Effects of Adverse Winter Weather Conditions on Highway Traffic and Driver Behaviors

By

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is the true copy of the thesis. I understand that my thesis may be made electronically available to the public.

CONTRIBUTION OF CO-AUTHORS

Based on the material presented in Chapter 2 a paper has been prepared and accepted for presentation at the Transportation Research Board (TRB) 93rd Annual Meeting to take place in January, 2014, Washington DC. I am the first author of this paper. Also as a first author, I will also prepare a conference paper based on Chapter 3. The author of the thesis would like to thank the following graduate students as a co-authors: Shahram Heydari (research assistant and co-author of the first paper, University of Waterloo), Sohail Zangenehpour, (PhD student and co-author of the article in preparation, McGill University) and Paul St-Aubin (PhD student and PhD student and co-author of the article in preparation, École Polytechnique de Montréal).

Abstract

This research looks into the impact of adverse winter weather conditions on highway driver behaviors using microscopic data from loop detectors and video cameras (e.g., hourly average speed, trajectories, lane changes, time-to-collisions measures). This thesis is composed of two main sections in addition to the introductory section: i) direct and lagged effects of adverse weather on hourly speeds and volumes; and ii) direct effect of adverse weather on driver behaviors (microscopic) measured at the vehicle level using video data.

The first part of the thesis presents a review of literature related to past research on the topic. The second part investigates the direct and lagged effects of adverse winter weather conditions on the operating speed in a number of highway segments in Ontario using a time-series approach. This is complemented by the analysis of hourly traffic volumes in the region of Montreal, Canada, using data from magnetic loop detectors as well. In speed modeling, the effect of adverse weather was studied using data from multiple sites including both urban and rural highways, considering weekdays versus weekends separately. For this purpose, a large dataset containing hourly traffic data, weather variables (e.g., temperature, snow, wind speed), and surface conditions was used. A few previous studies have examined the effect of snowstorms on traffic parameters; however, little research has been done regarding the spillover effects (lagged effects) that adverse weather conditions may have on travel demand and traffic patterns. Extreme events or weather conditions might have a strong effect on traffic conditions not only during the events, but also before and after the events. In this study, time-series regression techniques—in particular, Autoregressive Integrated Moving Average (ARIMA) models—were used to model the highway operating speed. These methods are able to consider the serial correlation among error terms. The results indicate that snowstorms have a statistically significant

effect on the speed. The lagged effects are however offset by the time and intensity of winter maintenance operations during and after the event. The effect of weather also varies depending on the type of site (urban or rural) and day of the week. Similarly, the effects of different weather variables including their lagged effects were analyzed using hourly traffic volume data. Despite the fact that information of the road surface condition was not available, this analysis is in accordance with previous finding, showing the utility of ARIMA approaches in modeling the highway volume as well. The results of this study can be applied in quantifying the mobility effect of winter weather and benefits of winter road maintenance.

In recent years, driver behavior analysis using microscopic (vehicle level) data is a topic that is attracting more attention in road safety analysis. This popularity has brought about research in many different innovative techniques and microscopic measures used to quantify and analyze driver behavior. In the second part of this thesis, it demonstrates a method of analyzing driver behavior using video data approach. This thesis elucidates both a manual and an automated, computer-based method to analyze driver behavior. It also uses the computer-based method to evaluate the effect of adverse winter weather conditions on the driver behavior of highway users. Both the manual and the automated approaches have been used with 15 video recordings obtained from three different locations on the Don Valley Parkway (DVP) in Toronto, Ontario. The results demonstrate the effectiveness of the automated method in analyzing driver behavior, as well as in evaluating the impact of adverse winter weather conditions on driver behavior.

Résumé

La thèse présente l'impact des conditions météorologiques hivernales défavorables sur les comportements des conducteurs de la route à l'aide de données microscopiques de détecteurs de mouvement et des caméras vidéo (e.g., la vitesse horaire moyenne, les trajectoires, les changements de voie, des mesures de temps à la collision) La thèse est composée de deux sections principaux, en plus de l'introduction: i) les effets directs et décalés des conditions météorologiques défavorables sur la vitesse et le volume horaire; et ii) l'effet direct des conditions météorologiques défavorables sur le comportement microscopique des conducteurs mesurées au niveau du véhicule à l'aide de données vidéo.

La première partie de la thèse propose une revue de la littérature sur le sujet. La deuxième partie examine les effets directs et décalés des conditions météorologiques hivernales défavorables sur la vitesse opérationnelle dans un certain nombre de segments de la route en Ontario en utilisant une approche de séries chronologiques. Ceci est complété par l'analyse des volumes de trafic horaires dans la région de Montréal, au Canada, en utilisant également les données de détecteurs de boucles magnétiques. Pour modéliser la vitesse, l'effet des conditions météorologiques défavorables a été étudié en utilisant des données provenant de plusieurs sites, dont deux autoroutes urbaines et rurales. Les jours de semaine et les week-ends ont été considérés séparément. A cet effet, une grande base de données contenant des données de trafic (organisée par heure), des variables météorologiques (e.g., température, neige, vitesse du vent), et des variables indiquant l'état de la surface de la route ont été utilisées. Certaines études antérieures ont examiné l'effet de tempêtes de neige sur les paramètres de trafic, mais peu a été fait en ce qui concerne les effets d'entraînement (effets différés) que les conditions météorologiques défavorables peuvent avoir sur la demande de voyage et sur les modèles de trafic. Les événements extrêmes ou les conditions météorologiques pourraient avoir un effet important sur les conditions de circulation, non seulement au cours de ces événements, mais aussi avant

et après ces événements. Dans cette étude, les techniques de régression chronologique - en particulier les modèles autorégressives moyennes mobiles intégré (ARIMA) - ont été utilisées pour modéliser la vitesse opérationnelle de l'autoroute. Ces méthodes sont en mesure d'examiner la corrélation sérielle entre les termes d'erreur. A partir des résultats, on peut déduire que les tempêtes de neige ont un effet statistiquement significatif sur la vitesse. Les effets décalés sont toutefois compensés par la durée et l'intensité des opérations d'entretien hivernal pendant et après l'événement. L'effet de la météo varie aussi en fonction du type de site (urbain ou rural) et le jour de la semaine. Les résultats de cette étude peuvent être appliqués pour quantifier l'effet de la mobilité des conditions météorologiques et les avantages de l'entretien des routes en hiver. De même, les effets des différentes variables météorologiques, y compris leurs effets décalés ont été analysés à l'aide des données de volume de trafic. Malgré que l'information de l'état de surface de la route n'était pas disponible, cette analyse est conforme aux financements antérieurs, montrant également l'utilité des approches ARIMA sur le volume de la route.

Au cours des dernières années, le comportement du conducteur en utilisant des données microscopique (niveau du véhicule) est un sujet qui attire plus d'attention à l'analyse de la sécurité routière. Cette popularité a entraîné des recherches sur de nombreux techniques novatrices et le développement de mesures microscopiques utilisées pour quantifier et analyser le comportement du conducteur. Dans la deuxième partie de cette thèse, une méthode est démontrée pour analyser le comportement du conducteur en utilisant l'approche de données vidéo. Cette thèse présente à la fois une démarche manuel et une méthode informatique automatisée pour analyser le comportement du conducteur. Il utilise également la méthode assistée par ordinateur pour évaluer l'effet des conditions météorologiques hivernales défavorables sur le comportement au volant des usagers de la route. Les méthodes manuel et automatique sont utilisées sur 15 enregistrements vidéo obtenus à trois endroits différents sur le Don Valley Parkway (DVP) à Toronto, en Ontario. Les résultats démontrent l'efficacité de la méthode automatisée pour analyser le comportement du conducteur, ainsi que dans l'évaluation de l'impact des conditions météorologiques hivernales défavorables sur le comportement des conducteurs.

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Chapter 1

INTRODUCTION

1.1 Background

Adverse weather conditions during winter, such as snowstorms and precipitation in general, have an important effect on traffic conditions (mobility) and road safety. Many studies have looked at road safety issues during winter, and one can refer to Usman (2011) for a review of the literature dedicated to such issues. After controlling for traffic conditions, the deterioration of road surface conditions combined with weather variables (e.g., visibility and precipitation) are found to increase accident probability and crash occurrence. A large literature has been devoted to the investigation of adverse weather, mobility and road safety. An important link has been found between crash occurrence and adverse weather. Rainy or snow conditions increase the chance of collision. However, less severe accidents are expected to happen during adverse weather since drivers adapt their behaviors. According to the historical crash data, it has been observed that during winter snowstorms the number of accidents for a particular section of a highway is proved to increase but the severity of these outcomes is found to be lower in average. The Alberta Traffic Collision Statistical report (2010) gives a summary of collision occurrence by month. Both the percentage of fatal collisions and the total number of collisions for each month are documented in that paper from which one can see that the numbers of collisions for the four months from December to March are higher than those of the other months, while the numbers of fatal collisions are much lower. Several studies have argued that this is due to driver behavior adaptations: drivers in principle reduce speeds, increase time gaps and space between vehicles. In addition, during the time when adverse weather occurs, traffic volumes are often slightly lower which provides more room for maneuver. It can also be hypothesized that the ratio of lane changing maneuvers is significantly reduced and as a consequence, vehicle interactions and risky situations or conflicts are reduced as well. All the driver behavior adaptations are translated into less severe interactions (at lower speeds) and less severe conflicts. When accidents occur, less energy is dissipated.

To investigate driver behavior under different road, traffic environment and weather conditions, two alternative approaches have been proposed in the literature to collect driving data, namely, roadside observation and vehicle-based tracking. In both of the two approaches, the main idea is to collect microscopic data, e.g. speeds during short intervals or speeds at the vehicle level.

In the literature, the effects of snow precipitation and other weather factors on highway traffic parameters have been investigated using hourly speed and volume data. However, most of the studies have not taken into account the potential time-serial correlation and lagged weather effects when modeling operating speeds and traffic volumes on highways. Also, few studies have explored the effect of road surface conditions. Furthermore, few studies have made use of video data to investigate driving adaptation during and after snowstorms. Accordingly, this thesis aims to model operating speeds and traffic volumes at the hourly and vehicle levels, taking into account surface conditions, serial correlation, and exploring lagged weather effects. It is not difficult to believe that the operating speed and the volume on highways at a particular hour can be affected by the road weather conditions at adjacent hours. In the hours following a snowstorm, it takes time to recover to good road surface conditions independently of the winter maintenance. Road surface conditions could remain slippery, so drivers might keep lower speeds than in clear surface conditions. In terms of traffic demand (volume), weather could change trip-makers' decision on their departure times. The occurrence of a snowstorm can change trip decisions. One can hypothesize that people may postpone, cancel or delay planned trips during a snowstorm. These changes are expected to lead to variations in traffic volumes before, during or after the snowstorm. The effect of the adverse winter weather conditions on highway traffic before or after the snow-event is refereed as spillover effect or lagged effect in this document. The first part of this thesis, Chapter 2, focuses mainly on analyzing the direct and spillover effect on the operating speed and the traffic volume. For this purpose, data from multiple sites and years is used – the data comes from segments of urban and rural highways in Ontario, Canada. Linear regression and autoregressive integrated moving average (ARIMA) models are used in this study.

In modeling speed, historical data from loop detectors is commonly utilized. Microscopic data to investigate driver behavior is less common given the difficulties and the needs of more advance sensors and software for automated collection. Several traffic data collection technologies, including the video image processor, laser sensor, ultrasonic sensor and microwave radar sensor; with few exceptions, most of these technologies are faced with issues during adverse weather conditions. Automated methods for generating trajectory data and deriving microscopic measures (trajectories) based on video is not new, but its use in winter surface and driving conditions is less popular. This research also explores its use on driver behavior using manual and automated approaches. For this purpose, a software referred as traffic intelligence (TIS) is used to process video data before, during and after storms.

In summary, adverse winter weather conditions have a great influence on the operating speed, the traffic volume, and the driver behavior. This thesis investigates the influence of adverse winter weather at different aggregation levels and the existence of spillover effects using alternative methods, sources of data and regions. The full understanding of traffic and driver behavior during winter can help with the optimal implementation of winter maintenance operations and other traffic management strategies, e.g., variable speed limits and proactive safety analysis.

1.2 Literature review

Highway safety is an area that has attracted a lot of attention in the transportation engineering literature. In particular, highway safety during wintertime is a topic that has attracted interest in recent years. Several studies have focused on the effects of weather conditions on road safety outcomes (Eisenberg and Warner, 2005; Fuller and Towards, 2005; Edwards, 1998). Past research has generally showed that adverse weather affects significantly traffic conditions (speeds and volumes) and safety (crash occurrence). Khattak and Knapp (2001) showed that accident rates increased significantly during snow events, and factors such as snow event duration, snow intensity, wind speed and traffic intensity all had a significant effect on crash risk. According to Alberta Traffic Collision Statistics (2010), however, the months of December, January, February and March experience less fatal crashes than other months (in percentage). This finding is a common pattern observed in cold-winter months on Canadian highway networks. In general, during the winter and specifically during snow events, road users are believed to adapt their driver behavior by reducing speeds and increasing gaps to avoid fatal collisions.

Previous studies have also examined the effect of snow events on traffic parameters, and have shown that snowstorms have a negative effect on speeds and traffic volumes on highways (Usman et al., 2011). Speed patterns have been mainly investigated using loop data from different locations at different data aggregation levels. However, lagged effect of snow precipitation and other winter weather condition variables have not been studied. More importantly, the use of microscopic data such as speeds, gap time, and lane changing at the vehicle level has rarely been explored, particularly in the Canadian context. Most past studies that used microscopic video data to study driver behavior have not dealt with winter weather conditions. Using a naturalistic driving approach, past research has studied driver–road interactions but with little focus on winter road conditions (Rakha et al., 2011).

Moreover, according to the methods and types of data used, the literature can be divided into two parts: a) studies investigating the weather effects on traffic parameters using historical loop detector data and b) studies looking at driver behaviors and weather conditions using video data.

1.2.1 Studies on Operating Speeds and Volumes

Many studies have investigated the factors influencing operating speeds and traffic volumes in rural and urban environments (Kanelaidis et al., 1990; Fambro et al., 2000; Fitzpatrick et al., 2003; Ali et al., 2007; Park et al., 2010; Eluru et al., 2013; Kwon et al, 2013). Most of these studies have investigated the effects of geometric characteristics or speed limits, using cross-sectional data primarily. Few studies have examined the effect of weather conditions on speeds and volumes (Liang et al., 1998; Agarwal et al., 2005; Donaher et al., 2012). These studies have generally shown that adverse weather conditions have a negative effect on the operating speeds and traffic volumes of highways. For instance, Agarwal et al. (2005) found that the main reduction in highway capacity and operating speeds was caused by severe rain and snow. This study found that heavy rain (more than 0.25 inch/hour) and heavy snow (more than 0.5 in/hour) reduced the volume by 10% - 17% and 19%-27% and reduced the speed by 4%-7% and 11% - 15%, respectively. Datla and Sharma (2008) have observed a significant reduction in traffic the volume due to snow-event for all types of highways. The authors indicated, accordingly, that the effect of rain and snow on the speed and the volume is not as significant as stated in the Highway Capacity Manual (2000). Using a linear regression approach, Donaher et al. (2012) also developed two different models for the speeds on rural and urban highways in Ontario using parameters such as wind speed, visibility, snow, and temperature. They found that operating speeds are also quite sensitive to adverse weather. In addition to weather, previous studies have investigated the link between highway traffic (i.e. speed and volume) and surface conditions or winter maintenance operations. For instance, the important role of winter maintenance operations on road safety has been studied recently by Usman et al. (2010, 2011). In their research, the authors introduced a road surface condition index (RSI) as a friction like surrogate measure of road surface conditions. They found that RSI plays an important role and influences both traffic volumes and speeds on highways (Usman et al., 2010).

Despite the importance of these previous efforts, few studies have investigated the potential lagged effects of adverse weather, in particular snow and/or rain precipitation on operating speeds and traffic volumes during wintertime. It is not surprising to observe reductions in the speed and the volume under adverse weather conditions. However, past studies have not looked at the possible lagged (spillover) effects of precipitation on highway traffic (speeds and volumes) before and after a snow/precipitation event. If snow precipitation affects a given road section, speeds, as well as traffic volumes, are expected to be negatively affected not only during the event but also before and after the event. Moreover, the impact of weather across different road types (urban versus rural highway) and day of week (weekdays versus weekends) has been investigated in this study. For instance, note that urban commuters seem to suffer more from the adverse weather such as winter storms.

Linear regression models are commonly used in modeling traffic characteristics (e.g., speed, traffic volume). However, time series models seem to be a better option (e.g., they allow one to consider correlation among time dependent error terms and lagged effects) in modeling traffic characteristics such as the traffic volume and the speed (Pipkin, 1989). In this regard, a number of studies have employed time series techniques. For instance, Ahmed and Cook (1979) have analyzed freeway traffic data using time series. Nicholson and Swann (1974) provided a long-term prediction for traffic volumes using ARIMA (Autoregressive Integrated Moving Average) models. Similarly, Okutani and Stephanedes (1984) adopted time series to make a dynamic short-term prediction of traffic volumes. Other studies have also investigated factors such as the speed and the congestion effects (Mahalel and Hakkert, 1985; Hall and Lam, 1988). Recent research efforts can be found in Kamarianakis and Prastacos, 2003; Li and Rose, 2011; and Vlahogianni and Karlaftis, 2012.

Using time series, very limited number of studies considered climate conditions (Vlahogianni and Karlaftis, 2012). Note that, for example, Pipkin (1989) aims to outline the ARIMA framework in modeling traffic flow series. Nevertheless, the author does not consider weather variables in that analysis. To complement this, the first part of this thesis investigates the direct and lagged effects of adverse weather conditions during winter on the operating speed and the traffic volume using a time-series modeling approach. This is in order to better understand speed and volume variations during, before, and after winter storms or other adverse weather conditions (extreme low temperatures and high wind speeds). For this purpose, a large dataset containing hourly traffic data from different highway segments in Ontario, weather variables (e.g., temperature, snow, wind speed), and surface conditions were used. In this study, time-series regression techniques (ARIMA models) are used to model the operating speed and the traffic volume. These methods allow one to consider the serial correlation among error terms. Chapter 2 provides information detailing all the steps followed in this study.

1.2.2 Driver Behavior Analysis

Instead of looking at traffic parameters, one can investigate driver behaviors using microscopic data (vehicle-level data) across different weather conditions. In extreme weather conditions, road users drive more cautiously to avoid incidents or crashes; as a result, drivers adapt their behavior. Some related studies have shown that weather conditions affect the driver behavior significantly (Näätänen and Summala, 1976; Rämä, 1999; Rämä, and R. Kulmala, 2000; Steyvers and Waard, 2000; Summala, 1996). Kilpeläinen and Summala (2007) concluded that the driver behavior is affected by the prevailing observable conditions predominantly. Ahmed (1999) enhanced the existing car-flowing models based on empirical work. In his paper, with microscopic data collected from real traffic lane-change behavior is modeled in three steps: decision-making of changing lane, choosing the target lane and gap acceptance. Different methods have been proposed for collecting microscopic traffic data. A literature review can be found in the "Traffic Detector" Handbook (2006) which provides details of various traffic-data collection methods. Several traffic data collection technologies have been used for microscopic data collection, including video-image processing, laser, ultrasonic and microwave-radar sensors, among others. Many studies have been carried out to investigate driver behaviors using these technologies, but few have focused on the impact of weather on both quality of the data and effect on traffic parameters. For instance, Zhang et al. (2007) developed a video-based vehicle detection and classification system for truck data collection. Also, Bham and Benekohal (2001) used aerial photographic techniques to collect data for accelerating behavior analysis. However, few studies have used the technologies to analyze the driver behavior under snow event conditions or have evaluated the data quality (issues) under adverse weather.

The use of video sensors is becoming increasingly popular in surrogate safety analysis. Different measures using automatic video analytics have been used to evaluate crash risk as an alternative to the classical safety approach, which is based on historical crashes (Saunier and Sayed, 2006; St-Aubin et al., 2013; Saunier et al, 2010; Versavel, 2007; Hu et al., 2003). St-Aubin et al. (2011a) presents one surrogate safety analysis approach for highway ramps using automated trajectory data to measure the time-to-collision (TTC) indicators and lane-changing measures. However, automated video-based methods have their limitations, as do many other technologies under adverse weather conditions (St-Aubin[1] et al, 2011). Video sensors can also suffer from other issues, e.g., field of view, calibration complexity, and traffic-congested conditions. As mentioned by St-Aubin[1] et al (2011), the accuracy of the approach relies highly on flow conditions and the quality of the video data. In addition, automatic video data processing can suffer from obstacles, field of view and angle of cameras, curved roadway sections, and occlusions from dense traffic and large vehicles, which lead to large tracking errors. Yet despite the limitations, the automated video data processing allows data collection for a rich set of microscopic traffic parameters.

To further explore the advantages and limitations of video data, this thesis investigates the use of manual and automatic methods of obtaining microscopic data. Manual video measures are obtained in conditions where automatic methods do not work. To validate the accuracy of manual methods, automatic video measures are generated and compared to the alternative approach. For this purpose, this research makes use of an open-source software, named Traffic Intelligence (TIS), which allows one to obtain trajectory data. Problems and potential solutions associated to the video data problem are also discussed in this document. To study the effect of adverse weather, especially driving conditions during snowstorms, automatic video analysis has significant room for improvement; semi-automatic methods are still feasible in order to obtain microscopic data.

1.3 Research Objectives

This research aims to investigate the effect of adverse weather conditions and road surface on highway traffic parameters and driver behaviors using hourly and vehicle level data coming from loop detectors and surveillance video cameras. More specifically, the objectives of this thesis are:

1. Develop the traffic operating speed and volume models for different kinds of highway sections on urban and rural areas. The models help identify salient weather factors as well as the differences between weekends vs. weekdays and road types.
2. Investigate the indirect or lagged effect of various kinds of variables on highway traffic parameters using a time-series approach;
3. Introduce a methodology to obtain microscopic data for the investigation of the driver behavior under different weather and surface conditions.

For each of these objectives, an important amount of work was needed to integrate and process various sources of data.

1.4 Thesis Outline

This thesis consists of four chapters. Chapter 1 provides an introduction to the topic, gaps in the literature, data sources and objectives. The literature review focuses on the area of traffic conditions under adverse winter weather conditions. Chapter 2 presents the methodology for the analysis of the direct and indirect (spill-over) effects of adverse winter weather conditions on operating speeds and traffic volumes using standard and time-series regression methods. The introduction of modeling methodology, as well as data sources and integration are given in this chapter. For this research, highways from both Ontario and Quebec are studied.

Chapter 3 describes the proposed methodology for deriving behavior patterns from video data. The methodology can be used with manual and video-based approaches and describes each of the steps ranging from site selection and data collection to analysis. The advantages and limitations of each approach are highlighted. Main results, issues and potential solutions with microscopic data analysis based on video data are documented.

Chapter 4 highlights the main conclusions and contributions of this research. Also, future work is identified in terms of data collection methods and empirical research.

Chapter 2

Direct and Spillover Effects of Adverse Winter Weather Conditions on Highway Traffic: A Time-Series Analysis

2.1 Effects on the Operating Speed

2.1.1 Methodology

The operating speed on highways is affected by different factors, e.g., weather conditions and traffic characteristics. Figure 2-1 illustrates how various factors affect the operating speed. The main objective of this study was to examine the effect of adverse weather conditions (in the form of snow) on the operating speed. In addition to the linear regression model, a time series approach in modeling the speed was adopted, which allowed the consideration of lagged effects as well. In particular, a time series event-based modeling approach was employed to study the trend of speeds under snowstorm events. For this purpose, the following models were used: Linear regression approach and ARIMA model.

