

The Impact of Cold and Snow on Weekday and Weekend Highway Total and Passenger Cars Traffic Volumes

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Abstract: Presented in this paper is an investigation of the impact of cold and snow on daily traffic volumes of total traffic and passenger cars. It is based on a detailed case study of five years of Weigh-In-Motion data recorded continuously at a highway site in Alberta, Canada. Dummy-variable regression models are used to relate daily traffic volumes with snowfall and categorized cold variables. The importance of all the independent variables used in the model are established by conducting tests of statistical significance. The total traffic and passenger car volumes are influenced by both the snowfall and the cold categories. Plots of the partial effect of each independent variable on the dependent variable are generated. It is found that a daily snowfall of 10 cm may cause a 25% reduction in the daily volume of passenger cars, and temperatures below -25°C may reduce the passenger car volumes by 10% or more. It is believed that the developed traffic-weather models of this study can benefit highway agencies in developing more advanced imputation method or identifying weather adjustment factors for accurate estimation of AADT from short duration traffic counts.

Keywords: Dummy variable regression, traffic statistics, vehicle classification, weigh-in-motion, winter-weather traffic model.

INTRODUCTION

Traffic volumes vary over time and locations on all roadways. Even if traffic streams are investigated for the same time and location, the variations of traffic volumes could differ substantially with weather conditions. Severe winter weather conditions in Canada and northern regions of the USA add another dimension to variations of traffic streams [1, 2]. Datla and Sharma [2] conducted a thorough investigation of impact of winter weather conditions (cold temperatures and snowfall) on highway traffic volumes. Their study concluded that winter weather causes significant variations in traffic volumes, and the magnitude of variation depends on the time of day, day of the week, location, highway type, and severity of the weather. However, their study and other similar studies published in the literature were conducted solely on the basis of total traffic volume data which is collected from permanent traffic counters (PTCs), including a mix of passenger cars and trucks. Moreover, none of the past studies in the literature provided detailed information regarding traffic patterns of total traffic and passenger cars separately in relation to the time of day, day of the week, season of the year, type of roadway, and severity of weather. Such a study could be very useful for transportation analyses for such purposes as the structural design of pavement, geometric design, highway life cycle analysis, project prioritization, and to develop traffic simulation models.

Recently, there has been a growing interest in encouraging the use of classification data in transportation studies, and it is believed that this trend is mainly due to the

rapid and widespread introduction of vehicle classification technologies. However, in spite of its importance in many applications, only a limited amount of classification data has been collected by highway agencies and, consequently, little analytical work on this subject has been conducted until recently. A majority of studies on traffic patterns have been conducted based merely on hourly total traffic volume.

The main purpose of this study is to investigate the variations of daily traffic volumes of total traffic and passenger car vehicle classes separately with winter weather (snow, temperature) conditions. Dummy-variable regression models are developed to define quantitatively the variations in those vehicle volumes under different weather conditions. The study uses Weigh-in-Motion (WIM) data on the provincial highway network in Alberta, Canada. The modeling work for the present research is carried out using CARPACKAGE, available in the statistical software R [3, 4].

LITERATURE REVIEW

Past studies that focus on the association of highway traffic with weather conditions can be categorized into three sub-categories. The first sub-category comprises the studies that focus mainly on the effect of weather on highway and traffic conditions [5-7]. These studies investigated a variety of weather conditions that cause variations in highway traffic flow. Colyar *et al.* [6] explained how weather events cause changes in roadway environments that affect traffic parameters and degradation in traffic flow conditions. Goodwin [7] tried to explain the impact of weather events on (a) driver behavior, (b) roadway safety, and (c) roadway mobility.

Second, a number of researchers have attempted to address quantitatively the association of traffic volumes with

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weather conditions [8-10]. All of these studies reported reductions in traffic due to adverse weather conditions and changes in traffic patterns with adverse weather conditions.

Third, some researchers focused on the traveler behaviour during adverse weather conditions. Hanbali and Kuemmel [8] pointed out that travelers' decision making behaviour can be affected by (a) their willingness to travel, (b) the importance of reaching their destinations, and (c) the difficulty of moving to the destination. They argued that a reduction in traffic movement occurs due to a traveler's desire to avoid travel during adverse weather conditions. Other studies [11-13] indicated that reductions in traffic during adverse weather conditions result mainly from trip adjustments, such as leaving for work early, and an avoidance of unnecessary and discretionary trips.

STUDY DATA

The provincial highway agency in Alberta, Canada, collects vehicle-by-vehicle WIM data at six highway sites on its network. These sites were installed in July 2004 and have continuously been collecting vehicle load data and other information for programs such as Alberta's Strategic Highway Research Program and Long Term Pavement Performance [14]. The WIM station selected for this research is located south of Leduc (near the City of Edmonton) on control section 26 of Highway 2A (2 lanes) and is referred to as LEDUC site in this paper. The two main reasons for selecting this site for the study were that:

- (1) there were no missing hourly traffic records at this site over the study period, which included five years of data from 2005 to 2009, and
- (2) there were several potential weather stations that could be used to extract snow fall and temperature data.

The LEDUC site serves both local and regional truck traffic with an AADT (average annual daily traffic) of over 6,000 vehicles per day. The truck traffic at this site is about 8% of the total traffic. Table 1 provides a number of details of the WIM site used for this study in terms of AADT (annual average daily traffic), PAADT (passenger cars annual average daily traffic), TAADT (truck annual average daily traffic), and percent trucks in the traffic.

Weather data were collected from Environment Canada weather information archives [15]. There were 598 weather stations operated by Environment Canada in the province of Alberta between the years 2005 and 2009. Each of these weather stations provide detailed weather parameters such as maximum, minimum, and mean temperature (measured in °C (centigrade)), total rain (millimeters), total snow (centimeters), total precipitation (millimeters) and snow on ground (centimeters) on a daily basis. Details of raw data format and measuring methods for each of these weather parameters are available from the Environment Canada website [15].

An important task involved in the present research was to define the approximate distance from the study WIM site within which weather conditions could be considered homogeneous. To address this issue, and to understand the common practice of designating weather stations around WIM or Automatic Traffic Recorder (ATR) sites, a literature review was conducted. Based on the research done by Andrey and Olley [16] and Datla and Sharma [2], it was found that weather conditions could be considered homogeneous within the area of 16~25km radius around the weather station. A Geographical Information Systems (GIS) base map including the 598 weather stations and the study WIM sites was developed, and weather stations were located according to the level of closeness to the study WIM site using a Proximity analysis module provided by GIS software ArcGIS 10 [17]. The weather station labeled 3012205 was closest (13 km) to the study site and had weather data without any missing portions; hence, it was used in this investigation.

METHODOLOGY

Individual vehicle-by-vehicle records were used to classify all the vehicles into 28 vehicle classes by employing an axle spacing method similar to the method used by the Florida Department of Transportation [18, 19]. These 28 classes of vehicles could easily be aggregated into the Federal Highway Administration's (FHWA) 13-category classification scheme. However, a preliminary analysis indicated that the truck volumes usually are very low compared to passenger cars. This might result in lack of sufficient samples to carry out detailed statistical analysis of truck traffic. Total traffic and passenger cars were used for the modelling purpose of this study.

