A full Bayes approach for traffic conflict-based before–after safety evaluation using extreme value theory

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ABSTRACT

A full Bayes approach is proposed for traffic conflict-based before-after safety evaluations using extreme value theory. The approach combines traffic conflicts of different sites and periods and develops a uniform generalized extreme value (GEV) model for the treatment effect estimation. Moreover, a hierarchical Bayesian structure is used to link possible covariates to GEV parameters and to account for unobserved heterogeneity among different sites. The proposed approach was applied to evaluate the safety benefits of a left-turn bay extension project in the City of Surrey, Canada, in which traffic conflicts were collected from 3 treatment sites and 3 matched control sites before and after the treatment. A series of models were developed considering different combinations of covariates and their link to different GEV model parameters. Based on the best fitted model, the treatment effects were analyzed quantitatively using the odds ratio (OR) method as well as qualitatively by comparing the shapes of GEV distributions. The results show that there are significant reduction in the expected number of crashes (i.e., $OR = 0.409$). In addition, there are apparent changes in the shape of GEV distributions for the treatment sites, where GEV distributions shift further away from the risk of crash area after the treatment. Both of these results indicate significant safety improvements after the left-turn bay extension.

1. Introduction

Conducting before-after safety evaluations is a key component of road safety programs that aim at identifying locations with safety problems and to remedy these problems through the application of effective countermeasures. The evaluation can determine the safety benefits (or absence thereof) derived from countermeasures and thus ensures that the limited funding available for road safety improvement is efficiently utilized.

Traditionally, before-after safety evaluation is conducted based on historical crash data, and the safety benefit is estimated from the reduction in the frequency and/or severity of crashes that can be attributed to treatments (Hauer, 1997; El-Basyouny and Sayed, 2010). A variety of methods have been proposed for the crash-based before-after safety evaluation, such as the state-of-the-practice empirical Bayes methods (Hauer, 1997; Persaud et al., 2001; Persaud and Lyon, 2007) and the state-of-the-art full Bayes methods (Yanmaz-Tuzel and Ozbay, 2010; El-Basyouny and Sayed, 2011; Sacchi et al., 2016). However, there are well-recognized quality and quantity issues associated with crash data. In addition, to draw statistically stable conclusions relatively, long periods (1–3 years) of crash data before and after the

treatment are required, which significantly influence the timeliness of the evaluation.

To avoid the limitations associated with crash data, the traffic conflict technique has been increasingly used in before-after safety evaluation studies. Compared to crashes, traffic conflicts occur more frequently, can be clearly observed, and can provide insights into the failure mechanism that leads to crashes (Zheng et al., 2014a; Sayed and Zein, 1999; Guo et al., 2019). Brown (1994) evaluated the treatment effects of signal installations using traffic conflicts defined by time-to-collision (TTC) less than 1.5 s. Tarrall and Dixon (1998) conducted a before-after analysis to evaluate the treatment effects of changes in left-turn signal phasing using field observed traffic conflicts. Ismail et al. (2010) analyzed the safety benefits of a scramble phase treatment based on traffic conflicts measured by different indicators which were automatically extracted form video using computer vision techniques. The same technique was also used in conflict-based before-after studies in Autey et al. (2012), Reyad et al. (2017), and Tageldin et al. (2018) for evaluating the safety effectiveness of right-turn smart channels, improved traffic signal visibility, and left-turn bay extension, respectively. All of the three studies used TTC as a conflict indicator and 3 s or 4 s thresholds to define traffic conflicts.

In order to estimate the treatment effects based on conflict frequencies, a specific threshold for the conflict indicator needs to be selected. The selection is somewhat arbitrary and the results of the evaluation may vary significantly depending on the selected threshold. As well, the conflict severity cannot be accounted for in the evaluation if only one threshold is used. To overcome these issues, a new framework of using extreme value theory (EVT) for conflict-based before-after safety evaluation was proposed in Zheng et al. (2018a) and Zheng and Sayed (2019b). Zheng et al. (2018a) evaluated the safety benefits of left-turn bay extension based on traffic conflicts collected from 3 treatment sites and 3 control sites using the EVT approach. They divided the conflict data into fixed-interval blocks and developed 12 (3 treatment sites times 2 periods plus 3 control sites times 2 periods) generalized extreme value (GEV) models for the block maxima extremes. The treatment effects were then evaluated quantitatively by the odds ratio values as well as visually by the changes in shapes of GEV distributions. Zheng and Sayed (2019b) evaluated the treatment effects of converting channelized right-turn lanes to smart channels based on traffic conflicts collected from three treatment intersections and one control intersection. The conflict extremes were determined by the peak over threshold approach and the corresponding generalized Pareto distribution (GPD) models were developed individually for each site & time period. A total of 16 GPD models were developed, 8 models for merging conflicts and 8 models for rear-end conflicts. They found a significant safety improvement following the smart channel treatment and showed that the findings were generally consistent with the crash-based before-after evaluation results (Sacchi et al., 2013).

Using EVT approaches for traffic conflict-based before-after safety evaluation can incorporate conflicts of different severity levels into the analysis and increase the prospects of making more comprehensive analysis of the treatment effects (Zheng et al., 2018a). Moreover, the treatment effects can be quantitatively determined based on expected crash frequencies or expected frequencies of most severe conflicts that are logically closest to crashes. Despite these advantages, the application of EVT suffers from limitations related to the scarcity nature of extremes. Although traffic conflicts are generally more observable than crashes, traffic conflict extremes (e.g., conflicts with very small TTC values) are relatively rare. More specifically, there would be only a small extreme samples for each site, and thus the estimation from the model individually developed for each site is usually subject to limited accuracy and large uncertainty. In view of this, this study proposes a full Bayes approach to combine conflict extremes of different sites as well as different periods for before-after safety evaluations. This allows overcoming the problem by using more data and sharing information from different sites and periods. Moreover, as stated in many crash-based before-after safety evaluation studies, the full Bayes method itself is capable of dealing with small sample issues, accounting for most uncertainty in the data, and accommodating complex model structures (Lan et al., 2009; El-Basyouny and Sayed, 2010; El-Basyouny and Sayed, 2011; Xie et al., 2019). The proposed approach for traffic conflict-based before-after safety evaluation in this study shares these advantages of the full Bayes method.