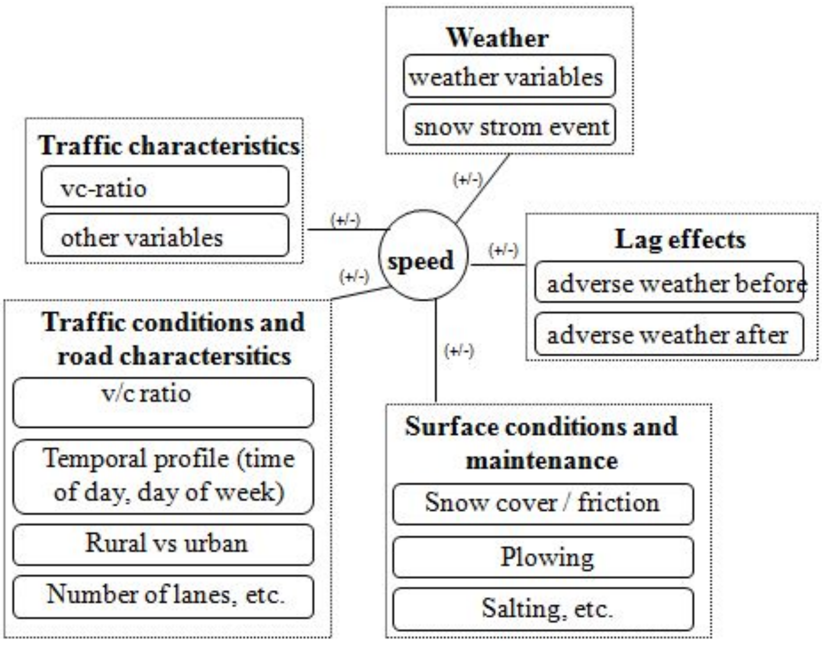


Figure 2-1 Relationship between Variables

Time-series linear regression models were used to investigate the effect of different factors on the speed. For the regression analysis, sites and data were segmented in different subsets according to the highway type in urban versus rural sites and weekend versus weekdays. The effect of weather conditions on traffic parameters was subsequently determined. Note that different criteria were used to select models, including the statistical level of significance of the weather factors. The variables used in the modeling were ones describing weather conditions, road conditions, winter road maintenance conditions, and traffic characteristics. Lagged snowstorm event variables were also used. To take into account the site-specific characteristics, a site-specific fixed effect is included in the analysis when obtaining the data from all sites.

2.1.1.1 Linear Regression Model

A linear regression model can be developed based on Equation 1.

$$V = \beta_0 + \beta_s X_s + \beta_w X_w + \beta_{rs} X_{rs} + \beta_{tr} X_{tr} + \beta_{lag} X_{lag} \quad (1)$$

where:

V: operating speed (in this paper it stands for the median speed)

X_s: vector of dummy variables for different sites

X_w: vector of weather condition variables

X_{rs}: vector of road surface condition variables

X_{tr}: vector of traffic characteristics

X_{lag}: vector of lagged variables

β_s, β_w, β_{tr}, β_{lag}: vectors of regression coefficients

β_0: constant

2.1.1.2 ARIMA Model

Under the ARIMA framework, we use a structural model with ARMA disturbances (Equations 2,3, and 4). For details on this type of models, see Harvey (1989) and Hamilton (1994). This model provides a mechanism to account for lagged effects and the associated correlations.

$$V_t = X_t\beta + \mu_t \tag{2}$$

$$\mu_t = \rho\mu_{t-1} + \theta\varepsilon_{t-1} + \varepsilon_t \tag{3}$$

$$\begin{aligned}\mu_t &= \rho_1(V_{t-1} - X_{t-1}\beta) + \rho_2(V_{t-2} - X_{t-2}\beta) + \ldots + \rho_p(V_{t-p} - X_{t-p}\beta)\\ &+ \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\varepsilon_{t-q} + \varepsilon_t\end{aligned} \tag{4}$$

where:

X_t: Vector of variables including the non-dummy lagged variables

β: Vector of regression coefficients

ρ: the first-order autocorrelation parameter

θ: the first-order moving-average parameter

$\varepsilon_t \sim$ i.i.d. $N(0,\sigma^2)$: white-noise disturbance

t: time

p: number of lags of autocorrelations

q: number of lags of moving averages

For computational purposes the statistical software R were utilized.

2.1.2 Data

The database consisted of observations from 22 urban and rural highway segments in Ontario, Canada (**Figure 2-2**). The original data is based on traffic and event-based datasets. In Usman et al. (2010), a detailed explanation of the event-based dataset is provided. The dataset used in this paper includes: weather conditions, traffic attributes, road surface condition, and winter operations data. After removing the missing and problematic observations, 22 sites were selected, five of which were urban highways. Additionally, a sample of three urban and three rural sites were used to examine the ARIMA model framework to model the speed. Rural and urban sites included 30335 and 30672 observations, respectively.

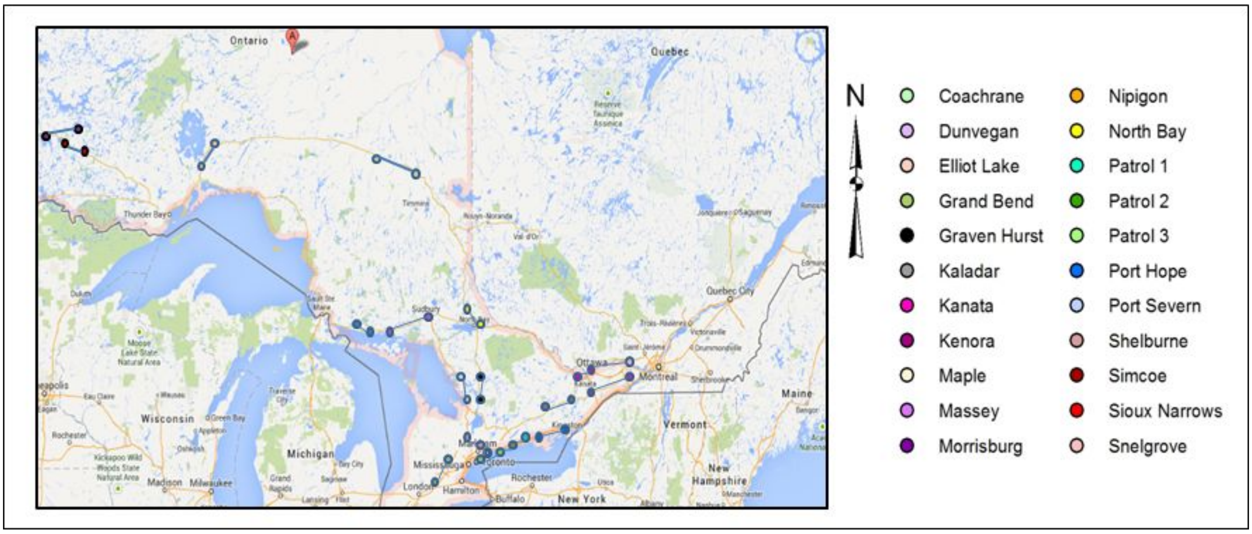


Figure 2-2 Spatial Distribution of Sites - Google Map

2.1.3 Data Processing and Explanation of Variables

A description of the variables and their descriptive statistics are summarized in **Table 2-1**. The original data comes from two databases, which were combined into one. Similarly, **Table 2-2** reports a summary statistics of the data analyzed by ARIMA models.

Table 2-1 Explanation of the Variables and Summary Statistics of Data

Variables	Explanation	Mean	Std. Dev	Min.	Max.
Speed (*V*)	median speed	104.63	10.15	60	125
Weather condition variables					
visibility	average visibility (Km) within the hour	17.92	7.53	5	40.20
wind peed	wind Speed (Km/hr) within the hour	10.90	8.59	0	69
temperature	temperature (°c)	-0.62	8.97	-40	28.35
hourlyppt	hourly snow (cm)	0.04	0.23	0	13.80
event indicator	snow event during the observation	0.15	0.36	0	1
Road surface condition variable (X_{rs})					
RSI	road surface index	0.89	0.16	0.05	1
Traffic characteristics variables (X_{tr})					
peak hour	8 a.m. to 11 a.m. and 5 a.m. to 8 a.m.	0.38	0.48	0	1
night hour	midnight to 6 a.m.	0.29	0.46	0	1
v/c ratio	volume capacity ratio	0.05	0.10	0	1
weekend	1 if weekend, 0 otherwise	0.28	0.45	0.0005	0.98
Lagged effect variables (X_{lag})					
laghourlyppt	snow in the previous hour	0.04	0.23	0	13.80
laghourlyppt_prev_2	snow in the previous two hours	0.04	0.23	0	13.80
lathourlyppt	snow in one hour after	0.04	0.23	0	13.80
lathourlyppt_lat_2	snow in two hours after	0.04	0.23	0	13.80
Number of observations: 134088					

Note: in this paper hourly precipitation means precipitation of snow

Table 2-2 Summary Statistics of Data Analyzed by ARIMA Models

	Rural sites											
Site Name:	Coachrane				Graven Hurst				Kaladar			
Variables	estimate	Std. Dev	Min	Max	estimate	Std. Dev	Min	Max	estimate	Std. Dev	Min	Max
speed	97.90	4.53	60	110	103.26	6.57	60	115	94.97	7.71	0	115
Weather condition variables												
visibility	19.61	7.63	0.20	25	13.55	6.08	0.10	24.10	19.79	7.16	0.20	24.10
windpeed	10.56	8.15	0	41	10.20	6.95	0	41.33	11.39	6.63	1	41.00
temperature	-6.27	11.31	-42.20	26.400	-0.57	8.61	-33.50	27.56	0.60	8.37	-30	25.35
hourlyppt	0.05	0.32	0	13.800	0.07	0.28	0	7.36	0.03	0.16	0	3.74
Event indicator	0.21	0.41	0	1	0.19	0.39	0	1	0.12	0.33	0	1
Road surface condition & Traffic characteristics variable												
RSI	0.89	0.17	1	0.100	0.89	0.16	0.05	1	0.93	0.11	0.05	1
peakhour	0.38	0.48	0	1.000	0.38	0.48	0	1	0.38	0.48	0	1
offpeak	0.33	0.47	0	1	0.33	0.47	0	1	0.33	0.47	0	1
nighthour	0.29	0.46	0	1	0.29	0.46	0	1	0.29	0.46	0	1
vcratio	0.02	0.01	0	0.122	0.16	0.12	0.006	0.77	0.03	0.03	0	0.38
weekend	0.29	0.45	0	1	0.29	0.45	0	1	0.29	0.45	0	1
Lagged effect variables												
laghourlyppt	0.05	0.32	0	13.800	0.07	0.28	0	7.36	0.03	0.16	0	3.74
laghourlyppt_prev_2	0.05	0.32	0	13.800	0.07	0.28	0	7.36	0.03	0.16	0	3.74
lathourlyppt	0.05	0.32	0	13.800	0.07	0.28	0	7.36	0.03	0.16	0	3.74
lathourlyppt_lat_2	0.05	0.32	0	13.800	0.07	0.28	0	7.36	0.03	0.16	0	3.74
N. of observations	6983				11784				11568			

	Urban sites											
Site Name:	Kanata				Maple				Patrol3			
Variables	estimate	Std. Dev	Min	Max	estimate	Std. Dev	Min	Max	estimate	Std. Dev	Min	Max
speed	114.28	11.80	60	125	109.00	8.90	60	125	112.14	13.66	60	125
Weather condition variables												
visibility	20.59	8.40	0.20	32.20	16.83	5.79	0.15	24.10	15.84	5.40	0.20	24.10
windpeed	12.06	7.28	0	40.75	10.99	9.46	0	56.67	12.28	10.52	0	63
temperature	-1.20	8.53	-32	26.95	2.41	7.53	-28.00	24.60	2.16	7.31	-25	24.23
hourlyppt	0.03	0.18	0	13.00	0.03	0.18	0	7.29	0.03	0.15	0	4.40
Event indicator	0.12	0.33	0	1	0.12	0.33	0	1	0.09	0.28	0	1
Road surface condition & Traffic characteristics variable												
RSI	0.93	0.10	0.100	1	0.84	0.23	0.07	1	0.92	0.14	0.07	1
peakhour	0.38	0.48	0	1	0.38	0.48	0	1	0.38	0.48	0	1
offpeak	0.33	0.47	0	1	0.33	0.47	0	1	0.33	0.47	0	1
nighthour	0.29	0.46	0	1	0.29	0.46	0	1	0.29	0.46	0	1
vcratio	0.01	0.001	0.007	0.013	0.31	0.23	0.02	0.73	0.01	0.001	0.005	0.009
weekend	0.29	0.45	0	1	0.29	0.46	0	1	0.30	0.46	0	1
Lagged effect variables												
laghourlyppt	0.03	0.18	0	13	0.03	0.18	0	7.29	0.03	0.15	0	4.400
laghourlyppt_prev_2	0.03	0.18	0	13	0.03	0.18	0	7.29	0.03	0.15	0	4.40
lathourlyppt	0.03	0.18	0	13	0.03	0.18	0	7.29	0.03	0.15	0	4.40
lathourlyppt_lat_2	0.03	0.18	0	13	0.03	0.18	0	7.29	0.03	0.15	0	4.40
N. of observations	9816				10680				10176			

For each observation, the new database contains site information, weather conditions, road surface conditions, and traffic factors. Site information includes: site location, date, and time of the observation. Weather condition variables include:

temperature, wind speed, visibility, hourlyppt (hourly snow) and its associated lagged effects. Note that this paper uses the road surface condition index (RSI) as the road surface condition variable. This index depends of the level of applied winter operations, instead of the commonly used friction measure. More details can be found in Usman et al. (2010).

Median and 85^{th} speeds were available in the data. However, because of the discrepancies noticed in the 85^{th} speeds, median speeds were used in this paper. In addition, volume-capacity ratio is used in the analysis to capture the potential effect of congestion on the operating speed. This ratio was calculated based on 2200 vehicles per hour per lane as the average lane capacity using the number of lanes for each highway segment. In order to account for daily variations, each day was divided into three periods of peak hours, non-peak hours, and night hours.

2.1.4 Results and Discussions

The results are reported for linear regression and time series separately. For model selection, the statistical level of significance (p-values and confidence intervals), correlations among explanatory variables (collinearity) and goodness-of-fit (R-square) were used as the main criteria. For instance, variables that were not statistically significant at the 5% level were dropped from the final models. This was complemented using a confidence interval of 95%. Correlations were tested to make sure that highly correlated variables are not included together in the same model. Note that the results discussed below, depending on the modeling approach, are divided into weekend versus weekdays and urban versus rural.

2.1.4.1 Linear Regression Model Results

The estimated parameters for speed models are presented in Table 2-3. The magnitudes of the parameters are generally in accordance with a past study conducted by Donaher et al. (2012). However, the lagged effects of snow, which were found to be significant in this research, were not considered in the latter study. It can be inferred from Table 2-3 that visibility, temperature, weekend, and RSI affect the speed positively in all cases. However, hourlyppt, laghourppt, laghourlyppt_prev_2, lathourppt, and lathourlyppt_lat_2 have a negative effect on the speed at both urban and rural sites. The wind speed has a negative effect on the speed only at rural sites. Note that, based on these results, after snow event lagged effects are more influential at reducing operating speeds among urban sites. Nevertheless, before a snow event, lagged effects have a greater effect on operating speeds on rural sites. When considering whole data, the latter factors affect operating speeds more significantly. The effects of peak hour and night hour vary depending on the type of site (i.e., urban or rural). For instance, peak hour affects the speed negatively at urban sites only. This also indicates the need to analyze urban and rural sites independently in order to suitably identify the effect of a potential contributing factor. In general, RSI, v/c ratio, and variables associated to snow are the most influential factors in describing the operating speed. It is important to mention the contradictory signs of the v/c ratio. The linear regression analysis implies that v/c ratio has a negative effect on the speed at urban sites. In rural areas, however, higher v/c ratios are associated higher operating speeds. One reason might be that the high traffic volume has a positive effect on road surface conditions, which can hardly been fully captured by RSI. Also, higher traffic provides visual guidance in rural areas resulting in higher operating speeds. This finding confirms the importance of a separate analysis for urban and rural sites to be able to correctly capture the impact of a given variable that might vary among sites with different characteristics. The analysis outcomes also indicated that speeds at urban sites are more sensitive to snow events compared to rural sites. The results also showed that weekends are slightly more sensitive to snow events compared to working days for both urban and rural sites. From Table 2-3, one can notice the importance of lagged effects for snow events. R^2 values are also reported in Table 2-3, which show a relatively reasonable model fit.

Table 2-3 Estimation Results - Linear Regression Model

	weekend				weekday				whole data	
variables	urban		rural		urban		rural		--	
	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat
visibility	0.26	17.21	0.09	20.54	0.33	18.92	0.10	15.82	0.13	42.35
wind speed	--	--	-0.03	-7.96	--	--	-0.03	-11.48	-0.02	-7.01
hourlyppt	-5.21	-9.3	-1.41	-11.54	-4.42	-6.81	-0.80	-9.23	-1.20	-12.78
temperature	--	--	0.02	5.67	0.05	3.82	0.04	17.39	0.04	16.88
RSI	8.25	16.26	9.66	42.7	10.80	18.55	7.61	56.01	9.03	63.21
weekend	--	--	--	--	--	--	--	--	1.28	30.65
Peak hour	-4.22	-18.93	1.15	15.5	-3.87	-16.8	0.95	23.95	0.38	8.52
night hour	1.56	6.88	-0.55	-7.19	2.41	9.75	-0.68	-16.08	-0.32	-6.75
v/c ratio	-7.26	19.28	10.88	13.46	-8.55	-19.16	10.52	21.65	-4.87	-18.18
laghourppt	-4.55	-6.68	-1.99	-15.3	-3.81	-6.79	-1.43	-17.16	-1.69	-18.18
laghourlyppt_prev_2	-2.50	-3.65	-2.11	-16.54	-2.64	-4.73	-1.78	-21.91	-1.85	-20.32
lathourlyppt	-4.76	-8.82	-1.22	-10.12	-4.70	-7.26	-1.19	-14.02	-1.43	-15.52
lathourlyppt_lat_2	-4.49	-8.37	-0.83	-7.03	-5.98	-9.32	-0.96	-11.63	-1.26	-13.97
constant	105.78		88.76		96.92		90.86		102.13	
Observations	6096		25272		14508		69960		115836	
R^2	0.39		0.72		0.32		0.61		0.49	

Note: -- indicates not applicable or not statistically significant

2.1.4.2 ARIMA Models Results

In addition to the simplistic linear regression model and to account for correlation among error terms, a sample of 6 sites (selected randomly) was analyzed using the structural equation with ARMA disturbances (described in methodology). Note that each site included a large number of observations. The results for rural and urban sites are reported in Tables 2-4 and 2-5, respectively. The ARIMA model outcomes, especially ρ, θ, and σ^2 values, show that the time series framework adopted in this study is an appropriate approach to analyze speed data. Similar to the linear regression model, visibility, RSI, and weekend have an increasing effect on the speed. The impact of snow and lagged effects associated to snow were found to be negative. However, peak hour and v/c ratio were not consistent among rural and urban sites. Under the ARIMA model, similar to the linear regression model, the effect of snow (including lagged effects) on the operating speed is smaller for rural highways compared to urban highways. It can be seen that the effect of "before snow event" lagged effects are greater compared to the "after snow event" lagged effects for both rural and urban sites. This is in contrast with the linear regression results. In addition, the weekend variable has a positive effect on operating speeds on urban sites while this variable is not statistically significant in modeling the speed on rural sites. Similarly, temperature was found to not be statistically significant at rural sites. Moreover, the v/c ratio is statistically significant (with a considerable impact) only for rural sites. In general, the most important effect is caused by RSI, snow event, and snow lagged effects at urban and rural sites. A sound conclusion about the effect of the wind speed cannot be drawn, as indicated by the results obtained.

Table 2-4 Estimation results - ARIMA model (Rural sites)

Site name:	Coachrane		Graven Hurst		Kaladar	
ARIMA(p,d,q):	1,0,1		2,0,1		2,0,1	
	estimate	t-stat	estimate	t-stat	estimate	t-stat
ρ_1	0.84	62.06	0.43	5.05	0.99	54.76
ρ_2	--	--	0.29	4.49	-0.04	-2.64
θ_1	-0.57	-29.96	0.23	2.59	-0.62	-40.68
θ_2	--	--	--	--	--	--
visibility	0.05	6.18	0.16	12.04	0.076	6.42
wind speed	--	--	-0.058	-4.03	--	--
hourlyppt	-0.55	-4.20	-0.93	-6.04	-1.22	-3.18
temperature	--	--	--	--	--	--
RSI	7.81	16.85	14.84	20.52	9.79	12.37
weekend	--	--	--	--	--	--
peak hour	--	--	0.20	2.02	-0.53	-2.10
night hour	-0.60	-4.50	-0.43	-2.93	0.45	2.92
v/c ratio	47.40	7.75	12.02	13.03	-5.99	-1.98
laghourlyppt	-1.04	-7.99	-0.72	-5.05	-1.16	-3.08
laghourlyppt_prev_2	-1.05	-8.25	-0.67	-5.20	-2.18	-5.80
lathourlyppt	-0.47	-3.64	-0.78	-5.46	-1.81	-4.76
lathourlyppt_lat_2	-0.41	-3.24	-0.72	-5.61	-1.19	-3.34
intercept(_cons)	89.45		87.55		84.88	
σ^2	11.17		10.56		28.59	

Note: -- indicates not applicable or not statistically significant

Table 2-5 Estimation results - ARIMA model (Urban sites)

Site name:	Kanata		Maple		Patrol3	
ARIMA(p,d,q):	3,0,1		1,0,2		3,0,1	
	estimate	t-stat	estimate	t-stat	estimate	t-stat
ρ_1	0.58	8.43	0.58	23.30	1.21	21.30
ρ_2	-0.22	-4.23	--	--	-0.40	-6.80
ρ_3	0.08	3.67	--	--	-0.07	-3.19
θ_1	0.19	2.72	0.31	10.73	-0.26	-4.54
θ_2	--	--	0.05	2.11	--	--
visibility	0.21	11.37	0.26	12.46	0.20	7.78
wind speed	-0.04	-1.77	0.07	5.39	-0.05	-3.87
hourlyppt	-3.17	-5.70	-2.86	-7.43	-6.96	-11.13
temperature	0.21	11.03	0.09	4.73	-0.04	-1.75
RSI	23.58	14.29	3.56	11.65	4.17	4.39
weekend	3.57	10.17	1.99	6.60	4.78	12.85
peak hour	2.71	9.49	1.28	6.69	-6.08	-23.55
night hour	4.75	16.06	0.44	2.29	2.62	10.10
v/c ratio	--	--	--	--	--	--
laghourlyppt	-3.19	-5.70	-2.86	-7.88	-6.19	-10.52
laghourlyppt_prev_2	-1.90	-3.85	-1.38	-4.82	-2.98	-6.24
lathourlyppt	-2.08	-3.77	-2.75	-7.57	-6.04	-10.31
lathourlyppt_lat_2	-0.83	-1.70	-1.95	-6.82	-3.68	-7.71
intercept(_cons)	85.47		99.80		106.62	
σ^2	62.96		26.57		40.03	

Note: -- indicates not applicable or not statistically significant

Figures 2-3 and 2-4, respectively, show the correlogram for autocorrelation function (ACF) and partial autocorrelation function (PACF) for site 7, as an example. In Figure 3, the x-axis indicates the lag and the y-axis indicates the autocorrelation for each lag. Note that the dashed line indicates the 5% significance level. The values falling outside the significance interval are away from zero and are therefore statistically significant. For example, the first 10 lags in Figure 3 are significant. In the case of the ARIMA process, one should take into account that the ACF alone cannot be used to make inferences related to the orders of dependence (Shumvay and Stoffer, 2011). Therefore, the PACF is used. For more details for ACF and PACF, one can refer to Shumvay and Stoffer (2011).

