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Macro-Spatial Approach for Evaluating the Impact of Socio-Economics, Land Use, Built Environment and Road Facility on Pedestrian Safety

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Abstract

With the increasing demand for sustainability, walking is being encouraged as a main active mode of transportation. However, pedestrians are vulnerable to severe injuries when involved in crashes, which can discourage road users from walking. Therefore, studying the factors that affect the safety of pedestrians is important. This paper investigates the relationship between pedestrian-vehicle crashes and various zone characteristics in the city of Vancouver. The goal is to assess the impact of socio-economics, land use, built environment, and road facility on pedestrian safety using macro-level collision prediction models. The models were developed using generalized linear regression and full Bayesian techniques. Both walking trips and vehicle kilometers travelled were used as the main traffic exposure variables in the models. The safety models showed that pedestrian-motorist crashes were non-linearly positively associated with the increase in traffic exposure. The crashes were also found positively associated with the socio-economic variables (i.e. employment and household densities), some built environment variables (transit stop, traffic signal, and light pole densities), commercial area density, and arterial-collector roads proportion. On the other hand, the models revealed a decline in the pedestrian-motorist crashes associated with the increase in the proportions of pedestrian-actuated signals and local roads, as well as the increase in the recreational and residential areas' densities. The spatial effects were accounted for in the full Bayes models and were found significant, which imply the importance of considering spatial correlation when developing macro-level pedestrian safety models.

Keywords: Pedestrian-Motorist Crashes, Macro-Level Collision Prediction Models, Zone Characteristics, Full Bayes, Spatial Effects.

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1. Introduction

Walking is being promoted as a sustainable active transportation mode that is inexpensive, ecologically friendly, and convenient for short trips. Walking falls into the moderate-intensity exercise range, and if performed regularly, can result in substantial amounts of energy expenditure, weight control, as well as other physical and mental health benefits (Bassett et al., 2008). Despite these benefits, pedestrians are regarded as vulnerable road users due to their fragility and slow movement, which make them at higher crash risk than other road users (Wang et al. 2016; ATC 2011; Zhang et al. 2014). Almost quarter of all deaths on the world's roads (22%) is among pedestrians (Toroyan 2013), despite the lower distances travelled by pedestrians compared to other road users. Accordingly, any policies suggested to increase walking mode share must be accompanied with safety measures. This can be attained by better understanding of the various factors contributing to the occurrence of pedestrian crashes. A number of former studies had investigated the factors that influence pedestrian crashes. However, most of those safety studies were undertaken at the micro level, i.e. evaluating safety issues at specific locations. Macro-level safety analysis can be effective in identifying safety problems at larger areas, capturing spatial trends, and establishing long-term planning safety improvement policies. At the macro-level, pedestrian crash modeling with implications for transportation planning is scarcely researched. Some previous studies analyzed both pedestrian and bike crashes (Dumbaugh and Li 2010; Siddiqui et al. 2012; Zhang et al. 2015; Amoh-Gyimaha et al. 2016), while others focused on pedestrian crashes only (Clifton and Kreamer-Fults 2007; Cottrill and Thakuriah 2010; Loukaitou-Sideris et al. 2007; Wier et al. 2009; Wang et al. 2016). Although important efforts were done in the former studies to investigate pedestrian safety on the macro-

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level, more research is needed to provide further empirical evidence on the various factors influencing pedestrian crashes, as well as adding new explanatory variables to the literature.

This study investigated pedestrian-motorist crashes at 134 traffic analysis zones (TAZs) in the city of Vancouver. Generalized linear regression (GLM) and full Bayesian (FB) techniques were used to develop macro-level collision prediction models (CPMs) that are capable of evaluating pedestrian safety. A comprehensive set of explanatory variables, including some new variables, was used to model pedestrian safety. The explanatory variables were divided into four main categories: socio-economic, land use, built environment, and road facility. Models were developed for each category to explicitly assess the effect of its variables on pedestrian safety, and to come up with appropriate safety policies. Two main exposure variables, i.e. walking trips and vehicle kilometers travelled, were used to represent both the pedestrian and vehicles traffic exposure in the developed models. The CPMs of the different categories were compared to find the model with the best fit. Afterwards, a joint model was developed to include variables from the different categories to yield the best predictability of pedestrian crashes. Spatial effects were also tested, in a full Bayes context, to evaluate its impact on the CPMs and the incorporated variables.

2. Previous Work

Several studies attempted to investigate pedestrian safety on a macro-level. This was applied on various levels of area aggregation such as census tract (Cottrill and Thakuriah 2010; Ukkusuri et al. 2011; Abdel-Aty et al. 2013), traffic analysis zone (TAZ) (Abdel-Aty et al. 2013; Wang et al.

