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A Meso-Level Analysis of Factors Contributing to Freeway Crashes on Weekdays and Weekends in China

Guangyu Liu [1], Shaohua Wang [1], Qiang Zeng [2,*] and Xiaofei Wang [2,*]

[1] Reconstruction and Expansion Management Office of Zhongjiang Highway, Jiangmen 529000, China; 13925001600@163.com (G.L.); 13926478664@163.com (S.W.)
[2] School of Civil Engineering and Transportation, South China University of Technology, Guangzhou 510641, China
* Correspondence: zengqiang@scut.edu.cn (Q.Z.); xiaofeiw@scut.edu.cn (X.W.)

Abstract: This paper presents an empirical investigation of the factors contributing to freeway crashes on weekdays and weekends, using a Bayesian spatial logistic model. The crash data from Kaiyang Freeway, China, in 2014 are used for the empirical investigation. The deviation information criterion (DIC) values indicate that the proposed spatial logistic model is clearly superior to a logistic model in analyzing weekday and weekend crashes. Additionally, significant spatial effects are found in adjacent freeway segments for both weekday and weekend crashes, which demonstrate the reasonableness of the proposed model. The results of parameter estimation suggest that: traffic volume, roadway segment length, and the proportions of vehicles in Classes 2 and 4 have significant effects on weekday and weekend crash incidences in the same direction; horizontal curvature, presence of a ramp, and average daily precipitation impact weekday crash incidence only; and the proportion of vehicles in Class 3 and vertical grade impact weekend crash incidence only. Some countermeasures from the perspectives of roadway design and traffic management have been proposed to reduce freeway crashes on weekdays and weekends, respectively.

Keywords: freeway crash; weekday and weekend; spatial logistic model; Bayesian estimation

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1. Introduction

Freeways play a pivotal role in roadway transportation and economic development. By the end of 2022, the total length of the freeways in China had reached 177,000 km, ranking first place in the world since 2011. Freeways provide the convenience of long-distance travel for motor vehicles, while leading to high crash rates and mass causalities, which have attracted great concern from transportation management agencies and the public.

To develop effective countermeasures for reducing the number of freeway crashes, it is of great importance to achieve a good understanding of the factors contributing to crash occurrences. In the past decade, there have been a number of studies that have focused on modeling crash frequency on freeways in China. For instances, Ma et al. [1] proposed a random-effects negative binomial (NB) model for examining the crash frequency of a 50 km freeway in China, and found that the roadway's width, vertical grade, and its ratio of horizontal curvature were significant factors in crash frequency. Zeng et al. [2] advocated Bayesian hierarchical models for the analysis of monthly crash counts on Kaiyang Freeway and confirmed significant temporal effects among them. Hou et al. [3,4] applied random-effects and random-parameters NB models to the analysis of the traffic crash frequency of eight freeways in China. The model estimation results indicated that factors pertaining to roadway geometric design (median barrier offset, horizontal curvature, vertical grade, and presence of a climbing lane); traffic composition (truck proportion); pavement conditions (distress ratio, rutting depth, and international roughness index); and weather conditions (hours of clear skies and average wind speed) have significant effects on crash frequency. Wen et al. [5] revealed the interactive effects of certain roadway and weather attributes on crash frequency, using a Bayesian spatio–temporal approach. However, none of them have considered the differences in crash risk between weekdays and weekends.

Significant variations of time (e.g., time of day and day of the week) are usually observed in travel activities and driving behaviors. Dangerous driving behaviors (and related traffic crashes) may be more frequent on weekends than on weekdays. A few previous studies [6–8] have investigated the risk factors associated with crash occurrence/injury severity between weekdays and weekends. Specifically, Adanu et al. [6] found that crashes involving drivers under the influence of alcohol or other drugs are more likely to result in severe injuries on weekends than on weekdays. Yu and Abdel-Aty [8] conducted a macro-level analysis of weekday and weekend crash frequencies which were aggregated by year, and a micro-level analysis of real-time crash risk on weekdays and weekends. The results were generally consistent and indicated that weekday crashes are more likely to occur under congested traffic conditions while weekend crashes are more likely to occur under free-flow conditions. Qu et al. [7] investigated the effect of points-of-interest (POI) on weekday and weekend crashes at a community level, using a multi-scale geographically weighted regression. The results suggested that more transportation POIs were associated with more crashes in the entire investigation area on weekdays and in only several communities on weekends. While the above findings have demonstrated the differences in the risk/severity of weekday and weekend crashes, to the best of our knowledge, there is no reported research that examines the factors contributing to freeway crashes on weekdays and weekends in China. Additionally, a macro-level analysis, where crashes are aggregated by years, may not provide a precise estimation of the safety effects of time-varying factors (e.g., traffic and weather conditions), and the high-resolution real-time traffic data necessary for a micro-level analysis are usually unavailable for most freeways in China. Thus, a weekly analysis (which is named a meso-level analysis) of weekday and weekend crash occurrences may be more suitable.

