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Investigating the impacts of crash prediction models on quantifying safety effectiveness of Adaptive Signal Control Systems

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ABSTRACT

Introduction: By handling conflicting traffic movements and establishing dynamic coordination between signalized intersections in real-time, Adaptive Signal Control Systems (ASCS) can potentially improve the operation and safety at signalized intersections and corridors. *Methods:* This paper develops a series of models accounting for model forms and possible predictors and implements these models in Empirical Bayes (EB) and Fully Bayesian (FB) frameworks for ASCS safety evaluation studies. Different models are validated in terms of the ability to reduce the potential bias and variance of prediction and improve the safety effectiveness estimation accuracy using real-world crash data from non-ASCS sites. This paper then develops the safety effectiveness of ASCS at six different corridors with a total of 65 signalized intersections with the same type of ASCS, in South Carolina. *Results:* Validation results show that the FB model that accounts for traffic volume, roadway geometric features, year factor, and spatial effects shows the best performance among all models. The study findings reveal that ASCS reduces crash frequencies in the total crash, fatal and injury crash, and angle crash for most of the intersections. The safety effectiveness of ASCS varies across the intersections with different features (i.e., AADT at major streets, number of legs at an intersection, the number of through lanes on major streets, the number of access points on minor streets, and the speed limit at major streets). *Conclusions:* ASCS is associated with crash reductions, and its safety effects vary with different intersection features. *Practical Applications:* The findings of this research encourage more ASCS deployments and provide insights into selecting ASCS deployment sites for reducing crashes considering the variation of the safety effectiveness of ASCS.

1. Introduction

Safety improvements at intersections have become one of 22 key domains in the American Association of State Highway and Transportation Officials Strategic Highway Safety Plan (Antonucci et al., 2004). Through traffic control and operational improvement strategies, the goal of this plan is to achieve a decrease in the frequency and severity of crashes at signalized intersections. Transportation agencies have been advancing new approaches and technologies to improve safety at signalized intersections.

Adaptive Signal Control System (ASCS) is typically deployed at intersections and corridors to improve operational performance, such as travel time and traffic delay. The ASCS requires detectors such as loop detectors and video detectors, and a communication network that allows for communicating with the local traffic controllers and/or the server. Compared to the conventional time of day signal control systems (i.e., pre-timed signal control and actuated signal control) with predefined signal plans (usually re-adjusted every two years), ASCS can change the signal timings (i.e., phase splits, phase sequence, offsets, and cycle length) in real-time to accommodate fluctuating traffic demand at intersections. Also, ASCS can adjust offsets to coordinate several intersections along a corridor, thus lead to fewer traffic stops along a corridor. Significant operational benefits of ASCS in both corridor and intersection have been documented (Eghtedari, 2005; Elkins et al., 2012; Fontaine et al., 2015; Kergaye et al., 2009; Khattak, 2016; Khattak et al., 2020; So et al., 2014). By handling conflicting traffic movements and establishing dynamic coordination between intersections in real-time, ASCS can potentially improve the operational traffic condition, which in turn will improve the safety of signalized intersections and corridors.

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Past studies have implemented the Empirical Bayes (EB) framework with the Poisson-Gamma model into ASCS safety evaluation studies (Jesus & Benekohal, 2019; Khattak, 2016). However, previous studies have not applied the Fully Bayesian (FB) framework with the Poisson-Lognormal model for any ASCS safety evaluation. More specifically, spatial correlations could exist in neighboring intersections along a corridor with ASCS. However, no studies have implemented spatial models in the safety evaluation of ASCS. Moreover, previous studies have not evaluated the performance of different crash prediction models in quantifying the safety effectiveness of ASCS.

To fill the above research gaps in ASCS safety evaluation, we: (a) implement the Poisson-Lognormal model and the spatial model into the ASCS safety evaluation; and (b) investigate how different crash prediction models impact the estimator of the safety effectiveness of ASCS in the EB and FB before-and-after studies. A series of models, including the Poisson-Lognormal models, Poisson-Gamma models, and spatial models, are compared and evaluated. Traffic volume, roadway geometric features, year factor, and spatial effect are used to produce different sets of models. The intersections and corridors in this study have the same ASCS type deployed. The algorithm of the particular type of ASCS is the same for each intersection and corridor in this study. ASCS optimizes the cycle length, splits, and offsets in real-time based on current traffic conditions to minimize overall traffic delays of the intersections, while guaranteeing reasonable coordination between intersections. The study focuses on evaluating the safety effectiveness of the particular ASCS system (which this paper refers to as "ASCS") without considering the variations between multiple ASCS types. ASCS effect may vary across sites due to specific features of the sites that are deployed with ASCS. To explore the variations in ASCS effect across sites, the study evaluates the safety effectiveness of ASCS for each corridor and each intersection.

