Accident Analysis and Prevention 127 (2019) 87–95

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Analyzing freeway crash severity using a Bayesian spatial generalized ordered logit model with conditional autoregressive priors

Qiang Zeng[a,b], Weihua Gu[b], Xuan Zhang[a], Huiying Wen[a], Jinwoo Lee[c,*], Wei Hao[d]

[a] School of Civil Engineering and Transportation, South China University of Technology, Guangzhou, Guangdong, 510641, PR China
[b] Department of Electrical Engineering, The Hong Kong Polytechnic University, Hong Kong Special Administrative Region, PR China
[c] The Cho Chun Shik Graduate School of Green Transportation, Korea Advanced Institute of Science and Technology, Daejeon, Republic of Korea
[d] School of Traffic and Transportation, Changsha University of Science and Technology, Changsha, Hunan, 410114, PR China

A R T I C L E I N F O

Keywords:
Freeway safety
Crash severity
Spatial correlation
Bayesian spatial
Generalized ordered logit model
Conditional autoregressive prior

A B S T R A C T

This study develops a Bayesian spatial generalized ordered logit model with conditional autoregressive priors to examine severity of freeway crashes. Our model can simultaneously account for the ordered nature in discrete crash severity levels and the spatial correlation among adjacent crashes without fixing the thresholds between crash severity levels. The crash data from Kaiyang Freeway, China in 2014 are collected for the analysis, where crash severity levels are defined considering the combination of injury severity, financial loss, and numbers of injuries and deaths. We calibrate the proposed spatial model and compare it with a traditional generalized ordered logit model via Bayesian inference. The superiority of the spatial model is indicated by its better model fit and the statistical significance of the spatial term. Estimation results show that driver type, season, traffic volume and composition, response time for emergency medical services, and crash type have significant effects on crash severity propensity. In addition, vehicle type, season, time of day, weather condition, vertical grade, bridge, traffic volume and composition, and crash type have significant impacts on the threshold between median and severe crash levels. The average marginal effects of the contributing factors on each crash severity level are also calculated. Based on the estimation results, several countermeasures regarding driver education, traffic rule enforcement, vehicle and roadway engineering, and emergency services are proposed to mitigate freeway crash severity.

1. Introduction

Roadway traffic crashes result in over 1.2 million fatalities and up to 50 million non-fatal injuries annually in the world, as well as an average global GDP loss of 3% (World Health Organization, 2015). To mitigate the enormous economic and emotional burden imposed on society by traffic crashes, a great number of efforts have been devoted to reducing the frequency of traffic crashes and alleviating their severity levels (Mannering and Bhat, 2014). Developing effective countermeasures for these purposes requires a comprehensive understanding of the factors contributing to the risk and severity of potential crashes. To this end, statistical models are often developed using historical crash data to establish an explicit relationship between crash frequency or severity and the factors pertaining to road users, vehicles, roadway infrastructure, traffic and weather conditions, level of emergency medical services (EMS), etc.

Traffic safety issues have long been a primary concern for freeway management agencies and researchers (Ahmed et al., 2011; Ma et al., 2015, 2017; Wen et al., 2018; Yu and Abdel-Aty, 2014; Yu et al., 2013; Zeng et al., 2017a). Most studies in this realm have focused on analyzing freeway crash frequencies, while crash severity has not received due attention to our best knowledge. Compared with other types of roadways (such as urban roads), crash rate in freeways may be lower due to the high-standard design, construction and maintenance of freeway infrastructures, and the simpler traffic environment (for example, no junction is present in freeway systems; see Milton and Mannering, 1998, and Zeng et al., 2018a). On the other hand, freeway crashes tend to have more severe outcomes, probably because of the higher vehicle speeds and the greater proportion of heavy vehicles. Freeway usually ranks the first among all roadway types in terms of the fatality rate. According to the statistics from the Traffic Management Bureau of Public Security Ministry in China, freeway crashes account

* Corresponding author.
E-mail addresses: zengqiang@scut.edu.cn (Q. Zeng), weihua.gu@polyu.edu.hk (W. Gu), 1270522359@qq.com (X. Zhang), hywen@scut.edu.cn (H. Wen), lee.jinwoo@kaist.ac.kr (J. Lee), haowei@csust.edu.cn (W. Hao).

https://doi.org/10.1016/j.aap.2019.02.029
Received 11 November 2018; Received in revised form 21 February 2019; Accepted 27 February 2019
Available online 04 March 2019

for only 5% of roadway crashes, while the fatalities resulting from freeway crashes account for about 10% of the total deaths in roadway crashes. In 2015, about one-third of the major roadway crashes involving ten or more fatalities in China have occurred on freeways. Therefore, a crash severity analysis is fully merited, which may suggest proper countermeasures for reducing the number of fatalities, degree of injuries, and amount of property loss in freeway crashes.

In previous studies on crash severity analysis, crash severity is usually measured by the most severe injury sustained by all the crash-involved road users (Mannering and Bhat, 2014). Despite its popularity, the most severe injury cannot represent all the adverse outcomes of traffic crashes. In China, police administration categorizes roadway crashes into four severity levels, namely the light crashes, medium crashes, severe crashes, and very severe crashes. These levels are defined by taking into account not only the injury severity, but also the amount of property damage and the number of people injured or killed. These levels construct a more comprehensive metric for crash severity. However, studies that use such metrics of crash severity are rare.

Due to the discrete nature of crash severity metric, discrete outcome models (such as logit and probit models) are usually developed to link crash severity to the observed risk factors. When the number of crash severity levels is greater than two, the ordered nature between these levels is a most important inherent characteristic. Ordered outcome models have a potential advantage over unordered outcome models (e.g., multinomial logit or probit models), because they can account for the correlation among neighboring severity levels by recognizing the ordered nature (Savolainen et al., 2011). In standard ordered logit and probit models, the latent propensity is specified as a linear function of the observed risk factors and is mapped to the observed severity levels defined by a set of fixed thresholds (Abdel-Aty, 2003). As illustrated by Eluru et al. (2008), however, the fixed thresholds may result in biased estimates for the factors' effects on the likelihood of certain severity levels. To address this issue, generalized ordered response models have been proposed, which allow the thresholds to vary with the observed explanatory variables.

Unobserved heterogeneity is another significant issue that is often associated with crash severity analysis (Mannering et al., 2016). This issue is often addressed using random-parameters models (Chen et al., 2018; Ma et al., 2018; Milton et al., 2008), Markov switching approaches (Malyshkina and Mannering, 2009), latent class/finite mixture methods (Yasmin et al., 2014) and combinations of the above methods (Xiong and Mannering, 2013; Xiong et al., 2014). Under the ordered response model framework, mixed (random-parameters) generalized ordered response model and its variants are developed to handle the ordered nature and unobserved heterogeneity simultaneously (Balusu et al., 2018; Eluru et al., 2008; Fountas and Anastasopoulos, 2017; Fountas et al., 2018; Xin et al., 2017; Yasmin et al., 2015a). To be sure, sometimes no explanatory variables were found to have significant heterogeneous effects, and thus the estimated mixed generalized ordered response model becomes a (fixed-parameters) generalized ordered response model (Castro et al., 2013; Eluru et al., 2008). Therefore, the latter has been employed in a number of recent studies under such conditions (Abegaz et al., 2014; Eluru, 2013; Eluru and Yasmin, 2015; Kaplan and Prato, 2012; Yasmin et al., 2015b). Please refer to Savolainen et al. (2011) and Mannering and Bhat (2014) for more detailed description and assessments on the methodological alternatives.