To this end, the current research aims to conduct a meso-level analysis of the factors contributing to freeway crashes on weekdays and weekends in China. Crash data for one year from Kaiyang Freeway, China, were collected for the empirical analysis, where the crashes were aggregated by weeks. Due to the scarcity of crash occurrences during the weekdays and weekends within a week, a binary outcome variable indicating whether there was a crash occurrence was used as the response variable in the regression analysis, which was consistent with the micro-level analysis of crash risk [8]. In addition, potential spatial correlation may exist across freeway segments [5]. Thus, a Bayesian spatial logistic model was proposed for the analysis. To demonstrate its strength, the proposed model was compared with a traditional logistic model.

The rest of the paper is structured into four sections. We introduce the freeway crash data used for the meso-level analysis in Section 2. We specify the formulations and Bayesian estimation process of the traditional and spatial logistic models in Section 3. The model estimation results are compared and illustrated in Section 4. Finally, some conclusions are drawn and some guides for future research are provided in Section 5.

2. Data Preparation

A one-year crash dataset from Kaiyang Freeway in Guangdong, China, in 2014 was collected for the meso-level transportation safety analysis. The freeway dataset was assembled with data on crash incidence, roadway inventory, traffic flow, and weather conditions. The length of Kaiyang Freeway is 125.2 km. We split it into 154 segments, mainly based on the homogeneities in vertical and horizontal alignment within each segment, which is consistent with the segmentation criteria used in many previous studies [2,5,9].

The crash data were derived from the Highway Maintenance and Administration Management System, which is managed by Guangdong Transportation Group. According to the system, 692 crashes occurred on Kaiyang Freeway in 2014. We mapped them to the split freeway segments, according to the crash locations. As mentioned above, this research aimed to investigate weekday and weekend crash risk via a weekly analysis. Thus, the whole year was divided into 52 weeks. The crashes on each freeway section were further mapped to the weekdays or weekends of a certain week, based on the crash date.

We obtained the Kaiyang Freeway geometric profile from Guangdong Province Communication Planning and Design Institute Co., Ltd. Following the standards specified in the Design Specification for Highway Alignment [10], many roadway characteristics, such as the number and width of lanes, were fixed along the freeway. As a consequence, five roadway attributes, including length, vertical grade, horizontal curvature, and presence of bridges and ramps, were extracted from the geometric profile and used as explanatory variables for crash modeling.

The traffic data were derived from the Guangdong Freeway Network Toll System. In the toll system, motor vehicles are grouped into five classes which are numbered from 1 to 5, based on their head height, axis number, wheelbase, and wheel number. Please refer to Zeng et al. [2] for the specific criteria for vehicle classification. We drew the daily traffic volume of each vehicle class in 2014 from the system. The normalized daily traffic volume was calculated as the weighted sum of the daily traffic volumes of the five classes. The weights for vehicle classes 1 to 5 were 1, 1.5, 2, 3, and 3.5, respectively, as recommended by the Guangdong Transportation Department. The normalized daily traffic volume was respectively summed up for weekdays and weekends within each week. To represent the traffic composition, the proportions of each vehicle class during weekdays and weekends were also calculated, respectively. Due to the perfect collinearity of the vehicle-class proportions, that of vehicles in class 1, *veh_1*, was set as the reference case.

We collected the daily data on precipitation and wind speed along the freeway from the Meteorological Information Management System which is managed by the Guangdong Climate Center. Each freeway segment was assigned to the nearest weather station, in reference to the Euclidean distances. The average daily precipitation and wind speed during weekdays and weekends were calculated and employed as weather-specific explanatory variables in this study.

Table 1 shows the description and descriptive statistics of the variables used for the empirical analysis. We conducted a Pearson correlation test for the explanatory variables in SPSS software (Version 22.0) and found that *veh_4* and *veh_5* were significantly correlated for both weekdays and weekends. To avoid the potential adverse impact of significant correlation on model estimation, *veh_5* was not used as an explanatory variable for modeling crashes.

Table 1. Description and descriptive statistics of the variables for modeling crashes on weekdays.