2. Data description

The data from a safety project of extending the length of left-turn bays in the City of Surrey, British Columbia, Canada is used. In the project, an approach of an intersection had the length of left-turn bay extended to accommodate more left-turn vehicles, reduce conflicts at the end of the intersection queue and reduce potential aggressive behavior of left-turn vehicles. The three intersections used in the study are the intersections of 64 Ave & King George Blvd, 72 Ave & King George Blvd, and Fraser Hwy & 168 St, as shown in Fig. 1. For each intersection, the treated approach (left-turn bay extended) was paired to a matching untreated approach (control site, left-turn bay unchanged) to mitigate the effect of confounding factors. The left-turn bay lengths of

control sites are approximately 85 m, 130 m and 85 m for intersections of 64 Ave & King George Blvd, 72 Ave & King George Blvd, and Fraser Hwy & 168 St, respectively. The left-turn bay lengths of treated sites were extended from 75 m to 180 m, 80 m to 135 m, and 75 m to 155 m for the intersections of 64 Ave & King George Blvd, 72 Ave & King George Blvd, and Fraser Hwy & 168 St, respectively.

Video cameras were used to collect traffic data from the left-turn lanes of the treatment and control sites. Two cameras were used for each intersection, one for the treatment site and the other for the control site. In order to cover the entire left-turn lane and an adequate area of the upstream through lane, an additional camera was used for the treatment site at the intersection of 72 Ave & King George Blvd. Video footages were recorded during daytime (06:00 to 21:00) on Tuesday June 10th, 2015 and Wednesday June 11th, 2015 before the treatment and on Tuesday June 1st, 2016 and Wednesday June 2nd, 2016 after the treatment. A total of approximately 270 h video footages were collected.

From these video footages, traffic conflicts on the treatment and control sites were extracted using an automated traffic conflict analysis system (Saunier and Sayed, 2007, 2008; Ismail et al., 2010). The system contains six main procedures, including camera calibration, feature tracking, feature grouping, prototype generation and matching, event generation, and conflict detection. The detailed procedures for the traffic conflict extraction can be found in Tageldin et al. (2018) and Zheng et al. (2018a). The target conflicts were those involving left-turn vehicles and taking place on the approach to an intersection. These conflicts were mainly rear-end conflicts that happened at the tail of a queue forming along the left-turn lane, and they could also happen between left-turn vehicles and through vehicles at the through lane upstream of the left-turn bay. During the conflict detection, the TTC values were calculated continuously frame by frame for any two consecutive vehicles on a collision course, and then the minimum TTC was used to represent the overall severity of the interaction. An example of the extracted TTC for conflicting left-turn vehicles is shown in Fig. 2. Finally, traffic conflicts with TTC less than 3 s were extracted for the following analysis, and a total of 4280 traffic conflicts were identified. The summary of video data collection and traffic conflict extraction is shown in Table 1.

3. Methodology

3.1. General framework

Similar to Zheng et al. (2018a), this study evaluates the safety effects of left-turn bay extension based on the fitted generalized extreme value (GEV) models. The main difference, however, is that instead of developing GEV models individually for each site & period situation, a uniform GEV model will be developed for the combined dataset. Through sharing information from different sites and periods, the model estimates are expected to be more accurate and with less uncertainty. In addition, the full Bayes method will be used for model estimation, and thus the non-regular problem associated with the maximum likelihood estimation method that was used previously can be avoided (Smith, 1985).

The general research framework is illustrated in Fig. 3. Traffic conflicts of 12 situations ((3 treatment sites + 3 control sites) × 2 periods) are combined for the uniform GEV model development. Time indicator (0 for before period and 1 for after period), treatment indicator (0 for control site and 1 for treatment site) and other factors are introduced into the model as covariates. The uniform GEV model is estimated by the full Bayes method, and then the GEV distribution for each situation can be obtained through the calibrated uniform GEV model with the specification of time indicator and site index. Finally, the treatment effects can be: i) qualitatively analyzed by comparing shapes of GEV distributions of matched treatment and control sites; and ii) quantitatively calculated using the odds ratio (OR) method with
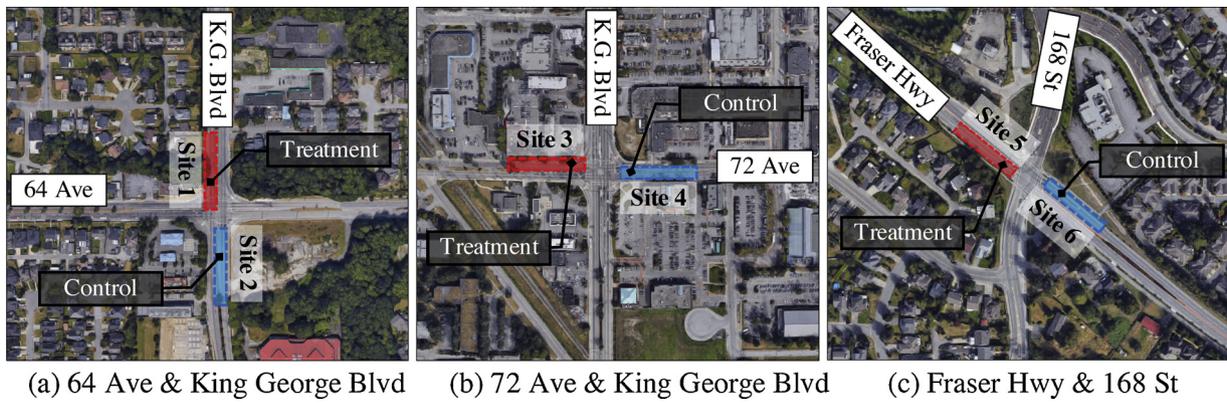
(a) 64 Ave & King George Blvd   (b) 72 Ave & King George Blvd   (c) Fraser Hwy & 168 St

Fig. 1. Study intersections with treatment and control sites.

crashes and severe traffic conflicts estimated from GEV distributions.

3.2. Extreme value theory and full Bayes method

3.2.1. Extreme value theory and the safety implication

Extreme value theory provides models for describing the distribution of extreme events, and it has been increasingly used for road safety analysis in recent years (Farah and Azevdo, 2017; Wang et al., 2018; Tarko, 2018; Zheng et al., 2018b; Wang et al., 2019; Zheng et al., 2019a; Zheng and Sayed, 2019a). An important approach to sample extreme events is the block maxima approach, in which observations are aggregated into fixed-interval blocks over time and the maxima of the blocks are treated as extremes. Mathematically, let $X_1, X_2, ..., X_n$ are independently and identically distributed random variables with unknown cumulative distribution function and $M_n = \max\{X_1, ..., X_n\}$ represents the block maxima. If there exists sequences of constants

$\{a_n > 0\}$ and $\{b_n\}$ such that

$$\Pr\left\{\frac{M_n - b_n}{a_n} \leq z\right\} \to G(z) \text{ as } n \to \infty \tag{1}$$

for a non-degenerate distribution function G, then G is a member of GEV family

$$G(z) = \exp\left\{-\left[1 + \xi\left(\frac{z - \mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{2}$$

defined on $\{z: 1 + \xi(z - \mu)/\sigma > 0\}$, where $-\infty < \mu < \infty$ is the location parameter, $\sigma > 0$ is the scale parameter and $-\infty < \xi < \infty$ is the shape parameter (Coles, 2001).

