Spatial joint analysis for zonal daytime and nighttime crash frequencies using a Bayesian bivariate conditional autoregressive model

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ABSTRACT

This study presents a joint analysis of daytime and nighttime crash frequencies at the zone level with consideration of spatial correlations. Crash data from 131 traffic analysis zones in Hong Kong in 2011 are investigated. A Bayesian bivariate conditional autoregressive model is proposed to establish links between crash frequencies and traffic attributes, road network characteristics, and land use patterns. The proposed model allows not only for the distinct heterogeneous and spatial effects of each dependent variable, but also for the correlations between them.

The parameter estimates indicate that more daytime and nighttime crashes are associated with more vehicle hours traveled and with networks that have greater global integration. Average speed alone has a significant negative effect on daytime crashes. The crash risk in commercial and other areas is lower than that in residential areas, but the crash risk in areas of mixed residential and commercial use is higher. Meanwhile, significant spatial autocorrelation emerges across zones and explains 46.7% and 48.2% extra-Poisson variations for daytime and nighttime crash frequencies, respectively. High positive correlations are found in both heterogeneous and spatial effects. These findings, together with its better performance on model fit than the univariate counterparts, demonstrate the strength of the proposed model.

Keywords: Zonal safety; Daytime and nighttime; Spatial correlation; Bivariate conditional autoregressive model; Bayesian inference.

1. Introduction

Since the US Federal Highway Administration issued the Safe, Affordable, Flexible, Efficient, Transportation Equity Act-A Legacy for Users (SAFETEA-LU) in 2005, considerable research efforts have been devoted to the incorporation of safety considerations into the transportation planning process (Abdel-Aty, Siddiqui, & Choi, 2013). Based on the concept of safety-conscious planning, safety-conscious practices should be comprehensively, routinely, and effectively incorporated into the entire transportation planning process (Hadayeghi, Shalaby, & Persaud, 2007). To provide decision-support tools for planners and engineers to implement proactive road safety planning, crash prediction models (CPMs) (also known as safety performance functions) at the macro level have become fairly routine components in traffic safety research, especially at the traffic analysis zone (TAZ) level (Zeng & Huang, 2014). Macro CPMs can be applied to identify factors that contribute to zonal crash occurrences, to monitor area-wide safety performance, and to provide suggestions for countermeasures aimed at improving regional traffic safety (Huang et al., 2016). Spatial correlation (also known as spatial dependency or spatial effect) is an important issue to consider in zonal crash analysis because the safety performance of adjacent regional units may be affected by common unobserved or unobservable factors (Quddus, 2008). Including spatial correlation in CPMs can improve model estimation and reduce model misspecification (Washington, Karlaftis, & Mannering, 2011).

Most studies analyze daytime and nighttime crashes together. This is due in part to the absence of detailed data, but it is also based on the assumption that the same crash occurrence mechanisms prevail during the day and at night. However, driving environments in the daytime and nighttime differ significantly, with varying environmental and traffic conditions that affect driver behavior and eventually crash propensity (Chen, Ma, & Chen, 2014). Several studies have modeled daytime and nighttime crash frequencies for road segments or intersections and shown substantial differences in their contributing factors (Chen et al., 2014; Dinu & Veeraragavan, 2011; Donnell, Porter & Shankar, 2010). However, to the best of our knowledge, no such study has reported on both daytime and nighttime crash frequencies simultaneously at the zonal level.

Due to the bivariate nature of crash data, it is necessary to consider the likely correlation between crash frequencies in daytime and nighttime; this correlation is derived from the effects of omitted confounding factors shared by crash frequency measures across the two periods. Although some studies account for the heterogeneous correlation among crash severities or types with bivariate or multivariate regression techniques (El-Basyouny & Sayed, 2009a; Ma & Kockelman, 2006; Park & Lord, 2007; Yu & Abdel-Aty, 2013; Zeng, Wen, Huang, Pei, & Wong, 2017b, 2018), bivariate or multivariate spatial correlation is seldom considered (Barua, El-Basyouny, & Islam, 2014). Moreover, univariate spatial modeling of daytime and nighttime crash frequencies may result in biased estimates because they may not be spatially independent of one another. Therefore, a bivariate spatial analysis is expected to control for heterogeneous correlations and correlated spatial dependencies of daytime and nighttime crash frequencies in the same observation unit.

From a methodological standpoint, many approaches, such as generalized estimation equations (Abdel-Aty & Wang, 2006), simultaneous autoregressions (Quddus, 2008), multiple membership (El-Basyouny & Sayed, 2009b), and geographic weighted Poisson regression (Hadayeghi, Shalaby, & Persaud, 2010; Li, Wang, Liu, Bigham, and Ragland, 2013; Xu & Huang, 2015), have been advocated to capture spatial correlation in crash frequency data, but most are specified for univariate modeling. The multivariate conditional autoregressive (CAR) model, which has been successfully applied to analyze crash frequencies at the macro level (e.g., cantons and census tracts) (Aguero-Valverde, 2013; Wang & Kockelman, 2013) and the micro level (e.g., roadway segments and intersections) (Barua et al., 2014; Ma, Chen, & Chen, 2017; Huang, Zhou, Wang, Chang, & Ma, 2017; Wen, Sun, Zeng, Zhang, & Yuan, 2018) by severity or transportation mode, is one state-of-the-art method for multivariate spatial modeling under a Bayesian framework.

In line with previous studies, the key objective of this study is to use the bivariate CAR model to simultaneously analyze zonal daytime and nighttime crash frequencies, accommodating spatial correlations among adjacent zones and the heterogeneous and spatial correlations between the two crash periods. To demonstrate the utility of the proposed model, it is compared with univariate CAR models in the Bayesian context via programming in the freeware WinBUGS. Crash data collected from 131 selected TAZs in Hong Kong are used in the empirical analysis.