While the continual advances in analytical methods have enabled us to more precisely assess the impacts of observed factors on crash severity, some critical issues still remain unsolved in the present crash severity prediction models. As a result, the validity of inference results may be significantly undermined. Typically, the spatial correlation (also termed "spatial dependency" and "spatial effect") among adjacent crashes, which has been commonly recognized in the analysis of crash frequencies and rates (Huang et al., 2016b; Ma et al., 2017; Quddus, 2008; Zeng and Huang, 2014a; Zeng et al., 2017b, b), is by-and-large overlooked when modeling crash severity. In the few studies that modeled spatial correlations between crash severities, some researchers have formulated the spatial correlation using the spatial lag structure or a mixed structure of spatial lags and spatial errors (Bhat et al., 2017; Castro et al., 2013; Prato et al., 2018; Zou et al., 2017), while others have employed a conditional autoregressive (CAR) prior to capture the spatial correlation between the injury severities of crashes occurring at adjacent locations (Meng et al., 2017; Xu et al., 2016). Quddus (2008) compared these two methods in the context of Bayesian inference and found that the CAR prior models yielded more trustworthy estimation results than the models using spatial lag or spatial error structure. The multivariate CAR model is also a state-of-the-art method for multivariate spatial modeling in traffic safety analysis (Barua et al., 2014, 2016; Cai et al., 2018; Huang et al., 2017; Liu and Sharma, 2018; Ma et al., 2017; Osama and Sayed, 2017). The empirical analyses conducted by Meng et al. (2017) and Xu et al. (2016) have further demonstrated the strength of CAR prior method used in the spatial models of crash severity. However, the binary logistic regression models proposed in the above-cited works cannot capture the ordered nature in crash data.

In light of the above, this paper examines the freeway crash severity in China using a Bayesian spatial generalized ordered logit model with CAR priors, which can account for the ordered nature of crash severity levels and the spatial correlation among crashes simultaneously, without being limited by fixed thresholds. A one-year crash dataset from the Kaiyang Freeway in Guangdong Province, China is used for the empirical investigation. To demonstrate the advantage of the proposed model, we compare the estimation results against those of a traditional generalized ordered logit model.

The rest of the article is structured as follows. Section 2 describes the freeway crash dataset. Section 3 furnishes the formulations of the traditional generalized ordered logit model and the proposed model. In Section 4, we present the Bayesian estimation processes for the two generalized ordered logit models, compare their estimation results, and examine the marginal effects of significant factors. Conclusions and directions for future research are discussed in Section 5.

2. Data preparation

We use the crash data from the Kaiyang Freeway in 2014, which was extracted from the Highway Maintenance and Administration Management System maintained by Guangdong Transportation Group. The four crash severity levels used in the data are defined by the Ministry of Public Security in China as follows:

(1) a *light crash* refers to one resulting in no more than two people slightly injured, or a property damage value of no more than 1000 CNY;
(2) a *medium crash* refers to one resulting in one or two people severely injured, or more than two people slightly injured, or a property damage value between 1000 and 30,000 CNY;
(3) a *severe crash* refers to one resulting in one or two fatalities, or three to ten people severely injured, or a property damage value between 30,000 and 60,000 CNY; and
(4) a *very severe crash* refers to one resulting in three or more fatalities, or over ten people severely injured, or one fatality plus over eight people severely injured, or two fatalities plus over five people severely injured, or a property damage value of over 60,000 CNY.

Among all the 691 freeway crashes reported in 2014, there are 355 light crashes (51.4%), 307 medium crashes (44.4%), 28 severe crashes (4.1%), and only one very severe crash (0.1%). We thus combine the severe and very severe crashes into one level in this paper because the latter is rare in reality. In the rest of this paper, this combined level will be termed as "severe crash".

The crash data recorded in the system also include: whether the involved driver(s) are professional or not, the involved vehicles' types and license numbers, weather condition, the EMS response time, and the crash type, time and location. Some of these variables are explained next. The binary driver type variable, *Professional driver*, is equal to 1 if at least one driver involved is professional, and 0 otherwise. Four additional binary variables are used to represent vehicle types: (1) *Passenger car* indicates whether all the vehicle(s) involved in a crash are passenger car(s); (2) *Coach* indicates whether at least one coach was involved; (3) *Truck* indicates whether at least one truck was involved; and (4) *Other vehicle* indicates whether at least a vehicle of other types (e.g., a vehicle with trailer) was involved. The binary variable *Non-local vehicle* indicates whether there is a non-local vehicle (i.e. not registered in Guangdong Province) involved in a crash. The EMS response time is defined as the duration between the crash reporting and the arrival of EMS at the crash site.

More details on the freeway design features at crash locations are extracted from the freeway's geometric profile. These include: horizontal curvature, vertical grade, and whether the crash location is on a bridge or near a ramp. To examine the spatial correlation in the crashes, we further divide the Kaiyang Freeway into 154 segments in a way such that each segment is approximately linear both horizontally and vertically. The same segmentation of this freeway has also been used in previous studies on crash frequency analysis (Wen et al., 2018; Zeng et al., 2017a).

Regarding traffic data, we use the five vehicle classes defined by the Guangdong Freeway Network Toll System with respect to vehicles' head height, axis number, wheel number, and wheelbase; see Table 1 for the details. We calculate the normalized daily traffic volumes of each vehicle class as its daily traffic volumes (which are collected from the system) multiplied by a specific weight. The weights for classes 1 to 5 are set to 1, 1.5, 2, 3 and 3.5, respectively, as recommended by the Guangdong Transportation Department. The percentage of each vehicle class is then calculated using the normalized traffic volumes. Note that traffic data in finer scales (e.g., hourly volumes) are unavailable. However, we believe the daily volume data serve as a fairly good proxy for the real-time traffic characteristics when and where crashes occurred.

Table 2 presents the definitions of the covariates used for analyzing freeway crash severity and their descriptive statistics. The Pearson correlation test results calculated by Statistical Package for the Social Sciences (SPSS) (IBM, 2017) suggest that *Veh_4* and *Veh_5*, i.e., the proportions of vehicles in classes 4 and 5 as defined in Table 1, are significantly correlated with a correlation coefficient greater than 0.6. With two highly-correlated risk factors, estimates of their effects may be biased. Hence, we remove *Veh_5* from the set of risk factors to eliminate the significant correlation between factors.

3. Model formulation

The crash severity levels are ordered by nature. For discrete outcome models with more than two outcomes, the ordered nature of the outcomes is often incorporated in the model to identify the correlation between adjacent outcomes (Savolainen et al., 2011). In this section, we present the traditional generalized ordered logit model and a new statistical model, termed "the spatial generalized ordered logit model", that can capture the spatial correlation among the crashes (Section 3.1). We then describe the method for calculating the effects of contributing factors on the probability of each crash severity level (Section 3.2).

3.1. Model specification

3.1.1. The traditional generalized ordered logit model

Generalized ordered logit models are often used for capturing the ordered nature in crash severity without suffering from the biases resulting from fixed thresholds (Eluru, 2013). Specifically, a latent propensity variable z_i is used as a basis for modeling the ordered ranking of severity levels for crash i, and is assumed to be a linear function of the covariates $\mathbf{X}_i$:

$$z_i = \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{1}$$

where $\boldsymbol{\beta}$ is a vector of estimable parameters associated with the covariate vector (including a constant element), $\mathbf{X}_i$; and ε_i is a residual term following a logistic distribution.

The severity level y_i of crash i is defined as follows:

$$y_i = \begin{cases} 1, & z_i \le \mu_{i,0} \\ 2, & \mu_{i,0} < z_i \le \mu_{i,1} \\ \vdots & \\ j & \mu_{i,j-2} < z_i \le \mu_{i,j-1} \\ \vdots & \\ J & z_i > \mu_{i,J-2} \end{cases} \tag{2}$$

where $j \in \{1, 2, ..., J\}$ represents an ordered severity level, numbered from the lowest (i.e., light crashes in the present paper) to the highest (i.e., severe crashes). The thresholds $\mu_{i,0}, \mu_{i,1}, ..., \mu_{i,J-2}$ denote the boundaries between these severity levels for crash i. To increase flexibility in assessing the covariates' effects, these thresholds are written in the following parametric form as proposed by Eluru et al. (2008):

$$\mu_{i,k} = \mu_{i,k-1} + \exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}),\ \forall\ k \in \{1,...,J-2\} \tag{3}$$

where $\mathbf{Z}_{i,k}$ is a vector of explanatory variables associated with the k th threshold (also including a constant element) and $\boldsymbol{\alpha}_k$ is a parameter vector to be estimated. For the uniqueness of identification, either the constant term in the latent propensity function or the first threshold $\mu_{i,0}$ must be fixed to zero. Here we specify $\mu_{i,0}$ (i.e. the threshold between light and medium crash levels) as 0 for all crashes and keep the constant term in the latent propensity function. Hence, in this paper only one threshold parameter vector $\boldsymbol{\alpha}_1$ (for the threshold between medium and severe crash levels, $\mu_{i,1}$) needs to be estimated.