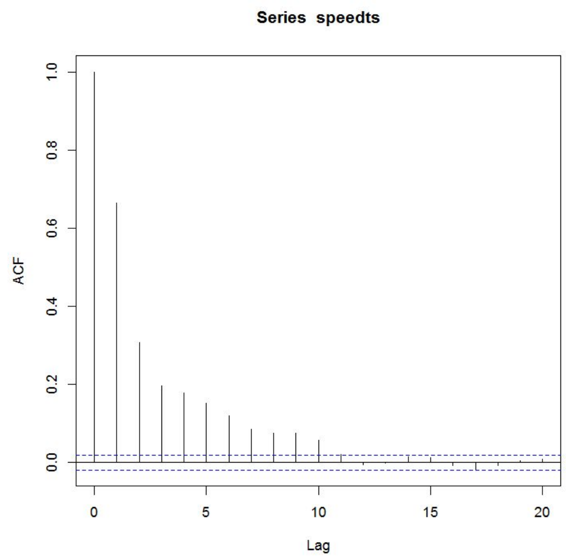


Figure 2-3 Autocorrelation (ACF)

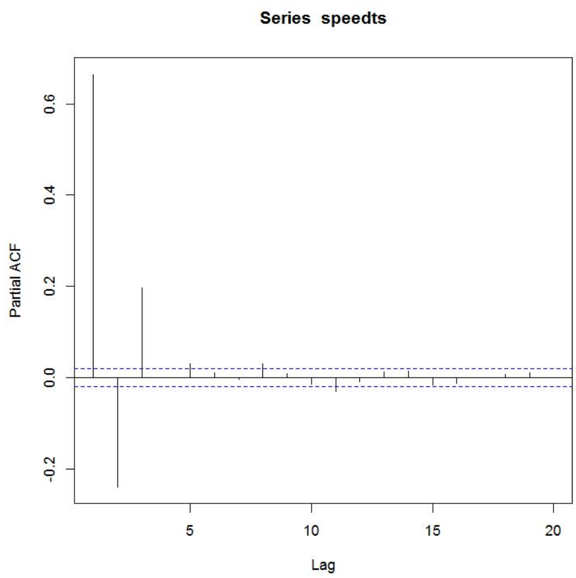


Figure 2-4 Partial Autocorrelation (PACF)

2.2 Effects on the Traffic Volume

2.2.1 Methodology

The traffic volume is affected by different factors as well. This part mainly looks into the snow precipitation and its lagged effect on the traffic volume. Similarly, the linear regression and ARIMA modeling approaches are utilized. The variables in this part are slightly different from the speed modeling outcomes, which are reported in **Table 2-6**. This work considers the volumes on highway bridges that act as links between the island of Montreal and Laval, in the Montreal metropolitan region.

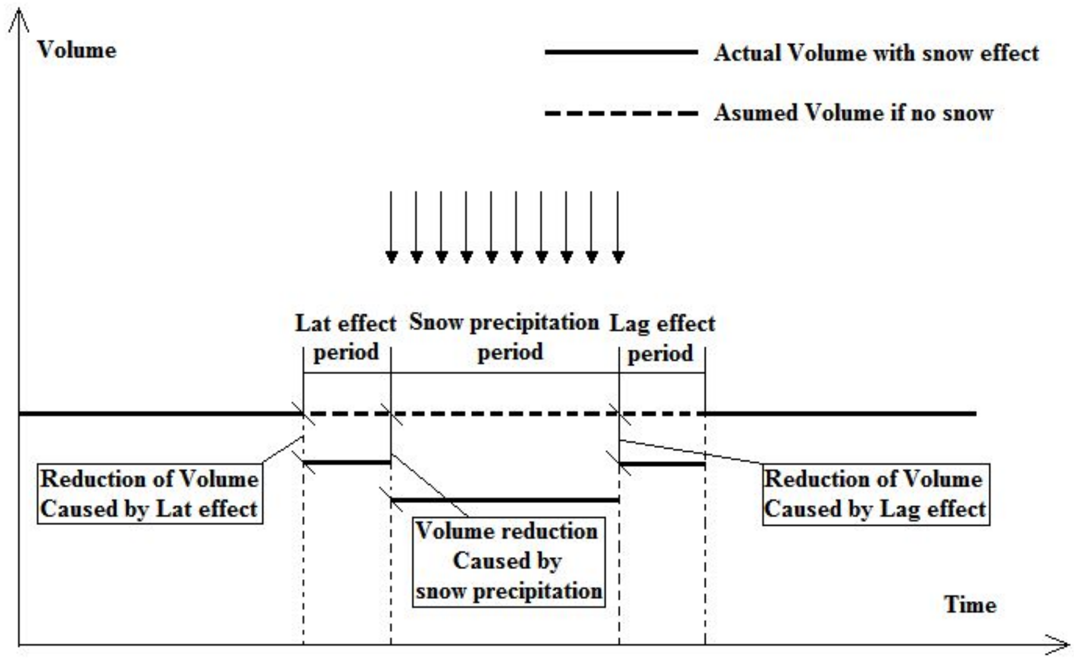


Figure 2-5 Effect of Snow Precipitation on the Traffic Volume

To investigate the effect of snow precipitation and its lagged effect, an assumption has been made that snow precipitation during the same hour and its lagged effect (after precipitation stops) reduces the traffic volume on highways. This assumption is illustrated in **Figure 2-5.**, where the volume is influenced more during snow precipitation period. This assumption is validated empirically using the case study of Montreal bridges. In **Figure 2-5**, the period t-1, in an hour t with precipitation is referred as “lat-effect”. Meanwhile, lag-effect period refers to the hour t+1, when precipitation is measured at time t.

2.2.1.1 Linear Regression Model

Following the approach proposed to model speed in the previous section, a similar approach of a log-linear regression model is used to represent the hourly traffic volume. This model is presented in Equation 5:

$$Q = \overline{Q}\exp(\beta_0 + \beta_s X_s + \beta_w X_w + \beta_{tr} X_{tr} + \beta_{lag} X_{lag}) \tag{5}$$

$$\ln(Q/\overline{Q}) = \beta_0 + \beta_s X_s + \beta_w X_w + \beta_{tr} X_{tr} + \beta_{lag} X_{lag} \tag{6}$$

where:

Q: traffic volume

$\overline{Q}$: average traffic volume for each site

X_s: vector of dummy variables for different sites

X_w: vector of weather condition variables

X_{tr}: vector of traffic characteristics

X_{lag}: vector of lagged variables

β_s, β_w, β_{tr}, β_{lag}: vectors of regression coefficients

β_0: constant

2.2.1.2 ARIMA Model

As an alternative approach to the standard linear regression, the ARIMA modeling approach presented in 7-9 is used. To estimate the parameters of these models, R software was utilized with its excellent computing efficiency.

$$\ln(Q/\overline{Q}) = X_t\beta + \mu_t \tag{7}$$

$$\mu_t = \rho\mu_{t-1} + \theta\varepsilon_{t-1} + \varepsilon_t \tag{8}$$

$$\begin{aligned} \mu_t &= \rho_1 \times [\ln(Q/\overline{Q})_{t-1} - X_{t-1}\beta] + \rho_2[n(Q/\overline{Q})_{t-2} - X_{t-2}\beta] + \ldots \\ &+ \rho_p[n(Q/\overline{Q})_{t-p} - X_{t-p}\beta] \\ &+ \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\varepsilon_{t-q} + \varepsilon_t \end{aligned} \tag{9}$$

where:

X_t: Vector of variables including the non-dummy lagged variables

β: Vector of regression coefficients

ρ: the first-order autocorrelation parameter

θ: the first-order moving-average parameter

$\varepsilon_t \sim$ i.i.d. $N(0,\sigma^2)$: white-noise disturbance

t: time

p: number of lags of autocorrelations

q: number of lags of moving averages

2.2.2 Data

For the hourly volume analysis, the database consists of automatic counts from highway bridges in Montreal Quebec, Canada (**Figure 2-6**). As for the speed, the dataset includes weather conditions (e.g., precipitation, temperature) and volume data. The number of sites corresponds to 5 with a total of 25,560 hourly observations.

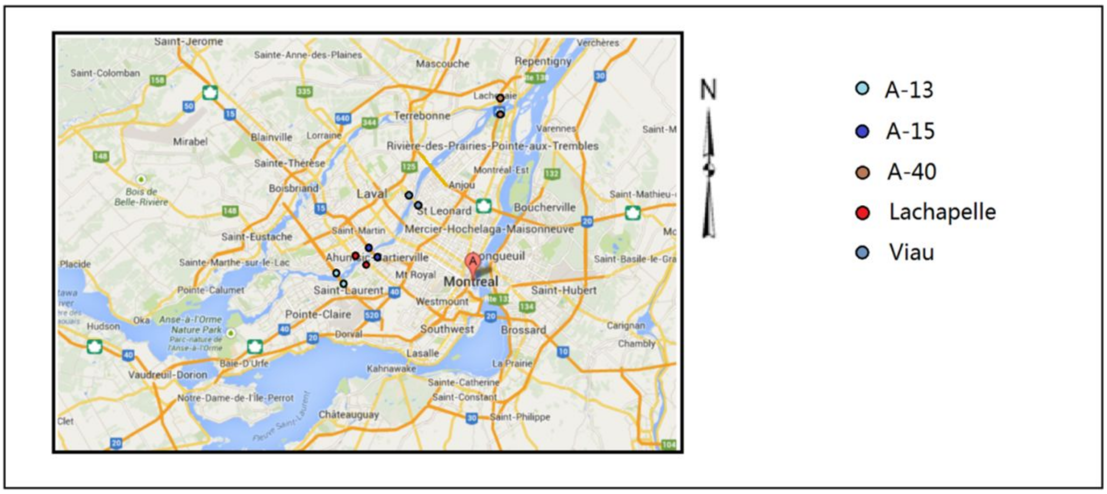


Figure 2-6 Spatial distribution of Sites – Google Map

2.2.3 Data Processing and Explanation of Variables

The variables used in volume modeling are in accordance with those used in speed modeling, except:

- ln_stvolume stands for "$\ln(Q/\overline{Q})$" in Equation 6 & 7

- It uses 0.1mm as the precipitation unit instead of using 1m to model the speed

A description of the variables and their descriptive statistics are summarized in Table 2-6.

Table 2-6 Summary statistics of data

Site Name:	All sites				A-13				A-15			
Variables	estimate	Std. Dev	Min	Max	estimate	Std. Dev	Min	Max	estimate	Std. Dev	Min	Max
Volume	2189.79	2013.72	0	9442	2938.44	2250.73	209	9442	3392.40	2100.89	224	8464
ln_stvolume	-0.42	0.98	-7.04	1.67	-0.39	0.93	-2.68	1.13	-0.34	0.88	-2.76	0.87
Weather condition variables												
Temperature	-3.70	6.78	-25.7	25.7	-3.49	6.49	-25.7	23.7	-4.09	6.66	-25.7	23.7
Hourlyppt	1.26	5.31	0	84	1.26	5.44	0	84	1.37	5.60	0	81.28
Traffic characteristics variable												
Weekend	0.28	0.45	0	1	0.26	0.44	0	1	0.28	0.45	0	1
Lagged effect variables (× 10^{-4}m)												
Laghourlyppt	1.26	5.31	0	84	1.26	5.44	0	84	1.36	5.60	0	81.28
Lathourlyppt	1.26	5.31	0	84	1.25	5.43	0	84	1.36	5.60	0	81.28
N. of observations	44640				9144				11136			

Site Name:	A-40				Lachapelle				Viau			
Variables	estimate	Std. Dev	Min	Max	estimate	Std. Dev	Min	Max	estimate	Std. Dev	Min	Max
Volume	2164.53	1543.97		6479	599.09	580.51	14	3319	540.39	462.96	24	2469
ln_stvolume	-0.39	0.92	-7.04	1.04	-0.59	1.21	-3.79	1.67	-0.43	0.96	-3.16	1.48
Weather condition variables												
Temperature	-3.80	6.81	-25.7	25.7	-3.54	7.06	-25.7	25.7	-3.30	7.00	-24.1	14.8
Hourlyppt	1.25	5.23	0	81.28	1.17	4.94	0	81.28	1.20	5.10	0	55
Road surface condition & Traffic characteristics variable												
Weekend	0.28	0.45	0	1	0.28	0.45	0	1	0.28	0.45	0	1
Lagged effect variables (× 10^{-4}m)												
Laghourlyppt	1.25	5.23	0	81.28	1.17	4.94	0	81.28	1.20	5.10	0	55
Lathourlyppt	1.25	5.22	0	81.28	1.17	4.94	0	81.28	1.20	5.10	0	55
N. of observations	25560				23568				10824			

For each observation, the database contains site information, weather conditions and volume data. Similar to the speed modeling, the site information includes: site location, date, and time of the observation. Different from modeling the speed, weather condition variables include: temperature, hourlyppt (hourly snow precipitation), and its associated lagged effects, while visibility is no longer included. Also, road surface condition variables, v/c ratio and other variables used in speed modeling are also no longer used since they are unavailable.

In the speed modeling, it was found that the lagged effect variables of precipitation (laghourlyppt and lathourlyppt) couldn't be applied in the same model due to the high colinearity of these two variables. To quantity and analyze their effect on the traffic volume, these two variables are tested in two models separately.

2.2.4 Results and Discussions

Similarly, the results are reported for linear regression and time series separately. When modeling the volume, the statistical level of significance (p-values and confidence intervals), correlations among explanatory variables (collinearity) and goodness-of-fit (R-square) were used as the main criteria. This method used the same level-of-significance of 5%. Most concerning variables were adopted while highly correlated variables were dropped. The results below from the linear regression modeling approach are demonstrated in two tables regarding the laghourlyppt and lathourlyppt separately. Also, different sites were studied.

2.2.4.1 Linear Regression Model Results

The estimated parameters for volume models are presented in **Table 2-7 & 2-8**. The results demonstrate that the lagged effects of snow in most models were found to be significant, a result that was not mentioned in the study conducted by Donaher et al. (2012). It can be inferred from **Table 2-7 & Table 2-8** that hourly precipitation, laghourppt, lathourppt affect the volume negatively in all cases. This indicates that traffic volumes decrease before, during and after a snowstorm event. Weekend also has a negative effect on the volume. The reason might be that more trips need to be made relating to jobs or other necessary purposes during weekdays. In Table 2-7 the variable hourlyppt is greater than the variable named laghourlyppt, and in table 2-8 the variable hourlyppt is greater than the variable lathourlyppt. It can be inferred that snowstorm and its lagged effect (for both before and after the snowstorm) reduces the traffic volume and the period during the snowstorm has greater effect on the periods before and after the snowstorm, announcing the assumptions mentioned in the beginning of 2.2.1 concerning **Figure 2-5. Tables 2-7** and **2-8**, show the importance of lagged effects for snow event in modeling the volume. The R^2 values reported show a reasonable, though not high, model fit.

Table 2-7 Estimation results - Linear regression model- Using Lag hourly precipitation

variables	All sites		A-13		A-15	
	estimate	t-stat	estimate	t-stat	estimate	t-stat
temperature	0.02	29.02	0.02	13.88	0.018	9.85
hourlyppt	-61.64	-6.07	-69.91	-3.42	-65.14	47.72
laghourppt	-33.10	-3.26	-36.77	-1.80	-37.16	2.77
weekend	-0.16	-16.32	-0.33	-15.54	-0.07	-27.46
constant	-0.42		-0.37		-0.30	
Observations	44639		9144		11136	
R^2	0.10		0.12		0.10	
variables	All sites		A-13		A-15	
	estimate	t-stat	estimate	t-stat	estimate	t-stat
temperature	0.02	14.07	0.02	11.3	0.02	11.31
hourlyppt	-69.72	-3.71	-15.72	-0.5	-68.08	-1.98
laghourppt	-40.76	-2.17	-9.31	-0.29	-9.80	-0.28
weekend	-0.16	-8.66	-0.14	-4.85	-0.10	-3.31
constant	-0.32		-0.67		-0.55	
Observations	11975		7680		4560	
R^2	0.12		0.09		0.08	

Table 2-8 Estimation results - Linear regression model- Using Lag hourly precipitation

variables	All sites		A-13		A-15	
	estimate	t-stat	estimate	t-stat	estimate	t-stat
temperature	0.02	29.06	0.02	13.9	0.02	14.46
hourlyppt	-56.29	-5.54	-63.58	-3.11	-60.27	-3.41
laghourppt	-42.40	-4.18	-47.95	-2.35	-45.31	-2.56
weekend	-0.16	-16.33	-0.33	-15.56	-0.07	-4.19
constant	-0.42		-0.37		-0.30	
Observations	44639		9144		11136	
R^2	0.10		0.12		0.10	
variables	A-40		Lachapalle		Viau	
	estimate	t-stat	estimate	t-stat	estimate	t-stat
temperature	0.02	14.08	0.02	11.29	0.02	11.40
hourlyppt	-65.42	-3.48	-19.59	-0.62	-66.97	-1.95
laghourppt	-48.31	-2.57	-1.91	-0.06	-32.95	-0.96
weekend	-0.16	-8.67	-0.14	-4.85	-0.10	-3.34
constant	-0.32		-0.67		-0.54	
Observations	11975		7680		4560	
R^2	0.10		0.08		0.09	

2.2.4.2 ARIMA Models Results

The ARIMA results for different sites are reported in **Tables 2-9 & 2-10**. The ARIMA model outcomes illustrate that the time series framework is a better alternative. As is the case when using the linear regression model, temperature has an increasing effect on the traffic volume, while hourly precipitation, lagged hourly precipitation (including the variables: laghourlyppt and lathourlyppt) and weekend have a negative effect. Same as in linear regression model, the variable hourlyppt has a greater negative effect on the traffic volume than the lagged precipitation variables, indicating the assumption from **Figure 2-5** to be correct. Problems occur only when the volume from the Viau site is modeled. It can be seen from **Tables 2-9 & 2-10** that using laghourlyppt, the variables hourlyppt and laghourlyppt have positive signs. Using lathourlyppt, the effect of lathourlyppt (-9.7709) is greater than hourlyppt (-1.4198) which goes to the opposite direction. There was a lot of construction on this bridge during the period of analysis – this means that traffic patterns on this bridge are different from the common trends or patterns.

Similarly, **Figures 2-7** and **2-8** show the correlogram for the autocorrelation function (ACF) and the partial autocorrelation function (PACF) at Site 1, respectively. In these tables, the dashed lines indicate that parameters are statistically significant at the 5% level. Also, for more details on ACF and PACF, one can refer to Shumvay and Stoffer (2011).

Table 2-9 Estimation results - ARIMA model - Using Lag hourly precipitation

Site name:	A-13		A-15		A-40		Lachapelle		Viau	
ARIMA(p,d,q):	2,0,1		1,0,1		1,0,1		1,0,0		2,0,1	
	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat
ρ_1	1.54	142.75	0.89	196.91	0.89	200.43	0.93	215.26	1.46	78.70
ρ_2	-0.68	-64.45	--	--	--	--	--	--	-0.59	-33.46
θ_1	0.06	3.94	0.67	111.83	0.60	100.18	--	--	0.11	4.62
θ_2	--	--	--	--	--	--	--	--	--	--
hourlyppt	-12.73	-2.52	-12.93	-2.55	-19.60	-3.43	-5.31	-0.43	10.73	1.12
temperature	0.0033	3.67	0.0014	2.00	0.0017	2.13	0.0075	3.75	0.0006	0.23
weekend	-0.12	-6.39	-0.04	2.81	-0.0014	0.08	-0.075	1.69	-0.05	1.80
laghourlyppt	-5.75	-1.14	-7.78	-1.56	-11.30	-1.98	-4.78	-0.39	8.13	0.85
intercept(_cons)	-0.35		-0.34		-0.37		-0.59		-0.45	
σ^2	0.06		0.06		0.08		0.20		0.08	

Note: -- indicates not applicable or not statistically significant

Table 2-10 Estimation results - ARIMA model - Using Lat hourly precipitation

Site name:	A-13		A-15		A-40		Lachapelle		Viau	
ARIMA(p,d,q):	2,0,1		1,0,1		1,0,1		2,0,1		2,0,1	
	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat
ρ_1	1.54	142.74	0.89	196.91	0.88	200.45	1.59	132.77	1.46	78.70
ρ_2	-0.68	-64.43	--	--	--	--	-0.72	-62.25	-0.59	-33.47
θ_1	0.06	3.94	0.67	111.77	0.60	100.13	-0.06	-3.56	0.11	4.59
θ_2	--	--	--	--	--	--	--	--	--	--
hourlyppt	-12.48	-2.46	-15.68	-3.08	-16.65	-2.89	-13.73	-1.78	-1.42	-0.15
temperature	-0.003	-3.33	0.0014	2.00	0.0017	2.13	0.0019	1.88	0.0007	0.27
weekend	-0.12	-6.40	-0.04	2.73	-0.0009	0.05	-0.03	-1.10	-0.05	1.81
lathourlyppt	-5.36	-1.06	-11.15	-2.19	-7.47	-1.30	-6.79	-0.88	-9.77	-1.02
intercept(_cons)	-0.35		-0.34		-0.38		-0.58		-0.44	
σ^2	0.07		0.06		0.08		0.03		0.08	

Note: -- indicates not applicable or not statistically significant

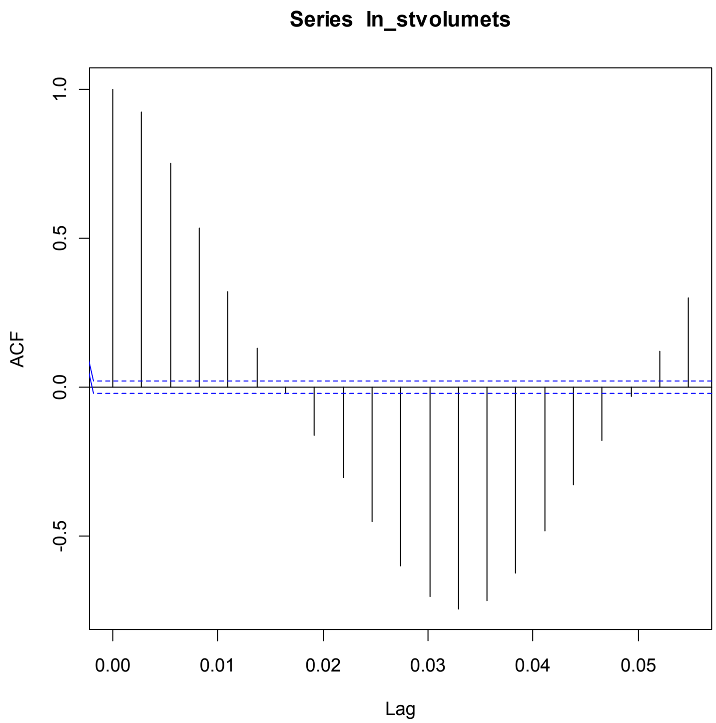


Figure 2-7 Autocorrelation (ACF)

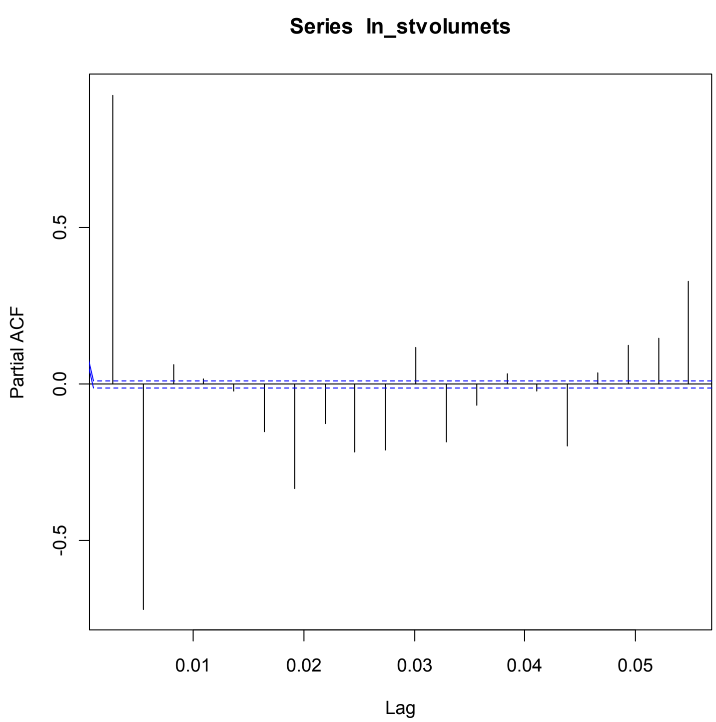


Figure 2-8 Partial Autocorrelation (PACF)

Chapter 3

Driver behavior analysis during winter weather conditions using video data: Issues and possibilities

Introduction

In order to fully understand driver behavior during adverse weather conditions, microscopic data will be necessary. This data can provide more insights with respect to the behavioral mechanics of an individual driver (vehicle) interacting with the road surface, traffic controls, other vehicles and weather factors. Accordingly, this research explores the possibilities of obtaining microscopic data from video sensors during wintertime and in particular during adverse weather conditions. The conditions in which video data could be useful as well as those in which alternative data collection methods should be explored are identified. As discussed in the introduction, video data collection has many advantages and shortcomings in driver behavior analysis; however, this data can also suffer from serious limitations in adverse winter weather conditions. This following chapter attempts to address the issue of driver behavior during winter conditions as well as limitations in data collection.