The remainder of this paper is organized as follows. The next section reviews the literature on zonal CPMs and daytime/nighttime crash analysis. Section 3 describes the crash data obtained from Hong Kong for the study. The proposed model and the criteria for model assessment are specified in Section 4. Section 5 introduces a detailed estimation of the proposed model and discusses the parameter estimation results. Finally, our conclusions and recommendations for future research are presented in Section 6.

2. Literature review

2.1. Zonal CPMs

Numerous studies of zonal CPMs have been conducted at various zone scales, ranging from states (Noland, 2003; Castro-Nuño, Castillo-Manzano, & Fageda, 2018), counties (Aguero-Valverde & Jovanis, 2006; Huang, Abdel-Aty, & Darwiche, 2010; Li et al., 2013), districts (Haynes, Jones, Kennedy, Harvey, & Jewell, 2007), census tracts/wards (Quddus, 2008; Wang & Kockelman, 2013), and postal codes (Lee, Abdel-Aty, & Choi, 2014) to traffic analysis districts (TADs) (Cai, Abdel-Aty, & Lee, 2017a; Cai, Abdel-Aty, Lee, & Eluru, 2017b), TAZs (Abdel-Aty, Siddiqui, Huang, & Wang, 2011; Guo, Pei, Yao, & Wong, 2015; Guo, Xu, Pei, Wong, & Yao, 2017; Hadayeghi et al., 2010; Huang et al., 2016; Xu & Huang, 2015), block groups (Levine, Kim, & Nitz, 1995), and local health areas (MacNab, 2004). Among these, TAZs are among the most prevalent zonal units because they can be easily integrated into the transportation planning process (Huang et al., 2016).

Various zone-level risk factors, including traffic characteristics such as traffic flow and average speed (Hadayeghi et al., 2010; Quddus, 2008); road facility conditions such as network topology (Guo et al., 2015, 2017), highway density/length (Huang et al., 2016; Quddus, 2008), and intersection density/number (Quddus, 2008; Xu, Huang, Dong, & Wong, 2017); socioeconomic and demographic indices, such as land use (Guo et al., 2015, 2017; Wang & Kockelman, 2013), employment (Quddus, 2008; Hadayeghi et al., 2010), household income (Huang et al., 2016; Xu et al., 2017), and population density (Huang et al., 2010); and environmental factors such as annual precipitation (Aguero-Valverde & Jovanis, 2006) have been widely investigated to interpret the observed cross-sectional variability of safety conditions.

Crash data are typically collected with reference to the location dimension, which results in spatial correlations among adjacent spatial units (Quddus, 2008). Thus, most zonal crash studies have accommodated spatial correlations in crash frequency modeling (Hadayeghi et al., 2010; Huang et al., 2010; Li et al., 2013; Guo et al., 2017; Xu et al., 2017); however, daytime and nighttime crashes are modeled together in these studies, which neglects the differences in the contributing factors to crash occurrence across these two periods.

2.2. Daytime/nighttime crash analyses

Daytime and nighttime CPMs are typically developed to estimate the effect of roadway lighting on traffic safety at intersections (Bullough, Donnell, & Rea, 2013; Donnell et al., 2010; Gross & Donnell, 2011; Isebrands, Hallmark, Li, McDonald, Storm, & Preston, 2010). Most of these studies suggest that installation of lighting would decrease intersection-related crashes at night but increase intersection-related crashes during the daytime. With respect to other risk factors, the magnitudes of these effects on daytime and nighttime crash frequencies have certain discrepancies. One related problem is that the effects of some factors on crash frequency can be significant during one period (daytime or nighttime) but insignificant during the other. For example, in an empirical analysis on intersection safety in Minnesota (Gross & Donnell, 2011), the presence of a depressed median on major roads was found to significantly reduce the occurrence of daytime crashes, but its effect on nighttime crash frequency was not significant (at a significance level of 95%).

Similarly, Chen et al. (2014) developed random-effects Tobit models for crash rate analysis using refined-scale panel data. They found that the roadway segment length, a low speed limit, and the on-ramp density had significant effects (at least at a significance level of 90%) only on daytime crash rates, whereas the truck percentage, the inside shoulder width, and the occurrence of snow had significant effects only on nighttime crash rates. Likewise, Dinu and Veeraragavan (2011) applied random-parameters Poisson models to two-lane undivided highways in India. The model estimates showed that some factors related to traffic composition and roadway geometry (including the proportion of trucks and motorized two-wheelers, the driveway density, and the horizontal curvature) had heterogeneous effects on crash frequency during only one period (either daytime or nighttime).

These findings suggest that considerable discrepancies exist in the traffic, roadway, and environmental attributes that affect daytime and nighttime crash frequencies and that it would be beneficial to take each of them as response variables of CPMs if the required data were available. Overall, a spatial joint analysis for daytime and nighttime crash frequencies in TAZs is fully merited. It is expected to identify their respective contributing factors and capture the effects of heterogeneous correlations and spatial dependencies.

3. Data preparation

A comprehensive crash dataset collected from the Hong Kong Traffic Information System is used in this study. TAZs defined in the Hong Kong Planning Vision and Strategy zoning system are used as the spatial units for the empirical analysis. Of the 338 TAZs in the zoning system, 131 are identified as having adequate traffic and roadway information. The traffic crashes reported within these areas in 2011 are aggregated by TAZ using geographical information system techniques. In the absence of exact data for the time of sunrise and sunset each day, the aggregated crashes are empirically divided into two groups according to the crash occurrence time: daytime crashes from 07:00 to 19:00 and nighttime crashes from 19:00 to 07:00, as suggested by Dinu and Veeraragavan (2011). Therefore, the daytime and nighttime crash counts can be obtained for each selected TAZ in 2011. Figs. 1 and 2 display the spatial distributions of the aggregated daytime and nighttime crashes, respectively.