Since the residual term ε_i is logistically distributed, the cumulative probability for crash i to exhibit a severity level up to j, $P_{i,j}$, can be calculated as:

$$P_{i,1} = \frac{\exp(\mu_0 - \boldsymbol{\beta}\mathbf{X}_i)}{1 + \exp(\mu_0 - \boldsymbol{\beta}\mathbf{X}_i)} = \frac{\exp(-\boldsymbol{\beta}\mathbf{X}_i)}{1 + \exp(-\boldsymbol{\beta}\mathbf{X}_i)} \tag{4}$$

Table 1
Vehicle classification.

Class	Criteria				Representative vehicle types
	Head height	Axis number	Wheel number	Wheelbase	
1	< 1.3 m	2	2-4	< 3.2m	Passenger car, jeep, pickup truck
2	≥1.3 m	2	4	≥3.2m	Minibus, minivan, light truck
3	≥1.3 m	2	6	≥3.2m	Medium-sized bus, large ordinary bus, medium-sized truck
4	≥1.3 m	3	6-10	≥3.2m	Large luxury bus, large truck, large trailer, 20-foot container truck
5	≥1.3 m	> 3	> 10	≥3.2m	Heavy truck, heavy trailer, 40-foot container truck

Table 2
Descriptive statistics of covariates for analyzing freeway crash severity.

Covariates	Description	Mean	S.D.
Professional driver	All drivers involved are non-professional = 0; otherwise = 1	0.025	0.155
Traffic volume	The normalized daily traffic volume in the day of crash (10^3 pcu[‡])	5.655	1.071
EMS response time	Duration between crash reporting and the arrival of EMS (min)	20.7	18.0
TRAFFIC COMPOSITION			
Veh_1[*]	The percentage of vehicles in class 1	42.2	12.2
Veh_2	The percentage of vehicles in class 2	2.5	0.7
Veh_3	The percentage of vehicles in class 3	21.3	3.3
Veh_4	The percentage of vehicles in class 4	6.1	2.1
Veh_5	The percentage of vehicles in class 5	27.9	9.7
VEHICLE TYPE			
Passenger car[*]	All vehicles involved are passenger cars = 1; otherwise = 0	0.571	0.495
Coach	At least one coach was involved = 1; otherwise = 0	0.072	0.259
Truck	At least one truck was involved = 1; otherwise = 0	0.324	0.468
Other vehicle	At least one other vehicle (e.g., a vehicle with trailer) was involved = 1; otherwise = 0	0.077	0.266
Non-local vehicle	All vehicles involved were registered in Guangdong Province (local vehicles) = 0; otherwise (at least one non-local vehicle was involved) = 1	0.27	0.443
WEATHER CONDITION			
Sunny[*]	Crash occurred in a sunny day = 1; otherwise = 0	0.707	0.456
Overcast	Crash occurred in an overcast day = 1; otherwise = 0	0.111	0.315
Rainy/Foggy	Crash occurred in a rainy or foggy day = 1; otherwise = 0	0.182	0.386
CRASH TYPE			
Single-vehicle crash[*]	The crash involved only one vehicle = 1; otherwise = 0	0.444	0.497
Rear-end crash	The crash is a rear-end one = 1; otherwise = 0	0.259	0.438
Angle crash	The crash is an angle one = 1; otherwise = 0	0.298	0.458
SEASON			
Spring	Crash occurred in February to April = 1; otherwise = 0	0.250	0.434
Summer	Crash occurred in May to July = 1; otherwise = 0	0.263	0.441
Autumn	Crash occurred in August to October = 1; otherwise = 0	0.284	0.451
Winter[*]	Crash occurred in November, December or January = 1; otherwise = 0	0.203	0.402
Day of week	Crash occurred on a weekend = 1; otherwise = 0	0.331	0.471
TIME OF DAY			
Before dawn[*]	Crash occurred during 0 to 6 a.m. = 1; otherwise = 0	0.224	0.417
Morning	Crash occurred during 6 a.m. to 12 p.m. = 1; otherwise = 0	0.392	0.489
Afternoon	Crash occurred during 12 to 6 p.m. = 1; otherwise = 0	0.207	0.405
Evening	Crash occurred during 6 p.m. to 12 a.m. = 1; otherwise = 0	0.178	0.383
ROADWAY GEOMETRY			
Horizontal curvature	The horizontal curvature of the freeway segment where the crash occurred (0.1 km^{-1})	1.888	1.222
Vertical grade	The grade of the freeway segment where the crash occurred (%)	0.768	0.664
Bridge	Crash occurred on a bridge = 1; otherwise = 0	0.570	0.495
Ramp	Crash occurred in the proximity of a ramp = 1; otherwise = 0	0.236	0.425

‡ pcu: passenger car unit.
* The reference category.

$$P_{i,j} = \frac{\exp(\mu_{j-1} - \boldsymbol{\beta}\mathbf{X}_i)}{1 + \exp(\mu_{j-1} - \boldsymbol{\beta}\mathbf{X}_i)} = \frac{\exp[\sum_{k=1}^{j-1}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}) - \boldsymbol{\beta}\mathbf{X}_i]}{1 + \exp[\sum_{k=1}^{j-1}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}) - \boldsymbol{\beta}\mathbf{X}_i]}, \ \forall j \in \{2, ..., J-1\} \tag{5}$$

$$P_{i,J} = 1 \tag{6}$$

Thus, the probability for crash i to exhibit a severity level j, $p_{i,j}$, is calculated as:

$$p_{i,1} = P_{i,1} = \frac{\exp(\mu_0 - \boldsymbol{\beta}\mathbf{X}_i)}{1 + \exp(\mu_0 - \boldsymbol{\beta}\mathbf{X}_i)} = \frac{\exp(-\boldsymbol{\beta}\mathbf{X}_i)}{1 + \exp(-\boldsymbol{\beta}\mathbf{X}_i)} \tag{7}$$

$$p_{i,j} = P_{i,j} - P_{i,j-1} = \frac{\exp(-\boldsymbol{\beta}\mathbf{X}_i)[\exp(\mu_{j-1}) - \exp(\mu_{j-2})]}{[1 + \exp(\mu_{j-1} - \boldsymbol{\beta}\mathbf{X}_i)][1 + \exp(\mu_{j-2} - \boldsymbol{\beta}\mathbf{X}_i)]} = \frac{\exp(-\boldsymbol{\beta}\mathbf{X}_i)\exp[\sum_{k=1}^{j-2}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k})]\{\exp[\exp(\boldsymbol{\alpha}_{j-1}\mathbf{Z}_{i,j-1})] - 1\}}{\{1 + \exp[\sum_{k=1}^{j-1}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}) - \boldsymbol{\beta}\mathbf{X}_i]\}\{1 + \exp[\sum_{k=1}^{j-2}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}) - \boldsymbol{\beta}\mathbf{X}_i]\}}, \ \forall j \in \{2, ..., J-1\} \tag{8}$$

$$p_{i,J} = 1 - P_{i,J-1} = \frac{1}{1 + \exp[\sum_{k=1}^{J-2}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}) - \boldsymbol{\beta}\mathbf{X}_i]} \tag{9}$$

3.1.2. The spatial generalized ordered logit model

As shown by Meng et al. (2017) and Xu et al. (2016), the spatial correlation among the severity levels of adjacent crashes can be captured by residual terms with Gaussian CAR prior. Specifically, for crash i occurring on freeway segment m, the latent variable z_i in Eq. (1) is modified to:

$$z_i = \boldsymbol{\beta}\mathbf{X}_i + \phi_m + \varepsilon_i \tag{10}$$

where the residual term ϕ_m denotes the spatial correlation of each crash on freeway segment m, and is assumed to follow a CAR Gaussian distribution:

$$\phi_m \sim N\left(\frac{\sum_{n\neq m}\phi_n\omega_{mn}}{\sum_{n\neq m}\omega_{mn}}, \frac{\sigma_\phi}{\sum_{n\neq m}\omega_{mn}}\right) \tag{11}$$

where ω_{mn} is the proximity weight between freeway segments m and n. The binary first-order proximity structure, which has been extensively used in previous studies (Meng et al., 2017; Xu et al., 2016; Zeng and Huang, 2014a), is employed to define these proximity weights. Specifically, if segments m and n are connected, $\omega_{mn} = 1$; otherwise, $\omega_{mn} = 0$. The $\sigma_\phi(>0)$ is the variance parameter of the spatial correlation term.

