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Bayesian spatial joint modeling of traffic crashes on an urban road network

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ABSTRACT

This study proposes a Bayesian spatial joint model of crash prediction including both road segments and intersections located in an urban road network, through which the spatial correlations between heterogeneous types of entities could be considered. A road network in Hillsborough, Florida, with crash, road, and traffic characteristics data for a three-year period was selected in order to compare the proposed joint model with three site-level crash prediction models, that is, the Poisson, negative binomial (NB), and conditional autoregressive (CAR) models. According to the results, the CAR and Joint models outperform the Poisson and NB models in terms of model fitting and predictive performance, which indicates the reasonableness of considering cross-entity spatial correlations. Although the goodness-of-fit and predictive performance of the CAR and Joint models are equivalent in this case study, spatial correlations between segments and the connected intersections are found to be more significant than those solely between segments or between intersections, which supports the employment of the Joint model as an alternative in road-network-level safety modeling.

1. Introduction

The past decade has witnessed a revolutionary advancement in statistical modeling of crash frequencies for various types of road entities. A number of innovative techniques have emerged, ranging from data mining techniques, multivariate analysis, spatiotemporal modeling, and random parameters to empirical Bayesian and full-Bayesian hierarchical approaches (Lord and Mannering, 2010). In the light of these techniques, model fitting and predictive performances have been significantly improved. However, almost all existing site-level crash prediction models (CPMs) only work for a single type of road entity, that is, either a node (intersection) or a link (road segment).

From another perspective, considerable efforts (Washington et al., 2006; Herbel et al., 2009) have recently been made to incorporate safety considerations into transportation planning practice, that is, Transportation Safety Planning (TSP).With the rapid development of TSP theories, zonal CPM has become a front-line research topic to help develop zonal safety monitoring and evaluation tools. Compared to traditional site-level crash prediction technologies (e.g. CPMs for intersections or road segments), the zonal CPMs promote the task of road safety improvement to a more macroscopic perspective.

Nevertheless, the safety problem is a microscopic problem and the direct causes of any road crash could be related to micro-level factors associated with a specific road segment or intersection or the driver–vehicle units involved. This leads to practical challenges in applying current zonal CPMs to the development of safety countermeasures. An immediate solution is to estimate the zonal safety situation by summing up crash predictions of all the road entities located within the zones of interest. However, as different types of road entities are necessarily associated with different categories of risk factors, the state-of-the-art crash prediction techniques, as mentioned above, are limited to road entities of a single type, which is clearly reflected in Parts C & D of the *Highway Safety Manual* (*HSM*) (AASHTO, 2010). As such, in response to the context of emerging TSP, there is a need for road-network-level safety evaluation and prediction. More specifically, the zone-level safety estimation approach could be developed from the perspective of a road network by simultaneously taking different categories of road entities into account.

In safety analyses at road-network level, spatial correlation is an important issue to be considered, because road entities that are in close proximity may share confounding factors. Recently, consideration of the spatial effect of adjacent road entities in crash prediction has been proven to significantly improve the model's predictive accuracy (Quddus, 2008). But previous studies of safety spatial

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analysis are again limited to individual types of road entities, that is, either intersections (Abdel-Aty and Wang, 2006) or segments (Aguero-Valverde and Jovanis, 2008). Undoubtedly, spatial correlations exist not only between adjacent road segments and between adjacent intersections, but also, perhaps even more importantly, between road segments and their connected intersections. Therefore, in the core of the road-network-level study is a joint modeling of traffic crashes of road links and nodes with consideration of spatial correlations. The joint modeling of intersections and the feeding road segments is expected to facilitate an overall better safety prediction at both site level and road-network level.

This study aims to (1) jointly model crash frequencies of intersections and the feeding road segments by explicitly accounting for spatial correlations in an urban road network, (2) compare the proposed joint model to traditional site-level models in terms of model fitting and predictive performance.

2. Literature review

2.1. Site-level CPM

Crash prediction for various road entities (e.g. intersections or road segments) has been developed for several decades. With regard to the methodological development of CPM, the basic Poisson model (Jovanis and Chang, 1986) requires the mean and variance of crash frequency to be equal and assumes that the analyzed observations are mutually independent. To handle the over-dispersion, spatiotemporal correlation, and multilevel heterogeneities among observations, models ranging from negative binomial (NB) (Miaou, 1994), Poisson-lognormal (Miaou et al., 2005), and zero-inflation (Shankar et al., 1997; Huang and Chin, 2010) to Conway–Maxwell–Poisson (Lord et al., 2008), finite mixture/latent class (Park and Lord, 2009; Park et al., 2010), Markov switching (Malyshkina et al., 2009), random effects or random parameters (Shankar et al., 1998; Anastasopoulos and Mannering, 2009), and multilevel models (Huang and Abdel-Aty, 2010) have been widely investigated. Moreover, some artificial intelligence models, such as the neural network (NN) (Abdelwahab and Abdel-Aty, 2002), Bayesian neural network (BNN) (Xie et al., 2007), and support vector machine (SVM) (Li et al., 2008) have also been developed to predict crash frequencies as they exhibit better non-linear approximation properties than traditional count models. Their application in crash prediction is limited by their non-transferability and the fact that they behave as black boxes. Lord and Mannering (2010) gave a more detailed description and assessment of these models.