2. Literature review

The following subsections discuss the crash prediction model and safety evaluation related studies of ASCS.

2.1. Crash prediction model

This subsection reviews the characteristics of the crash prediction models. In the FB method, the Bayesian models used to estimate the safety performance are similar to the concept of the Safety Performance Function (SPF) used in the EB method. This paper uses the same term "crash prediction model" for the convenience of discussion, instead of the Bayesian models in the FB methods and the SPF in the EB method.

2.1.1. Poisson-Gamma and Poisson-Lognormal Model

In general, there are two main types of models used in the estimation of crash frequency: (a) Poisson-Gamma, and (b) Poisson-Lognormal.

- *Poisson-Gamma Model*

When the Poisson mean is assumed to follow a gamma distribution, the Poisson-Gamma mix distribution results in Negative Binomial (NB) distribution (Carriquiry & Pawlovich, 2004; Khazraee et al., 2018), with Maximum Likelihood Estimation (MLE) used for parameter estimation. NB models have been widely used by many researchers (Elvik et al., 2017; Hauer, 1997; Hauer et al., 2002; Hovey & Chowdhury, 2005; Høye, 2015). In the EB framework, the NB model is used to account for the over-dispersion (i.e., the variance is much larger than the mean) of crash data.

- *Poisson-Lognormal Model*

When the Poisson mean is assumed to have a lognormal distribution, the Poisson-Lognormal model results in an unclosed form of the marginal distribution, which is difficult to handle using the MLE method. The Poisson-Lognormal model is typically integrated into the FB framework. The posterior distribution of the parameters of the Poisson-Lognormal model can be obtained using Markov Chain Monte Carlo (MCMC) simulation (Khazraee et al., 2018).

2.1.2. Spatial models

Spatial effects can be introduced into a Poisson-Lognormal model to consider the spatial correlation of adjacent road entities (Cai et al., 2018). Although many studies (Barua et al., 2016; Jonathan et al., 2016) have accounted for spatial effects in the development of crash prediction models, few studies (Sacchi et al., 2016) implement the spatial model in a before-and-after safety study. Spatial models can be integrated into the FB method but cannot be in current EB methods for safety evaluation (Gross et al., 2010). The assumption of the non-spatial models (i.e., Poisson-Gamma model and Poisson-Lognormal model) is that crashes are independent across sites. This assumption will be violated if the spatial correlation between sites within neighborhoods exists.

On the other hand, neighboring sites may share similar traffic and road conditions, similar driver behavior, and weather condition. As a result, it may result in similar safety levels for neighboring sites. Spatial effects usually exist, for example, among the adjacent intersections (which is the case of this study), adjacent corridors (Li & Wang, 2017), and the adjacent zone sharing the same border (Cai et al., 2018).

2.2. Safety evaluation of Adaptive Signal Control Systems

Safety benefits of ASCS have been demonstrated in recent studies. Fontaine et al. (2015) have evaluated the safety effects of InSync, an ASCS, for different corridors in Virginia using an EB before-and-after study. Based on the analysis, the authors have found that crashes are reduced by 17% due to ASCS. Dutta et al. (2010) have studied crash data for one type of ASCS (i.e., SCATS) and fixed-time signal control systems for two corridors in Michigan. The authors (Dutta et al., 2010) have evaluated the change in the crash rate before and after the ASCS deployment. The authors have found that the total crash rate is reduced by 6% after installing ASCS. The incapacitating injury and permanent injury crashes are reduced by 22% after ASCS deployment. The most significant improvement is found for non-incapacitating injury or temporary injury crashes, which is reduced by 35%. Fink et al. (2016) have studied the safety impacts of SCATS for 498 signalized intersections in Oakland County. The authors have performed a cross-sectional study and found a reduction of 19.3% in angle crashes associated with SCATS. This study found that SCATS does not reduce incapacitating injuries or fatality statistically significantly (Fink et al., 2016). Khattak (2016) evaluated 41 intersections in Pennsylvania where SURTRAC and InSync are installed. The author has implemented an EB before-and-after safety study and computed Crash Modification Factors (CMF) for total crashes, and fatal and injury crashes. The author found reductions of 34% and 45% in total crashes and fatal and injury crashes, respectively, due to ASCS. Khattak et al. (2019) have examined the impact of ASCS on injury severity outcomes. The authors have found that one type of ASCS (the name of the ASCS type is not mentioned in the paper) decreases the probability of minor injury and severe plus moderate crashes by 10.36% and 11.70%, respectively, while another type of ASCS (the name of the ASCS type is not mentioned in the paper) decreases the probability of minor injury and severe plus moderate crashes by 6.92% and 4.39%, respectively.