Variable	Definition	Weekday				Weekend			
		Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Crash	At least one crash occurred on a freeway segment during the weekdays/weekends within a week = 1; otherwise = 0	0.053	0.223	0	1	0.026	0.16	0	1
NTV	The normalized traffic volume during the weekdays/weekends (10^5 PCU [a])	1.65	0.35	1.18	3.00	0.72	0.18	0.49	1.54
Veh_1 *	The proportion of vehicles in Class 1	36.68	8.56	26.05	71.23	40.29	9.68	28.06	77.31
Veh_2	The proportion of vehicles in Class 2	2.59	0.53	1.55	5.50	2.49	0.57	1.44	5.57
Veh_3	The proportion of vehicles in Class 3	21.92	2.41	15.47	27.80	21.49	2.81	14.23	27.98
Veh_4	The proportion of vehicles in Class 4	6.81	1.28	2.32	9.21	6.29	1.42	1.82	9.36
Veh_5	The proportion of vehicles in Class 5	32.00	7.48	6.43	43.17	29.45	7.94	5.02	41.05
Length	The length of a freeway segment	0.81	0.30	0.15	2.00	0.81	0.30	0.15	2.00
Curvature	The horizontal curvature of a freeway segment (0.1 km^{-1})	1.77	1.26	0	4.35	1.77	1.26	0	4.35
Grade	The vertical grade of crash location (%)	0.74	0.57	0	2.91	0.74	0.57	0	2.91
Bridge	Presence of bridge =1; otherwise = 0	0.5	0.5	0	1	0.5	0.5	0	1
Ramp	Presence of ramp = 1; otherwise = 0	0.21	0.41	0	1	0.21	0.41	0	1
Wind speed	Average wind speed during the weekdays/weekends (m/s)	2.39	0.97	1.2	6.04	2.44	1.14	0.85	7.60
Precipitation	Average daily precipitation during the weekdays/weekends (mm)	4.70	8.91	0	64.08	3.90	8.98	0	54.1

* The reference category. [a] Passenger car unit.

3. Modeling Framework

We proposed a spatial logistic model for analyzing the crash incidences during weekdays and weekends. To demonstrate the performance of the proposed model, we compared it with a traditional logistic model. In this section, first, the formulations of the two models are explicitly specified (Section 3.1). Then, their estimation processes and comparison criteria are introduced (Section 3.2).

3.1. Model Specification

3.1.1. Logistic Model

Due to the binary outcome of the response variable (i.e., crash occurrence or not), mathematically, the logistic model (also named the binary logit model) is an appropriate approach for the analysis, which is consistent with real-time crash risk modeling [8]. As shown in Table 1, denote crash occurrence = 1 and no crash occurrence = 0. For any freeway segment i, denote $\pi_{i,t}$ as the probability of crash occurrence during the weekdays (weekends) in week t. The logit function of $\pi_{i,t}$ is assumed to be linearly associated with the explanatory variables:

$$logit(\pi_{i,t}) = \ln\left(\frac{\pi_{i,t}}{1-\pi_{i,t}}\right) = \beta_0 + \sum\nolimits_{j=1}^{J} \beta_j x_{i,t,j},\ i = 1,2,\cdots,N,\ t = 1,2,\cdots,T, \quad (1)$$

where $x_{i,j,t}$ is the observed value of the jth $(j = 1,2,\cdots,J)$ explanatory variable, x_j, on freeway segment i during the weekdays (weekends) in week t, and β_j is the regression coefficients corresponding to x_j. β_0 is a constant term. J, N, and T are the numbers of covariates, freeway segments, and weeks in the dataset, respectively.

To measure the effect of a certain explanatory variable on the odds of crash occurrence (i.e., $\pi_{i,t}/(1-\pi_{i,t})$) during weekdays/weekends, its odds ratio is usually calculated [11]. For any variable x_j, its odds ratio is expressed as:

$$OR_j = \frac{(\pi_{i,t}/(1-\pi_{i,t})|x_{i,1},\cdots,x_{i,j}+1,\cdots,x_{i,J})}{(\pi_{i,t}/(1-\pi_{i,t})|x_{i,1},\cdots,x_{i,j},\cdots,x_{i,J})} = \exp(\beta_j). \quad (2)$$