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2013; Lee et al. 2015b; Wang et al. 2016), and block group (Noland et al. 2013; Abdel-Aty et al. 2013). In these previous studies, macro-level crash prediction models attempted to relate pedestrian crashes to a variety of explanatory zonal features. A summary of significant associations from previous micro and macro level studies investigating pedestrian safety is summarized as follows.

Traffic volume has always been a significant predictor of pedestrian crashes (Dumbaugh and Li 2010; Lascala et al. 2000; Lee and Abdel-Aty 2005; Loukaitou-Sideris et al. 2007; Wier et al. 2009). Vehicle miles traveled (Abdel-Aty et al. 2013; Lee et al. 2015b) as well as average annual daily traffic (Loukaitou-Sideris et al. 2007; Wier et al. 2009) were found positively associated with pedestrian crashes. On the other hand, pedestrian exposure has been also critical for pedestrian crash modeling. Pedestrian exposure reflects the opportunity for a risky pedestrian-vehicle interaction to occur; however, it is very difficult to be measured directly since this would involve tracking the movements of all people at all times (Wang et al. 2016; Greene-Roesel et al. 2007). Greene-Roesel et al. (2007) summarized five common surrogate metrics used to describe pedestrian exposure; including population, number of pedestrians, number of trips, distance traveled, and time spent traveling. Wang et al. (2016) used population as a surrogate for pedestrian exposure, and it had a positive effect on pedestrian crashes. Amoh-Gyimaha et al. (2016) also found out that the population and percentage of commuters walking to work had a positive association with the number of pedestrian crashes.

Socio-economic and demographic factors are also among pedestrian crash predictors. An area's socioeconomic deprivation level was found associated with pedestrian crashes (Cottrill and Thakuriah 2010; Graham and Glaister 2003; Loukaitou-Sideris et al. 2007; Siddiqui et al. 2012). This is usually measured by proxy factors such as percentage of households without vehicles, the

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level of household income, and the unemployment rate. Median household income was found to have a negative effect on pedestrian crashes (Siddiqui et al. 2012; Lee et al. 2013), while percentage of residents living below the poverty line (Wier et al. 2009; Lee et al. 2015a) had positive effects on pedestrian crashes. Households without vehicles were also found to have a positive association with pedestrian crashes (Noland et al. 2013; Lee et al. 2015b; Siddiqui et al. 2012). Similarly, areas with a higher proportion of uneducated residents showed a positive effect on pedestrian crashes (Ukkusuri et al. 2011), while a higher proportion of high school graduates showed a negative effect (LaScala et al. 2000). The demographic features, such as population (Kim et al. 2006; Ukkusuri et al. 2011; Lee et al. 2015b), population density (Loukaitou-Sideris et al. 2007; Siddiqui et al. 2012), employment population (Wier et al. 2009; Siddiqui et al. 2012), and employment density (Loukaitou-Sideris et al. 2007) were all found to have a positive association with pedestrian crashes. Also, population characteristics had an important association with pedestrian crashes (Demetriades et al. 2004; Fontaine and Gourlet 1997; Johnson et al. 2004). The number of vulnerable road users, including children and older people, was found to be significantly correlated with pedestrian crashes. A higher number of pedestrian crashes were associated with a higher density of children (Abdel-Aty et al. 2013) and a lower percentage of resident population aged 65 and older (Wier et al. 2009).

Moreover, land use features could influence pedestrian activity and potentially lead to crashes. It was observed that pedestrian crashes were likely to increase with more residential land areas (Hadayeghi et al. 2007; Loukaitou-Sideris et al. 2007; Siddiqui et al. 2012; Wier et al. 2009). Other land use activities that generate traffic such as commercial, industrial, retail, and parks were also found to have positive association with pedestrian crashes (Kim et al. 2006; Ukkusuri et al. 2011; Pulugurtha et al. 2013). Wang and Kockelman (2013) introduced land use entropy

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and found out that balanced land development had a mild positive impact on reducing severe crashes, and could serve as a countermeasure for curbing pedestrian fatalities. Amoh-Gyimaha et al. (2016) also found out that mixed land use had a positive association with pedestrian crashes. Wang et al. (2016) concluded that pedestrian crashes were higher in TAZs with medium land use intensity than in TAZs with low and high land use intensity.