One study found that time exposure, as measured by vehicle hours traveled (VHT), is a more reasonable proxy for crash exposure (Pei, Wong, & Sze, 2012). In the current analysis, to estimate the traveled vehicle hours for each observation, the average annual daily traffic (AADT) and taxi global positioning system (GPS) datasets are collected. The AADT data and temporal and directional multiplicative factors are obtained from the Hong Kong Annual Traffic Census system, which provides hourly traffic volumes for more than 100 core stations in Hong Kong. The taxi GPS data are derived from 480 taxis traveling around Hong Kong that are equipped with GPS probes. The probe taxis report real-time information on location, data, time, direction, speed, and occupancy to the traffic control center at 30-second intervals.

The VHTs on all roadway segments within the study area are estimated using the following procedure. First, we estimate the hourly traffic volume of roadways without core stations following the linear data projection method proposed by Wong and Wong (2015), using the hourly traffic volume on roadways with core stations and the taxi flow volume on all roadways (please refer to the reference for more details on the data projection method). Second, we estimate the average travel speed for each hour according to the taxis' instantaneous speed information contained in the GPS dataset. These estimates are based on Pei, Wong, Ai, and Shi's (2009) findings that taxi speed is almost equivalent to actual travel speed in Hong Kong. Third, we calculate the hourly VHTs of each segment as the product of each segment's traffic volume and length divided by the average travel speed. Finally, we calculate the VHTs for daytime and nighttime periods in each TAZ as the sum of the VHTs on the covered hours and roadways. To explore the nonlinear relationship between crash frequency and VHT, the natural logarithm of VHT is modeled like the other explanatory variables.

The estimated travel speed is used as a risk factor to model zonal daytime and nighttime crash frequencies, together with road density, intersection density, land use pattern, and road network pattern. The road density is defined as the total length of roadway in a TAZ divided by its area, and the intersection density is calculated as the number of intersections in a TAZ divided by the total road length. The land use pattern of each selected TAZ is inferred by the percentage of trips in each zone, based on the trip pattern and purpose. Specifically, we categorize land use patterns into four groups: residential, commercial, mixed (combined commercial and residential use), and others (government, institution, or community), according to the primary (more than 50%) trip purpose within each zone. Residential area is set as the reference pattern.

Global integration, which measures the accessibility of the roadway network (Haq, 2001), is found an appropriate index to describe typical patterns of the road network patterns in Hong Kong (Guo et al., 2015, 2017). Therefore, it is used to quantify road network patterns in this research. The global integration value of roadway l, I_l, can be calculated by the following formulas:

$$I_l = \frac{D_n \times (n-2)}{2(MD_l - 1)}, \tag{1}$$

$$D_n = 2\{n[\log_2((n+2)/3)-1]+1\}/(n^2-3n+2), \tag{2}$$

where n is the number of roads within the network. MD_l is the mean depth of road l, that is, the average distance from road l to other roads, which is calculated as follows:

$$MD_l = \sum_{d=1}^{m} d \times N_d/(n-1), \tag{3}$$

where d is an integer and represents the shortest distance from road l, N_d denotes the number of roads with the shortest distance d, and m denotes the maximum shortest distance.

Table 1 summarizes the definitions and descriptive statistics of the variables used in model development. The results of the correlation tests and multicollinearity diagnoses suggest that these explanatory variables are statistically independent.

4. Methods

In this section, the formulations of the univariate and bivariate CAR models for analysis of zonal daytime and nighttime crash frequencies are successively specified. Two criteria, the deviance information criteria (DIC) and Bayesian R^2, are then proposed to evaluate the model fit performance in the context of Bayesian inference.

4.1. Model specification

4.1.1. Univariate CAR model

To explore the spatial correlations among the zonal units derived from the shared effects of unobserved confounding factors, the univariate CAR model is developed by incorporating a Gaussian CAR prior into the traditional Poisson log-normal model (Zeng & Huang, 2014). Specifically, the observed daytime $(k=1)$ /nighttime $(k=2)$ crash count $Y_{k,i}$ in TAZ i is assumed to follow a Poisson distribution, and a random term with CAR prior, $\phi_{k,i}$, is added into the link function. The model structure of the univariate CAR regression can be expressed as follows:

$$Y_{k,i} \left| \lambda_{k,i} \sim Poisson(\lambda_{k,i}), \quad k = 1, 2, \right. \tag{4}$$

$$\ln \lambda_{k,i} = \ln e_{k,i} + \mathbf{X}'_{k,i}\boldsymbol{\beta}_k + \theta_{k,i} + \phi_{k,i}, \tag{5}$$

where $\lambda_{k,i}$, $e_{k,i}$, $\mathbf{X}_{k,i}$, and $\boldsymbol{\beta}_k$ are the expected crash count, the crash exposure (i.e., the number of opportunities for crash occurrence), and the risk factors and regression coefficients corresponding to daytime and nighttime crashes in TAZ i, respectively.

$\theta_{k,i}$ is a residual term to account for unstructured heterogeneous effects of daytime and nighttime crash frequencies, which are assumed to follow an ordinary, exchangeable normal distribution:

$$\theta_{k,i} \sim normal(0, \sigma_k^u), \tag{6}$$

where $\sigma_k^u (> 0)$ is the variance of $\theta_{k,i}$.

