



Exploring a Bayesian hierarchical approach for developing safety performance functions for a mountainous freeway

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ABSTRACT

While rural freeways generally have lower crash rates, interactions between driver behavior, traffic and geometric characteristics, and adverse weather conditions may increase the crash risk along some freeway sections. This paper examines the safety effects of roadway geometrics on crash occurrence along a freeway section that features mountainous terrain and adverse weather. Starting from preliminary exploration using Poisson models, Bayesian hierarchical models with spatial and random effects were developed to efficiently model the crash frequencies on road segments on the 20-mile freeway section of study. Crash data for 6 years (2000–2005), roadway geometry, traffic characteristics and weather information in addition to the effect of steep slopes and adverse weather of snow and dry seasons, were used in the investigation. Estimation of the model coefficients indicates that roadway geometry is significantly associated with crash risk; segments with steep downgrades were found to drastically increase the crash risk. Moreover, this crash risk could be significantly increased during snow season compared to dry season as a confounding effect between grades and pavement condition. Moreover, sites with higher degree of curvature, wider medians and an increase of the number of lanes appear to be associated with lower crash rate. Finally, a Bayesian ranking technique was implemented to rank the hazard levels of the roadway segments; the results confirmed that segments with steep downgrades are more crash prone along the study section.

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1. Introduction

The COTrip system has been developed by Colorado Department of Transportation (CDOT) to provide the traveler with important information about travel time, congestion, adverse weather conditions and lane closure due to occasional avalanche danger, maintenance on the road and/or road crashes. This information is provided by as a part of an Intelligent Transportation System (ITS) and can be accessed through the website <http://www.cotrip.org>. In addition, the real time information is dynamically disseminated to road users via Dynamic Message Signs (DMS). In an effort to upgrade existing Intelligent Transportation System to include Variable Speed Limits (VSL), CDOT has ambitious plans to implement the system first within a 20 miles long section on Interstate 70 (I-70), this section experienced higher than average crash frequency over the last few years. It is expected to substantially improve safety by managing the speed limit along the section during adverse weather.

The section of interest features mountainous road geometry and frequent severe weather. As a result of this mountainous terrain, this section of the interstate highway features steep slopes up to 7%. Moreover, climate with all its aspects of temperature, humidity, precipitation and wind is dramatically impacted by the considerable high elevations. This section experienced relatively higher fatality rate, a 0.48 per 100 million vehicle miles traveled (MVMT), compared to the entire interstate system in 2004 (fhwa.dot). In order to come up with an effective ITS upgrade, it is vital for a preliminary evaluation of the contributing factors to crash occurrence and identification of hotspots.

This research attempts an exploratory safety analysis on this section of the freeway. In particular in this paper, we aim at (1) examining the effect of mountainous highway geometrics and traffic characteristics in adverse weather on the frequency of crashes, (2) identifying hazardous road segments and crash-prone time periods for more focus within an Advanced Traffic Management strategy.

To achieve the abovementioned objectives, vehicle crash data from I-70 in the state of Colorado were obtained for 6 years (2000–2005) together with roadway geometry, traffic characteristics, and adverse weather represented in the snow and dry

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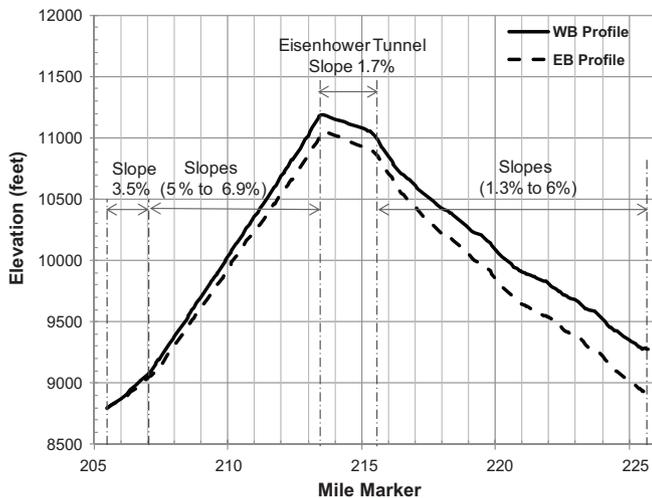


Fig. 1. Longitudinal profile.

season. A preliminary data exploration was first conducted to examine the important factors that may contribute to crash occurrence. Bayesian hierarchical models with random effects were used to fully account for the uncertainty associated with parameter estimates and provide exact measures of uncertainty on the posterior distributions of these parameters and hence overcome the maximum likelihood methods' problem of overestimating precision because of ignoring this uncertainty (Goldstein, 2003; Rao, 2003). Application of random effects models will help also in pooling strength across sets of related units and hence improve the parameter estimation in sparse data (i.e. crash frequency models) (Aguero-Valverde and Jovanis, 2007). Moreover, since the crash risk might be spatially correlated among adjacent roadway segments, Bayesian spatial models were also examined. Finally, Bayesian ranking technique was used to effectively rank the hazard levels associated with the roadway segments of analysis.

2. Description of roadway section

2.1. General description

The freeway section under consideration is a 20.13 miles long of I-70 starting at Mile Marker (MM) 205.673 at Silverthorne and ends at MM 225.80 at Silver Plume in Colorado. The section encompasses three main parts; the Eisenhower Memorial Tunnel of 1.69 miles long starting at MM 213.18 and ending at MM 214.87, about 7.5 miles of the west side of the tunnel and 11.60 miles of the east side. The Eisenhower Tunnel is a twin bore tunnel with 26 ft of travel width (two lanes of 13 ft each). The tunnel is the highest point along the interstate highway system with an elevation of 11,158 ft and an average grade of 1.7% rising toward the west (Colorado.info).

2.2. Road alignment

The section passes through extreme mountainous terrain. The horizontal alignment of this section has relatively several sharp horizontal curves' radii. In addition to the steep grades on the west and east sides of the tunnel, as shown in Fig. 1, the west side has grades up to about 7% while the east side has grades that vary from 1.3% to 6%.

