139,150	269,471	194,39	123,205	102,188	26,400	48,011	6,871	3,962
Sat	150,386	123,942	230,890	15,459	97,650	73,616	24,036	34,719	5,328	3,231
Average	154,030	133,856	243,309	17,339	112,501	87,478	24,870	40,321	6,018	3,343

Table 5-5: Site-specific traffic exposure adjustment variable for good-weather days

Day of week	Toronto			AST			London	ASL		
	Dixie	Missis sauga	Keele	Snelgr ove	Milt on	Maple	London	Woods tock	Simcoe	Grand Bend
Sun	1.06	1.16	1.06	1.05	1.08	1.12	1.02	1.09	1.11	1.07
Mon	1.22	1.23	1.28	1.28	1.29	1.31	1.22	1.16	1.45	1.02
Tue	1.26	1.30	1.28	1.28	1.30	1.34	1.25	1.20	1.55	1.04
Wed	1.25	1.36	1.30	1.31	1.31	1.39	1.20	1.23	1.58	1.05
Thu	1.28	1.38	1.35	1.34	1.39	1.43	1.21	1.27	1.61	1.10
Fri	1.33	1.44	1.34	1.41	1.46	1.51	1.25	1.42	1.71	1.23
Sat	1.18	1.32	1.20	1.13	1.16	1.22	1.18	1.04	1.35	1.11

Table 5-6: Site-specific traffic exposure adjustment variable for precipitation days

Day of week	Toronto			AST			London	ASL		
	Dixie	Missis sauga	Keele	Snelgr ove	Milt on	Maple	London	Woods tock	Simcoe	Grand Bend
Sun	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mon	1.13	1.30	1.18	1.23	1.24	1.29	1.19	1.11	1.45	0.98
Tue	1.15	1.38	1.21	1.28	1.31	1.30	1.16	1.16	1.49	0.97
Wed	1.19	1.31	1.23	1.30	1.27	1.30	1.22	1.21	1.47	0.99
Thu	1.22	1.32	1.25	1.30	1.33	1.35	1.21	1.24	1.55	1.03
Fri	1.29	1.33	1.33	1.39	1.37	1.47	1.25	1.39	1.64	1.21
Sat	1.14	1.18	1.14	1.11	1.08	1.06	1.14	1.01	1.27	0.99

Table 5-7: Average winter traffic exposure adjustment variable for good-weather days

Day of week	Toronto	AST	London	ASL
Sun	1.09	1.08	1.02	1.09
Mon	1.24	1.29	1.22	1.21
Tue	1.28	1.31	1.25	1.26
Wed	1.30	1.34	1.20	1.29
Thu	1.34	1.39	1.21	1.33
Fri	1.37	1.46	1.25	1.45
Sat	1.23	1.17	1.18	1.16

Table 5-8: Average winter traffic exposure adjustment variable for precipitation days

Day of week	Toronto	AST	London	ASL
Sun	1.00	1.00	1.00	1.00
Mon	1.21	1.25	1.19	1.18
Tue	1.25	1.29	1.16	1.21
Wed	1.24	1.29	1.22	1.23
Thu	1.26	1.33	1.21	1.27
Fri	1.31	1.41	1.25	1.41
Sat	1.15	1.08	1.14	1.09

Table 5-9 shows the reduction in traffic movements on different day of the week due to precipitation alone (e.g., by comparing traffic counts on precipitation days versus good-weather days). The reduction in traffic volume was similar in all study areas except London. The percentage reduction in London was somewhat different, possibly due to fewer count stations in London.

Table 5-9: Reduction in traffic volume due to precipitation conditions and day of week

Day of week	Toronto	AST	London	ASL
Sun	8%	8%	2%	8%
Mon	3%	3%	3%	2%
Tue	3%	1%	7%	4%
Wed	5%	4%	-1%	5%
Thu	6%	4%	0%	4%
Fri	4%	4%	0%	3%
Sat	7%	8%	4%	7%

Overall, the results demonstrate that precipitation has more influence on traffic volume during weekends than weekdays, and Sundays observe the highest reduction in traffic volume. This finding is in consistent with the findings of some earlier studies (Dalta & Sharma, 2010; Hanabali and Kuemmel, 1993; Knapp, et al. 2000; Keay & Simmonds, 2005). This finding indicates that drivers' behavioural adjustments work best to off-set the influences of precipitation during weekends, especially on Sundays, when people have more flexibility to make decisions about discretionary trips. The table also shows that traffic movements on Monday, Tuesday and Friday are the least affected by precipitation. This finding is found possibly due to the nature of trips made on those days in the study areas.

5.3 The results of the logistic regression models

The study developed several binary logistic regression models to estimate the influence of weather, traffic exposure, and time variables on the occurrence of high-crash days. The section begins by discussing the results of the three binary logistic regression models for Toronto. Thereafter, a comparison of three competing models is made to identify the best suitable model for the problem at hand. The last part of this section is then report a comparison of model results in all study areas to identify any spatial differences among them.

The results of the logistic regression models in Toronto (Tables 5-10, 5-11 and 5-12) confirmed the expectation that inclement weather, winter traffic exposure and time variables influence the occurrence of high-crash days. The different test statistics of the logistic regression models ensured that the models suited the data. The omnibus test results suggested that all models fitted the data relatively well with a large test statistic (385.652 to 490.417) and a small ρ-value (.000). The statistical significance of these tests provided the evidence that the combination of independent variables used in the model can explain the occurrence of high-crash days. The likelihood ratio test examines "the difference between -2 log likelihood for the full model with all predictors and -2 log likelihood for initial chi-square in null model" (Bruns & Bruns, 2008: 575). The results of the models showed that all the models with predictors had lower -2 log likelihood ratios than the null models with a constant only in them, suggesting that the inclusion of independent variables had notably improved the model and had reduced the errors in predicting high-crash days. The chi-square statistics from Hosmer and Lemeshow goodness-of-fit tests were insignificant at 95% confidence level, implying well-fitting models. The overall accuracies of three models for Toronto were satisfactory since the full models with the predictors correctly classified 88.5%, 91.7%, 88.8% of the cases, respectively.

In addition to odds ratios of the independent variables Exp (B) with upper and lower bounds defined at the 95% confidence interval, Table 5-10 to 5-12 also reports logistic coefficient (B), standard errors (S.E.), Wald statistics and ρ-values. The Wald statistics and associated ρ-values give an index of significance of each independent variable in the regression equation. It should be noted that all standard errors from the independent variables in the tables were lower than 2.0, indicating no numerical problems in the models.

Table 5-10 presents the results of the logistic regression model which followed the first definition of high-crash days, i.e., the 10% of days with highest daily crash counts. Among the nine risk factors, six factors significantly influenced the occurrence of high-crash days: temperature, snowfall, visibility obstruction, winter traffic exposure adjustment factors, months, and timing of precipitation. All the factors were categorical in nature, and as such they were represented by multiple independent variables (e.g., there are four temperature categories and therefore three comparisons with the baseline temperature category of <-10^{0}C). In summary, 13 out of 29 independent variables had statistically significant influences on the odds of high crash days. The results of the first model are summarized below:

Daily mean temperature had a significant influence on the likelihood of high-crash days. More specifically, as temperature increased, the odds of being a high-crash day decreased. This findings is in consistent with some previous findings (Andreescu & Frost, 1998; Brijs et al., 2008; Usman et al., 2011). In Toronto, almost one-third of the winter days had daily mean temperature of -10^{0}C to -3^{0}C. The model showed that high-crash days were 90% less likely to occur at -10^{0}C to -3^{0}C daily mean temperature in comparison to days with mean temperatures of less than -10^{0}C. However, at positive temperatures (>+2^{0}C), the odds of a high-crash day were very low (OR=0.008) but significant (ρ=0.000).