$\phi_{i,k}$ represents the spatial effect of the daytime/nighttime crash frequency in TAZ i, which is specified via the intrinsic (univariate) CAR prior proposed by Besag et al. (1974):

$$\phi_{k,i} \sim normal(\bar{\phi}_{k,i}, \sigma_{k,i}^u), \tag{7}$$

$$\bar{\phi}_{k,i} = \frac{\sum_{i \neq j} \phi_{k,j} \omega_{ij}}{\sum_{i \neq j} \omega_{ij}}, \tag{8}$$

$$\sigma_{k,i}^u = \frac{\sigma_k^{us}}{\sum_{i \neq j} \omega_{ij}}, \tag{9}$$

in which σ_k^{us} is the variance parameter in the univariate CAR prior. ω_{ij} is the entry with the adjacency index and weight for TAZs i and j in proximity matrix. Although various proximity structures have been investigated (Guo et al., 2017), the most prevalent structure, a 0-1 first-order neighbor, is used to define the proximity matrix in this study. Specifically, if TAZs i and j share a common border, $\omega_{ij} = 1$; otherwise, $\omega_{ij} = 0$.

The posterior proportion of variation explained by the spatial correlation term for each crash period is also of interest and is defined as follows (Aguero-Valverde, 2013):

$$\eta_k = \frac{sd(\phi_k)}{sd(\theta_k) + sd(\phi_k)}. \tag{10}$$

4.1.2. Bivariate CAR model

Although the univariate CAR model accommodates area-wide spatial correlations, it ignores correlations of heterogeneous and spatial effects between daytime and nighttime crash frequencies in the same spatial unit. To deal with this issue, a bivariate CAR model is proposed that can be extended to a multivariate version for joint modeling $K(K>2)$ of dependent variables (Barua et al., 2014). The difference in the model structure between the bivariate CAR and its univariate counterpart lies mainly in the specification of the residual terms. Specifically, to account for the correlation between heterogeneous effects, $\theta_{1,i}$ and $\theta_{2,i}$ are assumed to follow a bi-normal distribution with zero means:

$$\boldsymbol{\theta}_{it} \sim N_2(\mathbf{0},\boldsymbol{\Sigma}),\ \ \boldsymbol{\theta}_i = \begin{pmatrix} \theta_{1,i} \\ \theta_{2,i} \end{pmatrix},\ \ \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_{1,1}^b & \sigma_{1,2}^b \\ \sigma_{2,1}^b & \sigma_{2,2}^b \end{pmatrix}. \tag{11}$$

In the variance-covariance matrix $\boldsymbol{\Sigma}$, the diagonal elements ($\sigma_{1,1}^b$ and $\sigma_{2,2}^b$) are the variances of residual terms $\theta_{1,i}$ and $\theta_{2,i}$, and the off-diagonal elements ($\sigma_{1,2}^b$ and $\sigma_{2,1}^b$, $\sigma_{1,2}^b = \sigma_{2,1}^b$) are the covariance between $\theta_{1,i}$ and $\theta_{2,i}$. The correlation coefficient $\rho = \sigma_{1,2}^b \big/ \sqrt{\sigma_{1,1}^b \sigma_{2,2}^b}$ describes the correlation between $\theta_{1,i}$ and $\theta_{2,i}$.

To capture the correlation between the spatial effects of daytime and nighttime crash frequencies, a bivariate two-dimensional CAR prior is proposed. Given that the 0-1 first-order neighbor structure is used, the bivariate CAR prior can be expressed as the following:

$$\boldsymbol{\Phi}_i \sim N_2(\bar{\boldsymbol{\Phi}}_i, \boldsymbol{\Omega}/n_i),\ \ \boldsymbol{\Phi}_i = \begin{pmatrix} \phi_{1,i} \\ \phi_{2,i} \end{pmatrix},\ \ \bar{\boldsymbol{\Phi}}_i = \begin{pmatrix} \bar{\phi}_{1,i} \\ \bar{\phi}_{2,i} \end{pmatrix},\ \ \boldsymbol{\Omega} = \begin{pmatrix} \sigma_{1,1}^{bs} & \sigma_{1,2}^{bs} \\ \sigma_{2,1}^{bs} & \sigma_{2,2}^{bs} \end{pmatrix}, \tag{12}$$

in which $n_i = \sum_{i \neq j} \omega_{ij}$ is the number of TAZs adjacent to TAZ i, and $\bar{\phi}_{k,i} = \sum_{i \neq j} \phi_{k,j}\omega_{ij} \big/ n_i$. $\boldsymbol{\Omega}$ is the variance-covariance matrix for spatial correlation, where $\sigma_{1,1}^{bs}$ and $\sigma_{2,2}^{bs}$ reflect the spatial variances of daytime and nighttime crash frequencies, respectively, and $\sigma_{1,2}^{bs} (= \sigma_{2,1}^{bs})$ reflects the spatial covariance between them. To measure the correlation between the spatial effects, the correlation coefficient is calculated as: $\rho_s = \sigma_{1,2}^{bs} \Big/ \sqrt{\sigma_{1,1}^{bs}\sigma_{2,2}^{bs}}$.

4.2. Model assessment

The two most prevalent criteria in the context of Bayesian inference, DIC and Bayesian R^2, are used to assess the goodness-of-fit of the above models. DIC are considered a Bayesian equivalent of Akaike's information criterion that penalizes models with more parameters. It thus provides a Bayesian measure of model complexity and fitting (Spiegelhalter, Best, Carlin, & Van Der Linde, 2002) and is defined as

$$DIC = \overline{D} + pD\,, \tag{13}$$

where $\overline{D}$ is the posterior mean deviance that can be used to measure fitness or "adequacy," and pD is a complexity measure for the effective number of parameters. In general, if the DIC are lower, the model is preferred; and differences over 10 suggest the significantly better performance of the model with lower DIC (Spiegelhalter, Thomas, Best, & Lunn, 2005). Moreover, El-Basyouny and Sayed (2009a) showed that the DIC are additive under independent models and priors. Consequently, the DIC values of the univariate CAR models can be added to enable comparison to the DIC of the bivariate CAR model.