Lastly, significant correlations were also found between pedestrian crashes and road facilities (Loukaitou-Sideris et al. 2007; Wier et al. 2009; Abdel-Aty et al. 2013; Lee et al. 2015b). Traffic engineers found out that the intersections with higher number of pedestrian crossings had led to higher probabilities of vehicle-pedestrian crashes (Siddiqui et al. 2012; Abdel-Aty et al. 2013). Osama and Sayed (2017) found out that pedestrian crashes were positively associated with intersection density. Lengths of different road types as well as speed limits showed significant effects on pedestrian crashes (Quddus 2008; Kim et al. 2010; Abdel-Aty et al. 2013; Lee et al. 2015a, b). Most recently, Wang et al. (2016) investigated the association between pedestrian crash frequency and various roadway predictor variables, and indicated significant factors including length of major arterials, length of minor arterials, road density, average intersection spacing, and percentage of 3-legged intersections.

3. Data Collection

3.1 Data Sources

The zone-level CPMs developed in this study are based on 134 TAZs in the city of Vancouver. These zones represent discrete geographical areas defined by similar land uses or specific

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zoning/geographic features and are used to generate trips to the network based on the expected level of activity. Although it is generally desirable to use major road network components as boundaries, often adjacent homogenous land uses dictate that the zone be expanded to incorporate multiple blocks.

Explanatory variables that are related to socio-economics, land use, built environment, and road facility are included in the CPMs. Walk trips and vehicle kilometers travelled are incorporated in the models as exposure variables. The data needed for the explanatory variables is compiled using ArcGIS software for processing and visual representation, after being extracted from four main sources:

1. Insurance Corporation of British Columbia, a public automobile insurance company, provided the crash data for a 5 years period (2009-2013). Only pedestrian-motorist crashes are included in the analysis, as shown in Figure 1. A 5 years period is selected to collect an adequate sample size. The sample included 3 severity levels, i.e. fatality, injury, and property damage only. The total number of crashes is included in the analysis in order not to disperse the sample size. The reported crash data may have some limitations such as: unreported crashes due to low severity, and absence of records for cyclist-pedestrian crashes

2. Translink, the Metro Vancouver transportation authority, provided the geo-coded files for the city of Vancouver road network, land use, TAZ boundaries, and bus stops. Moreover, Translink provided the output of an Emme2 transportation planning model for the travel demand in Metro Vancouver in year 2011. Translink used the 2011 household travel survey to calibrate the model, and the 2011 cordon counts to validate the model assignments.

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3. The open data catalogue of city of Vancouver (<http://vancouver.ca/your-government/open-data-catalogue.aspx>) provided most of the city built environment data (i.e. intersections, traffic signals, and light poles).

4. Census Canada provided the socio-economic data (i.e. population, employment, and household data) of city of Vancouver according to 2011 census.

3.2 Analysis Variables

The variables included in the analysis are divided into six main categories; crashes, exposure, socio-economic, land use, built environment, and road facility. Table 1 provides the definitions and the descriptive statistics of the variables. The socio-economic variables (i.e. population, employment, and household) were already provided by the Emme2 model in a TAZ aggregated form, and are then divided by the corresponding TAZ area to compute their densities. As for the rest of the variables, the aggregation process at the zone level is done using the ArcGIS software as discussed below.

Pedestrian-motorist crash frequency is the only dependent variable. Crashes are aggregated at the different TAZs according to their geo-spatial locations. Boundary crashes are distributed between the adjacent TAZs according to the relative proportion of walking trips share at these zones. This way of distribution is selected due to the direct association between walking trips and both pedestrian activity and crash risk, as revealed by the models developed in this study and several previous studies (e.g. Amoh-Gyimaha et al. 2016; Wang et al. 2016).

A proxy exposure measure is used in this study for pedestrian traffic, i.e. walking trips (W), along with an actual exposure measure for vehicles traffic, i.e. VKT. Walking trips were already

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provided by the Emme2 model at the zones in an aggregated form, while the vehicle kilometer travelled was provided at a link level (from the Emme2 model), which made it easy to aggregate the total VKT at each TAZ.

For land use variables, the areas of the commercial, residential, and recreational zonings are aggregated at the different TAZs, and then divided by the corresponding TAZ area to obtain the density of each zoning type. Figure 2 shows the land use zonings at city of Vancouver.

For built environment indicators, the number of traffic signals, bus stops, and light poles are also aggregated at each TAZ, and then divided by the corresponding TAZ area to obtain the densities. Moreover, the number of pedestrian actuated traffic signals are aggregated and divided by the total number of traffic signals to calculate the proportion of pedestrian actuated traffic signals.

Finally, the freeway, arterial, collector, and local roads are represented as links, and their link lengths are aggregated at each TAZ. The aggregation of each road class is then divided by the road network total length to determine the proportion of each class of the total road network. Figure 3 shows the link-based road classes of city of Vancouver.

4. Methodology

GLM CPMs as well as FB spatial effects models are developed to investigate the impact of the explanatory variables on the pedestrian-motorist crashes with and without spatial effects. Both techniques are discussed as follow.