2.3. Climate

The section has a quite complex climate compared to most of the U.S. highways. The elevations in the vicinity of the area vary from

8700 ft to more than 14,000 ft on the highest peaks above the Eisenhower tunnel. The climate within this section is affected by the high altitudes and typically results in variations of all aspect of climate such as temperature, humidity, precipitation and, wind within short distance and time. The crash report identifies the weather and pavement conditions when a crash occurs. The plots of crash frequencies versus weather and road conditions (see Fig. 2) conform to the metrological data (climate.colostate.edu), suggesting that there are two main seasons: snow season from October through April and the dry season from May through September which experience small amount of rain, this can explain the small percentage of rain related crashes of 6% that occurred almost exclusively within the dry season. Regarding the distribution of weather-related crashes over the 6 years, 47% of the total crashes occurred within snowy weather where the pavement condition was icy, snowy or slushy, about 6% of the total crashes occurred in rain where the pavement was wet while all other 47% occurred within clear weather and dry pavement conditions. It is worth mentioning that small percentage of snow related crashes occurred within the defined dry season (about 2%) while a negligible number of rain related crashes occurred within the defined snow season (only 2 crashes on WB in the month of October within the 6 years). Classifying the climate into two main seasons will help us understand if there is a significant difference between crashes occurring within seasons that feature snow versus dry and the underlying seasonal effect on the roadway segments. Careful examination of the trends depicted in Fig. 2 produced these two main seasons. Although, all crashes related to weather and pavement conditions are aggregated within the two seasons to develop the data structure needed for the modeling effort of this study, the likelihood of crash occurrence in normal weather and dry pavement conditions remains constant in both seasons. Moreover, modeling the crash frequency of each specific weather condition (to account for a third rain season) would result in zero inflated problems associated with the short segments of the mountainous road section and the low crash frequency. Thus we were constrained by the data to use 2 main seasons, although more seasons might be possible on other freeways with higher crash frequencies and more distributed crashes per season.

3. Data preparation and preliminary crash analysis

There are many factors that contribute to crash occurrence, including driver behavior, traffic and geometric characteristics, weather conditions and interrelationships between these different factors. Unfortunately, the driver behavior factors are usually not available. Therefore, the available roadway, traffic and weather conditions factors were used in this study. There were two sets of data used in the study; roadway data and crash data. The roadway data were collected from CDOT, Roadway Characteristics Inventory (RCI) and Single Line Diagrams (SLD). The crash data were obtained from the road crash database maintained by CDOT.

A first but essential step in data preparation is road segmentation. Given the variation of road geometry, a major criterion employed for segmentation in this study was homogeneity in roadway alignment. According to the RCI data, both horizontal and vertical alignments were scrutinized. Moreover, a minimum-length criterion was set to 0.1 mile to avoid the low exposure problem and the large statistical uncertainty of the crash rate per short segment (Miaou, 1994). Segments shorter than 0.1 mile were combined with adjacent segment with similar geometrical characteristics as much as possible. For example, a 0.021 mile long straight segment was combined with the preceding segment with smooth curve of 39,755 ft radius, rather than the subsequent sharp-curved segment with 1813 ft radius. With this approach, 20 less-than-0.1 mile seg-

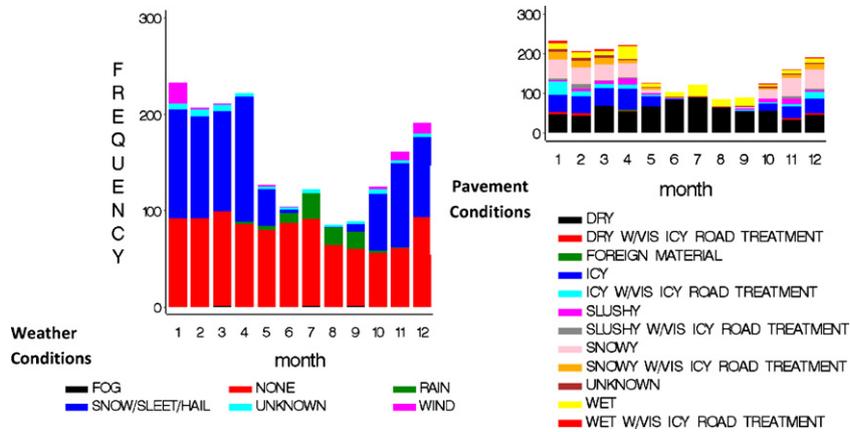


Fig. 2. Distribution of the monthly crashes by weather and pavement conditions for aggregated 6 years.

ments from 104 homogeneous segments were combined with their adjacent segments, resulting in 84 segments for each direction.

Table 1 illustrates the definitions and descriptive statistics of traffic, road geometrics, and weather characteristics for the segments.

Segment length and AADT are multiplied to estimate daily VMT to reflect the crash exposure for each segment. Among risk factors, of most interest are road alignment factors. The longitudinal grades are defined as a categorical variable with 8 categories gradually from upgrade (being positive) to downgrade (being negative), categorizing grades within 2% according to the American Association of State Highway and Transportation Officials (AASHTO, 2004) classification would help in reducing the number of short segments by combining the segments that share all other geometrical characteristics and fall within the same grade range and hence avoiding excessive zero frequency within short segments without losing interpretable useful information about grades. For segments with multiple grades, the equivalent grade for those segments was calculated in accordance with the Highway Capacity Manual (HCM, 2000) (Highway Capacity Manual 2000). Specifically, an overall average grade was calculated in case of no single portion of the grade is steeper than 4% or the total length of the grade is less than 0.75 mile. For some sub segments steeper than 4%, the HCM (2000) (Highway Capacity Manual 2000) composite grade procedure was used to determine an equivalent grade.

Defining variables for horizontal alignment is more complicated. The basic parameters, including curve radius, deflection angle, and degree of curvature, are parameterized for the curve contained in each segment. The curve direction is also monitored as safety effect may be different between left-side and right-side curves. Other variables speed limit, median width, shoulder width, number of lanes, and truck percentage, are also included as control variable although there are no much variation for these factors at the 20-mile freeway section.

In the study area, a total of 1877 crashes were reported over the study period (2000–2005), 804 and 1057 crashes occurred on the East and West bounds, respectively. Sixteen crashes were not assigned to any of the East or West directions and they were excluded from this study. Four hundred were rear end crashes, 234 turn over crashes and 370 were collision with guard rail or median barrier while the side swipe crashes were 223 on the mainline. Twenty five percent of the crashes occurred on curves with steep grades, about 60% occurred on straight segments with steep grades and the remaining 15% occurred on either curve or straight with flat grades.

Figs. 3 and 4 depict a preliminary crash distribution for east and west bound respectively. In the figures, each of the east and west

bound sections are divided into 3 miles long sub-sections. Each of these sub-sections has different number of homogenous segments according to roadway geometry as explained above (e.g. first section at MM 207 has 13 homogenous segments, starts at MM 206 and ends at MM 208).

As shown in Fig. 3, although the section that starts at MM 215 and ends at MM218 at the east bound has the second least number of 9 segments, it has the highest mean of the crash frequency of 6 and 18 for dry and snowy seasons, respectively. It is worth mentioning that the sub-section at MM 216 on east bound is located after the tunnel with average downgrade of 6.5%.

Generally, west bound has higher crash frequency within the 3 miles sub-sections than the east bound in both seasons. Similarly, the 3 miles section centered at MM 216 has the highest mean of the crash frequency of 5.56 followed by the sub-section at MM 213 having 5.30 in rain season while the sub-section at MM 213 experienced a mean of the crash frequency of 18 in the snow season.