2.2. Zone-level CPM

Numerous studies on zonal CPM have been conducted at various zone levels including state (Noland, 2003), county (Amoros et al., 2003; Noland and Oh, 2004; Huang et al., 2010), traffic analysis zone (TAZ) (Guevara et al., 2004; Aguero-Valverde and Jovanis, 2006), census ward (Hadayeghi et al., 2006), local health area (Quddus, 2008), and grid-based structure level (MacNab, 2004), and so on. Zone-level risk factors, including land use and socio-economic and demographic characteristics as well as road facility conditions such as network topology, highway density, and intersection density, have been widely investigated to interpret the observed cross-sectional variability of the safety situation. Compared to the site-level CPM, these studies omitted the specific characteristics of road segments and intersections within zones of analysis. As such, it would be beneficial if a road-network-level CPM were developed to incorporate the site-level factors in safety estimation for the zones in which the road network is located.

2.3. Road-network-level CPM

In one of the few studies which considered zone-level crash prediction from a road-network perspective, Lord and Persaud (2004) represented road networks as simplified digital networks. The study only accounted for safety effects of estimated traffic volume and segment lengths and neglected other characteristics of road entities. In the *HSM* (AASHTO, 2010), the collective safety level of an arterial or a road network is estimated by separate estimations for each road segment and intersection. To our knowledge, no previous study of road-network-level CPM has essentially taken into account spatial correlations among different types of road entities.

2.4. Spatial modeling in CPMs

In the development of both site-level CPM and zone-level CPM, numerous studies have shown that accounting for spatial correlation among the analyzed observations is a big step toward a better safety assessment. Following the recent development of Bayesian statistics, Bayesian spatial models (Banerjee et al., 2004) such as conditionally autoregressive (CAR) and simultaneous autoregressive (SAR) models have been applied in road safety analysis. In the CAR model, a regression component is directly introduced into the mean regression equation to account for spatial random effects, which are assumed to be auto-normal CAR distributed. This relatively simple model structure and its convenient employment in the context of Bayesian inference have facilitated its extensive usage in the past decade (Miaou et al., 2003; Aguero-Valverde and Jovanis, 2008; Mitra, 2009; Aguero-Valverde and Jovanis, 2010; Guo et al., 2010). See Wang et al. (2012) for a comprehensive review of spatial model applications in road safety research.

Unfortunately, almost all the existing CPMs merely work for a sole type of road entity or traffic zone. In response to the road-network-level CPM development, a joint modeling of traffic crashes of intersections and segments that accounts for the spatial correlations among heterogeneous types of road entities in a road network is required.

3. Methodology

3.1. Model specification

This study proposes a Bayesian spatial joint model to include both road segments and intersections located in an urban road network, by which the spatial correlations between heterogeneous types of entities could be considered. For the purpose of comparison, three sets of models, that is, Poisson, NB, and Bayesian spatial models with the CAR prior, are estimated separately for both segments and intersections of analysis.

3.2. Poisson model

Statistically, the stochastic crash occurrence is rationally assumed to be a Poisson process, which justifies the popular application of the Poisson distribution in modeling crash frequency.

$$Y_{it} \left| \lambda_{it} \sim Poisson\left(\lambda_{it}\right) = Poisson\left(\mu_{it} e_{it}\right)\right.$$

$$\log \lambda_{it} = \log e_{it} + X_{it}' \beta$$

where Y_{it} is the crash count at segment or intersection i during period t with the underlying Poisson mean λ_{it}. μ_{it} and e_{it}, which contribute to λ_{it}, denote risk factors (covariates X_{it} and the coefficients β) and exposure factors, respectively.

3.3. NB model

As over-dispersion which violates the "variance = mean" constraint of a Poisson model commonly exists in crash data, over-dispersed Poisson models have been proposed. The NB model, which is modified from the basic Poisson model by including an extra residual term, is employed in this research.

$\log \lambda_{it} = \log e_{it} + X'_{it}\beta + \theta_{it}$

$\exp(\theta_{it}) \sim \text{gamma}(a, a)$

over-dispersion parameter: $k = \frac{1}{a}$

where θ_{it} denotes the extra residual term for site i during period t.