From the GEV distribution of traffic conflicts, safety implications such as the risk of crash can be obtained (Songchitruksa and Tarko, 2006; Zheng et al., 2014b). For traffic conflicts measured by TTC, it is
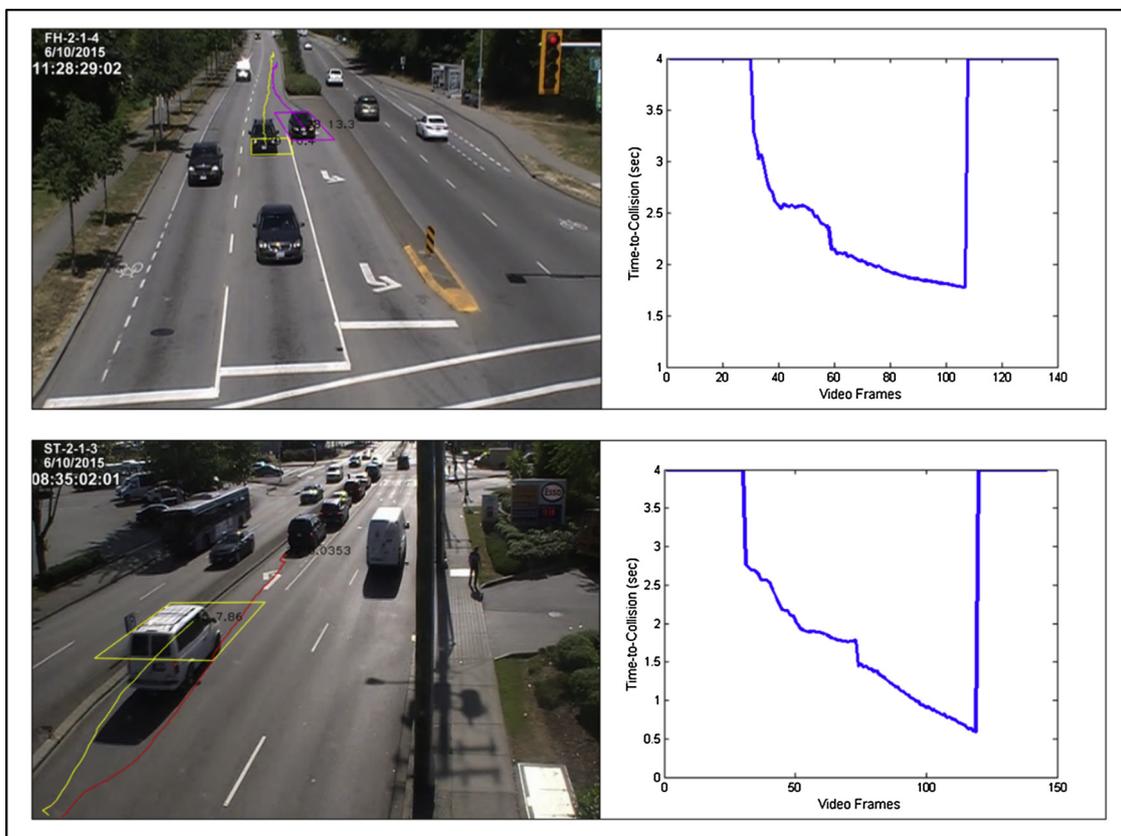

Fig. 2. TTC for conflicting left turn vehicles.

Table 1
Summary of video data collection.

Intersection	Site	Period	Time duration (h)	Event count	
				TTC ≤ 3 s	TTC ≤ 1.5 s
64 Ave & King George Blvd	Treatment	Before	22	1060	604
		After	15	61	55
	Control	Before	22	568	231
		After	22	152	51
72 Ave & King George Blvd	Treatment	Before	17/22[a]	944	589
		After	17/15[a]	182	84
	Control	Before	17	357	184
		After	15	159	81
Fraser Hwy & 168 St	Treatment	Before	15	421	271
		After	15	62	32
	Control	Before	15	207	158
		After	13	107	85

[a] Time durations are corresponding to two different cameras of the site.

known that a smaller TTC value means a higher risk of a traffic event ending up as a crash, and if the TTC ≤ 0 it indicates that a crash occurs. Therefore, by using of negated TTC, the risk of a target event (e.g., a crash, or a severe conflict) can be calculated from the tail region of fitted GEV distribution, and that is:

$$R_i = \Pr\{z_i \ge \delta\} = 1 - G_i(\delta) = 1 - \exp\left\{-\left[1 + \xi_i \frac{(\delta - \mu_i)}{\sigma_i}\right]^{-1/\xi_i}\right\} \quad (3)$$

Where, R_i is the risk of target event for block i, z_i is the maximum negated TTC of block i, and δ is a threshold value of negated TTC that defines the target events, including crashes defined by $\delta = 0$ (i.e., TTC = 0) and severe traffic conflicts defined by a negative value that is close to 0. The summation of R_i is the expected number of target events for the observation period t. For a longer period T, say $T = 1$ year, the estimated annual event number can be calculated as:

$$EN_T = \frac{T}{t} \sum_{i=1}^{N_t} R_i \quad (4)$$

where, N_t is the number of blocks during the observation period t. When $\delta = 0$, R_i is the risk of crash and EN_T is the expected number of crashes.