3.1 Methodology

This research was conducted by following the three main steps illustrated in **Figure 3-1**:

i) Highway site selection and collection of video data: Sites involved in this study were located along a major Toronto highway. Video recordings were taken at each site before, during and after winter storms.

ii) Classification and definition of indicators to investigate driver behaviors: Videos were classified according to traffic in free flow and congested conditions. The behavioral measures included operating speeds, lane changes, gap time, and conflict analysis.

iii) Video post-processing: Semi-automatic (manual) and automatic procedures were used. As part of the validation and testing, data obtained with a manual procedure was compared to data obtained with automatic procedures using computer vision algorithms implemented in *Traffic Intelligence Software - TIS* (St-Aubin[2] et al., 2011).

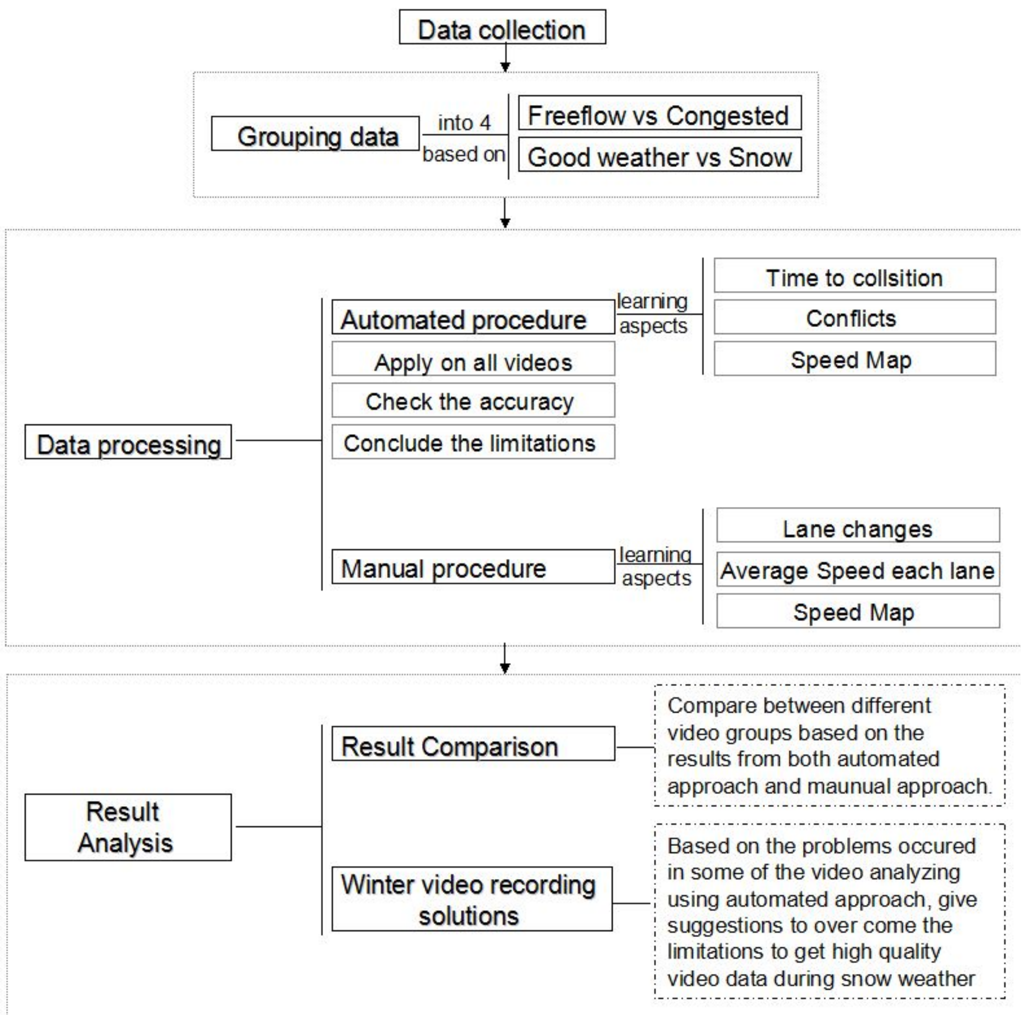


Figure 3-1 Data Collection, Treatment and Analysis

The rest of this section provides additional details with respect to each step.

3.1.1 Site selection and data

This study uses traffic data obtained from the City of Toronto's Traffic Management Centre. The data was collected by video cameras from the city's RESCU operation system. Study sites were carefully selected after reviewing all locations with cameras in the Toronto area. Three highway sites with typical access ramps were selected based on the fact that access ramps are among the most critical elements of a highway network. Data collection periods were determined based on weather forecasts at corresponding locations. During wintertime, weather conditions were constantly monitored in order to predict snow and precipitation events in advance from which video data before, during and after could be collected. In total, fifteen video recordings were collected at all three sites. The recordings covered the following weather and traffic conditions: i) snow precipitation, ii) snow on the road surface, iii) clear weather with no snow on the road surface, iv) free-flow traffic conditions, and v) congested traffic conditions. The different tasks are summarized in **Figure 3-2**.

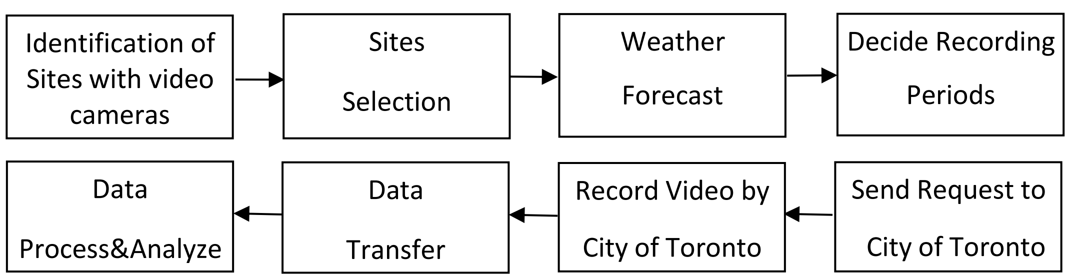


Figure 3-2 Data Collection Procedures

3.1.2 Data post-processing

Once data was collected, recorded videos from the City of Toronto were processed using both automatic and manual procedures. The recordings were classified according to the traffic and weather conditions.

A preliminary analysis of video quality was carried out to identify the most common issues for each site involved in the study. Some of the common weather-related issues associated with most cameras were i) intense and direct sunlight, ii) presence of frost or rain drops on the camera lens, and iii) the reflection of light from the wet road surface. These issues usually lead to poor video quality, which makes automated data processing, a task done using computer vision algorithms, more difficult. In fact, some weather conditions resulted in overly complicated and unclear video recordings, from which algorithms were unable to recognize distinct features and groups of objects. Such situations render automated driver analysis methods unusable, since they prevent vehicles from being accurately and reliably tracked by computer software. Unfortunately, only 4 out of 15 videos were clear enough to be processed. Among the 4 videos only 2 videos represent traffic in free flow conditions. **Table 3-1** lists the issues encountered when trying to use TIS to process the collected video data. Potential solutions to some of these issues are discussed later in the document.

Video processing was carried out using a manual and an automated process. The manual process was executed based on manually calculating vehicle speeds and lane change ratio. By setting a starting and ending line on the video records, study segments were defined. The lengths of the segments were measured using GoogleEarth software. By recording the time the randomly selected vehicles took to pass the segments, the speeds of these cars could be calculated based on the segment lengths. The number of cars and the total number of cars changing lanes were counted for each lane. Regarding the automated process, this is done using computer vision algorithms implemented in TIS. The techniques used in this software are explained by Saunier (2006), and Shi and Tomasi (1994). (Saunier, 2006; Shi and Tomasi, 1994).

The TIS software classifies the output of a generic feature-based moving object tracker (Saunier, 2006). This algorithm can be summarized in two steps:

1. Individual pixels are detected and tracked from frame to frame, and recorded as feature trajectories using the Kanade-Lucas-Tomasi feature tracking algorithm *(*Shi and Tomasi, 1994*)*.

2. The feature trajectories are then grouped based on consistent common motion in order to define a single moving object.

The parameters of this algorithm are calibrated through trial and error, leading to a trade-off between over-segmentation (one object being tracked as many objects) and over-grouping (many objects being tracked as one object).

Table 3-1 Typical Camera Issues in Video Data

Problem	**Glare from the sun**	**Frost/Raindrop on camera**
Problem Video	Video7	Video1, 6, 7, 10, 11
Screen example		
Issue	Sun light shines directly into to camera during sunset and sunrise	Frost and rain accumulates on the surface of the camera
Cause	Camera angle	Cameras are exposed in snow and have no protection from frost
Problem	**Reflection**	**Obstacle in between**
Problem Video	Video10, 11, 13	Video2, 3, 4, 12, 13
Screen example		
Issue	Water accumulates on the road surface during rain or snow melt. Water reflects the light coming from headlights of motor vehicles.	Obstacle occurs in between the camera and the study area.
Cause	Camera angle	Camera location

In addition to weather-related problems, congestion is another common issue with video data processing. Since computer vision algorithms only detect moving objects, automated video data processing cannot extract trajectories under congested conditions. During traffic jams, the velocity of some vehicles nears zero. In such conditions, the software is incapable of tracking the vast majority of vehicles, which renders the video recording useless. In addition to failing to properly track slow-moving vehicles, algorithms cannot detect the road environment or the presence of cars under most night-time conditions, since darkness causes many objects that make up the video image to become indistinguishable. Since the interest of this study was mainly to analyze driver behavior in free flow conditions, the video quality during congestion periods was not a relevant issue.

3.1.3 Microscopic measures

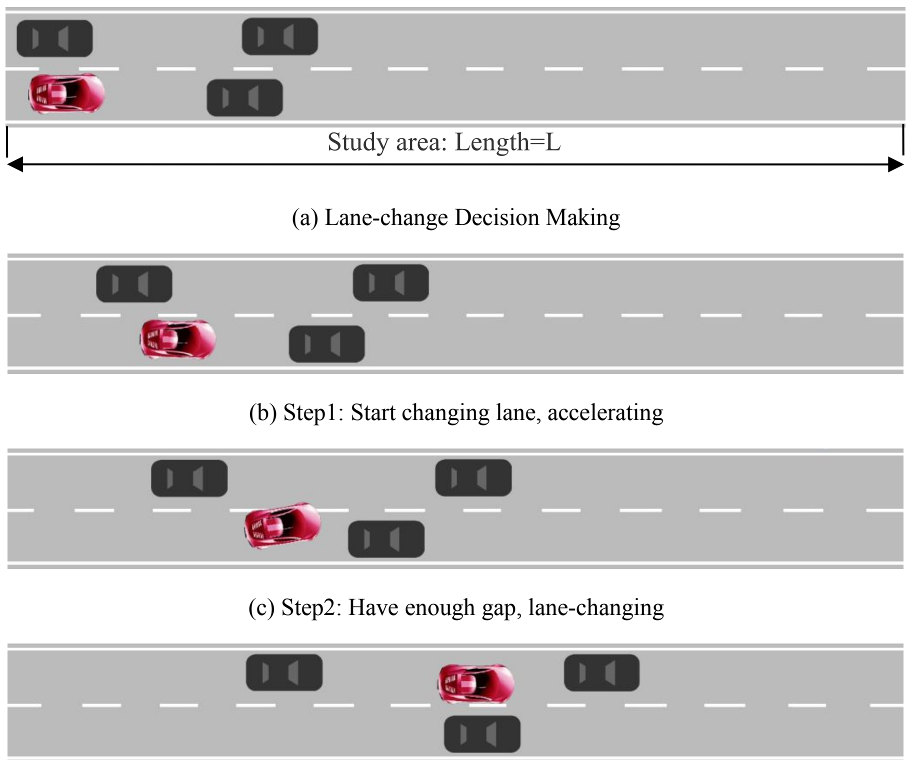
Driver behaviors and surrogate measures were defined for this study as follows:

a) Lane change ratio:

Several previous studies have used the number of lane changes to analyze driver behavior (Knoop[1] et al., 2012; Knoop[2] et al., 2012). However, the number of lane changes cannot be typically directly used to evaluate the effect of snow storm on driver behavior because they may vary greatly based on the total traffic volume. Therefore, the study introduced a variable indicating percentage of lane changes among the traffic known as the lane change ratio. The present study defines the lane change ratio as the number of lane change maneuvers divided by the total flow in a specified period of time, that is:

$$R_L = Q_L/Q$$

Where R_L is the lane change ratio, Q_L is the total observed number of lane change maneuvers and Q is the total vehicular flow in the same travel direction. **Figure 3-3** illustrates the 3-step lane changing process that needs to be identified in each of the observations (Ahmed, 1999). Note that the total flow is the number of cars entering the study area during the specified time period, and that the total number of lane changing maneuvers is restricted to those maneuvers taking place inside the study area.



(a) Lane-change Decision Making

(b) Step1: Start changing lane, accelerating

(c) Step2: Have enough gap, lane-changing

(d) Step3: Finish changing lane, decelerating

Figure 3-3 Sample of Lane Change Maneuvers

b) Vehicle-level Operating speeds:

Operating space speed simply corresponds to the time that a vehicle takes to travel a short distance L, which is calculated using the straightforward equation:

$$S_i = L / T_i$$

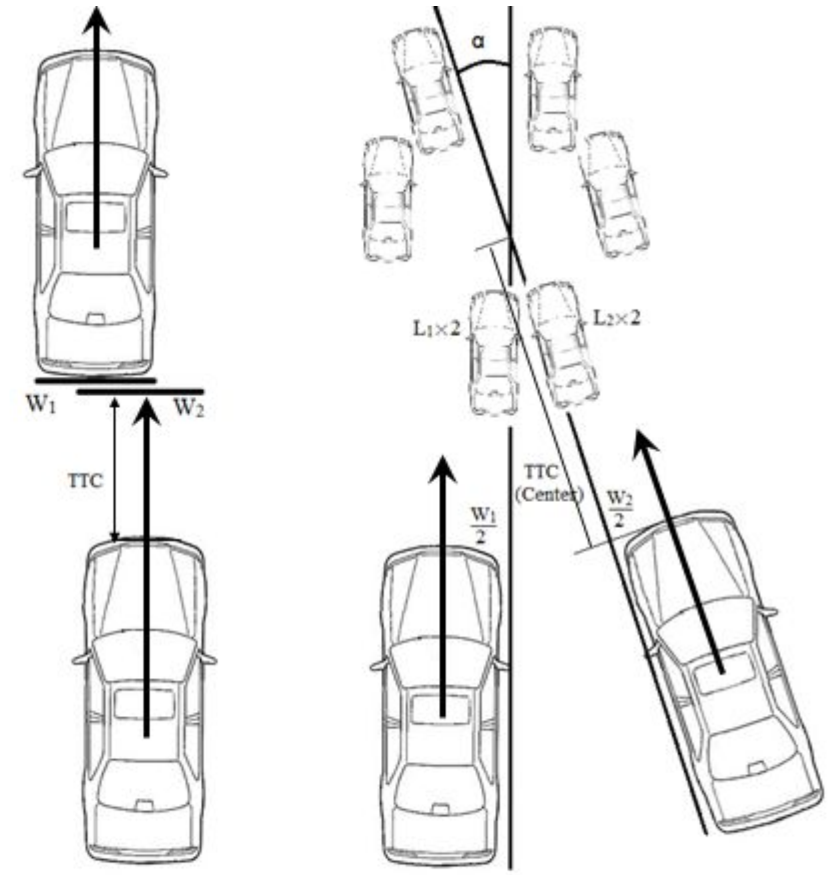
Where S_i is the travel speed for vehicle "i" as it crosses the study segment, L is the length of the study segment (from the starting line to the ending line) and T_i is the time that a vehicle takes to cross the study segment. The average operating speed is then computed as the sum of all the measured speed values divided by the total number of vehicles. In the manual approach, samples of 30 cars passing the selected area were randomly selected from each lane. All samples were taken under free-flow driving conditions in order to isolate the effects of other drivers. Due to the effect of high traffic volumes on the driver behavior, speeds under congested conditions were rarely collected. Moreover, samples were taken from both good and bad (snow) weather conditions. In this study, the average operating speed was used to validate the two approaches, as well as to analyze the effect of adverse winter weather conditions (snow) on highway driver behavior. **Note that** TIS registers the temporal speed, which is the speed of a moving object when its presence is detected. This can be expressed by the following equation:

$$S_t = \Delta L / \Delta T_i$$

In the automated approach, results of collision points, speed heat-map are all generated based on the temporal speeds. Average temporal speeds are discussed in the result section as part of the result summary for the automated approach.

c) Time-to-collision (TTC) as a surrogate measure

TTC has been defined earlier as "the time required for two vehicles to collide if they continue at their present speeds and on the same path" (van dar Horst and Hogema, 1993; Heyward and Near, 1972). Following the approach adopted in previous research conducted by St-Aubin[2] (2011), this study uses TTC as a surrogate safety measure. In the analysis of St-Aubin[2] (2011), as shown in Figure 3-4, TTC measures are classified according to two types of conflict: rear-end (type A), and lateral-diagonal (type C). The measures are computed using the TIS software, and represented with 'heat-maps'.



a. Type A-Rear-End Converging **b. Type C-Diagonal Converging**

Figure 3-4 Classification of TTC Measures (St-Aubin et al[2]., 2011)

3.2 Data

As previously mentioned, high quality video data was obtained at only three of the pre-selected sites in the Toronto area. These three locations (**Figure 3-5**) were therefore the only locations that could be included in the analysis. A brief description of each of the three selected sites is given in **Table 3-2** including site location, field of view and video number. **Table 3-3** provides descriptions of all 15 video recordings collected from these locations.

The weather condition and surface were used to classify each video; this method helped to classify whether surfaces were clear of or covered in snow. Traffic conditions were also determined based on volumes and operating speeds. Basically, videos taken during rush hours were classified as containing congested traffic conditions.

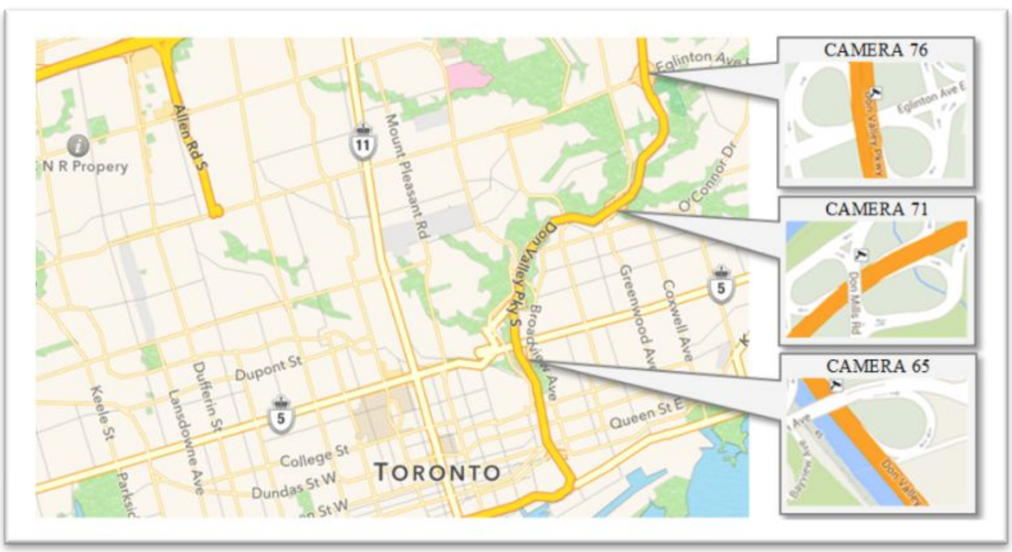


Figure 3-5 Spatial Distribution of Sites - Google Map

Table 3-2 Description of Sites

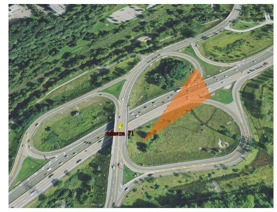
Site name	Camera 65	Camera 71	Camera 76
Site location	Don Valley Pkwy	Don Valley Pkwy	Don Valley Pkwy
Camera shooting area			
Sample view			
Videos of the camera	Video 2, 3, 4, 12, 13	Video 1, 6, 7, 10, 14	Video 5, 8, 9, 11, 15

Table 3-3 Description of Video Recordings

No. Of video	site of video	Duration	Date	Day	Weather condition	Road condition	Useful in TIS
1	Camera 71	21 mins	Feb 20th	Wed	snow	congested	No
2	Camera 65	22 mins	Feb 20th	Wed	good & wet surface	congested	No
3	Camera 65	46 mins	Feb 20th	Wed	good & wet surface	non congested	No
4	Camera 65	15 mins	Feb 25th	Mon	good weather	non congested	No
5	Camera 76	15 mins	Feb 20th	Wed	good weather	non congested	**Yes**
6	Camera 71	39 mins	Feb 21th	Thu	good & wet surface	congested	No
7	Camera 71	14 mins	Feb 21th	Thu	good & wet surface	non congested	No
8	Camera 76	12 mins	Feb 21th	Thu	good weather	congested	No
9	Camera 76	31 mins	Feb 21th	Thu	good weather	non congested	**Yes**
10	Camera 71	15 mins	Feb 22th	Fri	snow	non congested	No
11	Camera 76	14 mins	Feb 22th	Fri	snow	congested	No
12	Camera 65	1 hr	Feb 21th	Thu	good	non congested	No
13	Camera 65	15 mins	Feb 22th	Fri	snow	non congested	No
14	Camera 71	15 mins	Feb 25th	Mon	good weather	non congested	No
15	Camera 76	15 mins	Feb 25th	Mon	good weather	congested	No

Note: Date means date in which the data was collected

3.3 Some Results

The results are presented for both or manual video processing and automated video analysis using computer vision techniques. The accuracy of the manual process was validated by comparing the measurements between both approaches.

3.3.1 Manual approach

The results of average speeds across the three different weather conditions are presented in **Figure 3-6**. The three weather conditions are good weather without any form of precipitation, good weather, but snow on the surface, and poor weather with snow precipitating. As initially hypothesized, significant reductions are observed in speeds and lane change ratios under snow conditions. Average speeds of lanes under good weather condition are higher than those under good weather condition with wet road surface. Meanwhile, average speeds under snow condition are the lowest. For instance, on average, a reduction of more than 10 km/h along the site at Camera 71 can be observed. Interestingly, the impact is also observed in each of the lanes however, lane 3 (high-speed lane, left lane) is the one with the most significant impact (reduction). These results provide clear evidence of drivers adapting to snow storms and wet road surface conditions.