3.4. CAR model

As road segments are mutually connected by intersections, spatial correlations resulting from spatial confounding factors may exist for both adjacent segments and adjacent intersections. CAR, the most common spatial model applied in road safety studies, specifies the spatial correlations by residual terms with the Gaussian CAR prior.

$$\log \lambda_{it} = \log e_{it} + X'_{it}\beta + \theta_i + \phi_i$$

$$\theta_i \sim \text{normal}\left(0, \frac{1}{\tau_h}\right)$$

$$\phi_i \sim \text{normal}\left(\bar{\phi}_i, \frac{1}{\tau_i}\right)$$

with

$$\bar{\phi}_i = \frac{\sum_{i \neq j} \phi_j \omega_{ij}}{\sum_{i \neq j} \omega_{ij}} \text{ and } \tau_i = \frac{\tau_c}{\sum_{i \neq j} \omega_{ij}} \text{ and } \alpha = \frac{\text{sd}(\phi)}{\text{sd}(\theta) + \text{sd}(\phi)}$$

in which θ_i and ϕ_i denote the random effect and spatial correlation for site i, respectively. τ_h is the precision (reciprocal of the variance) of θ_i, while τ_c is the precision parameter in the CAR prior. ω_{ij} is the entry with the adjacency index and weight for sites i and j in proximity matrix ω. α represents the proportion of variability in the random effects that is due to spatial autocorrelation. Clearly, while ϕ_i represents the cross-sectional spatial correlation, θ_i reflects the global site-specific random effects with normal distribution.

3.5. Joint model

In a road network, compared with spatial correlations solely between segments or between intersections, the ones between segments and intersections may be more significant because of their direct connections with each other. Presumably, adjacent road segments and intersections may share more unobserved effects, such as speed and driver behaviors. As intersections and road segments necessarily have different sets of risk factors, the proposed Joint model employs an indicator variable to suggest whether the road entity is a segment or an intersection. The basic link function for the proposed Joint model is developed by modification of previous models, as follows: $\log \lambda_{it} = \log(r_i \times e^I_{it} + (1 - r_i) \times e^S_{it}) + r_i \times X^{I'}_{it}\beta^I + (1 - r_i) \times X^{S'}_{it}\beta^S + \theta_i + \phi_i$

where I and S denote intersections and segments respectively. If site i is an intersection, then $r_i = 1$; else if site i is a segment, $r_i = 0$. e^S_{it} and X^S_{it} and e^I_{it} and X^I_{it} denote exposure variables and covariates for road segments and intersections respectively.

Clearly, compared to the CAR model, although different sets of risk factors (X) are still used for explaining the crash count variability for corresponding types of road entities, the residual term is modified in the Joint model to account for spatial correlations not only between road entities of a sole type but also between heterogeneous types of entities including road segments and intersections.

Specifically, data analysts may decide the level of consideration of spatial correlation, and the cross-sectional spatial correlation ϕ_i can be flexible if adjacency indices and weights are specified in the proximity matrix ω, which subsequently results in a varied level of model complexity.

3.6. Crash exposure variables

Crash exposure could be described as the number of opportunities for crashes in a given time in a given area. The crash exposure of road segments is generally modeled by annual average daily traffic (AADT) (Miaou, 1994) or vehicle miles traveled (VMT) (Ahmed et al., 2011).

In the present study, the exposure function for road segments proposed by Qin et al. (2004) is employed to account for the potential non-linear relationship between crash frequency and traffic volume.$e^S_{it} = \text{AADT}^{\alpha_1}_{it} L^{\alpha_2}_i$

where e^S_{it} and AADT_{it} denote the exposure and AADT for segment i during period t with coefficients α_1 and α_2. L_i is the length of segment i.

For intersections, Miaou and Lord (2003) conducted a comprehensive evaluation of a number of possible forms and in this study we adopted the most typical one:$e^I_{it} = \text{AADT}^{\alpha_1}_{1,it}\text{AADT}^{\alpha_2}_{2,it}$

in which e^I_{it} denotes the exposure for intersection i during period t. $\text{AADT}_{1,it}$ and $\text{AADT}_{2,it}$ are traffic volumes for the major and minor approaches at the intersection, respectively.

3.7. Model comparison

In the context of Bayesian inference, the Deviance Information Criterion (DIC) and Bayesian R^2 are used for the evaluation of model fitting, whereas model predictive performance is compared by developing the Cross-Validation Predictive Density (CVPD).