The results of the first model also showed that rainfalls in general and small-accumulations of snowfall did not have any significant influence on high-crash days. Drivers in the Toronto seem to be adjusted to driving in the rain and light snowfalls during winter months (November-April). Moreover, vehicular engineering measures (i.e., snow tires and electronic stability control), drivers' adjustments, and effective winter road maintenance may offset the risk of traffic crashes during rainfalls and small-accumulation of snowfalls in the winter. However, these countermeasures do not appear to be as effective during medium to heavy snowfalls as driving becomes significantly risky in such hazardous weather conditions. The odds ratios for medium and heavy snowfall were approximately 9 times and 16 times higher than on a good weather day with no and/or negligible snowfall (<0.4 cm), respectively. This result confirmed the earlier finding that the intensity of snowfall matters in crash counts (Andrey, 2010).

Although the literature reports that driving during freezing rain can be very risky (Qin et al., 2006, Andrey et al., 2003), the model results did not detect any significant influence of freezing rain on the likelihood of high-crash days. Most probably, the rarity of such incidence in the study area (6% of the winter days), reduced traffic volumes and precautionary winter road maintenance were the reasons behind this finding.

The probability of high-crash days was influenced by visibility obstructions (fog, smoke or blowing snow) and by strong wind speed. This finding complements the findings of previous safety literature (Usman et al., 2011 on visibility obstruction; and Edwards, 1994 on wind). The odds ratio of a day with visibility obstructions increased approximately by two times in comparison to a day with clear weather condition. It appears that fog, smoke or blowing snow, which occur on 28% of winter days, restrict drivers' visibility and thus elevate the frequency of crashes. Therefore, these weather parameters increase the odds of high crash days. Also, the model was sensitive to strong wind only. The strong wind (average hourly wind speed of >32 km/h) significantly amplified the likelihood of a high-crash day by almost three times in comparison to low wind (average hourly wind speed of <16 km/h).

The model provided evidence that the proxy exposure variables for traffic volumes (winter traffic exposure adjustment factors) is highly significant and have a positive relationship with high-crash days. The odds ratio of a day with a winter traffic exposure adjustment factor of 1.11-1.20 was approximately 7 times higher than a day with winter traffic exposure adjustment factor of ≤1.10. The finding indicates that the higher the exposure, the greater the odds of a high crash day. Usually, weekends and precipitation conditions are associated with lower traffic exposure than weekdays and good weather conditions, and this lowered exposure reduces the probability of a high-crash day. This finding restate the findings of previous studies that inclement weather conditions reduce traffic exposure (Dalta & Sharma, 2010; Hanbali & Kuemmel, 1992; Knapp et al., 2000; Maze et al., 2006). The highest odds ratios occurred on days with a traffic exposure factor of >1.30, i.e. on those days when traffic volumes were the highest. This finding was as expected.

The likelihood of high-crash days varied throughout the winter season as shown by the 'months' variable in the table 5-10. The model showed that early winter months (November-December) were the most problematic. This result is in consistent with the finding of previous road safety studies (Farmer & Williams, 2005; cf. Pisano et al., 2008). As the winter season passed, the odds of high-crash day occurrence reduced gradually. The odds of high-crash days in January- February and March-April were 55.7% and 86.6%, respectively, lower in comparison to that of November-December. The probable explanation of this finding may be that the drivers take time to adjust to winter driving situations, thereby increasing collision frequency in early winter months.

Finally, if the precipitation events coincided with both morning and evening peak hours, the odds of high-crash days increased approximately 11 times more than a day with no precipitation during the peak hours. In this case, the likely explanation is that high traffic volume during the rush hours and precipitation act as compound hazards for the drivers.

Table 5-11 presents the results of the logistic regression model that applied the second definition of high-crash days, i.e., days with a z-score of greater than or equal to 1.5 for crash count. All the test statistics showed that this model also complied with the data. This model provided similar results to the first model described above. The magnitude of odds ratios and ρ values were similar. However, there was only one change in the nature of relationship which was indicated by coefficient B. This change was observed in the independent variable, strong wind speed (>32 km/h), which was relatively a rare incidence (occurred on 5% of winter days) in the study area. Strong wind did not have any significant influence on the probability of high-crash days in the second model.

Finally, Table 5-12 shows the results of the logistic regression which followed the third approach for defining high-crash day, i.e., the 10% of days having the largest positive differences between observed and expected crash counts. The model test statistics confirmed that the model also suited the data. The findings of this model regarding temperature, winter precipitations (rainfalls, snowfalls and freezing rains) and timing of precipitation were in consistent with the other two models. However, this model provided slightly different results in terms of visibility obstructions, wind speeds, winter traffic exposure adjustment factors, and months explanatory variables. Unlike the first model, this analysis found that visibility obstructions did not have any influence on the occurrence of high-crash days. However, the influence of strong wind was found significant in both the first model and the third model. In contrast to the earlier two models, the third model did not show any significant influence of the winter traffic exposure adjustment factor on the likelihood of high-crash days. This finding was expected because traffic exposure was intrinsic in the third definition of high-crash days. In the third definition, the expected traffic counts were calculated considering traffic exposure adjustment factors for years, months, and days of the week. Finally, the third model identified March-April, which coincided with the beginning of spring when the weather was warmer, did not have any significant influence on the odds of high crash days in comparison to November-December.

Table 5-10: Results of the first model in Toronto

Description of variables	Reference category	B	S. E.	Wald	ρ value	Odds ratio (OR)	95% CI	
							Lower	Upper
(1) Daily mean temperature	<-10^{0}C							
-10^{0}C to -3^{0}C		-2.303	0.318	52.543	0.000*	0.100	0.054	0.186
-2^{0}C to +2^{0}C		-4.188	0.441	90.368	0.000*	0.015	0.006	0.036
> +2^{0}C		-4.775	0.539	78.379	0.000*	0.008	0.003	0.024
(2) Daily total rainfall	No rainfall (<0.4mm)							
Low rainfall (0.4-2.0mm)		0.028	0.544	0.003	0.960	1.028	0.354	2.987
Medium rainfall (2.1-5.0mm)		0.440	0.558	0.623	0.430	1.553	0.521	4.633
Heavy rainfall (> 5.0mm)		0.771	0.519	2.211	0.137	2.163	0.782	5.978
(3) Daily total snowfall	No snowfall (< 0.4cm)							
Low snowfall (0.4-2.0cm)		0.250	0.325	0.590	0.442	1.284	0.679	2.427
Medium snowfall (2.1-5.0cm)		2.238	0.406	30.335	0.000*	9.372	4.227	20.782
Heavy snowfall (> 5cm)		2.778	0.533	27.126	0.000*	16.080	5.654	45.735
(4) Freezing rain (freezing rains, ice-pellets)	No							
Yes		0.003	0.434	0.000	0.994	1.003	0.429	2.347
(5) Visibility obstruction (fog, smoke, or blowing snow)	No							
Yes		0.824	0.308	7.159	0.007*	2.279	1.247	4.168
(6) Average hourly wind speed	Low wind (< 16 km/h)							
Medium wind (16-32 km/h)		0.096	0.223	0.184	0.668	1.100	0.711	1.703
Strong wind (> 32 km/h)		1.121	0.414	7.320	0.007*	3.067	1.362	6.908
(7) Winter traffic exposure adjustment factor	≤ 1.10							
1.11-1.20		1.901	0.697	7.433	0.006*	6.693	1.706	26.254
1.21-1.30		2.924	0.573	26.020	0.000*	18.624	6.054	57.288
> 1.30		3.837	0.607	39.984	0.000*	46.375	14.119	152.321
(8) Months	Nov-Dec							
Jan-Feb		-0.811	0.259	9.809	0.002*	0.444	0.267	0.738
Mar-Apr		-1.966	0.342	33.067	0.000*	0.140	0.072	0.274
(9)Timing of precipitation	No precipitation							
Either morning or evening		0.447	0.334	1.791	0.181	1.564	0.812	3.011
Both morning and evening		2.418	0.402	36.238	0.000*	11.224	5.108	24.664
(10) Constant		-2.201	0.657	11.222	0.001*	0.111		