3.2.2. Full Bayes method for model development

To combine data of different sites and periods, a three-layer hierarchical structure is used (Zheng et al., 2019b). The first layer of the hierarchy is a data layer where the data are modeled with a GEV as shown in Eq. (2); the second layer is a process layer, where a latent Gaussian process underlying extremes is characterized by a linear link that relates parameters of the data layer to certain covariates. In the process layer, the scale parameter is re-parameterized as $\phi = \log \sigma$ to meet the positiveness restriction on the parameter domain; the third layer consists of prior distributions of the parameters that control the latent process. To be specific, the model structure is as follows:

$$G(z_{ij}) = \exp\left\{-\left[1 + \xi_{ij}\left(\frac{z_{ij} - \mu_{ij}}{\sigma_{ij}}\right)\right]^{-1/\xi_{ij}}\right\} \quad (5)$$

$$\begin{cases} \mu_{ij} = \alpha_{\mu 0} + \boldsymbol{\alpha_\mu} X + \varepsilon_{\mu j} \\ \phi_{ij} = \alpha_{\phi 0} + \boldsymbol{\alpha_\phi} X + \varepsilon_{\phi j} \\ \xi_{ij} = \alpha_{\xi 0} + \boldsymbol{\alpha_\xi} X + \varepsilon_{\xi j} \end{cases} \quad (6)$$

where, z_{ij} be the ith recorded block maxima at site j; $\alpha_{\mu 0}$, $\alpha_{\phi 0}$ and $\alpha_{\xi 0}$ are intercept terms corresponding to the three model parameters; X is the covariate vector and $\boldsymbol{\alpha_\mu}$, $\boldsymbol{\alpha_\phi}$ and $\boldsymbol{\alpha_\xi}$ are the vectors of regression parameters; $\varepsilon_{\mu j}$, $\varepsilon_{\phi j}$, and $\varepsilon_{\xi j}$ are random error terms to account for additional heterogeneity that is not directly addressed by the covariates. It is noted that the random terms represent between-site variances, which are consistent for extremes in the same site but vary between different sites. Therefore, the process described in Eq. (6) can also be written as a random intercept model as follows:
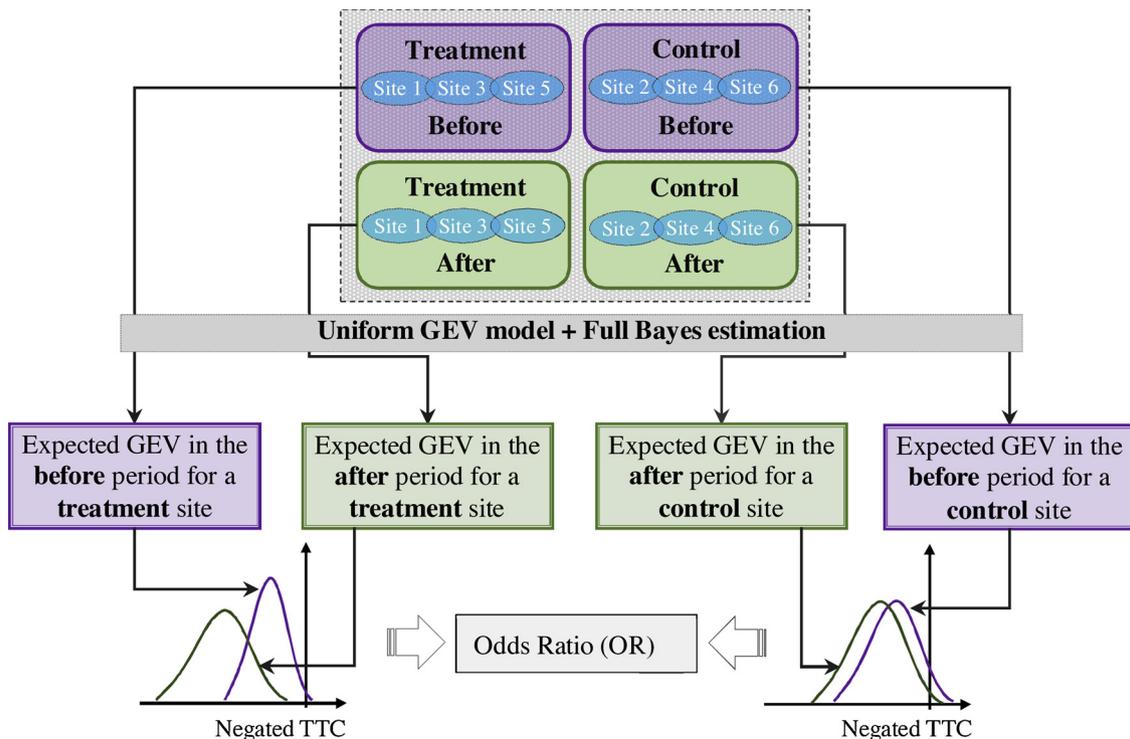

Fig. 3. Schematic diagram of general research framework.

Table 2
DIC values of the developed models.

Model	Description	DIC
M0	No covariates	797.6
M1	Adding Interact to μ based on M0	790.2
M2	Adding Interact to ϕ based on M0	793.0
M3	Adding Interact to ξ based on M0	792.0
M4	Adding Interact to three GEV parameters based on M0	625.1
M5	**Adding TTC1.5 to μ based on M4**	**595.7**
M6	Adding TTC1.5 to ϕ based on M4	616.6
M7	Adding TTC1.5 to ξ based on M4	619.8
M8	Adding TTC1.5 to three GEV parameters based on M4	592.3
M9	Adding Time to μ based on M5	595.5
M10	Adding Time to ϕ based on M5	592.8
M11	Adding Time to ξ based on M5	596.9
M12	Adding Time to three GEV parameters based on M5	610.3
M13	Adding Treat to μ based on M5	609.1
M14	Adding Treat to ϕ based on M5	606.0
M15	Adding Treat to ξ based on M5	632.6
M16	Adding Treat to three GEV parameters based on M5	596.5

$$\begin{cases} \mu_{ij} = \alpha_{\mu j} + \boldsymbol{\alpha_\mu} X \\ \phi_{ij} = \alpha_{\phi j} + \boldsymbol{\alpha_\phi} X \\ \xi_{ij} = \alpha_{\xi j} + \boldsymbol{\alpha_\xi} X \end{cases} \qquad (7)$$

Priors to parameters in Eq. (7) are assigned to characterize the latent process, and it is assumed that each parameter in this layer is independent to the others. Since there is no prior information on how the GEV parameters are related to covariates, the uninformative priors for parameters $\alpha_{\mu j}$, $\alpha_{\phi j}$, $\boldsymbol{\alpha_\mu}$, $\boldsymbol{\alpha_\phi}$, and $\boldsymbol{\alpha_\xi}$ are adopted. They are assumed to follow a normal distribution with zero mean and large variance, i.e., N $(0, 10^6)$. Considering that the shape parameter of the GEV is difficult to estimate with precision and meanwhile referring the information in previous studies as Songchitruksa and Tarko (2006) and Zheng et al. (2014b), the prior for shape parameter is set as $\alpha_{\xi j}$ ~ Unif(-1.5, 1.5). With the assigned priors, the posterior distributions of model parameters can be obtained through the Bayesian inference.