Consequently, the probability for crash i to exhibit a severity level j is calculated as:

$$p_{i,1} = P_{i,1} = \frac{\exp(\mu_0 - \boldsymbol{\beta}\mathbf{X}_i)}{1 + \exp(\mu_0 - \boldsymbol{\beta}\mathbf{X}_i)} = \frac{\exp(-\boldsymbol{\beta}\mathbf{X}_i - \phi_m)}{1 + \exp(-\boldsymbol{\beta}\mathbf{X}_i - \phi_m)} \tag{12}$$

$$p_{i,j} = P_{i,j} - P_{i,j-1} = \frac{\exp(-\boldsymbol{\beta}\mathbf{X}_i - \phi_m)[\exp(\mu_{j-1}) - \exp(\mu_{j-2})]}{[1 + \exp(\mu_{j-1} - \boldsymbol{\beta}\mathbf{X}_i - \phi_m)][1 + \exp(\mu_{j-2} - \boldsymbol{\beta}\mathbf{X}_i - \phi_m)]} = \frac{\exp(-\boldsymbol{\beta}\mathbf{X}_i - \phi_m)\exp[\sum_{k=1}^{j-2}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k})]\{\exp[\exp(\boldsymbol{\alpha}_{j-1}\mathbf{Z}_{i,j-1})] - 1\}}{\{1 + \exp[\sum_{k=1}^{j-1}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}) - \boldsymbol{\beta}\mathbf{X}_i - \phi_m]\}\{1 + \exp[\sum_{k=1}^{j-2}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}) - \boldsymbol{\beta}\mathbf{X}_i - \phi_m]\}}, \quad \forall j \in \{2,...,J-1\} \tag{13}$$

$$p_{i,J} = 1 - P_{i,J-1} = \frac{1}{1 + \exp[\sum_{k=1}^{J-2}\exp(\boldsymbol{\alpha}_k\mathbf{Z}_{i,k}) - \boldsymbol{\beta}\mathbf{X}_i - \phi_m]} \tag{14}$$

3.2. Marginal effects of the contributing factors

Practitioners often express great interest in understanding the marginal effects of a certain contributing factor on the probabilities of various crash severity levels. Unfortunately, these effects cannot be directly seen from the model coefficients $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}_k$, because the probabilities $p_{i,j}$ are not linear functions of the factors. Hence, we derive the marginal effects of contributing factors analytically. Specifically, for the case discussed in this paper (i.e. $J = 3$), the marginal effect of a continuous contributing factor x on $p_{i,j}$ is calculated by taking its first-order derivative with respect to x (Jalayer et al., 2018):

$$\frac{\partial p_{i,1}}{\partial x} = \beta^x p_{i,1}(p_{i,1} - 1) \tag{15}$$

$$\frac{\partial p_{i,2}}{\partial x} = \alpha^x \mu_{i,1} p_{i,3}(1 - p_{i,3}) + \beta^x p_{i,2}(p_{i,1} - p_{i,3}) \tag{16}$$

$$\frac{\partial p_{i,3}}{\partial x} = (\beta^x - \alpha^x \mu_{i,1}) p_{i,3}(1 - p_{i,3}) \tag{17}$$

where β^x and α^x are the coefficient estimates associated with variable x in the expressions of latent propensity z_i and threshold $\mu_{i,1}$, respectively.

In addition, the marginal effect of an indicator (binary) contributing factor x on $p_{i,j}$ is calculated by taking its first-order difference with respect to x and with $\Delta x = 1$. They are respectively:

$$\frac{\Delta p_{i,1}}{\Delta x} = \frac{\exp(-\tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \phi_m)[\exp(-\beta^x) - 1]}{[1 + \exp(-\tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \phi_m)][1 + \exp(-\tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \beta^x - \phi_m)]}, \tag{18}$$

$$\frac{\Delta p_{i,j}}{\Delta x} = \frac{\exp(-\tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \beta^x - \phi_m)\{\exp[\exp(\tilde{\boldsymbol{\alpha}}_1\tilde{\mathbf{Z}}_{i,1} + \alpha^x)] - 1\}}{\{1 + \exp[\exp(\tilde{\boldsymbol{\alpha}}_1\tilde{\mathbf{Z}}_{i,1} + \alpha^x) - \tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \beta^x - \phi_m]\}\{1 + \exp[-\tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \beta^x - \phi_m]\}} - \frac{\exp(-\tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \phi_m)\{\exp[\exp(\tilde{\boldsymbol{\alpha}}_1\tilde{\mathbf{Z}}_{i,1})] - 1\}}{\{1 + \exp[\exp(\tilde{\boldsymbol{\alpha}}_1\tilde{\mathbf{Z}}_{i,1}) - \tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \phi_m]\}\{1 + \exp[-\tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \phi_m]\}}, \tag{19}$$

$$\frac{\Delta p_{i,3}}{\Delta x} = \frac{\exp(-\tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \phi_m)\{\exp[\exp(\tilde{\boldsymbol{\alpha}}_1\tilde{\mathbf{Z}}_{i,1})] - \exp[\exp(\tilde{\boldsymbol{\alpha}}_1\tilde{\mathbf{Z}}_{i,1} + \alpha^x) - \beta^x]\}}{\{1 + \exp[\exp(\tilde{\boldsymbol{\alpha}}_1\tilde{\mathbf{Z}}_{i,1}) - \tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \phi_m]\}\{1 + \exp[\exp(\tilde{\boldsymbol{\alpha}}_1\tilde{\mathbf{Z}}_{i,1} + \alpha^x) - \tilde{\boldsymbol{\beta}}\tilde{\mathbf{X}}_i - \beta^x - \phi_m]\}} \tag{20}$$

where $\tilde{\mathbf{X}}_i$ and $\tilde{\mathbf{Z}}_{i,1}$ denote the vectors $\mathbf{X}_i$ and $\mathbf{Z}_{i,1}$ less element x, respectively, and $\tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\alpha}}_1$ denote the corresponding coefficient vectors (i.e., $\boldsymbol{\beta}$ less β^x and $\boldsymbol{\alpha}_1$ less α^x, respectively). Note that (18–20) are applicable to the spatial generalized ordered logit model only. For the traditional generalized ordered logit model, the CAR prior term ϕ_m should be removed from these equations.

The marginal effects are calculated for each individual crash. The average marginal effects of all the observations in the dataset are then reported in the following section.

4. Model estimation, comparison, and discussions

In Section 4.1, we describe the Bayesian estimation processes of the two models and two comparison methods built upon two metrics, respectively: the "deviance information criterion" (DIC) and the classification accuracy. The comparison results are presented and discussed in Section 4.2. The marginal effects of some significant contributing factors are examined in Section 4.3.

