Application of New Modelling Techniques to Perform Observational Before-After Safety Evaluations

by

Md Tazul Islam

A thesis submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Transportation Engineering

Department of Civil and Environmental Engineering
University of Alberta

Abstract

Speeding is the number one road safety problem in many countries around the world. Speeding contributes to as many as one third of all fatal crashes, and is considered an aggravating factor in crash severity. Because of the adverse consequences of speeding, speed management is considered to be the key strategy to reduce traffic fatalities and injuries. Any speed management strategy has an immediate effect on drivers speed choice and a long-term effect on crash occurrence; these effects can be referred to impact and outcome, respectively. A comprehensive evaluation process of any speed management strategy therefore should include impact evaluation based on speed data and outcome evaluation based on crash data. This evaluation is an important step in the road safety management process because the evaluation results can be used not only for economic justification of the strategy but also for future decision-making activities related to the allocation of funds and selection of appropriate remedial strategies. While the methodologies associated with before-after evaluation of speed and crash data have improved substantially in last two decades, there are several areas for improving the before-after evaluation methodologies in order to provide more reliable estimates of the safety effect of any speed management strategy. Therefore, the research in this thesis focuses on addressing key issues related to the modelling and application of before-after evaluation of i) speed data and ii) crash data. Vehicle speed data are collected from different sites over a period of time; hence, the speed data exhibit within-site and between-site variation. The conventional ordinary least-square regression model fails to capture these two variations of the speed data into the modelling framework. Similarly, crash data exhibits several specific features, such as correlation among severity levels and spatial correlation that need to be addressed into the modelling framework for the unbiased estimation of the model parameters. This thesis addressed several key issues by 1) developing appropriate

statistical test method to address and account for confounding factors and time trend in non-model based before-after speed data evaluation, 2) developing a mixed-effect intervention modelling approach for modelling and evaluating before-after speed characteristics that incorporate the clustering nature of speed data, 3) exploring multilevel heterogeneous model to address the heterogeneous site variances of speed data, 4) developing multivariate full Bayesian (FB) methodology for before-after evaluation of crash data that can take account for the correlation of crash data of different severity levels and comparing the results with univariate counterpart, 5) developing FB macroscopic spatial modelling approach for before-after evaluation of crash data that can address the limitations of the microscopic evaluation as well as incorporate spatial correlation of the crash data and comparing the results with non-spatial models, and 6) developing an alternative modelling methodology to address spatial correlation into the modelling of before-after evaluation of crash data and compare the results with other spatial models. Several advanced statistical models were developed for both speed and crash data and the models were compared for their goodness of fits. The applications of the various developed models have been demonstrated using both microscopic and macroscopic datasets collected for an urban residential posted speed limit reduction pilot program. The results provide strong evidence for (i) addressing the effect of confounding factors in non-model based speed data evaluation for more reliable estimate of the effect of a safety intervention, ii) considering the clustered nature of speed data into models used to conduct before-after evaluation, iii) incorporating heterogeneous site variances into multilevel modelling and evaluation of mean free-flow speed, iv) developing multivariate models for modelling and evaluation of crash by severity, v) incorporating spatial correlation in modelling of before-after crash data, and vi) using alternative spatial models to better capture the spatial correlation of crash data. Finally, the multilevel model with heterogeneous variance provided significant improvement in the goodness-of-fit over other models for speed data analysis. For crash data, multivariate spatial models provided significant improvement in the goodness-of-fit over other univariate or non-spatial models. Therefore, it is recommended to employ multilevel model with heterogeneous variance and multivariate spatial models for more reliable and unbiased estimate of the effect of a safety intervention on vehicle speed and crash data, respectively.

Preface

Articles published in refereed journals

1. **Islam, M. T.**, and El-Basyouny, K. (2015). Full Bayesian mixed intervention model for before-after speed data analysis. *Transportation Research Record: Journal of the Transportation Research Board*. In press.
2. **Islam, M. T.**, and El-Basyouny, K. (2015). Full Bayesian before-after safety evaluation of the posted speed limit reduction on urban residential area. *Accident Analysis and Prevention*, 80, 18-25.
3. **Islam, M. T.**, El-Basyouny, K., and Ibrahim, S. (2014). The impact of lowered speed limit in the City of Edmonton. *Safety Science*, 62, 483–494. (The author of this thesis contributed to the majority of the analysis and article writing while the last author contributed to the data collection and processing).
4. Barua, S., El-Basyouny, K., and **Islam, M. T.** (2014). A multivariate count data model of collision severity with spatial correlation. *Analytic Methods in Accident Research*, 3–4, 28–43. (The author of this thesis contributed to the development and writing of the methodology for this article).

To my parents and beloved wife

Acknowledgments

First of all, I am grateful to Almighty Allah, the Most Gracious and the Most Merciful for the strengths and blessings in completing this thesis.

I am highly grateful to my esteemed supervisor Dr. Karim El-Basyouny, Department of Civil and Environmental Engineering, University of Alberta, for his continuous guidance, thoughtful advices, patience and endless encouragement. Without his knowledge, perceptiveness, constructive comments and suggestions, I would have never completed this thesis. Outside research, I have learnt from him the positive attitude towards life. I also express my gratitude to my co-supervisor Dr. Tony Qiu for his support and knowledge regarding this topic.

I owe sincere thanks to the members of my supervisory, candidacy and final examination committee: Dr. Ahmed Bouferguene, Dr. Amy Kim, Dr. Ergun Kuru, Dr. Stevanus Tjandra, and Dr. Yongsheng Chen for their advice, support, and guidance. A special thanks to Dr. Luis F. Miranda-Moreno, Department of Civil Engineering, McGill University, for taking time out from his busy schedule to serve as my external examiner.

I thank my MSc supervisor Dr. Khandker M. Nurul Habib and BSc supervisor Dr. M. Ashraf Ali for inspiring me towards higher education and research. I also thank my all undergraduate and graduate professors who impacted by study through various courseworks and other supports.

I would like to sincerely acknowledge the financial support provided by Killam Trust (Izaak Walton Killam Memorial Scholarship), City of Edmonton Office of Traffic Safety (Traffic Safety Scholarship), Alberta Innovates –Technology Futures (Alberta Innovates Graduate Student Scholarships), Capital Region Intersection Safety Partnership (Urban Intersection Safety

Scholarship), Bruce F Willson Graduate Scholarship in Urban Engineering, FS Chia Doctoral Scholarship, Andrew Stewart Memorial Graduate Prize, and other University of Alberta funded scholarships. These financial supports enabled me to fully concentrate on my research.

A special thanks to graduate office advisors, Department of Civil and Environmental Engineering, University of Alberta, for their support in various scholarship applications.

I am thankful to the City of Edmonton Office of Traffic Safety (OTS) and its staff for providing and facilitating the necessary data to conduct this research. I also thank Ms. Shewkar Ibrahim and Dr. Tarek Sayed for sharing a valuable dataset for this research.

I wish to thank my colleagues and friends for their support and friendship during my undergraduate and graduate studies. A special thanks to my family friend, Dr. Md. Hadiuzzaman for his support from the very beginning of my undergraduate study.

I am deeply grateful to my parents and family members for their unconditional love and support. Their prayers and love are my inspiration to achieve greater things in life.

Finally, and most importantly, I would like to thank my lovely wife Kaynat Azad Bhuyan for her understanding and love. Without her faith, support and encouragement, I would not have finished this thesis.

Table of Contents

List of Figures

List of Tables

1.0 Introduction

This chapter provides a general introduction to the thesis and is divided into four parts. The first part presents problem statement that is necessary to understand the significance of the research problem. The second part discusses the research motivation by addressing the research gaps. The third part states the objectives of this research. The chapter concludes by describing the structure of this thesis.

1.1 Problem Statement

Speeding, as defined by excessive speed (driving above the speed limit) or inappropriate speed (driving too fast for the prevailing road and traffic conditions, but within the speed limit), is the number one road safety problem in many countries (OECD/ECMT, 2006). Speeding contributes to as many as one third of all fatal crashes, and is considered an aggravating factor in crash severity (OECD/ECMT, 2006; WHO, 2008). Speed is related to traffic safety in two ways: i) speeding increases the possibility of crash incidence, as high speeds adversely affect the stopping sight distance, allowing less time for error correction; and ii) crash severity is directly related to vehicle speed because of the physical relationship of mass and speed to energy (Elvik et al., 2004; Nilsson, 2004; Aarts and van Schagen, 2006; Hauer, 2009).

Because of the adverse consequence of speeding, speed management is considered to be the key strategy to reduce traffic fatalities and injuries (OECD, 2006). For example, vision zero or the safe system approach adopted by different countries around the world have identified effective speed management as the cornerstone to achieve the vision zero goal. Few example of speed management initiatives include, but not limited to public education or training, intensifying speed enforcement and penalties, improving road infrastructure, lowering speed limit, and adopting new technologies, such as intelligent speed adaptation (OECD, 2006).

Any speed management strategy has an immediate effect on drivers speed choice and a long-term effect on crash occurrence; these effects can be referred to impact and outcome, respectively. A comprehensive evaluation process of any speed management strategy therefore should include impact evaluation based on speed data and outcome evaluation based on crash data. This evaluation is an important step in the road safety management process because the evaluation results can be used not only for economic justification of a safety intervention but also for future decision-making activities related to the allocation of funds and selection of intervention.

While various methodologies are presented in the literature to evaluate safety interventions, several limitations still exist and this thesis explores the application of more advanced methodologies to reliably estimate the safety impacts and outcomes of these evaluations. For the impact evaluation, both non-model and model based approaches are developed while for the outcome evaluation, both macroscopic and microscopic full Bayesian approaches are developed. The following section discusses the specific issues related to previous research on before-after evaluations of safety interventions.

1.2 Research Motivations

A comprehensive review of literature on before-after evaluation of speed and crash data revealed several major issues:

- Numerous studies have performed before-after evaluations with speed data to investigate the effectiveness of safety interventions. Most evaluations have adopted a method of non-model-based naïve before-after speed data analysis where various speed-related performance measures (e.g., mean speed, 85th percentile speed) were compared and statistical tests were conducted to check whether the measures were statistically different between the before and after periods. These naïve before-after speed data analyses often fail to address the effect of various confounding factors and time trend into the evaluation and statistical test. Moreover, while non-model-based approach can provide valuable insights about the safety effects of an intervention, a model-based approach could be more promising and reliable, due to its capability to provide more insight about the factors affecting speed choice while taking into account the effects of confounding factors. Model-based approach for before-after evaluation of speed data has rarely been employed in traffic safety literature.

- In general, conventional ordinary least square (OLS) regression is the most commonly used method for modelling speed data, such as mean speed (TRC, 2011). This single level regression modelling method assumes that each observation of speed is independent. In reality, the speed data are often multilevel (i.e., at-least two-level) in nature, as the data are collected for multiple sites with multiple observations from each sites. The data collected from different sites can exhibit different speed characteristics because of the dissimilarity in site characteristics, such as geometric design, surrounding environment, etc. Similarly, within-site speed data can show variability because of the difference in driver characteristics, traffic flow, vehicle type, temporal pattern, etc. Therefore, the random variance in speed data can be divided into two categories: between-site and within-site (Poe and Mason, 2000). The conventional OLS regression method cannot address these two variances and hence can result in biases in speed prediction (Park et al, 2010a).

- The Empirical Bayesian (EB) approach has been extensively used in the before-after evaluation of crash data and is considered to be the current state-of-the–art approach to before-after evaluation. However, literature suggests the need to explore more sophisticated methods to eliminate the weaknesses of the current EB approach.
- The Full Bayesian (FB) approach has recently been introduced in safety research, which is reported to have more flexibility and advantages than the EB approach. It is important to perform an FB before-after evaluation and compare the results with an EB evaluation to understand the added benefits offered by the FB method.
- The FB method can address the multivariate nature of the crash data into the modelling formulation. However, the application of multivariate FB method for before-after safety evaluation was not widely explored in the existing literature.
- One major advantage of the FB method is its ability to consider spatial correlation in model formulation. A significant number of cross-sectional studies have included spatial correlation in the FB method and concluded that the inclusion of spatial correlation improves model goodness-of-fit and the precision of parameter estimates. However, its application in before-after safety evaluation has rarely been documented in the traffic safety literature.
- Microscopic (i.e., intersection or road segment as unit of analysis) before-after evaluations have been extensively used to evaluate traffic safety interventions. For network-wide interventions, such as neighbourhood speed limit reduction, application of the same methodology will require a separate evaluation for intersections and road

segments, and then they can be combined to obtain the complete evaluation. This requires substantial traffic data, which may not be readily available, especially for low-volume road segments and unsignalized intersections. Therefore, a macroscopic (i.e., area-level or network level) analysis could be an effective alternative approach to evaluate such types of safety interventions.

1.3 Research Objectives

Considering the methodological limitations of the previous studies and the potential to improve before-after safety evaluation methodology, the general objective of this thesis is to develop a robust methodology to perform an observational before-after safety evaluation of any speed management strategy. The objective can be broadly divided into two parts with part one focusing on speed data analysis and evaluation and part two focusing on crash data analysis and evaluation. The specific objectives of this research are highlighted below:

Objective 1: Develop and recommend a statistical method to address and account for confounding factors and time trend in non-model based before-after speed data analysis. To accomplish this objective, before-after evaluation with control group is employed and the conventional *t*-test is modified to take into account for the incorporation of the control group data. Moreover, a sensitivity analysis of headway is conducted to address the congestion effect. (An article is published in *Safety Science* that accomplishes this research objective).

Objective 2: Develop a model-based mixed modelling approach for analysis, modelling and evaluation of before-after speed characteristics that incorporate the clustering nature of the speed data. The traditional OLS regression models consider that the speed observations are independent, which is often not a realistic assumption. Therefore, mixed effect normal regression intervention model for free-flow speed and mixed effect binomial regression intervention model for speed compliance are introduced to address the clustering nature of speed data. (An article is published in *Transportation Research Record* that accomplishes this research objective).

Objective 3: Develop a multilevel modelling method to address heterogeneous site variance of speed data into the modelling framework for before-after safety evaluation. In the conventional mixed-effect model, it is assumed that the within site variances are homogeneous and also the model coefficients are fixed. To address these limitations, the multilevel intervention model with heterogeneous variance is introduced in this research.

Objective 4: Develop a multivariate full Bayesian (FB) methodology for before-after evaluation of crash data and compare the results with univariate counterpart. The crash data of different severity levels are often correlated and the univariate models fail to address these correlations. Multivariate models address the correlations between crash severity levels; therefore, they better represent the characteristics of the crash data. Multivariate Poisson-lognormal model for crash severity is developed for the before-after safety evaluation and the results are compared with the univariate Poisson-lognormal models. Another sub-objective includes comparing before-after safety evaluation results between the empirical and full Bayesian approaches. (An article is published in *Accident Analysis and Prevention* that accomplishes this research objective).

Objective 5: Develop a FB macroscopic (i.e., neighborhood-based) spatial modelling methodology for before-after evaluation and compare the results with non-spatial models. The macroscopic models eliminate the limitation associated with microscopic models for the evaluation of area-wide safety intervention. Both univariate Poisson-lognormal models with conditional autoregressive distribution and multivariate Poisson-lognormal model with multivariate conditional autoregressive distribution were developed. The results of these spatial models are compared with the univariate and multivariate Poisson-lognormal models.

Objective 6: Develop an alternative methodology to better address spatial correlation into the modelling in the before-after evaluation of crash data and compare the results with other spatial models. This methodology is expected to better incorporate the spatial correlation of the crash data.

1.4 Organization of the Thesis

The remainder of this thesis is organized into chapters:

Chapter 2 reviews the previous studies related to observational before-after safety evaluation methodology related to traffic safety research. This review discusses earlier studies on speed and crash data analysis and modelling for the evaluation of various traffic safety interventions. An overview of empirical Bayesian vs. full Bayesian approach, macroscopic vs. microscopic evaluation, univariate vs. multivariate approach, and spatial vs. non-spatial modelling methodology was described. The chapter concludes with the limitations in the literature regarding before-after safety evaluation methodologies.

Chapter 3 presents the developed methodology to model and evaluate speed and crash data in an observational before-after setting. The speed data evaluation methods include both non-model based and model based mixed-effect and multilevel intervention modelling approaches. The crash data evaluation methods include univariate and multivariate non-spatial and spatial modelling approaches. This chapter also presents the processes involved in the estimation and assessment of the models.

Chapter 4 describes the data sets used in this thesis to apply the developed methodology. The methodology was used to evaluate an urban residential speed limit reduction pilot program. Two main datasets used were speed survey data and crash data. Other supplementary data includes, but is not limited to, geometry, traffic control, census and weather data.

Chapter 5 presents the detail results of the speed characteristics analysis and evaluation. A comparison of alternative methods was discussed and recommendations were made.

Chapter 6 presents the results of crash data modelling and analysis. This includes the results of moth macroscopic and microscopic modelling and evaluation. A comparison of alternative methods was discussed and recommendations were made.

Chapter 7 concluded the thesis with summary of findings, research contribution and future research potential.

2.0 Literature Review

2.1 Introduction

This chapter presents a review of the literature related to before-after evaluations of speed and crash data. After presenting different types of observational before-after studies available for crash data analysis and their biases, a comparative description of empirical Bayesian vs. full Bayesian approach, macroscopic vs. microscopic evaluation, univariate vs. multivariate approach, and spatial vs. non-spatial modelling are presented. The chapter concludes with the research gaps in the literature regarding before-after evaluation methodologies.

2.2 Before-After Evaluation of Speed Data

Most of the earlier before-after safety evaluation studies using speed data employed simple before-after evaluations for analyzing speed data with few that used before-after evaluation with a comparison group. Most of the studies used non-model based approach and reported a quantitative reduction of mean or the 85th percentile speed in the after period, but did not offer any statistical tests to check whether or not these speed reductions were statistically significant (Webster and Schnening, 1986; Jansson, 1998; RTA, 2000; Hoareau et al. 2002; Hoareau and Newstead, 2004; Hoareau et al. 2006; Kloeden et al., 2004; Kamya-Lukoda, 2010; Bristol City Council, 2012). Furthermore, many of the confounding factors were not taken into consideration. Although some studies used a comparison group, they reported the mean or 85th percentile speed reduction for the treated and comparison group separately, except few that used the comparison group adjustment factor for quantifying the speed reduction in the treated group (Hoareau and Newstead, 2004). One recent study on speed limit reduction from 30 mph (48 km/h) to 25 mph

(40 km/h) used a t-test to showcase a statistically significant reduction of mean speed (Rossy et al., 2011). However, the study did not use free-flow speed to eliminate the effect of congestion. Another study on the evaluation of the effectiveness of gateway intervention in Italy performed a *t*-test for the mean speed and a Fisher test (*F* test) for speed variance (Dell'Acqua, 2011). However, none of the above studies took account of the time trend effect, derived from the comparison group, in their statistical analysis. There is a lack of clear guidelines on the methodology for evaluating speed data in a before-after setting.

Congestion is an important confounding factor in speed data analysis and evaluation (Vogel, 2002; Walter and Knowles, 2004), especially for any speed management intervention, because any speed management intervention has little or no influence during the time of congestion. A vehicle led by a slow moving vehicle cannot choose its desired speed. Thus, the before-after evaluation of speed data based on the speed of all the vehicles is confounded. While most of the earlier studies used mean speed as a measure of effectiveness for before-after evaluation; few studies used free-flow speed (Kloeden et al., 2004; Kloeden et al., 2006). A key with regard to free-flow speed is that there little agreement in the literature about defining free-flow vehicles (Giles, 2004). Studies in Australia used a minimum headway of 4 seconds to define free-flow speed (Radalj, 2001; Kloeden et al., 2004; 2006; Giles, 2004). Wasielewski (1979) showed that for freeways, the interaction between successive vehicles cease to zero for headways greater than 2.5 seconds. Pasenen and Salmivaara (1993) used a minimum headway of 3 seconds to distinguish free-flow speed, while Tarko and Figueroa (2004), Allpress and Leland (2010) and Dell'Acqua (2011) used a 5-second headway. The effect of assuming different headways on the evaluation of speed data has not been extensively explored in the literature. Walter and Knowles (2004) used two criteria for speed data sets collected from roads with speed limits of 30 mph, one that excludes speeds below 20 mph and another that both excludes speeds below 20 mph and headway less than 2 seconds. It was found that both criteria yielded almost the same results. In summary, earlier studies clearly suggest that the issue of identifying free-flow speed warrants further investigation.

In terms of the measure of performances (MOEs) for speed data evaluation, mean speed and 85th percentile speed are the most frequently used ones in earlier studies. A review of numerous literature shows that the evaluation of speed management interventions was based on one or more of the following MOEs related to speed data:

- *Mean Speed* (Webster and Schnening, 1986; Bloch, 1998; Road Directoriate, Denmark, 1999; Blume et al., 2000; Buchholz et al., 2000; RTA, 2000; Dyson et al., 2001; Hoareau et al. 2002; Banawiroon and Yue, 2003; Hoareau and Newstead, 2004; Kloeden et al., 2004; Pasanen et al., 2005; Ragnoy, 2005; Kloeden et al., 2006; Blomberg and Cleven, 2006; Cottrell et al., 2006; Hoareau et al. 2006; Kamya-Lukoda, 2010; Dell'Acqua, 2011; Rossey et al., 2011; Bristol City Council, 2012).
- *Mean Free-Flow Speed* (Shin et al., 2009; Kloeden et al., 2004; Kloeden et al., 2006).
- *Standard Deviation of Speed* (Dell'Acqua, 2011; Rossey et al., 2011).
- *85th Percentile Speed* (Webster and Schnening, 1986; Jansson, 1998; Road Directorate, Denmark, 1999; RTA, 2000; Blume et al., 2000; Buchholz et al., 2000; Dyson et al., 2001; Hoareau et al. 2002; Banawiroon and Yue, 2003; Hoareau and Newstead, 2004; Cottrell et al., 2006; Hoareau et al. 2006; Dell'Acqua, 2011; Rossey et al., 2011).
- *Speed Limit Compliance* (Road Directoriate, Denmark, 1999; Blomberg and Cleven, 2006; Blume et al., 2000; Cottrell et al., 2006).

- *Speeding Above a Threshold Value* (RTA, 2000; Buchholz et al., 2000; Hoareau et al. 2002; Hoareau and Newstead, 2004; Shin et al., 2009; Blomberg and Cleven, 2006).
- *Speed Profile* (Jansson, 1998; Road Directorate, Denmark, 1999; Kloeden et al., 2004; Kloeden et al., 2006).

2.3 Modelling Speed Characteristics

While the before-after evaluation with speed data is often limited to non-model based approach, recent literature suggests that the model based approaches are a more reliable framework for analyzing before-after speed data (Heydari et al., 2014). The conventional ordinary least squares (OLS) regression is the most widely used approach to investigate the effect of various factors on speed (TRC, 2011). In OLS regression, one assumption is that the observations are independent. This assumption does not always hold for data collected in groups or clusters (Poe and Mason, 2000). Speed data are typically collected from different sites over a period of time, and hence, data collected from a particular site are correlated. Modelling these data with a flawed assumption of data independence would lead either to an underestimation or to an overestimation of a study's findings (Park and Saccomanno, 2006; Park et al., 2010a; TRC, 2011).

In order to avoid the limitations of the OLS regression approach, a few studies have applied alternative methodologies to model speed data. One of the earliest studies by Tarris et al. (1996) used a panel data analysis approach to account for the group and time effect. The general expression for the model used by the authors is presented in Eq. 2-1. As seen, three error terms were included in the model; however, the parameters remained constant across the group and time period.

$$Y_{it} = \alpha + \beta' X_{it} + \varepsilon_{it} + u_i + w_t \tag{2-1}$$

where, Y_{it} is the speed for group *i* at time period *t*; α is the intercept, *X* is the explanatory variables; β' is the regression parameters; ε is the pure random error; u is the group disturbance; and w is the time period disturbance.

Poe and Mason (2000) applied a mixed model approach (Eq. 2-2) to account for the random effect of sites. The authors estimated two variants of the mixed model: single intercept, and separate intercepts for each sensor; they concluded that the mixed model with separate intercepts provided better results.

$$Y_{ijk} = \beta X_{ij} + Z_i \gamma_i + \varepsilon_{ijk} \tag{2-2}$$

where, Y_{ijk} is the vector of observed speeds for site *i*, sensor *j*, and driver/vehicle *k*; X is the matrix of geometric variables; β is the vector of fixed-effect parameters; Z is the design matrix for random-variable; γ is the vector of random-effect parameters; and ε is the error term.

Wang et al. (2006) used the random-intercept mixed-effect model approach (Eq. 2-3) to model 85th and 95th percentile speed.

$$Y_{ij} = \beta_{0i} + \beta X_j + \varepsilon_{ij};\ \beta_{0i} = \beta_0 + v_{0i} \tag{2-3}$$

where, Y_{ij} is the speed for subject (driver) *i* at site *j*; β_{0i} is the intercept for subject *i*; β_0 is the mean speed across the population; v_{0i} is the subject disturbance; *X* is the road feature; β is the regression parameter other than the intercept; and ε is the random error term.

Cruzado and Donnell (2010) used a multilevel model in their analysis with the model form shown in Eq. 2-4. The authors concluded that the multilevel model is preferred over a single-level (i.e., conventional OLS) model based on the log-likelihood test ratio.

$$\Delta Y_{jk} = \beta X_{jk} + s_k + \varepsilon_{jk} \tag{2-4}$$

where, ΔY_{jk} is the speed difference between tangent and horizontal curve for driver *j* at site *k*; *X* is the vector of explanatory variables; β is the regression parameter; s_k is the random intercept for site *k*; and ε is the random error term.

Park et al. (2010a) compared two single-level, a conventional multilevel, and a Bayesian multilevel model to analyze the speed differential. Eq. 2-5 to 2-7 present the model forms for the single-level model with a generic intercept for the groups, the single-level model with varying intercepts for the groups, and the multilevel model, respectively. The authors concluded that the multilevel models increased the precision and accuracy of the estimates of speed differential. The authors also suggested that the effect of using a more flexible multilevel model form, such as varying intercepts and varying slopes, should be investigated in the future.

$$y_{ij} \approx N\left(\alpha + \beta x_{1ij} + \gamma x_{2j}, \sigma_y^2\right) \text{ for } i = 1, \ldots\ldots, N; j = 1, \ldots. J \tag{2-5}$$

where, y_{ij} is the speed differential (in km/h) of the i^{th} vehicle at the j^{th} tangent/curve; $\alpha, \beta,$ and γ are regression parameters; x_1 is the vehicle speed at the tangent; x_2 is the inverse of the curve radius; and σ_y is the standard deviation for the individual-level errors.

$$y_{ij} \approx N\left(\alpha_j + \beta x_{1ij}, \sigma_y^2\right) \text{ for } i = 1, \ldots\ldots, N; j = 1, \ldots. J \tag{2-6}$$

where, α_j is the varying intercepts term.

$$y_{ij} \approx N\left(\alpha_j + \beta x_{1ij}, \sigma_y^2\right) \text{ for } i = 1,......,N; j = 1,....J \text{ and } \alpha_j \approx N\left(\gamma_0 + \gamma_1 x_{2j}, \sigma_\alpha^2\right) \tag{2-7}$$

where, σ_α is the standard deviation for the group-level errors; γ_0 and γ_1 are the group-level regression parameters.

Eluru et al. (2013) used a random-parameter (which can also be referred as random-slope or random-coefficient) mixed effect model for the proportions of vehicles in different speed bins. The corresponding model form is presented by Eq. 2-8. The appropriateness of using the mixed model was demonstrated by the authors.

$$y_{qp}^* = (\alpha' + \delta_q')Z_{qp} + \xi_q \tag{2-8}$$

where, y_{qp}^* is the latent propensity of vehicle speed for site q and data collection period p; Z_{qp} is the vector of explanatory variables; δ is the unknown parameters; α is the intercept; and ξ is the random error term to account for site effects.

Heydari et al. (2014) used a mixed effect model with a general expression as shown in Eq. 2-9 for before-after evaluation of posted speed limit. Very recently, Bassani et al. (2014) employed a random effect model for central tendency and deviation of speed by considering three different random errors (corresponding to the specific road, section within the road, and lane within the section) in addition to the pure random noise, as shown by Eq. 2-10.

$$y_{ij} = \beta_0 + \beta X_j + \varepsilon_{ij} + Z_{ij} u_i \tag{2-9}$$

where, y_{ij} is the response variable for site *i* and observation *j*; β_0 is the intercept term; *X* is the explanatory variables; β is the regression parameter other than the intercept; ε is the random error term; and *Z* is the design matrix for random effect u.

$$V_{rsl,i} = \beta_0 + \beta^C X_i^C + \beta^D (Z_p X_i^D) + a_r + a_s + a_l + \varepsilon_{rsl,i} \tag{2-10}$$

where, $V_{rsl,i}$ is the response variable for road *r*, section *s*, lane *l,* and observation *i*; β_0 is the general intercept; X^C and X^D are the explanatory variables influencing the mean speed and standard deviation, respectively; β^C and β^D are the regression parameters for the mean speed and standard deviation, respectively; a_r , a_s , and a_l are the random errors related to road, section, and lane, respectively; and ε is the error term associated with each observation.

The methodologies mentioned above provided significant improvement over the conventional ordinary least square (OLS) regression method in modelling speed characteristics (e.g., mean speed). Nevertheless, their application for before-after safety evaluation has rarely been reported in the literature. Moreover, as seen from the above model forms, a variety of alternative formulations have been used to take into account the hierarchical/multilevel nature of speed data. The naming of the models was often not consistent across studies. The literature shows that the multilevel model, hierarchical model, mixed-effect model, random-effect model, and random-parameter models were used interchangeably. However, according to Gelman and Hill (2007), one of the key components of a multilevel model is varying coefficient (i.e., varying intercept, varying slope, or both). Based on this definition, not all the models employed in earlier speed data analysis can be referred to as multilevel models; rather, they can be regarded as special cases of multilevel models. Literature suggests that restricting the coefficients to be constant/fixed when they actually vary across observations/sites can lead to inconsistent and bias coefficient estimates (Washington et al., 2003). The varying coefficient can also account for the unobserved heterogeneity that is likely to be present in the absence of an exhaustive list of explanatory variables (Anastasopoulos and Mannering, 2009). Similar to the concept of varying coefficient, it is possible that the within-site variances in speed data can vary across sites due to the presence of unobserved heterogeneity. Restricting the within-site variances to be constant/fixed across sites can also lead to bias coefficient estimates and consequent speed prediction. Existing studies on modelling speed characteristics have hardly investigated the effect of considering varying within-site variance on model coefficient estimates and speed prediction.

2.4 Before-After Evaluation of Crash Data

Among the three basic study designs (i.e., observational before-after; observational cross-sectional; experimental before-after) for evaluating the effectiveness of any safety measure, observational before-after studies are the most common (Highway Safety Manual, 2010). Observational before-after studies are subject to different biases (Carter et al., 2012). Based on whether a particular method addresses these biases, observational before-after evaluations can be one of the following types:

1. Simple or naïve before-after method
2. Before-after with comparison group method
3. Before-after with empirical Bayesian (EB) method
4. Before-after with EB and comparison group method, and
5. Before-after with full-Bayesian (FB) method.

The earliest method of before-after evaluation was the simple before-after method, where the observed crash frequencies between the before and after period were compared, as shown in Equation (2-11):

Time	Intervention Sites Crashes	Period
Before	B_{ti}	t_{bi}
After	A_{ti}	t_{ai}

Change in crashes for site i $= \dfrac{A_{ti}/t_{ai} - B_{ti}/t_{bi}}{B_{ti}/t_{bi}} = \dfrac{A_{ti}/t_{ai}}{B_{ti}/t_{bi}} - 1$ (2-11)

The simple before-after method is subject to various biases, including regression to the mean, time trend, and external factors, which lead to inaccurate and potentially misleading conclusions. To take account of the time trend and effect of external factors, the before-after with comparison group method was developed. In the before-after with comparison group method, change in crashes is calculated as shown in Equation (2-12):

Time	Intervention t Sites Crashes	Comparison Sites Crashes	Period
Before	B_{ti}	B_{ci}	t_{bi}
After	A_{ti}	A_{ci}	t_{ai}

Change in Crashes for site i $= \dfrac{\dfrac{B_{ci}/t_{bi}}{A_{ci}/t_{ai}}}{\dfrac{B_{ti}/t_{bi}}{A_{ti}/t_{ai}}} - 1$ (2-12)

The strength of the before-after with comparison group method lies in the proper selection of the comparison group to resemble the treated group in terms of traffic volume, geographic characteristics, proximity and crash frequency. Among these criteria, compatibility of the crash frequencies between the treated and the comparison group in the before period is key for a reliable evaluation result (Hauer, 1997). A compatibility check can be performed by calculating the Odds-Ratio (OR) for the crashes during the before period (Fleiss, 1981; Elvik, 1999; Pauw et al., 2012).

$$OR = \frac{T_t / T_{t-1}}{C_t / C_{t-1}} \tag{2-13}$$

Where

T_t =number of crashes in Treated group in year *t*

T_{t-1} =number of crashes in Treated group in year *t-1*

C_t =number of crashes in Comparison group in year *t*

C_{t-1} =number of crashes in Comparison group in year *t-1*

When the OR is close to 1, the comparison group is comparable to the treated group.