Historical weather records from the Environment Canada [15] climate database indicate that the province of Alberta experiences severe snowfall and cold conditions from November to March. Based on these observations, the study period for this research was selected to include the months of November to March for a period of five years (from 2005 to 2009). Since traffic patterns during long weekend statutory holidays in Alberta are very unique, special attention is needed to conduct research using data from holidays and their neighboring days [20]. For this reason, three holidays included in the study period (New Year's Day, Alberta Family Day (3rd Monday of February), and Christmas day) were excluded from the study.

A thorough analysis was carried out to understand the hourly, daily, and monthly traffic patterns of total and passenger cars at the LEDUC study site in Fig. (1). It was observed that passenger car traffic increases steadily from Monday to Friday and decreases slightly during weekends (Fig. 1b). The year-to-year monthly traffic patterns at the study site were found to be similar for both the total and the passenger cars (Fig. 1c).

Table 1. Traffic statistics for study WIM sites.

Highway	Lanes	Site name	AADT	PAADT	TAADT	Passenger Cars (%)	Trucks (%)
Highway 2A	2	Leduc Hwy 2A	7,562	6,969	592	92	8

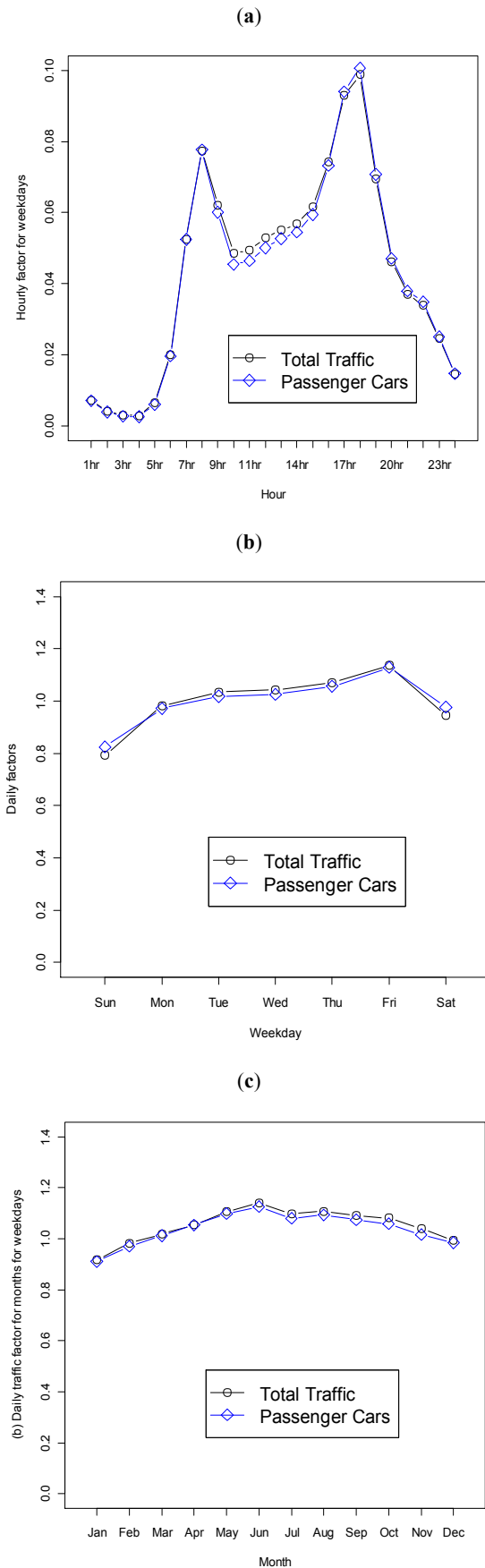


Fig. (1). Typical hourly, daily, and monthly variation of total and passenger cars for study site.

Before proceeding to modeling, the relationships among the dependent and independent variables identified for the modeling were carefully investigated with the help of scatter plots. As example, scatter plots for weekdays are presented in Fig. (2). A strong positive linear relationship was observed between daily passenger car volumes and the historical average expected daily passenger car volumes (first column in second row). A moderately negative linear relationship between daily volumes and SNOW was observed (second column in second row). A moderate positive linear relationship between daily volumes and TEMPERATURE was also observed (third column in second row), i.e., daily passenger car volumes increased with increase in daily average temperature, and decreased with increase of the amount of snowfall.

As depicted in Fig. (3), histograms (with the estimated probability density function) of temperature for the days with snow and for the days without snow were constructed separately using the study data. The results indicated that average temperature is colder during the days with snowfall (-10.94°C , 160 days during the study period) than the no snowfall days (-8.08°C , 350 days during the study periods).

A correlation analysis was also conducted to check multicollinearity among EDVF, snowfall and temperature considering the data from weekdays for the entire 5 years of study period. Table 2 shows the correlation coefficient values and p -value in parenthesis between the independent variables in proposed model specification. The correlation coefficients ranged from -0.09 to 0.23, which means that little to no correlation exists between independent variables. This observation could justify the inclusion of EDVF, SNOW (snowfall) and TEMP (temperature) as independent variables in the model.

Dummy-Variable Regression

Regression analysis has long been recognized as the most flexible and widely used technique to explain variation of quantitative dependent variables by establishing relationships between dependent variables and a specified set of independent variables in the form of additive and linear mathematical functions [21]. In this research, an attempt has been made to model the impact of weather on daily total traffic and passenger cars traffic volumes. For the purpose of mapping the relationships between daily traffic volume and weather factors, a dummy-variable regression model is proposed with two quantitative independent variables, i.e., EDVF, SNOW, and one qualitative (or categorical) independent variable, i.e., temperature categorized at 5°C intervals. Although other weather factors (wind, pavement conditions, etc.) also cause variations in daily traffic volumes, this research is limited to SNOW and temperature. The additive dummy-regression model formulated for this research is:

$$y_i = f \left(\begin{array}{c} \text{expected daily volume factor, snowfall,} \\ \text{temperature} \end{array} \right) = \beta_1 EDVF_i + \beta_2 SNOW_i + \sum_{j=1}^6 \gamma_j CC_{ij} + \varepsilon_i \quad (1)$$