4.1. Model estimation and comparison method

Since the traditional maximum likelihood estimation cannot be applied to models with CAR Gaussian priors (Meng et al., 2017), in this paper we use the Bayesian method to estimate the model parameters. The method is built upon Markov chain Monte Carlo (MCMC) simulation with Gibbs sampling algorithm, which can be easily implemented via the freeware WinBUGS (Lunn et al., 2000). To apply the Bayesian method, we first specify the prior distribution of each (hyper-)parameter in the models. Without additional knowledge, noninformative (vague) prior distributions are used for these (hyper-)parameters. Specifically, we use a diffused normal distribution denoted by $N(0, 10^4)$ as the priors of the coefficients in $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}_1$. The CAR priors are specified by the function *car.normal* in WinBUGS (Zeng and Huang, 2014a). A diffused gamma distribution, gamma(0.01, 0.01), is used as the prior of the precision parameter (i.e., the reciprocal of the variance parameter, $1/\sigma_\phi$). For each model, we run a chain of 150,000 MCMC simulation iterations, where the first 100,000 iterations act as a burn-in. The MCMC trace plots for the model parameters are inspected visually to ensure the simulations converge. In addition, we monitor the ratios between the Monte Carlo simulation errors and the respective estimates' standard deviations to ensure that they are less than 0.05 (a rule-of-thumb threshold).

We compare the models via DIC and the classification accuracies for each severity level and for the entire dataset. DIC is deemed as a Bayesian equivalent of Akaike's information criterion (Akaike, 1974) that takes model complexity into consideration. According to Spiegelhalter et al. (2002), DIC is defined as:

$$\text{DIC} = \bar{D} + pD \tag{21}$$

where $\bar{D}$ is the posterior mean deviance that can be used as a fitness or adequacy measure of the model, and pD is the effective number of parameters used to measure model complexity (this term is added to penalize models with more parameters). Generally, a model with a lower DIC value is preferred. DIC can be directly obtained from WinBUGS.

The classification accuracy for severity level j is defined as the proportion of accurate prediction in the set of data instances with observed severity level j (Zeng and Huang, 2014b), that is,

$$\text{CA}_j = \frac{\sum_{\bar{Y}_i = Y_i = j} Y_i}{\sum_{Y_i = j} Y_i} \times 100\%, \quad \forall j \in \{1,2,...,J\} \tag{22}$$

where $\bar{Y}_i$ represents the predicted crash severity level.

Similarly, the classification accuracy for the entire dataset is calculated as:

$$\text{CA\_ t} = \frac{\sum_{\bar{Y}_i = Y_i} Y_i / Y_i}{\sum_i Y_i / Y_i} \times 100\% \tag{23}$$

4.2. Model comparison results

The results of parameter estimation and model comparison are summarized in Table 3, where only the factors that have statistically significant (at 90% credibility level or above) effects on crash severity are included. The tabulated values outside the parentheses are the posterior means of parameters, and those inside the parentheses are

Table 3
Parameter estimation and model comparison results.

	Generalized ordered logit model		Spatial generalized ordered logit model	
	Latent propensity	Threshold between median and severe crash levels	Latent propensity	Threshold between median and severe crash levels
Professional driver	1.70 (0.77)**	—	1.68 (0.78)**	—
Truck	—	−0.44 (0.22)**	—	−0.45 (0.21)**
Other vehicle	—	−0.76 (0.30)**	—	−0.79 (0.30)**
Summer	0.72 (0.28)**	—	0.72 (0.30)**	—
Autumn	—	0.67 (0.31) **	—	0.64 (0.30) **
Afternoon	—	0.67 (0.27) **	—	0.64 (0.27)**
Overcast	—	0.60 (0.32) **	—	0.57 (0.32) *
Vertical grade	—	−0.47 (0.13)**	—	−0.46 (0.13)**
Bridge	—	0.37 (0.19)**	—	0.35 (0.20) **
Traffic volume	−0.24 (0.12)**	0.31 (0.11)**	−0.30 (0.11)**	0.31 (0.11)**
Veh_2	0.56 (0.17)**	—	0.50 (0.18)**	—
Veh_4	—	0.12 (0.06)**	0.08 (0.05)*	0.12 (0.06)**
EMS response time	0.02 (0.01)**	—	0.03 (0.01)**	—
Rear-end crash	−2.12 (0.25)**	−0.60 (0.27) **	−2.29 (0.27)**	−0.59 (0.27) **
Angle crash	−2.23 (0.25)**	−1.10 (0.24) **	−2.00 (0.28)**	−1.09 (0.25) **
ϕ_m	—	—	0.48 (0.17)**	—
$\bar{D}$	888		873	
pD	50		60	
DIC	938		933	
CA_1	78%		79%	
CA_2	76%		77%	
CA_3	7%		10%	
CA_t	74%		75%	

* Significant at the 90% credibility level.
** Significant at the 95% credibility level.

their posterior standard deviations.

First note that $\bar{D}$ of the spatial generalized ordered logit model (873) is lower than that of the traditional generalized ordered logit model (888), which indicates that the spatial model fits better with the data. This finding is consistent with previous studies on traffic safety analysis (Xu et al., 2016; Zeng and Huang, 2014a); i.e., explicitly accounting for the spatial correlation using CAR priors can improve the model's estimation power. Although the traditional model has fewer effective parameters (50 versus 60 for the spatial model; see Table 3), the spatial model still exhibits a lower DIC value (933 versus 938 for the traditional model). The difference in DIC is considered substantial (see Spiegelhalter et al., 2005), which suggests that the spatial model is preferred to the traditional one. The former's superiority in goodness-of-fit is further confirmed by its higher classification accuracies for each crash severity levels and the entire dataset, as revealed by the last four rows of Table 3. Note in particular the large difference between CA_3 of the two models (7% versus 10%), which indicates the prediction accuracy for severe crashes. Given the great loss caused by severe crashes, we reckon that the spatial model is more suitable to be used in traffic safety analysis.

The significance of spatial correlation is also verified by the estimated standard deviation of the spatial term ϕ_m (0.17), which is moderately significant as compared to the values found in previous studies (Xu et al., 2016; Zeng and Huang, 2014a). The significant spatial correlation is as expected and can be explained by some unobserved factors shared by the crashes occurring at neighboring locations. Examples of these unobserved factors may include the terrain feature, lighting condition, and traffic sign layouts. The spatial correlation unveiled from the data can also be used to suggest High Collisions Concentration Locations (Chung and Ragland, 2018).

Further comparison between the two models unveils that the significant factors contributing to the latent propensity and the threshold between median and severe crash levels in the traditional model are still significant in the spatial model, and that they take similar values in the two models. This partly demonstrates the consistency between the two models. Note too for most significant factors in the latent propensity function that the standard deviation increases after accounting for spatial correlation. This finding is also consistent with the conclusions of previous studies, i.e., that omitting spatial correlation would result in underestimation of the parameters' variances and potential misidentification of the contributing factors (Quddus, 2008).

The marginal effects of significant factors on the probability of each crash severity level are calculated for the two models via the method described in Section 3.2. The results are shown in Tables 4 and 5, respectively. Comparing the marginal effects in the two models, we find that most factors exhibit similar impacts on the likelihoods of all severity levels. Exceptions arise for two factors whose impacts on the likelihoods of certain severity levels are considerably different between the two models: *traffic volume* and *Veh_4*. For example, the marginal effect of *traffic volume* on the probability of medium crashes is positive in Table 4, while it is negative in Table 5. These differences again show how incorporating the spatial correlation would change the model predictions. In addition, Table 5 shows that, for *Veh_4* and *angle crash*, the marginal effects on the probabilities of light crashes and severe crashes exhibit the same sign. Note that these results cannot be obtained by standard ordered response models, because when the

Table 4
Marginal effects of significant covariates in the generalized ordered logit model.

	light crashes (%)	medium crashes (%)	severe crashes (%)
Professional driver	−25.4	15.2	10.2
Truck	0	−3.7	3.7
Other vehicle	0	−8.2	8.2
Summer	−11.6	8.9	2.7
Autumn	0	5.0	−5.0
Afternoon	0	4.5	−4.5
Overcast	0	3.6	−3.6
Vertical grade	0	−5.0	5.0
Bridge	0	3.0	−3.0
Traffic volume	3.8	0.4	−4.2
Veh_2	−8.9	6.8	2.1
Veh_4	0	1.3	−1.3
EMS response time	−0.38	0.29	0.09
Rear-end crash	42.0	−39.4	−2.6
Angle crash	43.8	−43.8	−0.0001