Although a carefully designed before-after with comparison group method can take account of several biases, it cannot address the regression to the mean bias nor the non-linear relationship between crash and exposure (Hauer, 1997). To overcome these two issues, the before-after with empirical Bayesian method was developed (Hauer 1997) and is the most extensively used method for the evaluation of safety interventions (Persaud and Lyon, 2007).

Evaluating the effectiveness of safety interventions under the before-after with empirical Bayesian method is a two-step process: 1) develop a safety performance function (SPF) from a reference group of sites using historical crash data to predict the number of crashes for the treated sites in the before period; 2) combine the predicted crashes with the observed number of crashes in the before period to estimate the expected average crash frequency for a treated site in the after period had the intervention not been implemented. The comparison of the observed after crash frequency to the expected crash frequency estimated with the empirical Bayesian method is used for the effectiveness evaluation.

$$\text{Change in Crashes for site } i = \frac{A_{ti}/t_{ai} - EB_{ti}/t_{bi}}{EB_{ti}/t_{bi}} = \frac{A_{ti}/t_{ai}}{EB_{ti}/t_{bi}} - 1 \qquad (2\text{-}14)$$

For site i, EB_{ti} is the expected crash frequency (obtained using empirical Bayesia) that would have occurred in the after period without intervention. A detailed description of the empirical Bayesian method is presented in the methodology chapter.

The before with empirical Bayesian method takes account of the regression to the mean bias and the non-linear relationship between crash and exposure (Shin et al., 2009). Also, if other independent variables are considered during the Safety Performance Function (SPF) development, this method can also take account of various external factors.

When the required data is available, the before-after with empirical Bayesian and comparison group method can be combined to estimate the change in crashes due to a intervention:

$$\text{Change in crashes for site } i = \frac{\left(B_{ci}/t_{bi}\right) / \left(A_{ci}/t_{ai}\right)}{\left(EB_{ti}/t_{bi}\right) / \left(A_{ti}/t_{ai}\right)} - 1 \qquad (2\text{-}15)$$

Although the before-after with empirical Bayesian and comparison method seems to have the capability to take account of all the biases of a before-after observational study, one potential limitation is that it assumes crashes have either Poisson or Poisson-gamma (negative binomial) distribution. Also, empirical Bayesian cannot take account of spatial correlations and correlation of crash of different severity levels. Further, empirical Bayesian requires a greater number of reference sites to develop the SPFs. Because of these issues, the full Bayesian (FB) method has recently been developed. The details of full Bayesian methodology for before-after safety evaluation are presented in the methodology chapter of this thesis.

2.5 Biases in Before-After Crash Data Analysis

A good summary of all possible biases in an observational before-after study is made by Carter et al. (2012). Some of the predominant biases (i.e, regression to the mean, maturity, and external factors) are described in this section to better understand the importance of using a robust method in the evaluation process.

Regression-to-the Mean (RTM)

RTM is defined as the tendency of sites with very high or low crash counts to return to the usual mean frequency of crashes in the following years. In most cases, transportation agencies/authorities select sites for safety intervention based on high crash frequency in the year/years immediately preceding the intervention. Selecting sites based on this criterion justifies the use of limited resources to improve safety. RTM bias arises if the sites are selected for safety intervention based on a short term high crash frequency. An evaluation of a safety intervention without addressing the RTM effect is likely to overestimate the safety benefit of the intervention.

The RTM phenomenon suggests that the crashes would have decreased even if no safety intervention is applied. If the site selection is not based on a high crash history, RTM might not bias the evaluation results. Figure 2-1 demonstrates the RTM phenomenon and its impact on the evaluation results. This figure clearly suggests that, if not properly addressed, RTM can demonstrate an illusion of safety benefit.

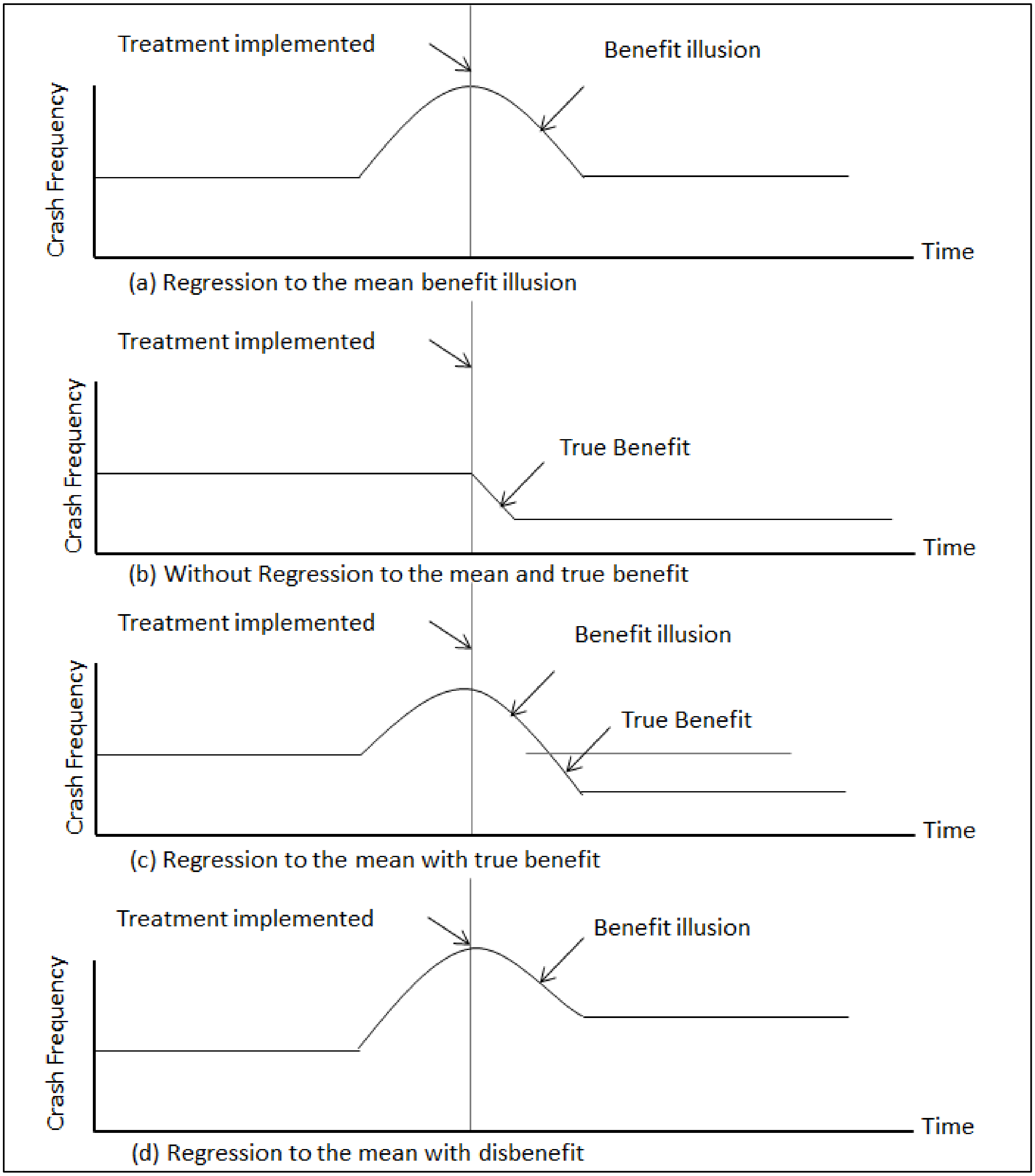

Figure 2-1: Illustration of the regression to the mean effect.

Maturation Effect

Crash frequencies on a site often show long-term trends due to temporal changes. This trend can be attributed by weather, demography, gas prices, vehicle types, or other unknown factors (Carter et al., 2012). These general trends in crash numbers over time are known as ‘maturation’. Crash trends before safety intervention can provide some insight on the expected trends during the post-intervention period. For example, there may be a steady decrease in crashes during the before period, which could be due to a number of factors mentioned above. One might expect the trend to continue in the after period regardless of the safety intervention, unless the underlying conditions change. Figure 2-2 illustrates the time trend effect where (c) suggests that the safety intervention has no effect on the crash frequency.

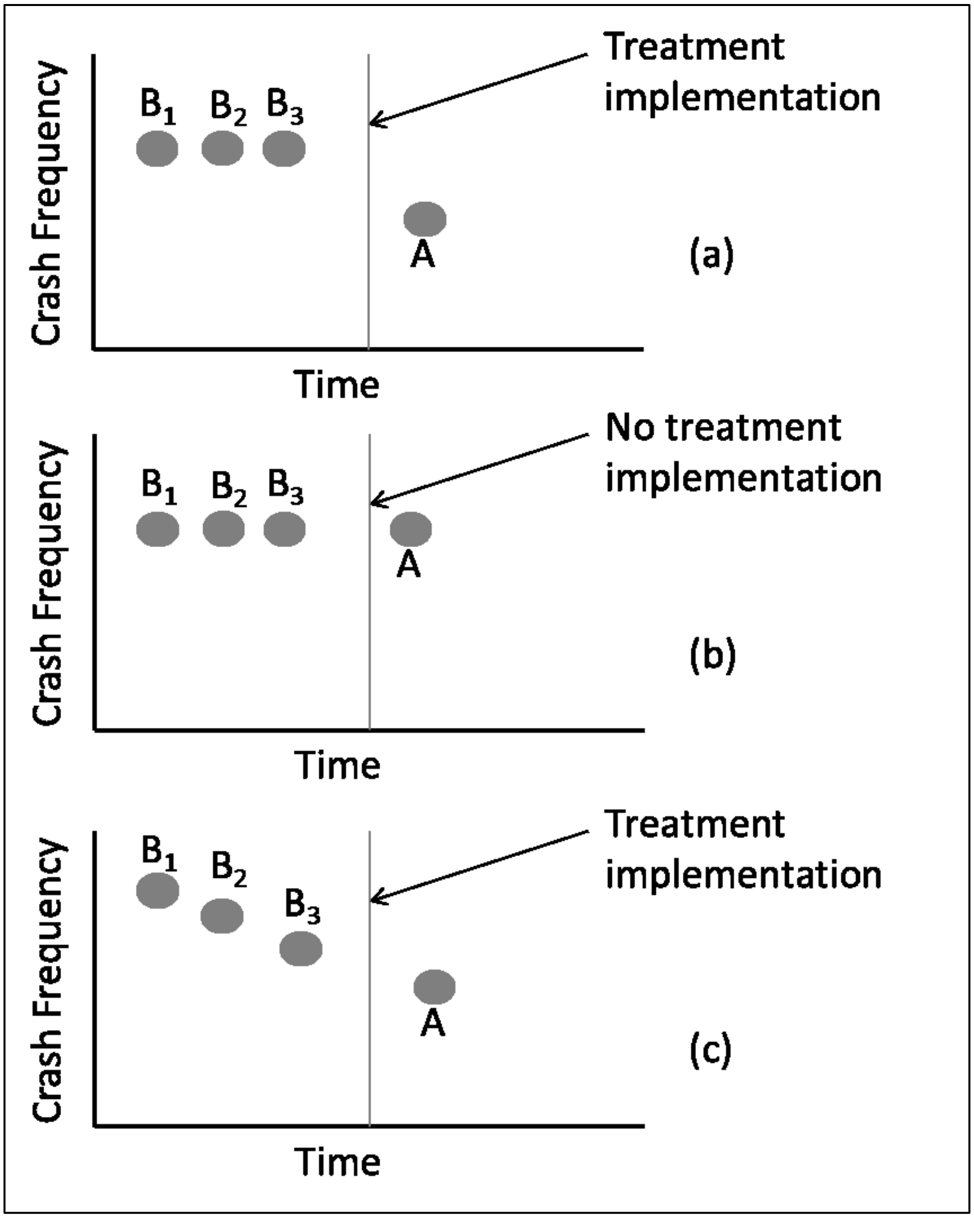

Figure 2-2: Illustration of the effect of maturation.

External Factors

Some external factors can be easily recognized and measured while others are difficult to do so. For instance, change traffic volume can be recognized and measured, and hence can be accounted for explicitly in the before-after analysis. A change in traffic volume in the after period can cause an underestimation or overestimation of the safety effect of an intervention, as the exposure level changes. Further, the relationship between traffic volume and the number of crashes are non-linear which can be taken into account by using robust evaluation methodology. In contrary to traffic volume, changes in driver behavior, economic condition, weather, etc. are often difficult to measure and incorporate in the simple study design.

2.6 Empirical Bayesian and Full Bayesian Methodology

It is evident from literature that regression to the mean can substantially influence the intervention evaluation results (Persaud and Lyon, 2007). The empirical Bayesian (EB) methodology has been developed to account for RTM bias that arises when sites are selected based on high crash frequency (Hauer, 1997). Since its inception, EB methodology has been used extensively in the before-after safety evaluation (Harkey et al., 2008) and is now considered to be the current state-of-the-art for before-after evaluation. However, recently, full Bayesian methodology has been introduced in the literature to perform before-after evaluation (Pawlovich et al., 2006; El-Basyouny and Sayed, 2010; El-Basyouny and Sayed, 2011; Li et al., 2008; Lan et al., 2009; Park et al., 2010b; Persaud and Lyon, 2010). A brief description of the basics of EB and FB methodology is presented below:

According to Bayesian theory, an inference of parameter θ is based on the following formula:

$$p(\theta \mid y) = \frac{p(\theta) l(y \mid \theta)}{m(y)} \tag{2-16}$$

Here, θ is the vector of parameters, y is the set of observed data, $p(\theta)$ is the prior distribution of θ, $l(y \mid \theta)$ is the likelihood function, $m(y)$ is the marginal distribution of data y, and $p(\theta \mid y)$ is the posterior distribution of θ.

The above formula tells that the Bayesian approach combine prior information with current information to estimate the expected crash frequency of an entity. The prior information can be obtained from a group of entity with similar characteristics and the current information is the observed number of crashes at any specific entity. The empirical Bayesian and full Bayesian are two related approach of combing prior information and current information (Persaud et al., 2010).

Hauer (1997) developed a standard form of empirical Bayesian statistical technique that is now widely applied to the analysis of traffic crash data. In the empirical Bayesian approach, a safety performance function (SPF) is developed from a reference group of sites having characteristics similar to those of treated sites. The regression parameters of the SPF are estimated using the maximum likelihood technique using crash data (Hauer et al., 2002; Miaou and Lord, 2003; Miranda-Moreno, 2006). The point estimate of the crashes from SPF is used as prior information which is then combined with the observed number of crashes to obtain an expected crash frequency (i.e., posterior).

In the full Bayesian approach, the posterior distribution is generated in single step by combing prior distribution and the data. One specific advantages of full Bayesian is that it uses Markov chain Monte Carlo (MCMC) simulation method to estimate the model parameters (Gilks et al., 1996). Hence, full Bayesian approach overcomes the limitations of the empirical Bayesian method, where the likelihood function needs to have a closed-form. The full Bayesian method thus can accommodate more flexible distributional assumptions such as Poisson- lognormal distribution. Further, it can accommodate multivariate model form and spatial correlation. In general, the full Bayesian method has many advantages over the widely accepted and extensively used empirical Bayesian approach that include, but are not limited to i) the capability of accounting for all uncertainties in the data and model parameters, ii) a single-step integrated procedure, iii) a small sample site requirement, iv) ability to include prior knowledge on the values of the coefficients in the modelling along with the data collected, v) the flexibility of choosing different distributional assumptions, vi) ability to consider spatial correlation in the model formulation, and vii) ability to consider correlation of multilevel data (Carriquiry and Pawlovich, 2004; El-Basyouny and Sayed, 2011; Gilks et al., 1996; Lan et al., 2009; Persuad et al., 2010).

A number of studies have used the FB method in observational before-after safety evaluations (El-Basyouny and Sayed, 2010, 2011, 2012a,b, 2013; Lan et al., 2009; Lan and Persaud, 2012; Lan and Srinivasan, 2013; Li et al., 2008; Park et al., 2010b; Pawlovich et al., 2006; Persaud et al., 2010). Recognizing the fact that the FB method is a relatively new approach in before-after safety evaluation, while the EB is a well-established and widely used method, a number of studies have compared safety evaluations obtained via these two methods. For instance, a study by Lan et al. (2009) evaluated the safety effects of intersection conversion from stop controlled to signalized control using both the EB and the univariate FB methods. The safety effects were found comparable; however, the FB method provided higher precision of the estimated safety effects. Later, Persaud et al. (2010) compared the univariate FB and EB methods in an assessment of the safety effects of the road diet program, with findings similar to those of Lan et al. (2009). Based on the above two studies, it was concluded that it may not be worth undertaking the complex FB approach, especially when data are available to conduct the EB approach (Persaud et al., 2010).

Meanwhile, Park et al. (2010b) applied the EB and the univariate and multivariate FB methods to evaluate the posted speed limit (PSL) reduction on various Korean expressways. They found that for the low sample mean, safety effects estimated by the two methods were quite different. Moreover, the precision of the EB estimates was found to be greater than that of the FB estimates, which is quite opposite to the findings of Lan et al. (2009) and Persaud et al. (2010). In terms of the deviance information criterion (DIC), authors found that the multivariate Poisson-lognormal (MVPLN) model provided a superior fit over the univariate PLN model, which is in line with earlier research on multivariate analysis (Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a; Park and Lord, 2007). It is worth noting that the model form used by Park et al. (2010b) is different from the one used by Lan et al. (2009) and Persaud et al. (2010).

Lan and Persaud (2012) used the univariate and multivariate FB methods to evaluate a hypothetical case. It was found that the PLN model was the best-fitted model in terms of the DIC. This finding is quite contrary to earlier studies on multivariate analyses, which showed that MVPLN models yielded lower DIC values compared to univariate PLN models (Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a; Park and Lord, 2007). However, the intervention effects obtained from the multivariate and univariate FB methods were found comparable. Referring to earlier studies (Lan et al., 2009; Persaud et al., 2010), it was concluded that it is still appropriate to conduct before-after safety evaluations using the EB method rather than the univariate and multivariate FB methods.

Recently, Lan and Srinivasan (2013) evaluated the safety effects of converting late nighttime flash (LNF) to normal phasing operation at signalized intersections, using both the univariate and multivariate FB and the EB methods. The MVPLN model provided a better fit to the data, based on a much lower DIC value. It was also reported that the effect of the intervention was estimated higher for the multivariate FB method, indicating that the EB and univariate FB methods underestimate the safety effects.

In summary, previous before-after safety evaluation studies often reported contradictory conclusions about the performance of the EB and the univariate and multivariate FB methods, in terms of both safety effects and model goodness of fit. In addition, in the earlier comparison of the FB and the EB methods, negative binomial (NB) distribution was assumed for the EB approach while PLN distribution was mainly assumed for the FB method. It might be more appropriate to use the same distributional assumption when comparing alternative approaches.

2.7 Microscopic and Macroscopic Models

Safety interventions are implemented mostly in microscopic level (either in intersection or road-segment). Consequently, most of the before-after evaluations of safety interventions are based on microscopic analysis. For instances, Sayed et al. (2006) evaluated Stop Sign In-Fill (SSIF) program for 380 intersections; El-Basyouny and Sayed (2011) evaluated the effect of certain safety intervention on intersection safety; Persaud et al. (2010) evaluated the conversion of road segments from a four-lane to a three-lane cross-section with two-way left-turn lane; Lan et al. (2009) evaluated the effect of conversion of rural intersections from stop-controlled to signalized. The explanatory variables considered in the microscopic model depend on whether the unit of analysis is intersection or road segment. A complete list of geometric design features, traffic control features, and site characteristics can be found in Highway Safety Manual (HSM, 2010). For network-wide interventions, such as neighbourhood speed limit reduction, application of the same methodology will require a separate evaluation for intersections and road segments, and then they can be combined to obtain the complete evaluation (HSM, 2010). This requires substantial traffic data, which may not be readily available, especially for low-volume road segments and unsignalized intersections. Therefore, a macroscopic (i.e., area-level or network level) analysis could be an effective alternative approach to evaluate such types of safety interventions. The use of macroscopic before-after evaluation is rarely found in the literature. However, a number of studies have developed macroscopic models to demonstrate the relationship between crash occurrence and numerous socio-demographic, road network, transportation demand and exposure variables (Aguero-Valverde, 2013; Amoros et al., 2003; Flask and Schneider, 2013; Hadayeghi et al., 2003; Hadayeghi et al., 2007; Hadayeghi et al., 2010; Huang et al., 2010; Lovegrove and Sayed, 2006; Noland and Quddus, 2004; Quddus, 2008; van Schalkwyk, 2008; Siddiqui et al., 2012; Song et al., 2006; Wang et al., 2012; Wei and Lovegrove, 2013; Wier et al., 2009). Among the studies on macroscopic modelling, unit of analysis varied from one study to another. For instance, Hadayeghi et al. (2003; 2007; 2010), Wang et al. (2012), and Wei and Lovegrove (2013) developed model for traffic analysis zone (TAZ); Lovegrove and Sayed (2006) used neighborhood as unit of analysis; Quddus (2008) used census ward as unit of analysis; Wier et al. (2009) used census tracts as unit of analysis; van

Schalkwyk (2008), Amoros et al. (2003), Huang et al., (2010) used county as unit of analysis. The above mentioned macroscopic models are developed to provide relevant information to the transportation planners so that the safety can be incorporated during the early stage of transportation network planning and designing.

2.8 Univariate and Multivariate Models

Crash data at a particular site or entity are usually classified by severity (e.g., fatal, injury, or property damage only), by the type of crash (e.g., angle, head-on, rear-end, sideswipe or pedestrian-involved), and/or by the number of vehicles involved (e.g., single or multiple), etc.

Crash data of different types or severities can be modelled either independently, known as the univariate approach (Aguero-Valverde and Jovanis, 2006; Ahmed et al., 2011; El-Basyouny and Sayed, 2010, 2012a,b; Lan et al., 2009; Lan and Persaud, 2012; Lan and Srinivasan, 2013; Li et al., 2008; Park et al., 2010b; Pawlovich et al., 2006; Persaud et al., 2010), or jointly, known as the multivariate approach (Aguero-Valverde and Jovanis, 2009; Aguero-Valverde 2013; Chib and Winkelmann, 2001; Deublein et al., 2013; El-Basyouny and Sayed, 2011, 2013; Lan and Persaud, 2012; Lan and Srinivasan, 2013; Ma et al., 2008; Park et al., 2010b; Park and Lord, 2007; Song et al., 2006; Tunaru, 2002; Ye et al., 2009). The multivariate approach takes into account that crash data of different severities or types are correlated, while the univariate approach fails to do so. Empirical evidence showed that the multivariate method of modelling crash data improves a model's goodness of fit (Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a; Ma et al., 2008; Park and Lord, 2007; Tunaru, 2002). However, despite the conceptual understanding and empirical evidence supporting the superiority of the multivariate approach over the univariate, its application to before-after safety evaluations has not been very common.

In the few before-after safety evaluation studies using multivariate modelling approach, the response variables were overlapping in nature (Lan and Persaud, 2012; Lan and Srinivasan, 2013; Park et al., 2010b). For instance, Lan and Persaud (2012) used total, right angle, left turn, and rear-end crashes; Lan and Srinivasan (2013) used total, injury and fatal, and frontal impact crashes for the multivariate FB analysis. In all of these cases, the response variables were not mutually exclusive. Total crash and any other particular crash type or severity for a site will be correlated, which does not necessarily indicate the multivariate nature of the crash data. These ways of classifying crash types or severities as the response variables for multivariate modelling are inconsistent with earlier applications of multivariate modelling for exploratory analysis. For instance, Song et al. (2006) used intersection, intersection-related, driveway access, and non-intersection crashes; Park and Lord (2007) used fatal, incapacitating-injury, non-incapacitating injury, minor injury, and property-damage-only (PDO) crashes; Ma et al. (2008) used fatal, disabling injury, non-disabling injury, possible injury, and PDO crashes; El-Basyouny and Sayed (2009a, 2011, 2013) used fatal and injury, and PDO crashes; Aguero-Valverde and Jovanis (2009) used fatal, major, moderate, minor, and PDO crashes; Anastasopoulos et al. (2012) used severe and non-severe crashes; and Wang and Kockelman (2013) used no-injury, possible injury, and injury crashes as the response variables in the multivariate models. In all these cases, the response variables were mutually exclusive. Therefore, the conclusions drawn from the previous before-after studies that used overlapping response variables for the multivariate method might be biased.

2.9 Spatial Model and Non-Spatial Models

Conventional crash prediction model with negative binomial (NB) distribution assumes that sites are independent of each other and hence can be regarded as non-spatial model. However, as crash data are collected with reference to location measured as points in space (Quddus, 2008), spatial correlation exists between observations (LeSage, 1998). A number of studies have shown the presence of spatial correlation in crash data (Levine et al., 1995; MacNab, 2004; Aguero-Valverde and Jovanis, 2006; 2008; 2010; Quddus, 2008; El-Basyouny and Sayed, 2009; Wang and Abdel-Aty, 2006; Guo et al., 2010; Ahmed et al, 2011; Aguero-Valverde, 2013). One common similarity among most of these spatial models is that the spatial component is incorporated mostly for univariate response variable.

Few studies focused on a multivariate spatial modelling approach in crash data analysis. Song et al. (2006) made four different assumptions on spatial correlation for modelling four types of crashes (intersection crashes, intersection-related crashes, driveway-related crashes, and non-intersection-related crashes). Using data from 254 counties in Texas, the authors found that the model with multivariate conditional autoregressive (CAR) and the model with correlated CAR outperformed the model with univariate CAR. The deviance information criterion (DIC) drop was reported as 13.6 when the multivariate CAR model was compared with the univariate CAR model.

Aguero-Valverde (2013) used univariate and multivariate spatial models to estimate excess crash frequency for 81 cantons. A variety of canton-level characteristics were included as independent variables in the model. Multivariate spatial models were found to be better fitted to the data, with a DIC drop of 10 compared to the univariate spatial models. However, the variances of the spatial errors were not significant. The author stated that this might be due to the small number of spatial units, as only 81 cantons were used. The author also ranked sites using the models, and found that the ranking of sites was similar for both models, but the spatial smoothing due to the multivariate CAR random effects was evident in some extreme values.

Similarly, Wang and Kockelman (2013) compared multivariate spatial models with univariate spatial and multivariate non-spatial models for pedestrian crashes. Using data for 218 traffic zones, the authors concluded that the multivariate CAR model outperformed the other two models a with very large drop in DIC values.

Narayanamoorthy et al. (2013) also proposed a spatial multivariate count model to jointly analyze the traffic crash-related counts of pedestrians and bicyclists by injury severity. Census tract was used as a unit of analysis to apply the proposed model. The results suggested that ignoring spatial effects can result in substantially biased estimation of the effects of exogenous variables. However, no comparison with univariate spatial models was made.

A recent study by Barua et al. (2015)*)* used two different datasets to compare the performance of multivariate CAR models with univariate CAR models. It was reported that the multivariate spatial models provided a superior fit over the univariate spatial models with a significant drop in the DIC value (35.3 for one dataset and 116 for another).

From the methodological standpoint on including spatial correlation in crash modelling, various approaches have been used in the literature. However, the most frequently used approach by far is CAR distribution for modelling spatial correlation. Moreover, Quddus (21) compared several distributions to address spatial correlation, and found that CAR distribution under a Bayesian framework can provide more appropriate and better inference over classical spatial models. In addition, El-Basyouny and Sayed (22) compared three different spatial models (i.e., CAR, multiple membership (MM), and extended multiple membership (EMM) with non-spatial Poisson-lognormal (PLN) model). The authors found that EMM and CAR models provided similar goodness-of-fit and outperformed the PLN and MM model.

2.10 Intervention and Conventional Model

In the full Bayesian before-after safety evaluation, two different modelling approaches are typically employed in the literature. In the first approach, before and after period crash data for a group of reference sites and only the before period data of treated sites are included to develop the model. While in the second approach, before and after period crash data for both treated and reference sites are included in the model with indicator variable to distinguish between before and after period. The former approach can be regarded as conventional approach as it follows the similar procedure used in empirical Bayesian (EB) approach while the later one is often referred as intervention model. In the existing literature, Pawlovich et al. (2006), Park et al. (2010b), El-Basyouny and Sayed (2010) and El-Basyouny and Sayed (2011) used full Bayesian intervention model for various before-after safety evaluation, while Li et al. (2008), Lan et al. (2009), Persaud et al. (2010) used conventional full Bayesian approach.

It is worth noting that when spatial effect is not considered in the model formulation for the before-after evaluation, both modelling approach are equally applicable. However, when the spatial effect of the data is addressed in the model formulation, conventional modelling approach cannot be used. This is because of the fact that the conventional approach includes only the before period data of the treated sites with both before and after period data of reference sites, thereby create an imbalance adjacent matrix for modelling spatial effect. Therefore, when spatial effect is included in the model formulated for before-after evaluation, intervention model approach was used in the current study.

2.11 Summary of Literature Review

Use of both speed and crash data for before-after evaluation of traffic safety intervention is quite common in the literature. However, several key issues have been identified that warrant further investigation for more reliable and unbiased estimate of the effect of a safety intervention. Most evaluations have adopted a method of non-model-based naïve before-after speed data analysis where various speed-related performance measures were compared and statistical tests were conducted to check whether the measures were statistically different between the before and after periods. These naïve before-after speed data analyse often fail to take account for the confounding factors and time trend effects, leading to bias in estimation of the effects of safety intervention on vehicle speed behavior. Furthermore, there is a lack of the use of appropriate statistical methods to verify that the actual speed reduction is significant. While different modelling techniques have been employed in the literature for modelling different speed characteristics, their application for before-after evaluation of speed data is rarely documented in the literature. Although non-model-based approach can provide valuable insights about the safety effects of an intervention, a model-based approach could be more promising and reliable, due to its capability to provide more insight about the factors affecting speed choice while taking into account the effects of confounding factors.

For modelling mean or 85th percentile speed, conventional ordinary least square (OLS) regression is the most commonly used method reported in the literature. This single level regression modelling method assumes that each observation of speed is independent. In reality, the speed data are often multilevel (at-least two-level) in nature, as the data are collected for multiple sites with multiple observations from each sites. The data collected from different sites can exhibits different speed characteristics because of the dissimilarity in site characteristics, such as geometric design, surrounding environment, etc. Similarly, within-site speed data can show variability because of the difference in driver characteristics, traffic flow, vehicle type, temporal pattern, etc. The conventional OLS regression method cannot address these two variances and hence can results in biases in speed prediction. While several alternative methodologies have been used in the literature to address the limitations of the OSL regression, they often fail to address the heterogeneity of the speed data.

For the before-after evaluation of crash data, the empirical Bayesian (EB) approach has been extensively used in the before-after evaluation of crash data and is considered to be the current state-of-the–art approach to before-after evaluation. However, recent literature explored the application of full Bayesian method to take account for the limitations associated with the empirical Bayesian method. The Full Bayesian (FB) approach has been reported to have more flexibility and advantages over the EB approach. Specifically, the FB method can address the multivariate nature of the crash data into the modelling formulation. However, the application of multivariate FB method for before-after safety evaluation was not widely explored in the existing literature.

One major advantage of the FB method is its ability to consider spatial correlation of crash data into the model formulation. A significant number of cross-sectional studies have included spatial correlation in the FB method and concluded that the inclusion of spatial correlation improves model goodness-of-fit and the precision of parameter estimates. However, its application in before-after safety evaluation has rarely been documented in the traffic safety literature.

Finally, microscopic (i.e., intersection or road segment as unit of analysis) before-after evaluations have been extensively used to evaluate traffic safety interventions. For network-wide interventions, application of the same methodology will require a separate evaluation for intersections and road segments, and then they can be combined to obtain the complete evaluation. This requires substantial traffic data, which may not be readily available, especially for low-volume road segments and unsignalized intersections. Therefore, a macroscopic (i.e., area-level or network level) analysis could be an effective alternative approach to evaluate such types of safety interventions. While use of macroscopic models for various exploratory analyses has been reported in the literature, their application to before-after safety evaluation was rarely found in the literature.

3.0 Methodology

This chapter presents the detail description of the methodology developed to model and evaluate speed and crash data in an observational before-after setting. This chapter also presents the processes involved in the estimation and assessment of the models

3.1 Before-After Speed Data Evaluation

This thesis develops both non-model and model based approach to evaluate the before-after speed data. For the model-based approach, two alternative modelling techniques were compared: one of them is generalized mixed-effect model and another is multilevel model. While the model-based approach is more appropriate and reliable, data constraint might limit the evaluation to non-model based approach only. The detail description of non-model based approach and the generalized mixed-effect model and the multilevel model are presented in next sub-sections.

3.1.1 Non-Model based Approach

This research used a before-after evaluation with control group to take account of the various biases. Several performance indicators are used to evaluate the impact effect:

i) Mean free-flow speed: Mean speed of vehicles having headway greater than 2 seconds;
ii) Standard deviation of speed: Measure of dispersion of the vehicle free-flow speeds calculated from deviation from the mean free-flow speed;
iii) Percentile speed plot: The distributions of vehicle speed by before-and-after periods;
iv) Level of speed limit violation: Calculated as the percentage of vehicles exceeding 50 km/h and 65 km/h; and
v) 85th percentile speed: Speed exceeded by 15% of the drivers.