The Bayesian R^2, which measures the global model fit, is used to estimate the ratio of the explained sum of squares to the total sum of squares (Zeng & Huang, 2014). The Bayesian R^2 values of daytime and nighttime crash frequencies, represented by R_1^2 and R_2^2, respectively, are calculated as

$$R_k^2 = 1 - \frac{\sum_{i=1}^{N}\left(Y_{k,i} - \lambda_{k,i}\right)^2}{\sum_{i=1}^{N}\left(Y_{k,i} - \overline{Y}_k\right)^2}, \tag{14}$$

$$\overline{Y}_k = \frac{1}{N}\sum_{i=1}^{N} Y_{k,t}, \quad k = 1,2. \tag{15}$$

In the above equations, $\overline{Y}_1$ and $\overline{Y}_2$ are the means of daytime and nighttime crash frequencies, respectively.

5. Model estimation and result analysis

5.1. Model estimation

Due to the complexity of the spatial models, the parameters and super-parameters are estimated by Bayesian methods using the Markov chain Monte Carlo (MCMC) techniques available in WinBUGS. Obtaining Bayesian estimates requires specification of the (super-) parameters' prior distributions, which reflect prior knowledge about the (super-) parameters. In the absence of sufficient knowledge, noninformative (vague) prior distributions are specified (Zeng & Huang, 2014; Zeng, Wen, Huang, & Abdel-Aty, 2017a). Specifically, a diffused normal distribution $N(0,10^4)$ is used for the priors of the regression coefficients (i.e., the elements of $\boldsymbol{\beta}_k$). A diffused gamma distribution $gamma(0.001, 0.001)$ is used for the priors of the precision (reciprocal of the variance) parameters, $1/\sigma_k^u$ and $1/\sigma_k^{us}$ $(k = 1,2)$. A Wishart prior, $W(\mathbf{P}, r)$, is used for $\boldsymbol{\Sigma}^{-1}$ and $\boldsymbol{\Omega}^{-1}$, where $\mathbf{P} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ represents the scale matrix and $r = 2$ is the degrees of freedom (Barua et al., 2014). For each model, a chain of 550,000 iterations of the MCMC simulation is made, with the first 50,000 iterations acting as a burn-in. The MCMC convergence is evaluated via visual inspection of the MCMC trace plots for the model parameters and monitoring of the ratios of the Monte Carlo errors relative to the respective standard deviations of the estimates.

5.2. Result analysis

Table 2 shows the (super-) parameter estimates and goodness-of-fit measures for the univariate and bivariate CAR models. From the results, it is evident that the bivariate model fits the zonal crash data better than the univariate models because the bivariate model has lower DIC (1702 for the bivariate model versus 1748 for the univariate models) and a higher Bayesian R^2 (R_1^2 = 0.927 and R_2^2 = 0.904 for the bivariate model versus R_1^2 = 0.923 and R_2^2 = 0.894 for the univariate models) for both daytime and nighttime crash frequencies. Moreover, the cumulative residual (CURE) plots of daytime and nighttime crash frequencies, as shown in Fig. 3, indicate that the ranges of the residuals in the univariate models are somewhat larger than those in the bivariate model, which further demonstrates the latter's strength regarding model fit. By explicitly modeling the correlation between daytime and nighttime crashes, the bivariate CAR model benefits from pooling strength across crash times and thereby reduces model misspecification (Aguero-Valverde, 2013). Specifically, the variances and covariances of both heterogeneous and spatial effects are all significant at the

95% credibility level. The statistically significant ρ and ρ_s are estimated to be 0.696 and 0.701, respectively. These results imply that daytime and nighttime crashes are highly correlated in a positive way due to heterogeneous and spatial effects. Heterogeneous (aspatial) correlations capture the effects of the missing risk factors shared by crash times within a TAZ (but not across TAZs), such as distinctive local lighting conditions and sight obstructions (Wang & Kockelman, 2013). In contrast, correlations in spatial effects are expected and attributable to omitted factors that are spatially clustered but more widely spread (thus affecting nearby TAZs) and are shared across crash times (Wang & Kockelman, 2013). Examples of such omitted factors include terrain features, weather conditions, and socioeconomic attributes.

Once the (aspatial and spatial) correlations between the response variables are considered, the magnitudes of the heterogeneous effects increase from 0.039 (0.074) to 0.147 (0.184) for daytime (nighttime) crashes, and the significance levels vary from 90% to 95%. In contrast, the spatial autoregression effects of daytime and nighttime crashes decrease, as reflected by the lower spatial variances in the bivariate model. As a consequence, the proportions of variation explained by the spatial effects decrease from 0.739 to 0.467 for daytime crashes and from 0.667 to 0.482 for nighttime crashes. Nonetheless, η_1 and η_2 are still significant at the 95% credibility level. In addition, we were interested to observe that the constant terms obtained from the univariate and bivariate models differ remarkably between daytime and nighttime cases. One plausible reason may be that some unobserved effects that are considered to be fixed in univariate models have been captured by the correlations between daytime and nighttime crash frequencies.

When the coefficient estimates of each explanatory variable in the univariate and bivariate models are compared, it can be seen that their plus or minus signs are almost consistent in the models and for daytime and nighttime crashes, but the significance levels differ for some factors. For example, although the effects of speed on daytime and nighttime crashes are significant at 95% and 90% credibility levels, respectively, in the univariate models, in the bivariate model, the effect of speed on daytime crashes is significant only at the 90% credibility level and is insignificant for nighttime crashes (i.e., less than the 90% credibility level). Given the outperformance of the bivariate CAR model, the parameter estimates for crash exposure and risk factors are mainly discussed.