To select a best model among models with different covariates, the Deviance Information Criterion (DIC) is employed. The basic principle of DIC is parsimony, obtaining the simplest model that explains as much of the variation in the data as possible (Spiegelhalter et al., 2002). The DIC is calculated as follows:

$$\text{DIC} = \bar{D} + p_D \qquad (8)$$

where $\bar{D}$ is the posterior mean deviance that measures the model fitting and p_D is the effective number of parameters in the model. Generally, a smaller DIC value indicates a better model. A difference greater than 5 can rule out the model with higher DIC value and a difference less than 5 means the two model are competitive (El-Basyouny and Sayed, 2012a, b).

3.3. OR method

With the fitted GEV distributions and estimated frequencies of crashes (or severe conflicts) for both treatment and control sites and before and after periods, the OR statistical method can be used to quantitatively evaluate the treatment effects. The OR can be calculated as follows (Tageldin et al., 2018; Zheng et al., 2018a):

$$OR = \frac{T_A/T_B}{C_A/C_B} \qquad (9)$$

where, T_B and T_A are conditions at treatment sites before and after treatment carried out respectively, and C_B and C_A are conditions at control sites before and after treatment carried out respectively. An OR of less than 1 indicates a desirable effect while greater than 1 indicates a deleterious effect. The treatment effect (TE) is calculated as:

$$TE = 1 - OR \qquad (10)$$

and the percent reduction in safety estimates is 100% $\times$ TE. A positive *TE* value indicates reduction in safety estimates and hence a safety improvement.

4. Results and discussion

4.1. Model estimation results

The observed traffic conflicts were divided into blocks with 20 min intervals with the consideration of bias-variance tradeoff (Zheng et al., 2018a), and the maximum of negated TTC of each block was used to fit the model. Four covariates were considered, including treatment indicator (Treat = 0 for treatment sites; Treat = 1 for control sites), time indicator (Time = 0 for before period; Time = 1 for after period), interact indicator (Interact = Treat*Time, a two-way interaction term representing the treatment effect on model parameters), and TTC1.5 (the number of conflicts with TTC $\leq$ 1.5 s in a block).

With different combinations of covariates and their link to different GEV parameters, a total of 17 models were developed, as shown in Table 2. Markov Chain Monte Carlo (MCMC) was applied using Win-BUGS to estimate model parameters. Two separate chains for each model parameter with different initial values were set to run 50,000 iterations and the first 20,000 iterations were discarded as burn-in samples. The posterior estimates were obtained from the remaining 30,000 iterations. The model convergence was checked by calculating the Gelman-Rubin statistic of two chains for each parameter as well as visually inspecting the trace plots of parameter chains (El-Basyouny and Sayed, 2009; Zheng et al., 2014c; Zheng and Ismail, 2017; Guo et al., 2018).

The model estimation results show that adding Interact to three GEV parameters and meanwhile adding TTC1.5 to the location parameter significantly improve the model fit in terms of DIC. The corresponding best fitted model is M5, and adding other covariates to M5 makes little improvement. The DIC difference between the model with minimum DIC value and M5 is less than 5. Therefore, M5 is considered the best fitted model. The Time indicator is not included in the model possibly because that there is no significant change of observed traffic conflicts at control sites in the before and after periods. A probable reason for the insignificance of Treatment indicator is that the difference in treatment and control sites is represented by site-specific random intercepts. The estimated parameters of the best model is shown in Table 3.

4.2. Treatment effect analysis

Based on the estimated uniform GEV model, the GEV distribution for each situation can be obtained, and the expected numbers of target events (i.e., crashes and the most severe conflicts) of each situation corresponding to different thresholds can be calculated using Eqs. (3) and (4). Then the OR and TE can be calculated using Eqs. (9) and (10) to quantitatively measure the treatment effects. The calculation results are shown in Table 4. The table shows that the overall reduction in total expected crashes is estimated at approximately 59.1% which is a significant reduction and indicates a remarkable improvement in safety after the treatment. Moreover, greater reductions are found in the most severe conflicts, which are 71.7%, 85.1% and 79.6% corresponding to thresholds of -0.03, -0.15 and -0.30, respectively. These reductions are almost consistent but also slightly smaller than the ones found in Zheng et al. (2018a), in which TEs were estimated based on GEV models developed individually for different sites and different periods. It is expected that using the full Bayes method that combines information from different sites for GEV model estimation would lead to more accurate estimates (Cooley et al., 2006; Zheng et al., 2019b). Thus, it is suggested that the TE = 59.1% would be a better estimation of treatment effects in terms of crashes comparing to TE = 63.9%.

Table 3
Estimated parameters of the best model.

Node	Mean	SD	2.50%	Median	97.50%
$\mu_0[1]$	−0.2605	0.0263	−0.3083	−0.2628	−0.2134
$\mu_0[2]$	−1.3060	0.0957	−1.4890	−1.2950	−1.1120
$\mu_0[3]$	−0.2395	0.0302	−0.2900	−0.2429	−0.1785
$\mu_0[4]$	−1.3450	0.1015	−1.5560	−1.3420	−1.1520
$\mu_0[5]$	−0.2481	0.0232	−0.2864	−0.2511	−0.1939
$\mu_0[6]$	−0.5876	0.0609	−0.7029	−0.5859	−0.4692
μ(TTC1.5)	0.0051	0.0019	0.0018	0.0056	0.0080
μ(Interact)	−0.9643	0.1039	−1.1720	−0.9630	−0.7653
$\phi_0[1]$	−1.6540	0.1070	−1.8470	−1.6630	−1.4230
$\phi_0[2]$	−0.0545	0.0999	−0.2348	−0.0596	0.1546
$\phi_0[3]$	−2.0890	0.0994	−2.2250	−2.0380	−1.8410
$\phi_0[4]$	−0.1273	0.0966	−0.3009	−0.1321	0.0755
$\phi_0[5]$	−1.5770	0.0886	−1.5410	−1.3750	−1.2210
$\phi_0[6]$	−0.4008	0.1329	−0.6578	−0.3867	−0.1789
ϕ(Interact)	1.7060	0.1079	1.5490	1.7340	1.9710
$\xi_0[1]$	−1.0240	0.1448	−1.4120	−1.0060	−0.7944
$\xi_0[2]$	−0.7168	0.1070	−0.9045	−0.7227	−0.4923
$\xi_0[3]$	−0.8058	0.1162	−1.0440	−0.7940	−0.6140
$\xi_0[4]$	−0.6500	0.0784	−0.8006	−0.6508	−0.4937
$\xi_0[5]$	−1.1730	0.0904	−1.4930	−1.3930	−1.1630
$\xi_0[6]$	−1.2290	0.1158	−1.4320	−1.2330	−1.0030
ξ(Interact)	0.1614	0.1336	−0.0733	0.1511	0.4401

However, this needs to be investigated in future with actual crash data.