DIC, proposed by Spiegelhalter et al. (2002), provides a Bayesian measure of model complexity and fitting. Specifically, DIC is defined as:

$\text{DIC} = D\left(\bar{\theta}\right) + pD,$

where $D\left(\bar{\theta}\right)$ is the posterior mean deviance that can be taken as a Bayesian measure of fitting, and pD is a complexity measure for the effective number of parameters. Generally, models with lower DIC values are preferred.

The Bayesian R^2 measure was proposed to estimate the ratio of the explained sum of squares to the total sum of squares (Ahmed et al., 2011). It could be viewed as a global model-fitting measurement

$$R^2_{Bayes} = 1 - \frac{\sum_{t=1}^{3}\sum_{i=1}^{n}(y_{it} - \lambda_{it})^2}{\sum_{t=1}^{3}\sum_{i=1}^{n}(y_{it} - \bar{y})^2}.$$

For convenience of comparison, R^2 values for intersections and segments were calculated as a whole for separate models,

$$WR^2_{Bayes} = 1 - \frac{\sum_{t=1}^{3}\sum_{i=1}^{n_i}(y_{it} - \lambda_{it})^2 + \sum_{t=1}^{3}\sum_{i=1}^{n_s}(y_{it} - \lambda_{it})^2}{\sum_{t=1}^{3}\sum_{i=1}^{n_i}(y_{it} - \bar{y})^2 + \sum_{t=1}^{3}\sum_{i=1}^{n_s}(y_{it} - \bar{y})^2}$$

where n_i and n_s are the numbers of intersections and road segments, respectively.

CVPD provides fairly flexible measures to examine the suitability for overall model predictive performance. In the case of models with large sample sizes, the k-fold CVPD is generally employed to save computational cost. Specifically, the dataset was divided into k groups of roughly equal sizes. Each time, a group was removed from the dataset, and each model was fitted with the remaining

$(k-1)$ groups. The fitted models were used to predict the removed group.

In the Bayesian framework, the predictive densities for observation at site i in time period t are

$$p(\hat{y}_{it} \left| x_{it}, D^{(\backslash s(it))}, M \right.) = \int p(\hat{y}_{it} \left| x_{it}, \theta, D^{(\backslash s(it))}, M \right.) \times p(\theta \left| D^{(\backslash s(it))}, M \right.) \mathrm{d}\theta$$

where $\hat{y}_{it}$ is the predictive crash number for observation (x_{it}, y_{it}), and $D^{(\backslash s(t))}$ is the data except the removed group $s(it)$. θ denotes all the parameters and hyper-parameters in the model, and M is all the prior knowledge, including the assumed model structures and prior specification of parameters.

Two criteria were used to estimate the goodness of the predictive performance. The first is the mean absolute deviance (MAD), and the second is the mean squared prediction error (MSPE). They are described as:

$$\mathrm{MAD} = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{n}\left|\hat{y}_{it} - y_{it}\right|, \ \mathrm{MSPE} = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{n}\left(\hat{y}_{it} - y_{it}\right)^2$$

where T is the number of time periods and n is the number of road segments or intersections.

These two criteria for road segments and intersections were calculated separately in three separate models, while they were calculated together in the Joint model. As for R^2, the weighted average by numbers of segments and intersections was calculated for the evaluation of the model prediction performance at the road-network level.

$$\mathrm{WMAD} = \frac{1}{(n_i + n_s)T}\left(\sum_{t=1}^{T}\sum_{i=1}^{n_i}\left|\hat{y}_{it} - y_{it}\right| + \sum_{t=1}^{T}\sum_{i=1}^{n_s}\left|\hat{y}_{it} - y_{it}\right|\right) = \frac{n_i}{(n_i + n_s)}\mathrm{MAD}_i + \frac{n_s}{(n_i + n_s)}\mathrm{MAD}_s$$

$$\mathrm{WMSPE} = \frac{1}{(n_i + n_s)T}\left(\sum_{t=1}^{T}\sum_{i=1}^{n_i}\left(\hat{y}_{it} - y_{it}\right)^2 + \sum_{t=1}^{T}\sum_{i=1}^{n_s}\left(\hat{y}_{it} - y_{it}\right)^2\right) = \frac{n_i}{(n_i + n_s)}\mathrm{MSPE}_i + \frac{n_s}{(n_i + n_s)}\mathrm{MSPE}_s$$

4. Data preparation and preliminary analysis

To demonstrate the proposed model, an urban road network in Hillsborough county of Florida was selected, as shown in Fig. 1. The network consists of 346 segments and 198 intersections. The disaggregated crash data for all segments and intersections in a three-year period (2005–2007) were obtained from the Crash Analysis Reporting (C.A.R.) system. While most of the site characteristics data were downloaded freely from the website of Florida Department of Transportation in GIS shapefile format, other site-specific factors, for example, the presence of left-turn/right-turn lanes at intersections, were manually collected from Google Earth.

