Federal Committee on Statistical Methodology

Spatio-Temporal Modeling of the Impact of Climate Change on Road Accidents – A Case Study of New Brunswick

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ABSTRACT

The objective of this research is to study the impact of climate change on the hazardous weather-related road accidents. The New Brunswick province of Canada is considered as a case study. The study uses road accident data collected from police accident reports for the period of 1997-2007. The climate change modeling uses thirty-year weather records of seven climate zones of New Brunswick, National Centers for Environmental Prediction (NCEP) re-analysis dataset, and large-scale simulation data from the Canadian Global Circulation Model, General Climate Model, and Coupled Global Climate Model (CGCM3). The large-scale simulation data from CGCM under SRES-A2 scenario during 21st century are used to model the climate in the future. This study develops an Exposure to Weather-Accident Severity (EWAS) index and estimate the relationship between EWAS index and weather-related explanatory variables of road accidents by applying negative binomial regression and Poisson regression models. The regression models find out that surface-weather condition, weather-driver's gender, weather-driver's age, weather-driver's experience and weather-vehicle's age have strong positive correlation with EWAS index. The surface-road alignment and surface-road characteristics have negative relationship with EWAS index. The spatial pattern of EWAS index with respect to weather-related explanatory variables is examined for the fifteen census divisions of New Brunswick province, which derives similar relationships. The climate change modeling estimates that the number of rainy days may increase in all climate zones and the number of snowy days and freezing days may decrease or stay the same in most of the climate zones during three 30-year periods of 21st century (i.e. 2011-2040, 2041-2070, 2071-2100). The findings of this study imply that more hazardous weather in future will result in increased accident severity.

Keywords: Accident severity, climate change, statistical downscaling, Negative binomial regression, Poisson regression

INTRODUCTION

Canada is one of the highest ranked countries in terms of road accident fatalities among countries of the Organization for Economic Cooperation and Development (OECD). In 2008, Canada was ranked 4th in terms of fatalities (7.18 per billion vehicle kilometers traveled) among OECD countries (Transport Canada, 2011). In 2009, total fatalities and serious injuries were 2,209 and 11,451, respectively. Although these casualty statistics in Canada are declined by 25% compared to the period of 1996-2001, these casualty counts are still high. Transport Canada (2011) identifies impaired driving, speed and aggressive driving, and occupant protection as the key contributing factors of road accidents (Transport Canada, 2011). Meteorological conditions are also important contributing factors of road accidents. During the period of 1999-2008, a total of 1,479,691 road accidents were registered in Canada out of which approximately 30% accidents were occurred during hazardous weather conditions (11% during cloudy, 10% during rainfall, 6% during freezing rainfall, 1% visibility limitation and 1% during strong wind). The proportions of vehicle damages, human injuries and fatalities from road accidents during hazardous weather conditions are similar to that of total accidents. However, occurrence of road accidents, during different hazardous weather conditions, varies from season to season. During the winter season (December – February) of the period 1999-2008, snowfall (not including drifting snow) is the most hazardous weather condition accounting for 15% - 17% of the road accidents, 14%-16% of vehicle and property damages, 15% - 17% of injuries and 16% - 19% of fatalities (Figure 1). During the fall season (September – November) of the same period, rainfall was the most hazardous weather condition responsible for 12% - 17% of total road accidents, 12% - 17% vehicle and property damages, 12% - 17% injuries and 9% - 14% fatalities (Figure 1). During the summer season (June – August) of the same period, rainfall is also the most hazardous weather condition for 8% - 10% road accidents, 8% - 11% vehicle and property damages, 9% - 11% injuries and 6% - 8% fatalities (Figure 1). During the spring season (March – May) of the same period, rainfall and snowfall are the most hazardous weather conditions (Figure 1). For example, in the month of March, 13% road accidents, 12% associated vehicle and property damages, 13% injuries, and 13% fatalities were occurred during the snowfall. However, during the months of April and May, the most dangerous weather condition is rainfall (Figure 1).

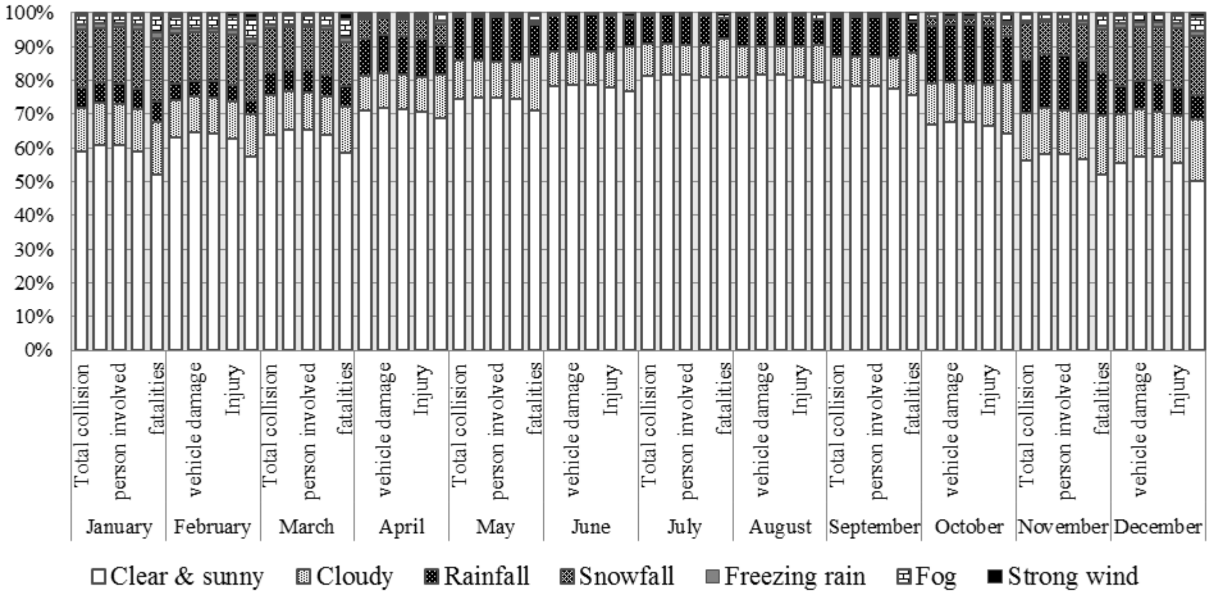

Figure 1: Road Accidents data during the period of 1999 – 2008 in Canada (Transport Canada, 2012)

Hazardous weather may not be the principal cause of road accidents, but it is an important contributing factor because of reduced visibility and loss of vehicle control. Considering exiting road accident statistics, even a very small percentage of motor vehicle accidents is attributable to hazardous weather conditions, a significant effort should be made to discover how Canadian travellers are vulnerable to weather conditions and how such vulnerabilities may be overcome (Andrey, et al., 2003).