In addition to the quantitative measure, using EVT approach also provides a tool to visually analyze the treatment effects by comparing the fitted GEV distributions. The fitted GEV distributions for treatment and control sites in the before and after periods are shown in Fig. 4, in which the solid lines represent the distributions obtained from the current study while the dashed lines represent the distributions from Zheng et al. (2018a). It is noted that the GEV distributions were drawn by taking the mean values of TTC1.5 for different situations. It can be seen from the figure that there are apparent changes in GEV distributions of treatment sites in the before and after periods, and in contrast the GEV distributions of control sites in the before and after periods are very similar. This is a clear evidence that shows the existence of treatment effects. Since GEV distributions of treatment sites in the after period go further away from the risk of crash area (i.e., the area with negated TTC ≥ 0), the change implies a safety improvement after the treatment.

Comparing the GEV distributions in the current study to the ones in Zheng et al. (2018a), it can be found that the GEV distributions of treatment sites are very similar but those of control sites are different. For control sites a major difference is that the changes of GEV distributions in the before and after periods are more apparent in Zheng et al. (2018a). In contrast, there are small changes in GEV distributions in the current study. To be more specific, this study shows that the GEV distributions of control sites in the before and after periods have the same scale parameter and shape parameter but a little different location parameter. The similarity of GEV distributions in the before and after periods for control sites seems reasonable, since there is little change at control sites except for the time of data collection. Moreover, the time effect is captured by the location parameter using covariates such as

TTC1.5.

5. Conclusions

A full Bayes approach was proposed to conduct a traffic conflict-based before-after safety evaluation using the extreme value theory. The approach is able to combine traffic conflicts of different sites (treatment sites and control sites) and different periods (the before period and after period) to develop a uniform GEV model for the treatment effect estimation. The approach was applied to a case of left-turn bay extension, in which traffic conflicts were collected from 3 treatment sites and 3 matched control sites in the before and after periods. A series of models were developed considering different combinations of covariates (i.e., treatment indicator, time indicator, interact indicator and TTC1.5) and their link to different GEV model parameters (i.e., location parameter, scale parameter and shape parameter). The treatment effects were then quantitatively calculated as well as qualitatively analyzed based on the best fitted GEV model.

The best fitted model is found to be the one with interact indicator added to three GEV parameters and TTC1.5 added to the location parameter of GEV. With the best fitted model, the treatment effect is estimated to be 59.1% in terms of crashes, and 71.7%, 85.1% and 79.6% in terms of the most severe conflicts corresponding to thresholds of −0.03, −0.15 and −0.30, respectively. The significant reductions in crashes and the most severe conflicts indicate considerable safety improvement after the left-turn bay extension. The improvement is also confirmed by the apparent differences of GEV distributions at treatment sites in the before and after periods.
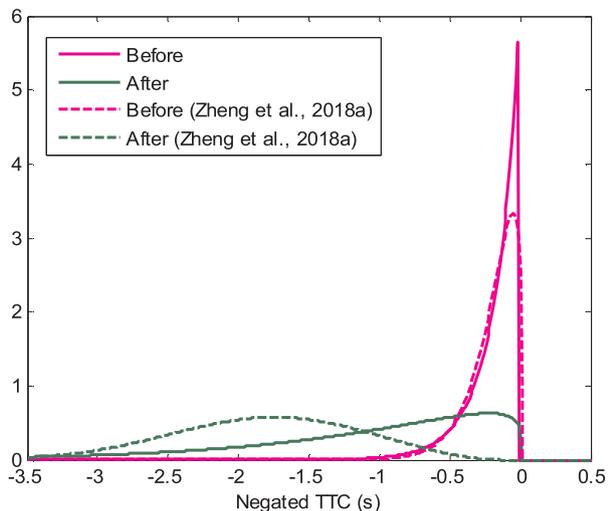
The treatment effects found in this study are generally in line with the ones in Zheng et al. (2018a). However, in this study the TE values are smaller and the changes of GEV distributions in the before and after periods at control sites are not as apparent as those in Zheng et al. (2018a). These differences seem to be reasonable and possibly a result of the advantages of the proposed full Bayes approach, which usually leads to more accurate model estimates because of allowing sharing information among different sites and periods as well as accounting for unobserved heterogeneity. Future before-after study based on crash data is needed to confirm the findings. Another future work is to collect more data from a larger number of sites. In this case, the heterogeneity in geometric alignments and other site-specific factors could be included in the GEV model, and then their influence on treatment effects can be explicitly investigated.
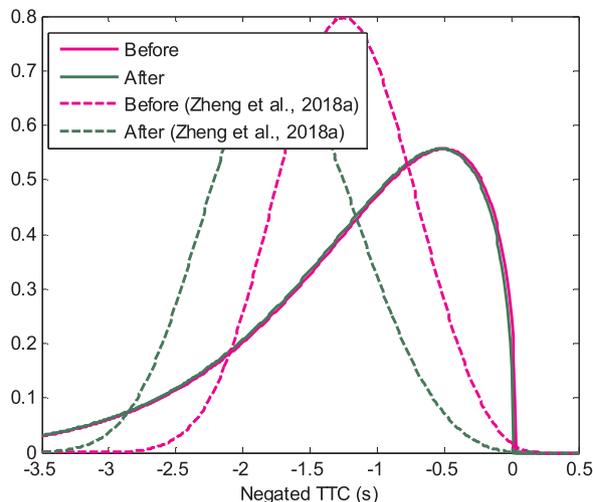
Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
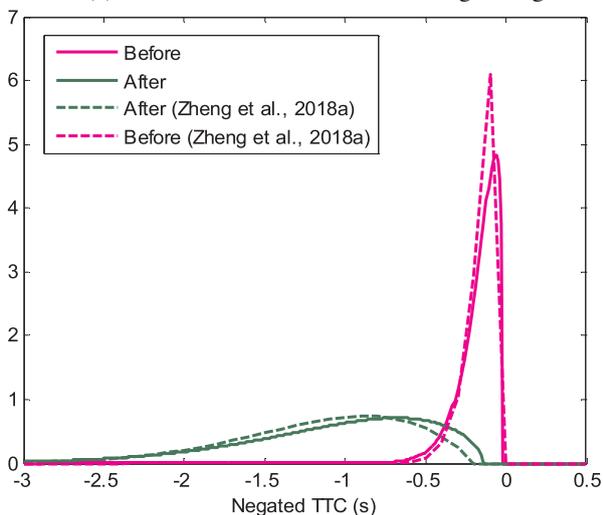
Acknowledgments

Table 4
Treatment effects of different thresholds.