Table 5
Marginal effects of significant covariates in the spatial generalized ordered logit model.

	light crashes (%)	medium crashes (%)	severe crashes (%)
Professional driver	−24.7	14.7	10.0
Truck	0	−3.7	3.7
Other vehicle	0	−8.7	8.7
Summer	−11.3	8.6	2.7
Autumn	0	4.8	−4.8
Afternoon	0	4.3	−4.3
Overcast	0	3.4	−3.4
Vertical grade	0	−1.7	1.7
Bridge	0	2.9	−2.9
Traffic volume	4.6	−2.5	−2.1
Veh_2	−7.8	6.0	1.8
Veh_4	−1.3	1.4	−0.1
EMS response time	−0.47	0.36	0.11
Rear-end crash	43.1	−40.2	−2.9
Angle crash	38.4	−39.7	1.3

thresholds between ordered severity levels are fixed, changing a single factor will always cause the probabilities of the lowest and highest levels (i.e. light and severe crashes) to vary in opposing directions (Eluru et al., 2008). This finding manifests the necessity of using a generalized ordered response framework instead of a standard one.

4.3. Interpretation of the parameter estimates and marginal effects

The results show that *professional drivers* have a significant positive effect on the latent severity propensity, which indicates that they are more likely to encounter severe crashes than non-professional drivers. Specifically, when at least one professional driver is involved, the likelihoods that the crash is medium and severe will increase by 14.7% and 10.0%, respectively, and the likelihood of a light crash will decrease by 24.7%. This result is reasonable because most professional drivers recorded in the dataset are coach drivers operating intercity bus services. They are more likely to experience driver fatigue due to the long working hours, which may increase the possibility of severe crashes (Islam and Mannering, 2006). In addition, the large number of occupants in a coach means more casualties may occur in a crash.

The negative signs of *truck* and *other vehicle* on the threshold between medium and severe crashes indicate that they are more likely to be involved in severe crashes: the probabilities of a severe crash will increase by 7.5% when a *truck* is involved, and by 2.8% when an *other vehicle* is involved. This may be due to the stronger crash aggressivity of these vehicles (Huang et al., 2011; Zeng et al., 2016), which would impose greater hazards on the other vehicle(s) involved in the same crash.

Regarding the *seasonal* effect, we find that summer is associated with a higher severity propensity as compared against winter. Specifically, in summer the probabilities of medium and severe crashes increase by 6.7% and 1.7%, respectively. These results are consistent with the findings of Jalayer et al. (2018). The reason is simple: the investigated freeway is near the South China Sea, where adverse weather conditions (e.g., typhoons and rainstorms) typically occurred in summers can significantly deteriorate the driving environment. On the other hand, the weather is generally good in autumns with adequate sunlight, comfortable temperature, and low rainfall. This is a reason why severe crashes are 4.8% less likely to occur in autumns than in winters.

The *time of day* has a significant influence on the threshold between medium and severe crashes. The results show that there are 4.3% fewer severe crashes in afternoons than before dawn (the reference category). This result is also as expected because drivers' vision is better in afternoons (Christoforou et al., 2010), and thus they have more time to perceive the potential hazards and react properly to alleviate the impact of an incoming crash. Moreover, speeding and fatigue/drowsy driving are more likely to appear before dawn, which are major causes of severe crashes (Huang et al., 2008).

Another interesting finding from the results is the positive coefficient for *overcast* on the threshold, resulting in a 3.4% lower odds of severe crashes on overcast days than on sunny days. This finding can be counterintuitive. Nevertheless, similar results were reported by previous studies (Abdel-Aty, 2003; Xie et al., 2009), in which the authors argued that drivers tended to drive slowly and cautiously on overcast days.

The results also show that for every 1% increase in the *vertical grade*, the probabilities of medium and severe crashes are expected to decrease and increase by 1.7%, respectively. This is also in line with the findings of previous studies (Christoforou et al., 2010; Savolainen and Mannering, 2007; Yu and Abdel-Aty, 2014). As pointed out by the above-cited works, a steeper grade renders a shorter sight distance, and thus less time for the drivers to take proper actions in response to upcoming crashes.

The positive effect of *bridge* on the threshold indicates that bridge segments are less prone to cause severe crashes: the likelihood of severe crashes decreases by 2.9% on bridge segments. The result may be attributed to the lower posted speed limits on bridges (Renski et al., 1999).

The negative and positive effects of *traffic volume* on the latent severity propensity and the threshold, respectively, suggest that the severity level increases as the traffic volume decreases. Specifically, a decrease of 1000 passenger car units in daily traffic volume results in that the probabilities of medium and severe crashes increase by 2.5% and 2.1%, respectively. This may be due to the higher travel speeds associated with low traffic volumes (Christoforou et al., 2010; Zeng et al., 2017b). Note that a vehicle traveling at high speed will significantly increase the severity level of any crash that involves it (Zeng et al., 2016).

Regarding the traffic composition, we find that a higher *proportion of vehicles in Class 2* tends to result in more severe crashes. Specifically, the probabilities of medium and severe crashes increase by 6.0% and 1.8%, respectively, for a 1% increase of Class-2 vehicles. A potential reason is that Class-2 vehicles have larger sizes than Class-1 vehicles (the reference category), and thus they are more likely to obstruct the view of the following vehicle drivers. We also find that a higher *proportion of Class-4 vehicles* results in increases in both the severity propensity and the threshold. The combined effects lead to a 1.3% decrease in the likelihood of light crashes, a 1.4% increase in the likelihood of medium crashes, and a 0.1% decrease in the likelihood of severe crashes, for a 1% increase of Class-4 vehicles.

During the post-crash period, EMS plays a key role in reducing severe human injuries by providing first aid treatments and transportation to hospitals. As expected, the *EMS response time* is positively correlated with the crash severity level. Table 5 shows that every additional minute taken by the EMS before arriving at the crash site will increase the probabilities of medium and severe crashes by 0.36% and 0.11%, respectively. Similar findings were reported by Gonzalez et al. (2009) and Lee et al. (2018).

Finally, regarding *crash type*, rear-end crashes and angle crashes are associated with a lower severity propensity and a smaller threshold between medium and severe crashes as compared to single-vehicle crashes (the reference category). Specifically, rear-end and angle crashes are 43.1% and 38.4% more likely to be light crashes, respectively, and are about 40% less likely to be medium crashes. On the other hand, the probability of severe crashes decreases by 2.9% for rear-end crashes but increases by 1.3% for angle crashes. This is generally consistent with the findings in many previous studies (e.g., Huang et al., 2011, 2016a; Zeng et al., 2016), where rear-end crashes are found to impose the least adverse impacts on the involved road users and vehicles.

5. Conclusions and future research directions

This paper proposes a Bayesian spatial generalized ordered logit model with CAR priors for analyzing key factors that affect the severity level of freeway crashes. Instead of the commonly used metric in the literature, i.e., the most severe injury involved in a crash, we use the four crash severity levels defined by the Ministry of Public Security in China. The new metric is more comprehensive since it accounts for not only the severity level of a single injury but also the number of injuries and deaths and the financial loss in a crash.

A one-year crash dataset collected from the Kaiyang Freeway in China is used to calibrate the model. The results suggest significant spatial correlations in the crash severity data. The superiority of our spatial model over a traditional generalized ordered logit model is manifested by the former's improved model fit. In brief, severe crashes are more likely to occur: i) when professional drivers, trucks or other heavy vehicles (especially those with trailers) are involved; ii) in summers and sunny days; iii) before dawn; iv) for angle crashes; v) on steeper slopes; vi) at locations other than bridges; vii) with a greater share of Class-2 vehicles (e.g. minibuses, minivans or light trucks); viii) when the EMS response is slow; and iv) under light traffic conditions.