ASCS is not always found to reduce crashes statistically significantly. Jesus and Benekohal (2019) have implemented the EB method to determine the safety effectiveness of the ASCS. The authors (Jesus & Benekohal, 2019) have found that the CMF of ASCS for fatal and injury crashes is 0.67, which is not statistically significant at a 0.05 significance level. CMFs of property damage only and total crashes are close to one, which indicates no crash reduction due to ASCS. The CMF for fatal, incapacitating injury, and non-incapacitating injury combined is 0.68, which is not significant at a 0.05 significance level. The angle, rear-end, incapacitating injury, and reported/not evident injury (this includes momentary unconsciousness, claims of no evident injuries, limping, complaints of pain, nausea, hysteria.) crashes show insignificant reductions.

3. Method

This section first discusses model forms in the development of crash prediction models in the EB and FB before-and-after study procedures. Then, this section provides a validation procedure that uses two criteria to validate possible models: (a) the potential bias and variance of prediction, and (b) the estimation accuracy of safety effectiveness.

3.1. Model development and evaluation procedure

This subsection introduces the models that would be incorporated into the EB and FB before-and-after study procedures. Traffic volume, roadway geometric features (e.g., the number of access points at an intersection, and the number of exclusive left-turn lanes, right-turn lanes, and through lanes on major or minor streets), year factor, and spatial effect are used to produce different sets of the models. For each model, four crash types of interest are accounted for: total crash, fatal and injury (F + I), rear-end crash, and angle crash. Two primary forms of models, Poisson-Gamma and Poisson-Lognormal, are introduced. A spatial model is also used with a Poisson-Lognormal model in this study to account for the spatial effect existing in the investigated sites. Model 1, Model 2, and Model 3 are implemented within the EB framework. Model 4A, Model 4B, Model 5A, Model 5B, Model 6A, and Model 6B are implemented within the FB framework.

3.1.1. EB Models

3.1.1.1. EB Model development. A general Poisson-Gamma model with two tiers is expressed as the following:

$$y_{m,it}P\tilde{o}isson(\lambda_{m,it}) \tag{1}$$

$$\lambda_{m,it}G\tilde{a}mma(\alpha,\phi) \tag{2}$$

where, $y_{m,it}$ is the observed crash frequency at an intersection i ($i = 1, 2, \ldots, 65$) on the corridor $m (m = 1, 2, \ldots, 6)$ in a given year t ($t = 2011, 2012, \ldots, 2018$); $\lambda_{m,it}$ is the Poisson mean. The expectation of $\lambda_{m,it}$, $E(\lambda_{m,it})$ is the expected yearly number of crashes at an intersection i on the corridor $m$in the year t for a specified crash type (i.e., total crash, F + I, rear-end, or angle crash). α is the shape parameter of Gamma distribution, and ϕ is the inverse scale parameter (i.e., rate parameter) of the Gamma distribution.

Three crash prediction models (called SPFs in the EB framework) are specified in terms of different explanatory variables. Model 1 and Model 2 account for the year factor by introducing annual multipliers. The year factor is often introduced into the crash prediction model to account for temporal variation of crash expectation, which accounts for possible unobserved factors such as weather conditions, road conditions, and vehicle technology improvements (Persaud et al., 2010). Model 3 accounts for the year factor by introducing the year variable as one of the explanatory variables in the model. Model 1 includes an annual multiplier, and Annual Average Daily Traffic (AADT) without considering the difference in roadway geometric features. Model 2 includes an annual multiplier, AADT, and roadway geometric features. Model 3 includes AADT, roadway geometric features, and the year factor.