The objective of this research is to study the impact of climate change on the hazardous weather-related road accidents. The New Brunswick province of Canada is taken as a case study.

LITERATURE REVIEW

Several studies (Cromley, 2007; Palutikof, 1991; Edwards, 1996) have examined the impact of hazardous weather conditions on road accidents. Edwards (1996) examined the spatial dimension of weather-related road accidents using accident data from UK Police Accident Report Forms. Edwards (1996) found a positive relationship between the incidences of weather hazards and road accidents. The analysis of road accident data at county level reveals a strong and consistent pattern of weather-accidents relationship, although the majority of the accidents in UK occurred during the non-hazardous and fine weather. The pattern of relationship between weather and accidents changes over seasons and locations – from north to south and west to east. Edwards (1999) conducted another study on the panel longitudinal data of road accidents in hazardous weather conditions for England and Wales. Like the outcomes of previous study (Edwards, 1996), this study also found out a relationship between accident occurrence in adverse weather and actual weather patterns. The county-wide data revealed that the cyclic nature of road accidents recorded in the various adverse conditions showed remarkable similarity to the occurrence of these hazards.

Andrey et al. (2003) conducted a study to identify the relationship between weather and accident risk in mid-sized Canadian cities (with different climates) by using a standardized method. The cities are Halifax-Dartmouth, Ottawa, Quebec, Hamilton, Waterloo region, and Regina. Andrey et al. (2003) estimated that precipitation is associated with a 75% increase in traffic accidents and a 45% increase in related injuries, as compared to 'normal' seasonal conditions. The snowfall effects were more pronounced than rainfall effects for accidents as a whole (Andrey et al., 2003). This study also revealed that the sensitivity to hazardous weather varied from city to city and the probability of risk of injury was lower than that of risk of accidents.

Fridström et al. (1995) applied generalized Poisson regression to estimate the contributions of various factors to monthly accident rates. This study was conducted at the county or provinces of Denmark, Finland, Norway and Sweden for the period of 1973-1987. The study identified that rainfall increased the accidents while snowfall decreased the accidents in the study areas. In case of fatal accidents, rainfall increased in Denmark but had no significance in Norway and Sweden.

Keay and Simmonds (2006) examined the impact of rainfall on daily road accidents in the metropolitan area of Melbourne, Australia, over the period of 1987–2002. The analysis of accident data, standardized for variation of traffic volume, indicated a complex effect of rainfall. Similarly, Andreescu and Frost (1998) identified a significant positive correlation between daily precipitation and daily number of accidents at Montreal, Canada using accident data from the period of 1990-1992.

Eisenberg (2004) found out that rainfall led to a stronger increase in the number of fatal accidents after a dry spell because the precipitation makes the roads slippery by clearing the oil accumulated on roads during dry periods. Eisenberg (2004) also observed that some states of US experienced greatly increased fatal accidents rates in wet conditions (e.g. Arizona and Maryland), while others were hardly affected at all (e.g. Connecticut and Indiana). Similar results were estimated by Eisenberg and Warner (2005) considering the snowfall as the hazardous weather condition. Fridstrøm (1999) also got a similar result for Norway.

Another important hazardous weather condition is fog or smog. Musk (1991) showed that accident rates and multiple accidents were increased during periods with thick fog. Drivers tend to maintain the speed or fail to reduce the speed under reduced visibility during hazardous weather conditions (White and Jeffrey, 1980; Musk, 1982). Drivers also tend to become isolated from the road environment while driving in fog, and cannot perceive speed and actual distance from the preceding vehicle (Miller, 1967). Moore and Cooper (1972) estimated that the number of accident injuries increased in fog, although the traffic volume decreased by 20%. Rosenfeld (1996) estimated that more than twice the numbers of people were killed in fog-related road accidents comparing to the death in hurricanes, lightning and tornadoes combined in US during the period of 1982-1991.

Most of the above studies have examined accident occurrences at fixed locations; very few have investigated temporal and spatial aspects of weather-related road accidents. Andersson and Chapman (2011) studied traffic accidents across the West Midlands during the winter months (December to February) with the aim of applying UKCIP (UK Climate Impacts Programme) climate change scenarios to determine how the number of days requiring winter road maintenance may change in the future and how this subsequently may affect road traffic accident statistics. Andersson and Chapman (2011) identified that under UKCIP climate-change-scenarios there would be a significant change to the winters experienced in the West Midlands. The study concluded that traffic accidents would be reduced because the low freezing temperatures would not be so frequent and the winter season would be shorter. This research studied the relationship between the climate change scenarios and road accidents only for the winter season; however did not consider other hazardous weather conditions. Moreover, there is a scope of work to establish the frequency and spatial extent of such adverse weather conditions to calculate accident risk during hazardous weather conditions.

METHODOLOGY

Data

The province of New Brunswick is located at the East coast in Canada and spans between 64˚ W- 69˚ W longitude and 45˚ N -48˚ N latitude (Figure 2). Data on road accidents, traffic flow, environmental conditions, and road geometry were collected for the road network of New Brunswick (Figure 2). The accident data, both single and multiple accidents, were based on police accident reports for the period of 1997-2007. The Accident Severity Index (ASI) was calculated summing the monetary values of Property Damage Only (PDO), injuries, and fatalities during accidents (Equation 1).

For this study, a 30-year continuous record (1961-1990) of daily rainfall, snowfall and mean temperature from different sources were used. The selected data for the 1961-1990 study period include: observed daily data for seven climate zones of the province (Figure 2), NCEP re-analysis dataset, and large-scale simulation data from the CGCM3. Also, the large-scale simulation data from Canadian GCM under SRES-A2 scenario during 21st century were used to model the climate in the future.

Attributes of Road Accidents

Accident severity, merely explained by total number of accidents, can misinterpret the randomness and severity of the accidents in a road network (Afghari, 2012). This study defines an Accident Severity Index (ASI) explaining severity of accidents (Equation 1). The ASI incorporates the proportional weights of injuries (I), fatalities (F) and *PDO*. The exact monetary implication of an injury, a fatality or a PDO depends on many other factors. Afghari (2012) identified the average monetary values of fatalities and injuries of the road accidents at the province of New Brunswick were 15 and 5 times higher than that for PDO. This study takes such monetary mean values and normalizes them by the mean cost of a PDO to obtain the coefficients used on the ASI (Equation 1).

$$ASI = PDO + 5I + 15F \quad (1)$$

Since the goal of this study is to determine the climate impact on the accident severity, an Exposure to Weather-Accident Severity (EWAS) Index was developed multiplying the severity of hazardous weather conditions for road accidents with ASI. The severity of hazardous weather condition is defined by 1-6 scale, where 1 defines 'clear and cloudy', 2 for 'raining', 3 for 'snowing', 4 for 'sleet or hail or freezing rain', 5 for 'fog or smoke or smog' and 6 for 'drifting snow'.