Separate investigations were made for time of day, day of week, and vehicle and road type. The appropriate method for testing the statistical significance of differences of mean speed before (μ_1) and after (μ_2) a intervention is a two-sample *t* test with either pooled variance (in case of equal variance) or separate variance (in case of unequal variance). The null hypothesis is that there is no difference in the mean speeds $(H_0 : \mu_1 = \mu_2)$, while the alternative hypothesis is that the post-intervention mean speed is reduced $(H_a : \mu_1 > \mu_2)$. For this thesis, failing to reject the null hypothesis means that the posted speed limit (PSL) reduction is not effective at the confidence level under consideration, while rejecting the null hypothesis indicates that the PSL reduction is effective in reducing vehicle speed. The corresponding equations, which were modified to account for the time trend effect estimated from the control communities, are:

$$t = \frac{(\bar{x}_2 - \bar{x}_1^*)}{SE} = \frac{\text{Speed Reduction}}{SE} \tag{3-1}$$

$$\bar{x}_1^* = \bar{x}_1 \times \text{Adjustment factor} \tag{3-2}$$

$$\text{Adjustment factor} = \frac{\text{Mean speed in the after period at control group}}{\text{Mean speed in the before period at control group}} \tag{3-3}$$

For t-test with pooled variance,

$$SE = \sqrt{S_p^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)} \tag{3-4}$$

$$S_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} \tag{3-5}$$

$$d.f. = n_1 + n_2 - 2 \tag{3-6}$$

For t-test with separate variance,

$$SE = \sqrt{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)} \tag{3-7}$$

With $$d.f. = \frac{\left(S_1^2/n_1 + S_2^2/n_2\right)^2}{\left(\frac{\left(S_1^2/n_1\right)^2}{n_1 - 1} + \frac{\left(S_2^2/n_2\right)^2}{n_2 - 1}\right)} \tag{3-8}$$

where,

$\bar{x}_1, \bar{x}_2 =$ pre- and post-intervention sample means

$s_1^2, s_2^2 =$ pre- and post-intervention sample variances

$n_1, n_2 =$ pre- and post-intervention sample sizes

$SE =$ standard error

$S_p^2 =$ pooled variance

Since this thesis involves a before-and-after evaluation with control group, an adjustment to the before period sample mean $(\bar{x}_1)$ using the data collected from the control group is required. The adjustment is carried out by multiplying $\bar{x}_1$ by the ratio of the mean speed in the after to the before period of the control group (using Eq. 3-3) to obtain an estimate of the expected mean speed in the after period, had no speed limit reduction been implemented (using Eq. 3-2). The literature indicates that the standard error be underestimated, because the control group ratio is applied without any measurement of uncertainty (Persaud and Lyon, 2009). Although it has been suggested that this lack of precision will not affect the final results, this thesis provides empirical evidence to support this suggestion.

While a particular intervention could result in a mean speed reduction, the standard deviation would increase, potentially threatening the safety of road users (Finch et al., 1994). The literature suggests statistical tests for speed variance to evaluate the effectiveness of speed reducing measures (Dell'Acqua, 2011). Thus, Fisher's *F*-test was conducted to check the change in speed variance. The null and alternative hypotheses are $H_0 : \sigma_1^2 \le \sigma_2^2$ and $H_a : \sigma_1^2 > \sigma_2^2$, respectively. In this thesis, if the before period is considered as sample 1 and the after period as sample 2, then rejecting the null hypothesis means that the speed variance has been reduced in the after intervention period.

A comparison was made between speed limit violation, and 85th percentile speed. In addition, percentile speed plots were created for both the treated and the control groups to differentiate the before versus after change in speed. These plots provide a clear visualization of the change in speed distribution.

3.1.2 Generalized Mixed Model Approach

While non-model based approach can provide valuable insights about the safety effects of an intervention, a model-based approach could be more promising, reliable and transferable, due to its capability to provide more insight about the factors affecting speed choice while taking into account the effects of confounding factors. This thesis applied mixed-effect normal intervention and mixed-effect binomial logistic intervention model for analysing mean free-flow speed and speed below or equal to various thresholds, respectively.

Let Y_{ij} denote mean free-flow speed at speed survey site *i (i=1,2…,N)* at hourly observation *j (j=* 1, 2*, ..., M)*. Under the mixed-effect modelling framework, Y_{ij} can be expressed as the following (Ntzoufras, 2009):

$$Y_{ij} \sim N(\mu_{ij}, \sigma_{\varepsilon}^{2}) \tag{3-9}$$

$$\mu_{ij} = \beta_0 + \beta_1 T_i + \beta_2 t_j + \beta_3 T_i t_j + \beta_4 x_4 + \beta_5 x_5 + \cdots \quad s_i \tag{3-10}$$

$$s_i \sim N(0, \sigma_s^{2}) \tag{3-11}$$

where variance component σ_s^2 measures the between-site variability, while σ_ε^2 accounts for the within-site variability (Ntzoufras, 2009); T_i is the indicator for intervention (equal to one for speed measurement at treated sites, zero for comparison sites); t_j is the indicator for time (one for the after period, zero for the before period); $x_4, x_5, \cdots$ are a set of variables representing different features specific to each site and the speed hour, such as hourly vehicle count, weekday versus weekend indicator, day versus night indicator, road class, road width, etc.; and $\beta_0, \beta_1, \ldots \beta_k$ are the regression coefficients. The model presented in Eq. (3-10) is referred to as the intervention model as it includes indicator variables to estimate the effect of the intervention.

The total variability of the response variable Y_{ij} is the sum of the within-site and between-site variability (i.e., $\sigma_s^2 + \sigma_\varepsilon^2$), while the covariance between two measurements of site *i* is equal to the between-site variability (i.e., σ_s^2) (Ntzoufras, 2009). Thus, the within-site correlation can be calculated as such:

$$\rho = \frac{\sigma_s^2}{\sigma_s^2 + \sigma_\varepsilon^2} \tag{3-12}$$

A value of ρ close to one suggests high within-site correlation, illustrating the importance of using a mixed model, while a value close to zero implies low within-site correlation, indicating that random effects do not improve the model

Let c_{ij} denote the number of vehicles at speed survey site i that are below or equal to a particular speed threshold for an hourly observation j, and V_{ij} denotes the total vehicle count for site i at hour j. If p_{ij} is the probability that the speed is below or equal to the speed threshold, then according to the mixed-effect binomial logistic modelling framework,

$$c_{ij} \sim Binomial(p_{ij}, V_{ij}) \tag{3-13}$$

$$logit(p_{ij}) = \beta_0 + \beta_1 T_i + \beta_2 t_j + \beta_3 T_i t_j + \beta_4 x_4 + \beta_5 x_5 \pm \cdots + \beta_k x_k + \varepsilon_{ij} + s_j$$

(3-14)

$$\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2),\ s_i \sim N(0, \sigma_s^2) \tag{3-15}$$

The definitions of the parameters and variables in Eq. (3-13) through (3-15) are the same as those presented for mixed-effect normal intervention model.

In full Bayesian approach, it is necessary to specify the prior distributions of the parameters in order to estimate the posterior distribution In the current thesis, the following priors were used for all models: $\beta \sim N(0, 100^2)$, $\sigma^{-2} \sim Gamma(0.001, 0.001)$.

Now to use the mixed-effect model, let μ_{TB} and μ_{TA} represent the predicted free-flow speed for the treated sites in the before and after periods, respectively, and let μ_{CB} and μ_{CA} represent the predicted free-flow speed for the comparison sites in the before and after periods, respectively. According to Park et al. (2010b), the ratio $r = \mu_{CA} / \mu_{CB}$ can be used to adjust the speed prediction for general trends between the before and after periods. The predicted speed in the after period for the treated site had the countermeasures not been applied is thus given by $\pi = \mu_{TB} \times r$. Now the change in speed due to the PSL reduction can be given by $\delta_s = \pi - \mu_{TA} = \mu_{TB} \times r - \mu_{TA}$. Under the FB framework, if the 95% credible interval of δ_s does not contain zero, then the change in speed due to the change in the PSL is statistically significant. A positive value of δ_s indicates that the PSL reduction was able to decrease the average free-flow speed, while a negative value indicates an increase in the average free-flow speed.

Often, the odds ratio (OR), also referred to as the index of effectiveness of the countermeasure, is calculated using the following formula:

$$OR = \mu_{TA}\mu_{CB} / \mu_{TB}\mu_{CA} \tag{3-16}$$

Following similar notations for the subscript mentioned above, the change in the probability of speed being below or equal to a particular threshold can be given by $\delta_c = p_{TA} - p_{TB} \times r$ where $r = p_{CA} / p_{CB}$. A positive value of δ_c indicates an increase in the probability in the after period. The odds ratio for this case can be expressed as the following:

$$OR = p_{TA}p_{CB} / p_{TB}p_{CA} \tag{3-17}$$

3.1.3 Multilevel Modelling Approach

The final modelling attempt made in this thesis for analyzing speed data was multilevel approach to model the hourly free-flow speed data. For the current data, a three-level model was formed. The multilevel model can be one of three types: varying-intercept, varying-slope, and varying-intercept with varying slopes (Gelman and Hill, 2007); however, the current thesis employed only the varying-intercept model. The other two model types are simply extensions of the employed model. The regression model corresponding to each level can be expressed by the following equations:

Level 1:

$$y_{ijk} = \alpha_{0jk} + \sum_{l=1}^{L} \alpha_l X_{il} + \varepsilon_{ijk}, \varepsilon_{ijk} \sim N(0, \sigma_\varepsilon^2) \quad (3\text{-}18)$$

Level 2:

$$\alpha_{0jk} = \beta_{0k} + \sum_{m=1}^{M} \beta_m X_{jm} + \eta_j, \eta_j \sim N(0, \sigma_\eta^2) \quad (3\text{-}19)$$

Level 3:

$$\beta_{0k} = \gamma_0 + \sum_{n=1}^{N} \gamma_n X_{kn} + \eta_k, \eta_k \sim N(0, \sigma_k^2) \quad (3\text{-}20)$$

Here, y_{ijk} is the hourly mean free-flow speed for observation i, $(i = 1,2,......,I)$, site j ($j = 1,2,....,J)$, and community $k(k = 1,2,3,.....,K)$; X_i, X_j, and X_k represent the sets of explanatory variables related to the observation, site, and community, respectively; α_l, β_m, and γ_n are the regression parameters related to $l(l = 1,2,...,L)$, $m(m = 1,2,...,M)$, and $n(n = 1,2,...,N)$

explanatory variables; γ_0 is the intercept term; ε_{ijk} is the error term; and η_j and η_k are the random effects related to site and community, respectively. The above equations can be used to derive the equations presented in section 2.3 of the literature review.

It is worth noting that the constant slopes were considered for all the explanatory variables, except for time period. For time period variable, varying slope by site type (i.e., treated versus comparison) was considered to account for the fact that the effect of the time period (i.e., before versus after) on the free-flow speed is expected to differ from the treated to the comparison sites.

The distribution of the error term in Eq. (3-18) represents homogeneous variance. The current thesis also considered an extension of this assumption where the variance was allowed to differ across sites, as shown by Eq. (3-21).

$$\varepsilon_{ijk} \sim N(0, \sigma^2_{\varepsilon[j]}) \tag{3-21}$$

In the current thesis, the following priors were used for all models: $\beta \sim N(0, 100^2)$, $\sigma^{-2} \sim Gamma(0.001, 0.001)$.

To use the model for the estimation of the effect of a intervention on free-flow speed, the same procedure outlined for the mixed-effect model can be used.

3.2 Before-After Crash Data Evaluation

A conventional way of expressing the overall safety effect of an intervention is to use the odds ratio (HSM, 2010). For the conventional EB and the FB methods, the odds ratio, also referred to as the crash modification factor (CMF), is expressed as the following:

$$OR_{overall} = \sum_{All\ sites} \gamma \,/\, \sum_{All\ sites} \pi \tag{3-22}$$

where γ is the observed number of crashes per site in the after period of the intervention, and π is the expected number of crashes per site that would have occurred in the after period without the safety intervention. The expected number of crashes, π, is estimated using a reference group of sites in both the EB and the FB approaches, although the procedure of estimation differs. The next sections describe the detailed procedure to obtain π, using the FB and the EB methods.

For the intervention modelling approach, the odds ratio is expressed as the following:

$$OR_{overall} = \theta_{TA}\theta_{CB}/\theta_{TB}\theta_{CA} \tag{3-23}$$

Where, θTB and θ_{TA} represent the predicted crash for the treated sites in the before and after periods, respectively, and θ_{CB} and θ_{CA} represent the predicted crash for the comparison sites in the before and after periods, respectively. If the eq. (3-22) and (3-23) is compared, $\pi = \theta_{TB}\theta_{CA}/\theta_{CB}$ and $\gamma = \theta_{TA}$.

The overall safety effectiveness as a percentage change in crash frequency across all sites can be expressed as

$$\text{Safety Effectiveness} = 100 \times (1 - OR_{overall}) \tag{3-24}$$

3.2.1 Modelling Crash Data

Crash data exhibits several unique characteristics that need to be addressed in the modelling to obtain unbiased prediction. Following are the features of the crash data that needs special attention:

a) Crash data are rare, random, discrete and non-negative event (Poisson variation).

b) Crash data are over-dispersed (Poisson extra-variation), meaning that the variance exceeds the mean of the crash counts.
c) Crash data exhibit spatial correlation, meaning that the assumption that the entities are independent from each other might be violated for crash data.
d) When multiple year of crash data are used, a general trend is obtained reveals in the data
e) Crash data exhibit correlation among different severity level or types.

Most of the literature related to the development of CPMs (also known safety performance functions (SPFs)) accounts for the first two features of crash data (El-Basyouny and Sayed, 2009; Lord and Mannering, 2010). However, CPMs should be able to capture each of the above features for reliable and accurate crash prediction. It is important to note here that the EB approach relies on the NB distribution, while FB can accommodate other distribution as well as the other features of the crash data mentioned above. A summary of the developed modelling scenarios for the before-after evaluation is presented in Table 3-1. As seen, different modelling formulations were considered that include both non-spatial and spatial models. For the empirical Bayesian method, Poisson-lognormal distribution was considered for consistency with the full Bayesian method.

Table 3-1 Modelling scenarios to be developed for before-after evaluation

1.	Full Bayesian (FB) Univariate model with Poisson-lognormal (PLN) distribution
2	FB Multivariate model with PLN (MVPLN) distribution
3.	FB Univariate model with PLN distribution and conditional autoregressive (CAR) spatial effect.
4.	FB MVPLN distribution and multivariate CAR (MVCAR) spatial effect.
5.	FB shared component model with PLN distribution and (CAR) spatial effect.
6.	Empirical Bayesian model with PLN distribution.

3.2.2 Full Bayesian Models

Let Y_{it}^{k} denote the observed crash count at entity *i (i*= 1, 2*, ..., n)* during time period *t* for a severity level *k (k*= 1, 2, ..., *K)*.

For the research in this thesis, entity *i* is neighborhood for macroscopic model and road segment for microscopic model; Furthermore, *t* refers a period of three years from October 2006 to September 2009 or October 2010-Sepetember 2013 for microscopic model, while individual year for macroscopic model; and *k* refers to two severity levels: severe (i.e., fatal and injury) and Property-damage-only (PDO) crashes.

Crash data are count data that is rare, random and non-negative. It is assumed that crashes at the *n* entities are independent and that

$$Y_{it}^{k} \mid \lambda_{it}^{k} \sim Poisson\,(\lambda_{it}^{k}) \qquad (3\text{-}25)$$

Where λ_{it}^{k} is the Poisson parameter. The probability of y_{it}^{k}, *k severe* crashes occur during period *t* for entity *i*, is given by

$$\Pr\{Y_{it}^{k} = y_{it}^{k} \mid \lambda_{it}^{k}\} = e^{-\lambda_{it}^{k}} \frac{\lambda_{it}^{k\,y_{it}^{k}}}{y_{it}^{k}\,!} \qquad (3\text{-}26)$$

Due to the over-dispersion of crash data, it is common to incorporate an error term in the Poisson parameter to capture the unobserved or unmeasured heterogeneity as shown below:

$$\lambda_{it}^{k} = \theta_{it}^{k} \exp(u_{i}^{k}) \qquad (3\text{-}27)$$

where θ_{it}^{k} is the systematic component of the model, determined by a set of covariates representing road segment-specific attributes and a corresponding set of unknown regression parameters and the term u_i^k represents heterogeneous random effects.

For microscopic model, θ_{it}^{k} can be expressed as

$$\ln(\theta_{it}^{k}) = \beta_0^k + \beta_1^k \ln(L_i) + \beta_2^k \ln(V_{it}) + \beta_3^k t + \sum_{j=4}^{J} \beta_j^k X_{ji} \tag{3-28}$$

where β_{0k} is the intercept; L_i is the length of road segment i; and V_{it} is the average AADT of road segment i for period t. β_{1k}, β_{2k}, and β_{3k} are the regression parameters for length, AADT, and time period, respectively. X_{ji} represents the set of covariates, other than length, AADT, and time period, while β_{jk} denotes the corresponding regression parameters. In Eq. (3-28), for the time period indicator variable, $t=0$ for the before period, and $t=1$ for the after period.

For macroscopic model, which is intervention model, the θ_{it}^{k} can be expressed as

$$\ln(\theta_{it}^{k}) = \beta_{0t}^k + \beta_1^k \ln(VKT_i) + \beta_{2t}^k T + \sum_{j=3}^{J} \beta_j^k X_{jit} \tag{3-29}$$

Where β_{0t}^k is the intercept; VKT_i is the vehicle-kilometer travelled for neighbourhood i; and T is the indicator variable with $T=1$ indicate treated neighbourhood and $T=0$ for reference neighbourhood. β_1^k and β_{2t}^k are the regression parameters for VKT, and indicator variable, respectively. X_{jit} represents the set of covariates, while β_j^k denotes the corresponding regression parameters.

Now, depending on the assumption made for the heterogeneous random effect u_{ik}, different Poisson-mixture models can be formulated. The two most commonly used Poisson-mixture models are PLN and Poisson-gamma (or negative binomial) models. Various empirical studies have shown the goodness of fit improves by using Poisson-lognormal (PLN) distribution since its tails are known to be asymptotically heavier than those of the Poisson-gamma distribution (Aguero-Valverde and Jovanis, 2008; Kim et al., 2002; Lord and Mannering, 2010; Lord and Miranda-Moreno, 2008; Miaou et al., 2003). Hence, PLN models were used in the current thesis. Moreover, the assumption made on u_{ik} will define whether the model is univariate or multivariate in nature.

For the univariate PLN models, where each group of crashes is modelled independently, ignoring the possible correlations, the following assumption is made:

$$\exp(u_i)\,|\sigma_u^2 \sim lognormal(0,\sigma_u^2) \text{ or } u_i|\sigma_u^2 \sim normal(0,\sigma_u^2) \quad (3\text{-}30)$$

Where σ_u^2 represents the within-entity (extra) variation and $k=1$.For σ_u^{-2}, following prior was used: gamma$(\varepsilon,\varepsilon)$, where ε is a small number (e.g., 0.01 or 0.001) (El-Basyouny and Sayed, 2009; Hadayeghi et al., 2010).

For multivariate PLN (MVPLN) models, where the crash data of different severity levels are modelled jointly, u_i^k denotes multivariate normal error distribution as shown below:

$$\exp(u_i^k)\,|\sim lognormal(0,\Sigma) \text{ or } u_i^k \sim Normal(0,\Sigma) \quad (3\text{-}31)$$

Where,

$$u_i^k = \begin{pmatrix} u_i^1 \\ u_i^2 \\ \cdots \\ u_i^k \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \cdots & \cdots \\ \sigma_{21} & \sigma_{22} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \sigma_{k1} & \sigma_{k2} & \cdots & \cdots \end{pmatrix} \quad (3\text{-}32)$$

The diagonal elements, of the variance-covariance matrix, Σ represent the variances, and the off-diagonal elements, σ_{hk} represent the covariance of u_i^h and u_i^k. For model estimation, following prior is used: $\Sigma^{-1} \sim Wishart\,(I,K)$, where I is the $K \times K$ identity matrix (Chib and Winkelmann, 2001; Congdon, 2006).

All the modelling formulation described above ignore the fact that the crash data exhibits spatial correlation. Spatial correlation can be accounted for in Eq. (3-27) by incorporating a spatial random effect (also known as spatial correlation or structured variation or structured error) as follows (El-Basyouny and Sayed, 2009):

$$\lambda_{it}^{k} = \theta_{it}^{k} \exp(u_i^k) \exp(s_i^k) \text{ or } \ln(\lambda_{it}^{k}) = \ln(\theta_{it}^{k}) + u_i^k + s_i^k \quad (3\text{-}33)$$

The spatial component s_i^k suggests that entities that are closer to each other are likely to have common features affecting their crash occurrence. Based on literature, the most common way of modelling spatial effect is to use first order conditional autoregressive (CAR) model. For the univariate model, spatial effect is assumed to have a univariate CAR distribution while for the multivariate model, multivariate CAR distribution is assumed.

The current thesis also developed a special modelling formulation to take account of the spatial effect which is known as shared component model. The application of this model was reported in the public health research (Knorr-Held and Best, 2001). Under this modelling formulation, Poisson parameter is expressed as

$$\ln(\lambda_{it}^{k}) = \ln(\theta_{it}^{k}) + \eta_i^k \quad (3\text{-}34)$$

Now, if there are two response variables (i.e., $k = 1$ &2), then

$$\eta_i^1 = \varphi_i \delta + \psi_i^1 \text{ and } \eta_i^2 = \varphi_i / \delta + \psi_i^2 \quad (3\text{-}35)$$

Here, ψ is response-specific random effect, φ is shared random effect, and δ is a scaling factor to allow the risk gradient associated with the shared component to be different for each response variable.

For response-specific random effect:

$$\psi_i^k = \varepsilon_{sp,i}^k + s_{sp,i}^k \quad (3\text{-}36)$$

Here, $\varepsilon_{sp,i}^{k}$ is the unstructured effect and $s_{sp,i}^{k}$ is the spatial effect for the response-specific random effect. $\varepsilon_{sp,i}^{k}$ is assumed to be normal distribution and $s_{sp,i}^{k}$ is assumed to be conditional autoregressive (CAR) distribution.

Similarly, for the shared random effect,

$$\varphi_i = \varepsilon_{sh,i} + s_{sh,i} \tag{3-37}$$

$\varepsilon_{sh,i}$ is the unstructured effect and $s_{sh,i}$ is the spatial effect for the shared random effect. $\varepsilon_{sh,i}$ is assumed to be normal distribution and $s_{sh,i}$ is assumed to be conditional autoregressive (CAR) distribution.

3.2.3 Gaussian Conditional Autoregressive (CAR) Distribution

The joint distribution of the spatial effect, s can be expressed as follows

$$\boldsymbol{s} \sim \boldsymbol{MVN}(\boldsymbol{\eta}, \boldsymbol{v}\Sigma) \tag{3-38}$$

Where $s = (s_1, s_2 ...., s_N)$, N is the number of entity (e.g., road segment), MVN indicates the N -dimensional multivariate normal distribution, η is the $1 \times N$ mean vector, $v > 0$ controls the overall variability of the s_i and Σ is an $N \times N$ positive definite and symmetric matrix presents the between-entity correlation.

Between-entity covariance matrix can be written in the following form (Thomas et al., 2004):

$$v\Sigma = v(I - \gamma C)^{-1} M \tag{3-39}$$

Where

$I = N \times N$ identity matrix

$M = N \times N$ diagonal matrix, with elements M_{ii} proportional to the conditional variance of $s_i \mid s_j$

$C = N \times N$ weight matrix, with elements C_{ij} denoting spatial association between entities i and j.

γ=controls overall strength of spatial dependence. γ=0 implies no spatial dependence.

For the covariance matrix in equation (3-38) and using standard multivariate normal theory (Besag and Kooperberg, 1995) the joint multivariate Gaussian model can be expressed in the form of a set of conditional distributions:

$$\boldsymbol{s_i} | \ \boldsymbol{s_{-i}} \sim \boldsymbol{N}\left(\boldsymbol{\eta_i} + \sum_j \boldsymbol{\gamma C_{ij}}\left(\boldsymbol{s_j} - \boldsymbol{\eta_i}\right), \boldsymbol{v M_{ij}}\right) \tag{3-40}$$

s_{-i} denotes all the elements of s except s_i

From modelling point of view, it is required to specify C , M and γ. Other constraints required ensuring $\sum$ being a positive definite and symmetric matrix is mentioned by Thomas et al. (2004).

CAR Model for Univariate

Univariate Gaussian CAR models (Besag et al., 1991) are most commonly used one for modelling spatial effects (Quddus 2008; El-Basyouny and Sayed, 2009; Wang et al., 2012; Guo et al., 2010). According to Besag et al. (1991), the matrix C can be defined as an adjacency matrix where $C_{ii} = 0$, and $C_{ij} = 1/n_i$ if entity i and j are adjacent and $C_{ij} = 0$ otherwise. The diagonal matrix M is defined as $M_{ii} = 1/n_i$. For these particular definition C and M, $\gamma = 1$. Here n_i is the number of neighbours of site i. Under these definitions, the conditional distribution equation (3-40) can be expressed as

$$\boldsymbol{s_i} | \ \boldsymbol{s_{-i}} \sim \boldsymbol{N}\left(\bar{\boldsymbol{s_\iota}}, \boldsymbol{\sigma_s^2}/\boldsymbol{n_i}\right), \ \bar{s}_i = \sum_{j \in C(i)} s_j / n_i \, , \ v = \sigma_s^2 \tag{3-41}$$

where $C(i)$ denotes the set of neighbors of entity i and σ_s^2 is the spatial variation.

In equation (3-41), s_i is normally distributed with conditional mean is the mean of adjacent spatial effects, while the conditional variance is inversely proportional to the number of neighbors. In the model estimation, it is required to specify prior distribution of σ_s^2. It is assumed that $\sigma_s^{-2} \sim gamma(\varepsilon, \varepsilon)$, where ε is a small number (e.g., 0.01 or 0.001).

CAR Model for Multivariate

For p-dimensional multivariate response variable, the spatial effect can be expressed as follows:

$$s_i = (s_{1i}, s_{2i} ...., s_{pi}), i = 1, 2, ..., N. \tag{3-42}$$

Keeping the same definition of C, M, and γ, the conditional distribution under multivariate assumption can be expressed as (Thomas et al., 2004):

$$\boldsymbol{s_i} | \ \boldsymbol{s_{1(-i)}}, \boldsymbol{s_{2(-i)}}, \ldots \sim \boldsymbol{MVN}\left(\bar{\boldsymbol{s_\iota}}, \boldsymbol{v}/\boldsymbol{n_i}\right), \ \bar{s}_i = (\bar{s}_{i1}, \bar{s}_{i2}, \ldots), \ \bar{s}_{ip} = \sum_{j \in C(i)} s_{jp} / n_i \tag{3-43}$$

$$v = \begin{pmatrix} \sigma_{s11} & \sigma_{s12} & \cdots & \cdots \\ \sigma_{s21} & \sigma_{s22} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \sigma_{sk1} & \sigma_{sk2} & \cdots & \cdots \end{pmatrix} \tag{3-44}$$

Similar to univariate CAR, it is required to specify prior distribution of v for model estimation.

For multivariate CAR model, following priors were used:

$v^{-1} \sim Wishart\ (I, K)$, where I is the $K \times K$ identity matrix (Aguero-Valverde, 2013).

3.2.4 Empirical Bayesian Approach

Within the EB framework, estimating the number of expected after-period crashes, π, involves two main steps: i) develop the safety performance function (SPF), and ii) combine the number of predicted crashes with the observed crashes to estimate π. The SPFs are developed independently for each crash group. Conventionally, a negative binomial (NB) distribution is used for developing the SPF within the EB framework (HSM, 2010). However, in the current thesis, PLN distribution was assumed for the EB approach to be consistent with the FB analysis. Before using the estimated SPFs of different crash groups in the EB method, they were calibrated with the reference group data for both the before and after periods (Hauer, 1997; Persaud and Lyon, 2007; Persaud et al., 2010). The purpose of performing the calibration is to account for the influence of various external factors that change from the before period to the after period and that cannot be accounted for through the available covariates in the model (Hauer, 1997).

According to the principle of the EB approach, the expected number of crashes at the treated sites before the implementation of intervention ($\mu_{\exp ected,ibk}$) is the weighted average of the predicted crashes ($\mu_{,ibk}$) and observed crashes (O_{ibk}) as shown below (Hauer, 1997):

$$\mu_{expected,ibk} = w_{ik}\mu_{,ibk} + (1 - w_{ik})O_{ibk} \tag{3-45}$$

Here, $$w_{ik} = \frac{1}{1 + \frac{Var(y_{ik})}{E(y_{ik})}} \tag{3-46}$$

For the PLN model (El-Basyouny and Sayed, 2009b),

$$E(y_{ik}) = \mu_{ibk}\exp(0.5\sigma_k) \text{ and } Var(y_{ik}) = \left[E(y_{ik})\right]^2\left[\exp(\sigma_k) - 1\right] \tag{3-47}$$

In the above equation, σ_k is the over-dispersion parameter for crash group k, which is obtained as a part of the PLN model estimation using the approximate maximum likelihood technique.

To address the change in traffic volume from the before period to the after period, a factor (r) is applied to $\mu_{expected,ibk}$ to obtain the $\mu_{expected,iak}$ (Hauer, 1997; HSM, 2010). Note that, since the current thesis used three years of crash data for both periods, no adjustment is needed for the duration of the before and after periods.

$$\pi_{ik} = \mu_{expected,iak} = \mu_{expected,ibk} \times r \tag{3-48}$$

where,

$$r = \frac{\mu_{iak}}{\mu_{ibk}} \tag{3-49}$$

Within the EB framework, the overall odds ratio obtained from Eq. 3-22 is biased, and hence an unbiased estimation of the overall odds ratio is calculated with the following equation (Hauer, 1997; HSM, 2010):

$$OR_{overall} = \frac{\sum_{\text{All sites}} \lambda \Big/ \sum_{\text{All sites}} \pi}{1 + Var\left(\sum_{\text{All Sites}} \pi\right) \Big/ \left(\sum_{\text{All Sites}} \pi\right)^2} \tag{3-50}$$

where,

$$Var\left(\sum_{\text{All sites}} \pi\right) = \sum_{\text{All sites}} \left[(\mathrm{r})^2 \times \mu_{\text{expected},ibk} \times (1 - w_{ik})\right] \tag{3-51}$$

Now, to examine the statistical significance of the safety effectiveness, the variance of the odds ratio is calculated using the following formula (HSM, 2010):

$$Var(OR) = \frac{\left(\sum_{\text{All sites}} \lambda \Big/ \sum_{\text{All sites}} \pi\right)^2 \left[1 \Big/ \sum_{\text{All sites}} \lambda + Var\left(\sum_{\text{All Sites}} \pi\right) \Big/ \left(\sum_{\text{All Sites}} \pi\right)^2\right]}{\left[1 + Var\left(\sum_{\text{All Sites}} \pi\right) \Big/ \left(\sum_{\text{All Sites}} \pi\right)^2\right]} \tag{3-52}$$

Standard error of safety effectiveness, $SE(\text{Safety Effectiveness}) = 100 \times \sqrt{Var(OR)}$

If $Abs\left[\text{Safety Effectiveness/SE(Safety Effectiveness)}\right] \geq 2.0$, the intervention effect is significant at the (approximate) 95% confidence level (HSM, 2010).

3.2.5 Parameter Estimation

The posterior distributions needed in the full Bayesian (FB) approach can be obtained using MCMC sampling techniques available in WinBUGS (Lunn et al., 2000). The Wishart distribution can be sampled using a Gibbs sampler. Monitoring convergence is important because it ensures that the posterior distribution has been found, thereby indicating when parameter sampling should begin. To check convergence, two or more parallel chains with diverse starting values are tracked to ensure full coverage of the sample space. Convergence of multiple chains is assessed using the Brooks-Gelman-Rubin (BGR) statistic (Brooks and Gelman, 1998). A value less than 1.2 of the BGR statistic indicates convergence. Convergence is also assessed by visual inspection of the MCMC trace plots for the model parameters, as well as by monitoring the ratios of the Monte Carlo errors relative to the respective standard deviations of the estimates; as a rule, these ratios should be less than 0.05.

For Empirical Bayesian (EB) approach, the NLMIXED procedure of statistical software, SAS version 9.3, was used to estimate the parameters of the PLN model (SAS Institute Inc., 2011). The Akaike information criterion (AIC) was used to compare alternative models, with a smaller AIC representing better fit. For the individual parameters to be significant, t-statistics were used at the 95% confidence level (5% level of significance).