*ρ<0.05

Omnibus test: Chi-square = 490.417, df = 20, p-value = 0.000, -2 Log likelihood = 617.105, Hosmer and Lemeshow Test: Chi-square = 10.060, df = 8, p-value = 0.261

Table 5-11: Results of the second model in Toronto

Description of variables	Reference category	B	S. E.	Wald	ρ value	Odds ratio (OR)	95% CI	
							Lower	Upper
(1) Daily mean temperature	<-10^{0}C							
-10^{0}C to -3^{0}C		-2.367	0.348	46.390	0.000*	0.094	0.047	0.185
-2^{0}C to +2^{0}C		-4.061	0.509	63.604	0.000*	0.017	0.006	0.047
> +2^{0}C		-5.245	0.704	55.522	0.000*	0.005	0.001	0.021
(2) Daily total rainfall	No rainfall (<0.4mm)							
Low rainfall (0.4-2.0mm)		0.003	0.665	0.000	0.996	1.003	0.273	3.690
Medium rainfall (2.1-5.0mm)		-0.615	0.821	0.562	0.453	0.541	0.108	2.700
Heavy rainfall (> 5.0mm)		0.666	0.651	1.047	0.306	1.946	0.544	6.970
(3) Daily total snowfall	No snowfall (< 0.4cm)							
Low snowfall (0.4-2.0cm)		-0.150	0.398	0.142	0.706	0.861	0.395	1.877
Medium snowfall (2.1-5.0cm)		1.705	0.428	15.834	0.000*	5.501	2.375	12.740
Heavy snowfall (> 5cm)		2.368	0.530	19.985	0.000*	10.676	3.780	30.149
(4) Freezing rain (freezing rains, ice-pellets)	No							
Yes		0.648	0.463	1.955	0.162	1.911	0.771	4.738
(5) Visibility obstruction (fog, smoke, or blowing snow)	No							
Yes		0.532	0.369	2.079	0.149	1.702	0.826	3.505
(6) Average hourly wind speed	Low wind (< 16 km/h)							
Medium wind (16-32 km/h)		-0.034	0.260	0.017	0.896	0.967	0.581	1.608
Strong wind (> 32 km/h)		0.326	0.521	0.392	0.531	1.386	0.499	3.847
(7) Winter traffic exposure adjustment factor	≤ 1.10							
1.11-1.20		1.916	0.752	6.496	0.011*	6.794	1.557	29.649
1.21-1.30		2.401	0.620	14.991	0.000*	11.033	3.272	37.197
> 1.30		3.009	0.659	20.866	0.000*	20.262	5.572	73.680
(8) Months	Nov-Dec							
Jan-Feb		-0.745	0.310	5.795	0.016*	0.475	0.259	0.871
Mar-Apr		-1.817	0.430	17.866	0.000*	0.163	0.070	0.377
(9) Timing of precipitation	No precipitation							
Either morning or evening		0.667	0.397	2.814	0.093	1.948	0.894	4.245
Both morning and evening		2.735	0.470	33.932	0.000*	15.413	6.141	38.688
(10) Constant		-2.214	0.721	9.441	0.002	0.109		

*ρ<0.05

Omnibus test: Chi-square = 385.652, df = 20, p-value = 0.000, -2 Log likelihood = 467.329, Hosmer and Lemeshow Test: Chi-square = 3.729, df = 8, p-value = 0.881

Table 5-12: Results of the third model in Toronto

Description of variables	Reference category	B	S. E.	Wald	ρ value	Odds ratio (OR)	95% CI	
							Lower	Upper
(1) Daily mean temperature	<-10^{0}C							
-10^{0}C to -3^{0}C		-2.293	0.325	49.704	0.000*	0.101	0.053	0.191
-2^{0}C to +2^{0}C		-4.250	0.464	83.957	0.000*	0.014	0.006	0.035
> +2^{0}C		-4.706	0.554	72.132	0.000*	0.009	0.003	0.027
(2) Daily total rainfall	No rainfall (<0.4mm)							
Low rainfall (0.4-2.0mm)		0.274	0.553	0.246	0.620	1.316	0.445	3.891
Medium rainfall (2.1-5.0mm)		0.392	0.606	0.419	0.517	1.480	0.451	4.855
Heavy rainfall (> 5.0mm)		1.054	0.538	3.842	0.050	2.870	1.000	8.236
(3) Daily total snowfall	No snowfall (< 0.4cm)							
Low snowfall (0.4-2.0cm)		0.517	0.326	2.520	0.112	1.678	0.886	3.179
Medium snowfall (2.1-5.0cm)		2.094	0.389	28.919	0.000*	8.118	3.784	17.413
Heavy snowfall (> 5cm)		2.966	0.515	33.119	0.000*	19.416	7.071	53.317
(4) Freezing rain (freezing rains, ice-pellets)	No							
Yes		0.089	0.416	0.046	0.831	1.093	0.484	2.468
(5) Visibility obstruction (fog, smoke, or blowing snow)	No							
Yes		0.576	0.323	3.177	0.075	1.779	0.944	3.350
(6) Average hourly wind speed	Low wind (< 16 km/h)							
Medium wind (16-32 km/h)		-0.035	0.230	0.023	0.881	0.966	0.616	1.515
Strong wind (> 32 km/h)		0.936	0.426	4.832	0.028*	2.551	1.107	5.880
(7) Winter traffic exposure adjustment factor	≤ 1.10							
1.11-1.20		0.686	0.516	1.772	0.183	1.987	0.723	5.459
1.21-1.30		0.568	0.364	2.431	0.119	1.765	0.864	3.605
> 1.30		0.718	0.410	3.059	0.080	2.050	0.917	4.581
(8) Months	Nov-Dec							
Jan-Feb		-0.983	0.289	11.598	0.001*	0.374	0.212	0.659
Mar-Apr		-0.483	0.295	2.677	0.102	0.617	0.346	1.100
(9) Timing of precipitation	No precipitation							
Either morning or evening		0.330	0.339	0.944	0.331	1.391	0.715	2.705
Both morning and evening		2.064	0.391	27.864	0.000*	7.878	3.661	16.953
(10) Constant		-0.260	0.507	0.264	0.607	0.771		

*ρ<0.05

Omnibus test: Chi-square = 398.693, df = 20, p-value = 0.000, -2 Log likelihood = 597.357, Hosmer and Lemeshow Test: Chi-square = 10.953, df = 8, p-value = 0.204

A comparison of the three models for Toronto is provided in Table 5-13. The table reveals that the model results were mostly insensitive to the definition of high-crash days. It is apparent from the table that the results were fairly consistent across the models in regard to the significance of independent variables and their relationships with high-crash days. The first two model were almost identical in their estimations of the influences of independent variables, except two discrepancies in terms of visibility obstruction and strong wind speed; however, their relationship direction (positive/negative association) were not an issue between the models. The third model also showed mostly consistent results but differed mainly in terms of winter traffic exposure's influence on high-crash days. According to the third model, the influence of traffic exposure on high-crash days was non-significant. This finding contradicted the findings of first two models and the safety literature (Dalta & Sharma, 2010; Hanabali and Kuemmel, 1993; Knapp, et al. 2000). The reason for this exception is explained in the above paragraph.