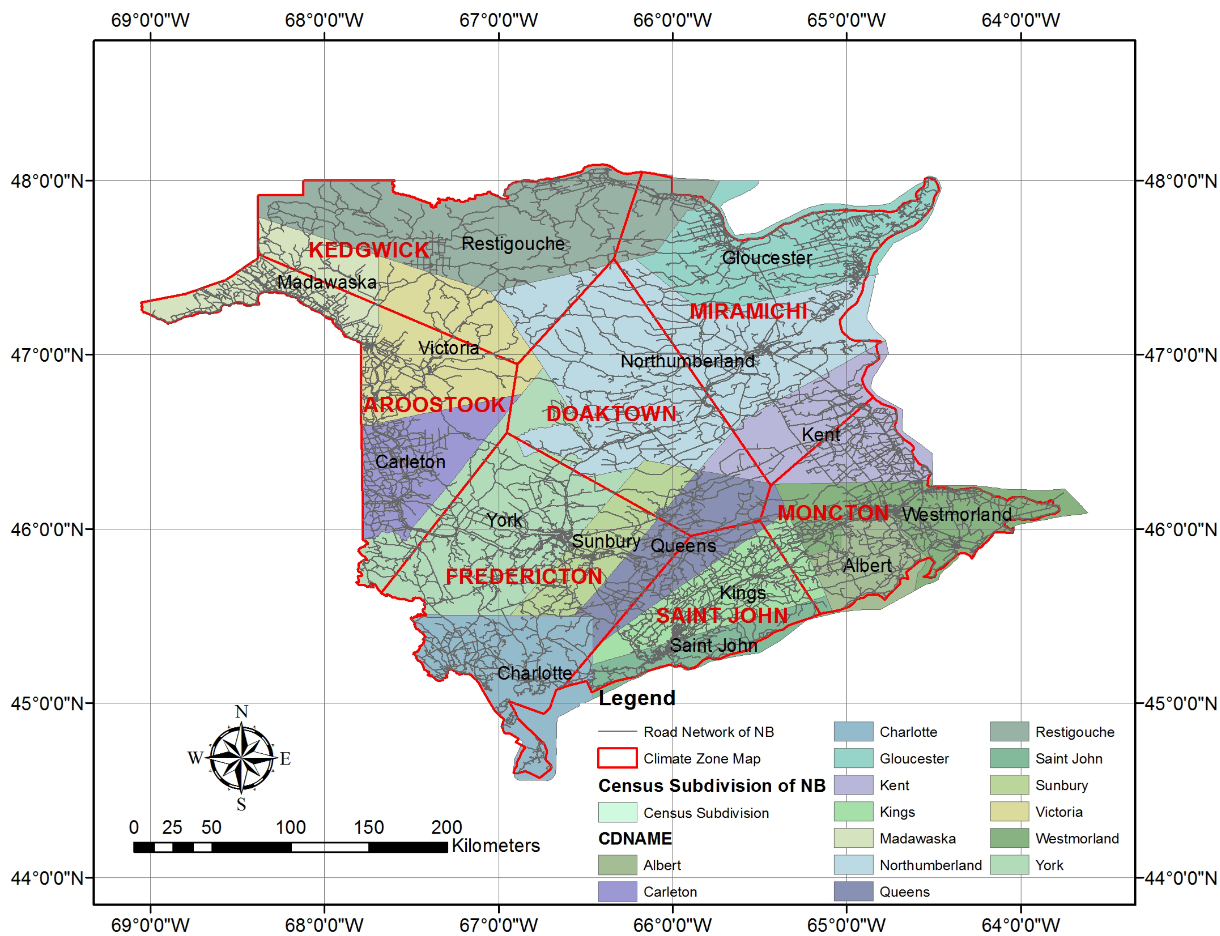

Figure 2: Map of the study area – New Brunswick

The relationship between hazardous weather condition and road accidents is complex. Edwards (1996) recommended that emphasis should be given on the interaction of weather conditions with other factors of road accidents such as road surface condition, vehicle types, road categories, vehicle manoeuver, and driver's age, sex and experience.

A wet road surface reduces the friction of the road surface in contact with a vehicle's tires because a thin film of water builds up between the road surface and the tires (Brodsky and Hakkert, 1988; OECD, 1976). A greater stopping distance is required for this reduced friction. The reduction of friction is more apparent especially at the curves where vehicles attempt turning maneuvers (Brodsky and Hakkert, 1988). Road characteristics, such as divided or undivided multiple lanes of roads are important factors of road accidents. About two-thirds of fatalities and 30% of injuries in road accidents occur on rural roads, typically undivided with two lanes (Transport Canada, 2011).

Poor light condition may aggravate the poor visibility during hazardous weather conditions. Technical advances have further complicated the picture (Edwards, 1996). Recent developments on safety features, such as anti-lock brakes, four-wheel drive and traction control, have improved the vehicles' handling in poor weather conditions. This may reduce or increase the accident risk. On the other hand, drivers may feel more confident when driving vehicles equipped with safety features and may take greater risk than they may otherwise do (Edwards, 1996).

Factors such as light condition, surface condition and road characteristics are major factors of road accidents; however, most accidents can be attributed to human error (Evans, 1991; West et al., 1993). To evaluate the impact of weather on road accidents, factor of human judgment must be included (Edwards, 1996). Transport Canada (2011) statistics estimated that young drivers (15-34 years age) accounted for 40% of the fatalities and 45% of the serious injuries. Different studies (Abdel-Aty & Abdelwahab, 2004) identified that driver's age and driver's gender had significant impact on the road accidents. Driver's age is associated with the road accidents because people have the Age-related macular degeneration (AMD) problem after a certain age (65 years and above) (RNIB, 2013). The AMD is an eye condition that affects a tiny part of the retina at the back of the eye and causes problems with the central vision (RNIB, 2013). Royal National Institute of Blind People (RNIB, 2013) also explains that more women have AMD problem than men. This study assumes that older drivers (age 65 years and above) and female drivers are more vulnerable to adverse weather condition during driving because of the visibility problem.

Based on the literature review, this study identified several factors of road accidents that can be affected by the hazardous weather condition such as: light condition, surface condition, road alignment, roadway characteristics, driver's gender, driver's age, driver's driving experience and vehicle's age. The selected variables were integrated with the weather condition in order to determine the combined-impact of weather and these attributes on the weather-accident severity (EWAS index). The redefined explanatory variables of EWAS index, with the extent of severity (ranking), are given in the Table 1.