The above findings have practical implications on the countermeasures for reducing severe crashes on freeways. For example, traffic management agencies and transportation companies should implement more measures (e.g., education programs) for ensuring safe driving of professional drivers. Traffic management agencies should also strengthen the enforcement against risky driving behavior (e.g., by increasing the number of patrols) during 0–6 a.m. of every day. Regarding the designs of vehicles and freeway infrastructure, efforts can be made to reduce the crash aggressivity for trucks and other heavy vehicles, and to eliminate or reduce the use of steep slopes. Finally, better incident management measures are recommended to facilitate timely responses of EMS. These measures may include real-time incident detection and reporting, deployment of optimally located EMS facilities, and emergency vehicle preemption.

The Bayesian spatial generalized ordered logit model can be applied to other datasets using different crash severity metrics, such as the KABCO scale used in the US, which consists of five levels: fatality, incapacitating injury, non-incapacitating injury, possible injury, and no injury/property damage only. Future research efforts will be steered toward this direction to examine the causal factors of severe crashes in different regions or countries of the world, and under different criteria for crash severity.

While the strength of the CAR prior in capturing spatial correlation has been verified in this paper, in the future we will examine other spatial modeling methods (e.g., geographic weighted regression; see Chiou et al., 2014, and Li et al., 2013) and compare their performance against the CAR prior method.

Lastly, although we did not identify any significant heterogeneity in the current dataset (results omitted for brevity), we plan to extend the current model to further account for the unobserved heterogeneity in crash severity pending the availability of more field data. This extension will also address the non-decreasing threshold variances problem that may arise in generalized ordered response models by carefully accounting for the correlations between random parameters in the model (Balusu et al., 2018).

Acknowledgments

This work was jointly supported by the Hong Kong Polytechnic University research fund [A/C Code: 1-ZVMA]; the Natural Science Foundation of China [No. 51578247, 71801095]; the National Key R&D Program of China [No. 2017YFC0803802]; and the Natural Science Foundation of Guangdong Province [No. 2017A030310161].

References

Abdel-Aty, M., 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. J. Saf. Res. 34 (5), 597–603.
Abegaz, T., Berhane, Y., Worku, A., Assrat, A., Assefa, A., 2014. Effects of excessive speeding and falling asleep while driving on crash injury severity in Ethiopia: a generalized ordered logit model analysis. Accid. Anal. Prev. 71, 15–21.
Ahmed, M., Huang, H., Abdel-Aty, M., Guevara, B., 2011. Exploring a bayesian hierarchical approach for developing safety performance functions for a mountainous freeway. Accid. Anal. Prev. 43 (4), 1581–1589.
Akaike, H., 1974. A new look at the statistical model identification. IEEE Trans. Autom. Control 19 (6), 716–723.
Balusu, S.K., Pinjari, A.R., Mannering, F.L., Eluru, N., 2018. Non-decreasing threshold variances in mixed generalized ordered response models: a negative correlations approach to variance reduction. Anal. Methods Accid. Res. 20, 46–67.
Barua, S., El-Basyouny, K., Islam, M.T., 2014. A full Bayesian multivariate count data model of collision severity with spatial correlation. Anal. Methods Accid. Res. 3, 28–43.
Barua, S., El-Basyouny, K., Islam, M.T., 2016. Multivariate random parameters collision count data models with spatial heterogeneity. Anal. Methods Accid. Res. 9, 1–15.
Bhat, C.R., Astroza, S., Lavieri, P.S., 2017. A new spatial and flexible multivariate random-coefficients model for the analysis of pedestrian injury counts by severity level. Anal. Methods Accid. Res. 16, 1–22.
Cai, Q., Abdel-Aty, M., Lee, J., Wang, L., Wang, X., 2018. Developing a grouped random parameters multivariate spatial model to explore zonal effects for segment and intersection crash modeling. Anal. Methods Accid. Res. 19, 1–15.
Castro, M., Paleti, R., Bhat, C.R., 2013. A spatial generalized ordered response model to examine highway crash injury severity. Accid. Anal. Prev. 52, 188–203.
Chen, F., Chen, S., Ma, X., 2018. Analysis of hourly crash likelihood using unbalanced panel data mixed logit model and real-time driving environmental big data. J. Saf. Res. 65, 153–159.
Chiou, Y.C., Fu, C., Chih-Wei, H., 2014. Incorporating spatial dependence in simultaneously modeling crash frequency and severity. Anal. Methods Accid. Res. 2, 1–11.
Christoforou, Z., Cohen, S., Karlaftis, M.G., 2010. Vehicle occupant injury severity on highways: an empirical investigation. Accid. Anal. Prev. 42 (6), 1606–1620.
Chung, K., Ragland, D., 2018. Discussion of theoretical and practical challenges in developing high collision concentration location detection procedures. Int. J. Urban Sci. 1–15.
Eluru, N., 2013. Evaluating alternate discrete choice frameworks for modeling ordinal discrete variables. Accid. Anal. Prev. 55, 1–11.
Eluru, N., Yasmin, S., 2015. A note on generalized ordered outcome models. Anal. Methods Accid. Res. 8, 1–6.
Eluru, N., Bhat, C.R., Hensher, D.A., 2008. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. Accid. Anal. Prev. 40 (3), 1033–1054.
Fountas, G., Anastasopoulos, P.C., 2017. A random thresholds random parameters hierarchical ordered probit analysis of highway accident injury-severities. Anal. Methods Accid. Res. 15, 1–16.
Fountas, G., Anastasopoulos, P.C., Abdel-Aty, M., 2018. Analysis of accident injury-severities using a correlated random parameters ordered probit approach with time variant covariates. Anal. Methods Accid. Res. 18, 57–68.
Gonzalez, R.P., Cummings, G.R., Phelan, H.A., Mulekar, M.S., Rodning, C.B., 2009. Does increased emergency medical services prehospital time affect patient mortality in rural motor vehicle crashes? A statewide analysis. Am. J. Surg. 197, 30–34.
Huang, H., Chin, H.C., Haque, M.M., 2008. Severity of driver injury and vehicle damage in traffic crashes at intersections: a bayesian hierarchical analysis. Accid. Anal. Prev. 40 (1), 45–54.
Huang, H., Siddiqui, C., Abdel-Aty, M., 2011. Indexing crash worthiness and crash aggressivity by vehicle type. Accid. Anal. Prev. 43 (4), 1364–1370.
Huang, H., Li, C., Zeng, Q., 2016a. Crash protectiveness to occupant injury and vehicle damage: an investigation on major car brands. Accid. Anal. Prev. 86, 129–136.
Huang, H., Song, B., Xu, P., Zeng, Q., Lee, J., Abdel-Aty, M., 2016b. Macro and micro models for zonal crash prediction with application in hot zones identification. J. Transp. Geogr. 54, 248–256.
Huang, H., Zhou, H., Wang, J., Chang, F., Ma, M., 2017. A multivariate spatial model of crash frequency by transportation modes for urban intersections. Anal. Methods Accid. Res. 14, 10–21.
IBM Corp, 2017. IBM SPSS Statistics for Windows, Version 25.0. Released. IBM Corp., Armonk, NY.
Islam, S., Mannering, F., 2006. Driver aging and its effect on male and female single-vehicle accident injuries: some additional evidence. J. Saf. Res. 37 (3), 267–276.
Jalayer, M., Shabanpour, R., Pour-Rouholamin, M., Golshani, N., Zhou, H., 2018. Wrong-way driving crashes: a random-parameters ordered probit analysis of injury severity. Accid. Anal. Prev. 117, 128–135.
Kaplan, S., Prato, C.G., 2012. Risk factors associated with bus accident severity in the United States: a generalized ordered logit model. J. Saf. Res. 43 (3), 171–180.
Lee, J., Abdel-Aty, M., Cai, Q., Wang, L., 2018. Effects of emergency medical services times on traffic injury severity: a random-effects ordered probit approach. Traffic Inj. Prev. https://doi.org/10.1080/15389588.2018.1468889.
Li, Z., Wang, W., Liu, P., Bigham, J.M., Ragland, D.R., 2013. Using geographically weighted Poisson regression for county-level crash modeling in California. Saf. Sci. 58, 89–97.
Liu, C., Sharma, A., 2018. Using the multivariate spatio-temporal bayesian model to analyze traffic crashes by severity. Anal. Methods Accid. Res. 17, 14–31.
Lunn, D.J., Thomas, A., Best, N., Spiegelhalter, D., 2000. WinBUGS-a bayesian modelling