Although all models fitted the data, the question remained as to which model was the most suitable for the problem and the data at hand. The logistic regression model calculates the correlation estimates Nagelkerke's R^2 to identify the strength of relationship between the predictors and the dependent variable. The theoretical value of Nagelkerke's R^2 ranges between 0 and 1. The Nagelkerke's R^2 of the first, the second and the third models were 0.558, 0.541 and 0.502, respectively, suggesting that the first model better explained the variability in the dependent variable.

As the accuracy of the logistic regression model cannot be determined by Nagelkerke's R^2, the *SPSS* software provides classification tables which estimate the proportion of cases that the model classifies correctly. Overall, the three models correctly classified 88.5%, 91.7% and

88.8% of the cases, but the accuracy of correctly predicted high-crash days were 60.0%, 48.6% and 43.2%, respectively. The usefulness of logistic regression model can be evaluated by examining the accuracy that is not achieved by chance. Logistic regression model can sometimes correctly predicts the case membership of groups, despite the non-existence of relationships between dependent and independent variables. This is known as by chance accuracy. The proportional by chance accuracy is calculated by adding the square percentage of cases in each group in the null models with a constant only. If the model's overall percentage accuracy rate in the full model with the predictors is 25% higher than the proportional by chance accuracy in the null model, then the model is considered useful. Using this test, it was found that only the first model passed the test.

Considering the percentage of correct high-crash day prediction and the result of by chance accuracy test, it was determined that the fist model was the most useful logistic regression model for the Toronto. Therefore, for the rest three study areas, only the first model had been run to compute the influence of weather, exposure and time variables on the likelihood of high-crash days.

Finally, the study examined the variability of the first model results across all study areas. Since the models used different datasets for different study areas, the effect sizes (value of odds ratios) of the models were not directly comparable. Instead, a comparison was carried in terms of the notable influence of independent variables (whether ρ value is significant or insignificant) and the association type (whether the odds ratio is OR>1 or OR<1) of independent variables with dependent variable.

Table 5-13: Comparison among the model results in Toronto

Description of variables	Reference category	Model 1 ρ	Model 2 ρ	Model 3 ρ	Model 1 OR	Model 2 OR	Model 3 OR
(1) Daily mean temperature	<-10⁰C						
-10⁰C to -3⁰C		x	x	x	-	-	-
-2⁰C to +2⁰C		x	x	x	-	-	-
> +2⁰C		x	x	x	-	-	-
(2) Daily total rainfall	No rainfall (<0.4mm)						
Low rainfall (0.4-2.0mm)		o	o	o	+	+	+
Medium rainfall (2.1-5.0mm)		o	o	o	+	-	+
Heavy rainfall (> 5.0mm)		o	o	o	+	+	+
(3) Daily total snowfall	No snowfall (< 0.4cm)						
Low snowfall (0.4-2.0cm)		o	o	o	+	-	+
Medium snowfall (2.1-5.0cm)		x	x	x	+	+	+
Heavy snowfall (> 5cm)		x	x	x	+	+	+
(4) Freezing rain (freezing rains, ice-pellets)	No						
Yes		o	o	o	+	+	+
(5) Visibility obstruction (fog, smoke, or blowing snow)	No						
Yes		x	o	o	+	+	+
(6) Average hourly wind speed	Low wind (< 16 km/h)						
Medium wind (16-32 km/h)		o	o	o	+	-	-
Strong wind (> 32 km/h)		x	o	.x	+	+	+
(7) Winter traffic exposure adjustment factor	≤ 1.10						
1.11-1.20		x	x	o	+	+	+
1.21-1.30		x	x	o	+	+	+
> 1.30		x	x	o	+	+	+
(8) Months	Nov-Dec						
Jan-Feb		x	x	x	-	-	-
Mar-Apr		x	x	o	-	-	-
(9) Timing of precipitation	No precipitation						
Either morning or evening		o	o	o	+	+	+
Both morning and evening		x	x	x	+	+	+

O = Non-significant + = Positive relationship

X = Significant - = Negative relationship

Table 5-14 compares the ρ value and the odds ratios of the first models in all study areas (Full model results are available in Table 5-10 and also in the Appendix A). There were not any noticeable differences in the models results among the study areas, except for medium wind speed (16-32 km/h). Medium wind did not have an influence on the occurrence of high-crash days in Toronto and London. However, it had significant influence on high-crash day occurrences in the two study areas surrounding them, possibly due to drifting snow along some roadway sections on high-speed roads.

Table 5-14 also shows that the independent variables that had significant influence on high-crash day occurrence were associated with high-crash days in the same direction (either positive or negative) across the study areas. The most interesting finding was that all categories of winter traffic exposure adjustment factor were highly significant in all study areas. Only one exception to this finding was observed in the Area Surrounding Toronto (AST) for the category of 1.11 to 1.20, which typically occurred in good weather condition on Saturday. In addition, as the traffic exposure increased, the likelihood of high-crash days also increased in all study areas. This finding is in consistent with the literature (Dalta & Sharma, 2010; Hanabali and Kuemmel, 1993; Knapp, et al. 2000). This finding also means that the winter traffic exposure adjustment factor worked well in the models and it was effective in explaining the occurrence of high-crash days.

Freezing rain was also found to be a significant risk factor in the Area Surrounding Toronto but it was found to be statistically not significant in the other three study areas. This finding may be a localized effect and may be related to winter road maintenance activities in this study area. Lastly, coincidence of precipitation timing with either morning or evening peak hours was significant in all study areas except Toronto, where the large volume of city traffic and the good road maintenance activities might offset the influence of this variable on the probability of high-crash days.