It is not a surprise that VHT was found to have significant (at the 95% credibility level) positive effects on both daytime and nighttime crash frequencies. As a measure of crash exposure, an increase in VHT brings about more opportunities for crashes. The coefficients (β_1 = 0.215 [SD = 0.042] and β_2 = 0.200 [SD = 0.042]) differ substantially from 1, which means that a nonlinear relationship exists between the daytime (nighttime) crash frequency and the VHT. This relationship is in line with the model assumptions and the findings in the literature (Guo et al., 2017). According to the parameter estimates, doubling the daytime VHT is expected to increase the number of crashes by 148%, and doubling the nighttime VHT is expected to increase the number of crashes by 144%.

The results show that the effect of average speed is only significant (at the 90% credibility level) for daytime crashes. The negative coefficient (β_1 = −0.011 [SD = 0.006]) indicates that the expected daytime crash frequency decreases by 1.1% for every 1 km/h increase in the average speed. This finding aligns with those of several studies (Gladhill &

Monsere, 2012; Guo et al., 2015, 2017); their authors argued that the lower crash risk in zones with higher average speeds may be attributed to favorable built environments, in which the road network configurations are more reasonable and road infrastructure is better maintained.

The significant positive (at least at the 90% credibility level) coefficients (β_1 = 0.303 [SD = 0.135] and β_2 = 0.281 [SD = 0.158]) for integration imply that more daytime and nighttime crashes tend to occur in zones with higher global integration. Increases of 35.4% and 32.4% were found in daytime and nighttime crashes, respectively, for every increase of 1 in the value of global integration. This result supports the earlier findings of Guo et al. (2017), who offered several explanations for the phenomenon. A TAZ with higher global integration suggests greater accessibility to the roadways within it and may thereby act as a conduit for daily travels. Heavier traffic volumes are thus expected in these TAZs than in less connected or accessible ones. A higher global integration suggests that the roadways within the zone may possess more connections (i.e., intersections) with other roads. Given the complicated vehicular maneuvers and frequent signal changes at intersections, the probability of crashes might increase. A higher global integration also indicates that the network may have more complicated routes, which likely give rise to more traffic conflicts. Moreover, the selected TAZs refer to three network patterns: grid, deformed grid, and irregular. A network with higher global integration is more likely to have a grid pattern. Most of the roads in a grid pattern network are straight, which may make the experience of driving monotonous and boring. Drivers may be more distracted, and driver fatigue may be intensified, thus increasing the crash risk.

The coefficient estimates show that, compared with residential areas, commercial areas have 31.1% and 38.5% fewer daytime and nighttime crashes, respectively, and other areas have 37.5% and 39.0% fewer daytime and nighttime crashes, respectively. The presence of additional overpasses, as shown in Fig. 4, may contribute to decreases in crash occurrences in commercial and other areas of Hong Kong. Overpasses allow conflicts between automobiles and pedestrians crossing a street to be avoided by keeping them apart. Moreover, shops in underground floors are common in Hong Kong's residential areas, as displayed in Fig. 5. These shops attract a large number of surrounding residents, which may lead to an increase in pedestrian-related crashes. In contrast, 43.7% more daytime crashes and 54.3% more nighttime crashes occur in mixed areas than in residential areas. This may be explained, in part, by the finding of Ewing and Dumbaugh (2009) that pedestrians are less likely to perceive their environment as safe in areas with a mixed land-use pattern than in areas with a monotonous land-use pattern.

6. Conclusions

This paper investigates the relationship between zone-level daytime and nighttime crash frequencies and various factors related to traffic, network, and land use, including VHT, average speed, roadway density, intersection density, network pattern, and land use pattern. A Bayesian bivariate CAR model is advocated for the joint analysis of daytime and nighttime crash frequencies in 131 TAZs in Hong Kong by accounting for zone-specific heterogeneity, spatial dependence across zones, and aspatial and spatial correlations between crash periods.

The results of Bayesian estimation show that VHT, the crash exposure measure, has a positive and nonlinear relationship with both daytime and nighttime crash frequencies. As the average speed increases, the daytime crash counts decrease significantly. More crashes are expected to occur in zones with greater global integration values (which are also more likely to be a grid network). Mixed-use areas are the most hazardous for road users, followed in order by residential areas, commercial areas, and other areas.

Significant heterogeneous and spatial effects are found in the bivariate CAR model. Spatial effects account for 46.7% and 48.2% of the extra-Poisson variations for daytime and nighttime crash frequencies, respectively. The correlations for heterogeneous and spatial effects are estimated at 0.696 and 0.701, respectively, both of which are highly significant. The results indicate that greater daytime risks are associated with greater nighttime risks because they may be affected by unobserved factors shared across the two periods within a TAZ or spatially clustered but widespread. Moreover, the bivariate CAR model is found to provide a superior fit over the two univariate CAR models because its (bivariate) DIC are much lower than the sum of their (univariate) DIC and because its Bayesian R^2 values for daytime and nighttime crashes are higher than the counterparts from the univariate models.

In summary, the empirical analysis recognizes the distinct risk-factors that make a significant contribution to daytime and nighttime crash frequencies in TAZs and demonstrates the applicability and superiority of the bivariate CAR model for the joint analysis. However, several enhancements may be pursued. For example, a number of socioeconomic, demographic, and environmental factors should be investigated, including employment, age cohorts, and roadway lighting/illumination. A random-parameters extension may also be pursued to capture heterogeneity in the explanatory variables' safety effects (Barua, El-Basyouny, & Islam, 2016). However, more field datasets are needed to validate the random-parameters model, because none of the factors in the Hong Kong dataset were found to have significant heterogeneous effects on daytime or nighttime crashes (results not shown).