framework: concepts, structure, and extensibility. Stat. Comput. 10 (4), 325–337.
Ma, X., Chen, F., Chen, S., 2015. Modeling crash rates for a mountainous highway by using refined-scale panel data. Transp. Res. Rec. 2515, 10–16.
Ma, X., Chen, S., Chen, F., 2017. Multivariate space-time modeling of crash frequencies by injury severity levels. Anal. Methods Accid. Res. 15, 29–40.
Ma, C., Hao, W., Xiang, W., Yan, W., 2018. The impact of aggressive driving behavior on driver-injury severity at highway-rail grade crossings accidents. J. Adv. Transp. https://doi.org/10.1155/2018/9841498. Article ID 9841498.
Malyshkina, N.V., Mannering, F.L., 2009. Markov switching multinomial logit model: an application to accident-injury severities. Accid. Anal. Prev. 41 (4), 829–838.
Mannering, F.L., Bhat, C.R., 2014. Analytic methods in accident research: methodological frontier and future directions. Anal. Methods Accid. Res. 1, 1–22.
Mannering, F.L., Shankar, V., Bhat, C.R., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Anal. Methods Accid. Res. 11, 1–16.
Meng, F., Xu, P., Wong, S.C., Huang, H., Li, Y.C., 2017. Occupant-level injury severity analyses for taxis in Hong Kong: a bayesian space-time logistic model. Accid. Anal. Prev. 108, 297–307.
Milton, J., Mannering, F., 1998. The relationship among highway geometrics, traffic-related elements and motor-vehicle accident frequencies. Transportation 25 (4), 395–413.
Milton, J., Shankar, V., Mannering, F., 2008. Highway accident severities and the mixed logit model: an exploratory empirical analysis. Accid. Anal. Prev. 40, 260–266.
Osama, A., Sayed, T., 2017. Investigating the effect of spatial and mode correlations on active transportation safety modeling. Anal. Methods Accid. Res. 16, 60–74.
Prato, C.G., Kaplan, S., Patrier, A., Rasmussen, T.K., 2018. Considering built environment and spatial correlation in modeling pedestrian injury severity. Traffic Inj. Prev. 19 (1), 88–93.
Quddus, M.A., 2008. Time series count data models: an empirical application to traffic accidents. Accid. Anal. Prev. 40 (5), 1732–1741.
Renski, H., Khattak, A., Council, F., 1999. Effect of speed limit increases on crash injury severity: analysis of single-vehicle crashes on North Carolina interstate highways. Transp. Res. Rec. 1665, 100–108.
Savolainen, P.T., Mannering, F.L., 2007. Probabilistic models of motorcyclists' injury severities in single-and multi-vehicle crashes. Accid. Anal. Prev. 39 (5), 955–963.
Savolainen, P.T., Mannering, F.L., Lord, D., Quddus, M.A., 2011. The statistical analysis of highway crash-injury severities: a review and assessment of methodological alternatives. Accid. Anal. Prev. 43 (5), 1666–1676.
Spiegelhalter, D.J., Best, N.G., Carlin, B.P., Van Der Linde, A., 2002. Bayesian measures of model complexity and fit. J. R. Stat. Soc. 64 (4), 583–639.
Spiegelhalter, D., Thomas, A., Best, N., Lunn, D., 2005. WinBUGS User Manual. MRC Biostatistics Unit, Cambridge, United Kingdom.
Wen, H., Sun, J., Zeng, Q., Zhang, X., 2018. The effects of traffic composition on freeway crash frequency by injury severity: a bayesian multivariate spatial modeling approach. J. Adv. Transp. https://doi.org/10.1155/2018/6964828. Article ID: 6964828.
World Health Organization, 2015. Global Status Report on Road Safety 2015. World Health Organization, Geneva, Switzerland.
Xie, Y., Zhang, Y., Liang, F., 2009. Crash injury severity analysis using Bayesian ordered probit models. J. Transp. Eng. 135 (1), 18–25.
Xin, C., Guo, R., Wang, Z., Lu, Q., Lin, P.S., 2017. The effects of neighborhood characteristics and the built environment on pedestrian injury severity: a random parameters generalized ordered probability model with heterogeneity in means and variances. Anal. Methods Accid. Res. 16, 117–132.
Xiong, Y., Mannering, F.L., 2013. The heterogeneous effects of guardian supervision on adolescent driver-injury severities: a finite-mixture random-parameters approach. Transp. Res. Part B 49, 39–54.
Xiong, Y., Tobias, J.L., Mannering, F.L., 2014. The analysis of vehicle crash injury-severity data: a Markov switching approach with road-segment heterogeneity. Transp. Res. Part B 67, 109–128.
Xu, X., Xie, S., Wong, S.C., Xu, P., Huang, H., Pei, X., 2016. Severity of pedestrian injuries due to traffic crashes at signalized intersections in Hong Kong: a Bayesian spatial logit model. J. Adv. Transp. 50 (8), 2015–2028.
Yasmin, S., Eluru, N., Bhat, C.R., Tay, R., 2014. A latent segmentation based generalized ordered logit model to examine factors influencing driver injury severity. Anal. Methods Accid. Res. 1, 23–38.
Yasmin, S., Eluru, N., Pinjari, A.R., 2015a. Analyzing the continuum of fatal crashes: a generalized ordered approach. Anal. Methods Accid. Res. 7, 1–15.
Yasmin, S., Eluru, N., Pinjari, A.R., 2015b. Pooling data from fatality analysis reporting system (FARS) and generalized estimates system (GES) to explore the continuum of injury severity spectrum. Accid. Anal. Prev. 84, 112–127.
Yu, R., Abdel-Aty, M., 2014. Analyzing crash injury severity for a mountainous freeway incorporating real-time traffic and weather data. Saf. Sci. 63, 50–56.
Yu, R., Abdel-Aty, M., Ahmed, M., 2013. Bayesian random effect models incorporating real-time weather and traffic data to investigate mountainous freeway hazardous factors. Accid. Anal. Prev. 50, 371–376.
Zeng, Q., Huang, H., 2014a. Bayesian spatial joint modeling of traffic crashes on an urban road network. Accid. Anal. Prev. 67, 105–112.
Zeng, Q., Huang, H., 2014b. A stable and optimized neural network model for crash injury severity prediction. Accid. Anal. Prev. 73, 351–358.
Zeng, Q., Wen, H., Huang, H., 2016. The interactive effect on injury severity of driver-vehicle units in two-vehicle crashes. J. Saf. Res. 59, 105–111.
Zeng, Q., Sun, J., Wen, H., 2017a. Bayesian hierarchical modeling monthly crash counts on freeway segments with temporal correlation. J. Adv. Transp. https://doi.org/10.1155/2017/5391054. Article ID: 5391054.
Zeng, Q., Wen, H., Huang, H., Abdel-Aty, M., 2017b. A Bayesian spatial random parameters Tobit model for analyzing crash rates on roadway segments. Accid. Anal. Prev. 100, 37–43.
Zeng, Q., Wen, H., Huang, H., Pei, X., Wong, S.C., 2018a. Incorporating temporal correlation into a multivariate random parameters tobit model for modeling crash rate by injury severity. Transportmetrica A 14 (3), 177–191.
Zeng, Q., Wen, H., Wong, S.C., Huang, H., Guo, Q., Pei, X., 2018b. Spatial joint analysis for zonal daytime and nighttime crash frequencies using a Bayesian bivariate conditional autoregressive model. J. Transp. Saf. Security 1–20.
Zou, W., Wang, X., Zhang, D., 2017. Truck crash severity in New York city: an investigation of the spatial and the time of day effects. Accid. Anal. Prev. 99, 249–261.