Table 1: Explanatory variables of the EWAS Index

Rank	Explanatory Variables							
	Light-weather	**Surface-weather**	**Surface-road alignment**	**Roadway - surface**	**Weather -driver's gender**	**Weather – driver's age**	**Weather-driving experience**	**Weather -vehicles age**
1	Day light-clear & cloudy	Dry-all weather condition	Dry-level & straight	Dry-undivided & one-way	Male-clear & cloudy	Clear & cloudy-age <65yrs.	Clear & cloudy-exp. ≥ 5yrs.	Clear & cloudy-new
2	Day light-raining	Snow-clear & cloudy	Dry-level & curve	Dry-divided with barrier/ median	Male-raining	Raining-age < 65 years	Raining-exp. ≥ 5 years	Raining-new
3	Day light-snowing	Snow-raining	Dry-straight with grade	Dry-Undivided & 2/multiple ln.	Male-snowing	Snowing-age < 65 years	Snowing-exp. ≥ 5 years	Snowing -new
4	Day light-freezing rain	Snow-snowing	Dry-curve with grade	Snow-undivided & one-way	Male-freezing rain	Freezing rain- age < 65 years	Freezing rain- exp. ≥ 5 years	Freezing rain-new
5	Day light-fog	Snow-freezing rain	Dry- hilly road	Snow-divided with barrier/ median	Male-fog	Fog- age < 65 years	Fog- exp. ≥ 5 years	Fog-new
6	Day light-drifting snow	Snow-fog	Snow-level & straight	Snow-Undivided & 2/multiple lanes	Male-drifting snow	Drifting snow- age < 65 years	Drifting snow- exp. ≥ 5 years	Drifting snow-new
7	Dark-clear & cloudy	Snow-drifting snow	Snow-level & curve	Ice-undivided & one-way	Female-clear & cloudy	Clear & cloudy-age ≥ 65 yrs.	Clear & cloudy-exp. 2-5yrs.	Clear & cloudy-medium
8	Dark-raining	Ice-clear & cloudy	Snow-straight with grade	Ice-divided with barrier/ median	Female-raining	Raining-age ≥ 65 years	Raining-exp. 2-5 years	Raining-medium

Rank	Explanatory Variables							
	Light-weather	**Surface-weather**	**Surface-road alignment**	**Roadway - surface**	**Weather -driver's gender**	**Weather – driver's age**	**Weather-driving experience**	**Weather -vehicles age**
9	Dark-snowing	Ice-raining	Snow-curve with grade	Ice-undivided & 2/multiple lanes	Female-snowing	Snowing-age ≥ 65 years	Snowing-exp. 2-5 years	Snowing - medium
10	Dark-freezing rain	Ice-snowing	Snow-hilly road	Wet-undivided & one-way	Female-freezing rain	Freezing rain- age ≥ 65 years	Freezing rain- exp. 2-5 years	Freezing rain-medium
11	Dark- fog	Ice-freezing rain	Ice-level & straight	Wet-divided with barrier/ median	Female-fog	Fog- age ≥ 65 years	Fog- exp. 2-5 years	Fog-medium
12	Dark-drifting snow	Ice-fog	Ice-level & curve	Wet-undivided & 2/multiple lanes	Female-drifting snow	Drifting snow- age ≥ 65 years	Drifting snow- exp. 2-5 years	Drifting snow-medium
13	Dusk-clear & cloudy	Ice-drifting snow	Ice-straight with grade				Clear & cloudy- exp < 2 years	Clear & cloudy-old
14	Dusk-raining	Wet-clear & cloudy	Ice-curve with grade				Raining-exp. < 2yrs.	Raining-old
15	Dusk-snowing	Wet-raining	Ice- hilly road				Snowing-exp. < 2yrs.	Snowing - old
16	Dusk-freezing rain	Wet-snowing	Wet-level & straight				Freezing rain-exp. < 2 years	Freezing rain- old
17	Dusk-fog	Wet-freezing rain	Wet-level & curve				Fog- exp.< 2 years	Fog- old
18	Dusk-drifting snow	Wet-fog	Wet-straight with grade				Drifting snow-exp.< 2 yrs.	Drifting snow-old
19	Dawn-clear & cloudy	Wet-drifting snow	Wet-curve with grade					
20	Dawn-raining		Wet-hilly road					
21	Dawn-snowing							
22	Dawn-freezing rain							
23	Dawn-fog							
24	Dawn-drifting snow							

Methods for accident analysis

Conventional multiple linear regression analysis, assuming that the dependent variable is continuous and normally distributed with a constant variance, are not applicable to accident analysis. This analysis lacks the distributional property necessary to adequately describe random, discrete, and non-negative events (Miaou, et al., 1992; Miaou and Lum, 1993). Accident severity indices normally use frequency models or correlation models structured on the basis of multivariate Poisson regression analysis, negative binomial regression analysis, or multivariate Poisson-lognormal regression analysis (El-Basyouny and Sayed, 2009). Wang et al. (1998) proposed a Poisson regression model (PR) to quantify the relationship between accident frequency and road geometry for Minnesota's rural arterial highways. The previous models ignored to measure the ability of explanatory factors to explain the accident severity and frequency. Multivariate Poisson-lognormal regression analysis is often preferred for accident severity indices as this analysis accounts for over-dispersion (extra Poisson variation) that is often observed in accident data (El-

Basyouny and Sayed, 2009). Moreover, this analysis also allows a full general correlation structure (El-Basyouny and Sayed, 2009).

Various researchers (Poch and Mannering, 1996; Abdel-Aty and Radwan, 2000; Sawalha and Sayed, 2001; Zang and Ivan, 2005) applied the Negative Binomial Regression (NBR) models in order to explain the relationship between the explanatory variables and road accident severity. Persaud and Musci (1995) investigated the relationship among hourly traffic volume, road geometries, and accident time (day light) on two- lane rural roads by applying the NBR model. The analysis revealed that accident potential was higher during the night for single accident vehicles. In case of multi-vehicle accidents, the accident potential was higher during daytime. Poch and Mannering (1996) analyzed the importance of geometric features and traffic aspects on the road accidents. Abdel-Aty and Radwan (2000) identified that traffic flow and road geometries are the major threats to road safety. Mountain et al. (1996) and Sawalha and Sayed (2001) conducted their research works in UK and Greater Vancouver, respectively. They identified that the length of road sections, traffic flow, intersections in corridors, and road alignment were the influential attributes of road accident severity. Pardillo and Llamas (2003) defined homogeneous sections with suitable lengths for two-lane rural roads in Spain. They derived that road accidents had significant correlations with vehicles' speed, density of accessibility, average stopping sight distance and road geometry issues. Zang and Ivan (2005) found out vehicles' speed and road alignment significantly influenced the road accidents.