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227 4.1 GLM CPMs

228 The GLM approach, which assumes a non-normal distribution error structure, is widely used for
 229 the development of CPMs since conventional linear regression models lack the distributional
 230 property to adequately describe crashes. This inadequacy is due to the random, discrete, non-
 231 negative, and sporadic nature that characterizes the occurrence of crashes (Sawalha and Sayed,
 232 2001); (Miaou et al. 1993); (Sawalha and Sayed 2006). A Negative Binomial error distribution
 233 assumption has become the standard for CPMs developed using the GLM approach (Sawalha
 234 and Sayed 2001); (Hauer et al. 1988). The model form used for CPMs should generally satisfy
 235 two conditions (Sawalha and Sayed 2006). First it should not yield negative results in terms of
 236 predicting crashes and should also predict zero crashes for zero traffic exposure (when there are
 237 no vehicles or bikes on the road). As well, there need to be a link function to transform the model
 238 into a linear form. Based on empirical studies (Sawalha and Sayed 2001) (Miaou et al. 1993), a
 239 commonly used model form includes an exposure measure (e.g. vehicle kilometers traveled)
 240 raised to some power and multiplied by an exponential function including the other non-
 241 exposure explanatory variables. The model can be expressed mathematically as shown in
 242 equation 1.

$$243 \quad E(Y) = a_0 V^{a_1} \exp(\sum b_j x_j) \quad (1)$$

244 Where $E(Y)$ is the predicted collision frequency, V is the measure of traffic exposure (VKT, W,
 245 etc.), x_j represents any other explanatory variables, and a_0 , a_1 , and b_j are model parameters. The
 246 recommended statistical methodology to add explanatory variables into a GLM CPM is a
 247 forward stepwise procedure (Sawalha and Sayed 2001). Variables are added one by one, and
 248 their significance is tested. Variables representing exposure must be included first. Two

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statistical measures are then used to assess the goodness of fit of the GLM models, including Pearson chi square (χ^2) and scaled deviance (SD) statistics (Sawalha and Sayed 2001). For a well-fitted model and a relatively large number of observations, the expected value of Pearson χ^2 and SD is approximately equal to the number of degrees of freedom (Sawalha and Sayed 2001).

4.2 FB CPMs with Spatial Effects

Analysis using FB hierarchical statistical models has become more popular for developing CPMs due to its flexibility and its ability to use prior information, which results in improving the accuracy of parameter estimates. Moreover, FB analysis can provide more accurate measures of uncertainty on the posterior distributions of the parameter estimates (El-Basyouny and Sayed 2009). Incorporating spatial effects in the CPMs is usually undertaken in a FB analysis context, which was found more suitable for spatial effects models due to its ability to implement complex correlation structures (Aguero-Valverde and Jovanis 2008).

Unobserved heterogeneity is an important issue when data is aggregated at a macro-level. Unobserved heterogeneity occurs when some of the many factors affecting the frequency of crashes are either not observable or such data may be nearly impossible to collect (Mannering and Bhat 2014). In the situation where these unobserved factors tend to correlate with observed factors, there is a potential of erroneous statistical inferences (Greene 1991); (Mannering and Bhat 2014); (Washington et al. 2010). Dong et al. (2015) pointed out that accounting for unobserved spatial correlation may help to improve the accuracy and robustness of crash prediction and avoid underestimation of standard errors for model parameters. More recently, many safety researchers have used Bayesian spatial analysis with conditional autoregressive (CAR) priors, which can effectively accommodate the spatial autocorrelations of study units

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(Siddiqui et al. 2012); (Noland et al. 2013); (Wang et al. 2013); (Wang and Kockelman 2013); (Amoh-Gyimaha et al. 2016).

Zone-based Poisson lognormal models that account for spatial effects are used in this study to handle over-dispersion in the count data, and account for both the unstructured and structured (spatially correlated) heterogeneities. The development of FB models in this study followed the procedure described by El-Basyouny and Sayed (2009). Y_i is assumed to be the number of crashes at zones i , and Y_i is assumed to follow a Poisson distribution with parameter λ_i as shown in equation 2. λ_i is considered itself a random variable and modeled according to equation 3.

$$Y_i \sim \text{Poisson}(\lambda_i) \quad (2)$$

$$\ln \lambda_i = a_0 + a_1 \ln(VKT_i) + a_2 \ln(W_i) + \sum_i b_i X_i + \mu_i + s_i \quad (3)$$

where a_0 is the intercept, a_1 , a_2 , and b_i are the model parameters, VKT_i is the vehicle exposure variable, W_i is the pedestrian exposure variable, X_i represents the explanatory variables, μ_i accounts for the unstructured heterogeneity among the zones, and s_i accounts for the spatially correlated heterogeneity among the zones. The unstructured heterogeneity follows a lognormal distribution as implied by equations 3 and 4, while the spatial effects are accounted for by Gaussian CAR techniques, and S_i is calculated according to equation 5. It should be noted that equation 1 is similar to equation 3 but without the spatial effects being included and with μ_i has a gamma distribution instead. Poisson-Lognormal distribution was used in the FB CPMs because it was proven to be more accurate for the FB analysis than the Poisson-Gamma distribution especially when assuming vague priors as shown by Lord and Miranda-Moreno (2008).