where,

i : refers to the i th observation

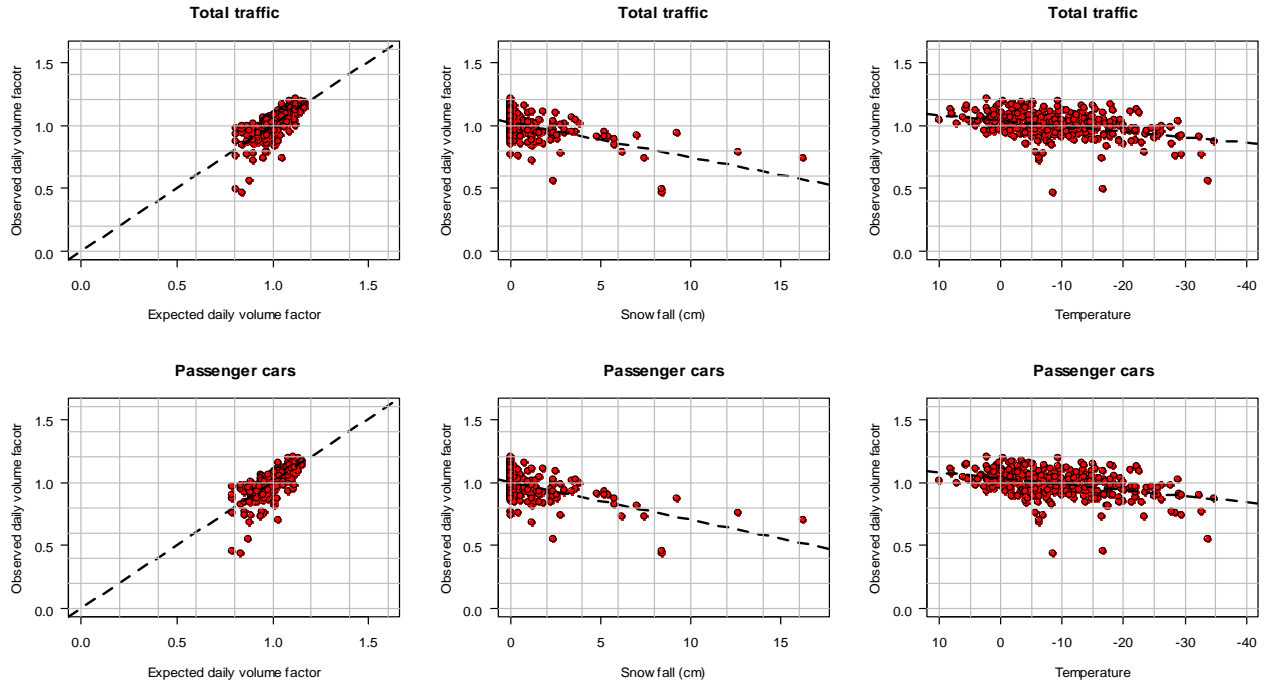


Fig. (2). Scatter plots of 5years modelling database for weekdays traffic for study site.

$\beta_1, \beta_2, \gamma_{1-6}$: regression coefficients estimated for the independent variables

y_i : estimated value of daily traffic volumes factor for vehicle class (passenger cars)

EDVF: expected daily volume factor calculated from the historically observed data

SNOW: amount of snowfall per day (cm)

CC_{i1-6} : $CC_{ij} = 1$ if observation i falls in category j , otherwise 0

ε_i : stochastic error term.

Normalized daily total volumes (ratio of traffic volume to average annual daily traffic volume, AADT), passenger car volumes (passenger car volume to passenger car AADT ratio) are used instead of actual volumes to take into consideration the yearly variations in traffic volumes. The EDVF is a factor obtained by using the following mathematical formula.

$$EDVF_{i,j,k} = \frac{\sum_{r=2005}^{r=2009} (DVF_{i,j,k})_r}{5}, \forall i, j \& k \quad (2)$$

where, i = A particular day of the week i.e. Monday – Friday, j = A particular week of the month for which all the weekday data are available i.e. Week 1 – Week 4 (5), k = A particular winter month of the year i.e. November – March, r = A counter for the years i.e. 2005 – 2009, $DVF_{i,j,k}$ = Daily volume factor for a given day in a given week for a given month in a particular year. Based on the knowledge gained from the literature [3, 21, 22], and for the sake of easy interpretation of the dummy-variable regression, the

temperature (daily mean temperature, measured in °C) has been considered as a categorical variable. In this research, temperature is categorized into 7 categories with 5 °C equal intervals by introducing six dummy regressors, i.e., CC_1 (-5°C ~ 0°C), CC_2 (-10°C ~ -5°C), CC_3 (-15°C ~ -10°C), CC_4 (-20°C ~ -15°C), CC_5 (-25°C ~ -20°C), and CC_6 (below -25°C). The baseline category (the days having over 0°C) is omitted in the model specifications because it is the reference category to which the other categories are compared.

Interpretation of Coefficients

The coefficient for EDVF (β_1) represents the slope of the regression plane, which indicates a change in the estimated value of the daily volume factor (y_i), responding to a unit increase (or decrease) of the EDVF value, while the SNOW variable is kept at its mean value. Similarly, the coefficient for SNOW (β_2) indicates a change in the y_i value responding to a unit change in snow fall, while the other independent variable, EDVF, is fixed at its mean value. The group differences (a difference of the estimated daily traffic volume factor between CC_1 and CC_2 , or between CC_1 and CC_3 , and so on) as the gross effect of being in CC_1 rather than CC_2 can simply be calculated by considering the algebraic difference of the coefficients of dummy variables estimated for corresponding cold categories (or levels) (i.e., γ_1, γ_2 or γ_1, γ_3). By conducting dummy-variable regression, we are able to identify the influence of weather factors (cold) that lead to the observed differences in daily traffic volume factors between cold categories. In a more intuitive manner, the regression equation (Eq. (1)) might be described geometrically using seven parallel regression planes, which

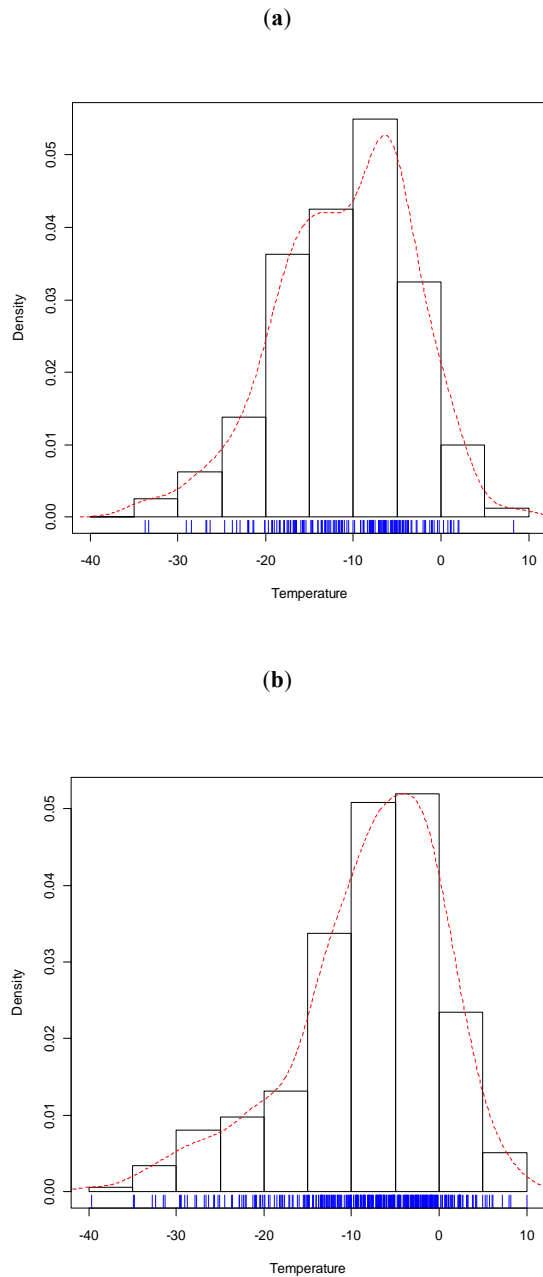


Fig. (3). Probability distribution plots for temperature during the days (a) with snow and (b) without snow.