3.1.2. Spatial Logistic Model

Unobserved factors (such as terrain features, traffic sign layouts, and lighting conditions in this research) may have similar effects on the crash risk of neighboring freeway segments, leading to spatial correlation among them [5]. Neglecting spatial correlation may result in biased model estimation. Aguero-Valverde and Jovanis [12] pointed out three advantages of taking spatial correlation into consideration: (1) model estimation may be improved, as site estimates are able to borrow strength from adjacent sites via spatial correlation; (2) model misspecification may be reduced, because spatial correlation can serve as a surrogate for unknown and related factors; (3) spatial correlation can provide information for grouping sites for further analysis. To accommodate the spatial correlation, a spatial logistic model was developed, via incorporating a residual term with CAR prior into the logit function [13,14]. Specifically, the Equation (1) was modified as:

$$logit(\pi_{i,t}) = \ln\left(\frac{\pi_{i,t}}{1-\pi_{i,t}}\right) = \beta_0 + \sum\nolimits_{j=1}^{J} \beta_j x_{i,t,j} + \varphi_i, \quad (3)$$

where the φ_i represents the spatial effect of freeway segment i, and is assumed to follow a CAR Gaussian distribution, first proposed by Besag et al. [15]:

$$\varphi_i \sim N\left(\frac{\sum_{l\neq i}\omega_{i,l}\varphi_l}{\sum_{l\neq i}\omega_{i,l}},\ \frac{\delta^2}{\sum_{l\neq i}\omega_{i,l}}\right), \quad (4)$$

where φ_l represents the spatial effect of freeway segment l, $\omega_{i,l}$ is the proximity weight between segments m and n. The prevalent adjacency-based first-order proximity structure was adopted to define the proximity weights: if freeway segments m and n are adjacent (i.e., sharing a common end), $\omega_{m,n} = 1$; otherwise, $\omega_{m,n} = 0$. δ is the standard-deviation parameter of spatial correlation.

3.2. Bayesian Estimation and Comparison Criteria

Due to the complexity of the spatial logistic model, we estimated the models by Bayesian methods. Specifying a prior distribution (implying the prior information) was required for each parameter/hyper-parameter. With reference to the previous studies [13,14], we specified a diffused normal distribution, $N(0, 10^4)$, as the prior of $\beta_j (j = 0, 1, 2, \cdots, J)$; and a uniform distribution, $U(0.01, 10)$, as the prior of δ.

The Bayesian estimation was conducted via programming in the freeware WinBUGS [16]. We set a chain of 60,000 Markov chain Monte Carlo (MCMC) simulation iterations for each model. The first 50,000 iterations were removed as burn-in, and the remaining 10,000 iterations were used to infer the posterior distribution of each parameter/hyper-parameter. The convergence of the MCMC simulations was assessed by visually inspecting the trace plots for the parameters of interest and monitoring if the Monte Carlo simulation error was less than 5% of the posterior standard deviation for each parameter.

In order to compare the overall performance of the models, the deviance information criterion (DIC), which can be directly and easily obtained in WinBUGS, was used. DIC provides as a combined measure of model fitting and complexity. According to the definition in Spiegelhalter et al. [17], it is calculated as:

$$DIC = \overline{D} + pD, \tag{5}$$

where $\overline{D}$ denotes the posterior mean deviance that is used to measure model fitting, and pD denotes the effective number of parameters that is used to measure model complexity. Generally, the model with a lower DIC value is preferred. According to Spiegelhalter et al. [18], empirically, more than 10 differences in DIC values suggest that the model with a higher DIC can be ruled out.

4. Result Analysis

4.1. Model Comparison

The results of the Bayesian estimation and the DIC for the models are shown in Table 2, where only the explanatory variables with significant effects (at least at the 90% credibility level) on crash incidence during weekdays or weekends are included. For both weekday and weekend crashes, the spatial logistic models yield lower $\overline{D}$ values than the logistic models with differences over 30. The results suggest that the spatial logistic model significantly outperforms the logistic model in approximating the relationship between weekday/weekend crash incidence and factors related to traffic, roadway, and environment. While the logistic models are more parsimonious, implied by their lower pD values, the fact that the spatial logistic models are over 10 DIC points lower indicates their better overall performance. These findings are in line with the previous studies on spatial modeling of crash frequency [5,12,19]; capturing spatial effects across roadway entities via CAR prior is able to improve model estimation and reduce model misspecification. In addition, the Bayesian estimates of the spatial standard-deviation parameter δ are significant at the 95% credibility level in both the weekday and weekend crash models. The results demonstrate the significant spatial correlation among the split freeway segments and further justify the reasonableness of the spatial logistic models.