$$u_i \sim \text{normal}(0, \sigma_u^2) \quad (4)$$

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$$S_i/S_{-i} \sim \text{normal}(\bar{S}_i, \frac{\sigma_s^2}{n_i}), \quad \bar{S}_i = \sum_{j \in C(i)} \frac{S_j}{n_i} \quad (5)$$

Where σ_u^2 is the unstructured heterogeneity variation, σ_s^2 is the spatial variation, and n_i , $C(i)$, and S_{-i} represent the number of neighbors of zone i , the set of neighbors of zone i , and the set of all spatial effects except S_i , respectively. Equation 5 is based on an adjacency-based proximity measure, where the conditional variance is inversely proportional to the number of neighboring zones, and the conditional mean is the mean of the adjacent spatial effects.

The spatial correlation effects are assessed by computing the spatial variation proportion of the total heterogeneity variation, according to equation 6. Significant spatial correlation exists when Ψ_s is found to be greater than 0.5 (Aguero-Valverde and Jovanis 2008). This implies that the neighbors of zones with high predicted crash frequencies will likely have high predicted crash frequencies and vice versa. Although incorporating spatial effects usually increases the CPM goodness of fit, the inclusion of spatial correlation can sometimes affect the estimation of parameters by making some variables non-significant although they were significant in the models without spatial effects (Karim et al. 2013).

$$\Psi_s = \frac{\sigma_s^2}{\sigma_s^2 + \sigma_u^2} \quad (6)$$

Markov chain Monte Carlo (MCMC) is applied using the WinBUGS tool to sample the posterior distribution and estimate the FB model parameters. MCMC methods can sample from the joint posterior distribution repeatedly by generating sequences of random points, the distribution of which converge to the target posterior distributions. A subsample is used for the purpose of monitoring convergence, and then excluded as a burn-in sample. Parameter estimation, performance evaluation, and inference are obtained by the following iterations.

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The explanatory variables are added into the FB CPM using a forward stepwise procedure as discussed in the previous subsection. Obtaining FB estimates requires the specification of prior distributions for the parameters reflecting the prior knowledge about the considered parameters. The prior may be informative or vague depending on the availability of the prior information. Diffused normal distribution with a zero mean and a large variance is the most commonly used vague prior to estimate the regression parameters (El-Basyouny and Sayed 2009). For the dispersion parameter, σ_u^2 , under the Poisson-lognormal model, the commonly used prior is a gamma distribution with parameters (ϵ, ϵ) , where the value of ϵ is a small number, e.g. 0.001 (Karim et al. 2013). For the Gaussian CAR models developed in this study, the prior distribution of σ_s^2 is assumed to be a gamma distribution with parameters $(1+\sum l_i/2, 1+n/2)$, where l_i is the term contributed by each zone and is calculated by equation 7.

$$l_i = n_i s_i (s_i - \bar{s}_i) \quad (7)$$

Two chains are used to run each model, and 20,000 MCMC iterations are discarded as burn in samples. The summary statistics of each chain are then estimated, and the convergences of the developed models are thoroughly checked to ensure that the posterior distribution has been found in order to begin parameter sampling. Convergence can be checked in several ways. First, two or more parallel chains with diverse starting values are tracked so that full coverage of the sample space is ensured. Brooks–Gelman–Rubin statistic can also be used, where convergence occurs if the value of Brooks–Gelman–Rubin statistic is less than 1.2 (El-Basyouny and Sayed 2009). Moreover, convergence can be checked by visually inspecting the MCMC trace plots of the model parameters. As a rule of thumb, convergence occurs when the ratio between the Monte Carlo error and the respective standard deviation of the estimates is less than 0.05.

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After obtaining convergence, additional 20,000 iterations are performed for each chain and the significance of the parameter estimates is tested using the 95% credible intervals. The FB model goodness of fit is judged by the Deviance Information Criteria (DIC). Spiegelhalter et al. (Spiegelhalter et al. 2002) proposed the DIC as a measure of model complexity and fit. As a goodness of fit measure, DIC is a Bayesian generalization of Akaike's information criteria that penalizes larger parameter models. According to Spiegelhalter et al. (2003), it is difficult to determine what would constitute an important difference in DIC; however, differences of more than 10 might definitely rule out the model with the higher DIC, and differences between 5 and 10 are considered substantial.