Regarding lane changing ratio**,** the results also show a clear reduction in the lane changing behavior. As illustrated in **Figure 3-7**, the lane changing ration went down from 0.12 (in the snow condition) to 0.07 (in the good weather condition) in Camera 71. This again confirms the initial hypothesis that drivers seem to make less lane changes when it is snowing or when the road surface is wet or covered with ice (or wet), compared to drier road and clearer weather conditions.

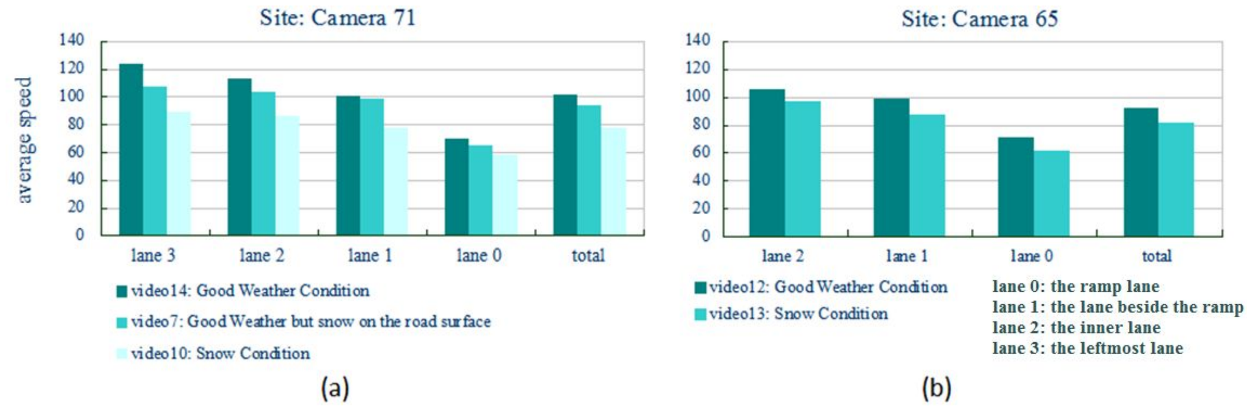


Figure 3-6 Comparison of Average Speeds

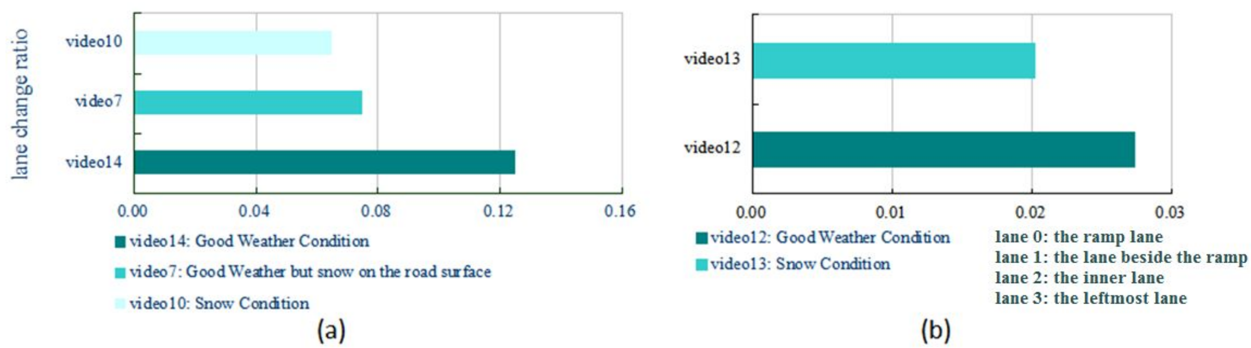


Figure 3-7 Comparison of Lane Change Ratio

3.3.2 Automated approach

In order to represent the automated approach, analysis of data from video 5 is used an example below. The TIS software has a 'mask' function, which allows for the application of a mask over the video. A mask enables the software to analyze trajectories in a certain area of the video. Using the masks, the speeds for different lanes are computed separately. The TIS software provides the object trajectories and speeds for each frame in the form of SQlite database. The average space speed for each individual vehicle is then computed. Average space speeds for each lane can then be calculated. **Table 3-4** shows the summary of the detected average space speeds for each lane. As expected, an important variation across lanes is observed. The differences between lane 0 and 3 is more than 30 km/hr. When entering the highway from the ramp, drivers tend to slow down and hesitate to make a lane change if the adjacent lane is busy or they continue to accelerate until they reach the speed limit if few cars are in the inner lane (extreme left lane). This behavior explains why the minimum temporal speeds in this lane vary between 12.34 km/h and 76 km/h.

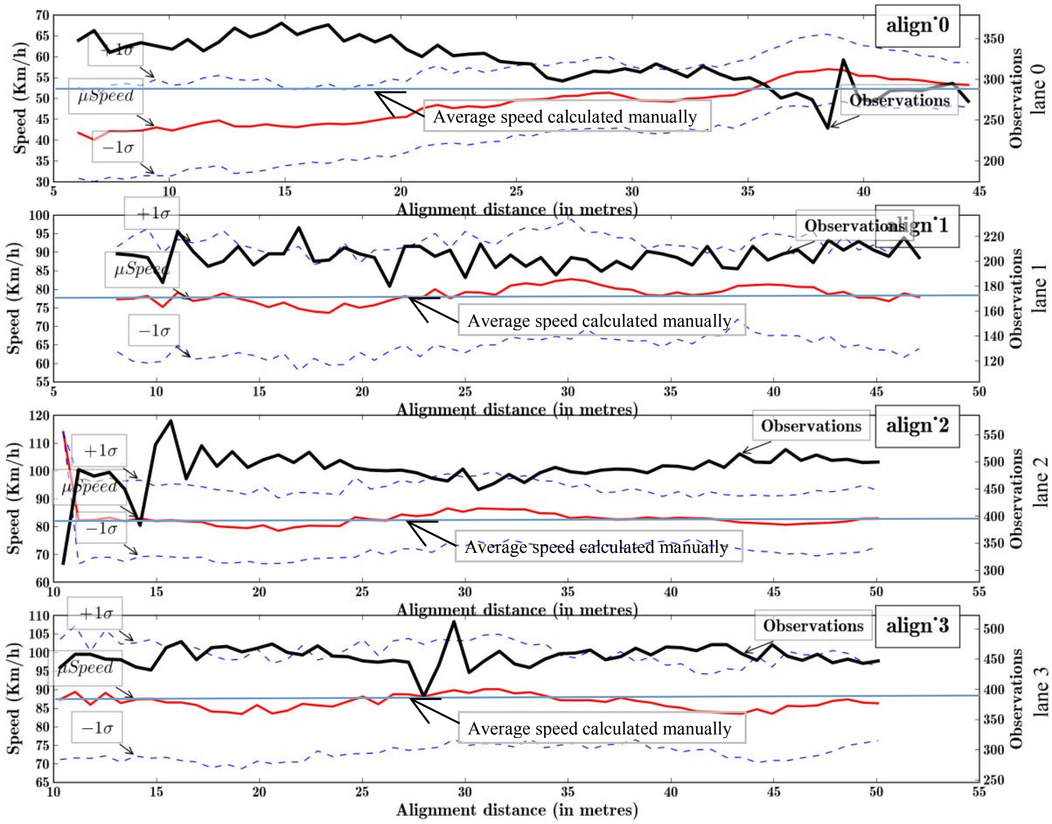
Table 3-4 the Summary of Automated-Detected Temporal Speeds for Video 5

	Total Number of Detected vehicles	Average speeds	Min	Max
Ramp (0)	181	51.21	12.34	76.12
Right (1)	291	68.75	24.12	105.29
Middle (2)	482	81.67	54.93	107.04
Extreme left (3)	707	85.61	62.09	110.10

The manual approach only registers the average operating speed. To validate the accuracy of manual observations, automated speeds were also computed with the TIS software. For this, samples of 20 observations of operating speeds collected by both methods were randomly selected and used to validate the effectiveness of the automated approach. Average operating speeds were calculated, and the results for each of the two methods are presented in **Table 3-5**. The results contained in **Table 3-5** show that the corresponding values of average operating speeds in each lane, obtained from the automated and manual methods, are very similar. The two approaches lead to approximately equal results. In fact, the largest discrepancy between two corresponding values obtained via different methods is only 2.56%, which occurs when comparing the operating speed in the highway's leftmost lane. Also noteworthy is the similarity between corresponding extreme values obtained from the different computational methods (automated versus manual). **Table 3-5** presents some of the results obtained through automated video analysis. Note that the measures are very close to those obtained with the manual approach. Despite the fact that the manual method is very accurate when computing speeds and obtaining volumes (counts), the automated method allows for the collection of speeds and the application of surrogate analysis. Furthermore, the automated approach based on the TIS software is both easily applicable and very practical. Detailed results generated by the TIS software are given below, in **Figure 3-8** and **Figure 3-9**.

Table 3-5 Average Operating Speeds Comparison of Samples Generated from Two Approaches

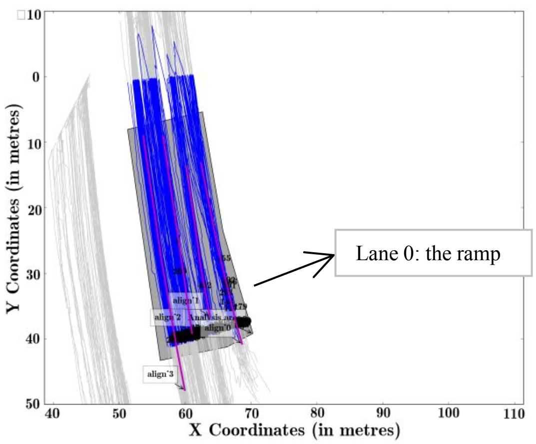
Length (0.104km)	Automated approach				Manual approach			
	No.Obs	AvgSpd	Min	Max	No.Obs	AvgSpd	Min	Max
Ramp (0)	20	51.93	41.70	70.67	20	52.33	38.88	64.80
Right (1)	20	78.43	66.37	101.76	20	78.49	64.80	97.20
Middle (2)	20	80.22	68.76	91.95	20	80.16	64.80	97.20
Extreme left (3)	20	85.43	72.69	97.85	20	87.62	77.76	97.20



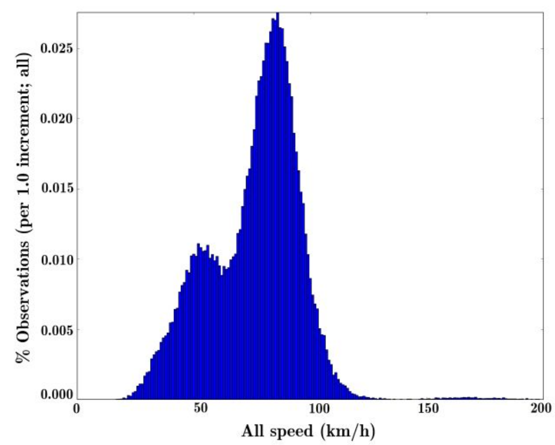
Note: The black line in the figure refers to the number of observations; the red line refers to the average speed of detected cars for a certain distance from the alignment starting point; the blue lines refers to the average speed for detected cars in different lanes.

Figure 3-8 the Summary of Detected Speeds

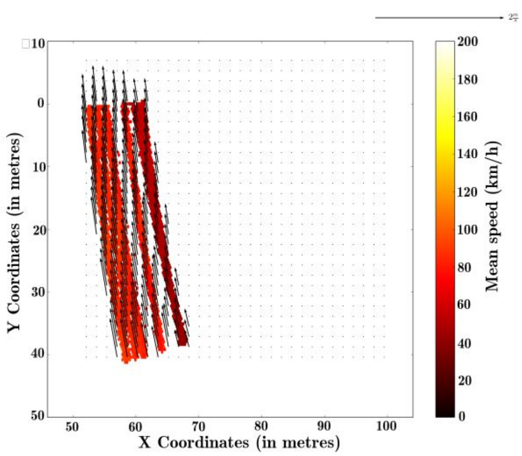
Figure 3-8 presents the vehicle speeds observed in different lanes, while **Figure 3-9** shows the values of several driver behavior measures generated by the automated approach. For the sake of comparison, the manually calculated average speeds are displayed in **Figure 3-8**. As can be seen in **Figure 3-8**, vehicle speeds computed using the automated method do not fluctuate greatly from the manually detected average speeds. This observation is additional evidence that the automated approach leads to accurate and reliable results. **Figure 3-9.a** shows detected object trajectories, and **Figure 3-9.b** presents their speed distributions. Most speed values fall within 0 km/h and 150 km/h which is a reasonable range for highway facilities. Similarly, **Figure 3-9.c** presents the distribution of speed values in different lanes while **Figure 3-9.d** relies on a speed heat-map to indicate the location and quantity of collision points.



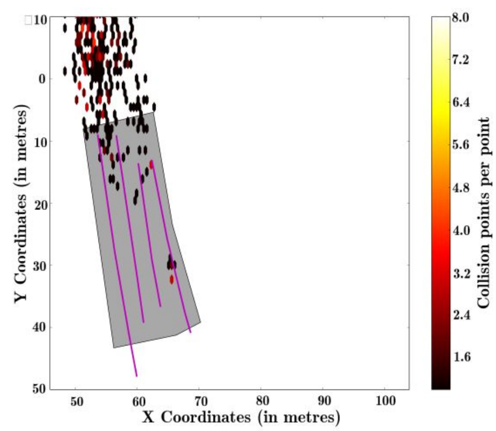
(a) Trajectories Result and Studying Zone



(b) Speed Distribution



(c) Speed Heat-Map



(d) Conflicts Point Heat-map

Figure 3-9 Results generated by Tracking-based Software

From **Figure 3-9**, one can see that speeds are lower on the ramp than in other lanes. As expected with the automated method, the traffic analysis software gives accurate values of driving behavior measures. Unfortunately, the typical camera issues mentioned in **Table 3-1** affected all recordings collected during snowy conditions. This research is therefore unable to use the automated approach to investigate the effect of snow conditions on highway driver behavior.

3.4 Discussion

The analysis of driver behavior using microscopic data can help to explain the adaptation mechanics of the driver in regards to the road surface condition and/or adverse weather during wintertime. In this study, driver speed adaptation is clearly observed in the available video data. The lane changing ratio was also used as an indicator. Based on this indicator, it was observed that the proportion of lane changing maneuvers significantly decreases with the presence of snow and snow precipitation on the road surface. To generate microscopic data, manual measures of speeds, lane changes and volumes were obtained through direct video manipulation. The manual measures were validated using automated video data analysis method using computer vision software. The automated method has the advantage of being much less time consuming and is low-cost; however, it does not perform appropriately under adverse weather conditions especially considering that video data collected from regular surveillance equipment which includes the highway camera is not of particular high quality and resolution. Several typical issues were encountered when processing the video data, which were documented in this paper. Potential solutions to the limitation of surveillance video data include i) applying special treatments to the camera to prevent the accumulation of snow or rain, ii) adjusting the angle of the camera to help get rid of reflection and direct sunshine, and iii) using thermal video cameras which can detect and track objects regardless of visible illumination using infrared radiation emitted from moving objects. More specifically, infrared technology works by detecting variations in temperatures which reflect changes in the quantity of radiation emitted by an object (persons and vehicles). In other words, warm objects are differentiated from cooler backgrounds allowing for the detection of vehicles and persons during winter conditions. Since thermal cameras only detect heat signatures in the area of study, they are unaffected by the glare of the sun and the headlight as well as reflections from water accumulated on the road surface. Moreover, thermal cameras are almost completely unaffected by darkness. They can clearly detect objects that pass through shadows, and are very effective at detecting vehicles at night. Considering the advantages mentioned above, it would surely be worthwhile to test the effectiveness of thermal cameras using the automated video data analysis method. Time and budget permitting, the benefits of combining the use of thermal and video cameras will be evaluated in future work.

Chapter 4

CONCLUSION AND FUTURE WORK

Many transportation studies have investigated the link between modeling the operating speed of vehicles and the built environment. However, less attention has been devoted to analyzing the effect of adverse weather conditions on operating speeds, especially by employing a time series approach and using disaggregate data during wintertime. The first part of this thesis studied how various weather factors and surface conditions affect the operating speed and the traffic volume during winter conditions. The direct and lag effects of weather was investigated. A host of potential contributing factors such as, visibility, wind speed, snow events, weekend, and peak hour, were taken into account in modeling the vehicular speed and volume based on two different sources of data respectively. Furthermore, the lagged effects of snow events were introduced into the analysis through a time series framework. This approach―which is referred to as a structural equation with ARMA disturbances―has some advantages compared to the classical methods. For instance, it accounts for autocorrelation among errors and is able to capture the impact of lagged effects. As a comparative model, the conventional linear regression model was also used to analyze the data.

For this study, hourly speed data from 22 sites (urban and rural highway segments) was used for modeling. The data included at least one winter season and information related to weather variables, site attributes, and traffic characteristics. Hourly volume data covered 6 sites (highway bridges connecting Montreal Island and areas outside the island). Both speed and volume models were developed using linear regression and time-series techniques. The existence of autocorrelation in the data was identified and treated partially using time-series analysis.

Among other things, the results suggested that snow events as well as their associated lagged effects have a decreasing impact on the operating speeds while visibility, RSI, and weekend periods have a positive effect on this variable. The analysis outcomes indicated that urban highways were more sensitive to snow events compared to rural highways. This thesis also highlighted the importance of separately analyzing urban versus rural sites as well as weekends versus weekdays since the impact of contributing factors might vary significantly. The regression analysis, for instance, showed that nighttime periods and v/c ratio have opposite effects on operating speeds on rural versus urban sites. Also, the differences between weekends and weekdays were also very clear. Similar patterns were also observed when using ARIMA models. From the ARIMA model outcomes, it can be inferred that the adopted time series framework performs well in modeling the operating speed data. Recall that the linear regression model fell short in effectively dealing with lagged effects and correlation issues. When modeling the volume, snow precipitation was shown to have a negative effect on the traffic volume, which indicates that travelers may change mode from public transit to driving in order to reduce their outdoor exposure during storm conditions.

Chapter 3 aimed to provide a better understanding of the effect of adverse winter weather on traffic parameters (speeds and lane changing behaviors) using microscopic video data. For this chapter, video data was collected at different sites and weather conditions. As part of the contributions of this research, a methodology was proposed for analyzing the effect of winter on highways using microscopic measures such as, vehicle-level speeds and lane change ratios. The procedure for extracting driver behavior information from video data was demonstrated. The results have shown that surface conditions during a snowstorm influences drivers to significantly lower their speeds. Speed reductions were observed in all lanes; however lane 3 was the most affected with reductions of more than 30 km/hr. Based on these results, it can be inferred that drivers employ a certain degree of risk compensation in order to avoid potential severe conflicts caused by a lack of tire friction on the road. This confirms the idea that driver behavior along highways is affected by snowstorms. Despite their limitations, the video-based results showed a certain risk compensation effect. Vehicle-level speeds significantly decreased during the wintertime, in particular when weather and road conditions were poor. This risk compensation phenomenon should translate into less severe crashes due to the longer braking distance which results in less kinetic energy. In other words, the consequences of a crash (probability of being injure or die) are proportional to the speed. As discussed by Wallman et al. (1997), if the speed of a vehicle is reduced from 100 to 90 km/h (10 %), braking distance is reduced by 19 %, and injuries and fatal accidents are expected to be reduced by 27 % and 34 %, respectively.

Most of the video data was processed manually given the limitations of computer vision techniques during adverse weather. However, the presented methodology based on manual video post-processing has been validated using computer vision software – refereed in this thesis as Traffic Intelligence Software. This software has the advantage of being able to process large amounts of data and compute surrogate measures such as, conflicts and post-encroachment times. Using videos with appropriate quality, the results were then validated. The use of alternative surrogate safety measures was illustrated, and the important potential problems have been identified for further research.

More work concerning different aspects of road safety needs to be studied such as, getting higher quality videos, defining and applying a proper measurement method for time gaps, and building lane-changing models using trajectory analytics software. The use of thermal video cameras and computer vision techniques will help data collection accuracy in both good and snowy weather conditions. The limitations of surveillance video data under snow conditions have been documented. With a limited Canadian winter period, the potential solutions have not yet been tested. Additional work needs to be done in order to collect high quality videos with thermal surveillance cameras. This automated method will reduce the need for manual approaches and collect more detailed driver behavior information from trajectory tracking software. The trajectory tracking software is still under development, and a script will be created to analyze the 3-steps lane-changing behavior (Ahmed, 1999). With thermal video collected under snow-storm conditions, detailed surrogate safety analysis on highway sections and ramps can be generated to investigate different targets such as, the economical and safety impacts of winter maintenance treatments, storm durations, occurrences of storms at nighttime, and driver adaptation to winter. A proactive approach to safety through the use of surrogate measures could help in the implementation of more effective winter maintenance operations.

REFERENCES

1. Agarwal, M., Maze, T. and Souleyrette, R. (2005). Impacts of Weather on Urban Freeway Traffic Flow Characteristics and Facility Capacity. *Proceedings of Mid-Continent Transportation Research Symposium*, Ames, Iowa. August 2005.

2. Ahmed, K. I. (1999). Modeling Drivers' Acceleration and Lane Changing Behavior. Massachusetts Institute of Technology, Submission of degree of Doctor of Science in Transportation Systems and Decision Sciences 1999.

3. Ahmed, S. and Cook, A. (1979). Analysis of Freeway Traffic Time-series Data Using Box-Jenkins Techniques. Transportation Research Record, 733, pp. 1-9.

4. Alberta Traffic Collision Statistics. (2010)

5. Ali, A., Venigalla, M. and Flannery, A. (2007). Prediction Models for Free Flow Speed on Urban Streets. *Proceedings of Annual Meeting of the Transportation Research Board*, Washington, D.C.

6. Bham, G. H., and Benekohal, R. F. (2001) ACCELERATION behavior OF DRIVERS IN A PLATOON. in *the First International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*.

7. Brockwell, A., Chan, N. H. and Lee, P. K. (2003). A Class of Models for Aggregated Traffic Volume Time Series, *Journal of the Royal Statistical Society Series C,* 01/2003 52(4)., pp.417-430.

8. Datla, S. and Sharma, S. (2008). Impact of Cold and Snow on Temporal and Spatial Variations of Highway Traffic Volumes, *Journal of Transport Geography Volume 16*, Issue 5, September 2008., pp.358-372.

9. Donaher, G., Fu, L. and Usman, T. (2012). Quantifying the Mobility Effects of Winter Road Conditions. *Proceedings of the 9th International Transportation Specialty Conference*, Edmonton, Alberta, Canada.

10. Edwards, B. J. (1998). The Relationship between Road Accident Severity and Recorded Weather. *Journal of Safety Research*, Vol. 4, no. 29, 1998, pp. 249-262.

11. Eisenberg, D., and Warner, K. E. (2005) Effects of snowfalls on motor vehicle collisions, injuries, and fatalities. *American Journal of Public Health*, Vol. 1, no. 95, 2005, pp. 120-124.

12. Eluru, N., Chakour, V., Chamberlain, M. and Miranda-Moreno, L. (2012). A Panel Mixed Ordered Probit Fractional Split Model: Modeling Vehicle Speed on Urban Roads in Montreal. *Presented at the 92th Annual Meeting of the Transportation Research Board*, Washington, D.C.

13. Fambro, D., Fitzpatrick, K. and Russell, C. (2000). Operating Speed on Crest Vertical Curves with Limited Stopping Sight Distance. *Transportation Research Record: Journal of the Transportation Research Board, No. 1701*, TRB, National Research Council, Washington, D.C., pp. 25–31.

14. Fitzpatrick, K., Carlson, P., Brewer, M., Wooldridge, M. and Miaou, S. (2003). Design Speed, Operating Speed, and Posted Speed Practices, *NCHRP Report 504,* Transportation Research Board, Washington, D.C.