Comparing the parameter estimations in the aspatial and spatial logistic models for weekday crash incidence, we can see that there are certain differences within the set of significant variables in the two models. Specifically, the parameter for *grade* is only significant in the logistic model, and the parameter for *curvature* is only significant in the spatial logistic model. Similar findings exist in the models for weekday crash incidence. For example, the parameter for *veh_4* is only significant in the spatial logistic model. A number of past studies [12,19] argued that accounting for spatial correlation is helpful in recognizing real factors contributing to traffic crashes.

Table 2. Results of Bayesian estimation and DIC for the weekday and weekend crash models [a].

	Weekday		Weekend	
	Logistic Model	**Spatial Logistic Model**	**Logistic Model**	**Spatial Logistic Model**
Constant	−4.54 (0.74) [b],**	−7.48 (0.83) **	−2.88 (0.71) **	−9.78 (0.70) **
NTV	1.03 (0.17) **	0.77 (0.16) **	1.51 (0.54) **	1.32 (0.56) **
Veh_2	−0.41 (0.12)	−0.23 (0.12) *	−0.39 (0.15) **	−0.39 (0.15) **
Veh_3	—	—	−0.09 (0.03) **	−0.08 (0.02) **
Veh_4	−0.09 (0.04) **	−0.12 (0.04) **	—	−0.11 (0.06) *
Length	1.06 (0.16) **	1.10 (0.19) **	1.14 (0.20) **	1.26 (0.24) **
Curvature	—	0.09 (0.05) *	—	—
Grade	0.21 (0.09) **	—	0.42 (0.12) **	0.38 (0.14) **
Ramp	0.29 (0.12) **	0.27 (0.14) *	—	—
Precipitation	0.01 (0.004) **	0.009 (0.005) *	—	—
δ	—	0.52 (0.13) **	—	0.46 (0.18) **
$\overline{D}$	3171	3117	1883	1845
pD	13	37	12	36
DIC	3184	3154	1895	1881

[a] Bridge and wind speed are not included, as their effects on crash injury severity are insignificant at the 90% credibility level in the three models. [b] Posterior mean (posterior standard deviation). * Significant at the 90% credibility level. ** Significant at the 95% credibility level.

4.2. Interpretation of Parameter Estimates

Due to the outperformance of the spatial logistic models for weekday and weekend crashes, our meso-level analysis mainly focuses on the parameter estimates in them. To quantitatively explain the effects of the significant factors, their odds ratios in the spatial logistic models are displayed in Table 3. According to the parameter estimation results in Table 2, some significant factors (including *curvature*, *ramp*, and *precipitation*) in weekday crashes do not have significant effects on weekend crashes, while some significant factors (including *veh_3* and *grade*) in weekend crashes do not have significant effects on weekday crashes. The significance levels of some common significant factors (e.g., *veh_2* and *veh_4*) are different. For some other common significant factors (e.g., *NTV*), the posterior mean of the parameter in the weekday crash model is much smaller than the counterpart in the weekend crash model. The apparent discrepancies in parameter estimates justify the necessity of investigating the respective contributing factors to weekday and weekend crashes.

Table 3. Odds ratios of significant factors in the spatial logistic models.

	Weekday	**Weekend**
NTV	2.16	3.74
Veh_2	0.795	0.677
Veh_3	—	0.923
Veh_4	0.887	0.896
Length	3.00	3.53
Curvature	1.094	—
Grade	—	1.46
Ramp	1.31	—
Precipitation	1.009	—

Specifically, the traffic volume variable, *NTV*, has significant effects on crash incidences on both weekdays and weekends. According to the parameter estimates, the crash occurrence odds during weekdays would increase by 116% (=2.16 − 1) for a 10^5 PCU increase in traffic volume, while the odds during weekends would increase by 274% for a

10^5 PCU increase in traffic volume. The results are generally consistent with engineering intuition and previous findings from crash frequency modeling [2–4]: more traffic brings about higher crash exposure, and thus is more likely to result in crash occurrences.

Regarding traffic composition, *veh_2*, *veh_3*, and *veh_4* have significantly negative effects on the crash incidence on weekends, which indicate that vehicles in Classes 2, 3, and 4, relative to vehicles in Class 1 (the reference group), are less likely to result in freeway crashes on weekends. According to their estimated parameters, specifically, the weekend crash odds would decrease by 32.3%, 7.7%, and 10.4% respectively, with a 1% increase in the proportions of vehicles in Classes 2, 3, and 4. *Veh_2* and *veh_4* also have negative effects on the crash incidence on weekdays. The posterior means of their parameters suggest that the weekday crash odds are expected to decrease by 20.5% and 11.3%, respectively, with a 1% increase in the proportions of vehicles in Classes 2 and 4.