5. Results

GLM CPMs are developed to combine the significant variables within each of the investigated categories (i.e. socio-economic, land use, built environment, and road facility). Afterwards, a model is developed to merge the variables from all the categories into one joint CPM in order to yield the best predictability. The procedure for selecting the variables for both the combined and joint models is a forward stepwise procedure. The order in which the variables are added is based on their p-value, from lowest to highest. Whether to add a variable to the model or remove it is decided based on the parameter's statistical significance. FB models are then developed to validate the GLM models results under the spatial effects.

Tables 2 and 3 show the estimation results of the GLM and FB CPMs. The models show good fit; with most of the explanatory variables are statistically significant at the 5% level. Different

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pedestrian exposure measures are tested to choose the best one to model pedestrian-motorist crashes along with the vehicle exposure measure (i.e. VKT). Walk trips were found to be a better pedestrian exposure measure than population, walk mode share, and population & employment according to a pre-analysis test that was performed. Walk trips and vehicle kilometer travelled variables are used as the main exposure variables in all the developed models. Positive associations are found between pedestrian collisions and both vehicle kilometers travelled and walk trips. These results are plausible and in agreement with previous studies by Amoh-Gyimah et al. (2016), Chen et al. (2016), and Cai et al. (2016). The exponents of the exposure variables are less than one, which supports the safety in numbers hypothesis introduced by Jacobsen (2003). Walk trips exponent has higher value than VKT exponent, which means that pedestrian exposure contribute more to the pedestrian-motorist crashes than the vehicle traffic exposure. The results for the different CPM categories are shown as follow.

5.1 Socio-Economic Model

The socio-economic CPM is primarily based on the explanatory variables extracted from census data. The model reveals positive associations between pedestrian crashes and both the employment and household densities. The results are reasonable since the aforementioned variables can be considered surrogate measures for traffic exposure, thereby explaining their positive associations with pedestrian crashes. The result for the employment density agrees with previous studies by Siddiqui et al. (2012) and Cai et al. (2016).

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5.2 Land Use Models

The models in this category incorporate explanatory variables that refer to land zonings within the TAZs. The results in Table 2 show that the increase in residential and recreational area densities is associated with a decline in the number of pedestrian crashes. The association of recreational area density with less pedestrian crashes is logical because these areas usually provide off-street and continuous paths for active transportation commuters reducing the conflict risk between the vulnerable commuters and vehicles. This result is consistent with a study by Ukkusuri et al. (2011), who found a negative association between parks total area and pedestrian crashes. The negative association between residential area density and pedestrian crashes can be justified by the ongoing traffic calming measures applied by city of Vancouver to promote active transportation and limit motorized traffic at the residential neighborhoods (<http://vancouver.ca/streets-transportation/traffic-calming-and-safety.aspx>).

On the other hand, the increase in commercial area density is found associated with the increase in pedestrian crashes. This can be attributed to the side street activities that raise the potential risk of a pedestrian going into conflict with motorized traffic. The association between commercial areas and pedestrian safety agrees with two previous studies (Kim et al. 2006; Ukkusuri et al. 2011).

5.3 Built Environment Models

Built environment variables refer to the elements that are physically present on the pedestrian and road networks. The models show that pedestrian crashes are positively associated with the transit stop, traffic signal, and light pole densities. More traffic signals imply the presence of

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higher number of wide intersections that usually include complex vehicle and pedestrian maneuvers elevating the probability of crash occurrence, which agrees by previous studies by Siddiqui et al. (2012) and Cai et al. (2016). Also, the presence of bus stops indicates the occurrence of interactions between buses, vehicles, and pedestrians, which is also expected to increase pedestrian crash risk; this agrees with the results from (Lee et al. 2015a). An unexpected finding is the positive association between light pole density and the pedestrian crashes. This can be attributed to the higher pedestrian volume (higher exposure) on the streets that have better lighting (more light poles), especially at night time. On the other hand, the proportion of pedestrian actuated traffic signals is found to be negatively associated with pedestrian crashes. This is logical since such facilities provide safer pedestrian crossing experience.

It is worth noting that the built environment GLM model including SigD, PoleD variables is found to be the best fit model representing pedestrian-motorist crashes among the different model categories.

5.4 Road Facility Models

For this category, higher proportion of arterial plus collector roads is found to be positively associated with cyclist crash frequency. This can be attributed to the higher speeds and the heavier vehicle traffic on these types of roads, which would increase the risk of severe interactions and conflicts between pedestrians and vehicles. On the other hand, a decline in pedestrian-motorist crash frequency is found associated with higher proportion of local roads. A likely reason for such negative association is the relatively low speeds on local roads, which would result in the increase in drivers' attentiveness, and, therefore, would reduce conflict

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potential. The former results agree with previous studies conducted by Wang and Kockelman, (2013) and Siddiqui et al. (2012).