3.2.6 Model Assessment

When different modelling approaches are used, it is important to compare the performance of the models and find the best-fitting model. This thesis adopted the Deviance Information Criterion (DIC) for model comparison. As a goodness-of-fit measure, DIC is a Bayesian generalization of Akaike's Information Criteria (AIC) that penalizes larger parameter models. Similar to the AIC, the model with the smallest DIC is estimated to be the model that would best predict a replicate dataset of the same structure as that currently observed (Spiegelhalter et al., 2002). According to Spiegelhalter et al. (2005), it is difficult to determine what would constitute an important difference in DIC. Very roughly, differences of more than 10 might definitely rule out the model with the higher DIC. Differences between 5 and 10 are considered substantial. However, if the difference in DIC is less than 5, and the models make very different inferences, then it could be misleading to report only the model with the lowest DIC. Basyouny and Sayed (2009a) showed that the DIC is additive under independent models. Therefore, DIC values of the univariate models were added to compare with the corresponding multivariate models. For the individual parameters to be significant, the credible interval at 95% confidence level should not contain zero.

For EB method, AIC was used to compare alternative models. For the individual parameters to be significant, t-statistics are used at 95% confidence level (5% level of significance).

4.0 Data Description

4.1 Background

Citizen Satisfactory Surveys conducted in 2004, 2007 and 2009 by the Edmonton Police Service (EPS) have identified speeding as the top community problem in Edmonton. Moreover, Edmonton City Councillors continuously receive speeding complaints, which are often validated through subsequent spot speed surveys. Consequently, the City of Edmonton Office of Traffic Safety (OTS) led a workshop and survey initiative to obtain community partners' and key stakeholders' views about the potential of reducing the speed limit on residential roads. Based on the recommendations that emerged from the workshop and online survey, a decision was made to reduce the speed limit from 50 km/h to 40 km/h on a select number of residential roads in the City of Edmonton.

The community selection process started in October of 2009 and ended in February 2010. The Analytic Hierarchy Process (AHP), a well-known multi-criteria decision analysis tool, was used to identify the top 25 neighborhoods, from which six candidate communities (eight neighbourhoods) were selected to undergo PSL reduction. Three more communities were selected to serve as control groups. Historical data for crashes, speed characteristics, traffic volume, vulnerable road users, speeding complaints, impaired driving and community league recommendations was used as the criteria in the AHP process (details of the community selection process can be found in Tjandra and Shimko, 2011). The installation of the new 40 km/h speed limit signs started in early April 2010, but the signs remained covered for the remainder of the month until the bylaws came into effect on May 1, 2010. No engineering nor infrastructure changes were made in the study area.

To ensure compliance with the new PSL and to reduce speeding, a variety of educational and enforcement measures were taken. Educational measures included i) a pre- and post-communication plan; ii) media campaign (local TV, print, radio, online); iii) speed display boards (also known as speed trailers), dynamic messaging signs and school dollies; and iv) community speed programs (Speed Watch, Neighborhood Pace Cars). In terms of enforcement, two types of mobile photo enforcement were used: safe speed community vans and covert photo-radar trucks. Enforcement was performed in three waves: the first wave was in June, where only safe speed community vans were used, while the second and third waves were in September and October, respectively, and these included both types of enforcement. Each of the six communities received approximately 200 hours of enforcement deployment between the time periods of May 2010 and October 2010. Enforcement before the speed limit reduction was quite random with maximum hours of deployment at approximately 100 hours over the same time period in 2009 (details about the enforcement activities can be found in El-Basyouny, 2011).

Effective May 1, 2010, posted speed limits (PSLs) in eight residential neighbourhoods (six residential communities: some communities are made up of multiple neighborhoods) were reduced from 50 km/h to 40 km/h. In this thesis, these neighbourhoods are referred as treated neighbourhoods. In addition to the treated neighbourhoods, the pilot program considered another three neighbourhoods as a control neighbourhood for speed data collection where the speed limits remained at 50 km/h. All the treated and control neighbourhoods belongs to three different neighbourhood designs, which are old, grid and new neighbourhood (Table 4-1). Old neighbourhoods are characterized by constrained road geometry with more curves and cul-de-sacs (Figure 4-1). Grid pattern neighbourhoods, as reflected in the name, have a typical grid road network system (Figure 4-2). New neighbourhoods have wider road dimensions with long curvilinear roads and loops, and cul-de-sacs oriented along the main collector roads (Figure 4-3). Table 4-2 presents other features of the six treated communities, including total population, land area and roadway width. To understand the spatial proximity of the selected communities, Figure 4-4 highlights the six communities on a City of Edmonton map.

Extensive speed and traffic survey data was collected as part of the project. In October 2011, PSL in Beverly Heights, Rundle Height, Twin Brooks, Westridge/Wolf Willow, and Oleskiw neighborhoods have reverted back to 50 km/h while the other three neighborhoods remained at 40 km/h speed limit.

Table 4-1 Neighborhoods Names and Groups

Neighbourhood Design	Group	Neighbourhoods Name
Old (1950's/1960's) neighbourhoods	Treated	Ottewell Woodcroft
	Control	Delwood
Grid-based neighbourhoods	Treated	King Edward Park Beverly Heights Rundle Heights
	Control	Forest/Terrace Heights
New (1970's/1980's) neighbourhoods	Treated	Twin Brooks Westridge/Wolf Willow Oleskiw
	Control	Brintnell

Table 4-2 General Features of each Treated Community

Community Name	Neighborhood Types	Population	Land Area (Square km)	Average Width of Road (m)	
				Collector	Local
Ottewell	Old	6,019	2.5	11.5	10.0
Woodcroft		2,617	1.29	11.5	10.0
King Edward Park	Grid	4,371	1.4	11.0	9.0
Beverly Heights*		3,375	1.38	11.0	9.0
Twin Brooks	New	6,694	2.14	12.5	11.0
Westridge/Wolf Willow**		1,415	0.75	12.5	11.0

*Beverly Heights community is made up of Beverly Heights and Rundle Heights neighbourhoods.
**Westridge/Wolf Willow community indicates both Westridge/Wolf Willow and Oleskiw neighbourhoods.

Figure 4-1: Aerial View of the Treated Old (1950's/1960's) Communities: Left: Woodcroft Right: Ottewell.

Figure 4-2: Aerial View of the Treated Grid-based Communities: Left: King Edward Park Right: Beverly Heights.

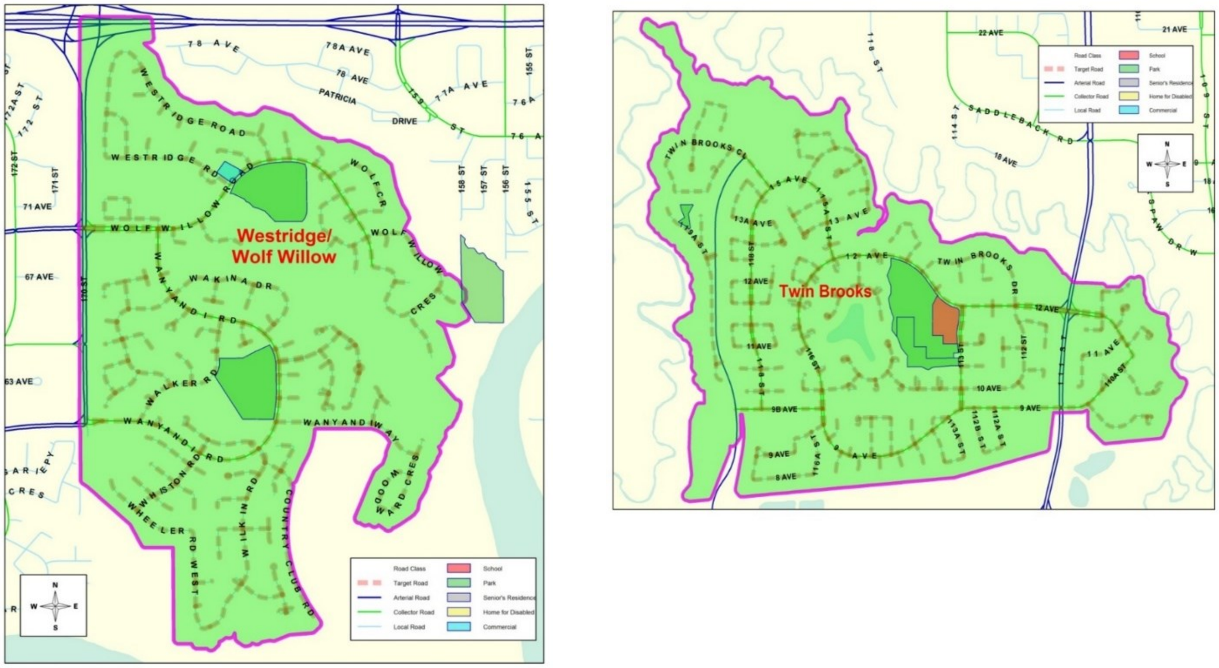

Figure 4-3: Aerial View of the Piloted New (1970's/1980's) Communities: Left: Westridge/Wolf Willow, Right: Twin Brooks

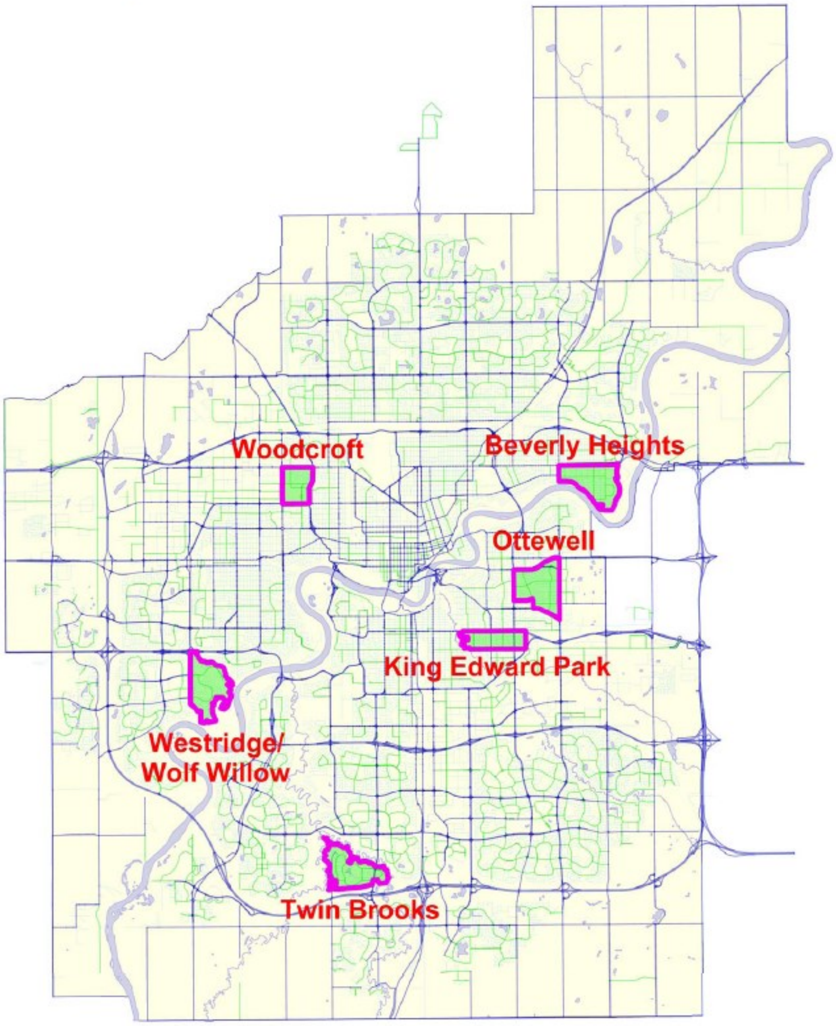

Figure 4-4: Map Showing Six Treated Communities.

For this thesis, numerous datasets were collected and processed to apply the developed methodology in an effort to evaluate the safety effects of the posted speed limit reduction pilot program. Many of these datasets were processed and linked through geographic information system (GIS). A description of the data sets is provided below.

4.2 Speed Data

Spot speed and traffic count data for this thesis were obtained from the City of Edmonton Office of Traffic Safety. Speed and traffic surveys were conducted using a Vaisala Nu-Metrics Portable Traffic Analyzer NC200. A comprehensive validation of the NC200 devices for their accuracy was made before deploying them for large scale data collection. These devices have built-in sensors that can detect, count, classify, and measure individual vehicular speeds. Continuous speed and traffic data was collected on a 24/7 basis for a period of seven months from April 1st to October, 31st, 2010. The data collected during April was used as a baseline representing the "before" conditions. Alternatively, the six months of data from May to October was used to represent the "after" conditions.

Surveys were conducted in a total of 65 locations within the eight treated and three control neighborhoods. There were a total of 51 and 14 locations surveyed within the treated and control neighborhoods, respectively. Among the 65 survey locations, 45 were on collector roads and 20 were on local roads. Speed survey locations within the neighbourhoods were randomly selected to capture the overall speed behavior in the selected neighborhoods. A detail list of the speed survey sites can be found elsewhere (El-Basyouny, 2011). There were two separate datasets, one for the treated group and another for the control group, comprising over 19 million and 5.1 million individual vehicle data records, respectively. However, this thesis used a subset of the data for the evaluation. Thus, the data for the third month (July, representing 3 months after the speed reduction implementation) and sixth month (October, representing 6 months after the speed reduction implementation) was used to perform two separate waves of evaluations.

Raw vehicle data was processed and screened before the start of the analysis. Individual vehicle data (including speed, vehicle classification, time, and date) was generated using custom software. Erroneous data points, such as vehicles with zero speed, were excluded from the analysis.

The vehicle type classification separated light vehicles from heavy vehicles. The operations of light and heavy vehicles are different, and their drivers are likely to respond in a different way to a PSL reduction. To be consistent with the city's classification structure, any vehicle with a length not exceeding 8.4 m was classified as a light vehicle (i.e., passenger vehicle, van or pickup); otherwise, it was classified as a heavy vehicle (i.e., bus, truck or tractor).

Data was further divided into time of day (i.e., night-time vs. day-time periods) and day of week (i.e., weekday vs. weekend) classifications representing temporal impact. There is a significant variation in daylight hours over the year in Canada. Therefore, the sunset/sunrise data maintained by the National Research Council of Canada (NRC) was collected. This data was merged with the speed data to identify whether the vehicles were travelling during the day-time or night-time hours. To account for the changes in speed behavior during the day of week, another time classification was used to differentiate between weekdays (Monday-Friday) and weekends (Saturday and Sunday). Any moving (i.e., statutory) holiday was included in the weekend category.

A potential confounding factor affecting the choice of driver speed is congestion. A driver traveling behind a slow moving vehicle may not be traveling at his or her preferred free-flow speed; such behaviour might act as a confounding factor in the analysis. Therefore, to obtain free-flow speed, we removed data for vehicles that were not traveling under free-flow conditions, thereby minimizing the influence of lead vehicles. Vehicles traveling at a headway of 2 (or less) seconds were deemed to not be traveling under free-flow conditions, and, subsequently, their records were removed. The 2-second rule stems from the City of Edmonton advisory that, under normal dry weather conditions, drivers follow a 2-second headway (Alberta's basic driver license handbook also recommends a 2-second headway rule under normal dry conditions). Vehicles having 2 seconds (or less) headway are referred to as "tailgating vehicles". Further, the studied roads are part of residential areas; hence, most of the traffic was local rather than commuter. Therefore, congestion was not an issue on these roads, which was verified through the continuous traffic data available. Additionally, Evans and Wasielewski (1983) noted that headway of 2.5-second in a freeway reduces the interaction of vehicles to nearly zero. Considering that freeways are typically high speed roads with speed limits of 80-110 km/h, while the studied roads are lower speed, urban residential roads with speed limits of 50 km/h or 40 km/h, it is reasonable to assume a headway cut-off value of 2-seconds. Moreover, a headway sensitivity analysis was performed to investigate headway impact on mean free-flow speed.

Speeding behavior on collector roads is sometimes quite different from speeding behavior on local roads; because of a comparatively high design standard with generous, wide lanes, Edmonton's collector roads encourage higher speeds. Thus, a separate investigation was performed to examine how the PSL reduction affects vehicle speed for these two road types.

Weather is another confounding factor. The literature indicates that drivers respond to poor weather conditions by reducing their speeds (Liang et al., 1998). To negate this issue, weather data, which was acquired from the National Climate Data and Information Archive maintained by Environment Canada, was matched with speed data to remove from the analysis any records of adverse weather, such as rainfall.

For the purpose of developing mixed-effect and multilevel model, one month of before data and one month of after data was used. After removing any records of adverse conditions, the final dataset consisted of 86,586 hourly observations for model development. In addition to the speed data obtained from the city, information on roadway width and the presence of bus stops was collected from separate databases. Further, the proportion of vans/buses/trucks was calculated by dividing the hourly count of these vehicles by the total hourly vehicles. Table 4-3 shows the summary of the data with the list of variables considered for the mixed effect model. As seen, time of day (i.e., daytime versus night-time), day of the week (i.e., weekdays versus weekend), and morning (7-9 AM) and evening (4-6 PM) peak hours were considered to take into account the temporal effects. Hourly traffic volume and the proportion of particular vehicle classes were used to take into account the effects of traffic and its composition on speed behaviour. Road width, road class, and the presence of bus stops were considered to represent roadway geometry and other road conditions. From the individual vehicle speed data, the number of vehicles per hour with speed below or equal to the thresholds of 50 km/h, 60 km/h, 70 km/h, and 80 km/h were calculated and often referred to in the thesis as the vehicles in compliance with those thresholds. This has been done to investigate the change in the speed profile after the PSL reduction.

The speed dataset clearly had a natural hierarchy with individual observations as Level 1, the site as Level 2, and the community as Level 3. Therefore, a multilevel (i.e., three-level) modelling approach was adopted. For the multilevel model, the data organization is little different from that of mixed-effect model. Table 4-4 presents the data for multilevel model.

Table 4-3 Summary Statistics of the Speed Data for Mixed-effect Model

	Variable	Mean	Std. Dev.	Min	Max
Treated sites (before period) 51 sites (38,559 Hours of observations)	Time of day (1 for daytime, 0 otherwise)	0.64	0.48	0	1
	Day of the week (1 for weekdays, 0 otherwise)	0.69	0.46	0	1
	Proportion of vans/buses/trucks	0.13	0.11	0	1
	Morning peak	0.03	0.16	0	1
	Evening peak	0.03	0.16	0	1
	Road width (metres)	10.51	1.95	6.55	14.5
	Road class (1 for collector, 0 for local)	0.72	0.45	0	1
	Presence of bus stop	0.42	0.49	0	1
	Traffic volume (vehicles/hour)	78.04	87.18	1	871
	Vehicles below or equal to 50 km/h (veh/hour)	40.11	46.09	0	472
	Vehicles below or equal to 60 km/h (veh/hour)	65.82	73.65	0	779
	Vehicles below or equal to 70 km/h (veh/hour)	74.69	83.79	0	846
	Vehicles below or equal to 80 km/h (veh/hour)	76.93	86.14	0	859
Treated sites (after period) 51 sites (30,135 Hours of observations)	Time of day (1 for daytime, 0 otherwise)	0.49	0.50	0	1
	Day of the week (1 for weekdays, 0 otherwise)	0.61	0.49	0	1
	Proportion of vans/buses/trucks	0.13	0.12	0	1
	Morning peak	0.02	0.14	0	1
	Evening peak	0.03	0.16	0	1
	Road width (metres)	10.52	1.97	6.55	14.5
	Road class (1 for collector, 0 for local)	0.72	0.45	0	1
	Presence of bus stop	0.42	0.49	0	1
	Traffic volume (vehicles/hour)	75.28	85.23	1	533
	Vehicles below or equal to 50 km/h (veh/hour)	50.82	58.41	0	468
	Vehicles below or equal to 60 km/h (veh/hour)	68.02	77.56	0	522
	Vehicles below or equal to 70 km/h (veh/hour)	72.91	83.03	0	528
	Vehicles below or equal to 80 km/h (veh/hour)	74.38	84.44	0	531
Comparison sites (before period) 14 sites (9,912 Hours of observations)	Time of day (1 for daytime, 0 otherwise)	0.63	0.48	0	1
	Day of the week (1 for weekdays, 0 otherwise)	0.69	0.46	0	1
	Proportion of vans/buses/trucks	0.13	0.10	0	1
	Morning peak	0.03	0.16	0	1
	Evening peak	0.03	0.16	0	1
	Road width (metres)	11.30	1.32	9	13.5
	Road class (1 for collector, 0 for local)	0.71	0.45	0	1
	Presence of bus stop	0.53	0.50	0	1
	Traffic volume (vehicles/hour)	74.49	70.39	1	361
	Vehicles below or equal to 50 km/h (veh/hour)	38.50	35.18	0	250
	Vehicles below or equal to 60 km/h (veh/hour)	64.04	60.64	0	339
	Vehicles below or equal to 70 km/h (veh/hour)	71.78	68.46	0	358
	Vehicles below or equal to 80 km/h (veh/hour)	73.58	69.88	0	360
Comparison sites (after period) 14 sites (7,980 Hours of observations)	Time of day (1 for daytime, 0 otherwise)	0.49	0.50	0	1
	Day of the week (1 for weekdays, 0 otherwise)	0.62	0.49	0	1
	Proportion of vans/buses/trucks	0.16	0.11	0	1
	Morning peak	0.02	0.14	0	1
	Evening peak	0.03	0.16	0	1
	Road width (metres)	11.36	1.25	9	13.5
	Road class (1 for collector, 0 for local)	0.70	0.46	0	1
	Presence of bus stop	0.54	0.50	0	1
	Traffic volume (vehicles/hour)	77.84	70.98	1	373
	Vehicles below or equal to 50 km/h (veh/hour)	35.73	32.39	0	226
	Vehicles below or equal to 60 km/h (veh/hour)	63.83	59.76	0	338
	Vehicles below or equal to 70 km/h (veh/hour)	73.77	68.52	0	366
	Vehicles below or equal to 80 km/h (veh/hour)	76.40	70.24	0	370

Table 4-4 Summary Statistics of the Speed Data for Multilevel Model

Variable	Mean	Std. Dev.	Min	Max
Level 1: Individual Observations (86,586)				
Time-of-day (1 for daytime, 0 nighttime)	0.57	0.49	0	1
Day-of-the-week (1 for weekdays, 0 otherwise)	0.66	0.47	0	1
Morning peak* (1 for 7-9 AM, 0 otherwise)	0.02	0.15	0	1
Evening peak* (1 for 4-6 PM, 0 otherwise)	0.03	0.16	0	1
Proportion of vans/buses/trucks	0.13	0.11	0	1
Traffic volume (vehicles/hour)	76.66	83.34	1	871
Time period (1 for after , 0 for before)	0.44	0.50	0	1
Level 2: Speed Survey Site (65)				
Road width (metre)	10.64	1.88	6.55	14.5
Road class (1 for collector, 0 for local)	0.69	0.47	0	1
Presence of bus stop (1 for yes, 0 for no)	0.45	0.50	0	1
Site type (1 for treated, 0 for comparison)	0.78	0.41	0	1
Level 3: Community (9)				
Type 1** (1 for old community, 0 otherwise)	0.33	0.5	0	1
Type 2 (1 for grid community, 0 otherwise)	0.33	0.5	0	1
Type 3 (1 for new community, 0 otherwise)	0.33	0.5	0	1

4.3 Crash Data

The Highway Safety Manual (HSM, 2010) recommends using at least three years of crash data for both before and after periods to perform before-after evaluation of safety intervention. Further, evaluation periods that are even multiples of 12 months in length are used to eliminate seasonal bias in the evaluation result. Moreover, it is recommended to exclude the entire year during which the safety intervention is implemented (HSM, 2010). Another fact in the pilot project of the City of Edmonton is that PSLs in some of the treated neighborhoods reverted back to 50 km/h in October 2011. Keeping these factors in mind, timeline presented in figure 4-5 was used in this research to perform before-after evaluation of crash data.

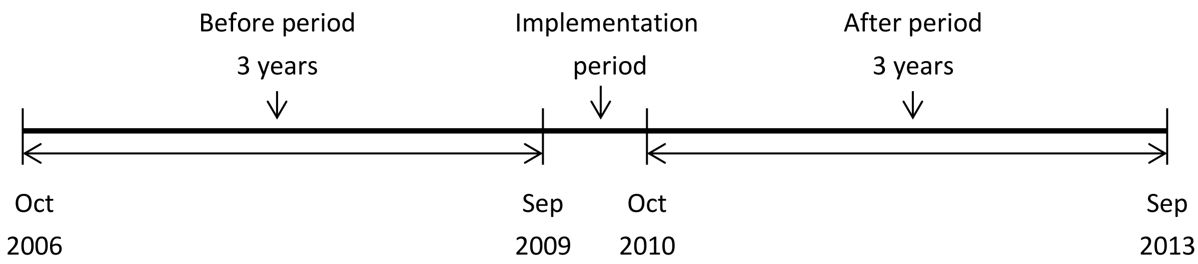

Figure 4-5: Before-After Crash Data Evaluation Timeline

Crash data for this research is obtained from the City of Edmonton's crash database known as Motor Vehicle Collision Information System (MVCIS). While the database records crashes by typical calendar year (i.e., January to December), this research has defined the calendar year as October to September. Based on the severity of crashes, they were divided into two types: severe crashes comprising of fatal and injury crashes, and properly-damage-only (PDO) crashes. Geo-coded crash data were aggregated by road segment for microscopic model and by neighborhood for macroscopic model. For data aggregation by road segment, it is required to first define the road segment. The City of Edmonton street network database, referred as Linear Referencing System (LRS) datum, defines road segments as a links between two nodes where nodes are the intersecting points of two roads (Figure 4-6a). However, in current research, nodes are defined as intersecting points of collector-collector or higher level roads (Figure 4-6b). Current research only focuses on residential roads, and hence all the residential collector roads in the City of Edmonton have been identified and the road network has been segmented as per the definition adopted. Once the segment definition is completed, the crash data was processed to differentiate road segment-related crashes from intersection-related crashes.

For the aggregation of crash data by neighborhood level, crashes occurring at the boundary of the neighborhoods were excluded for several reasons: i) neighborhood boundaries are often arterial and collector with speed limits higher than 50 km/h, while in this research, the reference group should have speed limit of 50 km/h ii) taking neighborhood boundary will cause duplicate counting of the boundary crashes, iii) posted speed limit was used to 40 km/h only for the roads within the boundary of the neighbourhood, and iv) it is unreasonable to attribute crashes occurred at the neighborhood boundary to the neighborhood characteristics (Wang et al., 2012).

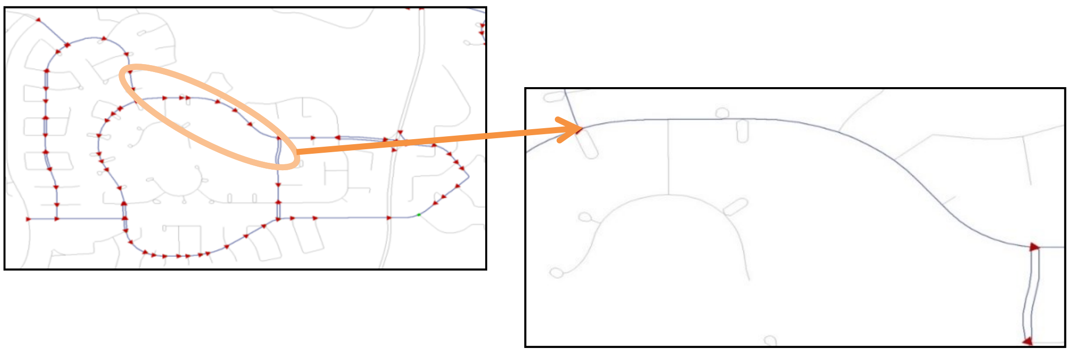

Figure 4-6: Road segment definition a) The City of Edmonton LRS datum, b) adopted in current thesis

4.4 Microscopic Data

Highway Safety Manual (HSM, 2010) summaries a list of variables related to geometric design and traffic control features that are typically used in microscopic crash prediction models (CMPs). An attempt was made to collect as many variables as possible from the various databases of the City of Edmonton. Two main databases used for geometric information are Spatial Land Inventory Management (SLIM) and Geo Engineering Access (GEA). Google map street view was used to collect some variables that were not available in the City's databases. Most of the variables were collected manually as no automation was available. A total of 287 urban residential collector road-segments were identified to use as a reference group for developing microscopic crash prediction model (CPM). Table 4-5 presents the descriptive statistics of these two-lane road segments. Table 4-6 presents the descriptive statistics of the two-lane treated road segments. Mean and standard deviation of crash data clearly shows that crash data are over-dispersed.

Table 4-5 Summary statistics of road-segment related reference data (sample size = 287 two-lane road segments)

Variable	Mean	SD	Minimum	Maximum
Before (Oct 2006–Sep 2009)				
Total crash	7.06	7.32	0	42
Severe (Fatal and Injury) crash	1.00	1.52	0	8
Property-damage-only (PDO) crash	6.06	6.24	0	36
AADT	2962	2285	97	11300
After (Oct 2010–Sep 2013)				
Total crash	6.36	6.39	0	43
Severe crash (Fatal and Injury)	0.93	1.45	0	8
Property-damage-only (PDO) crash	6.36	6.39	0	43
AADT	3037	2269	100	11700
Length in km	0.631	0.424	0.089	3.436
Bus stop number	6.64	5.72	0	35
Presence of bus stop	0.92	0.27	0	1
Bus stop density	11.42	7.93	0	68
Licensed premise number	2.62	6.31	0	69
Presence of licensed premise	0.50	0.50	0	1
Licensed premise density	6.16	16.12	0	132
Recreational centre number	1.21	1.46	0	6
Presence of recreational centre	0.54	0.50	0	1
Recreational centre density	2.65	4.47	0	40
Number of School	0.85	1.07	0	5
Presence of school	0.49	0.50	0	1
School density	1.72	2.73	0	17
Senior centre number	0.21	0.54	0	3
Presence of senior centre	0.15	0.36	0	1
Senior centre density	0.53	2.08	0	25
Access point number	4.76	4.28	0	28
Presence of access point	0.87	0.34	0	1
Access point density	7.41	4.85	0	25
Road width in metres	10.86	2.06	6	17
Presence of bike lane	0.11	0.32	0	1
Mid-block change	0.17	0.37	0	1
Presence of horizontal curve	0.49	0.50	0	1
Presence of street parking	0.67	0.47	0	1
Stop-controlled intersection density	1.23	2.27	0	12
Uncontrolled intersection density	6.07	4.75	0	27

Note: All density calculation is per kilometre.

Table 4-6 Summary statistics of road-segment related treated data (sample size = 27 two-lane road segments)

Variable	Mean	SD	Minimum	Maximum
Before (Oct 2006–Sep 2009)				
Total crash	3.96	2.67	0	10
Severe crash	0.74	0.94	0	4
PDO crash	3.22	2.17	0	9
AADT	2593	1730	700	6425
After (Oct 2010–Sep 2013)				
Total crash	3.15	2.67	0	11
Severe crash	0.26	0.53	0	2
PDO crash	2.89	2.42	0	9
AADT	2789	1749	700	6800
Length in km	0.415	0.215	0.058	0.837
Bus stop number	5.93	4.18	0	17
Presence of bus stop	0.99	0.219	0	1
Bus stop density	18.56	15.66	0	51
Licensed premise number	2.07	2.60	0	9
Presence of licensed premise	0.56	0.51	0	1
Licensed premise density	6.20	8.98	0	35
Recreational centre number	1.26	1.29	0	4
Presence of recreational centre	0.67	0.48	0	1
Recreational centre density	5.40	8.11	0	34
Number of School	1.41	1.31	0	4
Presence of school	0.74	0.45	0	1
School density	3.78	3.54	0	11
Senior centre number	0.33	0.48	0	1
Presence of senior centre	0.33	0.48	0	1
Senior centre density	1.30	2.27	0	8
Access point number	3.26	3.93	0	13
Presence of access point	0.67	0.48	0	1
Access point density	6.15	6.78	0	23
Road width in metres	10.68	1.57	8	13
Presence of bike lane	0.11	0.32	0	1
Mid-block change	0.04	0.19	0	1
Presence of horizontal curve	0.22	0.43	0	1
Presence of street parking	0.74	0.45	0	1
Stop-controlled intersection density	1.19	2.15	0	8
Uncontrolled intersection density	4.54	4.96	0	17

Note: All density calculation is per kilometre.

4.5 Macroscopic Data

In this research, the unit of analysis of the macroscopic model was residential neighborhood. Therefore, from all three types of neighborhoods (i.e, residential, commercial, and industrial), only the residential neighbourhoods are selected. Further, only the mature neighbourhoods that are no more under-construction were selected. Literature suggests the use of various exposures, road and traffic characteristic and socio-demographic variables in developing macroscopic crash prediction models (CPMs). Similar to the data collection from microscopic CMPs, these data was collected from various databases which involves both manual and automatic processes. The City of Edmonton Spatial Land Inventory Management (SLIM) database and GIS were used to obtain some of the geometric variables such as area of the neighborhood, total lane kilometers, etc. Socio-demographic variables were obtained from 2008, 2009, 2012 and 2013 municipal census data of the City of Edmonton. A summary statistics of the macroscopic variables related to 210 residential neighborhoods selected as reference group and eight selected as treated neighborhoods are presented in table 4-7 and table 4-8, respectively.