Length has significantly positive effects on the crash incidences on weekdays and weekends. The estimates of the corresponding parameters suggest that: with a one kilometer increase in the segment length, the weekday crash odds would increase by 200%, while the weekend crash odds would increase by 253%. The results are also in line with engineering intuition and the existing findings [2–4]: a longer roadway segment generally increases the amount of exposure of vehicles on it to dangers, and thus is more likely to result in crash occurrences.

Curvature and *ramp* are two roadway attributes that have significant effects on weekday crash incidence only. The estimated parameter for curvature implies that the weekday crash odds would increase by 9.4%, with a 0.1 km^{-1} increase in the horizontal curvature of a freeway segment. Roadway sections with a greater horizontal curvature (i.e., a smaller curve radius) lead to harsher transitions between tangent sections [20]. Stronger centrifugal forces are necessitated for vehicles traveling on them than on those with a smaller curvature, which would increase the likelihood of running-off-road crashes. The estimated parameter for ramp indicates that the weekday crash odds of freeway segments with ramps are 1.31 times those without ramps, with other factors being equal. The results are reasonable, because many vehicle interactions and conflicts appear when vehicles from ramps emerge into the traffic stream on the main lanes [21].

Grade has a significant effect on the weekend crash incidence only. The posterior mean of the parameter for grade is 0.38, which suggests that the weekend crash odds are anticipated to increase by 46% with a 1% increase in the vertical grade of a freeway segment. The result is generally consistent with those in the extant literature [20,22]: a high vertical grade would lead to a shorter sight distance. Thus, less time is available for drivers to perceive and properly respond to potential hazards. In addition, the speed variance of the traffic flow would be significantly increased on steep upgrades. More frequent overtaking maneuvers by vehicles with high speeds may lead to more traffic conflicts.

With regard to weather conditions, *precipitation* is found to have a significant effect on weekday crash incidence. According to its parameter estimates, a 1 mm increase in the average precipitation during the weekdays within a week is expected to increase the crash occurrence odds by 0.9%. Similar findings can be found in Pei et al. [21], who argued that precipitation makes the roadway surfaces slippery and thus reduces the skidding resistance. Meanwhile, visibility is usually impaired by precipitation. Reduced skidding resistance and lower visibility are linked to less time available for drivers to avoid crash occurrences.

5. Conclusions and Remarks

This research empirically analyzes the factors contributing to crash occurrence on weekdays and weekends at a weekly level, using a one-year crash dataset from Kaiyang Freeway, China. Due to the binary outcome of crash occurrence on weekdays/weekends, a Bayesian spatial logistic model is proposed for the empirical analysis, which can also account for the spatial correlation across adjacent freeway segments.

The results of DIC suggest that the overall performance of the spatial logistic model is significantly better than that of the traditional logistic model, whether for the analysis of weekday or weekend crashes. Significant spatial correlation is found in the weekday and weekend crash data. The parameter estimates in the spatial logistic models indicate that: (i) *NTV* and *length* are positively associated with the crash incidences of both weekdays and weekends; (ii) *veh_2* and *veh_4* are negatively associated with the crash incidences on both periods; (iii) *curvature*, *ramp*, and *precipitation* have significant effects on weekday crash incidence; and (iv) *veh_3* and *grade* have significant effects on weekend crash incidence.

The above findings have practical implications for developing specific countermeasures for reducing freeway crashes on weekdays and weekends. For example, in the process of freeway design, increasing the horizontal curve radius decreases weekday crash incidence, and avoiding steep vertical grades decreases weekend crash incidence. Deploying variable message signs along freeways and implementing variable speed limits on rainy days may be helpful to reduce traffic crashes on weekdays.

Nonetheless, there are some limitations in this research. For example, only one year of crash data, which are somewhat old and from one freeway, were used in the traffic crash analysis, where some important roadway attributes (e.g., number and width of lanes) were not included. We would like to investigate the effects of these factors on weekday and weekend crash incidences and the transferability of the analysis results to other freeways, if a more comprehensive crash dataset from recent years were to become available in the future. Another limitation is that the proposed model does not account for some other potential characteristics of crash data, such as unobserved heterogeneity [23–25] and temporal correlation (including linear trend, seasonality, etc.) [26]. Developing a more complicated (e.g., random parameters spatio–temporal logistic) model is advocated, when these characteristics also exist.

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