differ in their intercepts. For example, after fitting regression Eq. (1), a regression equation fitted for cold category CC_1 becomes $\hat{Y}_{cc1} = \beta_1 EDVF_i + \beta_2 SNOW_i + \gamma_1$, and, for CC_2 , it is $\hat{Y}_{cc2} = \beta_1 EDVF_i + \beta_2 SNOW_i + \gamma_2$. The coefficients $\gamma_1, \gamma_2, \dots$ and γ_6 represent the intercepts of the regression

planes for cold categories CC_1, CC_2, \dots and CC_6 , respectively. The influence of cold categories on the dependent variable y_i can be described by taking the example of categories CC_1 and CC_2 . Assuming that the two coefficients γ_1 and γ_2 are positive, and that γ_1 is greater than γ_2 , then, the value of $\gamma_1 - \gamma_2$ gives the constant vertical difference between the parallel regression planes for CC_1 and CC_2 , at the mean values of EDVF and the SNOW variables. The value, $\gamma_1 - \gamma_2$, in this research, can be interpreted as the increase of daily traffic factors (or daily traffic volumes) that could possibly be caused by the gross effect of being in CC_1 rather than CC_2 .

RESULTS AND DISCUSSION

As the traffic patterns were quite different for weekdays and weekends, modeling was carried out separately for weekdays and weekends. Tables 3 and 4 show the calibrated models using Eq. (1) and statistical test results for weekdays and weekends, respectively.

The overall goodness of fit of the regression model to sample data is evaluated by the squared multiple correlation coefficient (R^2). The values of R^2 for all models are over 0.99, which means that all the models fit well to the sample data. The value of the F statistic, which is used to assess the overall adequacy of the model, is significant at the 0.001 level for all the models. The incremental values of F -statistic are also shown in Tables 3 and 4. These values are used to test the null hypothesis of “no partial effect of cold categories ($H_0: \gamma_1 = \gamma_2 = \dots \gamma_6 = 0$)”. By comparing the overall value of R^2 of the model including the dummy-variables (Table 3) with the value of R^2 of the naive model, i.e., $y_i = \beta_1 EDVF_i + \beta_2 SNOW_i + \varepsilon_i$, it is possible to confirm statistically whether or not the inclusion of dummy variables is statistically significant. Below is an example for passenger cars in Model 2 of Table 3:

$$F = \frac{(R_{dummy}^2 - R_{Naive}^2)/(k_{dummy} - k_{naive})}{(1 - R_{dummy}^2)/(N - k_{dummy})}$$

$$F = \frac{(0.9977 - 0.997)/(9 - 2)}{(1 - 0.9977)/(375 - 9)} = 15.91$$

where, R_{dummy}^2 is the value of R^2 including dummy variables for Model 2, R_{Naive}^2 is the comparable measure for the naive model without dummy variables, N is the number of observations (days), k_{dummy} is the total number of independent variables including dummy variables (equal to 9), and k_{naive} is the total number of independent variables without including dummy variables (equal to 2). From the resulting value of 15.91, it can be concluded that, for passenger cars during weekdays, the inclusion of dummy-variables is statistically significant at or better than 0.001

Table 2. Weekdays correlation matrix for EDVF, snowfall and temperature for total traffic for 5 years study data.

Correlations	EDVF	SNOW	TEMP
EDVF	1.00000000	-0.12474919 (0.01564)	0.23102714 (0.000006179)
SNOW	-0.12474919 (0.01564)	1.00000000	-0.08712205 (0.09205)
TEMP	0.23102714 (0.000006179)	-0.08712205 (0.09205)	1.00000000

confidence level. In other words, there is a significant overall influence of cold categories on the volume of passenger cars.

The statistical significance for individual coefficients is evaluated by the *t*-statistic, and the significance level is indicated using a symbol (*) in Tables 3 and 4. Based on the results of the *t*-tests, the following general conclusions can be drawn from the results for weekday traffic presented in Table 3: The total and passenger car volumes are influenced by all the independent variables included in the model, i.e., the expected daily volume factor EDVF, snowfall, and the cold categories.

As mentioned earlier, the results of model development for the weekend traffic are presented in Table 4. It is interesting to note that statistical significance of the cold categories is not established for the total and passenger car volumes observed at the LEDUC site. One possible reason

for this could be that the sample size in terms of the total number of days of observations over the weekends (135) is much smaller than the sample size for the weekdays (375). The total sample size of 135 days of weekend traffic when distributed over the seven cold categories resulted in a very small sample size for most of the cold categories.

The variations of weekday and weekend daily traffic factors estimated by the study models in Tables 3 and 4 and the observed daily traffic factors are shown in the form of a scatter plot in Figs. (4, 5). An estimated regression line is also added in the same plot to show the level of closeness between the two values (see the first row in Figs. 4, 5). The accuracy of the calibrated models in terms of estimating the mean daily traffic factor for the seven temperature categories is shown with the help of line graphs in the second row of Figs. (4, 5). The dotted line with solid circles shows the mean values of observed daily traffic factors in each of the

Table 3. Results of daily factor model by passenger cars using dummy-variable regression for weekdays.

Variables	Total Traffic (Model 1)	Seven Fitted Regression Equations for Each Cold Categories for Total Traffic
EDVF	0.885 (0.036)***	$\hat{Y}_{baseline} = 0.885 * EDVF - 0.023 * SNOW + 0.139$ $\hat{Y}_{cc1} = 0.885 * EDVF - 0.023 * SNOW + 0.139$ $\hat{Y}_{cc2} = 0.885 * EDVF - 0.023 * SNOW + 0.137$ $\hat{Y}_{cc3} = 0.885 * EDVF - 0.023 * SNOW + 0.134$ $\hat{Y}_{cc4} = 0.885 * EDVF - 0.023 * SNOW + 0.120$ $\hat{Y}_{cc5} = 0.885 * EDVF - 0.023 * SNOW + 0.114$ $\hat{Y}_{cc6} = 0.885 * EDVF - 0.023 * SNOW + 0.031$
SNOW	-0.023(0.001) ***	
baseline	0.139 (0.038) ***	
CC ₁	0.139 (0.037) ***	
CC ₂	0.137 (0.036) ***	
CC ₃	0.134 (0.037) ***	
CC ₄	0.120 (0.037) **	
CC ₅	0.114 (0.037) **	
CC ₆	0.031 (0.037)	
R ²	0.9979	
F	19650***	
Change from R _{Naive} ²	0.0005	
Incremental F- statistic	12.44***	
Number of days	375	
Variables	Passenger Cars (Model 2)	Seven Fitted Regression Equations for Each Cold Categories for Passenger Cars
EDVF	0.868(0.037)***	$\hat{Y}_{baseline} = 0.868 * EDVF - 0.025 * SNOW + 0.162$ $\hat{Y}_{cc1} = 0.868 * EDVF - 0.025 * SNOW + 0.158$ $\hat{Y}_{cc2} = 0.868 * EDVF - 0.025 * SNOW + 0.154$ $\hat{Y}_{cc3} = 0.868 * EDVF - 0.025 * SNOW + 0.151$ $\hat{Y}_{cc4} = 0.868 * EDVF - 0.025 * SNOW + 0.131$ $\hat{Y}_{cc5} = 0.868 * EDVF - 0.025 * SNOW + 0.130$ $\hat{Y}_{cc6} = 0.868 * EDVF - 0.025 * SNOW + 0.040$
SNOW	-0.025(0.002)***	
baseline	0.162 (0.039)***	
CC ₁	0.158 (0.038)***	
CC ₂	0.154 (0.037)***	
CC ₃	0.151 (0.037)***	
CC ₄	0.131 (0.038)***	
CC ₅	0.130 (0.037)***	
CC ₆	0.040 (0.037)	
R ²	0.9977	
F	17600***	
Change from R _{Naive} ²	0.0007	
Incremental F- statistic	15.91***	
Number of days	375	