Model 1 (AADT + Annual multipliers):

$$E(\lambda_{m,it}) = a_{m,t}\exp(\beta_{m,0} + \beta_{m,maj-aadt}log(majorAADT_{m,it}) + \beta_{m,\min-aadt}log(minorAADT_{m,it})) \tag{3}$$

Model 2 (AADT + Roadway factor + Annual multipliers):

$$E(\lambda_{m,it}) = a_{m,t}\exp(\beta_{m,0} + \beta_{m,maj-aadt}log(majorAADT_{m,it}) + \beta_{m,\min-aadt}log(minorAADT_{m,it}) + \sum_{n=1,j=1}^{Q}\beta_{m,j}X_{mn,it}) \tag{4}$$

Model 3 (AADT + Roadway factor + Year):

$$E(\lambda_{m,it}) = \exp(\beta_{m,0} + \beta_{m,maj-aadt}log(majorAADT_{m,it}) + \beta_{\min-aadt}log(minorAADT_{m,it}) + \sum_{n=1,j=1}^{Q}\beta_{m,j}X_{mn,it} + \beta_{m,T}T_{m,it}) \tag{5}$$

where, $majorAADT_{m,it}$ is AADT of major roads at the intersection i on the corridor m in a given year t; $minorAADT_{m,it}$ is AADT of minor streets at the intersection i on the corridor m in a given year t; $X_{mn,it}$ is the n^{th} explanatory variable of roadway geometric features (e.g., the number of exclusive left-turn, right-turn lane(s) and through lane(s) on major or minor streets and the number of access point(s) at an intersection) for the intersection i in a given year t; Q is the total number of explanatory variables of roadway geometric features; $T_{m,it}$ is the year factor which is numeric, for example, 0 if year is 2011, 1 if year is 2012, and so on; $\beta_{m,T}$ is the coefficient for the year factor of Model 3; $\beta_{m,maj-aadt}$is the coefficient for AADT of major roads; $\beta_{m,\min-aadt}$is the coefficient for AADT of minor streets; $\beta_{m,0}$is the intercept and $\beta_{m,j}$is thej^{th} coefficient for roadway geometric features in the model; $a_{m,t}$is the annual multiplier which is obtained by dividing the sum of predicted number of crashes in a given year t by the sum of observed crashes in a given year t after the EB models are fitted.

3.1.1.2. EB Model estimation and evaluation. EB model estimation is performed in the R environment by calling the R package "MASS." Concerns about multicollinearity (MC) occurs if an explanatory variable is a function of other explanatory variables. Potential MC issues are checked by evaluating the Variance Inflation Factor (VIF) statistic. VIF values greater than 10 are used to check whether MC is of concern (O'Brien 2007). Using this criterion, the authors find that no MC issues exist among the explanatory variables used in this study. Akaike's Information Criterion (AIC) is used to select the set of variables used in the regression models (Bumham & Anderson, 2002). The best-fitted model is found with the lowest AIC. For example, roadway geometric features have some variables, including the number of exclusive left-turn lanes, right-turn lanes, and through lanes on major or minor streets and the number of the access points at an intersection. After model selection based on AIC, only a few roadway geometric variables will be kept.

3.1.1.3. EB before-and-after evaluation procedure. The expected number of crashes in the before period E_b, the long-term expected number of crashes for a site, is obtained by combining two different information sources: (1) the observed crash data for a site,O_b, and (2) the sum of the predicted number of crashes during the before period, P_b, estimated by the crash prediction models (i.e., Model 1, Model 2, and Model 3) for the individual site. E_b is obtained by using the following equation (Hauer, 1997; Persaud & Lyon, 2007),

$$E_b = wP_b + (1 - w)O_b \tag{6}$$

The weight factor is estimated from and ψ, which are estimated from the SPF development,

$$w = \frac{1}{1 + P_b/\psi} \tag{7}$$

where $\psi$is the value of the dispersion parameter obtained by the NB regression-based SPF.