5.5 Joint Model

The joint model combined various attributes from the different models' categories in order to yield the best predictability of pedestrian crashes. It is found to have the best fit among all the combined CPMs with all its variables (i.e. W, VKT, SigD, RecD, PoleD) significant, as shown in Table 2.

5.6 FB Models with Spatial Effects

FB models are then developed for both the combined and joint CPMs. The effects of the variables in the FB models are consistent with the results from the GLM CPMs. All the variables are found significant at 5 % level except four variables; RecD, ResD, PedAct, and PolesD. This is probably due to the inclusion of spatial effects, which was shown in a previous study that it could negatively impact the significance of some variables (Karim et al. 2013). The spatial effects are found substantial in all the FB models ($\psi \gg 0.50$) as shown in Table 3. This highlights the importance of considering spatial effects in the macro-level CPMs that investigate pedestrian safety, which agrees with few former studies (Wang et al. 2016; Amoh-Gyimah et al. 2016; Cai et al. 2016).

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6. Summary and Conclusions

This paper provides transportation engineers, planners, and policy makers with tools that can be used to improve pedestrian safety. The study used data from city of Vancouver, according to its 134 traffic analysis zones, to develop empirical macro-level CPMs incorporating variables related to exposure, socio-economics, land use, built environment, and road facility. A GLM technique was used to build CPMs for the various explanatory variables, followed by a FB analysis incorporating spatial effects. The CPMs were developed using two main exposure variables, i.e. vehicle kilometer travelled and walking trips.

The CPMs' results showed that pedestrian-motorist crashes were non-linearly and positively associated with both of the exposure variables. The exponents of the exposure variables were less than one supporting the "safety in numbers" hypothesis. The results also showed that the increase in pedestrian crashes was associated with the increase in socio-economic attributes such as employment and household densities. Built environment attributes such as transit stop, traffic signal, and light pole densities were found positively associated with pedestrian crash frequency, on the contrary of Pedestrian-actuated signals proportion that was found negatively associated with pedestrian crashes. Regarding land use, positive association was found between commercial area density and pedestrian crash frequency, while both residential and recreational area densities had negative associations with pedestrian crashes. For road network facilities, higher pedestrian crash frequency was found associated with more arterial and collector roads proportion, while a decline in pedestrian crashes was found associated with the increase in local roads proportion.

The built environment model was found to best fit the pedestrian-motorist crashes among the different GLM models categories (i.e. socio-economic, land use, built environment, and road

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facility). The results from the FB CPMs were consistent with the GLM ones; and showed considerable spatial effects in the model variation. This confirms the importance of accounting for spatial effects when investigating pedestrian safety on a macro-level. Most of the findings in this study agreed with the results from former studies in the literature, though more comprehensive set of pedestrian exposure and explanatory variables were used in the current study.

Several areas of further research can be investigated. First, it is recommended to include more variables that can be associated with the pedestrians' activity and safety in the CPMs such as pedestrian network structure, road network patterns, etc.; as this could add further insights to pedestrian safety. Moreover, the developed CPMs need to be validated by evaluating its transferability to various pedestrian environments. Lastly, the association between walkability and the various variables investigated in this study such as collisions, exposure, land use, built environment, and road facilities can be an interesting topic for future research.

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Tables

TABLE 1 Variables Definition and Data Summary (n=134 TAZs)

Variable	Description	Mean	SD	Min	Max
Crashes					
Coll	Pedestrian-Motorist Crashes over 5 Years	12.71	13.48	0	78
Exposure					
VKT	Vehicle Kilometer Travelled	4290.43	3327.54	189.46	22288.79
W	Number of Pedestrian Trips	3971.64	2677.49	247	13906
Socio-Economic					
PopD	Population Density (Population/Zone Area)	8391.82	6995.85	0	33658.9
EmpD	Employment Density (Employment/Zone Area)	12236.26	26399.07	84.54	170910
HhsD	Household Density (Households/Zone Area)	4165.2	4363.5	0	21418.8
Land Use					
ResD	Residential Density (Residential Areas/Zone Area)	0.34	0.20	0	0.67
CommD	Commercial Density (Commercial Areas/Zone Area)	0.08	0.11	0	0.58
RecD	Recreational Density (Recreational Areas/Zone Area)	0.10	0.13	0	0.91
Built Environment					
SigD	Signal Density (Number of Signals/Zone Area)	14.26	18.50	0	110.55
TransitD	Transit Stops Density (Number of Stops/Zone Area)	24.28	23.62	0	162.24
PoleD	Light Poles Density (Number of Poles/Road Network Length)	665.81	373.71	24.32	2188
Ped_Act	Proportion of Pedestrian Actuated Traffic Signal (Number of Pedestrian Actuated Signals/Total Traffic Signals)	0.39	0.32	0	1
Road Facility					
ArtColl_Prop	Arterial-Collector Roads Proportion (Arterial + Collector Roads Length/ Road network Length)	0.35	0.21	0.12	1
Loc_Prop	Local Roads Proportion (Local Roads Length/Road Network Length)	0.64	0.21	0	0.87