Table 4-7 Summary statistics of neighborhood related reference data (n = 210 residential neighborhoods)

Variable	Mean	Std. Dev.	Minimum	Maximum
Before				
Total crashes/year	29.15	30.87	0	215
Severe crashes/year	3.43	5.51	0	37
PDO crashes/year	25.72	26.03	0	184
log (VKT)	7.66	0.94	4.09	9.28
Population/year	3125	1438	385	8923
Proportion of students/year	0.24	0.06	0.07	0.43
Proportion of part-time employees/year	0.05	0.01	0.02	0.08
Proportion of full-time employees/year	0.44	0.06	0.14	0.57
Proportion of unemployed/year	0.02	0.01	0.00	0.07
Proportion of retired persons/year	0.12	0.06	0.02	0.38
Dwelling unit/year	1245	659	118	5162
Proportion of males/year	0.50	0.02	0.39	0.63
Proportion of population aged <=15	0.15	0.04	0.00	0.28
Proportion of population aged <=65	0.11	0.06	0.01	0.40
Proportion of households with zero cars	0.09	0.08	0.00	0.41
Proportion of households with >=2 cars	0.49	0.17	0.08	0.86
After				
Total crashes/year	24.11	25.95	0	178
Severe crashes/year	2.47	3.78	0	23
PDO crashes/year	21.64	22.66	0	158
log (VKT)	7.68	0.94	4.13	9.29
Population/year	3279	1654	332	10659
Proportion of students/year	0.23	0.05	0.07	0.42
Proportion of part-time employees/year	0.06	0.01	0.01	0.12
Proportion of full-time employees/year	0.40	0.06	0.14	0.53
Proportion of unemployed/year	0.02	0.01	0.001	0.07
Proportion of retired persons/year	0.12	0.05	0.02	0.32
Dwelling unit/year	1323	716	116	5214
Proportion of males/year	0.50	0.02	0.40	0.59
Proportion of population aged <=15	0.14	0.04	0.03	0.26
Proportion of population aged <=65	0.11	0.05	0.02	0.36
Proportion of households with zero cars	0.09	0.08	0.00	0.41
Proportion of household with >=2 cars	0.49	0.17	0.08	0.86
Number of traffic signals	0.58	1.38	0	8
Collector road length (km)	2.17	1.39	0	11.05
Local road length (km)	8.06	4.00	0	21.08
Total road length (km)	10.23	4.76	1.38	32.14
Old neighbourhood (1 for Yes, 0 for no)	0.23	0.42	0	1
Grid neighbourhood (1 for Yes, 0 for no)	0.12	0.32	0	1
New neighbourhood (1 for Yes, 0 for no)	0.52	0.50	0	1

Table 4-8 Summary statistics of neighborhood related treated data (n = 8 residential neighborhoods)

Variable	Mean	SD	Minimum	Maximum
Before				
Total crashes/year	33.92	23.78	4	93
Severe crashes/year	4.33	4.23	0	14
PDO crashes/year	29.58	20.37	4	82
log (VKT)	7.48	0.97	6.07	8.59
Population/year	3786	1661	1415	6694
Proportion of students/year	0.24	0.06	0.14	0.31
Proportion of part-time employees/year	0.05	0.02	0.03	0.08
Proportion of full-time employees/year	0.41	0.03	0.37	0.47
Proportion of unemployed/year	0.02	0.01	0.005	0.04
Proportion of retired persons/year	0.17	0.08	0.09	0.32
Dwelling unit/year	1569	672	485	2612
Proportion of males/year	0.49	0.02	0.44	0.53
Proportion of population aged <=15	0.14	0.04	0.09	0.22
Proportion of population aged <=65	0.16	0.08	0.08	0.30
Proportion of households with zero cars	0.12	0.11	0.006	0.33
Proportion of households with >=2 cars	0.51	0.22	0.22	0.79
After				
Total crashes/year	31.07	22.87	6	82
Severe crashes/year	2.71	2.70	0	8
PDO crashes/year	28.36	21.23	6	77
log (VKT)	7.50	0.97	6.11	8.60
Population/year	3975	1564	1356	6521
Proportion of students/year	0.21	0.04	0.15	0.29
Proportion of part-time employees/year	0.06	0.01	0.04	0.08
Proportion of full-time employees/year	0.38	0.03	0.35	0.43
Proportion of unemployed/year	0.02	0.01	0.004	0.05
Proportion of retired persons/year	0.18	0.07	0.09	0.27
Dwelling unit/year	1736	646	486	2581
Proportion of males/year	0.49	0.03	0.45	0.53
Proportion of population aged <=15	0.13	0.03	0.09	0.20
Proportion of population aged <=65	0.16	0.07	0.08	0.26
Proportion of households with zero cars	0.15	0.12	0.006	0.33
Proportion of households with >=2 cars	0.43	0.20	0.22	0.79
Number of traffic signals	0.63	0.74	0	2
Collector road length (km)	3.48	1.86	1.27	6.84
Local road length (km)	11.98	5.74	5.41	20.78
Total road length (km)	15.47	7.30	6.68	26.42
Old neighbourhood (1 for Yes, 0 for no)	0.25	0.46	0	1
Grid neighbourhood (1 for Yes, 0 for no)	0.25	0.46	0	1
New neighbourhood (1 for Yes, 0 for no)	0.50	0.53	0	1

5.0 Results of Speed Data Analysis and Evaluation

This chapter presents the results of the before-after speed data analysis performed for both non-model and model based approach. A comparison of alternative methods was discussed and recommendations were made.

5.1 Non-Model Based Approach

Four levels of evaluations were performed to examine the impact of the reduced posted speed limit reduction:

- Level 1: Analysis of the overall effects of the speed limit reduction;
- Level 2: Analysis by neighbourhood type (i.e., old, new, and grid);
- Level 3: Analysis by each community (eight neighborhoods belong to six communities); and
- Level 4: Analysis by each speed survey location.

For the first levels of analysis, weekdays versus weekend, day time versus night time, collectors versus local streets, and light versus heavy vehicle were analyzed separately.

Level 1: Overall Evaluation

The first evaluation combines the eight treated neighborhoods into one group and three control neighborhoods into another group. Table 5-1 shows the speed reductions for all combinations of the day-of-week and the time-of-day periods. All reductions were statistically significant at a 0.0001 level, irrespective of the pooled variance *t*-test and separate variance *t*-test. The results indicate that, without engineering intervention nor other changes to the roadway environment, drivers reduced their travel speed in response to the PSL reduction. These results are contrary to those in Stuster et al. (1998), which found that speed limit changes on low and moderate speed roads had little to no impact on travel speed. As shown in Table 5-1, there were slight speed reduction variations across time-of-day and day-of-week classifications. Mean free-flow speed for the control group showed a consistent increasing trend, indicating that the mean speed for the treated group would have increased without intervention. After accounting for this time trend effect of speed behavior (by using an adjustment factor), the overall mean free-flow speed was reduced by 3.86 km/h three months after intervention, which is equivalent to a 7.7% reduction. After six months, the overall reduction was 4.88 km/h, which is equivalent to a 9.7% reduction. This finding suggests that the speed reduction achieved midway through the project was sustained to the end of the pilot. Overall, the 10 km/h change in the PSL (from 50 km/h to 40 km/h) led to an overall speed reduction of 4.88 km/h, which represents 48.8% of the change in speed limit. A previous study by Finch et al. (1994) also found that lowering the speed limit results in an actual speed reduction of 25%.

As shown in Table 5-1, a separate investigation of light versus heavy vehicles revealed that the speed of heavy vehicles in the treated group was not noticeably reduced. However, when the speeds were adjusted by a control group, statistically significant reductions of 4.88 km/h and 5.57 km/h were found three months and six months after the PSL reduction, respectively. This result clearly demonstrates the necessity of incorporating the control group in the experimental design; otherwise, the conclusion drawn from the simple before-and-after analysis leads to an underestimation of the effectiveness of speed limit reduction, as clearly demonstrated by this thesis.

Alternatively, light vehicles in the treated group showed a noticeable reduction in speed, while the control group experienced a slight increase. In terms of road class, the average speed was higher on collector roads than on local roads. This result was expected, as collector roads are typically associated with a high design standard. Also, many collectors in the City of Edmonton have generous roadway widths, which tend to encourage higher speeds. The analysis reveals that speeds on both collector and local roads were reduced in the after periods and both reductions were statistically significantly. Control group data showed a speed increase for local roads, which implies that the speeding problem is drastically rising on local roads. Mean free-flow speed on local roads was reduced at a higher rate than that of collector roads when adjusted for potential trends. This indicates that the speed limit reduction was more effective in reducing vehicle speed on local roads compared to collectors.

The estimated reduction of mean free-flow speed can be used to estimate the expected crash reduction based on the available speed-crash relationship found in the literature. An extensively cited power model by Nilsson (2004) describes the relationship between speed and road safety in terms of six equations. All the equations have the same functional form with varying exponent values reflecting the different crash types. However, that power model does not provide any equation for estimating changes to property-damage-only (PDO) crashes due to speed change. Later, Elvik et al. (2004) evaluated the validity of the power model by means of a systematic review and meta-analysis. The results provided a strong support for the validity of the power model with a few different values of the exponents. Elvik et al (2004) developed an additional equation to estimate the change in PDO crashes due to changes in speed. Recently, Elvik (2009) has re-analyzed the power model and has developed separate equations for urban and rural areas. One earlier study performed a multivariate linear and non-linear analysis to investigate the relationship between speed and crashes (Finch et al., 1994). Based on both urban and rural data from Finland, Germany, Switzerland, and the USA, they concluded that for every 1 mph (1.6 km/h) increase in the mean speed, there is approximately a 5% increase in crashes.

No specific study was found that developed a relationship between speed and safety for urban residential roads with speed limits of 50 km/h. In the current thesis, overall mean free-flow speed during the before period was estimated at 50.49 km/h and the speed reduction after six months was found to be 4.88 km/h. The Elvik (2009) model would yield a fatal, injury and PDO crash reduction of 23.2%, 11.5 % and 7.8%, respectively. Based on a Finch et al. (1994) study, the reduction in overall crashes is 15.3%. These estimates indicate considerable reductions, given that the speed limit reduction was not supplemented by any costly engineering or infrastructure changes.

Table 5-1 Expected mean free-flow speed and speed variance reduction

		Vehicle Type		Road Type		Night time		Day time		Overall
		Light	Heavy	Collector	Local	Weekend	Weekday	Weekend	Weekday	
Treated (Speed, km/h)	Before	50.34	55.07	51.1	43.8	50.61	50.58	50.83	50.34	50.49
	3-mo After	47.01	53.03	47.71	43.22	46.83	47.06	46.99	47.39	47.23
	6-mo After	46.91	54.06	47.69	41.77	47.59	47.24	47.64	46.7	47.15
Control (Speed, km/h)	Before	50.13	50.75	50.74	47.22	49.62	49.58	49.97	50.37	50.16
	3-mo After	50.63	53.37	50.91	50.03	50.06	50.2	50.43	51.04	50.76
	6-mo After	51.55	54.95	51.46	52.51	51.16	51.66	51.74	51.83	51.69
Adjustment factor	3-mo After	1.01	1.052	1.003	1.06	1.009	1.013	1.009	1.013	1.012
	6-mo After	1.028	1.083	1.014	1.112	1.031	1.042	1.035	1.029	1.031
Speed Reduction (km/h)	3-mo After	-3.83	-4.88	-3.56	-3.19	-4.23	-4.15	-4.31	-3.62	-3.86
	6-mo After	-4.86	-5.57	-4.14	-6.94	-4.59	-5.46	-4.99	-5.1	-4.88
Pooled Variance	3-mo After	114.86	369.04	119.08	140.97	137.5	134.4	122.01	122.3	124.39
	6-mo After	113.12	377.72	117.8	137.26	131.72	126.58	118.54	122.34	123.1
Standard Error	3-mo After	0.01	0.094	0.011	0.043	0.05	0.04	0.02	0.01	0.01
	6-mo After	0.009	0.087	0.009	0.032	0.03	0.02	0.02	0.01	0.01
t value	3-mo After	-382.94*	-51.93*	-337.75*	-73.71*	-87.45*	-116.20*	-208.82*	-279.66*	-377.74*
	6-mo After	-549.92*	-64.35*	-445.73*	-215.36*	-141.08*	-242.54*	-267.22*	-390.51*	-538.93*
F (Critical *F*-value)	3-mo After	1.07 (1)	0.99 (1.01)	1.04 (1)	1.04 (1.01)	1.02 (1.01)	1.01 (1.01)	1.03 (1)	1.06 (1)	1.05 (1)
	6-mo After	1.10 (1)	0.94 (1.01)	1.05 (1)	1.09 (1.01)	1.08 (1.01)	1.12 (1.00)	1.1 (1)	1.06 (1)	1.07 (1)

* Significant at the 0.0001 level.

Changes in speed variance have important safety implications, as higher speed variances tend to be an indicator of more vehicle encounters and overtaking manoeuvres, which increase the probability of a crash (Garber and Gadiraju, 1989; Taylor et al., 2000; Aarts and van Schagen, 2006; SafetyNet, 2009; Dell'Acqua, 2011). Table 5-1 summarizes the results of the *F*-tests for the speed variance analysis three months and six months after reducing the PSL, respectively. Speed variances were significantly reduced for all combinations of time of day and day of week, as well as road and vehicle types; the only exception was heavy vehicles, which constituted less than 4% of the total number of vehicles. Based on the results of this global analysis, it is safe to conclude that the speed limit reduction was effective in not only reducing the mean speed, but also the speed variances. In addition to the reduction of mean free-flow speed, speed variance has decreased after the PSL reduction.

Table 5-2 presents the standard error and *t*-statistics for the combination of time of day and day of week to illustrate the effect of accounting or not accounting for the measurement of uncertainty in the control group. As the table suggests, the standard error was underestimated when the uncertainty was not added, though the magnitude of the underestimation was very little. In addition, though the values of the *t*-statistics slightly reduced when the measurement of uncertainly was added, *t*-statistics were not reduced enough to alter the statistical hypothesis test results.

Table 5-2 Comparison of standard error and t-statistics with and without correction for variance from control

		Night-time		Day-time		
		Weekend	Weekday	Weekend	Weekday	Overall
	Standard error					
Without correction for variance	3-mo After	0.0484	0.0357	0.0206	0.0129	0.0102
	6-mo After	0.0325	0.0225	0.0187	0.0131	0.0091
With correction for variance	3-mo After	0.0495	0.0366	0.0212	0.0135	0.0106
	6-mo After	0.0328	0.0227	0.0190	0.0133	0.0093
	t-statistics					
Without correction for variance	3-mo After	-87.45	-116.20	-208.82	-279.66	-377.74
	6-mo After	-141.08	-242.54	-267.22	-390.51	-538.93
With correction for variance	3-mo After	-85.50	-113.43	-202.97	-267.93	-364.61
	6-mo After	-139.85	-240.09	-262.30	-382.94	-525.42

To confirm the validity of the 2-second headway assumption that separates congested and uncongested conditions, a sensitivity analysis was performed.

Table 5-3 shows the impact of taking different headways on the reduction in mean free-flow speeds. As shown in the table, reductions in mean free-flow speed did not change considerably with the headways. This confirms that taking a 2-second headway is valid for the current dataset.

Table 5-3 Overall Mean free-flow speed and speed reduction for different headways

		Headway		
		>2 second	>3 second	>4 second
Mean Speed (km/h)	Before	50.49	50.56	50.57
	3-mo After	47.23	47.32	47.35
	6-mo After	47.15	47.28	47.30
Speed Reduction* (km/h)	3-mo After	3.26	3.24	3.23
	6-mo After	3.34	3.29	3.27

** Without control group adjustment*

Level 2: Evaluation by Neighborhood Design

The eight treated neighborhoods were grouped into three neighborhood types (old, new, grid), each with distinct road features and vehicle speed behavior. Thus, another analysis was conducted to investigate the change in speed by neighborhood type. Table 5-4 summarizes the free-flow speed reductions for each neighborhood type. All reductions were found to be statistically significant at the 0.01 level. For the pre-intervention period, the mean free-flow speed in the new neighborhoods was always higher than the PSL, whereas the old neighborhoods had a mean speed lower than the PSL. Grid neighborhoods had a mean speed almost equal to the PSL in the before period. The greatest reduction in speed was observed for the new neighborhoods followed by the grid and then the old neighborhoods. Overall, the speed reduction for the new neighborhoods after six months of intervention was found to be almost equivalent to the change of speed limit (10 km/h). Further investigation showed that the greatest speed reduction was observed during night-time weekdays. Speed reduction for heavy vehicles was found to be greater than for light vehicles.

Table 5-4 Mean Free-flow speed reduction by neighborhood type

		Night time		Day time		Overall
		Weekend	Weekday	Weekend	Weekday	
Treated(Old), km/h	Before	47.41	47.43	47.53	47.33	47.38
Speed Reduction (Old),	3-mo After	-2.88	-2.68	-2.55	-2.43	-2.42
km/h	6-mo After	-2.75	-3.40	-3.35	-3.77	-3.47
Treated(Grid), km/h	Before	49.66	49.78	50.23	49.98	49.99
Speed Reduction	3-mo After	-2.57	-2.60	-2.88	-2.70	-2.73
(Grid), km/h	6-mo After	-3.09	-3.51	-3.62	-3.74	-3.58
Treated(New), km/h	Before	53.17	53.08	53.3	52.72	52.92
Speed Reduction	3-mo After	-6.47	-6.24	-7.18	-5.58	-6.15
(New), km/h	6-mo After	-9.70	-11.20	-10.06	-10.16	-9.86

The *F*-tests for the variances (Table 5-5) showed that in all cases, the speed variance reduction was statistically significant in the after period, except for new neighborhoods three months after intervention. Note that new neighborhoods, which are typically characterized by generous lane width with no on-street parking, had a high mean speed in the before period. This finding suggests that it took drivers a longer period of time to adjust their speed choice to the lowered PSL, which might be a cause of higher speed variances at the early stage of the intervention.

Table 5-5 F-test results by neighborhood type

Community		Night time		Day time		Overall
		Weekend	Weekday	Weekend	Weekday	
Old	3-mo After	1.02 (1.02)	1.02 (1.02)	1.04 (1.01)	1.08 (1.01)	1.07 (1.00)
	6-mo After	1.07 (1.02)	1.10 (1.01)	1.09 (1.01)	1.03 (1.01)	1.04 (1.00)
Grid	3-mo After	1.05 (1.01)	1.04 (1.01)	1.04 (1.01)	1.06 (1.00)	1.06 (1.00)
	6-mo After	1.10 (1.01)	1.11 (1.01)	1.08 (1.01)	1.05 (1.00)	1.06 (1.00)
New	3-mo After	0.92 (1.02)	0.94 (1.02)	0.94 (1.01)	0.97 (1.01)	0.96 (1.00)
	6-mo After	1.04 (1.01)	1.08 (1.01)	1.07 (1.01)	1.03 (1.00)	1.04 (1.00)

Note: F-critical values are in parentheses

Figure 5-1 illustrates the speed percentiles for the treated and control neighborhoods. The figure shows that the cumulative speed distribution during the after period lies above that of the before period for the treated neighborhoods. This suggests that the intervention was successful in reducing speed, especially when in comparison to the control neighborhoods, which show increased speeding trends.

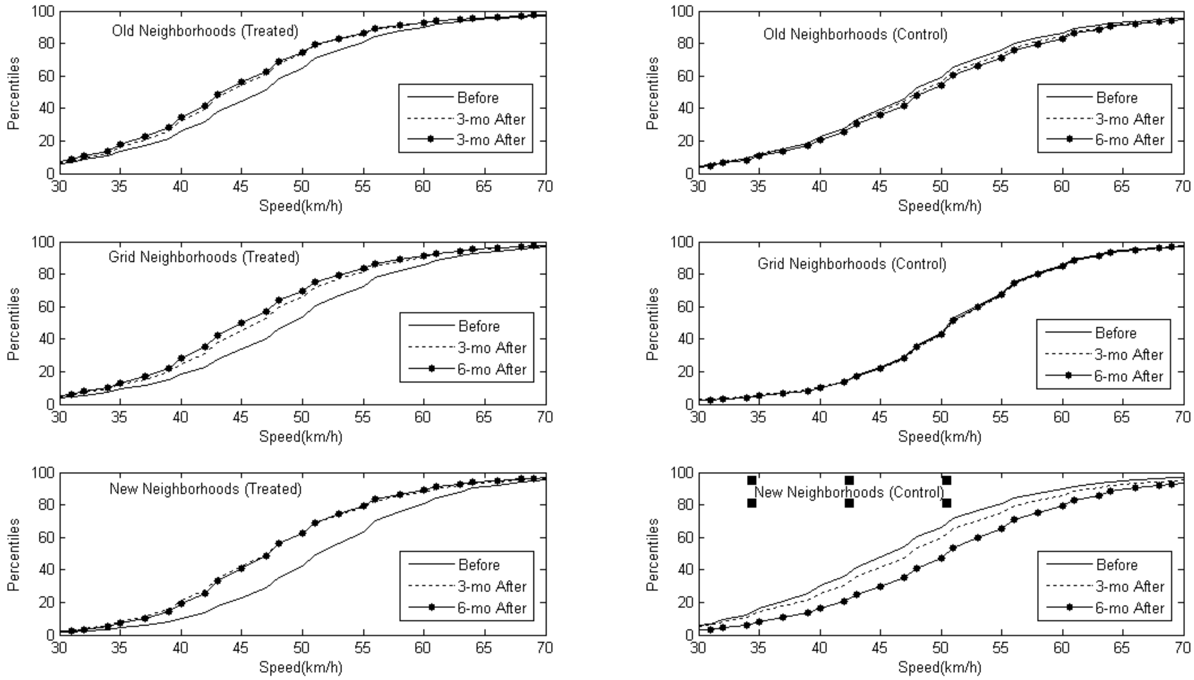

Figure 5-1 Percentile speed profile by each neighborhood type.

Figure 5-2 presents a comparison of the percentages of drivers exceeding 50 km/h and 65 km/h during the before and after period for both the treated and control neighborhoods. Two observations can be made from this figure: 1) while the treated neighborhoods experience a declining speeding trend at both 50 km/h and 65 km/h, the control neighborhoods experience an increasing trend; and 2) within the treated neighborhoods, the level of speeding is noticeably reduced from the before to the after period with a further declining trend between the three-month and six-month after period. These observations are clear indications of the effectiveness of the PSL reduction.

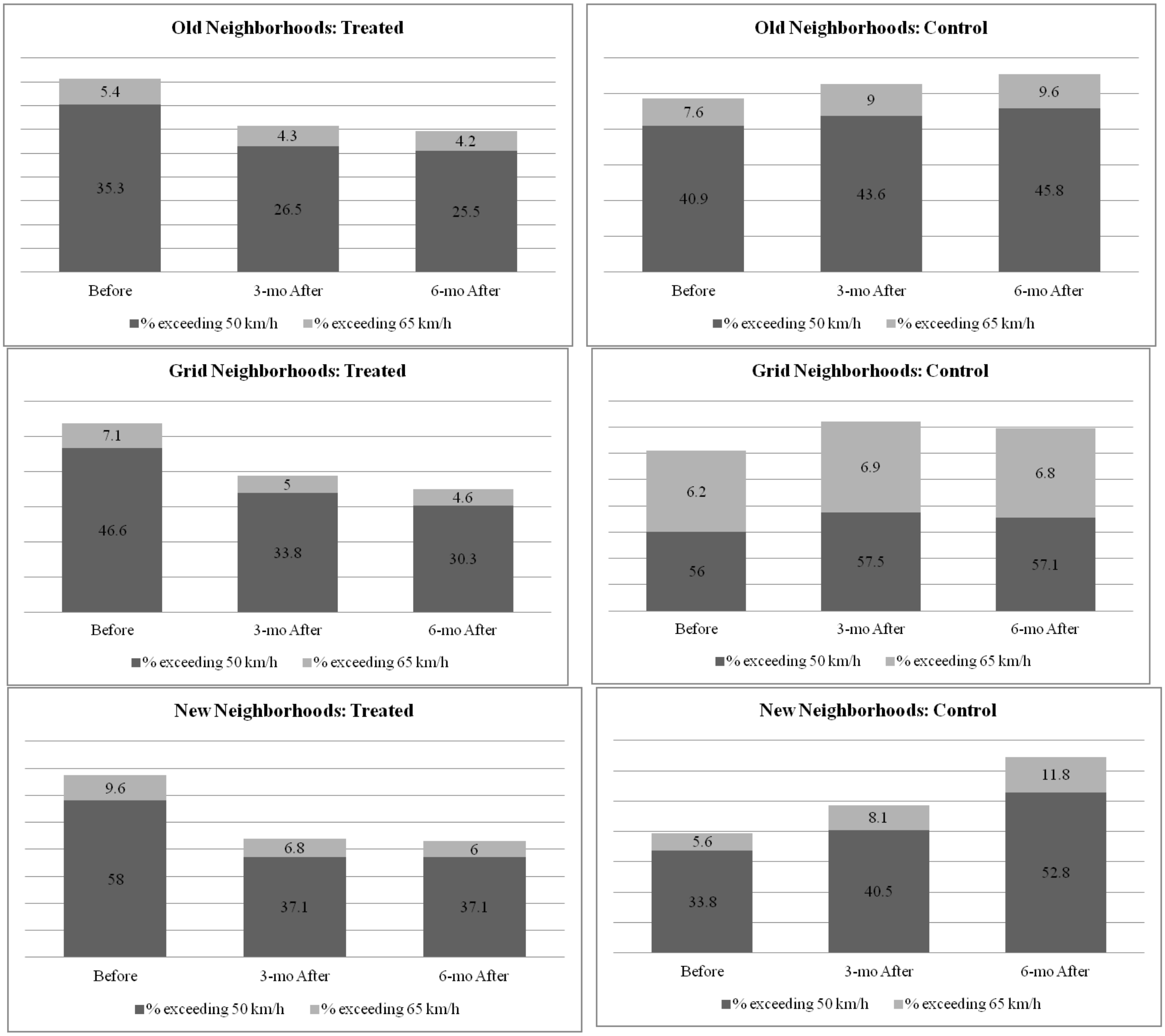

Figure 5-2 Speed limit compliance by neighborhood type.

Although not all speeders will get into or cause crashes, speeders are a major safety concern: they are statistically more likely to cause a crash than other drivers. This increased risk is a major safety problem on low speed roads, especially given the presence of vulnerable road users. The 85th percentile value can be seen as an indication of this problem. Error! Reference ource not found.Figure 5-3 shows the 85th percentile speed for the treated and control neighborhoods. The 85th percentile speed was reduced in the treated neighborhoods, in contrast to an increase in the control neighborhood. This figure indicates that more people in the treated neighborhood are driving at a lower speed in the after period compared to that of the before period.

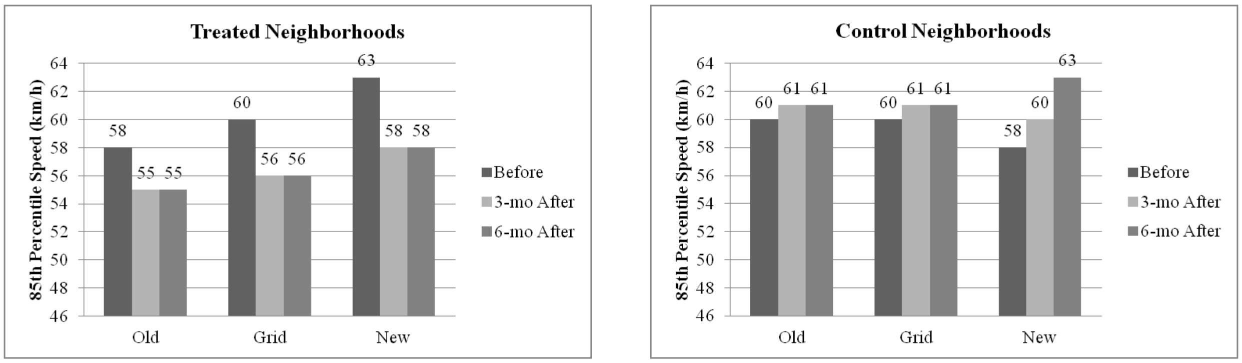

Figure 5-3 85th percentile speed by neighborhood type.

Level 3: Evaluation by Individual Community

A separate investigation by each of the six communities (eight neighborhoods belongs to six communities) was made to see if there exists any variation in speed reduction among them. Table 5-6 presents the summary of the results. As the Table shows the speed reduction in the first four communities (Old and Grid) are within the same range, while the last two communities (New) had higher speed reductions. One important finding here is that the higher speed reduction was observed at sixth month of the intervention compared to that of third month for all the communities. This indicates that the effectiveness of the speed limit reduction increased with time.

Table 5-6 Free-Flow Speed Reduction for each Community

		Night time		Day time		Overall
		Weekend	Weekday	Weekend	Weekday	
Ottewell	Before	48.6	48.32	48.19	46.94	47.45
Speed Reduction,	3rd Month	-2.51	-1.94	-2.26	-1.57	-1.78
km/h	6th Month	-2.68	-3.83	-3.38	-4.45	-3.67
Woodcroft	Before	46.28	46.59	46.9	47.63	47.33
Speed Reduction,	3rd Month	-3.07	-2.98	-2.71	-2.98	-2.81
km/h	6th Month	-2.82	-3.02	-3.31	-3.11	-3.30
King Edward	Before	51.84	52.01	51.98	51.26	51.52
Speed Reduction,	3rd Month	-2.43	-2.64	-2.61	-2.30	-2.41
km/h	6th Month	-3.11	-3.69	-3.56	-3.62	-3.40
Beverly Height	Before	48.52	48.57	49.12	49.03	48.96
Speed Reduction,	3rd Month	-2.54	-2.67	-2.96	-3.14	-3.02
km/h	6th Month	-3.18	-3.55	-3.81	-3.91	-3.76
Twin Brooks	Before	53.36	53.3	53.45	52.71	53
Speed Reduction,	3rd Month	-9.12	-9.02	-9.93	-7.81	-8.61
km/h	6th Month	-10.01	-11.44	-10.25	-10.19	-9.97
Westridge	Before	52.46	52.17	52.78	52.74	52.66
Speed Reduction,	3rd Month	-4.25	-3.86	-5.01	-4.48	-4.60
km/h	6th Month	-8.58	-10.19	-9.40	-10.08	-9.50

Level 4: Evaluation by Survey Sites

Table 5-7 shows the mean free-flow speeds and sample sizes for all three periods (before, 3-month after and 6-month after) and for all the treated and control sites. Mean free-flow speeds for the treated sites were not adjusted by control sites. As shown in the table, all treated sites, except for three (Site ID 13, 15 and 23) experienced a reduction in mean free-flow speed while all control sites, except two (Site ID 56 and 64) experienced an increase in mean free-flow speed for the 6-months after the intervention. When mean free-flow speeds in the intervention sites were adjusted by using control group data, speed reductions were statistically significant at the 0.05 level for all the treated sites, except Site ID 23. After applying the adjustment factor, calculated from the control group, speed reductions among treated sites were found to vary from 0.09-12.56 km/h with a mean value of 4.61 km/h. The *F*-tests showed that speed variances decreased in 27 of the 51 treated sites. Averaging over all sites, the compliance to the speed limit was 61% and 36% before and after the intervention, respectively. When the compliance rate within 15 km/h of the PSL was considered, average compliance rates were estimated at 94% and 86% before and after six months of intervention, respectively. Analysis by survey sites can provide useful information to the agencies to further investigate why some sites had high speed reduction, while others had little. This approach can help to identify supplementary engineering interventions for reducing vehicle speed.