Table 5-14: Comparison of the model results among the study areas

Description of variables	Reference category	Toronto		AST		London		ASL	
		ρ	OR	ρ	OR	ρ	OR	ρ	OR
(1) Daily mean temperature	<-10c								
-10^{0}C to -3^{0}C		0.000*	0.100	0.000*	0.192	0.000*	0.155	0.009*	0.467
-2^{0}C to +2^{0}C		0.000*	0.015	0.000*	0.210	0.000*	0.032	0.000*	0.171
> +2^{0}C		0.000*	0.008	0.000*	0.085	0.000*	0.040	0.000*	0.126
(2) Daily total rainfall	No rainfall (<0.4mm)								
Low rainfall (0.4-2.0mm)		0.960	1.028	0.102	0.507	0.587	0.815	0.336	0.705
Medium rainfall (2.1-5.0mm)		0.430	1.553	0.188	0.504	0.569	0.750	0.054	0.319
Heavy rainfall (> 5.0mm)		0.137	2.163	0.597	0.790	0.299	0.674	0.111	0.551
(3) Daily total snowfall	No snowfall (< 0.4cm)								
Low snowfall (0.4-2.0cm)		0.442	1.284	0.058	1.705	0.330	1.302	0.054	1.657
Medium snowfall (2.1-5.0cm)		0.000*	9.372	0.000*	7.487	0.026*	1.911	0.000*	3.946
Heavy snowfall (> 5cm)		0.000*	16.080	0.000*	22.265	0.001*	3.108	0.000*	6.652
(4) Freezing rain (freezing rains, ice-pellets)	No								
Yes		0.994	1.003	0.000*	4.538	0.694	0.883	0.359	1.298
(5) Visibility obstruction (fog, smoke, or blowing snow)	No								
Yes		0.007*	2.279	0.049*	1.698	0.000*	2.452	0.003*	1.918
(6) Average hourly wind speed	Low wind (< 16 km/h)								
Medium wind (16-32 km/h)		0.668	1.100	0.000*	2.261	0.856	1.036	0.001*	1.898
Strong wind (> 32 km/h)		0.007*	3.067	0.000*	7.635	0.297	1.949	0.016*	4.163
(7) Winter traffic exposure adjustment factor	≤ 1.10								
1.11-1.20		0.006*	6.693	0.901	1.068	0.000*	13.538	0.029*	2.064
1.21-1.30		0.000*	18.624	0.000*	3.037	0.000*	29.507	0.007*	2.003
> 1.30		0.000*	46.375	0.000*	3.812	-	-	0.001*	2.860
(8) Months	Nov-Dec								
Jan-Feb		0.002*	0.444	0.001*	0.453	0.000*	0.310	0.001*	0.471
Mar-Apr		0.000*	0.140	0.000*	0.095	0.000*	0.210	0.000*	0.300
(9)Timing of precipitation	No precipitation								
Either morning or evening		0.181	1.564	0.042*	1.794	0.000*	2.424	0.000*	2.632
Both morning and evening		0.000*	11.224	0.004*	2.931	0.000*	7.008	0.000*	6.069
(10) Constant		0.001*	0.111	0.001*	0.230	0.000*	0.074	0.000*	0.125

*ρ<0.05

The magnitude of the odd ratios in the table indicates that temperature, snowfall, visibility obstruction, wind speed and months had greater influence on the likelihood of high-crash day occurrence in the two surrounding study areas than the two main urban areas, Toronto and London. In contrast, winter traffic exposure played a greater role in determining high-crash days in Toronto and London.

Chapter 6

Discussion and Conclusion

The final chapter of this study is composed of seven sections. At first, the chapter highlights the major findings of the study, followed by a discussion and a set of recommendations. The next two sections identify the contribution of and acknowledge the limitations of the study, respectively. This chapter also gives some directions for the future studies. The final section concludes the study.

6.1 Summary of results

The section summarizes the key findings of the study related to the main objectives and research questions.

- The study develops three definitions of a high-crash day to conceptualize problematic time periods from an operational perspective. The first definition considers a simple approach and defines 10% of the days with the highest crash count throughout the years as high-crash days. The second definition is developed based on the normalized value of daily crash-counts and the days with z-score ≥ 1.5 are addressed as high-crash days. Finally, the third definition labels 10% of day as high-crash days which have the largest variation between observed and expected daily crash counts. Among the definitions, the first definition is identified as the most suitable to the models developed in this study.
- Irrespective of definitions, most high-crash days occur during the winter months (November to April). The incidence of high-crash days vary between 12% and 19% of winter days across the definitions.

- The study showed the potential value of targeting high-crash days as problematic time periods for road safety conditions because daily average crash counts are approximately twice as high on high-crash days relative to on non-high-crash days. The results of the study also reveal that high-crash days are extremely risky from an injury perspective, especially in the areas surrounding Toronto and London, as 25-35% of winter crashes and 23-32% of winter casualties happen on such days. All types of crashes increase on high-crash days; however, the change in crash risk is more noticeable in two surrounding study areas and also for property-damage-only crashes.
- The study developed a winter traffic exposure adjustment factor based on available traffic count data, considering day of week and measurable daily precipitation amount (> 0.4 cm). This traffic exposure variable can act as a substitute for continuous system-wide traffic volumes, which are often unavailable. This traffic exposure variable shows the relative risk exposure of day of the week for both good and precipitation days. The results of the study show that traffic exposure is inversely related with precipitation conditions and weekends. The reduction in traffic exposure due to precipitation conditions does not vary among the study areas. Precipitations have the least influence on traffic exposure on weekdays, at the beginning and at the end of the week (Monday, Tuesday and Friday).
- The study also developed three binary logistic regression models to estimate the simultaneous effects of weather conditions, traffic exposure, months and timing of precipitation on the occurrence of high-crash day. Given the dichotomous nature of the dependent variable, the logistic regression model is found useful in predicting high-crash day based on a number of categorical independent variables. The results show that these variables can reliability predict high-crash days. Six out of the nine risk factors considered

in this study were found to have significant influences on high-crash days. These factors were temperature, snowfall, visibility obstruction, winter traffic exposure adjustment factors, months and timing of precipitation. The study identified that high-crash days have a positive relationship with all these factors except temperature. Temperature is inversely related with high-crash days but the effect size (the value of odds ratios) is comparatively low. The results also confirm that forms of precipitation, intensity of precipitation, and timing of precipitation matter in the models developed in this study. Therefore, snowfall over rainfall, heavy snowfall over small accumulation of snowfall, and coincidence of precipitation timing with both morning and evening peak hours over no precipitation at all can greatly influence the probability of high-crash days. Moreover, there is a variation in the incidence of high-crash day throughout the winter season. The odds of high-crash days occurrence is the highest at the beginning of the winter (November-December).

- All three models suit the data and they are useful in explaining the occurrences of high-crash days. The results show that the situational risk factors as explanatory variables can reliably anticipate the likelihood of high-crash days despite the variation in the definition of high-crash days. All models give similar results but the first model, which address the first dentition of high-crash days, is most suited to the problems as revealed by different test statistics and by-chance-accuracy test. According to this model, the results are almost consistent in all study areas.

6.2 Discussion

Road safety is a multifaceted field of study with numerous risk factors and countermeasures. The foci in this field evolve over time and often the contemporary risk factors of either driver, vehicular or environmental receive the most attention. Although it is known from causal accident theory that traffic crashes are multi-casual events, engineering approaches to remediation still dominate even when driver errors are the trigger for the interventions. The considerable improvement in roadway and vehicle engineering as well as medical care has already made noticeable improvements in road safety (Transport Canada, 2011a). To achieve the Canadian road safety vision of having the safest roads in the world, it is now time to move the safety improvements forward to the next level by focusing also on other types of remediation related to driver and situational risk factors. In such context, this study attempts to create awareness among the stakeholders about the situational risk factors so that they can make decision to take appropriate countermeasures when such situations arise.

The study is also a new addition to the branch of road accident research, in its concentration on weather effects on crash counts. However, it is novel in a sense that it provides a model of high-crash situations at the daily level using different weather and temporal risk factors. The operational definitions of high-crash days make it easier to convey the study results to the professionals by providing practical evidence. By definition, high-crash days are supposed to deteriorate the safety conditions as opposed to normal days. The study results confirm this statement. Even though high-crash days occur only on few winter days, a notable increase of crash rate and a noticeable share of winter crashes and casualties on such days display the importance of focusing on high-crash days (Section 5.1). Moreover, a high concentration of high-crash days in the winter reconfirmed the earlier study findings that the mobility risk is higher in the winter than in the summer (Andreescu & Frost, 1998; Nilsson & Obrenovic, 1998).