4. Model specification

The factors affecting the occurrence of crashes could be conceptually categorized into two groups, associated with crash exposure and crash risk, respectively.

$$\text{Crash occurrence} \sim \text{Crash exposure} \times \text{Crash risk}$$

While exposure factors account for the amount of opportunities for crashes which traffic systems or drivers experience, the risk factors reflect the conditional probability that a crash occurs given unit crash exposure. Statistically, the stochastic crash occurrence is rationally assumed to be Poisson process, which justifies the popular use of the Poisson distribution to model crash frequencies (Jovanis and Chang, 1986).

$$y_{it} | \lambda_{it} \sim \text{Poisson}(\lambda_{it}) = \text{Poisson}(\mu_{it} e_{it})$$

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

in which, y_{it} is the crash count at segment i ($i = 1, \dots, 168$ (84 segments on each direction)) during season t ($t = 1$ for dry season, 2 for snow season) with the underlying Poisson mean λ_{it} . μ_{it} and e_{it} , contributing to λ_{it} , denote risk factors (covariates \mathbf{X}_{it} and the coefficients $\boldsymbol{\beta}$) and exposure factors, respectively. Based on parameter estimation, the Incidence Rate Ratio (IRR) is generally computed to more conveniently understand the impact of covariates, say k , on the expected crash frequency for one unit change of continuous

Table 1
Summary of variables descriptive statistics.

Variables	Description	Mean	Stdev	Min	Max
Response variable					
Crash frequency	Frequency of all crashes per segment	5.45	7.37	0	55
Exposure variables					
Segment length	Length of the road segment (mile)	0.24	0.16	0.099	0.92
AADT	Average annual daily traffic	27626	1889	25500	29300
Daily.VMT	Daily vehicle mile traveled	6582	4419	2267	23409
Risk factors					
Season	Dry = 0, snowy = 1	0.5	0.5	0	1
Grade	Longitudinal grade, eight categories: Upgrade: 0–2% = 1, 2–4% = 2, 4–6% = 3, 6–8% = 4; Downgrade: 0–(-2)% = 5, (-2)–(-4)% = 6, (-4)–(-6)% = 7, (-6)–(-8)% = 8	4.45	2.40	1	8
Curve radius	Curve radius (ft)	4396	6356	1348	39755
Deflection angle	Deflection angle of curve	21.07	13.43	1.02	48.90
Degree of curvature	Degree of the curve per segment with curves	2.39	1.13	0.14	4.25
Curve length	Length of the curve per segment with curves	0.17	0.09	0.01	0.48
Curve length Ratio	Percentage of curve length to total segment length	0.53	0.46	0	1
No of lanes	Number of lanes: 2 lanes = 0, 3 lanes = 1	0.42	0.49	0	1
Median width	Width of median (ft)	20.67	15.88	2	50
Outside Shoulder	Outside shoulder width (ft)	6.80	3.20	1	20
Inside shoulder	Inside shoulder width (ft)	3.99	1.83	0	12
Speed limit	Posted speed limit	60.95	4.8547	50	65
Truck percentage	Percentage of trucks	10.35	0.39	10	10.8

variables or binary effect for dummy variables (Haque et al., 2010).

$$IRR_k = \frac{E(y_{it} | \mathbf{X}_{it}, x_k + 1)}{E(y_{it} | \mathbf{X}_{it}, x_k)} = \exp(\beta_k)$$

In this current study, daily VMT, the product of AADT and length of road segment, is employed to reflect crash exposure associated with each road segment. Moreover, a time exposure coefficient (1 for dry season, log(5/7) for snow season) is used to offset the unbalanced design of seasons (5 month for dry season and 7 month for snow season). As shown in Table 1, risk factors include road alignment (grade and curve), road design (number of lanes, median width, and shoulders), traffic characteristics (speed limit and truck percentage), and the environmental factor (season).

In regard to model structure, given the “variance = mean” constraint of Poisson model, the Negative Binomial (NB) model has been extensively employed to deal with the over-dispersion problem in crash data (Miaou and Song, 2005; Persaud et al., 1997, 2001; Harwood et al., 2000; Hauer et al., 2002; Hovey and Chowdhury,

2005; Shankar et al., 1995). Nevertheless, as ordinary NB models only provides a blind account for individual heterogeneity, numerous techniques have recently been explored to more specifically accommodate for various crash data features, for example, zero-inflation model for excess zeros (Shankar et al., 1997; Carson and Mannering, 2001; Lee and Mannering, 2002; Lord et al., 2005; Lord et al., 2007), a two-state Markov switching count-data model to overcome the drawbacks of the traditional zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) (Malyskhina et al., 2009), spatial and time series model for spatiotemporal data (Aguero-Valverde and Jovanis, 2006; Quddus, 2008a,b; Huang et al., 2010), hierarchical model for multilevel data structure (Huang and Abdel-Aty, 2010). Furthermore, the use of variable dispersion parameters in negative binomial models has been reported useful to improve the model-fitting (Heydecker and Wu, 2001; Miaou and Lord, 2003; Miranda-Moreno et al., 2005; El-Basyouny and Sayed, 2006; Mitra and Washington, 2007; Lord and Park, 2008). Multivariate count models have also been applied to jointly model crash frequency at different levels of injury severity (Tunaru, 2002; Park

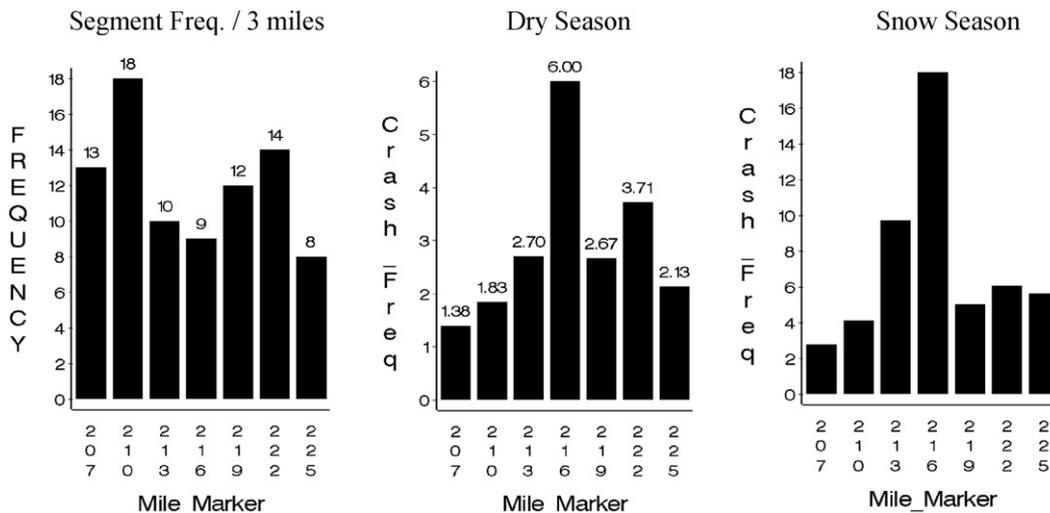


Fig. 3. East bound crash frequencies in dry and snowy seasons.