Table 5-7 Mean free-flow speed (km/h) and sample size for treated (ID: 1-51) and control sites ID: 52-64)

Site ID	Before		3-mo after		6-mo after	
	Sample Size	Mean Speed	Sample Size	Mean Speed	Sample Size	Mean Speed
1	53963	43.91	23315	44.09	36509	43.61
2	45259	50.89	31003	45.55	33984	47.78
3	13073	41.35	5841	40.15	9316	40.11
4	40189	51.76	28032	48.27	38867	49.31
5	6997	39.74	3026	40.38	6443	37.55
6	16468	41.97	8937	40.24	13820	40.55
7	10034	40.94	4078	40.08	9030	38.6
8	9103	39.15	4526	39.05	9387	38.47
9	93687	49.86	55774	49.47	75045	45.77
10	76319	49.88	57671	47.39	54362	47.31
11	36196	45.56	26260	43.05	26018	43.38
12	69647	53.09	49145	49.38	46672	52
13	26359	42.11	21552	41.39	19535	42.51
14	30163	40.54	23455	39.25	26528	40
15	21361	42.8	18480	43.5	17170	43.1
16	40466	44.06	31466	42.71	28898	42.13
17	38460	50.78	25784	48.95	25739	46
18	9202	37.3	7431	36.31	9002	36.04
19	120543	49.35	84785	48.44	88360	44
20	136626	47.48	91025	47.39	95115	45.6
21	148378	53.14	87332	50.12	107104	49.88
22	177473	58.96	122043	55.1	129476	55.93
23	11457	33.2	8186	33.01	9487	33.26
24	15650	41.15	10738	40.02	14036	39
25	10064	36.8	6647	35.06	8712	34.68

Site ID	Before		3-mo after		6-mo after	
	Sample Size	Mean Speed	Sample Size	Mean Speed	Sample Size	Mean Speed
26	7731	40.86	5104	39.12	7473	39.77
27	55266	48.9	38122	45.52	41348	47.46
28	39774	44.88	29909	45.2	28184	44.62
29	122066	52.84	67864	51.24	66777	48.71
30	133451	52.63	71532	48.98	80782	49.49
31	93832	52.38	57278	48.59	64491	47.2
32	140427	46.46	95018	43.55	102614	42.95
33	173623	49.27	105070	47.53	120644	46.72
34	246750	45.37	165389	42.58	197859	42.38
35	51414	52.78	31074	49.26	39214	48.71
36	11849	40.05	7545	41.09	7886	38.94
37	3570	40.19	2552	39.49	2690	39.74
38	24320	49.61	---	---	15784	44.73
39	26038	47.31	20729	45.94	18056	44.27
40	48327	50.37	41279	47.62	41181	48.57
41	208647	53.18	---	---	171973	49.51
42	102787	53.95	---	---	98436	47.33
43	109264	51.67	---	---	77383	48.37
44	147623	56.69	---	---	109354	51.63
45	98687	55.08	---	---	96721	50.66
46	79104	51.75	---	---	45241	47.82
47	53737	47.73	38710	45.59	40623	44.27
48	43454	52.17	34386	49.49	34502	46.79
49	62782	54.58	52296	50.21	52267	50.75
50	47730	49.37	30650	48.01	41626	44
51	111440	53.17	69014	51.39	86697	51.12
52	59935	45.18	38177	44.45	57691	49.12
53	34260	49.59	17177	50.86	37958	53.47
54	16294	53.61	25043	54.59	46708	57.23
55	64052	46.57	36023	48.33	62143	50.13
56	16508	43.53	11957	43.51	9649	43.44
57	14969	42.72	8380	42.03	12822	44.01
58	61362	49.19	33038	51.13	47798	50.85
59	31884	45.77	22362	46.46	30361	46.64
60	55630	54.28	33544	54.57	45546	55.51
61	128107	51.04	69034	49.53	99744	51.12
62	151016	50.69	93107	51.87	116439	51.31
63	110934	54.37	67005	55.24	85618	55.03
64	103624	51.43	57684	51.24	68950	50.7

**Site does not have data for 3-mo after period; One site has before data missing; hence total site reported is 64.*

5.2 Generalized Mixed-Effect Intervention Model

The posterior estimates of the parameters for all the mixed models were obtained using WinBUGS via two parallel chains with 50,000 iterations, 10,000 of which were excluded as a burn-in sample. The BGR statistics were less than 1.2; the ratios of the Monte Carlo errors relative to the standard deviations of the estimates were less than 0.05; and trace plots for all of the model parameters indicated convergence.

Free-Flow Speed Model

Table 5-8 presents the model estimation results for the linear mixed-effect model. Only variables found significant based on the 95% credible intervals were reported in this table. It is worth noting that the credible interval for a parameter estimate indicates that there is a 95% probability that the value of the parameter estimate will lie within the interval. As seen in the table, the correlation between observations was estimated as 0.52, indicating that the between-site variation consists of 52% of the total variation. This supports the necessity of taking into account the nested nature of the speed data while modelling. In other words, this finding justifies the use of the mixed-effect model for the current data. Moreover, the goodness-of-fit measure using the posterior predictive approach showed a *p*-value of 0.501, which is close to neither zero nor one, indicating that the observed pattern of the data is likely to be seen in the model-replicated data (Gelman et al., 1996).

Table 5-8 Results of Parameter Estimation and Evaluation of Mean Free-Flow Speed using Mixed-Effect Model

Variable	Parameter Estimate	Standard Deviation	Credible Interval	
			Lower Limit	Upper Limit
Intercept	42.970	2.247	40.990	50.920
Time of day (1 for day time, 0 otherwise)	-0.250	0.036	-0.320	-0.181
Day of the week (1 for weekdays, 0 otherwise)	-0.252	0.031	-0.313	-0.191
Evening peak (4-6 PM)	1.143	0.092	0.963	1.323
Proportion of vans/buses/trucks	9.577	0.143	9.297	9.856
Road class (1 for collector, 0 for local)	7.279	1.368	3.819	9.360
Traffic volume (vehicles/hour)	-0.0057	0.0003	-0.0063	-0.0052
Time period (1 for after, 0 for before)	1.148	0.066	1.018	1.277
Site type*time period	-3.823	0.074	-3.967	-3.679
Adjustment ratio, r	1.027	0.002	1.024	1.030
Odds ratio (OR)	0.923	0.002	0.919	0.930
Free-flow speed reduction, km/h	3.851	0.077	3.703	4.002
Within-site correlation	0.519	0.074	0.421	0.768

In terms of parameter significance, the results revealed various insights into vehicle speed behaviour. The parameter for the time-of-day indicator was found to be negative, indicating that night hours were associated with higher free-flow speed compared to day hours by an average amount of 0.25 km/h. The day-of-the-week variable showed that weekends were associated with higher free-flow speed compared to weekdays by 0.25 km/h. While morning peak hours (7-9 am) were found to be statistically insignificant, the evening peak hours (4-6 pm) were associated with higher mean free-flow speed by 1.14 km/h compared to off-peak hours.

The proportion of vans/buses/trucks was found to have a positive correlation with the free-flow speed, with a 10% increase in the proportion of these vehicles related to an increase of 0.96 km/h in the mean free-flow speed. Collector roads were associated with a mean free-flow speed 7.28 km/h higher than that of local roads. This might be due to the fact that collector roads are of a higher standard than the local roads in terms of their functional class (Gattis and Watts, 1999). It is worth noting that the credible interval of the parameter estimate for collector roads is relatively broad, ranging between 3.82 and 9.36 km/h. An increase in hourly traffic volume was associated with a decrease in the mean free-flow speed, demonstrating the fundamental relationship between speed and traffic flow.

The parameter estimate for the time period (i.e., after period versus before period) was positive, indicating that the mean free-flow speed increased in the after period. However, when the interaction between the site type (i.e., treated versus comparison) and time period was considered, the parameter estimate is negative, indicating that the PSL reduction reduced the mean free-flow speed in the treated sites in the after period. The positive parameter estimate of the time period basically indicates the trend of increased speeding among the comparison sites.

Regarding the before-after evaluation and the results seen in Table 5-8, the adjustment ratio was statistically greater than one, indicating that the mean free-flow speed follows an increasing trend for the study area. This implies the necessity of factoring the time trend effect into the before-after speed data analysis. The odds ratio was statistically less than one, indicating that the PSL reduction was effective in reducing the mean free-flow speed. The reduction of mean free-flow speed was found to be 3.85 km/h with a credible interval away from zero, indicating a statistically significant reduction of the mean free-flow speed in the after period. Furthermore, the credible interval for the mean free-flow speed reduction indicates that the PSL reduction has a 95% probability of reducing the mean free-flow speed between 3.7 km/h and 4.0 km/h.

Probability of Speed below or Equal to Thresholds

Table 5-9 presents the model estimation results for the binomial logistic models for speed below or equal to various speed thresholds. As seen in the table, in all cases, the within-site correlations were found significant, justifying the need to use mixed-effect models. Moreover, the posterior predictive approach of checking the model goodness of fit revealed *p*-values of 0.446, 0.185, 0.162, and 0.149 for the model of 50 km/h, 60 km/h, 70 km/h, and 80 km/h thresholds, respectively. These values indicate that all the models are adequate in replicating the observed patterns of the data.

Table 5-9 Results of Parameter Estimation and Evaluation of Probability of Speed below or Equal to Various Thresholds

Variable	Speed below or equal to 50 km/h			Speed below or equal to 60 km/h		
	Parameter Estimate	Credible Interval		Parameter Estimate	Credible Interval	
		Lower Limit	Upper Limit		Lower Limit	Upper Limit
Intercept	0.170	-0.956	0.817	-0.263	-0.855	0.385
Time of day (1 for daytime, 0 otherwise)	0.025	0.017	0.033	0.139	0.130	0.148
Day of the week (1 for weekdays, 0 otherwise)	0.070	0.063	0.078	0.074	0.065	0.082
Evening peak (4-6 PM)	-0.128	-0.147	-0.108	-0.053	-0.073	-0.032
Proportion of vans/buses/trucks	-1.743	-1.799	-1.687	-2.385	-2.448	-2.322
Road width (metres)	0.528	0.238	0.817	0.550	0.220	0.882
Presence of bus stops	0.836	0.355	1.444	0.295	0.051	0.705
Time period (1 for after, 0 for before)	-0.188	-0.203	-0.172	-0.198	-0.214	-0.181
Site type*time period	0.871	0.854	0.889	0.768	0.750	0.787
Adjustment ratio, r	0.878	0.875	0.882	0.949	0.947	0.950
Odds ratio (OR)	1.376	1.370	1.382	1.112	1.109	1.114
Probability increase	0.200	0.197	0.202	0.092	0.090	0.093
Within-site correlation	0.452	0.123	0.799	0.424	0.035	0.846

Variable	Speed below or equal to 70 km/h			Speed below or equal to 80 km/h		
	Parameter Estimate	Credible Interval		Parameter Estimate	Credible Interval	
		Lower Limit	Upper Limit		Lower Limit	Upper Limit
Intercept	0.343	-1.108	1.777	0.096	-6.077	5.457
Time of day (1 for day time, 0 otherwise)	0.235	0.223	0.247	0.257	0.239	0.274
Day of the week (1 for weekdays, 0 otherwise)	0.065	0.054	0.076	0.072	0.056	0.088
Morning peak (7-9 AM)	*-0.025*	*-0.054*	*0.003*	-0.045	-0.086	-0.004
Proportion of vans/buses/trucks	-2.959	-3.041	-2.878	-3.264	-3.380	-3.147
Road width (metres)	0.509	0.105	0.881	*0.522*	*-0.055*	*1.044*
Time period(1 for after, 0 for before)	-0.188	-0.209	-0.166	-0.181	-0.212	-0.151
Site type*time period	0.547	0.523	0.572	0.403	0.367	0.438
Adjustment ratio, r	0.981	0.980	0.982	0.993	0.992	0.993
Odds ratio (OR)	1.030	1.029	1.031	1.009	1.009	1.010
Probability increase	0.028	0.027	0.029	0.009	0.009	0.010
Within-site correlation	0.502	0.078	0.926	0.586	0.191	0.948

Note: Statistically insignificant variables are marked by italic font with grey background.

In terms of the parameter estimation, results for rates of speed below or equal to various speed thresholds were found quite consistent. The daytime and weekdays were associated with increased probability of speed below or equal to the threshold for all four speed thresholds considered. It is interesting to note that the effect of the daytime on the probability augmented gradually with increase of the speed thresholds. These results are in line with a recent study by Heydari et al. (2014). Evening peak hours were associated with a decrease in the probability of speed below or equal to the 50 km/h and 60 km/h speed thresholds, and insignificant effects to the 70 km/h and 80 km/h speed thresholds when compared to off-peak hours. This result suggests that drivers tend to do minor speeding during the evening peak hours. On the contrary, the morning peak hours were associated with a decrease in the probability of speed below or equal to the 80 km/h speed threshold with insignificant effects for other thresholds. When these results are compared with the finding on mean free-flow speed, it is seen that the models of speed probability for various speed thresholds provided more detailed insight into the effect of peak hours compared to the model of free-flow speed, which provided an aggregated effect. A recent study showed that peak hours were associated with lower probability of speed being below or equal to various speed thresholds (Heydari et al., 2014). However, no differentiation was made between morning and evening peak hours in that analysis. The current thesis demonstrated the need to differentiate between morning and evening peak hours, as the effects of these two peak times on speed behaviour were different.

The proportion of vans/buses/trucks was associated with decreased probability of speed below or equal to various speed thresholds, with a gradually augmented effect as the speed threshold increased. This result implies that the vehicle composition has a dominating effect on vehicle speed behaviour. The result from the free-flow speed model was also in line with this finding, as presented in Table 5-8. One of the findings that seems quite counter-intuitive was the effect of road width on speed probability. It was found that the probability of speed below or equal to all speed thresholds except 80 km/h increased as the road width increased. This contradicts the common belief that wider roads encourage speeding. One of the reasons for this result might be related to the data deficiency. In the current thesis, the road widths among the sites did not vary greatly, with many sites having almost similar road widths. For this reason, added to the observation that road width was not significant in the free-flow speed model shown in Table 5-8, the effect of road width on the probability of speed below or equal to various thresholds rate deserves further exploration. The presence of bus stops was associated with an increase in speed probability below or equal to 50 km/h and 60 km/h speed thresholds, with no significant effect for 70 km/h and 80 km/h speed thresholds. A possible reason for the presence of bus stops being significant in increasing the probability of speed below or equal to these thresholds is that the presence of a bus at the bus stop acts as a speed-impeding factor.

The parameter for the time period was negative, indicating that the probability of speed below or equal to various thresholds decreased in the after period. However, when the interaction between the time period and site type was considered, it was seen that the probability of speed below or equal to various thresholds increased for the treated sites in the after period. The time period alone essentially dictates the overall trend of increased speeding in the study area.

The evaluation results showed that the adjustment ratios for all four speed thresholds were always less than one, indicating the need to take into account the time-trend effect in the before-after evaluation of the speed data. Another observation is that the adjustment factors neared one as the speed threshold increased, meaning that the time trend is more dominant for lower speed thresholds. All the odds ratios were greater than one, indicating that the PSL reduction was effective in increasing the probability of speed below or equal to various speed thresholds. Moreover, the value of the odds ratio decreased as the speed threshold increased, indicating that the effect of the PSL reduction is higher for low-speeding vehicles. The increases in the probability of speed below or equal to various thresholds were estimated as 20.0%, 9.2%, 2.8%, and 0.9% for the speed thresholds of 50 km/h, 60 km/h, 70 km/h, and 80 km/h, respectively. The credible intervals were also found very narrow. Overall, these results indicate that the speed distribution shifted to the left in the treated sites during the after period.

5.3 Multilevel Model

The posterior estimates of the model parameters were obtained via two chains with 50,000 iterations, 10,000 of which were excluded as a burn-in sample using WinBUGS. The BGR statistics were less than 1.2; the ratios of the Monte Carlo errors relative to the standard deviations of the estimates were less than 0.05; and trace plots for all of the model parameters indicated convergence.

Table 5-10 presents the model estimation and before-after evaluation results. As seen, the DIC value for the heterogeneous within-site variance model was much lower than for the model with homogeneous within-site variance, indicating that the former model fit the data much better than the latter one. To further illustrate the result of the heterogeneous variance model, Figure 5-4 shows the variance by site. This figure clearly shows that the variances changed substantially from one site to another. The homogeneous variance model basically considers the pooled variance from the variances shown in Figure 1 and the pooled variance was found to be 18.8. Evidently, the variance of many sites is substantially different from the pooled variance. In summary, the DIC value together with the information illustrated in Figure 5-4 clearly implies that the assumption of homogeneous within-site/group/subject variance might not be the appropriate one and could lead to a biased estimation of model parameters.

The posterior predictive approach of checking the model's goodness of fit showed *p*-values of 0.499 and 0.573 for the homogeneous and heterogeneous within-site variance models, respectively, both of which are close to neither zero nor one, indicating that the observed pattern of the data is likely to be seen in the model-replicated data (Gelman et al., 1996).

Table 5-10 Results of Multilevel Model Estimation and Before-After Evaluation

Variable	Homogeneous Within-Site Variation				Heterogeneous Within-Site Variation			
	Parameter	Std. Dev.	Credible Interval		Parameter	Std. Dev.	Credible Interval	
			Lower Limit	Upper Limit			Lower Limit	Upper Limit
DIC	499800				486200			
Level 1								
Time-of-the-Day	-0.250	0.036	-0.320	-0.180	-0.115	0.031	-0.176	-0.054
Day-of-Week	-0.256	0.032	-0.314	-0.190	-0.277	0.027	-0.330	-0.225
Evening Peak	1.143	0.093	0.961	1.324	1.017	0.078	0.865	1.171
Proportion of Vans/Buses/Trucks	9.577	0.144	9.296	9.861	9.440	0.142	9.162	9.722
Hourly Traffic Volume	-0.0057	0.0003	-0.0063	-0.0052	-0.0059	0.0002	-0.0063	-0.0056
Time Period (treated)	-2.674	0.034	-2.741	-2.608	-2.922	0.029	-2.979	-2.863
Time Period (Comparison)	1.147	0.067	1.017	1.278	1.109	0.058	0.997	1.223
Level 2								
Road Width	0.561	0.257	0.050	1.059	0.626	0.303	0.008	1.212
Road Class	6.434	1.153	4.156	8.696	6.417	1.162	4.131	8.707
Level 3								
Intercept	35.43	2.86	29.78	41.15	34.71	3.36	28.03	41.79
Type 3 (New Community)	3.73	1.45	0.92	6.57	3.83	1.41	1.07	6.59
Before-After Evaluation								
Adjustment Ratio	1.039	0.001	1.037	1.042	1.038	0.001	1.036	1.040
Odds Ratio	0.911	0.001	0.909	0.914	0.907	0.001	0.905	0.910
Speed Reduction (km/h)	4.417	0.073	4.273	4.560	4.628	0.064	4.503	4.753

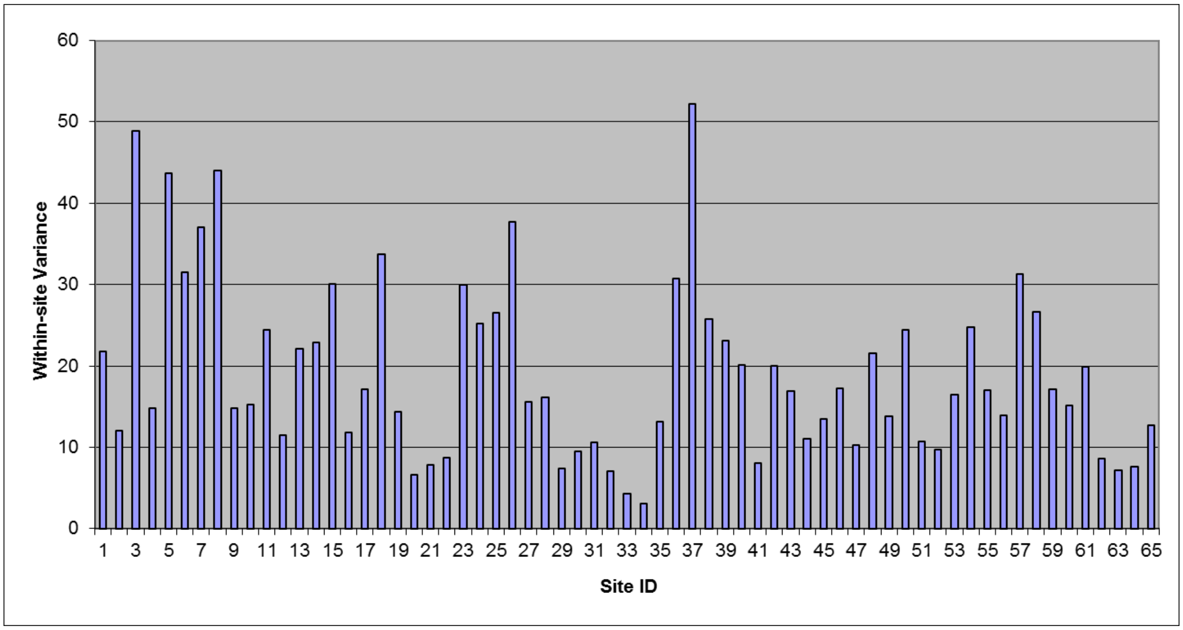

Figure 5-4 Within-Site Variances by Speed Survey Site

The different variance components of the model showed that within-site, between-site, and between-community variances were 18.8, 16.5, and 0.4, respectively. The within-site correlation was calculated to be 46.4% of the total variation. Therefore, it can be concluded that for the current data, use of OLS regression could lead to a biased estimation of parameter values, as the within-site correlation is substantially high.

The results of the parameter estimation showed that a significant number of variables in each of the three levels was found to be statistically significantly associated with the mean free-flow speed. A slight difference in the parameter estimates was found between the homogeneous and heterogeneous within-site variance models. Moreover, the precision of the parameter estimates for the Level 1 variables improved in the heterogeneous variance model. For Level 1, nighttime, weekend, evening peak hours (4-6 pm), and the proportion of vanss/buses/trucks were associated with an increase in mean free-flow speed. Morning peak hours (7-9 am) were found to have an insignificant effect on mean free-flow speed when compared to off-peak hours. The increase in traffic volume was associated with a decrease in the mean free-flow speed, indicating the fundamental relationship between speed and traffic flow. The effect of the time period showed that in the after period, the mean free-flow speed increased in the comparison sites, while it decreased in the treated sites. This finding implies the need to use a comparison group in the before-after evaluation to capture the effect of the general trend. For Level 2, road width and collector roads were found to be statically significant and positively related to the mean free-flow speed, which is quite intuitive. Wider roads encourage speeding, which is one of the main governing factors for road-diet programs undertaken by various transportation agencies across the world. Collector roads carry more through traffic than local roads and therefore are expected to have higher speed (Gattis and Watts, 1999). For level 3, grid communities were found to be statistically insignificant, while new communities were found to be significant and positively associated with the mean free-flow speed. This finding is also intuitive, as new communities have less parking with long curvilinear roads, compared to old communities with more curves and on-street parking.

Often, the mixed model was used in the literature with a constant intercept term. To illustrate the appropriateness of the multilevel model (i.e., varying coefficient), Figure 5-5 shows the intercepts by site. As seen, the intercept term varied substantially from one site to another, dictating that the constant intercept assumption might be violated or too restrictive.

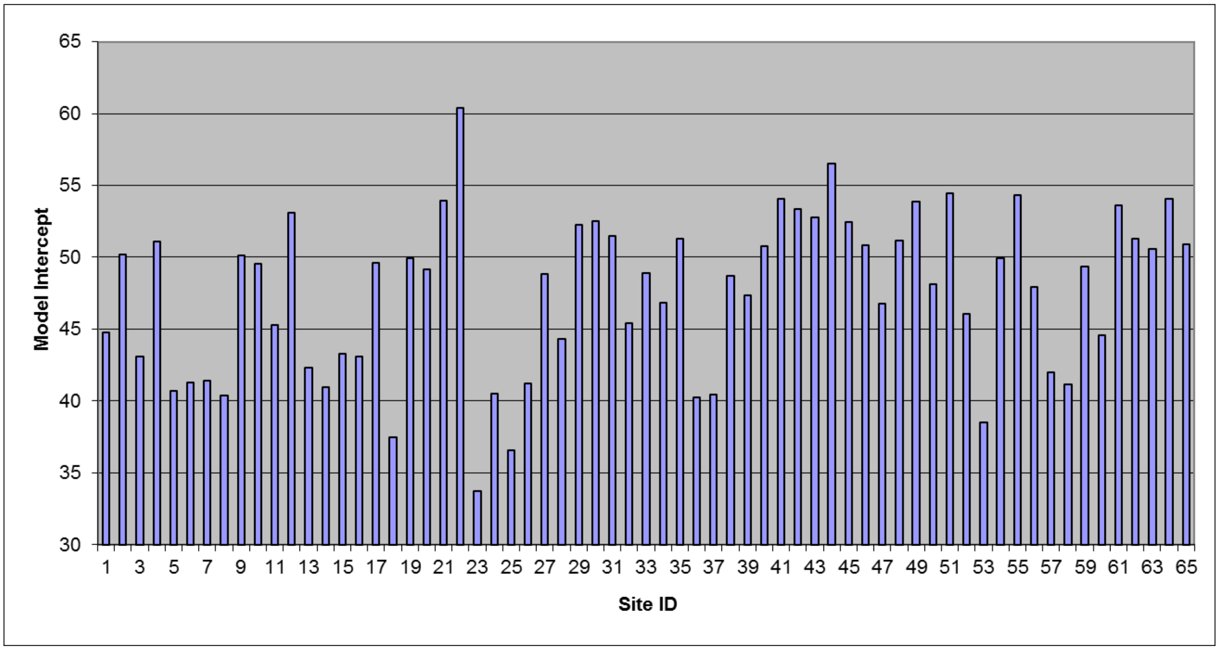

Figure 5-5 Model Intercepts by Speed Survey Site for Heterogeneous Variance Model.

The before-after evaluation results presented in Table 5-10 show that the adjustment factor was greater than one, implying the necessity of factoring the time trend effect into the before-after speed data analysis. Moreover, the odds ratio was statistically less than one, indicating that the PSL reduction is effective in reducing the mean free-flow speed. The reduction of mean free-flow speed was estimated to be 4.6 km/h using the heterogeneous variance model. It was also observed that the homogeneous variance model slightly underestimated the speed reduction.

5.4 Comparison between Mixed-Effect and Multilevel Model

This thesis employed three different modelling techniques for mean free-flow speed: i) mixed effect model, ii) multilevel model with homogeneous variance, and iii) multilevel model with heterogeneous model. The comparison of the goodness-of-fit of the three models as well as the mean free-flow speed reductions estimated by the three models is presented in Table 5-11.

Several conclusions can be drawn from the findings. In terms of the DIC value, mixed-effect model and multilevel model with homogeneous variance is comparable, as no change in the DIC value is obtained. The multilevel model with heterogeneous variance outperformed the mixed effect model and multilevel model with homogeneous variance, as a significant drop in the DIC value is observed.

The before-after evaluation of the mean free-flow speed reduction shows that the multilevel model with heterogeneous variance estimated the highest reduction of the speed while mixed effect model presents the lowest reduction. The precision of the estimates indicated by the standard deviation shows that the multilevel model with heterogeneous variance yielded the highest precision. Although the DIC values for mixed effect model and multilevel model with homogeneous variance are the same, the precision of the estimate of speed reduction is higher for multilevel model with homogeneous variance.

Based on these findings, it is recommended to use multilevel model for modelling free-flow speed and evaluating safety effect of countermeasures. The conventional mixed-effect model substantially underestimated the effectiveness of the PSL reduction. Therefore, a multilevel model with heterogeneous variance is preferred for evaluating the effectiveness of any safety intervention using speed data.

Table 5-11 Comparison of Goodness-of-fit and free-flow speed reduction evaluation by mixed effect and multilevel models

Models	DIC	Estimated Mean Free-Flow Speed Reduction (Standard deviation)[credible interval]
Mixed effect model	499800	3.85 (0.077) [3.7,4.0]
Multilevel model with homogeneous variance	499800	4.42(0.073) [4.27,4.56]
Multilevel model with heterogeneous variance	486200	4.63 (0.064) [4.5,4.75]

6.0 Crash Data Analysis and Evaluation Results

This chapter presents the results of crash data modelling and evaluation. The results are divided into two parts: microscopic (i.e., road-segment based) modelling results and macroscopic (i.e., neighbourhood-based) modelling results. Finally, a comparison of the results among different modelling formulations was discussed.

6.1 Microscopic Models

For the microscopic crash data modelling and evaluation road segment was used as unit of analysis. It is worth noting that for this dataset, no spatial correlation was observed. This is quite intuitive as the road segments distribution was random across the city. Therefore, for microscopic modelling, no spatial correlation was considered.

The posterior estimates of the model parameters for the FB methods were obtained via two chains with 50,000 iterations, 10,000 of which were excluded as a burn-in sample using WinBUGS. The BGR statistics were less than 1.2; the ratios of the Monte Carlo errors relative to the standard deviations of the estimates were less than 0.05; and trace plots for all of the model parameters indicated convergence.

Table 6-1 and Table 6-2 present the parameter estimates of the two models that use the FB method: i) univariate and ii) multivariate with severe and PDO crashes, respectively. Table 6-3 presents the parameter estimation results for the PLN models under the EB method.

Table 6-1 Summary of model estimation results under univariate FB method

Variables	**Parameter Estimate**±Standard Deviation (95% credible interval in parentheses)		
	Total	**Severe**	**PDO**
Intercept	-3.2750±0.3270 (-3.9080, -2.6260)	-5.8880±0.6133 (-7.1000, -4.7100)	-2.8080±0.3158 (-3.4330,-2.1850)
ln(Length)	0.7154±0.0530 (0.6134, 0.8201)	0.6862±0.0.0921 (0.5073, 0.8664)	0.7815±0.0510 (0.6820,0.8806)
ln(AADT)	0.5971±0.0382 (0.5215, 0.6712)	0.6874±0.0769 (0.5390, 0.8386)	0.5612±0.0400 (0.4829,0.6407)
Licensed premise number	0.0317±0.0041 (0.0236,0.0400)		0.0302±0.0042 (0.0219,0.0385)
Presence of licensed premise		0.5112±0.1154 (0.2893, 0.7363)	
Presence of access point	0.3601±0.1067 (0.1496,0.5690)		
Presence of school	0.2073±0.0598 (0.0875, 0.3233)		0.2001±0.0619 (0.0798,0.3211)
Presence of street parking	0.2915±0.0638 (0.1666, 0.4183)		0.3398±0.0630 (0.2148,0.4640)
Stop-controlled intersection density		0.0823±0.0196 (0.0442,0.1211)	
Uncontrolled intersection density		0.0296±0.0117 (0.0068,0.0532)	
Time period	*-0.0871±0.0566 (-0.1969, 0.0234)*	*-0.0876±0.1030 (-0.2921, 0.1188)*	*-0.0896±0.0586 (-0.2031, 0.0261)*
p	0.4619	0.1845	0.4594
DIC	2908	1399	2796
DIC (Severe + PDO)		4195	

Note: Insignificance at 95% credible interval is marked by italicized font.

Table 6-2 Summary of model estimation results under multivariate FB method

Variables	**Parameter Estimate**±Standard Deviation (95% credible interval in parentheses)	
	Severe	**PDO**
Intercept	-6.1480±0.6460 (-7.4470,-4.8970)	-2.5450±0.3380 (-3.2110,-1.8880)
ln(Length)	0.7121±0.0966 (0.5236,0.9033)	0.7022±0.0525 (0.6018,0.8055)
ln(AADT)	0.7027±0.0795 (0.5460,0.8606)	0.5121±0.0428 (0.4287,0.5963)
Presence of licensed premise	0.5106±0.1183 (0.2798,0.7440)	0.3384±0.0635 (0.2173,0.4663)
Presence of street parking	*0.1346±0.1192 (-0.0923, 0.3705)*	0.3372±0.0676 (0.2029, 0.4691)
Stop-controlled intersection density	0.0861±0.0206 (0.0451,0.1266)	0.0430±0.0130 (0.0169,0.0684)
Uncontrolled intersection density	0.0312±0.0121 (0.0073,0.0552)	*0.0030±0.0070 (-0.0108,0.0166)*
Time period	*-0.0791±0.1050 (-0.2863, 0.1258)*	*-0.0866±0.0611 (-0.2029, 0.0342)*
p	0.25	0.58
Correlation	0.71	
DIC	4145	

Note: Insignificance at 95% credible interval is marked by italicized font.

Table 6-3 Summary of model estimation results under EB method

Variables	**Parameter Estimate**±Standard Error (*P*-value in parentheses)		
	Total	**Severe**	**PDO**
Intercept	-3.4089±0.3371 (<0.0001)	-6.0512±0.6301 (<.0001)	-3.3572±0.3464 (<0.0001)
ln(Length)	0.7153±0.0539 (<0.0001)	0.7056±0.0966 (<.0001)	0.7126±0.0555 (<0.0001)
ln(AADT)	0.6040±0.0393 (<0.0001)	0.6983±0.0790 (<.0001)	0.5775±0.0403 (<0.0001)
Licensed premise number	0.0313±0.0042 (<0.0001)		0.0316±0.0042 (<0.0001)
Presence of licensed premise		0.5143±0.1200 (<.0001)	
Presence of access point	0.4039±0.1091 (0.0002)		0.4109±0.1130 (0.0003)
Presence of school	0.2102±.0608 (0.0006)		0.1831±0.0623 (0.0034)
Presence of street parking	0.2938±0.0650 (<0.0001)		0.3178±0.0669 (0.0009)
Stop-controlled intersection density		0.0837±0.0262 (<.0001)	
Uncontrolled intersection density		0.0322±0.0123 (0.009)	
AIC	2996.2	1362.5	2859.2

The result of the posterior predictive approach showed no anomalies in any of the univariate or multivariate models. All the p values shown in Table 6-1 and Table 6-2 are close to neither zero nor one, indicating the adequacy of the models.

All the microscopic (e.g., road-segment based) models in the current thesis, irrespective of FB or EB, are remarkably consistent in terms of the significant variables, with very few exceptions. For instance, the presence of school was statistically significant in the univariate FB and the EB models, while they were insignificant in multivariate models. The parameter estimates of the models among different approaches differ little.