A challenge in crash data preparation is to designate each crash as intersection-related or segment-related, especially for those close to intersections (Wang et al., 2008). In the C.A.R. system, crashes that occur within about 50 and 250 ft of the stop line are defined respectively as "at intersection" and "influenced by intersection". In our study, crashes reported as both "at intersection" and "influenced by intersection" are categorized as intersection-related while the others are segment-related.

For the years 2005–2007, AADT data were only available for roadways on the National Highway System (NHS), that is, NHS = 1. But AADT data were recorded for all segments in 2012. To estimate the AADT for segments off the NHS in 2005–2007, the scale factors for each year were calculated by $s_t = \frac{\sum_{i \in \text{on-system}} \mathrm{AADT}_i^t}{\sum_{i \in \text{on-system}} \mathrm{AADT}_i^{2012}}$, with t = 2005, 2006, 2007; $i \in on-system$ means that the segment i is on the NHS.

Tables 1 and 2 illustrate the definitions and descriptive statistics of site characteristics for segments and intersections, respectively.

Collinearity diagnoses for the risk factors of segments and intersections were conducted in SPSS. In the results, the eigenvalue of the variable "median" is 0.06, and its condition index is more than 32, indicating that the presence of the median is significantly collinear with other factors. Therefore, the variable "median" was excluded from the models for segments.

Moran's I was used to reflect whether observed crashes are spatially correlated among adjacent road entities (Banerjee et al., 2004):

$$\text{Moran's} \quad I = \frac{n\sum_i\sum_j \omega_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\left(\sum_{i \neq j}\omega_{ij}\right)\sum_i (Y_i - \bar{Y})^2}$$

where n is the total number of road entities; Y_i and Y_j are the total crash counts in the three years at entities i and j. $\bar{Y}$ is the global average of crash counts at all segments or intersections. The values of Moran's I for segments and intersections were 1.09 and 1.04 with z-scores of 4.17 and 2.35, respectively, which indicated that the crash counts of segments and intersections were spatially clustered at 95% significance level.

The spatial proximity matrices for development of the CAR and Joint models were obtained from the digital road network using GIS techniques. For all the spatial proximity matrices, adjacency weights of 0–1 were employed. If two road entities are adjacent, then the weight is 1; otherwise, the weight is 0. For CAR models, any two intersections that are connected by a certain segment or two segments that approach the same intersection are viewed as adjacent. In the Joint model, only two road entities directly connected each other are considered adjacent.

5. Results and discussion

5.1. Model estimation

With the advances in computing methods, Bayesian inference has enjoyed a dramatic increase in usage due to its ability to handle very complex models. Freeware WinBUGS has become a popular platform to make the Bayesian inference, which is well-known for its flexible programming environment. We developed all the proposed models in WinBUGS and the CAR priors were specified by the function of car.normal to reflect the spatial proximity relationship of the entities in the road network analyzed.

Non-informative priors were specified for other model parameters with normal distributions $(0, 10^4)$. With the relatively large amount of data, the non-informative priors may have little effect on the posterior distribution of the parameters (Gelman et al., 2004). For each model, a chain of 500,000 iterations was set. After the convergence, another 50,000 iterations were set to make summaries for the parameters.

A three-fold CV, where the dataset was divided into three groups by year (i.e. 2005, 2006, 2007), was applied to evaluate the models' predictive performance. This division was developed to keep the integrality of the spatial proximity matrices for the CAR and Joint models. Each time, the sub-dataset of any two years was input for the training of the models, and the estimated parameters were subsequently used to predict the crash counts for the removed year.

5.2. Model comparison

The results of the model comparison are shown in Table 3. Clearly, the significantly over-dispersed parameters in the NB

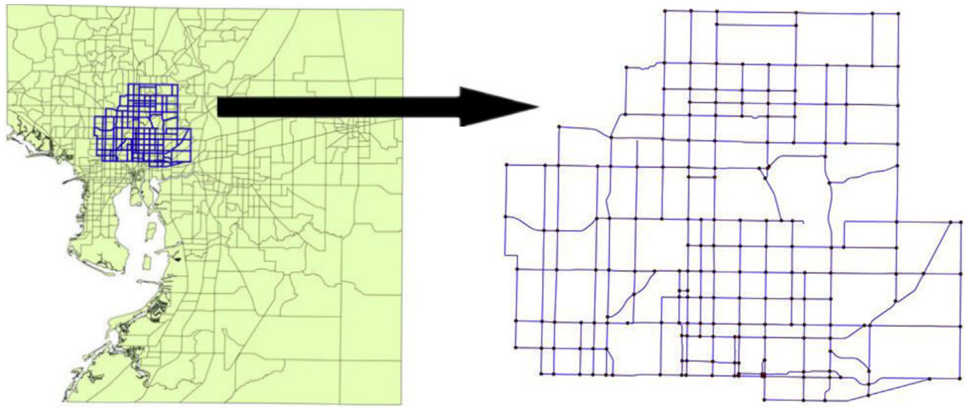

Fig. 1. The selected road network in Hillsborough.