Funding

This study was jointly supported 1) the Joint Research Scheme of National Natural Science Foundation of China/Research Grants Council of Hong Kong under Grant Nos. 71561167001 & N_HKU707/15, 2) the Natural Science Foundation of China under Grant Nos. 51578247, 713711921, and 71671100; 3) the Natural Science Foundation of Guangdong Province under Grant No. 2017A030310161; 4) the Research Fund for Fok Ying Tong Education Foundation of Hong Kong under Grant No. 142005; 5) Fundamental Research Funds for the Central Universities under Grant Nos. 2017BQ026, and 2016zzts050; 6) Postdoctoral Fellow Scheme of the University of Hong Kong.

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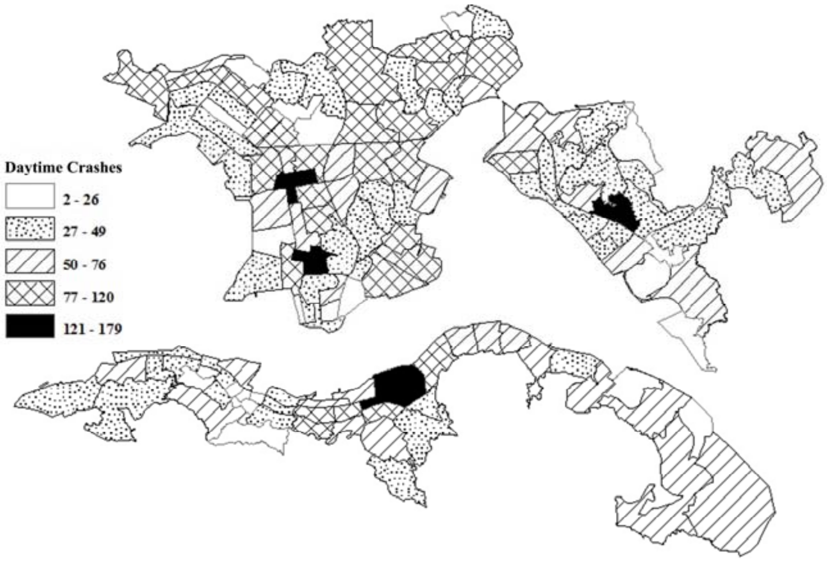


Fig. 1. Spatial distribution of daytime crashes across the 131 TAZs in Hong Kong.

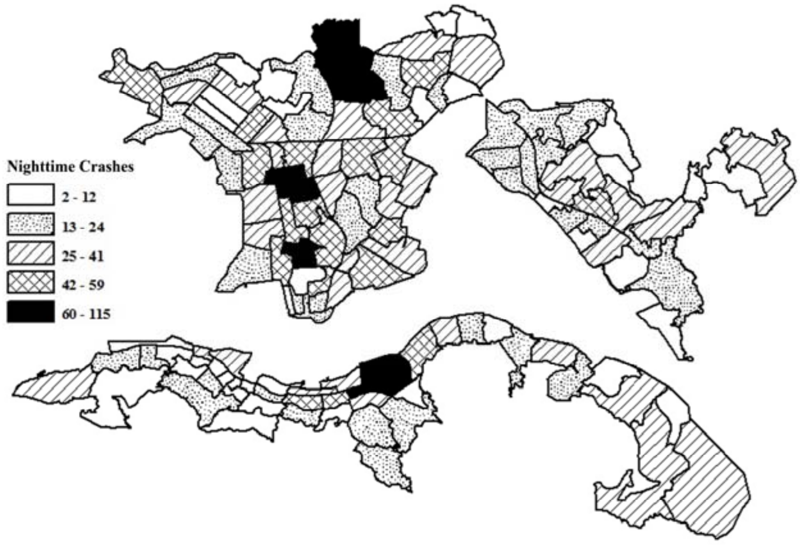
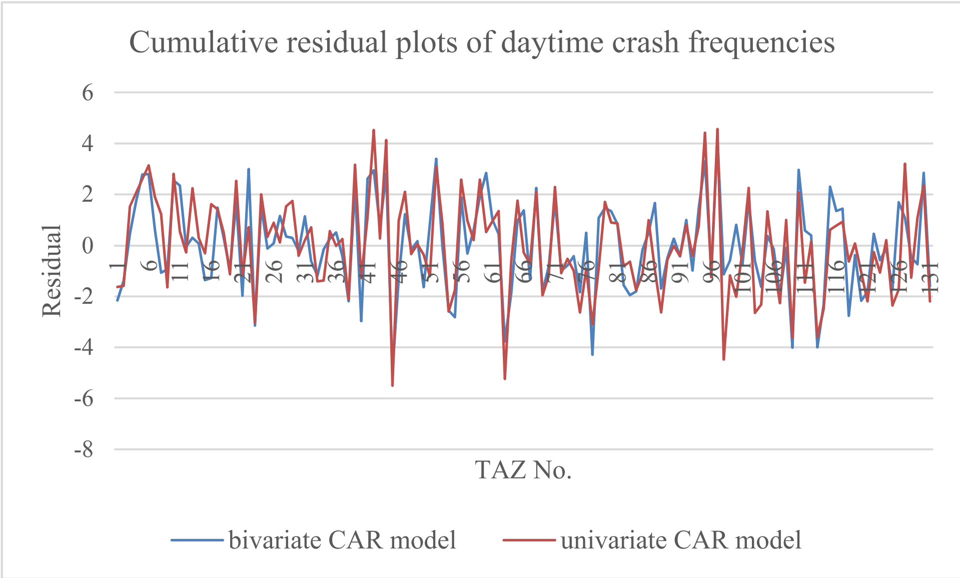
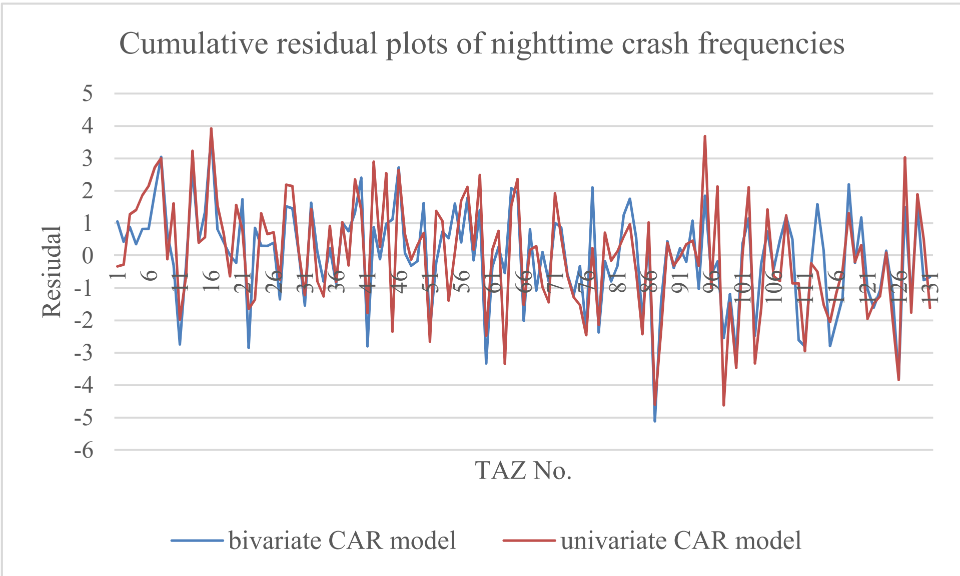