The parameter estimates for length and AADT are highly significant with positive signs in all of the models, indicating the credibility of the models. Further, total and PDO crash models yielded the same variables as statistically significant, demonstrating the dominance of PDO crashes in total crashes. In general, licensed premises, access points, and street parking were statistically significant and positively related to both total and PDO crashes, while licensed premises, stop-controlled intersection density, and uncontrolled intersection density were significant and positively related to severe crashes. As the multivariate models with severe and PDO crashes appeared to be the best models for the current dataset, further discussion on the model parameters is restricted to only the multivariate models with severe and PDO crashes. It is worth noting that the correlation between severe and PDO crashes as found from the multivariate model is 0.71.

The presence of licensed liquor premises was associated with 67% and 40% increases of severe and PDO crashes, respectively. This result is intuitive, as the percentage of impaired driving is expected to be higher near licensed premises. Furthermore, the above percentages show that while the presence of licensed premises increases the risk for both severe and PDO crashes, severe crashes have a higher likelihood of occurring. These findings align with previous research conclusions (Cotti et al., 2014).

The presence of street parking was associated with a 40% increase in PDO crashes but demonstrated a statistically insignificant association with severe crashes. This might be attributed to the fact that street parking leaves less space on the road for driving vehicles, hence the increased likelihood of crashes (Edquist et al., 2012). However, as the crashes between driving vehicles and parked vehicles typically involve sideswiping, they are more likely to be PDO crashes.

Stop-controlled intersection density was associated with 9% and 4% increases of severe and PDO crashes, respectively. Uncontrolled intersection density was associated with a 3% increase of severe crashes but had no statistically significant impact on PDO crashes. These results might be attributed to the fact that the crashes in these intersections are most likely to be right-angle crashes, and consequently, more severe.

In terms of the time trend of crashes, as expressed by the time period variable, the results of both the univariate and multivariate FB models were consistent. Crashes were found to have a general declining trend, although statistically insignificant in all cases. However, despite their insignificancy, they were kept in the model for the before-after safety evaluation because of their practical importance. The time trend is one of the major confounding factors in before-after safety evaluation, the exclusion of which would lead to a biased estimation of the safety effects. The time trend variable addresses the effects of external factors, such as change in weather, economy, etc., that cannot be addressed in the model with appropriate variables. Overall, the time trend variable indicates that the total, severe, and PDO crashes were reduced by 9%, 8%, and 9%, respectively.

6.2 Microscopic Evaluations

The models presented in the above section were used to evaluate the safety effects of reducing the urban residential PSL. Table 6-4 presents the results of the before-after safety evaluation under different approaches. As observed in the table, the EB method underestimated the effects on total and PDO crashes, and overestimated for severe crashes. The notable difference between the EB and the univariate FB approaches was that the estimates of the effects had much lower standard deviations for the FB approach, indicating that the precision of the estimates was much higher for the FB approach. This finding aligns with previous research findings by Lan et al. (2009) and Persaud et al. (2010), but contradicts the findings of Park et al. (2010b). Moreover, while only severe crash reduction in the EB method was statistically significant at a 95% confidence level, all the reductions in the univariate FB method were statistically significant. This finding indicates that the conclusion drawn from the EB method, regarding the effectiveness of a safety intervention, could be misleading.

Table 6-4 Effect of PSL reduction on crash frequency using microscopic data

Method	**Crash Reduction Percentage (**Standard Deviation)		
	Total	**Severe**	**PDO**
EB	17.9 (10.9)	59.5 (16.3)**	10.1 (12.5)
Univariate FB	26.0 (3.0)	51.36 (4.6)	17.1 (4.3)
Multivariate FB (Sev & PDO) *	22.0 (3.8)	49.9 (4.8)	17.9 (4.2)

Note: *total crash frequency is obtained by summing the multivariate severe and PDO crashes; **only crash group in EB found statistically significant at 95% confidence level.

The multivariate FB approach with severe and PDO crashes estimated safety effects similar to the univariate FB method for severe and PDO crashes. However, the multivariate approach showed a slightly lower effect for total crashes. Similar to the univariate FB approach, all the estimates in the multivariate FB approach were statistically significant, and the precision of the safety effects was greater than in the EB method. The precision of the calculated safety effects was similar for the univariate and the multivariate FB approaches.

As the multivariate FB models provided better fit to the data with significantly lower DIC values compared to the univariate FB models, the safety effects estimated in the multivariate FB approach are favoured over those calculated via other methods. It is worth noting that the estimated safety effects for total crashes in the multivariate FB method were found by combining the severe and PDO crashes; therefore, the total crash reduction calculated in the multivariate approach accumulated the potential uncertainty of the estimates of severe and PDO crashes. Hence, the best estimate of safety effects for the total crashes would be the one obtained from the univariate FB approach.

Based on the above results in Table 6-4, the most appropriate estimate of crash reduction would be 26%, 50%, and 18% for the total, severe, and PDO crashes, respectively. The highest safety benefit was realized for severe crashes, which is quite intuitive and expected, given the fact that the effect of speed on crash severity is evident in the literature. Using the speed-crash relationship, it was estimated that the expected total crash reduction would be 15%. The current finding based on the crash data provided a slightly higher estimate of the total crash reduction. This indicates that existing empirical speed-crash relationships might provide a conservative estimate of crashes for urban residential areas.

The reduction of various crashes is statistically significant and quite substantial, given that no costly engineering measures, such as geometry or infrastructure change, were undertaken in the program. The PSL reduction was accompanied by only a public education campaign and enforcement. These findings suggest that reducing the PSL could be an effective speed management strategy to improve the safety of urban residential collector roads.

6.3 Macroscopic Models

For macroscopic analysis, the unit of analysis was residential neighbourhood. Five different models were developed in this thesis to perform before-after safety evaluation: (i) univariate Poisson-lognormal (PLN), (ii) multivariate Poisson-lognormal (MVPLN), (iii) univariate Poisson-lognormal with CAR distribution (PLN-CAR), (iv) multivariate Poisson-lognormal with multivariate CAR distribution (MVPLN-CAR), and (v) Poisson lognormal shared component model with CAR distribution.

For each model, the posterior estimates were obtained via two chains with 50,000 iterations, 10,000 of which were excluded as a burn-in sample using WinBUGS. The BGR statistics were less than 1.2; the ratios of the Monte Carlo errors relative to the standard deviations of the estimates were less than 0.05; and trace plots for all of the model parameters indicated convergence.

The model estimation results are presented in Table 6-5 to Table 6-9. The models differ a little in terms of the significant variables and their estimates. In general, the variables found to be statistically significant and associated with both types of crashes are vehicle kilometres travelled, the number of traffic signals, grid network pattern, dwelling units, proportion of population aged equal to or below 15 years, proportion of population aged equal to or above 65 years, and proportion of households with two or more cars. For indicator variables related to treated neighbourhoods, all are insignificant, except for year 1. Other variables listed in the data description section were found to be statistically insignificant.

Table 6-5 Results of macroscopic univariate Poisson lognormal model

	Total crash				Severe crash				Property-damage-only crash			
	mean	sd	val2.5pc	val97.5pc	mean	sd	val2.5pc	val97.5pc	mean	sd	val2.5pc	val97.5pc
Intercept1	0.242	0.346	-0.451	0.871	-2.461	0.444	-3.374	-1.601	0.178	0.293	-0.403	0.759
Intercept 2	0.244	0.346	-0.452	0.872	-2.512	0.444	-3.418	-1.656	0.183	0.293	-0.398	0.766
Intercept 3	0.275	0.346	-0.420	0.904	-2.596	0.444	-3.510	-1.735	0.226	0.293	-0.352	0.808
Intercept 4	0.141	0.346	-0.553	0.770	-2.774	0.446	-3.682	-1.919	0.102	0.292	-0.475	0.686
Intercept 5	-0.104	0.346	-0.796	0.524	-2.909	0.446	-3.828	-2.056	-0.155	0.293	-0.731	0.422
Intercept 6	0.007	0.346	-0.683	0.636	-2.985	0.445	-3.894	-2.136	-0.021	0.293	-0.599	0.558
log(VKT)	0.365	0.039	0.292	0.444	0.433	0.052	0.331	0.539	0.348	0.034	0.280	0.414
Signal No.	0.171	0.023	0.126	0.217	0.258	0.031	0.196	0.318	0.155	0.026	0.108	0.217
Grid	-0.353	0.116	-0.584	-0.135					-0.329	0.100	-0.535	-0.125
Dwelling	0.345	0.031	0.280	0.406	0.325	0.062	0.206	0.442	0.362	0.032	0.297	0.427
Pop<=15	-0.724	0.402	-1.556	0.047								
Pop>=65	-0.931	0.321	-1.558	-0.289					-1.038	0.315	-1.646	-0.403
Car>=2	-0.622	0.218	-1.023	-0.186	-1.414	0.273	-1.936	-0.890	-0.685	0.189	-1.031	-0.303
Treated1	0.287	0.176	-0.053	0.646	0.645	0.244	0.158	1.115	0.231	0.178	-0.112	0.595
Treated2	0.161	0.177	-0.173	0.526	0.418	0.263	-0.101	0.929	0.124	0.179	-0.222	0.484
Treated3	0.188	0.177	-0.147	0.541	0.073	0.289	-0.511	0.633	0.194	0.177	-0.150	0.553
Treated4	0.093	0.179	-0.252	0.454	0.162	0.296	-0.429	0.746	0.079	0.178	-0.260	0.443
Treated5	-0.062	0.183	-0.411	0.305	-0.275	0.361	-1.025	0.394	-0.046	0.185	-0.398	0.318
Treated6	0.219	0.178	-0.124	0.574	0.473	0.286	-0.097	1.023	0.189	0.180	-0.160	0.556

Table 6-6 Results of macroscopic univariate Poisson lognormal model with CAR distribution

	Total crash				Severe crash				PDO crash			
	mean	sd	val2.5pc	val97.5pc	mean	sd	val2.5pc	val97.5pc	mean	sd	val2.5pc	val97.5pc
Intercept1	0.557	0.399	-0.283	1.295	-2.551	0.487	-3.499	-1.622	-0.518	0.984	-2.123	0.991
Intercept 2	0.559	0.3999	-0.283	1.297	-2.603	0.488	-3.551	-1.673	-0.509	0.985	-2.117	0.998
Intercept 3	0.591	0.400	-0.251	1.329	-2.689	0.488	-3.638	-1.761	-0.464	0.984	-2.066	1.045
Intercept 4	0.457	0.399	-0.383	1.194	-2.868	0.490	-3.824	-1.934	-0.593	0.984	-2.199	0.915
Intercept 5	0.211	0.399	-0.630	0.948	-3.003	0.490	-3.958	-2.072	-0.852	0.985	-2.458	0.656
Intercept 6	0.322	0.399	-0.519	1.059	-3.079	0.490	-4.036	-2.148	-0.720	0.985	-2.326	0.790
log(VKT)	0.272	0.037	0.200	0.345	0.419	0.056	0.310	0.531	0.247	0.035	0.181	0.316
Signal No.	0.175	0.024	0.125	0.223	0.246	0.031	0.185	0.310	0.169	0.020	0.130	0.209
Grid	*-0.154*	*0.094*	*-0.337*	*0.032*					*-0.142*	*0.090*	*-0.317*	*0.040*
Dwelling	0.343	0.029	0.285	0.398	0.346	0.067	0.211	0.474	0.364	0.033	0.301	0.428
Pop<=15	-0.882	0.388	-1.631	-0.101					-0.856	0.397	-1.637	-0.063
Pop>=65	-1.030	0.310	-1.633	-0.411					-1.112	0.305	-1.721	-0.527
Car>=2	-0.574	0.244	-1.047	-0.107	-1.327	0.345	-1.991	-0.638	-0.549	0.204	-0.961	-0.156
Treated1	0.271	0.162	-0.054	0.584	0.504	0.267	-0.018	1.021	0.238	0.156	-0.074	0.538
Treated2	0.144	0.162	-0.183	0.462	0.282	0.281	-0.279	0.818	0.127	0.157	-0.188	0.431
Treated3	0.171	0.161	-0.153	0.486	-0.064	0.309	-0.681	0.509	0.199	0.154	-0.099	0.496
Treated4	0.074	0.163	-0.249	0.393	0.033	0.312	-0.592	0.624	0.085	0.159	-0.233	0.393
Treated5	-0.081	0.170	-0.422	0.250	-0.413	0.373	-1.182	0.287	-0.043	0.167	-0.380	0.277
Treated6	0.200	0.164	-0.125	0.519	0.343	0.308	-0.270	0.933	0.192	0.157	-0.118	0.499

Table 6-7 Results of macroscopic multivariate Poisson lognormal model

	Severe crash				PDO crash			
	mean	sd	val2.5pc	val97.5pc	mean	sd	val2.5pc	val97.5pc
Intercept1	-2.654	0.473	-3.559	-1.697	0.131	0.291	-0.406	0.755
Intercept 2	-2.695	0.473	-3.598	-1.748	0.138	0.291	-0.406	0.758
Intercept 3	-2.768	0.475	-3.676	-1.816	0.183	0.292	-0.358	0.801
Intercept 4	-2.948	0.475	-3.871	-1.991	0.055	0.291	-0.481	0.674
Intercept 5	-3.086	0.474	-4.001	-2.136	-0.203	0.291	-0.743	0.413
Intercept 6	-3.161	0.476	-4.070	-2.206	-0.070	0.291	-0.614	0.552
log(VKT)	0.530	0.056	0.421	0.636	0.361	0.036	0.288	0.430
Signal No.	0.242	0.042	0.165	0.321	0.151	0.031	0.097	0.208
Grid	-0.430	0.167	-0.763	-0.117	-0.348	0.111	-0.577	-0.142
Dwelling	0.202	0.050	0.104	0.300	0.353	0.031	0.291	0.417
Pop>=65	-1.215	0.560	-2.304	-0.046	-0.875	0.321	-1.526	-0.276
Car>=2	-1.585	0.319	-2.148	-0.943	-0.626	0.208	-0.999	-0.226
Treated1	0.745	0.273	0.215	1.297	0.242	0.180	-0.086	0.603
Treated2	0.510	0.283	-0.025	1.074	0.138	0.182	-0.192	0.504
Treated3	0.156	0.316	-0.450	0.805	0.210	0.179	-0.117	0.592
Treated4	0.231	0.318	-0.403	0.862	0.095	0.182	-0.233	0.468
Treated5	-0.218	0.369	-0.950	0.497	-0.032	0.191	-0.390	0.350
Treated6	0.514	0.307	-0.093	1.085	0.203	0.182	-0.126	0.592

Table 6-8 Results of macroscopic multivariate Poisson lognormal model with multivariate CAR

	Severe crash				PDO crash			
variable	mean	sd	val2.5pc	val97.5pc	mean	sd	val2.5pc	val97.5pc
Intercept1	-2.234	0.474	-3.175	-1.326	0.742	0.312	0.109	1.332
Intercept 2	-2.258	0.473	-3.195	-1.351	0.761	0.311	0.132	1.350
Intercept 3	-2.361	0.477	-3.305	-1.450	0.790	0.313	0.155	1.381
Intercept 4	-2.547	0.478	-3.489	-1.633	0.660	0.313	0.026	1.252
Intercept 5	-2.673	0.476	-3.618	-1.762	0.409	0.312	-0.222	0.999
Intercept 6	-2.765	0.477	-3.707	-1.849	0.534	0.313	-0.099	1.126
log(VKT)	0.432	0.055	0.325	0.539	0.264	0.036	0.196	0.337
Signal No.	0.246	0.032	0.187	0.312	0.170	0.022	0.130	0.213
Dwelling	0.266	0.048	0.170	0.360	0.350	0.029	0.294	0.407
Pop<=15	*-1.255*	*0.832*	*-2.624*	*0.136*	-0.802	0.398	-1.445	-0.128
Pop>=65	-1.233	0.549	-2.297	-0.152	-0.944	0.305	-1.534	-0.338
Car>=2	-1.327	0.333	-1.964	-0.659	-0.621	0.208	-0.999	-0.197
Treated1	0.577	0.261	0.055	1.081	0.251	0.163	-0.068	0.571
Treated2	0.341	0.273	-0.202	0.867	0.145	0.164	-0.178	0.459
Treated3	-0.007	0.300	-0.609	0.566	0.218	0.163	-0.103	0.531
Treated4	0.065	0.308	-0.560	0.652	0.102	0.165	-0.224	0.418
Treated5	-0.378	0.364	-1.128	0.310	-0.025	0.172	-0.360	0.307
Treated6	0.364	0.299	-0.236	0.940	0.209	0.166	-0.116	0.532

Table 6-9 Results of macroscopic Poisson lognormal shared component model

	severe				PDO			
	mean	sd	val2.5pc	val97.5pc	mean	sd	val2.5pc	val97.5pc
Intercept1	-2.587	0.569	-3.748	-1.531	0.387	0.395	-0.494	1.092
Intercept 2	-2.611	0.568	-3.771	-1.557	0.408	0.394	-0.471	1.111
Intercept 3	-2.715	0.571	-3.879	-1.653	0.436	0.396	-0.445	1.143
Intercept 4	-2.901	0.571	-4.068	-1.840	0.305	0.396	-0.576	1.013
Intercept 5	-3.027	0.570	-4.193	-1.970	0.055	0.395	-0.826	0.760
Intercept 6	-3.119	0.572	-4.287	-2.054	0.179	0.396	-0.705	0.886
log(VKT)	0.445	0.054	0.338	0.554	0.279	0.034	0.212	0.346
Signal No.	0.244	0.031	0.184	0.305	0.168	0.022	0.125	0.214
Dwelling	0.267	0.053	0.163	0.370	0.348	0.031	0.287	0.410
Pop<=15	*-1.257*	*0.855*	*-2.920*	*0.443*	-0.818	0.401	-1.614	-0.037
Pop>=65	-1.250	0.537	-2.299	-0.194	-0.957	0.304	-1.544	-0.355
Car>=2	-1.344	0.345	-2.024	-0.681	-0.655	0.224	-1.080	-0.224
Treated1	0.610	0.264	0.089	1.119	0.279	0.167	-0.049	0.609
Treated2	0.373	0.277	-0.188	0.906	0.172	0.168	-0.157	0.501
Treated3	0.020	0.301	-0.589	0.598	0.244	0.166	-0.083	0.573
Treated4	0.093	0.308	-0.523	0.687	0.128	0.170	-0.208	0.462
Treated5	-0.352	0.361	-1.083	0.327	0.002	0.176	-0.347	0.350
Treated6	0.393	0.301	-0.210	0.963	0.237	0.169	-0.100	0.567

The parameter estimate for the log transformation of vehicle kilometres travelled was highly significant and positively associated with both severe and PDO crashes. This is intuitive and logical, as the vehicle kilometre travelled represents the level of exposure. Across the different models, the estimates varied from 0.416 to 0.525 for severe crashes and from 0.243 to 0.358 for PDO crashes. The higher value of the estimate for severe crashes denotes that the effect of vehicle kilometres travelled on crash frequency is higher for severe crashes than PDO crashes.

The number of traffic signals within the neighbourhood was significant and positively associated with both severe and PDO crashes, indicating that as the number of traffic signals increases, the probability of crash occurrence for both severity levels increases. Moreover, the effect of the number of traffic signals is higher for severe crashes when compared to PDO crashes.

The road network pattern was found to be significant only in non-spatial models. The results show that neighbourhoods with grid pattern road networks are associated with fewer crashes compared to other road network patterns.

The dwelling unit number for the neighbourhood was significant and positively associated with both severe and PDO crashes, irrespective of the models. The parameter estimates varied from 0.206 to 0.352 for severe crashes and from 0.348 to 0.367 for PDO crashes. The current thesis also attempted to include neighbourhood population in the model. However, because of the high correlation between population and dwelling units, both variables could not be included in the same model. When only population was included, the resulting models had a higher DIC value than the models with dwelling unit. Therefore, in the final models, dwelling unit was used.

In terms of population age distribution, the proportion of the population aged 15 years or below was found to be significant and negatively associated with PDO crashes in the spatial model. This finding might be expected, as the higher proportion of this age group indirectly represents fewer drivers and therefore less exposure in the neighbourhood. The proportion of the population aged 65 years or above was also significant and negatively associated with both severe and PDO crashes. This finding is consistent with previous research (Quddus, 2008; Huang et al., 24).

Table 6-10 presents the variance-covariance estimates for different models. Irrespective of the model type, variances for heterogeneous error were always statistically significant. This indicates the need to incorporate a heterogeneous error term in the model. Moreover, the value of heterogeneous variance was higher for severe crashes than PDO crashes, which denotes that severe crashes exhibit more randomness than PDO crashes. Furthermore, for the multivariate PLN and multivariate PLN CAR models, the covariance between severe and PDO crashes for heterogeneous error was statistically significant, indicating the appropriateness of using multivariate models for crash severity. In the univariate model, this covariance between the severity levels is ignored.

The correlation between severe and PDO crashes for the heterogeneous error was statistically significant and very high. The multivariate PLN model estimated the correlation as 91%, while the multivariate PLN CAR model estimated it as 0.93%. This high correlation indicates that a higher number of PDO crashes is associated with a higher number of severe crashes, as the numbers of both types are likely to rise due to the same deficiencies in neighbourhood design or other unobserved factors, or both (El-Basyouny and Sayed, 2009b).

For the univariate spatial model, the variance of the spatial error was statistically significant for PDO crashes, but insignificant for severe crashes. This indicates that the proximate neighbourhoods are more closely related to PDO crashes than severe crashes for the current data. Therefore, including spatial error is more likely to improve model prediction significantly only for the PDO crashes, rather than severe crashes.

For spatial error, the correlation between severe and PDO crashes, as found for the multivariate CAR model, was estimated as 65%; however, it was not statistically significant. One of the potential reasons for the spatial correlation not being significant is that the boundary crashes were excluded from the analysis. With boundary crashes being distributed among the adjacent neighbourhoods, higher spatial correlation could have been expected. Another reason could be the fact that the model has two random error components, with the heterogeneous component accounting for a substantial portion of the random effect (Aguero-Valverde, 2013).

Table 6-10 Variance Estimate for Error Components

Variance for univariate PLN model			Variance for multivariate PLN model	
Total	0.20 (0.02)		Severe	PDO
Severe	0.27(0.04)		0.34 (0.05)	0.91 (0.02)
PDO	0.19 (0.02)		0.23 (0.03)	0.19 (0.02)
Variance for univariate PLN CAR model				
	For heterogeneous error		For spatial error	
Total	0.08 (0.04)		0.19 (0.11)	
Severe	0.23 (0.04)		0.05 (0.06)	
PDO	0.06 (0.03)		0.21 (0.09)	
Variance-covariance matrix for multivariate PLN with multivariate CAR model				
	For heterogeneous error		For spatial error	
	Severe	PDO	Severe	PDO
Severe	0.19(0.06)	0.93 (0.12)	0.15 (0.16)	0.65 (0.53)
PDO	0.12 (0.05)	0.08 (0.04)	0.14 (0.14)	0.15 (0.12)

Gray colour indicates correlation; parentheses indicate standard deviation.

Table 6-11 indicates that for severe crash, about 74% of the total between-neighbourhood variation is captured by the shared component, while for PDO crash about 64% of the total between-neighbourhood variation is captured by the shared component. Delta is greater than 1, indicating that the shared component has a slightly stronger association with severe crash than with PDO crash.

Table 6-11 Variation explained by shared component in Shared Component PLN model

	mean	sd	val2.5pc	val97.5pc
Severe	0.739	0.190	0.404	0.962
PDO	0.636	0.275	0.221	0.967
Delta (association)	1.167	0.048	1.088	1.269

6.4 Macroscopic Evaluation

The macroscopic models were used to evaluate the safety effects of reducing the urban residential PSL. Table 6-12 presents the results of the before-after safety evaluation under different models. As observed in the table, the estimated crash reductions and the precision are almost the same across different models. The crash reduction estimates are 13%, 24% and 12% for total, severe and PDO crashes, respectively. While the total and PDO crash reductions are statistically significant at the 95% credible interval, the severe crash reduction is significant at the 90% credible interval.

Although the model parameter estimates differ a little among various models, the crash reduction estimates show no noticeable differences. One potential reason for this could be related to the data used in the current thesis. As seen from Table 4-7, the changes in different explanatory variables between the before and after period for the treated group are quite minimal. Therefore, differences in model parameter estimates provided little impact on the before-after evaluation results. However, this might not be the case for all safety interventions. If an intervention affects other factors (e.g., traffic volume) in addition to the number of crashes, it may be possible that different models estimate significantly different crash reductions. Moreover, there were only eight treated neighbourhoods in the current thesis; analysis with more treated sites could yield different results.

The PSL was reduced for all roads within the boundaries (excluding boundary roads) of the treated residential neighbourhoods. This includes collector and local road segments and the associated intersections. To conduct a model-based microscopic (i.e., intersection and road segment level) safety evaluation for the entire study area, it is necessary to collect exposure data (i.e., traffic volume) for all road segments and intersections. However, the data were not available, as road agencies often do not collect traffic volume data for low-volume residential collector and local road segments and intersections. Based on the microscopic evaluation using road segment data, the total, severe and PDO crash reductions were estimated as 26%, 50% and 18%, respectively. These crash reduction estimates are substantially different from the macroscopic findings, especially for severe crashes.

The differences in results between the microscopic (i.e., collector road segments) and the macroscopic (i.e., neighbourhoods) safety evaluation of the same PSL reduction are intuitive and reasonable. This PSL reduction resulted in a mean free-flow speed change from 51.1 to 47.7 km/h (3.4 km/h reduction) for collector roads and from 43.8 to 41.8 km/h (2.0 km/h reduction) for local roads. Given the higher impact of PSL reduction on speed for collector roads, it is expected that the overall reduction of crashes, and specifically severe crashes, will be higher for collector roads than local roads. Therefore, when both collector and local roads are combined in the safety evaluation, which is the case for macroscopic evaluation, the resulting crash reduction will be less than that for only collector roads.

Finally, the estimated crash reductions are quite high, given the fact that the current PSL reduction program did not include any costly infrastructure/geometrical changes. Rather, the program included only changes in posted speed limit signs, together with a brief educational and enforcement campaign. Therefore, based on the current results, it is fair to conclude that the PSL reduction integrated with education and enforcement could be an effective countermeasure to improve safety on urban residential roads.

Table 6-12 Effect of PSL Reduction on Crash Frequency

Model	Crash Reduction in Percentage (Std. dev. in parentheses)		
	Total	Severe	Property-damage-only
PLN	12.95 (4.91)	24.9 (13.05)	11.28 (5.28)
PLN with CAR	13.39 (4.93)	24.50 (13.17)	11.72 (5.27)
MVPLN		24.05 (13.13)	12.00 (5.24)
MVPLN with MVCAR		23.97(13.27)	11.88 (5.25)
Shared component PLN		23.90 (13.07)	11.27 (5.33)

All are significant at 95%, except those with the gray colour that are significant at 90% credible interval.

6.5 Comparison of Models

As several model formulations are considered in this research, a comparison of the models is presented in this section. For microscopic safety evaluation, univariate and multivariate Poisson-lognormal models are considered. The model selection criteria for microscopic models are presented in Table 6-13. The differences in DIC values are significant between the two models. As observed, the sum of the DICs of the univariate severe and PDO crash model is 4195; whereas, for the multivariate model with the same response variables, the DIC value is 4145. The drop in the DIC value for the multivariate model is 50. Because the difference between the DIC values is greater than 10, it can be concluded that the multivariate model is preferred over the univariate model for severe and PDO crashes, for the current dataset (Spiegelhalter et al., 2005).

The before-after evaluation results showed no noticeable differences in the estimates of crash reductions between the univariate and multivariate models. This could be related to the small differences in various characteristics of the treated sites between the before and after periods. Therefore, further application of the models with different dataset could be conducted to verify the current findings.

Table 6-13 Microscopic Models Comparison using Deviance Information Criteria (DIC)

Model	**DIC**
Poisson-lognormal	4195
Multivariate Poisson-lognormal	4145

For safety evaluation using macroscopic data, five different modelling formulations are considered. The model selection criteria for macroscopic models is presented in Table 6-14. The differences in DIC values are significant among the five models (Spiegelhalter et al., 2005). Among the traditional models (First four), the best-performing model is the multivariate Poisson-lognormal with multivariate conditional autoregressive (MVPLN CAR) model, while the worst one is the Poisson-lognormal (PLN) model. This finding is intuitive, as the former model accounts for the correlation between crash severity levels as well as spatial correlation, while the latter ignores them. Between the Poisson-lognormal with conditional autoregressive (PLN CAR) and the multivariate Poisson-lognormal (MVPLN) model, the latter is better fitted. This denotes that for the current dataset, the effect of correlation between the crash severity levels is more influential than spatial correlation. However, the developed new spatial model (i.e., shared component model) yielded the lowest DIC value, indicating the best performing model among the five models for the current dataset.

One of the reasons for having weaker spatial correlations for the current dataset is that the boundary crashes are excluded from the analysis. The current research uses the developed methodology to evaluate an urban residential posted speed limit (PSL) reduction pilot program. The PSL reduction was implemented only for roads within the boundary of the neighborhoods. Therefore, for both treated and reference neighbourhoods, boundary crashes were excluded.

The macroscopic before-after safety evaluation results show hardly any differences among different models. One potential reason for this could be related to the data used in the current research. The changes in different explanatory variables between the before and after period for the treated neighbourhoods are very little. Therefore, differences in model parameter estimates provided little impact on the before-after evaluation results. Moreover, there were only eight treated neighbourhoods in the current thesis; analysis with more treated sites could yield different results.

Table 6-14 Macroscopic Model Comparison using Deviance Information Criteria (DIC)

Model	DIC
Poisson-lognormal	12349
Poisson-lognormal with conditional autoregressive	12297
Multivariate Poisson-lognormal	12270
Multivariate Poisson-lognormal with multivariate conditional autoregressive	12230
Shared component Poisson-lognormal model	12210

7.0 Conclusions, Contributions and Future Research

This chapter summarizes the main conclusions, contributions of the thesis and finally the areas for future research.

7.1 Summary and Conclusions

The research in this thesis aimed at applying new modelling techniques to perform observational before-after safety evaluations. It is recommended that the comprehensive safety evaluation of any speed management strategy should include the evaluation of both speed data (i.e., impact evaluation) and crash data (i.e., outcome evaluation).

The first objective of this research was to develop a non-model based methodology for before-after evaluation of speed data that can address the effect of confounding factors and time trend. This method can be specifically beneficial if limited data doesn't allow using a model-based approach in the before-after evaluation of speed data. A before-and-after study design with a control group was recommended and the conventional *t*-test was modified to account for the confounding factors and time trend. Furthermore, effect of accounting or not accounting for the measurement of uncertainty in the control group on the *t*-test results was illustrated. Results showed that the standard error was underestimated when the uncertainty was not added, although the magnitude of the underestimation was small for the current dataset. Moreover, a sensitivity analysis of the vehicle headways was conducted to define the free-flow speed and to address the confounding effect of congestion. It was found that for the current dataset, a headway of greater than 2 seconds was sufficient to separates congested and uncongested condition.

The second objective of this research was to develop a model-based methodology to conduct before-after evaluation of the speed data. The full Bayesian mixed-effect normal regression and binomial logistic regression models were developed for mean free-flow speed and speed compliance, respectively. The results revealed that the between-site variation represented a substantial portion of the total variation, indicating the necessity of using a mixed model for analyzing speed data. The ordinary least square regression model failed to address this within-site variation in the speed data. Moreover, the evaluation results showed that the time trend effect was significant, indicating the need to account for it in the before-after evaluation of speed data.

The third objective was to develop a methodology to take account for the multilevel nature of the speed data as well as the heterogeneous within-site variances. To accomplish this objective, multilevel model with heterogeneous within-site variances was developed to analyze the hourly free-flow speed data. Another multilevel model with homogeneous within-site variances was developed to compare the results. The results showed that the deviance information criteria value for the heterogeneous within-site variance model was much lower than for the model with homogeneous within-site variance, indicating that the former model fit the data much better than the latter one. Moreover, the variances changed substantially from one site to another, implied that the assumption of homogeneous within-site/group/subject variance might not be the appropriate one and could lead to a biased estimation of model parameters. The before-after evaluation results showed that the adjustment factor was greater than one, implying the necessity of factoring the time trend effect into the before-after speed data analysis. In addition, it was observed that the homogeneous variance model slightly underestimated the speed reduction. Furthermore, the standard deviations of the mean free-flow speed reductions showed that the precision of the estimate improved when heterogeneous variance model was used.

The fourth objective of this research was to develop and apply the full Bayesian multivariate model in the before-after safety evaluation and compare the results with the univariate counterpart. For the univariate models, both the empirical and full Bayesian approach were adopted. The multivariate Poisson-lognormal and the univariate Poisson-lognormal models were developed to accomplish this objective. According to the lower DIC value, the multivariate model of crash severities was preferred over the univariate models for the current data. The before-after safety evaluation results showed that the full Bayesian approach provides more precise estimates of safety effects. Moreover, for severe crashes, where the safety effects are relatively large, both the empirical Bayesian and full Bayesian approaches draw the same conclusion, while for total and PDO crashes, where the safety effects are relatively small, the conclusions drawn from these two approaches are quite opposite in terms of the statistical significance of crash reduction. Hence, caution should be taken in drawing conclusions from the EB approach, especially when the effect on safety is relatively small compared to the standard deviation. The multivariate full Bayesian approach estimated safety effects similar to the univariate full Bayesian method for both severe and PDO crashes. In addition, the precisions of the calculated safety effects were similar for the univariate and the multivariate FB approaches.