Eisenberg (2004) applied the NBR method to estimate the relationship between precipitation and traffic accidents in the US during the period of 1975-2000. The amount of precipitation, snowfall and snow depth were considered as the explanatory variables of accident counts. Eisenberg (2004) considered the location-month combination as a dummy variable and included vehicle-mile traveled (VMT) for each location-year as the 'offset' term in the regression model.

Since both of the NBR and PR models were applied to estimate the relationship of accident severity with its explanatory variables, this study applies both models. The relationship between EWAS index for a particular accident incident (*i*) at a particular month (*t*) can be expressed by Equation 2.

$$Function\,(EWAS_{it}) = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_8 X_{8it} \qquad (2)$$

β_0 is intercept, and $\beta_1, \beta_2, \ldots . \beta_8$ are regression coefficients with the assumption that the EWAS index follows a negative binomial distribution with parameters α ($0 \leq \alpha \leq 1$) and γ ($\gamma \geq 0$). That is, the probability that the EWAS index is defined by a known of set of predictor variables, $X_1, X_2, \ldots . X_8$. The NBR function can be expressed by Equation 3.

$$\Pr(Y_{it} = EWAS_{it};\, \alpha, \gamma) = \frac{(EWAS_{it} + \gamma - 1)!}{(EWAS_{it})!(\gamma - 1)!} \frac{\alpha^{EWAS_{it}}}{(1+\alpha)^{(EWAS_{it}+\gamma)}} \qquad (3)$$

On the other hand, assuming the EWAS index follows a Poisson distribution, the relationship between EWAS index for a particular accident incident (*i*) at a particular month (*t*) can be expressed by Equation 4.

$$\log(EWAS_{it}) = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_8 X_{8it} \qquad (4)$$

Method for climate change modeling

To determine the impact of climate change on the road accident severity, this study needs to understand climate change scenarios. The Intergovernmental Panel on Climate Change (IPCC) presented a supplementary report in 1992 and proposed six different climate change scenarios based on the world population and political, social, economical, technological, and environmental changes in the world by the end of 21st century. This report was assessed in 1995 and the IPCC published the Special Report on Emission Scenarios (SRES) in 2001. The IPCC proposed four different families of climate change scenarios as *A*1, *A*2, *B*1, and *B*2. These scenarios predict the GHGs emission in the atmosphere by the end of 21st century.

Earth-science scientists developed a series of Global Climate Models (GCMs) to predict the future changes in the world climate after getting strong evidence on climate change. These GCMs are coupled with emission scenarios to model the effects of human activities on the future climate and predict the atmospheric parameters by the end of 21st century. GCMs have been recognized to be able to represent reasonably well the main features of the distribution of basic climate parameters at global scales, but outputs from these models are often characterized by coarse resolutions that limit their direct application for many impact studies. Hence, downscaling methods have been proposed for describing the linkage between the large-scale climate variables given by GCMs to the observed predictands at local sites (Nguyen et al., 2006). These downscaling methods are based on the assumption that large-scale weather exhibits a strong influence on local-scale weather conditions (Fowler et al., 2007). In general, there are two broad downscaling methods: dynamical downscaling and statistical downscaling (Wilby & Dawson, 2007; Xu, 1999; Yarnal et al., 2001). Dynamical downscaling methods or Regional Climate Models (RCM) are based on physical dynamics between synoptic variables (as predictors) and local-scale variables (as predictands) and it uses GCM variables to define time-varying atmospheric boundary conditions around a finite domain, while the statistical downscaling methods rely on the empirical relationship between regional scale predictors and local scale predictands (Wilby & Dawson, 2007).

This study applied Statistical DownScaling Method (SDSM) to evaluate the changes in the number of rainy, snowy, and freezing days in New Brunswick. The SDSMs are classified into three categories based on the nature of the chosen predictors: Perfect Prognosis (PP), Model Output Statistics (MOS) and Stochastic Weather Generators (SWGs). Each of these downscaling methods has their own strengths and weaknesses that have been summarized in several review papers (Hewitson & Crane, 1996; Maraun et al., 2010; Wilby & Wigley, 1997; Xu, 1999). The PP method was applied in this study.

The PP method establishes a statistical relationship between observed large-scale predictors and observed local-scale predictands (i.e. precipitation, temperature). In the context of climate change, the main assumption of the PP method is the capability of the simulated large-scale predictors in representing a physically plausible realization of the future climate (Maraun, et al., 2010). This method divides downscaling scheme into two steps: first, the selection of informative large-scale predictors, and second the development of a statistical model for making a linkage between the large-scale predictors and the local-scale predictands. The ideal predictors should be informative, make physical sense, strongly correlated with the target variable, realistically represented by the GCMs while capturing multiyear variability, and finally collectively reflect the climate change signal (Wilby et al., 2004).

In this study, the observed data in seven different climate zones of New Brunswick province (Figure 2) for 30 years had been applied to select the large-scale predictors. The best predictors, with the highest explained variance, are selected. The reanalysis data (NCEP) during calibration period (1961-1975) had been used to estimate a relationship between the selected predictors and predictands. The robustness of developed relation was validated using the reanalysis data at validation period (1976-1990). The calibration and validation procedure certifies the correctness and robustness of the selected predictors and if there were a good fit between observed and calibrated predictands during the validation period the estimated relationship had been applied to GCM predictors to generate scenarios during reference and future time period. Finally, the number of rainy and snowy days in each month were calculated assuming days with more than 1 mm of precipitation as the rainy days and days with mean temperature of -4ºC to 0 ºC as the freezing days.

ANALYSIS AND DISCUSSION

Spatial-temporal analysis of road accidents

The NBR and PR analysis were executed to estimate the relationship between the EWAS Index and the selected predictors. The fitness of the models was verified by testing the likelihood statistics, Wald chi-square test and likelihood ratio test of random effects. Log likelihood statistics estimated for determining whether convergence to stable estimates had been attained for the NBR and PR models. Since it uses maximum likelihood estimate, the maximum difference between the log likelihood of null and full model explains the fitness of the model.

The Wald statistic represents the square of the ratio between the regression coefficient and its standard error. This statistic follows a chi-square distribution with degree of freedom (df), which is equal to the standard normal distribution squared. The Chi-Square distribution is merely the distribution of the sum of the squares of a set of normally distributed random variables. Its value stems from the fact that the sum of random variables from any distribution can be closely approximated by a normal distribution. Wald chi-square statistics (df = 8), with a *p*-value of 0.00, show the statistical significance of both NBR and PR models (Table 2).

The likelihood-ratio tests define whether the data are better modeled using a panel structure or whether a pooled structure is preferred. The likelihood ratio value with a *p*-value of 0.00 justifies that the random effects (panel) parameterization with beta distribution is preferred over the pooled (constant dispersion) model (Table 2).