15. Fuller, R. (2005). Towards a general theory of driver behavior. *Accident Analysis and Prevention*, Vol. 3, no. 37, 2005, pp. 461-472.

16. Goodwin, C. L. (2002). Weather Impacts on Arterial Traffic Flow. Federal Highway Administration, Washington D.C., prepared for Road Weather Management Program 2002.

17. Hamilton, J. D. (1994). Time Series Analysis. Princeton: Princeton University Press.

18. Hanbali, L. F., and Barrow, D. (1993). Traffic Volume Reductions due to Winter Storm Conditions. *Transportation Research Record: Journal of the Transportation Research Board*, no. 1387, 1993, pp. 159-164.

19. Hall, F., Lam, T. (1988). The Characteristics of Congested Flow on a Freeway Across Lanes, Space dnd Time. *Transportation Research.* 22A, pp. 45-56.

20. Harvey, A. C. (1989). Forecasting, Structural Time Series Models and the Kalman Filter. Cambridge, Cambridge University Press.

21. Heyward, J. C. (1972). Near miss determination through use of a scale of danger. The Pennsylvania State University, Pennsylvania, TTSC 7115, 1972.

22. Highway Capacity Manual (2010). Transportation Research Board of the National Academies of Science, USA.

23. Hu, W., X. Xiao, D. Xie, and T. Tan. (2003). Traffic Accident Prediction Using Vehicle Tracking and Trajectory Analysis. *IEEE*, 2003, pp. 220-225.

24. Kilpeläinen, M., and H. Summala. (2007). Effects of weather and weather forecasts on driver behavior. *Transportation Research Part F: Traffic Psychology and Behavior*, Vol. 10, 2007, pp. 288-299.

25. Liang, W., Kyte, M., Kitchener, F. and Shannon, P. (1998). The Effect of Environmental Factors on Driver Speed: A Case Study. Transportation Research Record 1635. *Transportation Research Board, National Research Council, Washington, D.C., USA*. 1998, pp. 155-161.

26. Kanellaidis, G., Golias, J., and Efstathiadis, S. (1990). Drivers Speed Behavior on Rural Road Curves. *Traffic Engineering & Control,* Vol31, No. 7, pp. 414-415.

27. Kamarianakis, Y., Prastacos, P. (2003). Forecasting traffic flow conditions in an urban network: Comparison of multivariate and univariate approaches. *Transportation Research Record: Journal of the Transportation research Board.* 1857, pp. 74-78.

28. Keay, K. and Simmonds, I. (2005). The association of rainfall and Other Weather Variables with Road Traffic Volume in Melbourne, Australia, *Accident Analysis and Prevention*, pp.109-124.

29. Khattak, A. J., and Knapp. K. K. (2001). Snow event effects on interstate highway crashes. *Journal of Cold Regions Engineering*, Vol. 4, no. 15, 2001, pp. 219-229.

30. Knapp, K. K., Kroeger, D. and Giese, K. (2000). Mobility and Safety Impacts of Winter Storm Events in A Freeway Environment. *FINAL REPORT*, Iowa State University, February 2000.

31. Knapp, K.K. and Smithson, L. D. (2000). Winter storm event volume impact analysis using multiple-source archived monitoring data. *Transportation Research Record: Journal of the Transportation Research Board*, no. 1700, 2000, pp. 10-16.

32. Knoop, V. L., Hoogendoorn, S. P., Shiomi, Y., and Buisson, C. (2012). Quantifying the Number of Lane Changes in Traffic. *Transportation Research Record: Journal of the Transportation Research Board,* no. 2278, 2012, pp. 31-41.

33. Knoop, V. L., Wilson, R. E., Buisson, C., and van Arem, B. (2012). Number of Lane Changes Determined by Splashover Effects in Loop Detector Counts. *IEEE,* pp. 1525-1534.

34. Kumar, M., Wang, S. (2006). Impacts of Weather on Rural Highway Operations. *Final Report, Prepared for the U.S. Department of Transportation*, June 2006.

35. Kwon, T.J., Fu, L., and Jiang, C. (2013). "Effect of Winter Weather and Road Surface Conditions on Macroscopic Traffic Parameters", accepted for publication in *Transportation Research Record: Journal of the Transportation Research Board, National Research Council.* Washington D.C., USA.

36. Li, R. and Rose, G. (2011). Incorporating uncertainty into short-term travel time predictions. *Transportation Research Part C: Emerging Technologies.* 9 (6), pp. 1006-1018.

37. Mahalel D. and Hakkert, A. (1985). Time-series Model for Vehicle Speeds" *Transportation Research.* 19B, pp. 217-225.

38. Näätänen, R., and Summala, H. (1976). Road-user behavior and traffic accidents. in *Amsterdam and New York*: North-Holland/American Elsevier.

39. Nicholson, H. and Swann, C. (1974). The Prediction of Trllffic Flow Volumes Based on Spectral Analysis. *Transportation Research.* 8, pp. 533-538.

40. Park, B. J., Zhang, Y. and Lord, D. (2010). Bayesian Mixture Modeling Approach to Account for Heterogeneity in Speed Data, *Transportation Research Part B: Methodological* 44 (5), 662-673.

41. Rämä, P. (1999). Effects of weather-controlled variable speed limits and warning signs on driver behavior. *Transportation Research Record: Journal of the Transportation Research Board*, no. 1689, 1999, pp. 53-59.

42. Rämä, P., and Kulmala, R. (2000). Effects of weather-controlled variable message signs for slippery road conditions on driving speed and headways. *Transportation Research Part F: Traffic Psychology and Behavior*, Vol. 2, no. 3, 2000, pp. 85-94.

43. Rakha, H., Du, J., Park, S., Guo, F., Doerzaph, Z., Viita, D., Golembiewski, G., Katz, B., Kehoe, N. And Rigdon, H. (2011). Feasibility of Using In-Vehicle Video Data to Explore How to Modify Driver Behavior that Causes Nonrecurring Congestion, Report S2-L10-RR-1. *Transportation Research Board.*

44. Saunier, N., and Sayed, T. (2006). A feature-based tracking algorithm for vehicles in intersections. *IEEE*.

45. Saunier, N., Sayed, T., and Ismail, K. (2010). Large Scale Automated Analysis of Vehicle Interactions and Collisions. *Transportation Research Record: Journal of the Transportation Research Board*, December 2010, pp. 42-50.

46. Shi, J., and Tomasi, C. (1994). Good Features to Track. Proceedings of IEEE Conference on Computer Vision and Pattern Recognition CVPR-94, 1994, pp. 593-600.

47. Shumway, R. H. and Stoffer, S. D. (2011). Time series analysis and its applications, Third Edition. Springer.

48. St-Aubin[1], P., Miranda-Moreno, L. F. and Saunier, N. (2011). Analysis of Driver Behavior and Collision Risks for Protected Freeway Entrance and Exit Ramps: Trajectories and Surrogate Safety Measures. in *the 21st Canadian Multidiscilinary Road Safety Conference*, Hlifax, Nova Scotia, 2011.

49. St-Aubin[2], P., Miranda-Moreno, L. F. and Saunier, N. (2011). A surrogate Safety Analysis at Protected Freeway ramps using Cross-sectional and Before-After Video Data. *Transportation Research Record: Journal of the Transportation Research Board*, Washington DC., 2011.

50. St-Aubin, P., Saunier, N., Miranda-Moreno, L. F., and Ismail, K. (2013) Detailed Driver Behavior Analysis and Trajectory Interpretation at Roundabouts using Computer Vision Data. In *Transportation Research Board Annual Meeting Compendium of Papers*.

51. Steyvers, F., and Waard, D. de. (2000) Road-edge delineation in rural areas: effects on driver behavior. *Economics*, Vol. 2, no. 43, 2000, pp. 223-238.

52. Summala, H. (1996). Accident risk and driver behavior. *Safety Science*, Vol. 1-3, no. 22, 1996, pp. 103-117.

53. Time Series - Introduction to Time-series Commands. (n.d.). In *Data Analysis and Statistical Software,* http://www.stata.com/features/time-series/ts-arima.pdf.

54. *Traffic Detector Handbook:Thrid Edition*. (2006).

55. Usman, T., Fu, L. and Miranda-Moreno, L. (2010). Quantifying safety benefit of winter road maintenance: Accident frequency modeling, *Accident Analysis and Prevention*, pp.1878-1887.

56. Usman, T., Fu, L. and Miranda-Moreno, L. (2011). Winter Road Safety: Effects of Weather, Maintenance Operations, and Road Characteristics. *Presented at the International Conference on Transportation Information and Safety.* ICTIS 2011, pp. 1152-1159.

57. Usman, T. (2011). Models for Quantifying Safety Benefit of Winter Road Maintenance. *PhD Final Report, Depart of Civil Engineering, University of Waterloo.*

58. van der Horst, R., and Hogema, J. (1993). TIME-TO-COLLISION AND COLLISION AVOIDANCE SYSTEMS. in *6th ICTCT workshop Salzburg*.

59. Versavel, J. (2007) Traffic Data Collection: Quality Aspects of Video Detection. in *Transportation Research Board*, Washington.

60. Vlahogianni, E. I., Karlftis, M. G. (2012). Comparing traffic flow time-series under fine and adverse weather conditions using recurrence-based complexity measures. *Nonlinear Dynamics.* 69, pp. 1949-1963.

61. Yu, G. and Zhang, C. (2004). Switching ARIMA Model Based Forecasting for Traffic Flow. *Proceeding of International Conference on Acoustics, Speech, and Signal Processing - ICASSP, vol.2*, pp. ii-429-32.

62. Zhang, G., Avery, R. P. and Wang, Y. (2007). Video-Based Vehicle Detection and Classification System for Real-Time Traffic Data Collection Using Uncalibrated Video Cameras. *Transportation Research Record: Journal of the Transportation Research Board*, October 2007, pp. 138-147.

Appendix A: Details of Study areas in Modeling Approaches

Table A-1 Details of the Studying Sites in Speed Modeling

Site ID	Name_site	Highway	urban	rural	Site ID	Name_site	Highway	urban	rural
1	Coachrane	11		1	12	Nipigon	11		1
2	Dunvegan	417		1	13	North Bay	11		1
3	Elliot Lake	108		1	14	Patrol1	401	1	
4	Grand Bend	21		1	15	Patrol2	401	1	
5	Graven Hurst	11		1	16	Patrol3	401	1	
6	Kaladar	7		1	17	Port Hope	401		1
7	Kanata	417	1		18	Port Severn	400		1
8	Kenora	17		1	19	Shelburne	10		1
9	Maple	400	1		20	Simcoe	3		1
10	Massey	17		1	21	Sioux Narrows	71		1
11	Morrisburg	401		1	22	Snelgrove	10		1

Site ID	Site	Location
1	Cochrane	Jct 655 14km east of Smooth Rock Falls to 26.2 Km west of smooth rock falls
2	Dunvegan	St Laurent Blvd to Quebec Border
3	Elliot Lake	Jct of Hwy 108 - Sec Hwy 639
4	Grand Bend	From Grand bend 21 at IC 34 of 402 TO Grand bend 21 at IC 84
5	Gravenhurst	Gravenhurst 11 at Severn Bridge to Gravenhurst 11 at IC 117
6	Kaladar	Heritage Line to Highway 41/4
7	Kanata Patrol	March road to St Laurent Blvd
8	Kenora	Manitoba Border to the Vermilion Bay Patrol Yard (located 3.1 km West of the Hwy 647 Jct.)(Plus the Hwy 17A "Kenora By-Pass" which is 33.6 km)
9	Maple	Maple Leaf Dr. to Canal Road
10	Massey	Hwy 17 - CR 4 to Sec Hwy 553 Imperial Street (Massey)
11	Morrisburg	Hwy 16 to Quebec Border

Table A-2 Details of the Studying Sites in Volume Modeling

Site ID	Name_site	Highway
1	A-13	Autoroute Chomedey
2	A-15	Route Transcanadienne
4	A-40	Autoroute de Rive-Nord
5	Lachapelle	Boulevard Cure-Labelle
6	Liau	Boulevard des Laurentides

Note: volume data were collected from highway bridges, and the details can be referred in Chapter2.

Appendix B: Coefficients of Variables in Modeling Speed

Table B-1 Coefficients of Variables for the Whole Dataset

	visibility	windspeed	hourlyppt	temperature	rsi	eventindicator	day_week	peakhour	nighthour	vcratio
visibility	1	--	--	--	--	--	--	--	--	--
windspeed	-0.0038	1	--	--	--	--	--	--	--	--
hourlyppt	-0.2358	0.0811	1	--	--	--	--	--	--	--
temperature	-0.0444	0.1195	-0.092	1	--	--	--	--	--	--
rsi	0.3682	-0.1494	-0.2732	0.1602	1	--	--	--	--	--
eventindicator	-0.3401	0.1568	0.3589	-0.2278	-0.4783	1	--	--	--	--
day_week	-0.0159	0.0508	0.011	-0.0076	-0.0162	0.0239	1	--	--	--
peakhour	0.0329	0.1464	0.0026	0.1397	0.0383	-0.0049	-0.0077	1	--	--
nighthour	-0.0249	-0.0994	-0.0332	-0.1179	-0.0362	0.0052	0.0025	-0.4938	1	--
vcratio	-0.0799	-0.0412	0.0041	0.0613	-0.0099	-0.0114	0.0026	0.1116	-0.1351	1

Table B-2 Coefficients of Variables for Urban Sites during Weekends

	visibility	windspeed	hourlyppt	temperature	rsi	eventindicator	peakhour	nighthour	vcratio
visibility	1								
windspeed	0.1004	1							
hourlyppt	-0.2214	0.1001	1						
temperature	0.067	0.0818	-0.115	1					
rsi	0.2349	0.0736	-0.1096	0.3072	1				
eventindicator	-0.2703	0.106	0.3899	-0.2091	-0.3195	1			
peakhour	0.0165	0.1403	0.0177	0.1118	-0.0023	0.0422	1		
nighthour	-0.0009	-0.0982	-0.0617	-0.0987	-0.0145	-0.0418	-0.4963	1	
vcratio	0.0173	-0.06	0.0061	0.0937	-0.1471	0.0248	0.3436	-0.2939	1

Table B-3 Coefficients of Variables for Rural Sites during Weekends

	visibility	windspeed	hourlyppt	temperature	rsi	eventindicator	peakhour	nighthour	vcratio
visibility	1	--	--	--	--	--	--	--	--
windspeed	0.0157	1	--	--	--	--	--	--	--
hourlyppt	-0.2351	0.0817	1	--	--	--	--	--	--
temperature	-0.0352	0.1514	-0.0715	1	--	--	--	--	--
rsi	0.3746	-0.1481	-0.2822	0.1951	1	--	--	--	--
eventindicator	-0.3713	0.1149	0.3415	-0.2327	-0.5311	1	--	--	--
peakhour	0.0043	0.1662	0.0082	0.1567	0.0284	0.0057	1	--	--
nighthour	0.0034	-0.1259	-0.0411	-0.1272	-0.0086	-0.01	-0.497	1	--
vcratio	-0.0999	-0.0238	-0.0041	0.109	0.0436	-0.035	0.2329	-0.1854	1

Table B-4 Coefficients of Variables for Urban Sites during Weekdays

	visibility	windspeed	hourlyppt	temperature	rsi	eventindicator	peakhour	nighthour	vcratio
visibility	1	--	--	--	--	--	--	--	--
windspeed	0.0625	1	--	--	--	--	--	--	--
hourlyppt	-0.2115	0.0629	1	--	--	--	--	--	--
temperature	-0.0289	0.065	-0.1277	1	--	--	--	--	--
rsi	0.2583	-0.0165	-0.1915	0.2663	1	--	--	--	--
eventindicator	-0.2471	0.1301	0.3674	-0.2821	-0.399	1	--	--	--
peakhour	0.0303	0.1188	-0.0138	0.1313	0.0406	-0.0261	1	--	--
nighthour	-0.0103	-0.089	-0.0184	-0.1255	-0.0611	0.0311	-0.4968	1	--
vcratio	0.0241	-0.0517	-0.022	0.0011	-0.1588	0.0277	0.0671	-0.1229	1

Table B-5 Coefficients of Variables for Rural Sites during Weekdays

	visibility	windspeed	hourlyppt	temperature	rsi	eventindicator	peakhour	nighthour	vcratio
visibility	1	--	--	--	--	--	--	--	--
windspeed	0.0259	1	--	--	--	--	--	--	--
hourlyppt	-0.2282	0.0735	1	--	--	--	--	--	--
temperature	-0.0685	0.1214	-0.0955	1	--	--	--	--	--
rsi	0.3766	-0.1663	-0.2912	0.1485	1	--	--	--	--
eventindicator	-0.3217	0.1466	0.3559	-0.2262	-0.5032	1	--	--	--
peakhour	0.0222	0.1521	-0.0045	0.158	0.0433	-0.0121	1	--	--
nighthour	-0.013	-0.0996	-0.0293	-0.1299	-0.041	0.0115	-0.4974	1	--
vcratio	-0.0998	-0.0388	0.0034	0.0754	0.0323	-0.0253	0.1697	-0.1643	1

Appendix C: Coefficients of Variables in Volume Modeling

Table C-1 Coefficients of Variables for the Whole Dataset

	hourlyppt	temperature	relhumidity	windspeed	weekend
hourlyppt	1	--	--	--	--
temperature	0.0143	1	--	--	--
relhumidity	0.11	-0.0728	1	--	--
windspd	0.0351	-0.0858	0.0494	1	--
weekend	-0.0088	-0.015	-0.0204	-0.014	1

Table C-2 Coefficients of Variables for Weekdays

	hourlyppt	temperature	relhumidity	windspeed
hourlyppt	1	--	--	--
temperature	0.0116	1	--	--
relhumidity	0.1011	-0.0695	1	--
windspd	0.028	-0.0897	0.0525	1

Table C-3 Coefficients of Variables for Weekends

	hourlyppt	temperature	relhumidity	windspeed
hourlyppt	1	--	--	--
temperature	0.0315	1	--	--
relhumidity	0.184	-0.0823	1	--
windspd	0.0809	-0.0769	0.0404	1

Appendix D: Linear Regression Results in Volume Modeling Using Lag-effect of snowstorm event

Table D-1 Linear Regression Results for All sites

Source	SS	df	MS	
				Number of obs = 44639
---				F(17, 44621) = 287.73
Model	4203.99	17	247.29	Prob > F = 0
Residual	38350.01	44621	0.86	R-squared = 0.0988
---				Adj R-squared = 0.0984
Total	42554.00	44638	0.95	Root MSE = 0.92707

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.019	0.0007	29.02	0	0.018	0.021
hourlyppt	-61.637	10.1550	-6.07	0	-81.541	-41.733
laghourlyppt	-33.099	10.1660	-3.26	0.001	-53.025	-13.174
hour8	0.086	0.0221	3.91	0	0.043	0.129
hour9	0.330	0.0221	14.98	0	0.287	0.374
hour14	0.755	0.0220	34.23	0	0.711	0.798
hour15	0.973	0.0221	44.11	0	0.930	1.016
year1	(dropped)					
year2	0.037	0.0154	2.42	0.015	0.007	0.068
year3	-0.034	0.0179	-1.9	0.058	-0.069	0.001
year4	-0.032	0.0145	-2.23	0.025	-0.061	-0.004
year5	-0.089	0.0146	-6.07	0	-0.117	-0.060
weekend	-0.161	0.0098	-16.32	0	-0.180	-0.141
siteid1	0.092	0.0783	1.18	0.238	-0.061	0.246
siteid2	0.154	0.0782	1.97	0.048	0.001	0.308
siteid4	0.106	0.0782	1.36	0.175	-0.047	0.259
siteid5	-0.099	0.0783	-1.26	0.208	-0.252	0.055
siteid6	0.034	0.0792	0.43	0.67	-0.121	0.189
_cons	-0.421	0.0787	-5.35	0	-0.575	-0.267

Table D-2 Linear Regression Results for Site A-13

Source	SS	df	MS	
				Number of obs = 9144
--				F(12, 9131) = 105.47
Model	958.72	12	79.89	Prob > F = 0
Residual	6916.51	9131	0.76	R-squared = 0.1217
--				Adj R-squared = 0.1206
Total	7875.24	9143	0.86	Root MSE = 0.87033

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.020	0.0014	13.88	0	0.017	0.023
hourlyppt	-69.905	20.4505	-3.42	0.001	-109.992	-29.817
laghourlyppt	-36.771	20.4741	-1.8	0.073	-76.905	3.363
hour8	0.196	0.0458	4.27	0	0.106	0.285
hour9	0.323	0.0458	7.05	0	0.233	0.412
hour14	0.688	0.0457	15.05	0	0.599	0.778
hour15	1.033	0.0457	22.59	0	0.944	1.123
year1	0.080	0.0286	2.81	0.005	0.024	0.136
year2	0.022	0.0397	0.57	0.571	-0.055	0.100
year3	(dropped)					
year4	0.056	0.0270	2.06	0.039	0.003	0.109
year5	0.061	0.0283	2.15	0.032	0.005	0.116
weekend	-0.326	0.0210	-15.54	0	-0.367	-0.285
_cons	-0.369	0.0220	-16.81	0	-0.412	-0.326

Table D-3 Linear Regression Results for Site A-15

Source	SS	df	MS		
				Number of obs	= 11136
--				F(11, 11124)	= 108.16
Model	829.05	11	75.37	Prob > F	= 0
Residual	7751.34	11124	0.70	R-squared	= 0.0966
--				Adj R-squared	= 0.0957
Total	8580.39	11135	0.77	Root MSE	= 0.83475

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.018	0.0012	14.45	0	0.015	0.020
hourlyppt	-65.136	17.6722	-3.69	0	-99.776	-30.495
laghourlyppt	-37.160	17.6948	-2.1	0.036	-71.845	-2.475
hour8	0.114	0.0398	2.86	0.004	0.036	0.192
hour9	0.340	0.0398	8.55	0	0.262	0.418
hour14	0.757	0.0397	19.04	0	0.679	0.835
hour15	0.916	0.0398	23.03	0	0.838	0.994
year1	(dropped)					
year2	0.007	0.0228	0.32	0.748	-0.037	0.052
year3	(dropped)					
year4	-0.023	0.0225	-1.02	0.305	-0.067	0.021
year5	-0.062	0.0227	-2.75	0.006	-0.107	-0.018
weekend	-0.073	0.0176	-4.18	0	-0.108	-0.039
_cons	-0.299	0.0186	-16.03	0	-0.335	-0.262

Table D-4 Linear Regression Results for Site A-40

Source	SS	df	MS		
---				F(12, 11962)	= 105.88
Model	976.88	12	81.41	Prob > F	= 0
Residual	9197.00	11962	0.77	R-squared	= 0.096
---				Adj R-squared	= 0.0951
Total	10173.89	11974	0.85	Root MSE	= 0.87684

Number of obs = 11975

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.017	0.0012	14.07	0	0.015	0.020
hourlyppt	-69.722	18.7751	-3.71	0	-106.524	-32.920
laghourlyppt	-40.762	18.7961	-2.17	0.03	-77.606	-3.919
hour8	0.096	0.0403	2.39	0.017	0.017	0.175
hour9	0.209	0.0403	5.19	0	0.130	0.288
hour14	0.721	0.0403	17.91	0	0.642	0.800
hour15	0.990	0.0403	24.58	0	0.911	1.069
year1	0.006	0.0274	0.2	0.841	-0.048	0.059
year2	0.006	0.0286	0.21	0.832	-0.050	0.062
year3	(dropped)					
year4	-0.033	0.0257	-1.28	0.201	-0.083	0.017
year5	-0.099	0.0257	-3.84	0	-0.149	-0.048
weekend	-0.155	0.0179	-8.66	0	-0.190	-0.120
_cons	-0.317	0.0209	-15.17	0	-0.357	-0.276