A correction factor that accounts for the length of the after period, changes in traffic volumes, and changes in roadway geometric characteristics is multiplied with E_b to obtain the E_a. This factor is the ratio of the sum of the after-period SPF predictions, P_a and the sum of the before-period SPF predictions, P_b. Thus, E_a can be obtained below,

$$E_a = E_b \frac{P_a}{P_b} \tag{8}$$

The observed number of crashes at a site with treatment during the after period (O_a) is then compared to the expected number of crashes on the same site (E_a), which is the expected number of crashes that would have occurred if the treatment had not been implemented. An estimate of the index of safety effectiveness of treatment, θ, is:

$$\theta = \frac{\sum_{all} O_a / \sum_{all} E_a}{1 + Var\left(\sum_{all} E_a\right) / \left(\sum_{all} E_a\right)^2} \tag{9}$$

$$Var\left(\sum_{all} E_a\right) = \sum_{all} \left[(P_a/P_b)^2 E_b (1 - w)\right] \tag{10}$$

where, $\sum_{all} O_a$ is the summation of O_a for all studied sites; $\sum_{all} E_a$ is the summation of E_a for all studied sites.

The estimated percentage of reduction in crashes is $100(1 - \theta)$. For example, a value of $\theta = 0.45$ indicates a 55% decrease in crashes with treatment. The uncertainty of the index of effectiveness (i.e., standard deviation) is calculated by taking the square root of the variance of θ. The variance of θ is (Hauer, 1997; Persaud & Lyon, 2007):

$$Var(\theta) = \frac{\theta^2 \left(\frac{Var\left(\sum_{all} O_a\right)}{\left(\sum_{all} O_a\right)^2} + \frac{Var\left(\sum_{all} E_a\right)}{\left(\sum_{all} E_a\right)^2} \right)}{\left(1 + \frac{Var\left(\sum_{all} E_a\right)}{\left(\sum_{all} E_a\right)^2}\right)^2} \tag{11}$$

In the Eq. (10), the assumption is that the ratio P_a to P_b is a constant variable, not a random variable, which would affect the Eq. (9) and Eq. (11) containing the term $Var\left(\sum_{all} E_a\right)$.

3.1.2. FB models

3.1.2.1. FB model development. A general Poisson-Lognormal model is introduced with multiple hierarchical levels in the following:

$$y_{m,it} P\tilde{o}isson(\lambda_{m,it}) \tag{12}$$

$$\log(\lambda_{m,it}) = \sum_{j=0}^{p} \beta_{mj,B} B_{mj,it} + \varepsilon_{m,it} \tag{13}$$

$$\varepsilon_{m,it} \tilde{N}ormal(0, \sigma_\varepsilon^2) \tag{14}$$

$$\beta_{mj,B} \tilde{N}ormal(0, \sigma_{\beta,j}^2) \tag{15}$$

where, $y_{m,it}$ is the observed crash frequency at the intersection i on the corridor m in a given year t; $\lambda_{m,it}$ is the Poisson mean. $B_{mj,it}$ is the explanatory variable in the model. $\beta_{mj,B}$ is the j^{th} coefficient for the explanatory variable in the model. P is the total number of explanatory variables. The distribution of parameters such as $\lambda_{m,it}$, $\beta_{mj,B}$, and $\varepsilon_{m,it}$ in the model is evaluated based on the estimation of the posterior distribution of these parameters using the FB approach. In the FB models, $\lambda_{m,it}$ is the site-specific expected crash frequency, and each $\lambda_{m,it}$ represents a model parameter. $\varepsilon_{m,it}$ is introduced to account for the variation across intersections and years. σ_ε^2 is assumed to follow a prior Inv-Gamma (0.001, 0.001) distribution for all models based on previous studies (Cai et al., 2018; Carriquiry & Pawlovich, 2004; Sacchi & Sayed, 2014). $\sigma_{\beta,j}^2$ is set to 1000 for all the prior distributions of $\beta_{mj,B}$ for all models resulting in a non-informative prior distribution for $\beta_{mj,B}$ (Persaud et al., 2010). Consequently, estimation of the posterior distribution of $\beta_{mj,B}$ largely depends on observed data.

Three FB non-spatial models are defined in terms of different explanatory variables. Model 4A and Model 5A introduce a random effect to account for variation caused by the various intersections and years, while Model 6A directly treats the year factor as a covariate in the model. Based on the inclusion of the spatial effect into the models, three different FB spatial models-Model 4B, Model 5B, and Model 6B are developed. A corridor-specific ASCS indicator variable $I_{m,it}$ that labels the after period during which ASCS is installed on the corridor m is included as shown below (1 is the after period; 0 otherwise). $\beta_{m,I}$ is the coefficient of the ASCS presence indicator variable of the following models. The authors initially have included the interaction variables into the model to account for the possible interaction between ASCS and AADT and the interaction between ASCS and roadway geometric features in the model. But the interaction variables are not significant. Thus, the interaction variables are not used for the following models.