Usually safety research is conducted in either urban or rural areas. Only a few studies that consider both areas for safety analysis show that the crash risk in higher in rural areas than in urban areas (Andrey et al., 2012). The consideration of spatial collision pattern in the current study also confirms this finding because the two surrounding study areas (which includes large rural areas) are found to have more elevated crash and casualty counts on high-crash days than the main two urban study areas, Toronto and London.

The over representation of less-severe (property-damage-only) crashes on high-crash days indicates that drivers make some behavioural adjustments to high-risk driving situations as illuminated by Zero Risk Theory (Summala, 1996). Past studies on driver's adaptation to weather hazard show that drivers make headway increment (Andrey et al., 2003) and speed adjustment in inclement weather conditions (Andrey et al., 2005; Andrey et al., 2013; Edwards, 2002). The current study results complement previous findings indicating that drivers' behavioural adjustments to weather hazards are not effective enough to avoid property-damage-only crashes on high-risk situations.

The study makes a novel methodological contribution to the road safety field by developing a proxy exposure variable to traffic volume. The relative risk exposure variable in the study confirms a well-known safety finding that the traffic exposure reduces in precipitation conditions (Hanabali and Kuemmel, 1993; Knapp, et al. 2000) and on weekends (Keay & Simmonds, 2005). The results also show that the proxy exposure variable can reasonably replace the traffic volume data. This finding agrees with previous studies on the finding that a greater exposure is associated with a higher crash-risk (Knapp, et al. 2000; Maze et al., 2006).

The models developed in the study show that apart from exposure, weather conditions and their timing can estimate the odds of high-crash days. Among these factors, temperature, snowfall, visibility obstruction, exposure, timing within the season (months) and timing of precipitation have significant influence on the probability of a high-crash day. In this way, the study makes it easier to predict high-crash days when such weather conditions occur.

The model results also agree with the literature on the findings that the forms of precipitation matter in high-crash counts and snowfall has greater effects than rainfalls (Andrey, 2010; Qui & Nixon, 2008). Moreover, by showing a greater probability of high-crash days in the early winter months than the latter months, the study complements the earlier research findings about the variability of crash-risk within the season (Farmer & Williams, 2005; cf. Pisano et al., 2008). This information can be used to make greater efforts on winter road maintenance activities at the beginning of the winter season. The model findings on visibility obstructions, strong wind and temperature are in consistent with the following previous studies: Abdel-Aty et al. (2011) on visibility obstructions; Edwards (1994) on strong wind; and Usman et al. (2011) on temperature.

Finally, the study demonstrates the value of logistic regression in high-crash counts analysis although this model is more widely used in safety literature on accident severity analysis. As such, the study shows an alternative to negative binomial model, poisson regression models and relative risk analysis, which are more popular in accident frequency analysis. Even though the results are consistent among the three models developed in the study, the first model is the most plausible as found by the results of the study. The practical implication of this model is that this model is useful in determining the likelihood of a high-crash days based on weather and exposure variables in all study areas.

6.3 Recommendations

The results of the study indicate that inclement weather conditions have significant influence on high-crash days in all four study areas. Therefore, some road safety interventions are necessary to reduce risk of weather-related traffic crashes on such days in Southern Ontario. The road safety interventions are mainly categorized based on their focus on human, vehicular and environment. These interventions should be introduced at all three phases of a crash occurrence – pre-crash, crash and post-crash. An easy way to conceptualize the road safety interventions is to organize them in a Haddon matrix, a dynamic injury prevention framework developed in the 1970’s (Haddon, 1972). To reduce crash-risk, several safety interventions from all cells of Haddon matrix are recommended. An example of a Haddon matrix for road safety is given in Appendix-B (Fig. B-1).

Based on the concept of Haddon matrix, following strategies could be considered to reduce the weather-related crash-risk in Southern Ontario.

6.3.1 Interventions to reduce exposure

To reduce the exposure to weather-related crash-risk, the residents of the study areas can choose to do telework to avoid trips during severe winter storms. The Environment Canada should provide reliable weather forecast and warning messages to the residents of the study areas. Moreover, the local transit authorities should introduce free transit day when severe winter storm alerts are in place.

6.3.2 Interventions for crash prevention

To prevent the crashes from occurring, road safety interventions are needed at policy level. Ministry of Transport should incorporate driver training during different inclement weather conditions, especially for snowfall, in their graduate driver licencing program in Ontario. In addition, they should also make snow-tire mandatory for vehicles in Ontario during the winter seasons because the current study shows that snowfall have a significant influence on high-crash days. The local authorities should pre-schedule their traffic operation and enforcement when there is a possibility of high-crash days as shown by the study models. Moreover, they can effectively distribute road safety resources and personnel to plan for high-crash days. More efforts should be given to strengthen the winter road maintenance in two study areas surrounding Toronto and London as these two areas have high-risk of crashes and casualties on high-crash days as found by the study results.

6.3.3 Interventions during the crash

In order to reduce the severity of injury during the event of a weather-related crash, some vehicular and roadway environmental measures would be effective. Anti-lock braking system (ABS) and Electronic Stability Control (ESC) would give drivers better control of vehicles when driving during the inclement weather conditions in the winter. Electronic Stability Control is mandatory on all new Canadian vehicles as of September1, 2011 (Transport Canada, 2011a). In addition, dynamic speed sign to show variable speed limits and emergency traffic regulations (like road closure) are important road safety measures.

These results can be applied in dynamic traffic management and information campaigns, for example, by posting warning for reduced visibility via roadside message signs or via onboard navigation system. Considering the local weather conditions, safe maximum speed for driving can also be posted to guide the drivers in inclement weather conditions. However, road safety researchers often debate on the effectiveness of weather forecast and weather warning on driver behavioural adjustments (Andrey et al., 2001; Al-Ghamdi, 2007; Kilpelainen & Summala, 2007).

6.3.4 Interventions for post-crash

Some road safety interventions are needed to reduce the consequences of injury from weather-induced traffic crashes in the study areas. Further research should consider the response time needed to get to the crash scene, especially during inclement weather conditions and across different situations.

6.4 Contributions of the study

The study contributes to our understanding of temporal-spatial patterns in road collisions by focusing on high-crash situations using a temporal lens, something that is seldom done in road safety research. In this way, the study complements the past studies, which focus on the spatial concept of high-risk situations, and concentrated mainly on black spot analysis.

The crash profiles of high-crash days has broaden our understanding of the need to target these days for safety improvement. In addition, the models developed in the study may help to initiate countermeasures that can notably decrease the traffic crashes and casualties on such days. Moreover, the study explains to what extent weather conditions account for these occurrences. Promotion of such situational awareness may help stakeholders to develop effective winter road safety policies, such as those stressing road closures and driver training. The findings of the study could also assist in planning countermeasures like effective distribution of resources and personnel, weather advisories, winter road maintenance, and emergency traffic regulations (e.g., use of safe speed signage during inclement weather events).

Finally, the study makes two methodological contributions to the road safety research. First, the study develops a proxy traffic exposure variable to surrogate traffic volume when continuous traffic volume data are unavailable. Lack of adequate exposure data is one of the main hurdles to include exposure variable in road safety studies. Following the basic methodology developed here, a more comprehensive traffic exposure variable could be developed by adding new weather variables. Last, the study also develops statistical models that can explain the likelihood of high-crash days based on weather, traffic exposure, months and timing of precipitation. Such model may create situational awareness for all road users.