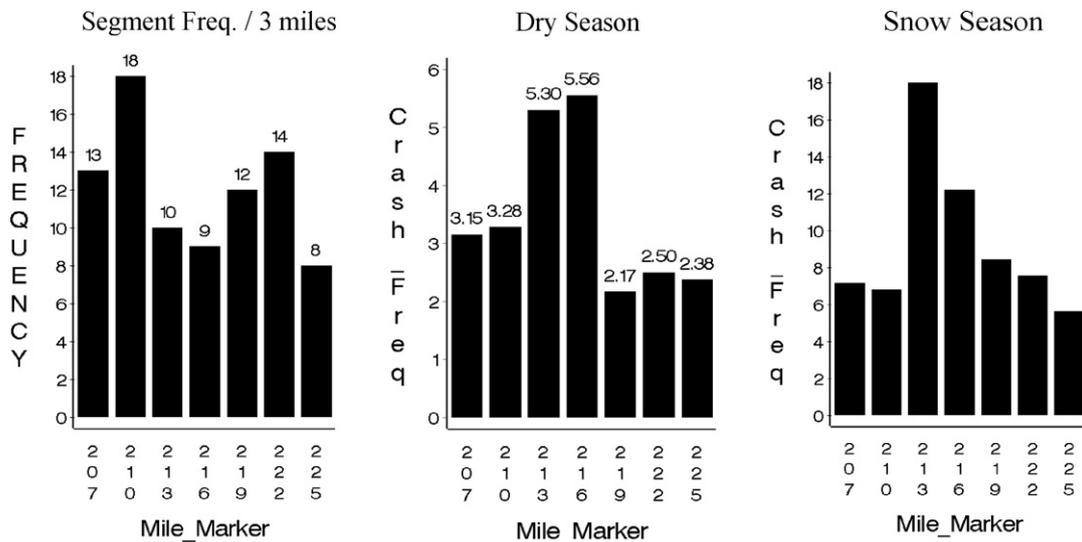


Fig. 4. West bound crash frequencies in dry and snowy seasons.

and Lord, 2007; Ma et al., 2008; Ye et al., 2009; Agüero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a). More recently, a more flexible random parameter modeling approach, including random intercept and/or random slope, is emerging in the literature, in which model parameters are allowed to vary from site to site (Li et al., 2008; Anastasopoulos and Mannering, 2009; Huang et al., 2008, 2009; El-Basyouny and Sayed, 2009b; Huang and Chin, 2010). Lord and Mannering (2010) provided a detailed review of the key issues associated with crash-frequency data as well as an assessment of the strengths and weaknesses of the various methodological approaches that have been used to address these problems.

Despite the availability of various statistical model selection measures, selection of appropriate crash prediction models should be dependent on the characteristics of the specific crash data. Specifically, we have three basic observations for the current crash data: (a) Over-dispersion: the data may be highly over dispersed as the overall mean and variance equal to 5.45 and 54.32, respectively, as shown in Table 1; (b) Site-specific structure: each segment has two observations; crash count during each of the dry and the snow seasons. Hence, random effects may be appropriate to account for the global site-specific effects; (c) Spatial distribution: as road segments are mutually connected, spatial heterogeneities, resulting from spatial confounding factors, may exist for adjacent segments.

Based on these observations, two alternative models are suggested, i.e. random effect model (also called hierarchical Poisson model) and spatial model, both of which are modified from the basic Poisson model.

$$\begin{aligned} \text{Random effect model: } \log \lambda_{it} &= \log e_{it} + \mathbf{X}'_{it} \boldsymbol{\beta} + \theta_i \\ \exp(\theta_i) &\sim \text{gamma}(a, a) \\ \text{overdispersion parameter: } k &= \frac{1}{a} \end{aligned}$$

$$\begin{aligned} \text{Spatial model: } \log \lambda_{it} &= \log e_{it} + \mathbf{X}'_{it} \boldsymbol{\beta} + \theta_i + \phi_i \\ \theta_i &\sim \text{normal} \left(0, \frac{1}{\tau_i} \right) \\ \phi_i &\sim \text{normal} \left(\bar{\phi}_i, \frac{1}{\tau_i} \right) \text{ with} \\ \bar{\phi}_i &= \frac{\sum_{i \neq j} \phi_j \omega_{ij}}{\sum_{i \neq j} \omega_{ij}} \text{ and } \tau_i = \frac{\tau_c}{\sum_{i \neq j} \omega_{ij}} \\ \alpha &= \frac{\text{sd}(\phi)}{\text{sd}(\theta) + \text{sd}(\phi)} \end{aligned}$$

Clearly, the random effect model is actually a slight modification of the ordinary NB model, in which the two observations associated with one same segment share an equal extra error component. In the spatial model, the extra variance component consists of two parts, θ_i for site-specific random effects, denoting the global extra-Poisson variability, and ϕ_i for spatial correlation with the Gaussian Conditionally Autoregressive prior (CAR model, Besag, 1974). It is noted that θ_i is assumed to be Normal distribution rather than the Gamma distribution in the random effects model. This is because the multivariate normal distribution is more convenient computationally while combining with the Gaussian spatial component (ϕ_i) than the multivariate version of Gamma distribution (Huang et al., 2010). This also is suggested by the literature that Poisson Lognormal PLN was found to provide the best statistical fit for the spatial model (Milton et al., 2008; Anastasopoulos and Mannering, 2009; Li et al., 2008; El-Basyouny and Sayed, 2009a). Regarding ω , the proximity matrix, a 0–1 adjacency weight is employed. In other words, each segment is specified an equal weight to its adjacent segment(s). With the model specification, α denotes the proportion of variability in the random effects that is due to spatial heterogeneity, in which, sd is the empirical marginal standard deviation function.

Although the most common CAR model is employed in this study to model spatial effects, there are other techniques available in the literature such as Simultaneous Autoregressive (SAR), Moving Average (MA) (Congdon, 2007), and Multiple Membership (MM) (Goldstein, 1995; Goldstein et al., 1998; Langford et al., 1999). El-Basyouny and Sayed (2009c) compared CAR, MM and Extended Multiple Membership (EMM) to the traditional PLN model, they concluded that EMM provided the best fit with a little better performance than CAR and both EMM and CAR outperformed the MM and PLN.

The candidate models could be estimated conveniently by Bayesian inference using the freeware WinBUGS package (Lunn et al., 2000). The CAR model is embedded in the function “car.normal” in GeoBUGS, an add-on to WinBUGS that fits spatial models. The DIC, a Bayesian generalization of AIC, is used to measure the model complexity and fit (Spiegelhalter et al., 2003). In addition, a R^2 -type Bayesian measure is developed to evaluate the model fitting,

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

Table 2
Parameters estimates.