	Treatment		Control		OR	*p*-value	TE	TE[a]
	Before	After	Before	After				
$\delta = 0$	30.2	6.1	141.6	69.8	0.409	0.056	59.1%	63.9%
$\delta = -0.03$	1437.4	291.0	553.0	395.3	0.283	0.000	71.7%	73.2%
$\delta = -0.15$	18409.1	2173.9	4494.6	3566.1	0.149	0.000	85.1%	88.9%
$\delta = -0.30$	29148.2	4921.1	8334.3	6892.9	0.204	0.000	79.6%	86.1%

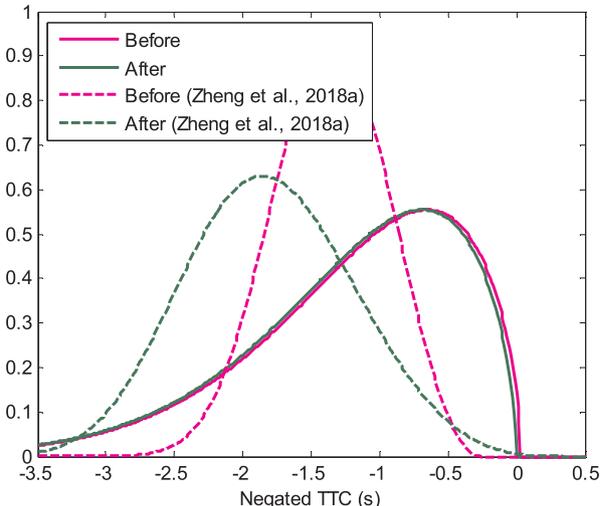[a] The TEs are from Zheng et al. (2018a).

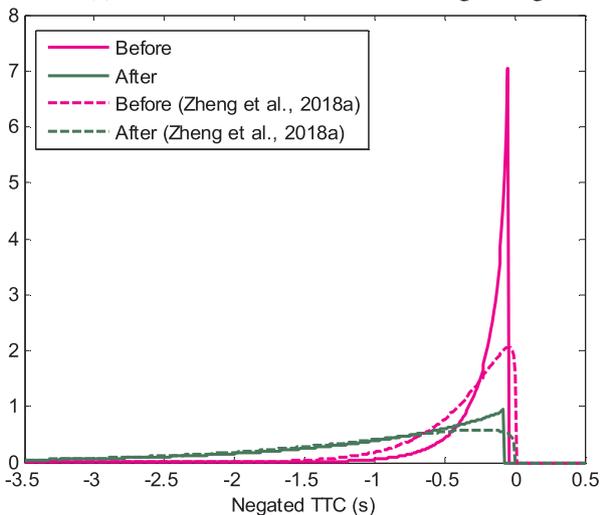(a) Treatment site of 64 Ave & King George Blvd

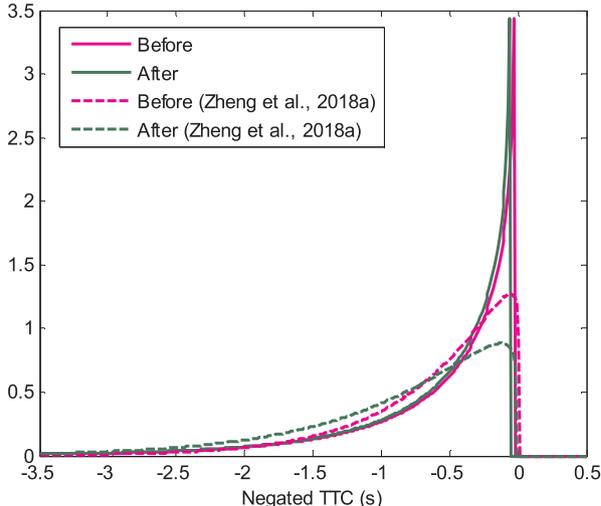(b) Control site of 64 Ave & King George Blvd

(c) Treatment site of 72 Ave & King George Blvd

(d) Control site of 72 Ave & King George Blvd

(e) Treatment site of Fraser Hwy & 168 St

(f) Control site of Fraser Hwy & 168 St

Fig. 4. Fitted GEV distributions for treatment and control sites in the before and after periods.

References

Autey, J., Sayed, T., Zaki, M., 2012. Safety evaluation of right-turn smart channels using automated traffic conflict analysis. Accid. Anal. Prev. 45, 120–130.

Brown, G.R., 1994. Traffic conflict for road user safety studies. Can. J. Civ. Eng. 21, 1–15.

Coles, S., 2001. An Introduction to Statistical Modeling of Extreme Values. Springer-Verlag, London, UK.

Cooley, D., Naveau, P., Jomelli, V., Rabatel, A., Grancher, D., 2006. A Bayesian hierarchical extreme value model for lichenometry. Environmetrics 17, 555–574.

El-Basyouny, K., Sayed, T., 2009. Urban arterial accident prediction models with spatial effects. Transp. Res. Rec.: J. Transp. Res. Board 2102, 27–33.

El-Basyouny, K., Sayed, T., 2010. A full Bayes approach to before-after safety evaluation with matched comparisons: a case study of stop-sign in-fill program. Transp. Res. Rec.: J. Transp. Res. Board 2148, 1–8.

El-Basyouny, K., Sayed, T., 2011. A multivariate intervention model with random parameters among matched pairs for before–after safety evaluation. Accid. Anal. Prev. 43 (1), 87–94.

El-Basyouny, K., Sayed, T., 2012a. Measuring direct and indirect treatment effects using safety performance intervention functions. Saf. Sci. 50, 1125–1132.

El-Basyouny, K., Sayed, T., 2012b. Measuring safety treatment effects using full Bayes non-linear safety performance intervention functions. Accid. Anal. Prev. 45, 152–163.

Farah, H., Azevdo, C.L., 2017. Safety analysis of passing maneuvers using extreme value theory. IATSS Res. 41 (1), 12–21.