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TABLE 2 GLM Analysis Estimates

Model Coll=	K	AIC	df	SD	X ²
Socio-Economic					
0.0008W ^{0.61} VKT ^{0.54} exp(2.8x10 ⁻⁵ HhsD*+0.56x10 ⁻⁵ EmpD)	5.88	881.7	129	138.40	143.79
Land Use					
0.0007W ^{0.69} VKT ^{0.47} exp(1.40CommD)	5.88	876.9	130	139.13	140.29
0.0014W ^{0.70} VKT ^{0.45} exp (-1.07RecD-0.74ResD)	6.13	873.9	129	138.59	142.86
Built Environment					
0.0006W ^{0.63} VKT ^{0.54} exp (0.0077SigD+5.9PoleD)	6.75	866.6	129	137.76	142.93
0.0006W ^{0.70} VKT ^{0.50} exp (0.0066TransitD-0.30PedAct)	6.17	872.4	129	137.65	139.29
Road Facility					
0.0005W ^{0.72} VKT ^{0.47} exp (0.81Art_Coll)	6.09	872.8	130	138.76	144.98
0.0012W ^{0.72} VKT ^{0.47} exp (-0.79Loc_Prop)	6.02	873.5	130	138.66	144.59
Joint Model					
0.0008W ^{0.59} VKT ^{0.53} exp (6.86PoleD-0.79RecD+0.006SigD*)	6.94	864.3	128	137.35	144.47

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667 * Significant at the 10% level

668 All other parameters are significant at the 5% level or higher

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672 **TABLE 3 FB Analysis Estimates**

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Socio-Economic			Land Use		Built Environment						Road Facility				Joint Model	
Variable	Estimate	SD	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2		Estimate	SD
			Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD		
Intercept	-7.30	0.91	-6.98	0.92	-7.31	0.0.91	-7.07	0.91	-7.36	0.91	-7.51	0.91	-6.57	0.93	-6.92	0.93
VKT	0.43	0.094	0.34	0.09	0.36	0.08	0.35	0.089	0.36	0.088	0.32	0.089	0.31	0.08	0.36	0.08
W	0.73	0.11	0.86	0.10	0.82	0.10	0.78	0.11	0.84	0.10	0.86	0.10	0.85	0.10	0.76	0.11
EmpD	0.72x10 ⁻⁵	0.35x10 ⁻⁵	-	-	-	-	-	-	-	-	-	-	-	-	-	-
HhsD	4.6x10 ⁻⁵	2x10 ⁻⁵	-	-	-	-	-	-	-	-	-	-	-	-	-	-
RecD	-	-	-0.68*	0.46	-	-	-	-	-	-	-	-	-	-	-0.37*	0.46
ResD	-	-	-0.57*	0.38	-	-	-	-	-	-	-	-	-	-	-	-
CommD	-	-	-	-	1.50	0.64	-	-	-	-	-	-	-	-	-	-
SigD	-	-	-	-	-	-	0.010	0.0036	-	-	-	-	-	-	0.0095	0.003
TransitD	-	-	-	-	-	-	-	-	0.0064	0.002	-	-	-	-	-	-
PoleD	-	-	-	-	-	-	2.75*	3.81	-	-	-	-	-	-	3.27*	3.87
PedAct	-	-	-	-	-	-	-	-	-0.22*	0.20	-	-	-	-	-	-
Art_Coll	-	-	-	-	-	-	-	-	-	-	0.96	0.35	-	-	-	-
Loc_Prop													-0.94	0.35	-	-
ψ	0.96	0.039	0.98	0.003	0.98	0.002	0.98	0.003	0.98	0.002	0.98	0.002	0.98	0.002	0.98	0.003
DIC	787.54		788.96		787.84		787.14		787.93		786.82		786.63		787.37	

674 -Not Applicable

675 * Non significant at the 5% level

676 All other parameters are significant at the 5% level or higher

Figures

FIGURE 1 Heat Map of Pedestrian-Motorist Crashes at City of Vancouver TAZs

FIGURE 2 Land Use Zonings at City of Vancouver

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FIGURE 3 City of Vancouver Road Facility Inventory

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