Model	Poisson			Random effect			Spatial		
	Credible interval			Credible interval			Credible interval		
	Mean	2.5%	97.5%	Mean	2.5%	97.5%	Mean	2.5%	97.5%
Season [snow]	0.600	0.501	0.698	0.600	0.499	0.702	0.600	0.498	0.710
Season [dry] (reference)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Grade[1]	-1.302	-1.538	-1.072	-1.287	-1.797	-0.778	-1.041	-1.950	-0.097
Grade[2]	-0.855	-1.026	-0.685	-0.870	-1.322	-0.422	-0.458	-1.400	0.534
Grade[3]	-0.786	-0.949	-0.617	-0.907	-1.285	-0.516	-0.316	-1.251	0.679
Grade[4]	-0.530	-0.735	-0.328	-0.297	-0.845	0.277	0.237	-0.745	1.286
Grade[5]	-1.193	-1.421	-0.981	-1.167	-1.674	-0.657	-0.663	-1.374	0.047
Grade[6]	-0.888	-1.084	-0.704	-0.857	-1.322	-0.386	-0.434	-1.095	0.244
Grade[7]	-0.698	-0.884	-0.515	-0.672	-1.175	-0.185	-0.281	-0.886	0.342
Grade[8] (reference)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Degree of curvature	-0.032	-0.066	0.003	-0.048	-0.131	0.035	-0.050	-0.132	0.029
Three road lanes	-0.484	-0.620	-0.346	-0.509	-0.846	-0.157	-0.435	-1.119	0.321
Median width	-0.007	-0.010	-0.003	-0.006	-0.015	0.003	-0.012	-0.027	0.002
k (dispersion parameter)	-	-	-	0.418	0.305	0.561	-	-	-
sd(Φ_i): Spatial correlation	-	-	-	-	-	-	0.469	0.297	0.710
sd(θ_i): site-specific random effect	-	-	-	-	-	-	0.584	0.481	0.686
α	-	-	-	-	-	-	0.441	0.330	0.560
pD: no of effective variables	11.9	-	-	117.3	-	-	122.3	-	-
DIC	1903	-	-	1456	-	-	1468	-	-
R ² (with error terms)	0.61	0.59	0.62	0.88	0.86	0.90	0.88	0.86	0.90
R ² (without error terms)	-	-	-	0.52	0.32	0.60	0.39	0.02	0.56

which estimates the proportion of explained sum of squares to total sum of squares. It could be regarded as a global model-fitting measurement.

5. Results and discussion

5.1. Model estimation and diagnostics

In model estimation, with no prior knowledge of the likely range of values of the parameters for mountainous freeway section, non-informative priors were specified for parameters. For each model, three chains of 20,000 iterations were set up in WinBUGS based on the convergence speed and the magnitude of the dataset. All the models were converged reasonably through visual inspection on the history plots and confirmed by the Brooks, Gelman and Rubin convergence diagnostics (Brooks and Gelman, 1998). After ensuring the convergence, first 10,000 samples were discarded as adaptation and burn-in. To reduce autocorrelation, only every tenth samples of the rest were retained for parameter estimation, calculation of DIC and Bayesian R², as well as site rankings.

Exploratory modeling indicated that the crash frequencies are not significantly associated with *Speed Limit*, *Truck Percentage*, *Percentage of Curve Length* in all the three models. This was expected since there is a little variation in those variables between segments; the speed limit and the truck percentage are almost identical along the considered section and hence they were excluded from the final models. Results of model estimation with the remaining factors are summarized in Table 2.

Comparisons among the three candidate models imply very interesting findings. On one hand, the over-dispersion observed in crash data is confirmed by the extra variance components of the random effect model and the spatial model. Specifically, significant dispersion parameter is identified in the random effect model ($k = 0.418$, 95%CI(0.305, 0.561)). In the spatial model, variance components from spatial correlation and site-specific random effects are 0.469 (95%CI(0.297, 0.710)) and 0.584 (95%CI(0.481, 0.686)), respectively, which apparently indicate the proportion of the over-dispersion accounted by the spatial clustering is 44.1% ($\alpha = 0.441$, 95%CI(0.330, 0.560)). Moreover, model diagnostic measures confirmed that the random effect and spatial models outperform the

Poisson model by accounting for over-dispersion. Specifically, DIC is substantially reduced from 1903 in Poisson to 1456 in the random effect model and 1468 in the spatial model. The Bayesian R² is increased from 0.61 to 0.88.

On the other hand, however, while all the parameters are significant in the Poisson model except of *Degree of curvature*, some of them come out to be insignificant in the random effect model (*Grade(4)*, and *Median Width*). This phenomenon becomes more remarkable especially in the spatial model where almost all the variables turn out to be insignificant despite having the same sign as in the basic Poisson model. Another interesting observation from the parameter coefficients is that the safety effects of most of the geometry-dependant factors fade away gradually from Poisson through the other two, e.g. *Grade*, *Degree of curvature*, and *Percentage of Curve Length* etc. But the non-geometry-dependant factor (*Season*) remains constant (0.600 in Poisson, random effect model and spatial model).

Furthermore, based on estimation of pD (the number of effective variables in Bayesian model) and R², we found that, compared to the random effect model, the spatial model has equal R² (0.88) and has only an increase of 5 effective variables (pD from 117.3

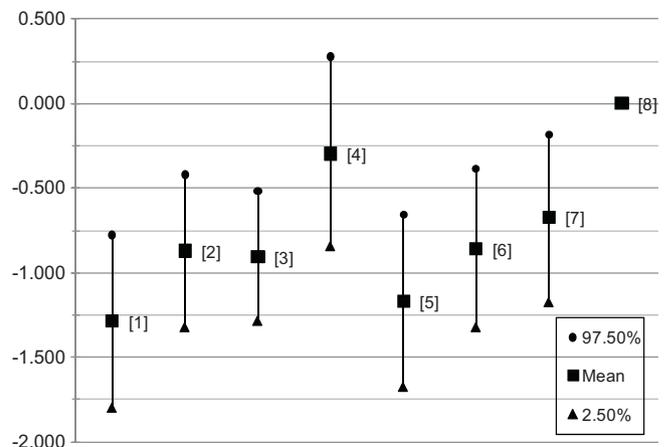


Fig. 5. Grade coefficients.