Fig. 2. Spatial distribution of nighttime crashes across the 131 TAZs in Hong Kong.



(a)



(b)

Fig. 3. Cumulative residual plots of daytime and nighttime crash frequencies.

Fig. 4. Typical scene in a commercial area in Hong Kong.

Fig. 5. Typical scene in a residential area in Hong Kong.

Table 1. Descriptive statistics of the variables.

Variable	Description	Mean	SD	Min.	Max.	Percent
Response variables						
Daytime	Daytime crash count per TAZ	35.9	21.7	2	117	
Nighttime	Nighttime crash count per TAZ	16.5	12.5	1	75	
Crash exposure						
VHT[1]	Daytime vehicle hours traveled	452,432	357,697	6,957	1,867,394	
VHT[2]	Nighttime vehicle hours traveled	213,007	197,153	4,209	1,205,817	
Risk factors						
Speed[1]	Daytime average speed	23.0	10.7	8.58	71.6	
Speed[2]	Nighttime average speed	28.7	12.3	10.5	75.7	
Integration	Global integration	1.15	0.43	0.48	3.62	
Road_dens	Roadway length (km) per km^2	50.1	15.0	21.2	109	
Inter_dens	Number of intersections per km	3.56	1.47	1.21	11.2	
Land use	Residential (reference)					58.7
	Commercial					19.1
	Mixed					13.0
	Others					9.2

Table 2. Parameter estimation in the univariate and bivariate CAR models [a].

	Univariate CAR		Bivariate CAR	
	Daytime	Nighttime	Daytime	Nighttime
Constant	-7.435(3.213) [b]	-46.61(2.426)*	6.049(2.677)*	-0.432(4.348)
VHT	0.130(0.058)*	0.161(0.064)*	0.215(0.042)*	0.200(0.059)*
Speed	-0.015(0.006)*	-0.010(0.005)**	-0.011(0.006)**	-0.008(0.005)
Integration	0.344(0.130)*	0.315(0.146)*	0.303(0.135)*	0.281(0.158)**
Commerical	-0.327(0.149)*	-0.526(0.167)*	-0.358(0.149)*	-0.486(0.174)*
Mixed	0.357(0.151)*	0.422(0.175)*	0.361(0.163)*	0.434(0.188)*
Others	-0.457(0.177)*	-0.501(0.199)*	-0.470(0.181)*	-0.495(0.215)*
Heterogeneous variance [c]	0.039(0.047)**	0.074(0.070)**	0.147(0.043)*	0.184(0.059)*
Spatial variance [d]	0.764(0.298)*	0.655(0.371)*	0.360(0.207)*	0.435(0.255)*
η_k	0.739(0.163)*	0.667(0.185)*	0.467(0.080)*	0.482(0.079)*
R^2	0.923	0.894	0.927	0.904
DIC	937	811	1702	
$\sigma_{1,2}^{b} = \sigma_{2,1}^{b}$	—	—	0.118(0.046)*	
$\sigma_{1,2}^{bs}(=\sigma_{2,1}^{bs})$	—	—	0.303(0.207)*	
ρ	—	—	0.696(0.117)*	
ρ_s	—	—	0.701(0.194)*	

[a] *Road_dens* and *Inter_dens* are excluded, as none of their effects on daytime or nighttime crash frequency

is significant (less than the 90% credibility level).

[b] Estimated mean (standard deviation) for the parameter.

[c] Heterogeneous variance refers to σ_k^u in the univariate model or $\sigma_{k,k}^b$ in the bivariate model.

[d] Spatial variance refers to σ_k^{us} in the univariate model or $\sigma_{k,k}^{bs}$ in the bivariate model.

[*] Significant at the 95% credibility level.

[**] Significant at the 90% credibility level.