Table 1
Descriptive statistics for segment-related variables.

Variable	Description	Mean	sd	Min.	Max.
Response variables					
Crash2005	Crash count per segment in 2005	12.82	19.458	0	199
Crash2006	Crash count per segment in 2006	12.92	20.527	0	235
Crash2007	Crash count per segment in 2007	10.43	15.613	0	105
Exposure variables					
Length	Segment length (km)	0.856	0.484	0.065	2.830
AADT	Average annual daily traffic (10^3 pcu[a])	17.12	16.73	0.35	70
Risk factors					
Funclass	Principal arterial = 1, minor arterial = 2, others = 3	2.29	0.8	1	3
Speedlimit	Posted speed limit	37.59	7.235	25	50
NHS	State-maintained roads = 1, otherwise 0	0.38	0.487	0	1
Lane	Number of lanes	3.18	1.43	1	8
Access	Number of access roads/segment length	12.16	7.66	0	39.35
Surface	Pavement condition: good/very good = 1, poor/fair = 0	0.46	0.50	0	1
Median	Presence of median: yes = 1, no = 0	0.42	0.495	0	1

[a] pcu: Passenger car units.

models for both segments (k = 0.63) and intersections (k = 0.30) confirm that the datasets analyzed are over-dispersed. As shown by the values of DIC and WR^2, which measure the model fitting, the NB, CAR, and Joint models outperform the Poisson model to a substantial extent. The result is reasonable in that all three revised models include extra residual terms to account for the over-dispersion, which may have been raised by a number of possible sources such as observation-specific/site-specific heterogeneities, spatial correlation, or unobserved confounding factors. Different from the traditional NB model, a number of advanced approaches have been recently developed, such as random parameters and finite-mixture models which could deal with possible heterogeneities caused by variable effects of risk factors across road entities or even groups of road entities (groupings which could

Table 2
Descriptive statistics for intersection-related variables.

Variable	Description	Mean	sd	Min.	Max.
Response variables					
Crash2005	Crash count per intersection in 2005	12.38	11.973	0	62
Crash2006	Crash count per intersection in 2006	12.40	11.942	0	57
Crash2007	Crash count per intersection in 2007	10.31	11.210	0	67
Exposure variables					
Major_AADT	AADT on major approach (10^3 pcu[a])	25.10	18.40	2.6	70
Minor_AADT	AADT on minor approach (10^3 pcu)	7.97	8.24	0.35	43
Risk factors					
No_leg	Number of legs: four legs = 1, three legs = 0.	0.69	0.465	0	1
Traffic_signal	Presence of traffic signal: yes = 1, no = 0.	0.54	0.5	0	1
Major_sl	Speed limit on major approach	39.37	6.663	25	50
Minor_sl	Speed limit on minor approach	34.72	7.075	25	50
Major_left	Presence of left-turn lane on major approach: yes = 1, no = 0	0.69	0.465	0	1
Major_right	Presence of right-turn lane on major approach: yes = 1, no = 0	0.25	0.433	0	1
Minor_left	Presence of left-turn lane on minor approach: yes = 1, no = 0	0.64	0.482	0	1
Minor_right	Presence of right-turn lane on minor approach: yes = 1, no = 0	0.24	0.430	0	1

[a] pcu: Passenger car units.

Table 3
Model comparison.

Model	Poisson		NB		CAR		Joint
	Segment	Intersection	Segment	Intersection	Segment	Intersection	
k	–	–	0.63 (0.56, 0.70)[a]	0.30 (0.25, 0.36)	–	–	–
sd(Φ)	–	–	–	–	0.38 (0.24, 0.56)	0.30 (0.14, 0.53)	0.40 (0.28, 0.51)
sd(θ)	–	–	–	–	0.75 (0.65, 0.83)	0.47 (0.23, 0.58)	0.64 (0.56, 0.71)
α	–	–	–	–	0.33 (0.23, 0.46)	0.39 (0.26, 0.70)	0.38 (0.29, 0.47)
pD	10	11	712	381	296	166	463
DIC	10190	4481	5314	3226	5178	3166	8346
R^2	0.646	0.627	0.965	0.914	0.923	0.876	0.915
WR^2	0.642	0.956	0.914	0.915			
MAD	7.05	5.58	10.11	7.70	4.57	4.63	4.59
MSPE	144.2	65.5	354.7	140.1	68.7	45.5	60.2
WMAD		6.51		9.23		4.59	4.59
WMSPE		115.6		276.6		60.3	60.2

[a] Estimated mean (95% Bayesian credible interval) for the parameter.

account for spatial correlations) (Xiong and Mannering, 2013). Herein, the approach we use gives the explicit specification of spatial correlation between adjacent road segments/intersections based on the spatial adjacency structure.