Regression coefficients with standard errors (in parentheses)

***Coefficient is statistically significant at the 0.001 level, ** 0.01 level, * 0.05 level.

Table 4. Results of daily factor model by passenger cars using dummy-variable regression for weekend.

Variables	Total Traffic (Model 3)	Seven Fitted Regression Equations for Each Cold Categories for Total Traffic
EDVF	0.980 (0.055)***	$\hat{Y}_{baseline} = 0.980 * EDVF - 0.024 * SNOW + 0.054$ $\hat{Y}_{cc1} = 0.980 * EDVF - 0.024 * SNOW + 0.061$ $\hat{Y}_{cc2} = 0.980 * EDVF - 0.024 * SNOW + 0.044$ $\hat{Y}_{cc3} = 0.980 * EDVF - 0.024 * SNOW + 0.035$ $\hat{Y}_{cc4} = 0.980 * EDVF - 0.024 * SNOW + 0.010$ $\hat{Y}_{cc5} = 0.980 * EDVF - 0.024 * SNOW + 0.003$ $\hat{Y}_{cc6} = 0.980 * EDVF - 0.024 * SNOW - 0.066$
SNOW	-0.024 (0.003)***	
baseline	0.054 (0.047)	
CC ₁	0.061 (0.045)	
CC ₂	0.044 (0.044)	
CC ₃	0.035 (0.046)	
CC ₄	0.010 (0.046)	
CC ₅	0.003 (0.043)	
CC ₆	-0.066 (0.048)	
R ²	0.9954	
F	3039***	
Change from R ² _{Naive}	0.0017	
Incremental F- statistic	6.65***	
Number of days	135	
Variables	Passenger Cars (Model 4)	Seven Fitted Regression Equations for Each Cold Categories for Passenger Cars
EDVF	0.975 (0.058)***	$\hat{Y}_{baseline} = 0.975 * EDVF - 0.027 * SNOW + 0.063$ $\hat{Y}_{cc1} = 0.975 * EDVF - 0.027 * SNOW + 0.070$ $\hat{Y}_{cc2} = 0.975 * EDVF - 0.027 * SNOW + 0.053$ $\hat{Y}_{cc3} = 0.975 * EDVF - 0.027 * SNOW + 0.041$ $\hat{Y}_{cc4} = 0.975 * EDVF - 0.027 * SNOW + 0.011$ $\hat{Y}_{cc5} = 0.975 * EDVF - 0.027 * SNOW + 0.005$ $\hat{Y}_{cc6} = 0.975 * EDVF - 0.027 * SNOW - 0.066$
SNOW	-0.027 (0.003)***	
baseline	0.063 (0.052)	
CC ₁	0.070 (0.050)	
CC ₂	0.053 (0.048)	
CC ₃	0.041 (0.050)	
CC ₄	0.011 (0.050)	
CC ₅	0.005 (0.047)	
CC ₆	-0.066 (0.053)	
R ²	0.9951	
F	2822***	
Change from R ² _{Naive}	0.0019	
Incremental F- statistic	6.97***	
Number of days	135	

Regression coefficients with standard errors (in parentheses).

***Coefficient is statistically significant at the 0.001 level, ** 0.01 level, * 0.05 level.

seven cold categories, and the solid line with diamonds shows the mean values of daily traffic factors estimated using the proposed model. It should be noted that the observed and the estimated mean values of the daily volume factors for all cold categories are so close that the two lines overlap each other in the plots.

Application of winter weather model developed in this study would be useful tool to estimated traffic reduction due to weather factors, mainly temperature or snowfall. We tried to understand the effect of cold on total traffic and passenger cars volume using models 1 to 4 with the concept of the percentage reductions (PRs) developed in the study conducted by Datla and Sharma [2].

The reductions in both total traffic and passenger car traffic volume for each cold category are presented in Figs. (6a) and (6b), respectively. The highest reduction for total traffic is observed for CC₆ (-14%) for weekend traffic, for CC₆ (-10%) for weekdays traffic. The lowest reduction is observed for CC₂ (0.19%) for weekdays traffic. In case of passenger car, the lowest and highest PRs are for CC₁ (-0.39%) for weekdays and CC₆ (-14%) for weekend respectively. For the remaining categories: CC₂~CC₅, the PRs value increases as cold approaches to CC₅. The percentage reduction is a little bit higher in case of weekend traffic for both total and passenger cars traffic; weekend traffics reduce at a higher rate as the weather become colder.