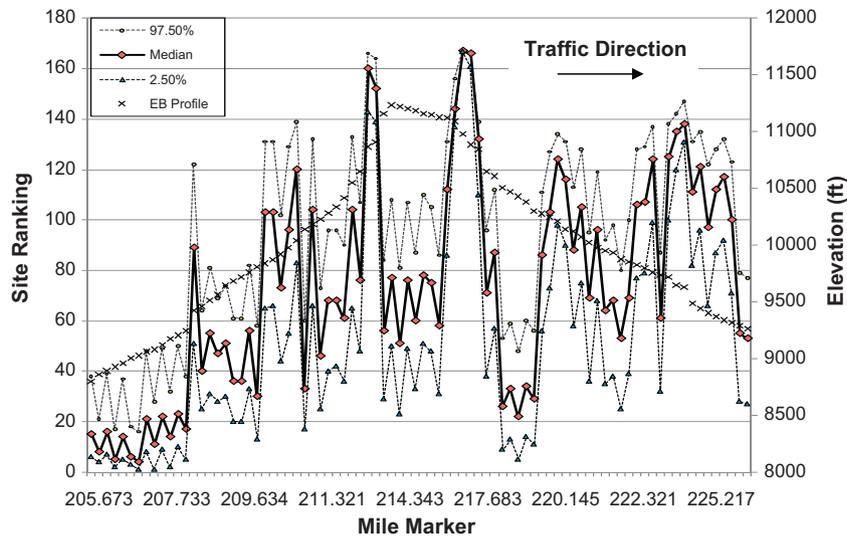


Fig. 6. East-bound segment ranking.

to 122.3). With all these observations, we argue that the spatial model does not actually outperform the random effect model. This may be reasoned that the spatial heterogeneity mostly depends on road geometries among adjacent segments, which have been accommodated for by the well-defined geometry-dependent factors in the models. In other words, with explicit consideration for various road geometric factors in the model, the specification for spatial effect becomes redundant and hence, may reduce the significance of the geometric factors instead. We further confirmed this argument by calculating an R^2 which does not include residual terms for crash expectations (i.e. λ_{it}), as shown by R^2 (without error terms) in Table 2. Clearly, results indicate that the inclusion of error terms reduced the model-fitting proportion explained by the risk factors, especially in the spatial model.

In summary, the over-dispersion problem in Poisson model is effectively addressed by the random effect and spatial models, but the spatial model may have the problem of redundantly accounting for geometry-dependant effect. Therefore, the random effect model, which has the least DIC, is selected for further model inference and site ranking. The adequacy of the random effects assumption may be assessed with lack-of-fit statistics, although

these statistics test the fit of the model as a whole rather than the specific random effects assumption. This random effects assumption may be made less restrictive if θ is allowed to vary with specific site effects.

5.2. Interpretation of risk factors

Season was found to significantly affect crash occurrence ($\beta=0.600$, 95%CI (0.499, 0.702)), the Incident Rate Ratios are obtained by exponentiation of the regression coefficients $\exp[\beta]$. IRR value shows that the risk of crashes during snow season was approximately 82% higher than the crash risk in dry season, given all other variables constant. The increased crash risk within the snow season may be explained by the confounding effect of the snowy, icy, or slushy pavement conditions during the snow season, and exacerbated by the steep slopes. This finding is important for officials to pay more attention and devote more resources during snow season than in dry season for traffic management.

Road alignment factors, i.e. slope and curve, are the other key variables of interest. Preliminary analysis on the data indicates that more than 85% of the total crashes occurred on steep grades (Grade

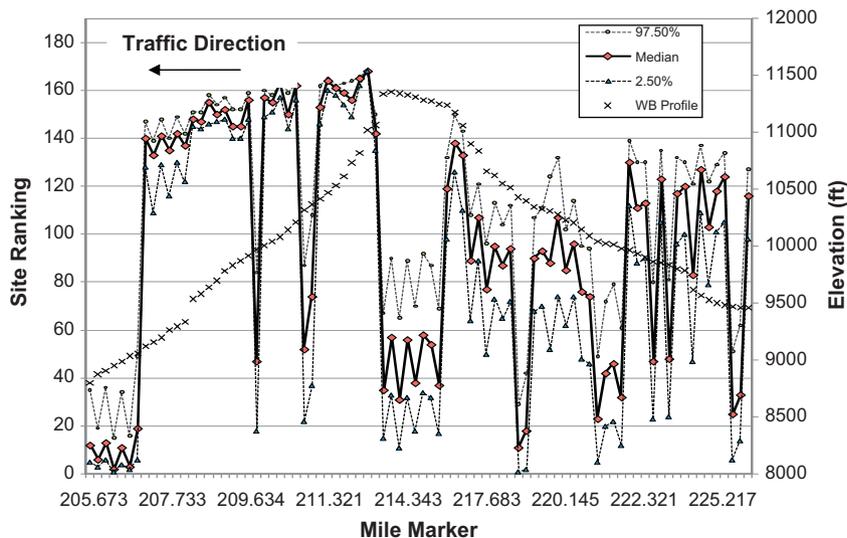


Fig. 7. West-bound segment ranking.

<−2% or >2%). Steep grades are often considered implausible in design, and all design manuals recommend avoiding or keeping minimal the use of steep slopes. Nevertheless, this is not the case with mountainous terrain highways since the steep grades cannot be easily avoided. Longitudinal slope comes out to be significant as indicated in Table 2. The effects of various slopes are compared to *Grade*[8] (reference condition, steep slope ranges from −6% to −8%). Fig. 5 shows the slope coefficients and their 95% credible intervals, it can be noted that in order, *Grade*[8] is the most hazardous slope followed by *Grade*[4], *Grade*[7], *Grade*[2], *Grade*[6], *Grade*[3], *Grade*[5] then *Grade*[1]. Generally, trends in the results indicate that the steeper the slope, the higher the crash risk; and segments with upgrade slope are safer than corresponding downgrades in the same slope range. These results are consistent with the preliminary analysis and complementary to existing findings that the steep grades may increase the likelihood of crash occurrence (Shankar et al., 1995; Chang and Chen, 2005).

In regard to the curve effect, although not statistically significant, the result implies that a unit increase in *Degree of curvature* ($\beta = -0.048$, 95%CI(−0.131,0.035), IRR=0.95) is associated with a 5% decrease in the crash risk, with all other factors equal. Actually, it is not uncommon that high degree of curvature was found to be associated with decrease in crash likelihood (Shankar et al., 1995; Anastasopoulos et al., 2008; Chang and Chen, 2005). Previous studies argued that the feeling of danger along sharp curves might make the drivers compensate by driving more cautiously, leading to lower crash rate instead.

Other variables included in the models are *Number of Lanes* and *Median Width*. Results revealed that segments with three lanes ($\beta = -0.509$, 95%CI(−0.846, −0.157), IRR=0.6) are 40% less in crash risk than two-lane segments, with all other factor being equal. This finding conforms to the study by Park et al. (2010). The increase of safety due to the increase in number of lanes is plausible since this freeway has a high percentage of trucks which could be confined to the 2 right lanes providing more space for other vehicles, contributing to easier maneuvers and less speed variance. Median width is associated with a tiny positive effect ($\beta = -0.006$, 95% CI (−0.015, 0.003), IRR=0.99), which is only significant in the Poisson model. The increasing safety associated with wide median is well known as median works as division for traffic in opposite directions and a recovery area for out-of-control vehicles (Anastasopoulos et al., 2008; Shankar et al., 1998).