The statistical significance of the explanatory variables of the EWAS index is displayed by the *p*-value, listed under the column $P>|Z|$. For both of the regression models (negative binomial and Poisson), the *p*-value is 0.000, below the standard threshold of 0.05, meaning that the coefficients of the explanatory variables are statistically significant (Table 3).

Table 2: Fitness of regression models for all accident data of New Brunswick

Fitness parameters	Negative Binomial regression	Poisson regression
Log likelihood (without model)	-563460	-563460
Log likelihood (with model)	-301937.26	-563234.19
Wald chi square (8) Prob > chi square	8653.86 0.000	127227.43 0.0000
Likelihood-ratio test vs. pooled: chibar2(01) Prob>=chibar2	77.58 0.000	431.31 0.000

The NBR and PR models explain the positive relationship between the explanatory variables and the EWAS index except in the cases of surface-road alignment and surface-road characteristics. The potentiality of weather-accident severity will be increased with the adverse light condition and adverse weather condition. For every one rank increases in light-weather condition, the log count of the EWAS index is expected to increase by 0.006 and 0.024 for NBR and PR models, respectively (Table 3). That means, a single unit degradation of light-weather condition would increase the weather-accident severity (EWAS) by 0.6% for NBR model and 2.4% for PR model (Table 3). Similarly, the weather-accident severity can be increased with the poor surface conditions and poor weather conditions. A single unit degradation of surface-weather condition can contribute 7.1% (NBR model) and 7.6% (PR model) increase of weather-accident severity (Table 3).

Female drivers are more vulnerable to weather-accident severity comparing to the male drivers. If the driver is female, the weather-accident severity (EWAS) can be increased by 2.4% (NBR model) and 3.7% (PR model) (Table 3). Similarly, the older drivers are more vulnerable to weather-accident severity because of the visibility problems. Senior drivers, with an age of 65 years and above, increase the probability of weather-accident severity by 3.1% (NBR model) and 5.6% (PR model) (Table 3).

Table 3: Model summary for Negative Binomial regression and Poisson regression models

Variables	Coefficient		Std. error		Z-value		P>|Z|		95% confidence internal			
	NBR	PR	NBR	PR	NBR	PR	NBR	PR	NBR		PR	
Light-weather condition	.006	.024	.0007	.0003	9.80	81.34	0.00	0.00	.006	.008	.006	.008
Surface-weather condition	.071	.076	.0024	.0010	29.47	73.86	0.00	0.00	.066	.075	.066	.075
Surface-road alignment	-.011	.004	.0019	.0008	-5.40	4.67	0.00	0.00	-.014	-.007	-.014	-.007
Surface-road character	-.048	-.065	.0039	.0017	-12.3	-37.9	0.00	0.00	-.055	-.040	-.055	-.040
Weather-driver's gender	.024	.037	.0009	.0004	27.63	97.06	0.00	0.00	.022	.025	.022	.025
Weather-driver's age	.031	.056	.0011	.0005	27.07	113.0	0.00	0.00	.029	.034	.029	.034
Weather-driver's experience	.013	.023	.0006	.0003	21.10	84.39	0.00	0.00	.012	.015	.012	.015
Weather-vehicle's age	.014	.019	.0005	.0002	25.47	80.25	0.00	0.00	.013	.015	.013	.015

The less driving experience increases the probability of weather-accident severity because of less driving experience in the adverse weather and the lack of knowledge of what-to-do during the adverse weather conditions. Less driving experience increases the accident severity by 1.3% (NBR model) and 2.3% (PR model) during the adverse weather conditions (Table 3). In most of the driving cases on highway, the less-experienced drivers suddenly reduce the speed of the vehicles or overlap the lane demarcation because of the poor visibility and collided by the following and side vehicles, respectively.

The old vehicles are more vulnerable to weather-accident severity comparing to the new vehicles probably because the brakes and traction control of new vehicles are obviously performing better than those of old vehicles. The older vehicles contribute 1.4% (NBR model) and 1.9% (PR model) increase of accident severity during the adverse weather conditions (Table 3). This result shows the opposite explanation of the findings of a study conducted by Edwards (1996). Edwards (1996) shows that drivers of new vehicles are taking more risk and vulnerable to road accidents as the vehicles are well-equipped with different safety features. The positive relation between weather-vehicle's age and weather-accident severity reveals that new vehicles with well-equipped safety features are less exposed to weather-accident severity.

The surface-road characteristics attribute has inverse relationship with the EWAS index in both regression models, while surface-road alignment has inverse relationship with the EWAS index only in the NBR model. One-unit increase of surface-road character severity can contribute 4.8% (NBR model) and 6.5% (PR model) decrease of accident severity during the adverse weather conditions (Table 3). Similarly, the NBR model shows that one-unit increase of surface-road alignment severity can contribute to 1.1% decrease of accident severity during the adverse weather conditions (Table 3). The drivers are at their highest caution when driving at hilly and curves (vertical and horizontal) roads, especially during the poor surface-weather conditions. This is why; less weather-accident severity is observed for the poor-surface road alignment during the hazardous weather condition. Similarly, the drivers are more alert driving on an undivided road with two or multiple lanes especially when the surface and weather conditions are adverse to drive.

The regression models were performed for each census division of New Brunswick in order to determine the spatial-longitudinal behavior of the EWAS index with respect to the predictor variables in each census division. The fitness tests verified the fitness of the regression models (Table 4 and 5) except in the case of NBR model for the Saint John census division (Table 4).

Table 4: Fitness of NBR model for census divisions of New Brunswick

Census Division	Log likelihood (without model)	Log likelihood (with model)	Wald chi2 (prob> chi2)	Likelihood-ratio test vs. pooled chibar2 (Prob>=chibar2)
Saint John	-58476.95	-31676.423	1014.02 (0.000)	1.24 (0.132)
Charlotte	-13882.19	-6898.908	280.66 (0.000)	14.38 (0.000)
Sunbury	-13686.54	-6701.22	224.13 (0.000)	28.14 (0.000)
Queens	-8468.78	-3955.98	119.64 (0.000)	28.93 (0.000)
Kings	-38085.54	-20262.16	635.41 (0.000)	28.70 (0.000)
Albert	-12250.65	-6569.62	207.85 (0.000)	15.40 (0.000)
Westmorland	-131655.56	-78416.51	2263.90 (0.000)	50.23 (0.000)
Kent	-19137.27	-9925.10	326.43 (0.000)	33.18 (0.000)
Northumberland	-40210.328	-21530.925	522.42 (0.000)	12.25 (0.000)
York	-76901.75	-43028.64	1113.55 (0.000)	14.41 (0.000)
Carleton	-19417.75	-9071.76	324.16 (0.000)	25.13 (0.000)
Victoria	-17720.7	-9057.26	263.73 (0.00)	2.55 (0.055)
Madawaska	-22492.47	-11833.5	417.08 (0.000)	15.91 (0.0000
Restigouche	-18931.2	-9477.52	323.8 (0.000)	44.01 (0.000)
Gloucester	-66729.16	-32633.4	987.7 (0.000)	25.32 (0.000)