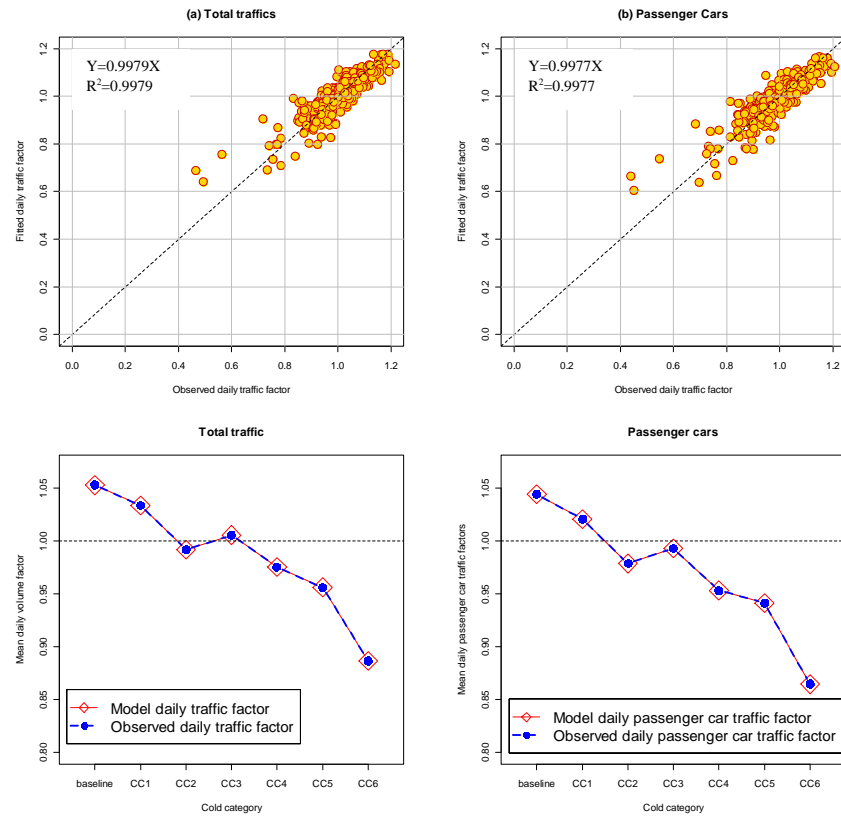


Fig. (4). Results of dummy-variable regression models of weekdays for **(a)** total traffic and **(b)** passenger cars.

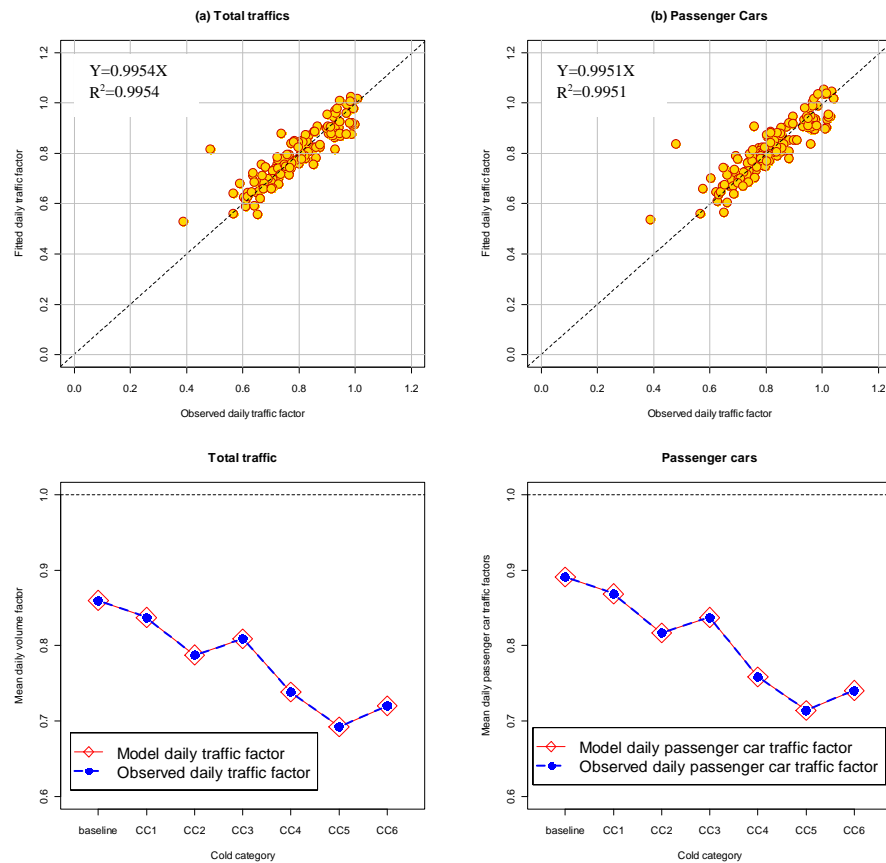


Fig. (5). Results of dummy-variable regression models of weekends for **(a)** total traffic and **(b)** passenger cars.

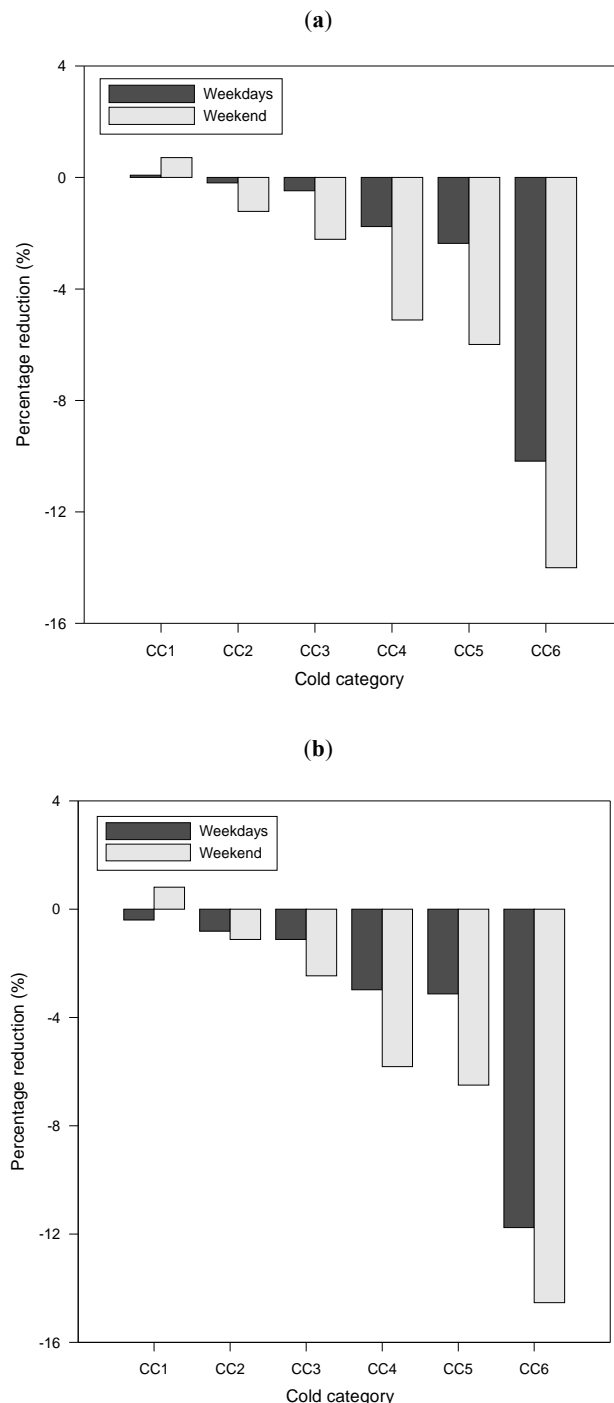


Fig. (6). Percentage reduction for each cold category for (a) total traffic and (b) passenger cars.