Guo, Y., Li, Z., Wu, Y., Xu, C., 2018. Evaluating factors affecting electric bike users' registration of license plate in China using Bayesian approach. Transp. Res. F Traffic Psychol. Behav. 59, 212–221.

Guo, Y., Essa, M., Sayed, T., Haque, M.M., Washington, S., 2019. A comparison between simulated and field-measured conflicts for safety assessment of signalized intersections in Australia. Transp. Res. C Emerg. Technol. 101, 96–110.

Hauer, E., 1997. Observational Before–After Studies in Road Safety. Pergamon Press, Elsevier Science Ltd., Oxford, United Kingdom.

Ismail, K., Sayed, T., Saunier, N., 2010. Automated analysis of pedestrian-vehicle conflicts: context for before-and-after studies. Transp. Res. Rec. J. Transp. Res. Board 2198, 52–64.

Lan, B., Persaud, B., Lyon, C., Bhim, R., 2009. Validation of a full Bayes methodology for observational before-after road safety studies and application to evaluation of rural signal conversions. Accid. Anal. Prev. 41 (3), 574–580.

Persaud, B.N., Retting, R.A., Garder, P.E., Lord, D., 2001. Safety effect of roundabout conversions in the United States: empirical Bayes observational before-after study. Transp. Res. Rec. J. Transp. Res. Board 1751, 1–8.

Persaud, B., Lyon, C., 2007. Empirical Bayes before–after safety studies: lessons learned from two decades of experience and future directions. Accid. Anal. Prev. 39 (3), 546–555.

Reyad, P., Sacchi, E., Ibrahim, S., Sayed, T., 2017. Traffic conflict-based before–after study with use of comparison groups and the empirical Bayes method. Transp. Res. Rec. J. Transp. Res. Board 2659, 15–24.

Saunier, N., Sayed, T., 2007. Automated analysis of road safety with video data. Transp. Res. Rec. J. Transp. Res. Board 2019, 57–64.

Saunier, N., Sayed, T., 2008. Probabilistic framework for the automated analysis of the exposure to road collision. Transp. Res. Rec. J. Transp. Res. Board 2083, 96–104.

Sacchi, E., Sayed, T., deLeur, P., 2013. A comparison of collision-based and conflict-based safety evaluations: the case of right-turn smart channels. Accid. Anal. Prev. 59, 260–266.

Sacchi, E., Sayed, T., El-Basyouny, K., 2016. A full Bayes before-after study accounting for temporal and spatial effects: evaluating the safety impact of new signal installations. Accid. Anal. Prev. 94, 52–58.

Sayed, T., Zein, S., 1999. Traffic conflict standards for intersections. Transp. Plan. Technol. 22 (4), 309–323.

Smith, R.L., 1985. Maximum likelihood estimation in a class of nom-regular cases. Biometrika 72, 67–90.

Songchitruksa, P., Tarko, A.P., 2006. The extreme value theory approach to safety estimation. Accid. Anal. Prev. 38, 811–822.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., Van der Linde, A., 2002. Bayesian measures of model complexity and fit. J. R. Stat. Soc. B 64, 1–34.

Tageldin, A., Sayed, T., Ismail, K., 2018. Evaluating the safety and operational impacts of left-turn bay extension at signalized intersections using automated video analysis. Accid. Anal. Prev. 120, 13–27.

Tarrall, M., Dixon, K., 1998. Conflict analysis for double left-turn lanes with protected-plus-permitted signal phases. Transp. Res. Rec. J. Transp. Res. Board 1635, 105–112.

Tarko, A.P., 2018. Estimating the expected number of crashes with traffic conflicts and the Lomax distribution – a theoretical and numerical exploration. Accid. Anal. Prev. 113, 63–73.

Wang, C., Xu, C., Xia, J., Qian, Z., Lu, L., 2018. A combined use of microscopic traffic simulation and extreme value methods for traffic safety evaluation. Transp. Res. C 90, 281–291.

Wang, C., Xu, C., Dai, Y., 2019. A crash prediction method based on bivariate extreme value theory and video-based vehicle trajectory data. Accid. Anal. Prev. 123, 365–373.

Xie, K., Ozbay, K., Yang, H., Yang, D., 2019. A new methodology for before-after safety assessment using survival analysis and longitudinal data. Risk Anal. 39 (6), 1342–1357.

Yanmaz-Tuzel, O., Ozbay, K., 2010. A comparative full Bayesian before-and-after analysis and application to urban road safety countermeasures in New Jersey. Accid. Anal. Prev. 42 (6), 2099–2107.

Zheng, L., Ismail, K., Meng, X., 2014a. Traffic conflict techniques for road safety analysis: open questions and some insights. Can. J. Civ. Eng. 41, 633–641.

Zheng, L., Ismail, K., Meng, X., 2014b. Freeway safety estimation using extreme value theory approaches: a comparative study. Accid. Anal. Prev. 62, 32–41.

Zheng, L., Ismail, K., Meng, X., 2014c. Shifted gamma-generalized pareto distribution model to map the safety continuum and estimate crashes. Saf. Sci. 64, 155–162.

Zheng, L., Ismail, K., 2017. A generalized exponential link function to map a conflict indicator into severity index within safety continuum framework. Accid. Anal. Prev. 102, 23–30.

Zheng, L., Sayed, T., Tageldin, A., 2018a. Before-after safety analysis using extreme value theory: a case of left-turn bay extension. Accid. Anal. Prev. 121, 258–267.

Zheng, L., Ismail, K., Sayed, T., Fatema, T., 2018b. Bivariate extreme value modeling for road safety estimation. Accid. Anal. Prev. 120, 83–91.

Zheng, L., Sayed, T., Essa, M., 2019a. Validating the bivariate extreme value modeling approach for road safety estimation with different traffic conflict indicators. Accid. Anal. Prev. 123, 314–323.

Zheng, L., Sayed, T., Essa, M., 2019b. Bayesian hierarchical modeling of the non-stationary traffic conflict extremes for crash estimation. Anal. Methods Accid. Res. 23, 100100.

Zheng, L., Sayed, T., 2019a. From univariate to bivariate extreme value models: approaches to integrate traffic conflict indicators for crash estimation. Transp. Res. C Emerg. Technol. 103, 211–225.

Zheng, L., Sayed, T., 2019b. Application of extreme value theory for before-after road safety analysis. Transp. Res. Rec. J. Transp. Res. Board 2673 (4), 1001–1010.