By observing the estimated values of spatial evaluation measures ($\alpha = 0.33$ for the segment-CAR model, 0.39 for the intersection-CAR model, and 0.38 for the Joint model), we may conclude that the consideration of spatial correlations between adjacent entities is reasonable in comparison with the unstructured extra residual term employed in the NB model. More specifically, the segment-CAR model, intersection-CAR model, and Joint model account for 33%, 39%, and 38% of the extra-variability in crash count distributions, respectively. Moreover, an interesting difference in over-dispersion between the segment-CAR model and intersection-CAR model is observed. All the values of k, sd(Φ), and sd(θ) in the segment-CAR model are higher than those in the intersection-CAR model, which implies a higher over-dispersion of the segment-related crash data. This is consistent with the previous results of Moran's I evaluations.

Technically, the NB model deals with the over-dispersion by using an extra residual term (θ_{it}) identical to each analyzed observation. In comparison, the CAR and Joint models not only include the site-specific random effects but also account for the possible site-level spatial correlation and network-level spatial correlation, respectively. Clearly, the latter two models are more reasonable than the NB model in terms of the way in which the model is fitted to the specific data structures. This is clearly confirmed by the higher DIC values of the NB models. Interestingly, we found an even higher value of WR^2 for the NB model (0.956) than for the CAR model (0.914) and Joint model (0.915). Compared to DIC, WR^2 can only evaluate the goodness of fit but neglects the model parsimony. Therefore, their discrepancy in estimated values is not surprising given the unstructured residual terms of the NB model, which consequently lead to more complicated models with more effective parameters, as reflected by the pD values (cf. Table 3). Moreover, in spite of the improved model fitting, the model predictive performance, evaluated by the CVPD, would most be probably weakened when more unstructured parameters were added. This is, very surprisingly, confirmed by the fact that the NB model has the worst predictive performance (WMAD = 9.23, WMSPE = 276.6), even compared to the Poisson model (WMAD = 6.51, WMSPE = 115.6).

Comparing the Joint model with the CAR models, we found that although the proportions of extra-variability accounted for are similar (α), the sd(Φ) value of the Joint model (0.40) is higher than those of the CAR models (0.38 and 0.30). It is reasonable that the spatial correlation between intersections and their connected segments may be more significant than the ones between adjacent intersections or adjacent segments. Unfortunately, the possible advantage of the Joint model is not adequately reflected in the estimated values of model fitting and predictive performance (cf. DIC, WR^2, WMAD, WMSPE), which are very close to each other. Note that their difference in model specification resides in the way in which cross-entity spatial correlation is accounted for, where the CAR model considers it separately in node–node and link–link style, while the Joint model considers the node-link correlation simultaneously. The equivalent predictive performance implies that, for the specific datasets in the present case study, the account of correlation for the same types of entities may be adequate to reflect the cross-entity spatial correlation. Nevertheless, it is again worth noting that the Joint model provides a more reasonable and convenient means of spatial modeling at road-network level. More field datasets are needed to further confirm the possible merits of the Joint model in model-fitting.

5.3. *Interpretation of explanatory variables*

Although the present study is focused on the model comparison, a good understanding on the explanatory variables is also important to partially justify the model validity. The results of parameter estimation in the NB, CAR and Joint models using the full set of data are summarized in Table 4.

Overall, most of the important factors reflecting basic road geometry and traffic volumes are significant at the 95% significance level. The coefficients in the CAR and Joint models are more consistent with each other and have substantial differences from those in the NB model, which indicates the effect of considering the spatial correlation on the parameter estimation. Nevertheless, the plus or minus signs of the parameters in all three models are generally consistent and conform to empirical engineering judgments and previous studies (AASHTO, 2010).

Specifically, the exposure variables for the segment and intersection are all significantly positive. The length of the road segment seems to have a heavier weight on crash exposure than AADT, which may imply a non-linear relationship between segment crash counts and the vehicle miles traveled (i.e. AADT × segment length) (Lord and Persaud, 2004; Qin et al., 2004). For the intersection, it is clear that the traffic volume on major approaches plays a more important role than that on minor approaches in reflecting crash exposure.