Model 4A (AADT):

$$\begin{aligned} E(\lambda_{m,it}) = \exp(&\beta_{m,0} + \beta_{m,maj-aadt} log(majorAADT_{m,it}) \\ &+ \beta_{m,\min-aadt} log(minorAADT_{m,it}) + \beta_{m,I} I_{m,it} + \varepsilon_{m,it}) \end{aligned} \tag{16}$$

Model 4B (AADT + Spatial effect):

$$\begin{aligned} E(\lambda_{m,it}) = \exp(&\beta_{m,0} + \beta_{m,maj-aadt} log(majorAADT_{m,it}) \\ &+ \beta_{m,\min-aadt} log(minorAADT_{m,it}) + \beta_{m,I} I_{m,it} + \varepsilon_{m,it} \\ &+ s_{m,i}) \end{aligned} \tag{17}$$

Model 5A (AADT + Roadway factor):

$$\begin{aligned} E(\lambda_{m,it}) = \exp(&\beta_{m,0} + \beta_{m,maj-aadt} log(majorAADT_{m,it}) \\ &+ \beta_{m,\min-aadt} log(minorAADT_{m,it}) + \beta_{m,I} I_{m,it} \\ &+ \sum_{n=1,j=1}^{Q} \beta_{m,j} X_{mn,it} + \varepsilon_{m,it}) \end{aligned} \tag{18}$$

Model 5B (AADT + Roadway factor + Spatial effect):

$$\begin{aligned} E(\lambda_{m,it}) = \exp(&\beta_{m,0} + \beta_{m,maj-aadt} log(majorAADT_{m,it}) \\ &+ \beta_{m,\min-aadt} log(minorAADT_{m,it}) + \beta_{m,I} I_{m,it} \\ &+ \sum_{n=1,j=1}^{Q} \beta_{m,j} X_{mn,it} + \varepsilon_{m,it} + s_{m,i}) \end{aligned} \tag{19}$$

Model 6A (AADT + Roadway factor + Year):

$$\begin{aligned} E(\lambda_{m,it}) = \exp(&\beta_{m,0} + \beta_{m,maj-aadt} log(majorAADT_{m,it}) \\ &+ \beta_{m,\min-aadt} log(minorAADT_{m,it}) + \beta_{m,I} I_{m,it} \\ &+ \sum_{n=1,j=1}^{Q} \beta_{m,j} X_{mn,it} + \beta_{m,T} T_{m,it} + \varepsilon_{m,it}) \end{aligned} \tag{20}$$

Model 6B (AADT + Roadway factor + Year + Spatial effect):

$$E(\lambda_{m,it}) = \exp(\beta_{m,0} + \beta_{m,maj-aadt} log(majorAADT_{m,it}) + \beta_{m,\min-aadt} log(minorAADT_{m,it}) + \beta_{m,I} I_{m,it} + \sum_{n=1,j=1}^{Q} \beta_{m,j} X_{mn,it} + \beta_{m,T} T_{m,it} + \varepsilon_{m,it} + s_{m,i}) \quad (21)$$

where, $s_{m,i}$ could be considered as a latent variable that captures the effect of unknown or unmeasured covariates that are assumed spatially structured. The intrinsic Conditional Autoregressive (CAR) model (Besag et al., 1991) is used for estimating $s_{m,i}$, which is given by:

$$s_{m,i}|s_{m,j} \sim Normal\left(\frac{\sum_{j\in\partial_i} w_{ij}s_{m,j}}{\sum_{j\in\partial_i} w_{ij}}, \frac{1}{\tau_s \sum_{j\in\partial_i} w_{ij}}\right), \quad j \neq i \quad (22)$$

where ∂_i is the set of intersections adjacent to i;w_{ij} is a spatial proximity weight; $\tau_s$is the precision parameter which is the inverse of the variance. τ_s is assumed to follow a prior Gamma (0.001, 0.001) (Cai et al., 2018). $w_{ij}$is equal to 1 for $i \in \partial_i$; otherwise, $w_{ij}$is equal to 0.