6.5 Limitations of the study

The study has some limitations. Firstly, the actual traffic exposure data that was the continuous traffic volume data were unavailable for the entire study period. Even though the literature unanimously recognize the importance of this variable, unavailability of traffic exposure data usually discourage road safety researchers to include this variable in their safety analysis, Therefore, the study developed the proxy variable for traffic volume.

Secondly, the study used climatological weather data from nearby weather stations contrary to local weather information observed at the collision spots. It may trigger a measurement problem because some weather information is very local, such as visibility obstruction (fog, smoke, blowing snow). The use of weather data from either Road Weather Information System (RWIS) or collision record may reduce this problem. However, in a previous study (Andrey & Olley, 1990), precipitation data from Environment Canada weather stations were found to be generally applicable to nearby urban areas for road safety analyses.

Thirdly, although the study used daily crash count to define high-crash days and the daily average traffic counts for developing winter traffic exposure adjustment factors, it did not differentiate between through traffic and the trips taken by the residents in the study areas because of unavailability of this information in traffic and collision database. Therefore, some bias may have been introduced in the models.

Fourthly, the study applied basic logistic regression model and did not used any compound variable, such as cold-snowy, to estimate the influence of weather on high-crash days. Use of compound variables may have added more accuracy into the models.

Finally, the model aggregated data at the daily level. Such temporal aggregation of weather data (e.g., rainfalls) may produce a bias in model results as warned by a recent safety literature (Usman et al., 2011). Further research is needed to quantify this bias.

6.6 Future research

Moving forward, there is a need of more studies to investigate high-crash days, including year round high-crash days and summer high-crash days, in order to comprehensively understand the safety implications of high-crash days. As collecting traffic volume data is almost always troublesome, the need for proxy traffic exposure variable will remain high in road safety studies. Therefore, future studies should be carried out to make the traffic exposure adjustment factor more precise, and this can be done by including new explanatory variables so that it can more accurately surrogate traffic volume. The development of risk exposure variable may be adjusted depending on the interest of road safety researchers. In addition, similar studies like this one could be conducted by using weather data from Road Weather Information System (RWIS) or by applying different statistical models (e.g., negative binomial regression) to estimate the variation in model results. Similarly, future studies should develop a model including compound weather variables (e.g., snowy and foggy) to identify the influence of interactive weather variables on high crash counts. Future analyses should also investigate the effects of holidays and weekends on high-crash days. Again, drivers' behavioural adjustment on days with high crash counts is another interesting topic for forthcoming studies. Finally, future road safety researchers should investigate spatial and temporal clustering of high crash counts using geo-coded accident data in order to apply more effective safety interventions.

6.7 Conclusions

Traffic crashes often increase rapidly at problematic locations, at problematic time periods and for problematic drivers, who are more prone to crashes. The focus of this study is on problematic time periods when crash risk is highly elevated. In order to complement the past studies' focus on event-based analysis or seasonal analysis and to address the problematic time periods, an attempt has been made to analyse high-risk crash conditions at the daily level, considering the spatial differences between the urban areas and their surrounding areas in Southern Ontario. The objectives of this study are to identify safety benefits of targeting the days with high crash count, and to develop as well as to test a model that can reliably predict high-crash days based on some weather and temporal risk factors. In the absence of real exposure data, an attempt has also been made to develop a relative risk exposure variable using the data at hand.

After developing three operational definitions of high-crash days, the study investigated their safety implications. The results show that focusing on high-crash days is a valuable approach because a small number of high-crash days have noticeable consequences on roads in all study areas. The areas surroundings Toronto and London tend to be affected more than these two cities on such days. If adequate precautionary or corrective actions are taken on such days, larger safety improvements are possible than would occur with less focused approaches. As such, greater safety benefits may come with the optimal utilization of resources and personnel.

More attention is needed for the two surrounding study areas to remedy high-crash situations because high-crash days have more elevated collisions and casualty counts in these two areas than Toronto and London, which are more urbanized.

The three binary logistic regression models developed in the study demonstrate that weather, traffic exposure, months and timing of precipitation as the explanatory variables can conveniently explain the likelihood of high-crash days and this explanation is almost universal in all study areas. These models advance our knowledge of the likelihood of a high-crash day. For example, if a severe winter storm with heavy snowfalls, high wind speed, and blowing snow occur on an early winter month, the probability of high-crash days is almost obvious as demonstrated by the models. Such models assist in creating situational awareness among the road users and to take precautionary measures as appropriate.

The study supports some findings from earlier safety literature (Andrey, 2010; Maze et al., 2006; Nilsson & Obrenovic, 1998). For example, snow is more hazardous than rain; crash risk vary within the winter season; and exposure matter in safety analysis. The study further shows that the relative risk exposure variable developed in the study is an appropriate variable to reliably substitute traffic volume. In this way, the study gives an example of safety analysis when real exposure data is unavailable or inaccessible, which is often the case in real world situations.

Finally, the current study follows a novel approach in focusing on high-crash days. Although the study was successful in demonstrating the importance of high-crash days and in explaining their profiles, further research is needed to broaden our understanding of high-crash situations so that appropriate interventions can be taken beforehand.

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Appendix A: The logistic regression models

Table A-1: Results of the first model in Area Surrounding Toronto

Description of variables	Reference category	B	S. E.	Wald	ρ value	Odds ratio (OR)	95% CI	
							Lower	Upper
(1) Daily mean temperature	<-10^{0}C							
-10^{0}C to -3^{0}C		-1.653	0.306	29.115	0.000*	0.192	0.105	0.349
-2^{0}C to +2^{0}C		-1.562	0.344	20.622	0.000*	0.210	0.107	0.412
> +2^{0}C		-2.464	0.430	32.894	0.000*	0.085	0.037	0.198
(2) Daily total rainfall	No rainfall (<0.4mm)							
Low rainfall (0.4-2.0mm)		-0.679	0.415	2.672	0.102	0.507	0.225	1.145
Medium rainfall (2.1-5.0mm)		-0.686	0.521	1.734	0.188	0.504	0.181	1.398
Heavy rainfall (> 5.0mm)		-0.235	0.445	0.279	0.597	0.790	0.330	1.891
(3) Daily total snowfall	No snowfall (< 0.4cm)							
Low snowfall (0.4-2.^{0c}m)		0.533	0.281	3.607	0.058	1.705	0.983	2.957
Medium snowfall (2.1-5.0cm)		2.013	0.372	29.293	0.000*	7.487	3.612	15.521
Heavy snowfall (> 5cm)		3.103	0.540	33.010	0.000*	22.265	7.725	64.172
(4) Freezing rain (freezing rains, ice-pellets)	No							
Yes		1.512	0.376	16.171	0.000*	4.538	2.171	9.484
(5) Visibility obstruction (fog, smoke, or blowing snow)	No							
Yes		0.529	0.269	3.885	0.049	1.698	1.003	2.874
(6) Average hourly wind speed	Low wind (< 16 km/h)							
Medium wind (16-32 km/h)		0.816	0.209	15.276	0.000*	2.261	1.502	3.403
Strong wind (> 32 km/h)		2.033	0.367	30.658	0.000*	7.635	3.718	15.680
(7) Winter traffic exposure adjustment factor	≤ 1.10							
1.11-1.20		0.066	0.533	0.015	0.901	1.068	0.376	3.034
1.21-1.30		1.111	0.307	13.092	0.000*	3.037	1.664	5.543
> 1.30		1.338	0.306	19.088	0.000*	3.812	2.092	6.949
(8) Months	Nov-Dec							
Jan-Feb		-0.793	0.233	11.574	0.001*	0.453	0.287	0.715
Mar-Apr		-2.349	0.328	51.209	0.000*	0.095	0.050	0.182
(9)Timing of precipitation	No precipitation							
Either morning or evening		0.585	0.287	4.141	0.042*	1.794	1.022	3.151
Both morning and evening		1.075	0.369	8.481	0.004*	2.931	1.421	6.045
(10) Constant		-1.468	0.438	11.217	0.001	0.230		