Unsurprisingly, more crashes generally tend to occur on road segments with more lanes, more accesses, higher speed limits, and worse pavement conditions. Moreover, local and connector roads (Funclass[3]) are prone to lower crash rates than principal arterials. For intersections, three critical risk factors are found, which are the presence of traffic signals, the number of intersecting legs, and the speed limit on major approaches. All three coefficients are significantly positive, indicating that more crashes tend to occur at intersections with signal controls, with four intersecting legs, and

Table 4
Parameter estimation.

Model	NB	CAR	Joint
Road segment			
Length	**1.137 (1.034, 1.241)**[a]	**1.267 (1.099, 1.448)**	**1.23 (1.068, 1.397)**
AADT	**0.283 (0.210, 0.365)**	**0.471 (0.357, 0.607)**	**0.443 (0.295, 0.575)**
Lane	**0.167 (0.102, 0.228)**	**0.137 (0.036, 0.209)**	**0.145 (0.050, 0.227)**
Access	**0.022 (0.012, 0.032)**	**0.025 (0.008, 0.041)**	**0.022 (0.008, 0.038)**
Speedlimit	0.009 (−0.002, 0.021)	0.012 (−0.002, 0.026)	0.008 (−0.008, 0.024)
Surface	**−0.280 (−0.419, −0.137)**	−0.084 (−0.302, 0.140)	−0.094 (−0.296, 0.121)
NHS	−0.001 (−0.193, 0.192)	0.190 (−0.118,0.521)	0.212 (−0.088, 0.492)
Funclass[2]	−0.015 (−0.192, 0.146)	0.151 (−0.163, 0.418)	0.112 (−0.200, 0.383)
Funclass[3]	**−0.485 (−0.725, −0.251)**	−0.018 (−0.445, 0.313)	−0.058 (−0.488, 0.329)
Intersection			
Major_AADT	**0.463 (0.368, 0.553)**	**0.466 (0.282, 0.614)**	**0.456 (0.328, 0.623)**
Minor_AADT	**0.159 (0.090, 0.226)**	**0.158 (0.025, 0.293)**	**0.203 (0.061, 0.326)**
Traffic_signal	**0.463 (0.325, 0.591)**	**0.51 (0.290, 0.753)**	**0.538 (0.308, 0.811)**
No_leg	**0.360 (0.227, 0.491)**	**0.419 (0.199, 0.637)**	**0.416 (0.172, 0.654)**
Major_sl	**0.020 (0.008, 0.029)**	**0.024 (0.007, 0.040)**	**0.031 (0.011, 0.052)**
Minor_sl	0.008 (−0.002, 0.017)	0.007 (−0.009, 0.022)	0.003 (−0.013, 0.019)
Major_left	**0.212 (0.037, 0.380)**	0.242 (−0.019, 0.513)	0.181 (−0.101, 0.486)
Major_right	0.093 (−0.042, 0.231)	0.066 (−0.156, 0.289)	0.081 (−0.171, 0.328)
Minor_left	−0.140 (−0.293, 0.019)	−0.129 (−0.364, 0.1)	−0.182 (−0.462, 0.092)
Minor_right	0.112 (−0.030, 0.252)	0.158 (−0.075, 0.403)	0.112 (−0.198, 0.383)

[a] Estimated mean (95% Bayesian credible interval) for the parameter.

with higher speed limits. All these observations from the parameter estimation generally accord with common sense regarding traffic engineering.

6. Conclusion

This research proposes a Bayesian joint CPM for road segments and intersections in an urban road network by specifically accounting for their spatial correlations. A road network in Hillsborough, Florida, has been selected for model development and comparison with traditional site-level models, that is, Poisson, NB, and CAR models. The results show that the Joint and CAR models outperform the Poisson and NB models in model fitting and predictive performance, which indicates that the consideration of spatial correlations between adjacent entities is reasonable. Moreover, the spatial correlations between intersections and their feeding segments are found to be more significant than those solely between adjacent intersections or adjacent segments, which supports the employment of the Joint model as an alternative in road-network-level safety modeling.

Although the goodness-of-fit and predictive performance of the CAR and Joint models are equivalent in the present case study, the proposed Joint model provides a more reasonable and convenient means of crash frequency modeling at road-network level. Mostly, the results of the explanatory variables are reasonable and consistent with the findings of previous studies, which partially validate the proposed model.

Compared to traditional road-entity-level CPMs, the Joint model proposed provides a new perspective at road-network level by taking into account varied types of road entities plus their spatial correlation within an integrated network. Further research efforts could be made to its advantages in network-level applications, such as crash prediction of corridors, travel paths and TAZs.

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