The partial effect of each independent variable on the dependent variable is presented graphically in Figs. (7, 8). The solid line shows the estimated values from the calibrated model, while the dotted lines give 95% confidence intervals around the model estimates. The models shown in Tables 3 and 4 were used to develop plots of the partial effect of EDVF on the dependent variable (DVF), and they were generated by fixing SNOW to its average value in the sample data and keeping the temperature at a weighted mean value for the seven cold categories. These plots are shown in the

first column of Figs. (7, 8). for weekdays and weekends, respectively. The distribution of EDVF values is shown on the x-axis of the graph with a one dimensional scatter bar. A similar procedure was followed to develop plots for the partial effect of SNOW (see the second column in Figs. 7, 8). In this case EDVF was fixed at its average, and the temperature was kept at its weighted mean value. The partial effect of cold is plotted in the third column in Figs. 7, 8). In this case, both EDVF and SNOW were fixed at their average values to compute the estimated value of daily traffic volume factor for each cold category. The first and second rows in these figures show the plots for total traffic, passenger cars, respectively.

The first column in Fig. (7). clearly shows a close and positive relation between EDVF and the daily traffic volumes for both total and passenger cars traffic. Also, all two plots show a similar trend. The first and second rows in the second column show a decrease in daily passenger cars and total traffic volumes with an increase in the amount of snowfall. The third column in Fig. (7) gives similar results for temperature. The partial effect of cold categories on the total traffic and passenger car volume is clearly indicated by the downward trend in the mean daily volume factors. These plots confirm the previous findings of statistical tests of significance using the incremental *F*-test described earlier in this section. The partial effect of independent variables on the dependent variable for weekends is presented in Fig. (8). The total traffic and passenger car plots are generally similar to weekdays, except with differences in magnitude. The plots of the partial effect of cold seem to exhibit a downward trend in the factor values for the total and passenger car traffic volume. However, the effect is not significant according to the statistical tests performed in this study.

CONCLUSION

The literature clearly indicates that severe weather conditions trigger variations in highway traffic. In the study conducted by Datla and Sharma [2], it is noted that total highway traffic volumes decrease with increases in the severity of cold temperatures. During extremely cold weather (below -25°C), the average winter daily traffic volume is reduced by about 30%. Weekend traffic volumes are more susceptible to cold than weekday numbers for all types of highways. The results presented in this study strongly confirm the findings reported in previous research study conducted by Datla and Sharma [2]. However, past studies in this area were limited to total traffic. Understanding of passenger cars (or behaviour) separately from total traffic mix under severe weather conditions could provide useful information for transportation planning and engineering applications. An attempt has been made in this study to quantify the traffic variations under different weather conditions (mainly SNOW and COLD). Vehicle classification data from the WIM site located on a highway site (LEDUC) in the province of Alberta, Canada, were used in this study. The WIM traffic data were grouped into two classes, i.e., total traffic, passenger cars.

A number of conclusions can be drawn from these tests. Firstly, the total traffic and passenger car volumes for weekdays are influenced by all the independent variables

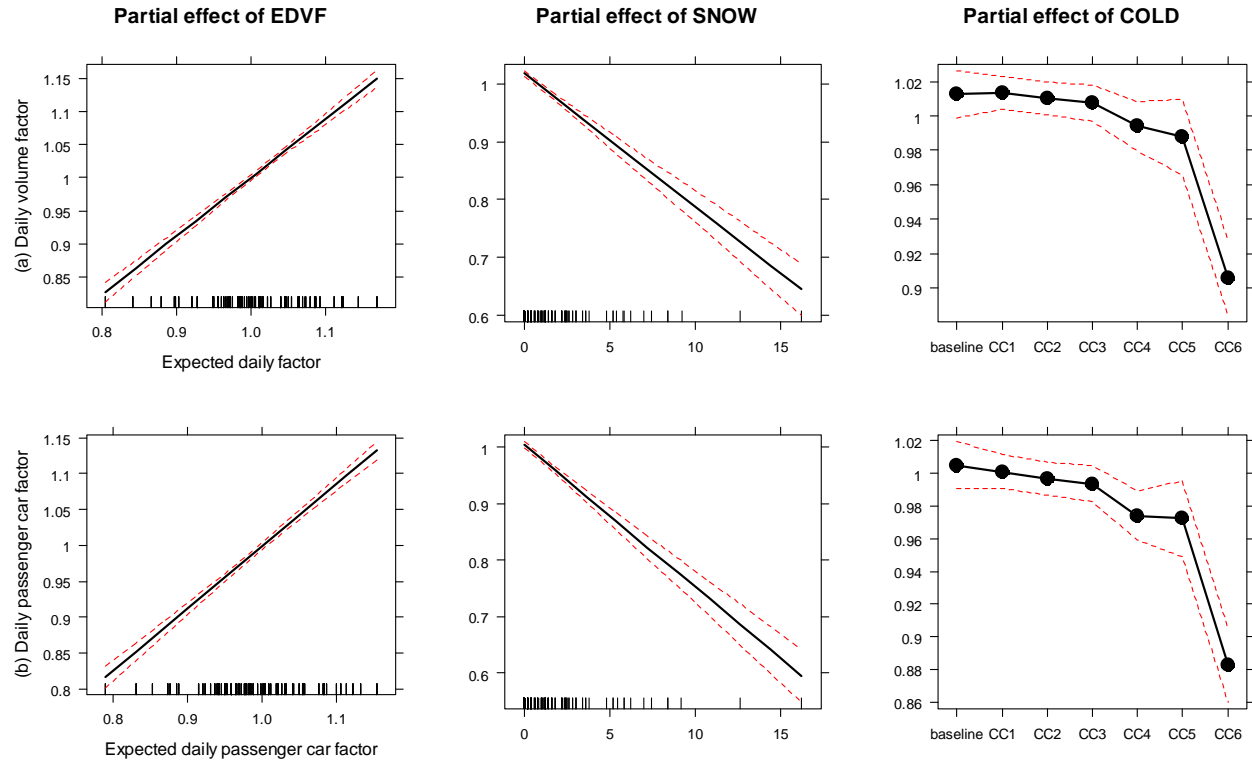


Fig. (7). Partial effect of each variable on daily weekday volume factor for (a) total traffic, (b) passenger cars.