*ρ<0.05

Omnibus test: Chi-square = 431.727, df = 20, p-value = 0.000, -2 Log likelihood = 746.301, Hosmer and Lemeshow Test: Chi-square = 7.008, df = 8, p-value = 0.535

Table A-2: Results of the first model in London

Description of variables	Reference category	B	S. E.	Wald	ρ value	Odds ratio (OR)	95% CI	
							Lower	Upper
(1) Daily mean temperature	<-10^{0}C							
-10^{0}C to -3^{0}C		-1.861	0.299	38.824	0.000*	0.155	0.087	0.279
-2^{0}C to +2^{0}C		-3.453	0.388	79.186	0.000*	0.032	0.015	0.068
> +2^{0}C		-3.222	0.428	56.756	0.000*	0.040	0.017	0.092
(2) Daily total rainfall	No rainfall (<0.4mm)							
Low rainfall (0.4-2.0mm)		-0.204	0.376	0.295	0.587	0.815	0.390	1.704
Medium rainfall (2.1-5.0mm)		-0.287	0.504	0.325	0.569	0.750	0.279	2.015
Heavy rainfall (> 5.0mm)		-0.394	0.379	1.081	0.299	0.674	0.321	1.418
(3) Daily total snowfall	No snowfall (< 0.4cm)							
Low snowfall (0.4-2.0cm)		0.264	0.271	0.950	0.330	1.302	0.766	2.215
Medium snowfall (2.1-5.0cm)		0.648	0.291	4.941	0.026*	1.911	1.080	3.383
Heavy snowfall (> 5cm)		1.134	0.339	11.183	0.001*	3.108	1.599	6.041
(4) Freezing rain (freezing rains, ice-pellets)	No							
Yes		-0.125	0.316	0.155	0.694	0.883	0.475	1.641
(5) Visibility obstruction (fog, smoke, or blowing snow)	No							
Yes		0.897	0.229	15.278	0.000*	2.452	1.564	3.845
(6) Average hourly wind speed	Low wind (< 16 km/h)							
Medium wind (16-32 km/h)		0.035	0.195	0.033	0.856	1.036	0.706	1.519
Strong wind (> 32 km/h)		0.667	0.639	1.089	0.297	1.949	0.557	6.821
(7) Winter traffic exposure adjustment factor	≤ 1.10							
1.11-1.20		2.606	0.634	16.908	0.000*	13.538	3.910	46.874
1.21-1.30		3.385	0.631	28.746	0.000*	29.507	8.562	101.690
> 1.30								
(8) Months	Nov-Dec							
Jan-Feb		-1.170	0.242	23.454	0.000*	0.310	0.193	0.498
Mar-Apr		-1.561	0.273	32.675	0.000*	0.210	0.123	0.359
(9)Timing of precipitation	No precipitation							
Either morning or evening		0.885	0.236	14.113	0.000*	2.424	1.527	3.846
Both morning and evening		1.947	0.305	40.884	0.000*	7.008	3.858	12.728
(10) Constant		-2.604	0.682	14.590	0.000*	0.074		

*ρ<0.05

Omnibus test: Chi-square = 356.267, df = 19, p-value = 0.000, -2 Log likelihood = 751.255, Hosmer and Lemeshow Test: Chi-square = 3.976, df = 8, p-value = 0.859

Table A-3: Results of the first model in the Area Surrounding London

Description of variables	Reference category	B	S. E.	Wald	ρ value	Odds ratio (OR)	95% CI	
							Lower	Upper
(1) Daily mean temperature	<-10⁰C							
-10⁰C to -3⁰C		-0.761	0.291	6.844	0.009*	0.467	0.264	0.826
-2⁰C to +2⁰C		-1.766	0.351	25.306	0.000*	0.171	0.086	0.340
> +2⁰C		-2.071	0.425	23.756	0.000*	0.126	0.055	0.290
(2) Daily total rainfall	No rainfall (<0.4mm)							
Low rainfall (0.4-2.0mm)		-0.349	0.363	0.925	0.336	0.705	0.346	1.437
Medium rainfall (2.1-5.0mm)		-1.144	0.594	3.705	0.054	0.319	0.099	1.021
Heavy rainfall (> 5.0mm)		-0.596	0.374	2.542	0.111	0.551	0.265	1.147
(3) Daily total snowfall	No snowfall (< 0.4cm)							
Low snowfall (0.4-2.0cm)		0.505	0.262	3.715	0.054	1.657	0.992	2.770
Medium snowfall (2.1-5.0cm)		1.373	0.268	26.296	0.000*	3.946	2.335	6.669
Heavy snowfall (> 5cm)		1.895	0.322	34.686	0.000*	6.652	3.541	12.498
(4) Freezing rain (freezing rains, ice-pellets)	No							
Yes		0.261	0.285	0.841	0.359	1.298	0.743	2.267
(5) Visibility obstruction (fog, smoke, or blowing snow)	No							
Yes		0.651	0.216	9.081	0.003*	1.918	1.256	2.930
(6) Average hourly wind speed	Low wind (< 16 km/h)							
Medium wind (16-32 km/h)		0.641	0.191	11.207	0.001*	1.898	1.304	2.762
Strong wind (> 32 km/h)		1.426	0.590	5.847	0.016*	4.163	1.310	13.229
(7) Winter traffic exposure adjustment factor	≤ 1.10							
1.11-1.20		0.724	0.331	4.779	0.029*	2.064	1.078	3.951
1.21-1.30		0.694	0.258	7.271	0.007*	2.003	1.209	3.317
> 1.30		1.051	0.302	12.090	0.001*	2.860	1.582	5.172
(8) Months	Nov-Dec							
Jan-Feb		-0.753	0.228	10.883	0.001*	0.471	0.301	0.737
Mar-Apr		-1.205	0.267	20.372	0.000*	0.300	0.178	0.506
(9)Timing of precipitation	No precipitation							
Either morning or evening		0.968	0.222	18.918	0.000*	2.632	1.702	4.070
Both morning and evening		1.803	0.286	39.859	0.000*	6.069	3.467	10.622
(10) Constant		-2.082	0.403	26.719	0.000*	0.125		

*ρ<0.05

Omnibus test: Chi-square = 371.069, df = 20, p-value = 0.000, -2 Log likelihood = 789.927, Hosmer and Lemeshow Test: Chi-square = 9.544, df = 8, p-value = 0.298

Appendix B: The Haddon Matrix

Table B-1: The Haddon Matrix

Phase		Factors		
		Human	Vehicles and Equipment	Environment
Pre-crash	Crash prevention	Information Attitudes Impairment Police enforcement	Road worthiness Lighting Braking Handling Speed Management	Road design and road layout Speed limit Pedestrian facilities
Crash	Injury prevention during the crash	Use of restraints Impairment	Occupant restraints Other safety devices Crash-protective design	Crash-protective roadside objects
Post-crash	Life sustaining	First-aid skill Access to medics	Ease of access Fire risk	Rescue facilities Congestion

Source: Peden et al., 2004, p.13