Table 5: Fitness of PR model for census divisions of New Brunswick

Census Division	Log likelihood (without model)	Log likelihood (with model)	Wald chi2 (prob> chi2)	Likelihood-ratio test vs. pooled chibar2 (Prob>=chibar2)
Saint John	-58476.95	-58406.812	14365.94(0.000)	138.08 (0.000)
Charlotte	-13882.197	-13784.954	4794.70 (0.000)	186.45 (0.000)
Sunbury	-13686.53	-13554.96	3220.54 (0.000)	262.41(0.000)
Queens	-8468.78	-8273.09	1772.98 (0.000)	391.07 (0.000)
Kings	-38085.55	-37887.67	7778.50 (0.000)	395.04 (0.000)
Albert	-12250.65	-12145.96	3476.00 (0.000)	207.85 (0.000)
Westmorland	-131655.56	-131455.25	27556.59 (0.00)	397.32 (0.000)
Kent	-19137.27	-18965.96	4439.14 (0.000)	341.20 (0.000)

Census Division	Log likelihood (without model)	Log likelihood (with model)	Wald chi2 (prob> chi2)	Likelihood-ratio test vs. pooled chibar2 (Prob>=chibar2)
Northumberland	-40210.328	-40105.428	6617.60 (0.000)	209.67 (0.000)
York	-76901.75	-76832.72	13341.94 (0.000)	137.38 (0.000)
Carleton	-19417.75	-19161.23	8298.4 (0.000)	496.61 (0.000)
Victoria	-17720.7	-17661.8	3828.87 (0.000)	117.00 (0.000)
Madawaska	-22492.4	-22414.07	7586.3 (0.000)	151.68 (0.000)
Restigouche	-18931.2	-18765.5	6788.8 (0.000)	326.3 (0.000)
Gloucester	-66729.16	-66605.7	17462.2 (0.000)	241.00 (0.000)

The relationship between the explanatory variables and the EWAS index in each census division of New Brunswick is explained by NBR model (Table 6) and PR model (Table 7). The NBR and PR models estimated that the surface-weather condition, weather-driver's gender, weather-driver's age, weather-driver's experience and weather-vehicle's age have strong positive relations with the EWAS index for each of census division of New Brunswick (Table 6 and 7). These results (Table 6 and 7) echo the same outcomes from the NBR and PR analyses for the New Brunswick (Table 3). Similar to the province-wise (New Brunswick) scenario (Table 4), in most of the census divisions, the surface-road character has negative relationship with the weather-accident severity except in Sunbury (for NBR and PR models), Carleton (PR model) and Victoria (PR model) (Table 6 and 7). However, the positive contribution of weather-road character to weather-accident severity index (EWAS) is very low (Table 6 and 7).

This study observes a mixed relationship between surface-road alignment variable and the EWAS index for different census division. The relationship is positive at Charlotte (0.6%), Queens (4.5%), Kings (0.7%), Albert (1.25%), Northumberland (0.04%), and Restigouche (1.5%) according to the estimation of NBR model (Table 6).

Table 6: Regression coefficient of explanatory variables in NBR model

Census Division	Explanatory variables							
	Light-weather condition	Surface-weather condition	Surface-road alignment	Surface-road character	Weather-driver's gender	Weather-driver's age	Weather-driver's experience	Weather-vehicle's age
Saint John	.017	.05	-.009	-.0228	.0226	.0332	.009	.014
Charlotte	.0012	.078	.006	-.089	.0233	.051	.0169	.0189
Sunbury	-.003	.055	-.0268	.008	.029	.041	.013	.017
Queens	-.008	.0404	.045	-.094	.0217	.0414	.0176	.0126
Kings	-.0015	.0708	.007	-.0726	.0232	.0288	.0121	.0142
Albert	.010	.0964	.0125	-.121	.022	.0257	.01	.014
Westmorland	.012	.08	-.015	-.054	.02	.0276	.0144	.009
Kent	.003	.093	-.00009	-.0935	.0199	.0184	.02	.0169
Northumberland	.0006	.059	.0004	-.052	.0259	.027	.0159	.0159
York	.008	.052	-.006	-.027	.024	.032	.009	.009
Carleton	.007	.093	-.002	-.102	.033	.044	.012	.02
Victoria	-.002	.04	-.001	-.015	.016	.048	.018	.014
Madawaska	.015	.078	-.041	-.017	.03	.035	.012	.018
Restigouche	.024	.065	.015	-.093	.032	.038	.023	.013
Gloucester	.006	.09	-.003	-.09	.027	.024	.014	.015

Table 7: Regression coefficient of explanatory variables in PR model

Census Division	Explanatory variables							
	Light-weather condition	Surface-weather condition	Surface-road alignment	Surface-road character	Weather-driver's gender	Weather-driver's age	Weather-driver's experience	Weather-vehicle's age
Saint John	.033	.052	-.009	-.0109	.035	.057	.017	.0207
Charlotte	.0158	.056	.0124	-.048	.032	.0904	.029	.038
Sunbury	.005	.0448	-.018	.053	.045	.0557	.018	.0157
Queens	.0185	.0502	.0957	-.174	.0416	.069	.025	.013
Kings	.01	.104	.039	-.164	.024	.053	.0197	.0164
Albert	.023	.141	.052	-.237	.034	.0508	.0196	.0256
Westmorland	.0259	.095	.0098	-.105	.0325	.0476	.0248	.013

Census Division	Explanatory variables							
	Light-weather condition	Surface-weather condition	Surface-road alignment	Surface-road character	Weather-driver's gender	Weather-driver's age	Weather-driver's experience	Weather-vehicle's age
Kent	.0197	.129	.005	-.135	.024	.02	.03	.02
Northumberland	.0157	.0507	.004	-.033	.042	.048	.026	.021
York	.029	.042	-.007	.0008	.034	.055	.018	.012
Carleton	.016	.168	.049	-.27	.058	.068	.019	.032
Victoria	.006	.049	-.008	.009	.024	.085	.024	.013
Madawaska	.04	.109	-.049	-.037	.045	.055	.017	.027
Restigouche	.05	.06	.038	-.099	.051	.075	.04	.013
Gloucester	.024	.08	.02	-.096	.042	.05	.023	.02

Similarly, the PR model estimates the positive relationship between surface-road alignment variable and the EWAS index at Charlotte (1.24%), Queens (9.57%), Kings (3.9%), Albert (5.2%), Westmortland (0.9%), Kent (0.5%), Northumberland (0.4%), Carleton (4.9%), Restigouche (3.8%) and Gloucester (2%) (Table 7). These positive relationships explain that the combination of poor road alignment (e.g. hilly road, curved road etc.) and road surface condition (wet, ice, snow etc.) aggravates the weather-accident severity in these areas.