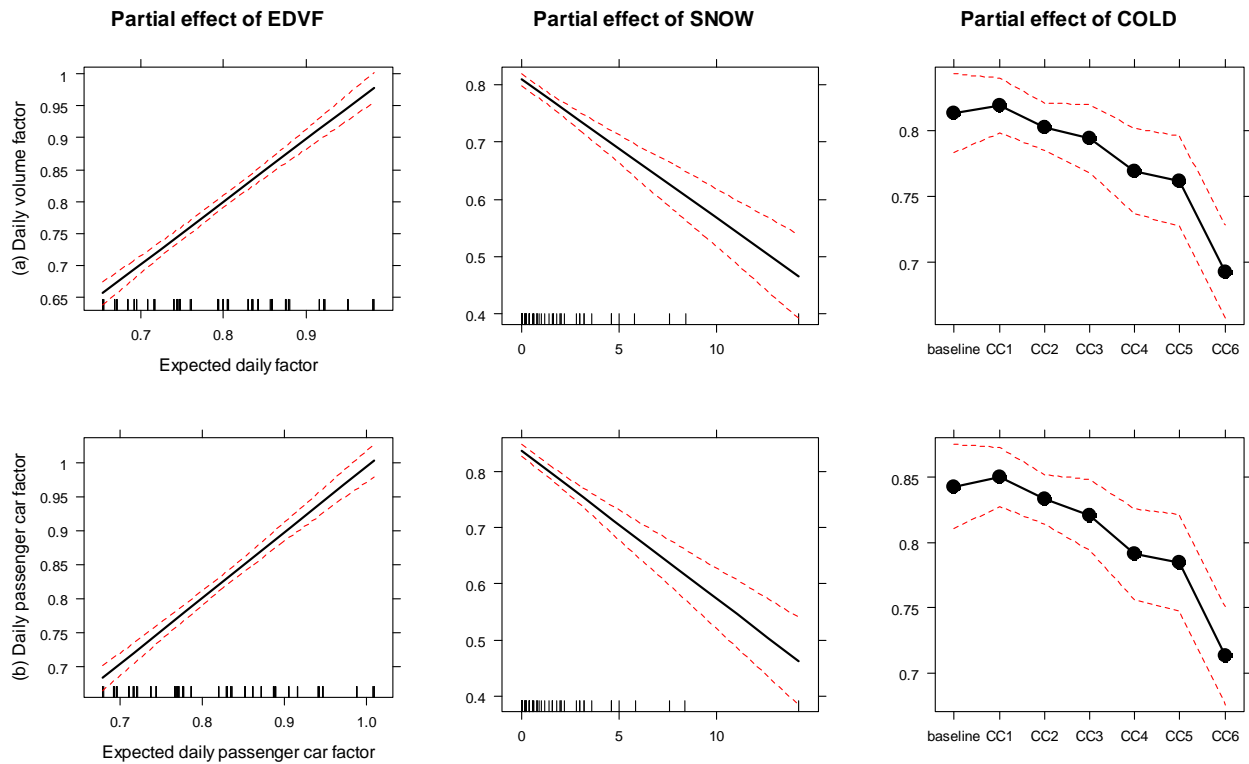


Fig. (8). Partial effect of each variable on daily weekend volume factor for (a) total traffic, (b) passenger cars.

included in the model, i.e., the expected daily volume factor EDVF, snowfall, and the cold categories. Inclusion of cold categories variables in the model was also justified in this

study by conducting an incremental F -test for the developed models.

It is evident from the research that passenger cars are more vulnerable to adverse weather conditions. This vulnerability to severe weather conditions could be attributed to such behaviour of drivers as choosing flexible departure times, changing routes, or canceling travel entirely and being able to make trip adjustments by avoiding discretionary trips.

The conclusions of this study are based on five years of WIM data collected from a single site in the province of Alberta. Further research work is currently underway to study the remaining five WIM sites, which are operating on highway segments carrying provincial and interprovincial truck traffic. Future research will also focus on interaction impacts of snow and cold variables on truck traffic.

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CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

REFERENCES

- [1] K. K. Knapp, and L. D. Smithson, "Winter storm event volume impact analysis using multiple-source archived monitoring data," *J. Transport. Res. Board*, vol. 1700, pp. 10-16, 2000.
- [2] S. Datla, and S. Sharma, "Impact of cold and snow on temporal and spatial variations of highway traffic volumes," *Journal of the Transportation Geography*, vol. 16, no. 5, pp. 358-372, 2008.
- [3] J. Fox, *An R Companion to Applied Regression*. Sage Inc.: Thousand Oaks, California, 2011.
- [4] R Development Core Team: *A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, ISBN 3-900051-07-0, 2010.
- [5] ITT Industries, Inc., System Division. *Identifying and Assessing Key Weather-Related Parameters and Their Impacts on Traffic Operations Using Simulation*. Publication FHWA-HRT-04-131. FHWA, U.S. Department of Transportation, 2003.
- [6] J. Colyar, and J. Halkias, "Identifying and assessing key weather-related parameters and their impacts on traffic operations using simulations," In: *73th Annual Meeting of Institute of Transportation Engineers*, Washington, DC, 2003.
- [7] L. C. Goodwin, *Weather impacts on arterial traffic flow*. The Road Weather Management Program, FHWA, US Department of Transportation: Washington, DC, 2002.
- [8] R. M. Hanbali, and D. A. Kuemmel, "Traffic volume reduction due to winter storm conditions," *J. Transport. Res. Board*, no. 1387, pp. 159-164, 1993.
- [9] Y. A. Hassan, and J. J. Barker, "The impact of unseasonable or extreme weather on traffic activity within lothian region, Scotland," *J. Transport. Geogr.*, vol. 7, no. 3, pp. 209-213, 1999.
- [10] K. Keay, and I. Simmonds, "The association of rainfall and other weather variables with road traffic volume in Melbourne, Australia," *Accident Anal. Prev.*, vol. 37, no. 1, pp. 109-124, 2005.
- [11] P. J. Maki, "Adverse weather traffic signal timing," In: *69th Annual Meeting of Institute of Transportation Engineers*, Las Vegas, 1999.
- [12] K. Markku, and S. Heikki, "Effects of weather and weather forecasts on driver behavior," *Transport. Res. Part-F Traffic*, vol.10, no. 4, pp. 288-299, 2007.
- [13] T. H. Maze, M. Agarwal, and G. D. Burchett, "Whether weather matters to traffic demand, traffic safety, and traffic operations and flow," *J. Transport. Res. Board*, No. 1948, pp. 170-176, 2006.
- [14] P. Kilburn, *Alberta Infrastructure & Transportation Weigh in Motion Report*. Government of Alberta, Transportation, 2008.
- [15] Weather Office, Environment Canada, Gatineau, Quebec, Canada. www.climate.weatheroffice.gc.ca/climateData/canada_e.html [Accessed: Oct 20, 2010.]
- [16] J. Andrey, and R. Olley, "Relationships between weather and road safety, past and future directions," *Climatol. Bull.*, vol. 24, no. 3, pp. 123-137, 1990.
- [17] *ArcGIS 10 Help Library: Geographic Information System (GIS)*. ArcGIS 10, Environmental System Research Institute, Inc., Redlands, California, 2010.
- [18] R. Mussa, V. Kwigizile, and M. Selekwa, "Probabilistic Neural Networks Application for Vehicle Classification," *J. Transport. Eng. ASCE*, vol. 132, no. 4, pp. 293-302, 2006.
- [19] J. H. Wyman, G. A. Braley, and R. I. Stephens, *Field Evaluation of FHWA Vehicle Classification Categories*. Publication DTFH-71-80-54-ME-03. FHWA, U.S. Department of Transportation, 1985.
- [20] Z. Liu, and S. Sharma, "Statistical Investigations of Statutory Holiday Effects on Traffic Volumes," *J. Transport. Res. Board*, No. 1945, pp. 40-48, 2006.
- [21] M. A. Hardy, *Regression with Dummy Variables*. Sage Inc.: Newbury Park, California, 1993.
- [22] J. Fox, *Applied Regression Analysis and Generalized Linear Models*, Sage Inc.: Thousand Oaks, California, 2008.

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