5.3. Ranking of sites

The ranking of sites is important to enable officials to pay more attention to those sites with high crash risk. Sites can be ranked by the probability that a site is the worst or by posterior distribution of ranks (Tanaru, 2002). The separate rankings for dry and snow seasons were produced based on the estimation on λ_{it} , the estimated rankings tables are not presented here for brevity. The results confirmed that sites with steep grades are drastically affected during snow season and those segments received significantly higher risk ranks than in the dry season. Moreover, an overall site ranking is developed by rating the weighted average of crash expectations in the two seasons (λ_{i1} for dry season and λ_{i2} for snow season), i.e., $\text{Safety_Site}_i = 0.42 \times \lambda_{i1} + 0.58 \times \lambda_{i2}$ to offset the unbalanced design of seasons (5 month for dry season and 7 month for snow season) as explained in the model specification section.

For illustration, the overall site rankings for the 84 segments are plotted on the longitudinal profile for eastbound and westbound, as shown in Figs. 6 and 7, respectively. Sites with high rank values are more dangerous while sites with low rank values are safer. The results appear to be in good agreement with results from the preliminary analysis that the steep downgrade sections received the high risk ranks in general. The segments at Eisenhower tunnel seem

to be safer in both east and west bounds. However, the segments just before and after the tunnel received relatively high rank on the eastbound. On the westbound, the downgrade segments received most of the high ranks.

6. Conclusion

This paper presents an exploratory investigation of the safety problems of a mountainous freeway section of unique weather condition. Hierarchical Full Bayesian models were developed to relate crash frequencies with various risk factors associated with adverse weather, road alignments and traffic characteristics. Using the calibrated model, the sites were ranked in term of crash risk for further safety diagnostics and mitigation.

In modeling, it was found that while the random effect and spatial models outperform the Poisson model, the spatial model may have the problem of redundantly accounting for the geometry-dependant effect. Therefore the random effect model is selected for model inference.

Crash risk during snow season was estimated to be approximately 82% higher than the crash risk in dry seasons. Results also identified clear trends associated with the effect of slopes, i.e. the steeper the slope, the higher the crash risk; and segments with upgrade slope are safer than downgrades in the same slope range. The degree of curvature is negatively correlated with crash risk, which is consistent with previous studies that some visual variation of the road alignment may help with drivers' alertness increase and hence decrease crash risk. Median width and number of lanes also showed to be effective in affecting crash risk. Segments with three lanes are 40% less in crash risk than two-lane roads. Based on site ranking, segments succeeding the tunnel in both east and west bounds received the highest rank of hazardous sites. These segments feature steep slopes and reduction in number of lanes for the east bound. In particular sites with steep slopes should receive more attention from officials and decision makers during snow season to control the excess of crash rate during this season. Also, the identified sites could be included in the strategy for choosing the location of future Variable Speed Limits.

While this study is exploratory in nature, it provides good overall understanding of the effects of roadway geometrics and weather on crash frequencies of mountainous freeways. This study represents a step toward future research incorporating real-time weather and traffic data on the individual crash level.

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References

- Aguero-Valverde, J., Jovanis, P.P., 2006. Spatial analysis of fatal and injury crashes in Pennsylvania. *Accident Analysis and Prevention* 38, 618–625.
- Aguero-Valverde, J., Jovanis, P.P., 2007. Identifying road segments with high risk of weather-related crashes using full bayesian hierarchical models. *Compendium of papers CD-ROM, Transportation Research Board 86th Annual Meeting, Washington, D.C.*
- Aguero-Valverde, J., Jovanis, P.P., 2009. Bayesian multivariate Poisson log-normal models for crash severity modeling and site ranking. In: Presented at the 88th Annual Meeting of the Transportation Research Board.
- American Association of State Highway and Transportation Officials (AASHTO), 2004. *A Policy on Geometric Design of Highways and Streets*, fifth ed. Washington, DC, ISBN: 1-56051-263-6.
- Anastasopoulos, P.C., Mannering, F., 2009. A note on modeling vehicle accident frequencies with random-parameters count models. *Accident Analysis and Prevention* 41, 153–159.