Climate change modeling

The analysis of changes in rainy days shows that the number of rainy days will increase during all months in New Brunswick except in Aroostook zone in which the number of rainy days will decrease during summer and will increase during other months. Number of snowy days may decrease for all zones in the province except in Moncton zone in which the number of snowy days may increase during January and February. Also, there is an increasing trend in Aroostook zone during the months that snowfall occurs. Number of freezing days will have the same trend in all zones of New Brunswick and it will increase during winter and March and it will decrease in other months. Generally, the average temperature will increase in future and this increase will cause more freezing days (in the range of -4 º C to 0 º C) during winter and March.

The average changes in the ratio of annual rainy, snowy, and freezing day were summarized in Table 8. The table shows that the number of rainy days may increase for all of the zones and the number of snowy days and freezing days may decrease or stay the same for most of the zones in the province. More specifically, the average number of rainy days may increase by 34, 31, 24, and 21 days per year during 2071-2100 at Doaktown, Fredericton, Aroostook, and Miramichi zone respectively and the average number of freezing days may decrease by 9, 8, 5, and 4 days per year during the same period at Moncton, Saint John, Fredericton and Aroostook zone respectively and it may increase by 3 days per year in Doaktown.

Table 8: Annual average changes in the ratio of rainy, snowy and freezing days in New Brunswick

	Rainy Days			**Snowy days**			**Freezing days**		
Zone	**2011**	**2041**	**2071**	**2011**	**2041**	**2071**	**2011**	**2041**	**2071**
Aroostook	0.01	0.04	0.07	0.01	0.01	0.02	0.00	0.00	-0.01
Miramichi	0.02	0.04	0.06	-0.01	-0.01	-0.01	0.00	0.00	0.00
Doaktown	0.03	0.06	0.09	0.00	0.00	0.00	0.00	0.01	0.01
Fredericton	0.03	0.06	0.09	-0.02	-0.02	-0.02	0.00	0.00	-0.01
Kedgwick	0.00	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.00
Moncton	0.01	0.01	0.00	0.02	0.03	0.04	0.00	-0.01	-0.02
Saint John	0.02	0.03	0.03	0.00	-0.01	-0.02	0.00	-0.01	-0.02

Impact of climate change on accidents

The NBR and PR models estimates that the combined effects of hazardous weather conditions and different predictors of road accidents (which can be affected by hazardous weather conditions) are enormous not only in the province-wise scenario, but also in each census division. The increase of adverse weather conditions (e.g. raining, snow and freezing rain) should have an adverse impact on accident severity. The climate change scenario for three different periods (2011-2040, 2041-2070, 2071-2100) reveals that the ratio of hazardous weather days will be increased in most of the climate zones of New Brunswick during the 21st century. More hazardous weather will result in increased accident severity.

CONCLUSION

The Road Safety Strategy 2015, developed by Transport Canada, identifies impaired driving, speed and aggressive driving, and occupant protection as the factors of road accidents. Uncontrollable meteorological conditions are also important contributing factors for road accidents. The objective of this research is to study the impact of climate change on the hazardous weather-related road accidents. The New Brunswick province of Canada is considered as a case study.

The road accident data of New Brunswick were collected from the police accident reports. This study developed an Exposure to Weather-Accident Severity (EWAS) Index multiplying the severity of hazardous weather conditions for road accidents with the Accident Severity Index (ASI). The ASI incorporated proportional monetary implications of injuries, fatalities, and PDO. The road accident attributes, which could be affected by the hazardous weather conditions, were considered as the explanatory factors of the EWAS index. These are light-weather condition, road surface-weather condition, road surface-road alignment, roadway-surface condition, weather-driver's age, weather-driver's gender, weather-driving experience, and weather-vehicle's age.

For climate change modeling, this study used a 30-year continuous record (from 1961-1990) of daily rainfall, snowfall and mean temperature. The selected data included observed daily data for seven climate zones in the province, NCEP re-analysis dataset, and large-scale simulation data from the CGCM3. This study also used large-scale simulation data from Canadian GCM under SRES-A2 scenario during 21st century.

The relationship between the EWAS index and predictors was examined by the negative binomial regression (NBR) and Poisson regression (PR) models. The NBR and PR models explain the positive relationship between the explanatory variables and the EWAS index except in the cases of surface-road alignment and surface-road characteristics. The drivers are at their highest caution when driving at hilly terrain and curves (vertical and horizontal), especially on poor surface-weather conditions. This is why; less weather-accident severity is observed for the poor-surface road alignment during the hazardous weather condition. Similarly, the drivers are more alert driving on an undivided road with two or multiple lanes especially when the surface and weather conditions are adverse to drive.

The spatial pattern of the EWAS index with respect to explanatory variables was examined for the fifteen census divisions of New Brunswick. The NBR and PR models estimated that the surface-weather condition, weather-driver's gender, weather-driver's age, weather-driver's experience and weather-vehicle's age have strong positive relation with the EWAS index for each of the census divisions of New Brunswick. These echo the same outcomes from the NBR and PR analyses for the New Brunswick province. Similar to the province-wise scenario, in most of the census divisions, the surface-road character has negative relationship with the weather-accident severity except in Sunbury (for NBR and PR models), Carleton (PR model) and Victoria (PR model). The PR model estimates the positive relationship between surface-road alignment variable and EWAS index at Charlotte, Queens, Kings, Albert, Westmortland, Kent, Northumberland, Carleton, Restigouche, and Gloucester. These positive relationships explain that the combination of poor road alignment (e.g. hilly road, curved road etc.) and road surface condition (wet, ice, snow etc.) aggravates the weather-accident severity in these areas.

The climate change modeling estimated that the number of rainy days may increase for all of the climate zones and the number of snowy days and freezing days may decrease or stay the same for most of the zones in the province. For example, the average number of rainy days may increase by 34, 31, 24, and 21 days per year during 2071-2100 at Doaktown, Fredericton, Aroostook, and Miramichi zone respectively and the average number of freezing days may decrease by 9, 8, 5, and 4 days per year during the same period at Moncton, Saint John, Fredericton and Aroostook zone respectively. The freezing days may increase by 3 days per year in Doaktown. More hazardous weather will result in increased accident severity. This study suggests that the Road Safety Strategy 2015 of Transport Canada should not only adopt the holistic approaches based on the impaired driving, speed and aggressive driving, occupant protection, it should also take protective measures for the hazardous weather conditions to reduce the accident severity.

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