Table D-5 Linear Regression Results for Site Lachapalle

Source	SS	df	MS		
				Number of obs = 7680	
--				F(10, 7669) = 70.47	
Model	942.53	10	94.25	Prob > F	= 0
Residual	10256.75	7669	1.34	R-squared	= 0.0842
--				Adj R-squared = 0.083	
Total	10173.89	11974	0.85	Root MSE	= 1.1565

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.022	0.0019	11.3	0	0.018	0.025
hourlyppt	-15.715	31.5738	-0.5	0.619	-77.608	46.178
laghourlyppt	-9.312	31.6013	-0.29	0.768	-71.259	52.636
hour8	-0.047	0.0663	-0.71	0.48	-0.177	0.083
hour9	0.555	0.0663	8.37	0	0.425	0.685
hour14	0.940	0.0663	14.18	0	0.810	1.070
hour15	1.058	0.0663	15.95	0	0.928	1.188
year1	(dropped)					
year2	0.254	0.0347	7.33	0	0.186	0.322
year3	(dropped)					
year4	0.082	0.0305	2.7	0.007	0.023	0.142
year5	(dropped)					
weekend	-0.143	0.0294	-4.85	0	-0.200	-0.085
_cons	-0.670	0.0247	-27.17	0	-0.718	-0.622

Table D-6 Linear Regression Results for Site Viau

Source	SS	df	MS	
				Number of obs = 4560
--				F(10, 4549) = 42.07
Model	358.14	10	35.81	Prob > F = 0
Residual	3872.40	4549	0.85	R-squared = 0.0847
--				Adj R-squared = 0.0826
Total	4230.54	4559	0.93	Root MSE = 0.92264

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.023	0.0020	11.31	0	0.019	0.027
hourlyppt	-68.081	34.4135	-1.98	0.048	-135.548	-0.614
laghourlyppt	-9.803	34.4308	-0.28	0.776	-77.304	57.698
hour8	-0.005	0.0687	-0.07	0.943	-0.140	0.130
hour9	0.261	0.0687	3.8	0	0.126	0.396
hour14	0.657	0.0687	9.57	0	0.522	0.792
hour15	0.798	0.0687	11.61	0	0.663	0.932
year1	(dropped)					
year2	0.241	0.0414	5.83	0	0.160	0.322
year3	0.131	0.0411	3.19	0.001	0.050	0.211
year4	(dropped)					
year5	(dropped)					
weekend	-0.102	0.0307	-3.31	0.001	-0.162	-0.041
_cons	-0.545	0.0382	-14.28	0	-0.620	-0.470

Appendix E: Linear Regression Results in Volume Modeling Using Lat-effect of snowstorm event

Table E-1 Linear Regression Results for All sites

Source	SS	df	MS	
				Number of obs=44639
--				F(17, 44621)=288.18
Model	4209.88	17	247.64	Prob > F=0
Residual	38344.12	44621	0.86	R-squared=0.0989
--				Adj R-squared=0.0986
Total	42554.00	44638	0.95	Root MSE=0.927

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.019	0.0007	29.06	0	0.018	0.021
hourlyppt	-56.290	10.1538	-5.54	0	-76.191	-36.388
lathourlyppt	-42.404	10.1504	-4.18	0	-62.299	-22.509
hour8	0.087	0.0221	3.94	0	0.044	0.130
hour9	0.331	0.0221	15.02	0	0.288	0.374
hour14	0.754	0.0220	34.2	0	0.711	0.797
hour15	0.970	0.0220	44.01	0	0.927	1.014
year1	(dropped)					
year2	0.037	0.0154	2.4	0.016	0.007	0.067
year3	-0.034	0.0179	-1.93	0.054	-0.069	0.001
year4	-0.033	0.0145	-2.25	0.024	-0.061	-0.004
year5	-0.089	0.0146	-6.09	0	-0.117	-0.060
weekend	-0.161	0.0098	-16.33	0	-0.180	-0.141
siteid1	0.092	0.0783	1.18	0.238	-0.061	0.246
siteid2	0.154	0.0782	1.97	0.048	0.001	0.308
siteid4	0.106	0.0781	1.35	0.175	-0.047	0.259
siteid5	-0.099	0.0783	-1.26	0.208	-0.252	0.055
siteid6	0.034	0.0792	0.43	0.67	-0.121	0.189
_cons	-0.420	0.0787	-5.34	0	-0.574	-0.266

Table E-2 Linear Regression Results for Site A-13

Source	SS	df	MS	
				Number of obs=9144
--				F(12, 9131)=105.69
Model	960.45	12	80.04	Prob > F=0
Residual	6914.79	9131	0.76	R-squared=0.122
--				Adj R-squared=0.1208
Total	7875.24	9143	0.86	Root MSE=0.87022

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.020	0.0014	13.9	0	0.017	0.023
hourlyppt	-63.580	20.4390	-3.11	0.002	-103.645	-23.515
lathourlyppt	-47.950	20.4302	-2.35	0.019	-87.998	-7.903
hour8	0.197	0.0458	4.29	0	0.107	0.286
hour9	0.324	0.0457	7.09	0	0.235	0.414
hour14	0.687	0.0457	15.03	0	0.598	0.777
hour15	1.031	0.0457	22.54	0	0.941	1.120
year1	0.081	0.0286	2.83	0.005	0.025	0.137
year2	0.023	0.0397	0.58	0.559	-0.055	0.101
year3	(dropped)					
year4	0.056	0.0270	2.07	0.038	0.003	0.109
year5	0.061	0.0283	2.15	0.031	0.005	0.116
weekend	-0.326	0.0210	-15.56	0	-0.368	-0.285
_cons	-0.368	0.0219	-16.79	0	-0.411	-0.325

Table E-3 Linear Regression Results for Site A-15

Source	SS	df	MS		Number of obs=11136
--					F(11, 11124)=108.38
Model	830.56	11	75.51		Prob > F=0
Residual	7749.83	11124	0.70		R-squared=0.0968
--					Adj R-squared=0.0959
Total	8580.39	11135	0.77		Root MSE=0.83467

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.018	0.0012	14.46	0	0.015	0.020
hourlyppt	-60.268	17.6703	-3.41	0.001	-94.905	-25.631
lathourlyppt	-45.311	17.6658	-2.56	0.01	-79.939	-10.683
hour8	0.114	0.0398	2.88	0.004	0.036	0.192
hour9	0.341	0.0397	8.59	0	0.263	0.419
hour14	0.756	0.0397	19.01	0	0.678	0.833
hour15	0.913	0.0397	22.98	0	0.836	0.991
year1	(dropped)					
year2	0.007	0.0228	0.31	0.754	-0.038	0.052
year3	(dropped)					
year4	-0.023	0.0225	-1.04	0.301	-0.068	0.021
year5	-0.063	0.0227	-2.76	0.006	-0.107	-0.018
weekend	-0.074	0.0176	-4.19	0	-0.108	-0.039
_cons	-0.298	0.0186	-15.99	0	-0.335	-0.262

Table E-4 Linear Regression Results for Site A-40

Source	SS	df	MS	
				Number of obs=11975
--				F(12, 11962)=106.06
Model	978.36	12	81.53	Prob > F=0
Residual	9195.53	11962	0.77	R-squared=0.0962
--				Adj R-squared=0.0953
Total	10173.89	11974	0.85	Root MSE=0.87677

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.017	0.0012	14.08	0	0.015	0.020
hourlyppt	-65.419	18.7715	-3.48	0	-102.214	-28.624
lathourlyppt	-48.307	18.7652	-2.57	0.01	-85.090	-11.524
hour8	0.097	0.0403	2.4	0.016	0.018	0.176
hour9	0.209	0.0403	5.2	0	0.131	0.288
hour14	0.720	0.0403	17.88	0	0.641	0.799
hour15	0.987	0.0403	24.52	0	0.908	1.066
year1	0.006	0.0274	0.22	0.827	-0.048	0.060
year2	0.006	0.0286	0.22	0.83	-0.050	0.062
year3	(dropped)					
year4	-0.033	0.0257	-1.27	0.203	-0.083	0.018
year5	-0.098	0.0257	-3.84	0	-0.149	-0.048
weekend	-0.155	0.0179	-8.67	0	-0.191	-0.120
_cons	-0.316	0.0209	-15.16	0	-0.357	-0.275

Table E-5 Linear Regression Results for Site Lachapelle

Source	SS	df	MS	
--				F(10, 7669)=70.46
Model	942.42	10	94.24	Prob > F=0
Residual	10256.86	7669	1.34	R-squared=0.0841
--				Adj R-squared=0.083
Total	11199.27	7679	1.46	Root MSE=1.1565

Number of obs=7680

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.022	0.0019	11.29	0	0.018	0.025
hourlyppt	-19.594	31.5800	-0.62	0.535	-81.499	42.312
lathourlyppt	-1.911	31.5743	-0.06	0.952	-63.805	59.983
hour8	-0.047	0.0663	-0.7	0.481	-0.177	0.083
hour9	0.555	0.0663	8.37	0	0.425	0.685
hour14	0.940	0.0663	14.18	0	0.810	1.070
hour15	1.058	0.0663	15.95	0	0.928	1.188
year1	(dropped)					
year2	0.254	0.0347	7.33	0	0.186	0.322
year3	(dropped)					
year4	0.082	0.0305	2.7	0.007	0.023	0.142
year5	(dropped)					
weekend	-0.142	0.0294	-4.85	0	-0.200	-0.085
_cons	-0.670	0.0247	-27.18	0	-0.719	-0.622

Table E-6 Linear Regression Results for Site Viau

Source	SS	df	MS	Number of obs = 4560
--				F(10, 4549) = 42.48
Model	361.30	10	36.13	Prob > F=0
Residual	3869.24	4549	0.85	R-squared=0.0854
--				Adj R-squared=0.0834
Total	4230.54	4559	0.93	Root MSE=0.92226

ln_stvolume	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
temp	0.023	0.0020	11.4	0	0.019	0.027
hourlyppt	-66.974	34.3829	-1.95	0.051	-134.382	34.521
lathourlyppt	-32.946	34.4132	-0.96	0.338	-100.412	0.433
hour8	-0.003	0.0687	-0.05	0.963	-0.138	0.131
hour9	0.261	0.0686	3.8	0	0.126	0.395
hour14	0.656	0.0686	9.56	0	0.522	0.791
hour15	0.796	0.0687	11.59	0	0.661	0.931
year1	(dropped)					
year2	0.238	0.0414	5.76	0	0.157	0.319
year3	0.127	0.0410	3.09	0.002	0.047	0.207
year4	(dropped)					
year5	(dropped)					
weekend	-0.102	0.0307	-3.34	0.001	-0.162	-0.042
_cons	-0.539	0.0381	-14.12	0	-0.613	-0.464

Appendix F: ACF&PACF charts for ARIMA models in Modeling speed

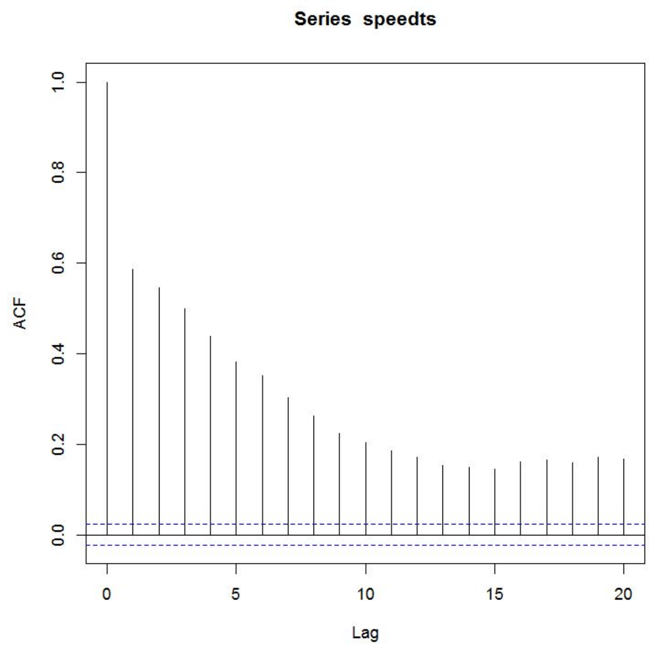
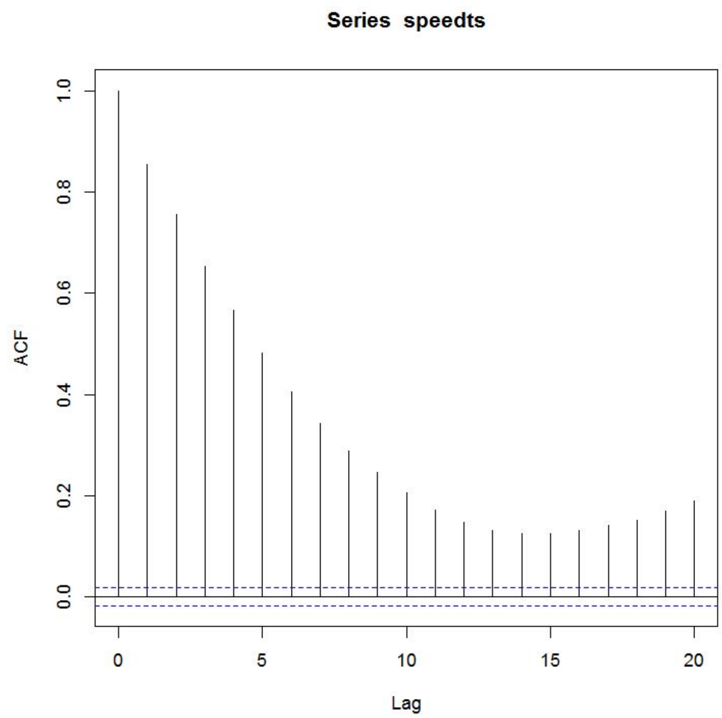


Figure F-1 ACF and PACF for the site of Coachrane



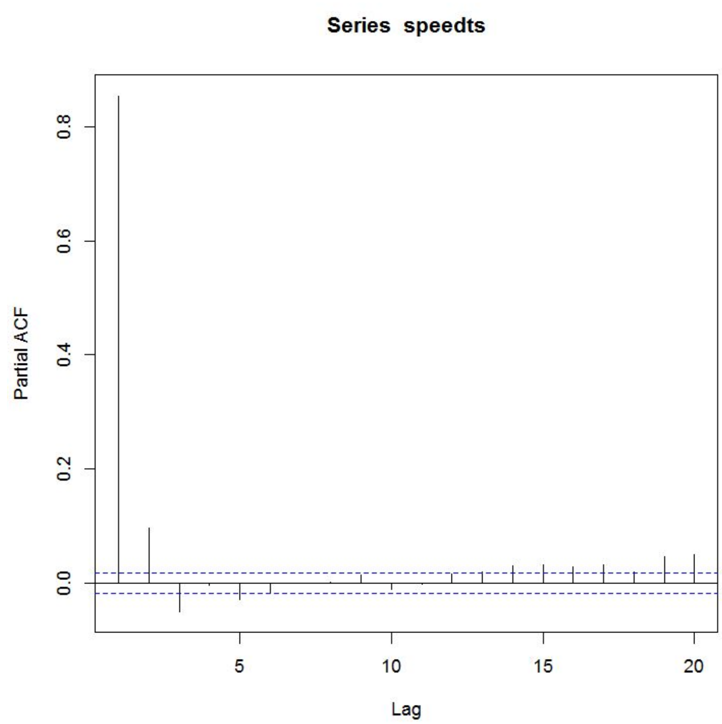
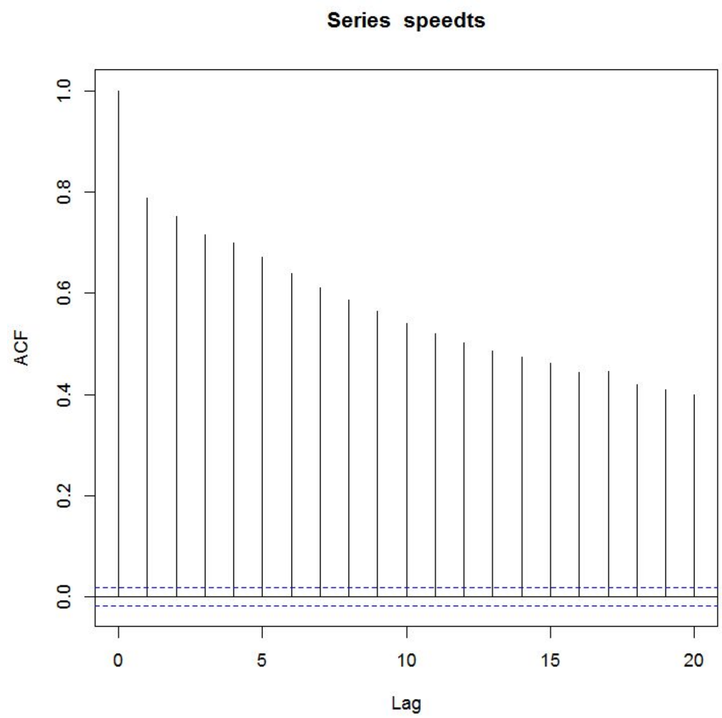


Figure F-2 ACF and PACF for the site of Graven Hurst



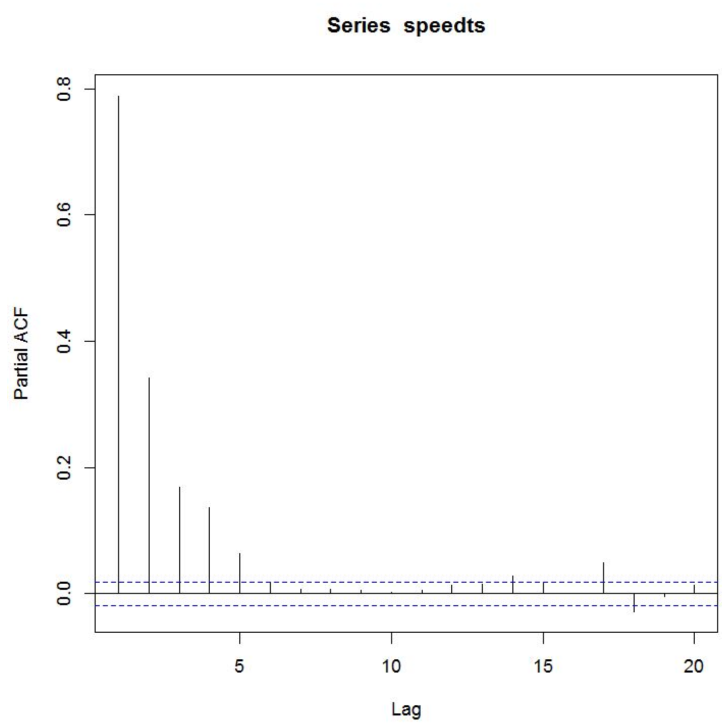
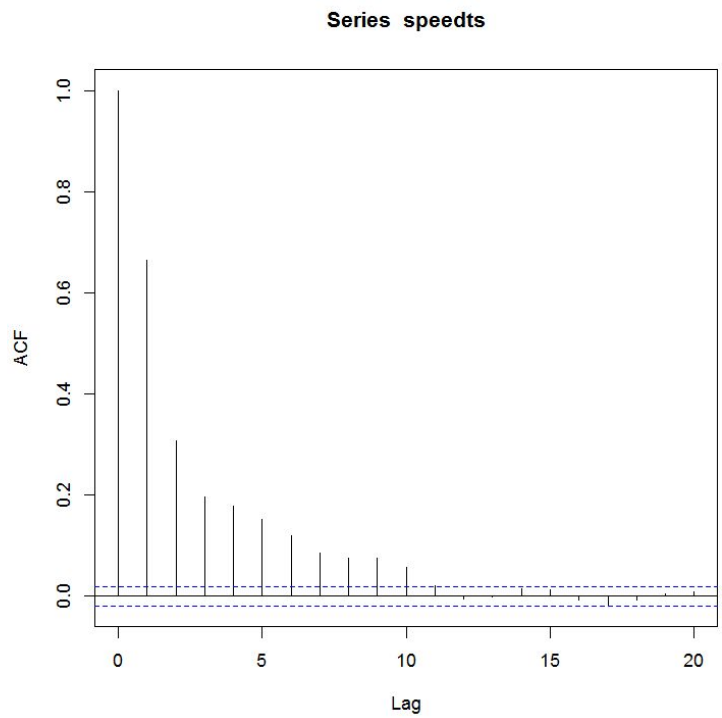


Figure F-3 ACF and PACF for the site of Kaladar



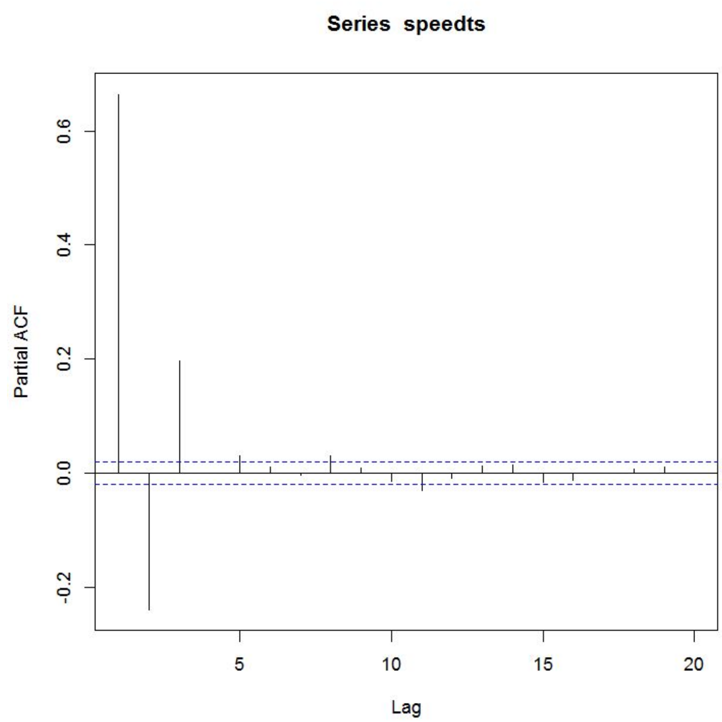
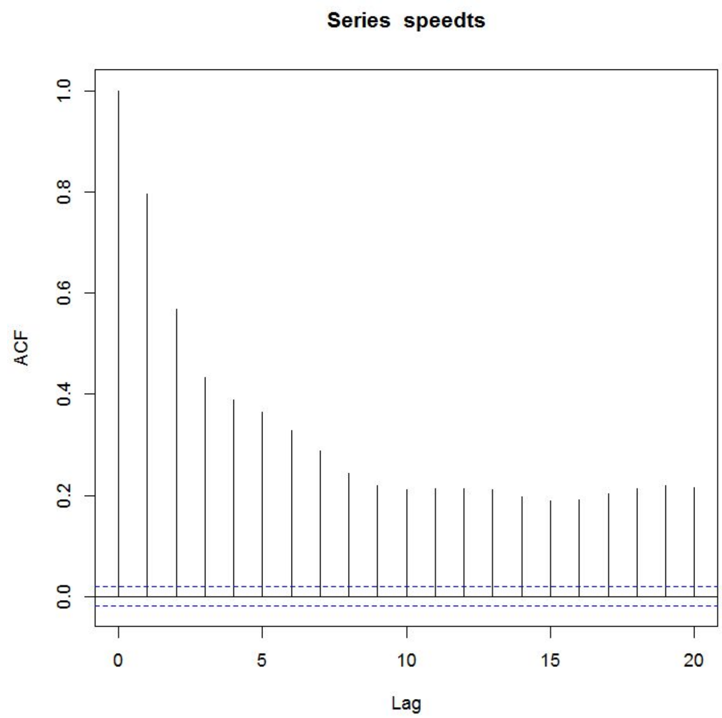