The fifth objective was to incorporate spatial correlation in the full Bayesian macroscopic before-after safety evaluation using crash data and compare the results with non-spatial models. For the spatial models, univariate Poisson-lognormal with conditional autoregressive and multivariate Poisson-lognormal with multivariate conditional autoregressive models were developed. For the non-spatial models, univariate Poisson-lognormal and multivariate Poisson-lognormal models were developed. It was found that the multivariate Poisson-lognormal with multivariate conditional autoregressive model outperformed the other models based on the deviance information criteria. The before-after safety evaluation results showed that the differences in crash reduction estimated under different models were negligible. This could be due to the small number of treated sites present in the current thesis, or a result of excluding boundary crashes from the analysis. Moreover, the comparison between microscopic and macroscopic safety evaluation showed intuitive findings.

Finally the sixth objective of this research was to explore alternative modelling methodology to better capture the spatial correlations of the crash data in the before-after safety evaluation. A novel shared component spatial model was developed for jointly modelling crash severities. The model considered that the random error is divided into shared error and individual response specific error. Each of these error components was assumed to be composed of heterogeneous error and spatial error. Results showed that the developed new spatial model yielded the lowest DIC value, indicating the best performing model among the all spatial and non-spatial model developed in this research. The before-after safety evaluation results provided similar estimation of crash reduction as found in other spatial models. Again, this could be could be due to the small number of treated sites present in the current data.

7.2 Contributions to the State-of-the-Art

This research provides methodological alternatives for the comprehensive evaluation of any speed management strategy. The specific contributions to the state-of-the-art are highlighted below:

- The development of a systematic framework and appropriate statistical method for non-model based analysis of speed data that can take account the effect of confounding factors and time trend.
- The development of full Bayesian mixed-effect intervention model for the before-after evaluation of speed data that can eliminate the limitation of the ordinary least square regression method.
- The development of full Bayesian multilevel models with homogeneous and heterogeneous site variances to better address the randomness in the speed data.
- The demonstration of the fact that by applying advanced statistical methods for analyzing speed data, safety effect can be estimated more precisely.
- The introduction of macroscopic crash modelling for the before-after safety evaluation of area-wide safety intervention.
- The introduction of conventional full Bayesian multivariate models for the before-after safety evaluation using crash data.
- The demonstration of the fact the empirical Bayesian safety evaluation can lead to misleading conclusion about the statistical significance of the safety effects when the the safety effects are relatively small.
- The development of full Bayesian macroscopic spatial models for the before-after safety evaluation using crash data.
- The introduction of a new methodology to incorporate spatial correlation in crash modelling for the before-after safety evaluation.

7.3 Limitations and Future Research

A small number of treated sites for the macroscopic crash analysis might be a determinant factor why the evaluation results showed similar findings despite the fact that various developed crash models differs in terms of goodness-of-fits. Therefore, further investigation of the developed methodology for different dataset with higher number of treated sites is needed to realize the benefits of using these advanced models for the before-after safety evaluation. Moreover, the traffic exposure and other characteristics didn't change considerably between the before and after period for the current application. Therefore, a change in the parameter values across different models didn't contribute to the substantial differences in the before-after evaluation results.

The current thesis excluded the boundary crashes when developed the macroscopic models. This is due to the fact that the posted speed limit reductions program, evaluated using the developed methodology, was restricted to the roadways within the neighbourhood boundaries (excluding the boundary roadways). It is expected that when the boundary collisions are included, there will be more strong spatial correlation among the adjacent spatial units. This might explain why the spatial correlations in different models were sometimes found very small.

The current research suggests that a comprehensive evaluation of a speed management strategy should include both speed and crash data analysis and evaluation. One important component in traffic safety is how road users' perception and behavior change in response to any traffic safety intervention. The change in speed and crash after the implementation of any safety intervention can be assumed as the outcome of the fundamental changes in road users' behaviors. Therefore, the safety evaluation can be extended to evaluate the fundamental changes in road users' behaviors in response to safety intervention. Obviously, the main challenge with this is the collection of reliable data.

The use of crash data for the safety evaluation requires waiting for a long time after the implementation of the safety intervention to have any statistically valid investigation. One alternative approach to conduct before-after safety evaluation is to use surrogate safety measures. Recently, video-based conflict analysis technique has been developed that can automatically quantify the conflicts based on the video captured (Autey, 2012). In this technique, time-to-collision is used to define the conflict and its severity. However, one of the issues with conflict based before-after safety evaluation is that the relationship between conflict and crash is not well-established. Rigorous studies are required to understand the conflict and crash relationship to justify the validity of drawing conclusion about safety impact of any intervention based on conflict based before-after safety analysis.

For incorporating spatial correlation into crash modelling, conditional autoregressive assumption is the most commonly used technique. However, Geographic Weighted Poisson Regression (GWPR) (Hadayeghi et al., 2010), and Generalized Estimating Equations (GEE) (Abdel-Aty and Wang, 2006) have been advocated by other researchers to address spatial correlation into crash modelling. Each of this approach has its own advantages and disadvantages. Future studies could investigate these approaches in the before-after safety evaluation context.

The current thesis demonstrated the need to address heterogeneity in the speed data for unbiased parameter estimates and more precise inference. In the future, other advanced statistical methods, such as latent class model (Behnood et al., 2014), Markov switching approaches (Malyshkina and Mannering, 2009; Xiong et al., 2014) could be explored for addressing the unobserved heterogeneity present in speed data. Moreover, speed data often demonstrates bimodality, skewness, or kurtosis (Park et al., 2010c). Future studies on before-after evaluation of speed data should address these issues into the modelling.

The spot speed data used in the current thesis provides speed characteristics at a particular point on a roadway segment. While for the free-flow traffic condition or roadway with lower traffic volume, spot speed data can reasonably be used to represent the speed characteristics for the entire road segment, for congested roadway, space mean speed is a better performance measures than the spot speed. With the advances in technology, space mean speed data can be estimated more reliably and hence can be used in future studies for the before-after safety evaluation.

References

Aarts, L., and van Schagen, I. (2006). Driving speed and the risk of road crashes: A review. Accident Analysis and Prevention 38 (2), 215–224.

Aguero-Valverde, J. (2013). Multivariate spatial models of excess crash frequency at area level: Case of Costa Rica. Accident Analysis and Prevention 59, 365– 373.

Aguero-Valverde, J., and Jovanis, P.P. (2006). Spatial analysis of fatal and injury crashes in Pennsylvania. Accident Analysis and Prevention 38, 618–625.

Aguero-Valverde, J., and Jovanis, P.P. (2008). Traffic analysis of road crash frequency using spatial models. Transportation Research Record 2061, 55–63.

Aguero-Valverde, J., and Jovanis, P.P. (2009). Bayesian multivariate Poisson Log-normal models for crash severity modeling and site ranking. Transportation Research Record 2136, 82-91.

Aguero-Valverde, J., and Jovanis, P.P. (2010). Spatial correlation in multilevel crash frequency models: Effects of different neighboring structures. Transportation Research Record 2165, 21–32.

Ahmed, M., Huang, H., Abdel-Aty, M., and Guevara, B. (2011). Exploring a Bayesian hierarchical approach for developing safety performance functions for a mountainous freeway. Accident Analysis and Prevention 43, 1581–1589.

Allpress, J.A., and Leland, L.S. Jr. (2010). Reducing traffic speed within roadwork sites using obtrusive perceptual countermeasures. Accident Analysis and Prevention 42(2), 377-383.

Amoros, E., Martin, J. L., and Laumon, B. (2003). Comparison of road crashes incident and severity between some French counties. Accident Analysis and Prevention 35(4), 537–547.

Anastasopoulos, P.C., Shankar, V.N., Haddock, J.E., and Mannering, F.L. (2012). A multivariate Tobit analysis of highway accident-injury-severity rates. Accident Analysis and Prevention 45, 110-119.

Anastasopoulos, P.Ch., and Mannering, F. (2009). A note on modeling vehicle accident frequencies with random-parameters count models. Accident Analysis and Prevention 41, 153–159.

Archer, J., Fortheringham, N., Symmons, M., and Corben, B. (2008). The impact of lowered speed limits in urban and metropolitan areas. Report No. 276, Transport Accident Commission (TAC).

Banawiroon, T., and Yue, W.L. (2003). A further investigation of 40 km/h speed zone case study of Unley of South Australia. Proceedings of the Eastern Asia Society for Transportation Studies 4, 965–978.

Barua, S., El-Basyouny, K., and Islam, M. T. (2014). A multivariate count data model of collision severity with spatial correlation. Analytic Methods in Accident Research 3–4, 28–43.

Bassani, M., Dalmazzo, D., Marinelli, G., and Cirillo, C. (2014). The effects of road geometrics and traffic regulations on driver-preferred speeds in Northern Italy: An exploratory analysis. Transportation Research Part F 25, 10–26.

Behnood, A., Roshandeh, A., Mannering, F. (2014). Latent class analysis of the effects of age, gender, and alcohol consumption on driver-injury severities. Analytic Methods in Accident Research 3-4, 56-91.

Besag, J. (1974). Spatial interaction and the statistical analysis of lattice systems. Journal of the Royal Statistical Society B 36(2), 192–236.

Besag, J., and Kooperberg, C. L. (1995). On conditional and intrinsic autoregressions. Biometrika, 82, 733--746.

Besag, J., York, J., and Mollié, A. (1991). Bayesian image restoration with two applications in spatial statistics. Annals of the Institute of Statistical Mathematics 43, 1-75.

Bloch, S. A. (1998). A comparative study of the speed reduction effects of photo radar and speed displays boards. Transportation Research Record 1640, 27-36.

Blomberg, R. D., and Cleven, A. M. (2006). Pilot test of heed the speed, A program to reduce speeds in residential neighborhoods. U.S. Department of Transportation, National Highway Traffic Safety Administration.

Blume, M.C., Noyce,D. A., and Sicinski, C. M. (2000). The effectiveness of a community traffic safety program. Transportation operations: Moving into the 21st Century, Institute of Transportation Engineers Annual Conference, ITE CD-008.

Bristol City Council. (2012). 20 mph speed limit pilot areas. Monitoring Report. http://www.bristol.gov.uk/page/20mph-speed-limit-pilot-areas.

Brooks, S. P., and Gelman, A. (1998). Alternative methods for monitoring convergence of iterative simulations. Journal of Computational and Graphical Statistics 7, 434-455.

Buchholz, K., Baskett, D., and Anderson, L. (2000). Collector street traffic calming: a comprehensive before – After Study. ITE Annual Meeting and Exhibit. CD-ROM.

Carriquiry, A, Pawlovich, M.D. (2004). From empirical Bayes to full Bayes: Methods for analysing traffic safety data.

Carter, D., Srinivasan, R., Gross, F., and Council, F. (2012). Recommended protocols for developing crash modification factors. NCHRP 20-7(314) Final Report.

Chib, S., and Winkelmann, R. (2001). Markov chain Monte Carlo analysis of correlated count data. Journal of Business and Economic Statistics 19, 428–435.

Congdon, P., (2006). Bayesian statistical modeling. John Wiley & Sons, New York, 2nd edition.

Cotti, C., Dunn, R.A., Tefft, N. (2014). Alcohol-impaired motor vehicle crash risk and the location of alcohol purchase. Social Science and Medicine 108, 201-209.

Cottrell, W. D., Kim,N., Martin,P.T., and Perrin, H. J. Jr.(2006). Effectiveness of traffic management in Salt Lake City, Utah. Journal of Safety Research 37, 27 – 41.

Cruzado, I. and Donnell, E. T. (2010). Factors affecting driver speed choice along two-lane rural highway transition zones. Journal of Transportation Engineering 136(8), 755-764.

Dell'Acqua, G. (2011). Reducing traffic injuries resulting from excess speed: low-cost gateway intervention in Italy. Transportation Research Record 2203, 94–99.

Deublein, M.,Schubert, M., Adey, B.T., Köhler,J., Faber, M.H. (2013). Prediction of road accidents: A Bayesian hierarchical approach.Accident Analysis and Prevention 51, 274–291.

Dyson, C., Taylor, M., Woolley, J., and Zito, R. (2001). Lower urban speed limits-trading off safety, mobility and environmental impact. 24th Australian Transport Research Forum.

Edquist, J., Rudin-Brown, C.M., Lenné, M.G. (2012). The effects of on-street parking and road environment visual complexity on travel speed and reaction time. Accident Analysis and Prevention 45, 759-765.

El-Basyouny, K., 2011. Speed limit reduction on residential roads: A pilot project. Final Report, Office of the Traffic Safety, City of Edmonton.

El-Basyouny, K., and Sayed, T. (2009a). Collision prediction models using multivariate Poisson-lognormal regression. Accident Analysis and Prevention 41, 820-828.

El-Basyouny, K., and Sayed, T. (2009b). Urban arterial accident prediction models with spatial effects. Transportation Research Record 2102, 27–33.

El-Basyouny, K., and Sayed, T. (2009c). Accident prediction models with random corridor parameters. Accident Analysis and Prevention 41, 1118–1123.

El-Basyouny, K., and Sayed, T. (2010). Full Bayes approach to before-and-after safety evaluation with matched comparisons case study of stop-sign in-fill program. Transportation Research Record 2148, 1–8.

El-Basyouny, K., and Sayed, T. (2011). A full Bayes multivariate intervention model with random parameters among matched pairs for before–after safety evaluation. Accident Analysis and Prevention 43, 87–94.

El-Basyouny, K., Sayed, T. (2012a). Measuring direct and indirect intervention effects using safety performance intervention functions. Safety Science 50, 1125-1132.

El-Basyouny, K., Sayed, T. (2012b). Measuring safety intervention effects using full Bayes non-linear safety performance intervention functions. Accident Analysis and Prevention 45, 152-163.

El-Basyouny, K., Sayed, T. (2013). Evaluating the signal head upgrade program in the city of Surrey. Accident Analysis and Prevention 50, 1236-1243.

Eluru, N., Chakour, V., Chamberlain, M., and Miranda-Moreno,L. F. (2013). Modeling vehicle operating speed on urban roads in Montreal: A panel mixed ordered Probit fractional split model. Accident Analysis and Prevention 59, 125– 134.

Elvik, R. (1999). Assessing the validity of evaluation research by means of meta-analysis. Ph-D Dissertation. 44 Report 430. Oslo, Institute of Transport Economics.

Elvik, R., Christensen, P., and Amundsen, A. (2004). Speed and road accidents: An evaluation of the Power model. The Institute of Transport Economics (TOI), (Report No. 740/2004), Norway.

Evans, L., Wasielewski, P. (1983). Risky driving related to driver and vehicle characteristics. Accident Analysis and Prevention 15, 121–136.

Federal Highway Administration (FHWA). (2012). Methods and practices for setting speed limits: An informative report. FHWA-SA-12-004.

Finch, D., Kompfner,P., Lockwood,C., and Maycock, G. (1994). Speed, speed limits and accidents. Project Report 58, Transportation Research Laboratory, Wokingham.

Flask, T., and Schneider, W. (2013). A Bayesian analysis of multi-level spatial correlation in single vehicle motorcycle crashes in Ohio. Safety Science 53 , 1–10.

Fleiss, J. (1981). Statistical methods for rates and proportions. Second edition. John Wileys and Sons, New 42 York.

Garber, N.J., and Gadiraju, R. (1989). Factors affecting speed variance and its influence on accidents. Transportation Research Record 1213, 64-71.

Gattis, J. L., and Watts,A. (1999). Urban street speed related to width and functional class. Journal of Transportation Engineering 125(3), 193-200.

Gelman, A., and Hill, J. (2007). Data analysis using regression and multilevel/hierarchical models. Cambridge University Press, New York.

Gelman, A., Meng, X., Stern, H. (1996). Posterior predictive assessment of model fitness via realized discrepancies. Statistica Sinica 6, 733-807.

Giles, M. J. (2004). Driver speed compliance in Western Australia: a multivariate analysis. Transport Policy 11, 227-235.

Gilks, W.R., Richardson, S., and Spiegelhalter, D.J. (1996). Markov Chain Monte Carlo in practice. London: Chapman and Hall.

Guo, F., Wang, X., and Abdel-Aty, M. (2010). Modeling signalized intersection safety with corridor-level spatial correlations. Accident Analysis and Prevention 42(1), 84-92.

Hadayeghi, A., Shalaby, A.S., and Persaud, B.N. (2003). Macrolevel accident prediction models for evaluating safety of urban transportation systems. Transportation Research Record 1840, 87-95.

Hadayeghi, A., Shalaby, A.S., Persaud, B.N., and Cheung, C. (2007). Safety prediction models proactive tool for safety evaluation in urban transportation planning applications. Transportation Research Record 2019, 225-236.

Hadayeghi, A., Shalaby, A.S., Persaud, B.N., and Cheung, C. (2010). Development of planning level transportation safety tools using Geographically Weighted Poisson Regression. Accident Analysis and Prevention 42, 676–688.

Harkey, D.L., Srinivasan, R., Baek, J., Persaud, B., Lyon, C., Council, F.M., Eccles, K., Lefler,N., Gross, F., Hauer, E., and Bonneson, J. (2008). Crash reduction factors for traffic engineering and its improvements. NCHRP Report 617. Washington, D.C.: Transportation Research Board.

Hauer, E. (1997). Observational before-after studies in road safety: Estimating the effect of highway and traffic engineering measures on road safety. Pergamon Press, Elsevier Science Ltd, Oxford, UK.

Hauer, E. (2009). Speed and safety. Transportation Research Record 2103, 10-17.

Hauer, E., Kononov, J., Allery, B., and Griffith, M.S. (2002). Screening the road network for sites with promise. Transportation Research Record 1784, 27–32.

Hauer, E., Ng, J., and Lovell, J. (1988). Estimation of safety at signalized intersections. Transportation Research Record 1185, 48-61.

Heydari, S.,Miranda-Moreno, L. F. and Fu, L. (2014). Speed limit reduction in urban areas: A before–after study using Bayesian generalized mixed linear models. Accident Analysis and Prevention 73, 252–261.

Highway Safety Manual (HSM). (2010). American Association of State Highway and Transportation Officials (AASHTO).

Hoareau, E., and Newstead, S. (2004). An evaluation of the default 50 km/h speed limits in Western Australia. Report No. 230, Monash University Accident Research Centre.

Hoareau, E., Newstead,S., and Cameron, M. (2006). An evaluation of the default 50 km/h speed limit in Victoria. Report No. 261, Monash University Accident Research Center, Australia.

Hoareau, E., Newstead,S., Oxley, P., and Cameron, M. (2002). An evaluation of the 50 km/h speed limits in South East Queensland. Report No. 264, Monash University Accident Research Centre.

Huang, H., Abdel-Aty, M. A., and Darwiche, A. L. (2010). County-level crash risk analysis in Florida: Bayesian spatial modeling. Transportation Research Record 2148, 27–37.

Jonsson, T. (1998). A Study of 30 km/h zone-design in Stockholm. ICTCT workshop.

Kamya-Lukoda, G. (2010). Interim evaluation of the implementation of 20 mph speed limits in Portsmouth. Final Report, Department for Transport, UK.

Kim, H., Sun, D., and Tsutakawa, R.K. (2002). Lognormal vs. gamma: extra variations. Biometrical Journal 44 (3), 305–323.

Kloeden, C. N., Woolley, J. E., and McLean, A. J. (2004). Evaluation of the South Australian default 50 km/h speed limit. CASR Report Series, CASR005, Centre for Automotive Safety Research, University of Adelaide, Australia.

Kloeden, C. N., Woolley, J. E., and McLean, A. J. (2006). Further evaluation of the south australian default 50 km/h speed limit. CASR Report Series, CASR034, Centre for Automotive Safety Research, University of Adelaide, Australia.

Knorr-Held, L., and Best, N.G. (2001). A shared component model for detecting joint and selective clustering of two diseases. Issue Journal of the Royal Statistical Society: Series A 164(1), 73-85.

Lan, B., Persaud, B., (2012) .Evaluation of multivariate Poisson lognormal Bayesian methods for before-after safety evaluations. Journal of Safety and Security 4, 193-210.

Lan, B., Persaud, B., Lyon, C., and Bhim, R. (2009). Validation of a Full Bayes methodology for observational before–after road safety studies and application to evaluation of rural signal conversions. Accident Analysis and Prevention 41, 574–580.

Lan, B., Srinivasan, R. (2013). Safety evaluation of discontinuing late night flash operations at signalized intersections. Transportation Research Record 2398, 1-9.

LeSage, J. P. (1998). Spatial econometrics. Department of Economics, University of Toledo.

Levine, N., Kim, K.E., and Nitz, L.H. (1995). Spatial analysis of Honolulu motor vehicle crashes. I. spatial patterns. Accident Analysis and Prevention 27 (5), 663–674.

Li, W., Carriquiry, A., Pawlovich, M., and Welch, T. (2008). The choice of statistical models in road safety countermeasures effectiveness studies in Iowa. Accident Analysis and Prevention 40 (4), 1531–1542.

Liang, W. L., Kyte, M., Kitchener, F., and Shannon, P. (1998). Effect of environmental factors on driver speed: A case study. Transportation Research Record 1635, 155–161.

Lord, D., and Mannering, F. (2010). The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. Transportation Research Part A 44, 291–305.

Lord, D., and Miranda-Moreno, L.F. (2008). Effects of low sample mean values and small sample sizes on the parameter estimation of hierarchical Poisson models for motor vehicle crashes: a Bayesian perspective. Safety Science 46, 751-770.

Lovegrove, G. R., and Sayed, T. (2006). Macro-level collision prediction models for evaluating neighbourhood traffic safety. Can. J. Civ.Eng. 33(5) , 609–621.

Lunn, D., Thomas, A., Best,N., and Spiegelhalter, D. (2000). WinBUGS - A Bayesian modelling framework: concepts, structure, and extensibility. Statistics and Computing 10,325-337.

Ma, J., Kockelman, K.M., and Damien, P. (2008). A multivariate Poisson-lognormal regression model for prediction of crash counts by severity, using Bayesian methods. Accident Analysis and Prevention 40, 964–975.

MacNab, Y.C. (2004). Bayesian spatial and ecological models for small-area accident and injury analysis. Accident Analysis and Prevention 36 (6), 1028–1091.

Malyshkina, N., Mannering, F. (2009). Markov switching multinomial logit model: an application to accident-injury severities. Accident Analysis and Prevention 41 (4), 829–838.

McCullagh, P., and Nelder, J.A. (1989). Generalized linear models, 2nd Edition. Chapman and Hall, London.

Miaou, S.P., and Lord, D. (2003). Modeling traffic crash-flow relationships for intersections: dispersion parameter, functional form, and Bayes versus empirical Bayes. Transportation Research Record 1840, 31-40.

Miranda-Moreno, L.F. (2006). Statistical models and methods for identifying hazardous locations for safety improvements. Ph.D. Dissertation. Department of Civil Engineering, University of Waterloo, Waterloo, Ontario, Canada.

Mitra, S. (2009). Spatial autocorrelation and Bayesian spatial statistical method for analyzing intersections prone to injury crashes. Transportation Research Record 2136, 92–100.

Narayanamoorthy, S., Paleti, R., and Bhat, C. R. (2013). On accommodating spatial dependence in bicycle and pedestrian injury counts by severity level. Transportation Research Part B: Methodological 55, 245-264.

Nilsson, G. (2004). Traffic safety dimension and the power model to describe the effect on speed safety. Bulletin 221, Lund Institute of Technology, Lund.

Noland, R. B., and Quddus, M.A. (2004). A spatially disaggregate analysis of road casualties in England. Accident Analysis and Prevention 36, 973–984.

Ntzoufras, I. (2009). Bayesian modeling using WinBUGS. John Wiley & Sons, Inc., New Jersey.

OECD/ECMT Transport Research Centre. (2006). Speed management. ISBN 92-821-0377-3. Retrieved from: http://www.internationaltransportforum.org/jtrc/safety/speed.html.

Park, B, J, Zhang, Y, and Lord D. (2010c). Bayesian mixture modeling approach to account for heterogeneity in speed data. Transportation Research Part B: Methodological 44(5), 662–673.

Park, E. S., Park, J., and Lomax, T.J. (2010b). A fully Bayesian multivariate approach to before–after safety evaluation. Accident Analysis and Prevention 42, 1118–1127.

Park, E.S., and Lord, D. (2007). Multivariate Poisson–lognormal models for jointly modeling crash frequency by severity. Transportation Research Record 2019, 1–6.

Park, P. Y., Miranda-Moreno, L. F. and Saccomanno, F. F. (2010a). Estimation of speed differentials on rural highways using hierarchical linear regression models. Canadian Journal of Civil Engineering 37(4), 624–637.

Park, Y. J., and Saccomanno, F. F. (2006). Evaluating speed consistency between successive elements of a two-lane rural highway. Transportation Research Part A: Policy and Practice 40(5), 375–385.

Pasanen, E., Seppala, H., and Haglund, T. (2005). Speed limits in the City of Helsinki. Helsinki City Planning Department, Traffic Planning Division, Finland.

Pasenen, E., Salmivaara, H. (1993). Driving speeds and pedestrian safety in the city of Helsinki. Traffic Engineering and Control 34,308–310.

Pauw, E. D., Thierie, M., Daniels, S., and Brijs, T. (2012). Safety effects of restricting the speed limits from 90 to 70 km/h. Presented at 91th Annual Conference of the Transportation Research Board, Washington, D.C.

Pawlovich, M.D., Li, W., Carriquiry, A., and Welch, T. (2006). Iowa's experience with road diet measures: Use of Bayesian approach to assess impacts on crash frequencies and crash rates. Transportation Research Record 1953, 163–171.

Persaud, B., and Lyon, C. (2007). Empirical Bayes before–after safety studies: Lessons learned from two decades of experience and future directions. Accident Analysis and Prevention 39(3), 546–555.

Persaud, B., and Lyon, C. (2009). Evaluation of the effectiveness of intersection safety cameras and impacts for traditional speed enforcement. Technical Report, City of Edmonton and Office of Traffic Safety.

Persaud, B.,Lan, B., Lyon, C., and Bhim, R. (2010). Comparison of empirical Bayes and full Bayes approaches for before–after road safety evaluations. Accident Analysis and Prevention 42,38–43.

Poe, C. M., and Mason, J. M. (2000). Analyzing influence of geometric design on operating speeds along low-speed urban streets: Mixed-model approach. Transportation Research Record 1737, 18-25.

Quddus, M. (2008). Modelling area-wide count outcomes with spatial correlation and heterogeneity: An analysis of London crash data. Accident Analysis and Prevention 40, 1486–1497.

Quddus, M. (2013). Exploring the relationship between average speed, speed variation, and accident rates using spatial statistical models and GIS. Journal of Transportation Safety & Security 5(1), 27-45.

Radalj, T. (2001). Driver speed compliance in Western Australia, Paper Presented at the Road Safety Forum, Hew Roberts Lecture Theatre, The University of Western Australia, Nedlands.

Ragnoy, A. (2005). Speed limit changes: Effects on speed and accidents. Institute of Transport Economics. TOI Report 784.

Road Directorate, Denmark. (1999). Speed management in urban areas: A framework for the planning and evaluation process. Report No. 168, Ministry of Transport.

Roads and Traffic Authority (RTA). (2000). 50 km/h urban speed limit evaluation. Summary Report, New South Wales.

Rossy, G., Sun, C., Jessen, D., and Newman, E. (2011). Residential speed reduction case studies. 90th Annual Meeting of the Transportation Research Board, Washington, D.C.

SafetyNet, 2009. Speeding. European Commission, Directorate-General Transport and Energy.

SAS Institute Inc. (2011). SAS/STAT® 9.3 User's Guide. Cary, NC.

Sawalha, Z., and Sayed, T. (2001). Evaluating the safety of urban arterial roadways. Journal of. Transportation Engineering, ASCE 127(2), 151-158.

Sayed, T., El-Basyouny, K., and Pump, J. (2006). Safety evaluation of stop sign in-fill program. Transportation Research Record 1953, 201-210.

Shin, K., Washington, S.P., and Schalkwyk, I. (2009) Evaluation of the Scottsdale Loop 101 automated speed enforcement demonstration program. Accident Analysis and Prevention 41, 393-403.

Siddiqui, C., Abdel-Aty, M., and Choi, M. (2012). Macroscopic spatial analysis of pedestrian and bicycle crashes. Accident Analysis and Prevention 45, 382– 391.

Song, J.J., Ghosh, M., Miaou, S., and Mallick, B. (2006). Bayesian multivariate spatial models for roadway traffic crash mapping. Journal of Multivariate Analysis 97, 246 – 273.

Spiegelhalter, D., Thomas, A., and Best, N. (1996). Computation on Bayesian graphical models. Bayesian Statistics 5, 407–425.

Spiegelhalter, D., Thomas, A., Best, N., and Lunn, D. (2005). WinBUGS user manual. MRC Biostatistics Unit, Cambridge.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., and Van der Linde, A. (2002). Bayesian measures of model complexity and fit. Journal of the Royal Statistical Society B 64, 1–34.

Stuster, J., Ciffman, Z., Warren, D. (1998). Synthesis of safety research related to speed and speed management. Publication FHWA-RD-98-154, U.S. Department of Transportation.

Tarko, A.P., and Figueroa, A.M. (2004). Advanced modeling of percentile free-flow speeds –An example of two-lane tangent road segments. TRB Annual Meeting CD-ROM.

Tarris, J. P., Poe, C. M., Mason, J. M., and Goulias, K. G. (1996). Predicting operating speeds on low- speed urban streets: regression and panel analysis approaches. Transportation Research Record 1523, 46-54.

Taylor, M.C., Lynam, D.A., Baruya, A. (2000). The effects of drivers' speed on the frequency of road accidents. TRL Report, No. 421. Transport Research Laboratory TRL, Crowthorne, Berkshire.

Thomas, A., Best, N., Lunn, D., Arnold, R., and Spiegelhater, D. (2004). GeoBUGS user manual. Version 1.2.

Tjandra, S.A., and Shimko, G. (2011). Selecting communities for piloting the new reduced speed limit on residential roads in the City of Edmonton. Annual Conference of the Transportation Association of Canada, Edmonton, Alberta.

Transportation Research Board. (1998). Managing speed: Review of current practice for setting and enforcing speed limits. Special Report 254.

Transportation Research Circular (TRC), (2011). Modeling operating speed: Synthesis report. Number E-C151, Transportation Research Board of the National Academics, 201.

Tunaru, R.(2002). Hierarchical Bayesian models for multiple count data. Austrian Journal of Statistics 31(3), 221-229.

van Schalkwyk, I. (2008). The development of aggregated macrolevel safety prediction models. Arizona State University.

Vogel, K. (2002). What characterizes a "free vehicle" in an urban area? Transportation Research Part F 5, 15–29.

Walter, L.K., and Knowles, J. (2004). Effectiveness of speed indicator devices on reducing vehicle speeds in London – Technical appendices. Transport Research Laboratory, PPR 314.

Wang, J. (2006). Operating speed models for low speed urban environments based on in-vehicle GPS data. PhD dissertation, Georgia Institute of Technology.

Wang, X., and Abdel-Aty, M. (2006). Temporal and spatial analysis of rear-end crashes at signalized intersections. Accident Analysis and Prevention 38 (6), 1137-1150.

Wang, X., Jin, Y., Abdel-Aty, M., Tremont, P.J., and Chen, X. (2012). Macrolevel model development for safety assessment of road network structures. Transportation Research Record 2280, 100–109.

Wang, Y., and Kockelman, K.M. (2013). A Poisson-lognormal conditional-autoregressive model for multivariate spatial analysis of pedestrian crash counts across neighborhood. Accident Analysis and Prevention 60, 71-84.

Washington, S. P., Karlaftis, M. G., and Mannering, F. L. (2010). Statistical and econometric methods for transportation data analysis. Second Edition, Chapman and Hall/CRC .

Wasielewski, P. (1979). Car-following headways on freeways interpreted by the semi-Poisson headway distribution model. Transportation Science 13(1), 36-55.

Webster, K., and Schnening, F. (1986). 40 km/h speed limit trials in Sydney Sydney: Traffic Authority of New South Wales, Research Note RN 6186.

Wei, F., and Lovegrove, G. (2013). An empirical tool to evaluate the safety of cyclists: Community based, macro-level collision prediction models using negative binomial regression. Accident Analysis and Prevention 61, 129-137.

Wier, M., Weintraub, J., Humphreys, E.H., Seto, E., and Bhatia, R. (2009). An area-level model of vehicle-pedestrian injury collisions with implications for land use and transportation planning. Accident Analysis and Prevention 41, 137–145.

World Health Organization (WHO). (2008). Speed management: A safety manual for decision-makers and practitioners. Geneva, Global Road Safety Partnership.

Xiong, Y., Tobias, J., Mannering, F. (2014). The analysis of vehicle crash injury-severity data: A Markov switching approach with road-segment heterogeneity. Transportation Research Part B 67, 109–128.

Ye, X., Pendyala, R.M., Washington, S.P., Konduri, K., and Oh, J. (2009). A simultaneous equations model of crash frequency by collision type for rural intersections. Safety Science, 47 (3), 443–452.