- Anastasopoulos, P.C., Tarko, A.P., Mannering, F., 2008. Tobit analysis of vehicle accident rates on interstate highways. *Accident Analysis and Prevention* 40, 768–775.
- Basag, J., 1974. Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society B* 36 (2), 192–236.
- Brooks, S.P., Gelman, A., 1998. Alternative methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics* 7, 434–455.
- Carson, J., Mannering, F.L., 2001. The effect of ice warning signs on ice-accident frequencies and severities. *Accident Analysis and Prevention* 33 (1), 99–109.
- Chang, L.Y., Chen, W.C., 2005. Data mining of tree-based models to analyze freeway accident frequency. *Journal of Safety Research* 36, 365–375.
- Congdon, P., 2007. *Bayesian Statistical Modelling*. John Wiley & Sons, Inc.
- El-Basyouny, K., Sayed, T., 2006. Comparison of two negative binomial regression techniques in developing accident prediction models. *Transportation Research Record* 1950, 9–16.
- El-Basyouny, K., Sayed, T., 2009a. Urban arterial accident prediction models with spatial effects. *Transportation Research Record* 2385, 27–33.
- El-Basyouny, K., Sayed, T., 2009b. Accident prediction models with random corridor parameters. *Accident Analysis and Prevention* 41 (4), 1118–1123.
- El-Basyouny, K., Sayed, T., 2009c. Collision prediction models using multivariate Poisson-lognormal regression. *Accident Analysis and Prevention* 41 (4), 820–828.
- Goldstein, H., 1995. *Multilevel Statistical Models*. Arnold, London.
- Goldstein, H., 2003. *Multilevel Statistical Models*, third ed. Hodder Arnold, London.
- Goldstein, H., Rasbash, J., Plewis, I., Draper, D., Browne, W., Yang, M., Woodhouse, G., Healy, H., 1998. *A User's Guide to MLwiN*. Institute of Education, London.
- Haque, M.M., Chin, H.C., Huang, H., 2010. Applying Bayesian hierarchical models to examine motorcycle crashes at signalized intersections. *Accident Analysis and Prevention* 42 (1), 203–212.
- Harwood D., Council F., Hauer, E., Hughes, W., Vogt, A., 2000. Prediction of the expected safety performance of rural two-lane highways. Report No. FHWARD-99-207.
- Hauer, E., Harwood, D.W., Council, F.M., Griffith, M.S., 2002. The empirical Bayes method for estimating safety: a tutorial. *Transportation Research Record* 1784, 126–131.
- Heydecker, B.G., Wu, J., 2001. Identification of sites for accident remedial work by Bayesian statistical methods: an example of uncertain inference. *Advances in Engineering Software* 32, 859–869.
- Highway Capacity Manual, 2000. Transportation Research Board, Washington, D.C. (Chapter 23, Appendix A).
- Hovey P.W., Chowdhury, M., 2005. Development of crash reduction factors. Technical Report. Prepared for the Ohio Department of Transportation, 14801.
- Huang, H., Abdel-Aty, M., 2010. Multilevel data and Bayesian analysis in traffic safety. *Accident Analysis and Prevention* 42 (6), 1556–1565.
- Huang, H., Abdel-Aty, M., Darwiche, A.L., 2010. County-level crash risk analysis in Florida: Bayesian spatial modeling. *Transportation Research Record* 2148, 27–37.
- Huang, H., Chin, H.C., 2010. Modeling road traffic crashes with zero-inflation and site-specific random effects. *Statistical Methods & Applications* 19 (3), 445–462.
- 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. *Accident Analysis and Prevention* 40, 45–54.
- Huang, H., Chin, H.C., Haque, M.M., 2009. Empirical evaluation of alternative approaches in identifying crash hotspots: naive ranking, empirical Bayes and full Bayes. *Transportation Research Record* 2103, 32–41.
- Jovanis, P., Chang, H., 1986. Modeling the relationship of accident to mile traveled. *Transportation Research Record* 1068, 42–51.
- Langford, I.H., Leyland, A.H., Rasbash, J., Goldstein, H., 1999. Multilevel modelling of the geographical distributions of diseases. *Applied Statistics* 48 (2), 253–268.
- Lee, J., Mannering, F.L., 2002. Impact of roadside features on the frequency and severity of run-off-roadway accidents: an empirical analysis. *Accident Analysis and Prevention* 34 (2), 149–161.
- Li, W., Carriquiry, A., Pawlovich, M., Welch, T., 2008. The choice of statistical models in road safety countermeasures effectiveness studies in Iowa. *Accident Analysis and Prevention* 40 (4), 1531–1542.
- Lord, D., Mannering, F., 2010. The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives. *Transportation Research Part A* 44, 291–305.
- Lord, D., Park, Y.J., 2008. Investigating the effects of the fixed and varying dispersion parameters of Poisson-gamma models on empirical Bayes estimates. *Accident Analysis and Prevention* 40, 1441–1457.
- Lord, D., Washington, S., Ivan, J.N., 2007. Further notes on the application of zero-inflated models in highway safety. *Accident Analysis and Prevention* 39 (1), 53–55.
- Lord, D., Washington, S., Ivan, J.N., 2005. Poisson, Poisson-gamma and zero-inflated regression models of motor vehicle crashes: balancing statistical fit and theory. *Accident Analysis and Prevention* 37 (1), 35–46.
- Lunn, D.J., Thomas, A., Best, N., Spiegelhalter, D., 2000. WinBUGS—a Bayesian modelling framework: concepts, structure, and extensibility. *Statistics and Computing* 10, 325–337.
- Ma, J., Kockelman, K.M., Damien, P., 2008. A multivariate Poisson-lognormal regression model for prediction of crash counts by severity, using Bayesian methods. *Accident Analysis and Prevention* 40, 964–975.
- Malyshkina, N.V., Mannering, F.L., Tarko, A.P., 2009. Markov switching negative binomial models: an application to vehicle accident frequencies. *Accident Analysis and Prevention* 41 (2), 217–226.
- Miaou, S.P., 1994. The relationship between truck accidents and geometric design of road section: Poisson versus negative binomial regression. *Accident Analysis and Prevention* 26, 471–482.
- Miaou, S.P., Song, J.J., 2005. Bayesian ranking of sites for engineering safety improvement: decision parameter, treatability concept, statistical criterion and spatial dependence. *Accident Analysis and Prevention* 37, 699–720.
- Miaou, S.P., Lord, D., 2003. Modeling traffic crash-flow relationships for intersections: dispersion parameter, functional form, and Bayes versus empirical Bayes. *Transportation Research Record* 1840, 31–40.
- Milton, J., Shankar, V., Mannering, F., 2008. Highway accident severities and the mixed logit model: an exploratory empirical analysis. *Accident Analysis and Prevention* 40 (1), 260–266.
- Miranda-Moreno, L.F., Fu, L., Saccomanno, F.F., Labbe, A., 2005. Alternative risk models for ranking locations for safety improvement. *Transportation Research Record* 1908, 1–8.
- Mitra, S., Washington, S., 2007. On the nature of over-dispersion in motor vehicle crash prediction models. *Accident Analysis and Prevention* 39, 459–468.
- Park, B.-J., Fitzpatrick, K., Lord, D., 2010. Evaluating the effects of freeway design elements. Compendium of papers CD-ROM, Transportation Research Board 89th Annual Meeting, Washington, D.C.
- Park, E.S., Lord, D., 2007. Multivariate Poisson-lognormal models for jointly modeling crash frequency by severity. *Transportation Research Record* 2019, 1–6.
- Persaud, B.N., Hauer, E., Retting, R., Vallurapalli, R., Mucsi, K., 1997. Crash reductions following traffic signal removal in Philadelphia. *Accident Analysis and Prevention* 29, 803–810.
- Persaud, B.N., Retting, R.A., Garder, P.A., Lord, D., 2001. Safety effect of roundabout conversions in the United States: empirical Bayes observational before–after study. *Transportation Research Record* 1751, 1–8.
- Quddus, M.A., 2008a. Modeling area-wide count outcomes with spatial correlation and heterogeneity: an analysis of London crash data. *Accident Analysis and Prevention* 40, 1486–1497.
- Quddus, M.A., 2008b. Time series count data models: an empirical application to traffic accidents. *Accident Analysis and Prevention* 40 (5), 1732–1741.
- Rao, J.N.K., 2003. *Small Area Estimation*. Wiley, New York.
- Shankar, V., Albin, R., Milton, J., Mannering, F., 1998. Evaluating median crossover likelihoods with clustered accident counts: an empirical inquiry using the random effects negative binomial model. *Transport Research Record* 1635, 44–48.
- Shankar, V., Mannering, F., Barfield, W., 1995. Effect of roadway geometrics and environmental factors on rural accident frequencies. *Accident Analysis and Prevention* 27 (3), 371–389.
- Shankar, V.N., Milton, J.C., Mannering, F.L., 1997. Modeling accident frequencies as zero-altered probability process: an empirical enquiry. *Accident Analysis and Prevention* 29 (6), 829–837.
- Spiegelhalter, D.J., Best, N.G., Carlin, B.P., Linde, V.D., 2003. Bayesian measures of model complexity and fit (with discussion). *Journal of the Royal Statistical Society B* 64 (4), 583–616.
- Tanaru, R., 2002. Hierarchical Bayesian models for multiple count data. *Austrian Journal of Statistics* 31, 221–229.
- Tunaru, R., 2002. Hierarchical Bayesian models for multiple count data. *Austrian Journal of Statistics* 31 (3), 221–229.
- Ye, X., Pendyala, R.M., Washington, S.P., Konduri, K., Oh, J., 2009. A simultaneous equations model of crash frequency by collision type for rural intersections. *Safety Science* 47 (3), 443–452.

Further reading (Web references)

- <http://www.fhwa.dot.gov/interstate/faq.htm> (accessed in June 25, 2010).
- <http://www.coloradodot.info/travel/eisenhower-tunnel/description.html> (accessed in June 28, 2010).
- <http://climate.colostate.edu/climateofcolorado.php> (accessed in June 29, 2010).