Figure F-4 ACF and PACF for the site of Kanata



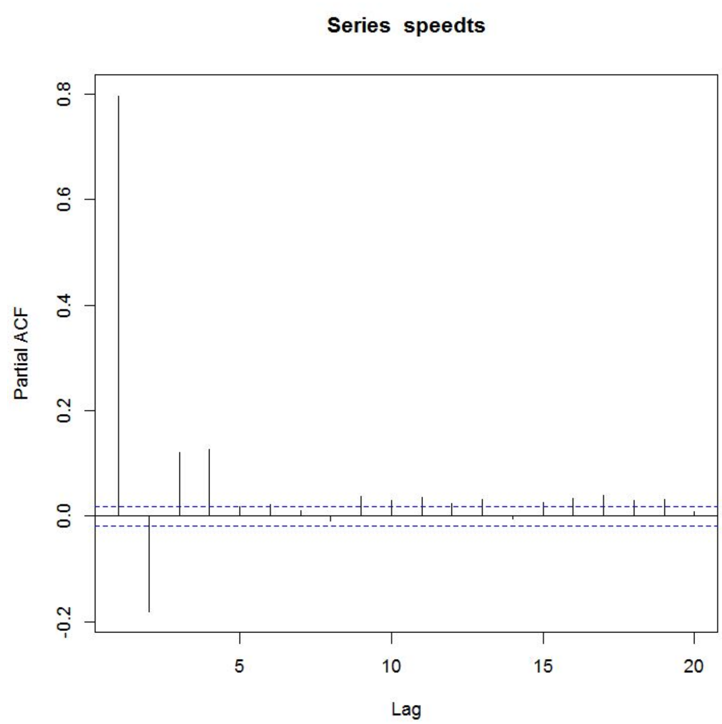


Figure F-5 ACF and PACF for the site of Maple

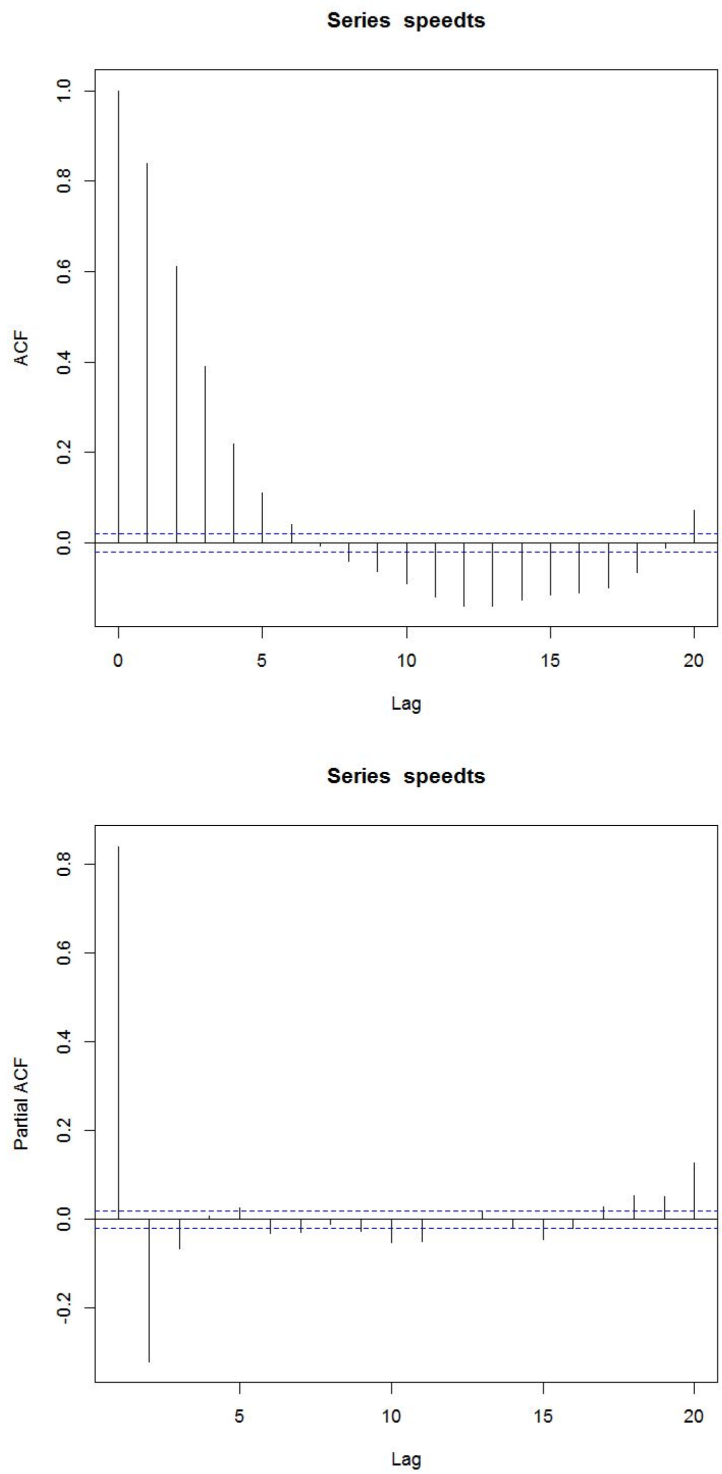


Figure F-6 ACF and PACF for the site of Patrol3

Appendix G: ACF&PACF charts for ARIMA models in Modeling speed

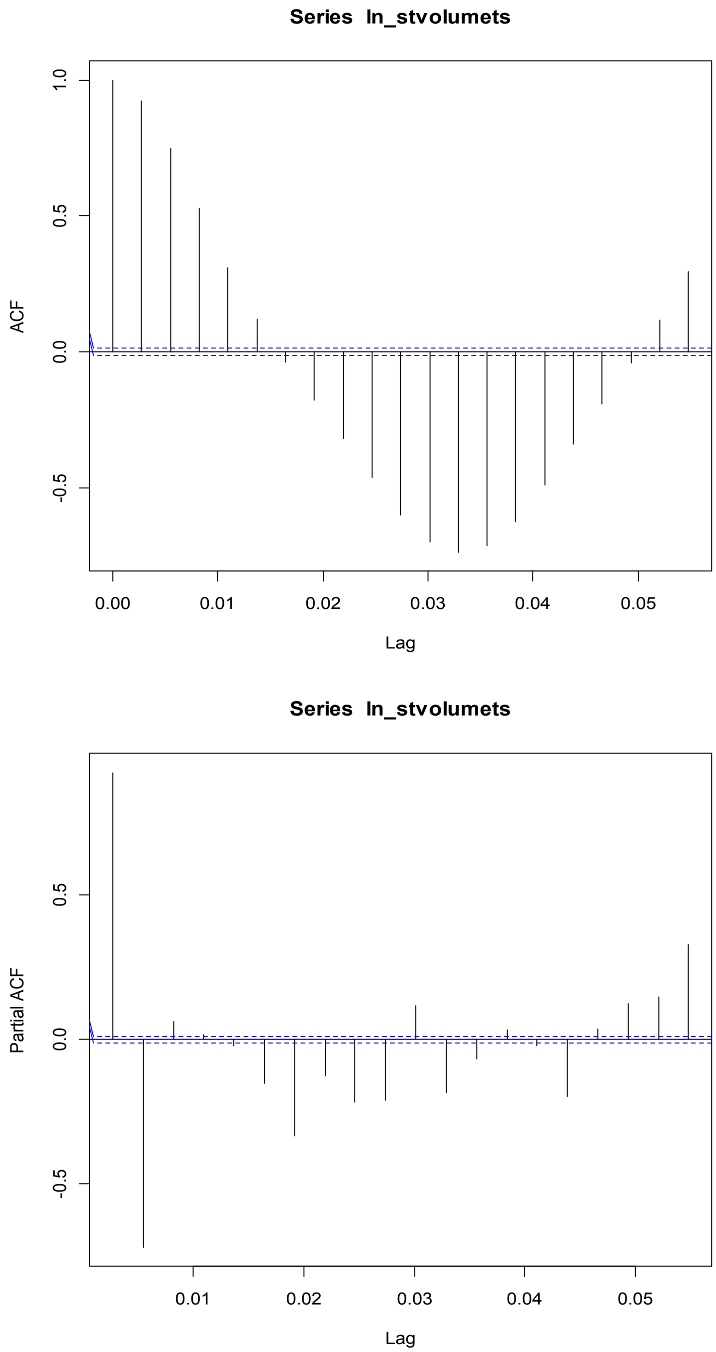
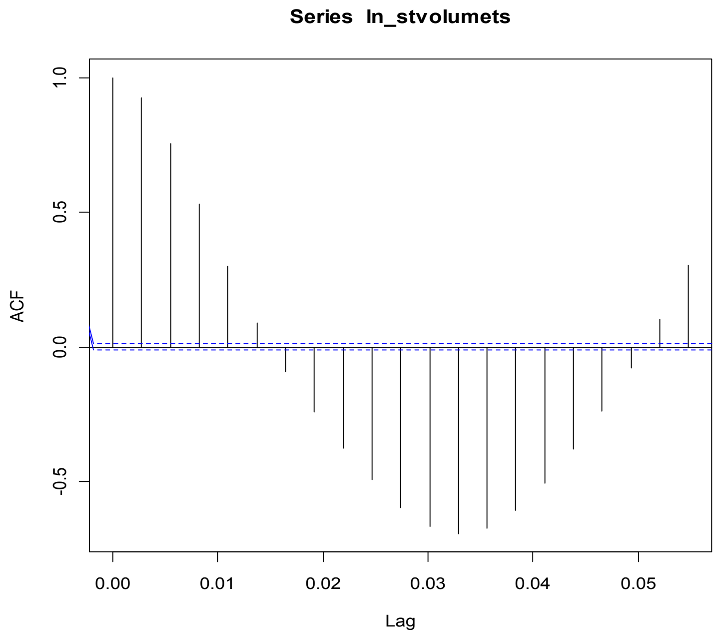


Figure G-1 ACF and PACF for the site of A-13



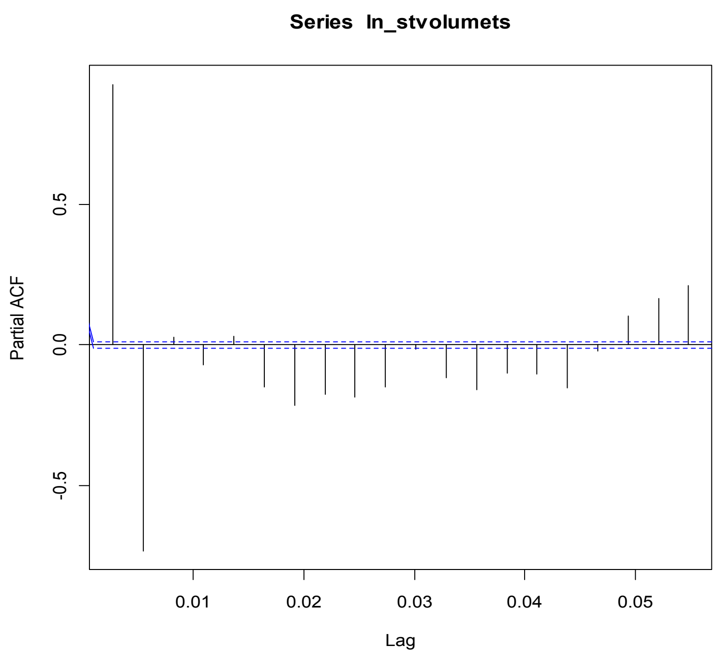


Figure G-2 ACF and PACF for the site of A-15

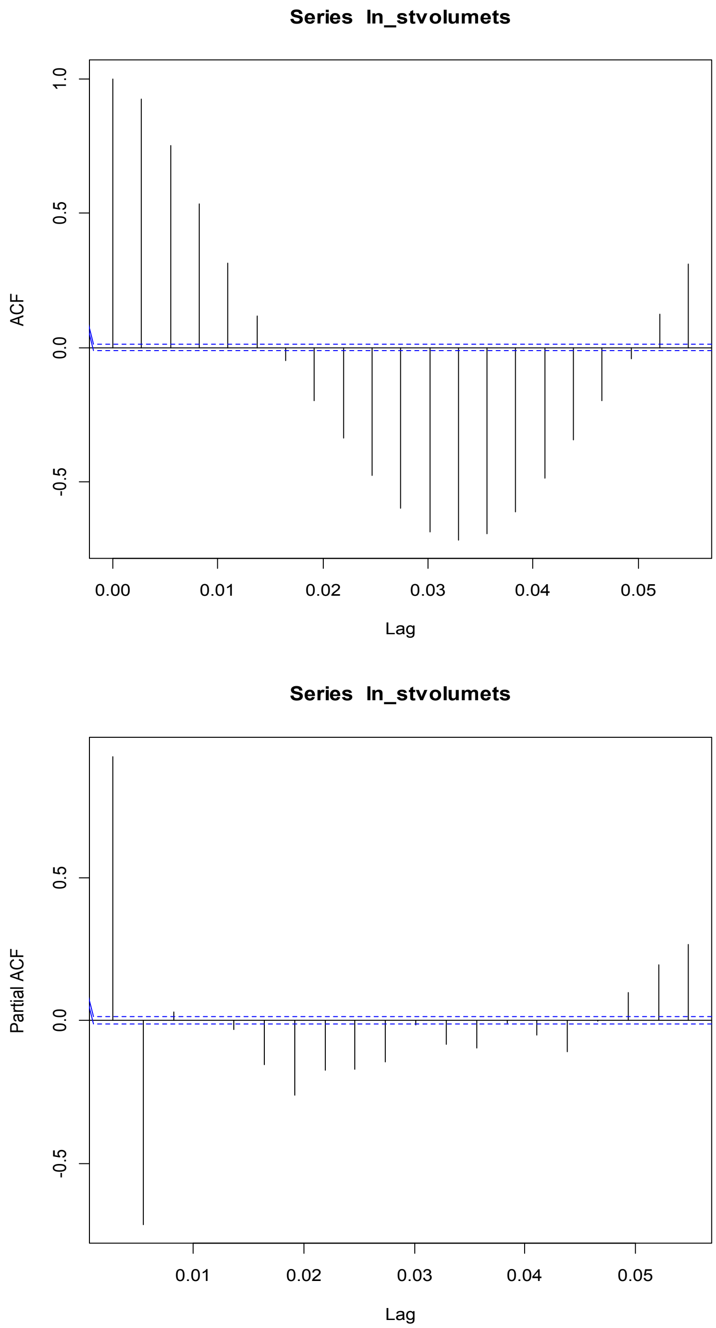
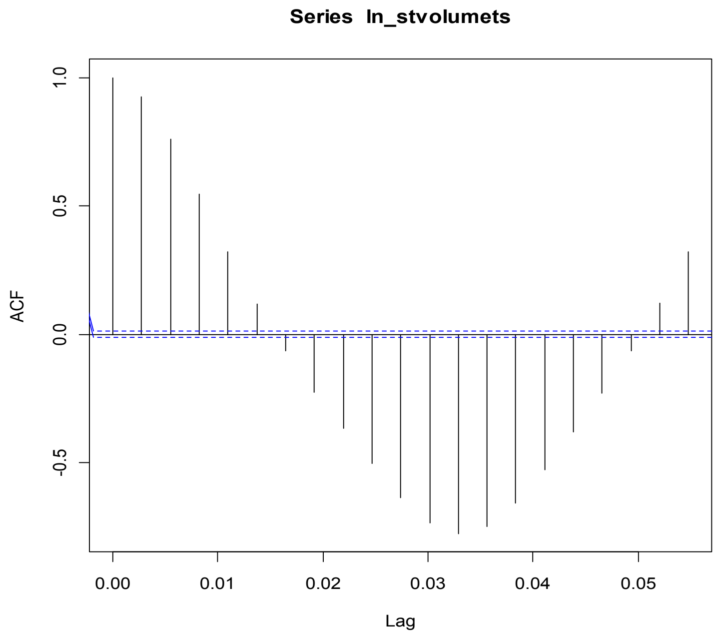


Figure G-3 ACF and PACF for the site of A-40



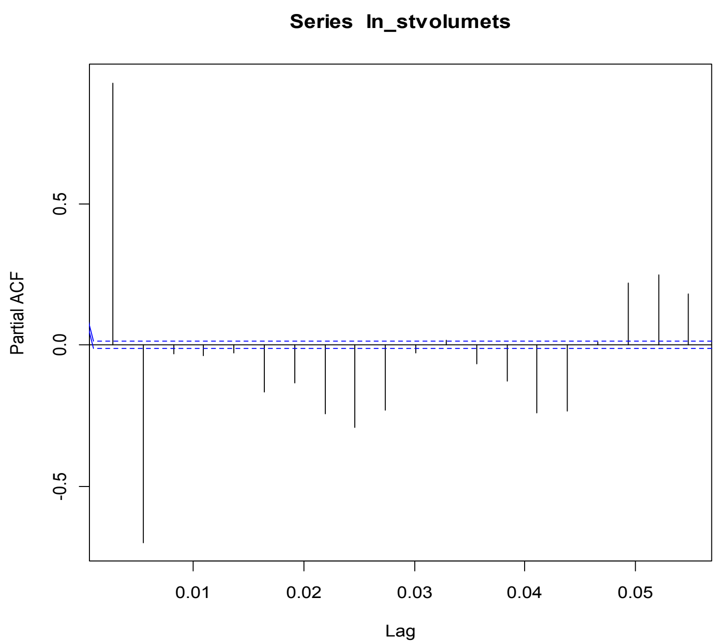


Figure G-4 ACF and PACF for the site of Lachapelle

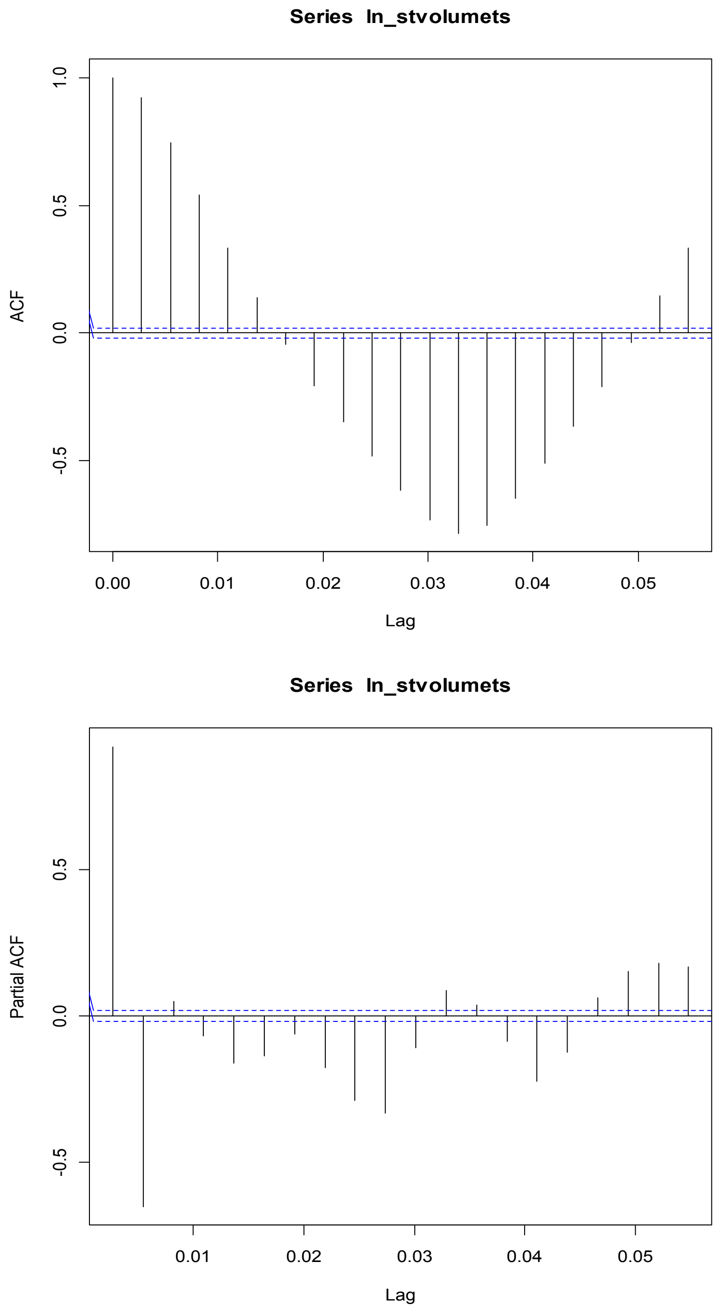


Figure G-5 ACF and PACF for the site of Viau

Appendix H: Camera Locations for Video Data Approach

Table H Geometric Locations of Cameras

Canera ID	Latitude	Longitude	Road	Cross Road
65	43.65669632	-79.35257721	DVP	Eastern Ave.
71	43.70013046	-79.33774567	DVP	Don Mills Rd.
76	43.72317886	-79.33032227	DVP	Eglinton Ave.

Appendix I: Detailed Statistical Description of Video data

Table I-1 Average Speed for Each Lane for Different Videos

					AVERAGE SPEED			
Name of Video	**Road condition**	**Camera**	**Length**	**Weather condition**	**Extreme left (3)**	**Middle (2)**	**Right (1)**	**Ramp (0)**
#1	congested	71	0.0992152		--	--	--	--
#2	congested	65	0.0846182		--	--	--	--
#3	non congested	65	0.0846182	**water on road**	--	84.854	80.803	62.809
#4	non congested	65	0.0846182	good weather	--	95.2	82.33	63.46
#5	non congested	76	0.1046534		87.62	80.16	78.49	52.33
#6	congested	71	0.0992152		--	--	--	--
#7	non congested	71	0.0992152	good wet road	107.908	104.133	101.183	65.657
#8	congested	76	0.1046534		--	--	--	--
#9	non congested	76	0.1046534		79.484	74.164	70.421	53.364
#10	non congested	71	0.0992152	snow	90.196	86.693	77.816	59.233
#11	congested	76	0.1046534	snow	--	--	--	--
#12	non congested	65	0.0846182	good	--	106.141	99.877	71.845
#13	non congested	65	0.0846182	snow	--	97.324	88.554	62.042
#14	non congested	71	0.0992152	good dry road	124.886	113.750	99.492	70.172
#15	congested	76	0.1046534		--	--	--	--

Table I-2 Counts of the Number of the Lane Change Behaviors for Different Lanes

	CHANGING LANES FROM/TO						
Name of Video	**3 to 2**	**2 to 3**	**2 to 1**	**1 to 2**	**1 to 0**	**0 to 1**	**total**
#1	0	5	0	5	71	51	132
#2	****	****	6	2	28	3	39
#3	****	****	29	18	24	10	81
#4	****	****	5	9	1	16	31
#5	4	18	1	11	0	97	131
#6	1	15	2	21	81	154	274
#7	4	6	1	4	22	47	84
#8	0	0	2	4	2	26	34
#9	14	11	9	14	0	109	157
#10	6	10	1	1	60	5	83
#11	1	4	4	6	13	7	35
#12	****	****	31	25	21	11	88
#13	****	****	6	5	0	1	12
#14	3	5	1	1	88	24	122
#15	1	3	6	6	0	36	52

Table I-3 Counts of the Number of Cars for Different Lanes

	NUMBER OF CARS EACH LANE					
Name of Video	**Extreme left (3)**	**Middle (2)**	**Right (1)**	**Ramp (0)**	**Total # of cars**	**Percentage of lane changes**
#1	505	455	464	101	1525	0.086557377
#2	****	164	116	70	350	0.111428571
#3	****	1258	822	312	2392	0.033862876
#4	****	314	240	144	698	0.044412607
#5	89	440	179	183	891	0.147025814
#6	1143	1130	1042	205	3520	0.077840909
#7	518	410	285	85	1298	0.064714946
#8	300	265	229	75	869	0.039125432
#9	926	733	367	195	2221	0.070688879
#10	414	392	270	34	1110	0.074774775
#11	233	203	201	46	683	0.05124451
#12	****	1639	1115	462	3216	0.027363184
#13	****	131	234	228	593	0.020236088
#14	366	304	266	40	976	0.125
#15	430	393	340	99	1262	0.041204437