3.1.2.2. FB model estimation and evaluation. "OpenBUGS" is open-source software that performs Bayesian inference using the Gibbs sampling algorithm. Bayesian model estimation and MCMC simulation are performed in the R environment by calling the R package "R2OpenBUGS." For each FB model, two Markov chains are used in MCMC simulations. Each chain has 200,000 iterations and a total of 20,000 iterations are discarded during the burn-in (i.e., warm-up) period. Bayesian estimation provides posterior probability distributions and Bayesian Credible Intervals (BCI) for statistical inference. Before implementing the estimation of the posterior distribution of parameters of interest, convergence must be checked in the MCMC simulation. As a rule of thumb, Rhat statistics (i.e., scale reduction factor) less than 1.2 (Brooks et al., 1998) is used to identify convergence. Also, viewing graphical summaries and the number of effective samplings (i.e., the number of independent samples drawn from the posterior distribution in the MCMC simulation) for the parameters of interest could help to check the convergence. Deviance Information Criterion (DIC) can be used to determine the best set of predictors for each FB model (Spiegelhalter et al., 2002). In general, differences of more than 10 (DIC value) may suggest that the FB model with lower DIC is preferred (Spiegelhalter et al., 2002). Also, the significance of the spatial effect is evaluated to determine if the spatial effect exits in the crash data.

3.1.2.3. FB before-and-after evaluation procedure. In the FB before-and-after study procedure, Crash Reduction Rate (CRR) is calculated (Lan et al., 2009; Persaud et al., 2010; Yanmaz-Tuzel & Ozbay, 2010), as

$$CRR = 1 - \frac{\sum_{all} O_a}{\sum_{all} \mu_a} \quad (23)$$

$\frac{\sum_{all} O_a}{\sum_{all} \mu_a}$ is similar to the index of the safety effectiveness used in the EB method.

The observed number of crashes at a site with treatment during the after period (O_a) is compared with the expected number of crashes on the same site (μ_a), which is the number of crashes that would have occurred if the treatment had not been implemented. μ_a can be obtained through developing crash prediction models (i.e., Model 4A, Model 4B, Model 5A, Model 5B, Model 6A, and Model 6B) in the FB procedure. $\sum_{all} \mu_a$ is the summation of μ_a for all studied intersections on a corridor across studied years for corridor-specific safety effectiveness calculation or the summation of for a specific intersection across studied years for intersection-specific safety effectiveness calculation.

CRR is obtained directly by MCMC simulation. The uncertainty of CRR can be evaluated with a 95% BCI by MCMC simulation. The significance of CRR can be determined if the 95% BCI does not contain zero.

3.2. Validation of the before-and-after evaluation methods

This section provides a validation procedure that uses two criteria to validate EB and FB models: (a) the potential bias and variance of prediction, and (b) the estimation accuracy of safety effectiveness. In this way, EB and FB models are compared using the same criteria adopted in this study.

3.2.1. Evaluation of potential bias and variance of prediction

Root Mean Square Error (RMSE) is used to compare the potential bias and variance of prediction among different models. RMSE is also used to measure the quality of an estimator and represent the model prediction error and the model goodness of fit. A lower value of RMSE indicates a smaller difference between the estimated value and the actual observed crash frequency for non-ASCS intersections. The equation is shown below:

$$RMSE = \sqrt{\frac{\sum_{i\in N}\sum_{t\in T}(E_{it} - O_{it})^2}{NT}} \quad (24)$$

where, E_{it} is the expected number of the crashes of non-ASCS intersections in an intersection i in the year t; O_{it} is the observed crashes of non-ASCS intersections in an intersection$i$ in the year t; $N$is the total number of non-ASCS intersections used for validation; T is the total number of years.

In the EB procedure, the expected number of crashes in the subsequent years for a specific intersection can be estimated by multiplying a correction factor due to the difference between the subsequent years and the predecessor year by the expected number of crashes in the predecessor years. For example, the estimated crash in 2012 for an intersection can be obtained by multiplying the correction factor due to the difference between 2011 and 2012 by the expected number of crashes in 2011. Likewise, the estimated crash frequency in 2013, 2014, 2015, 2016, and 2017 can be predicted in this way. In the FB procedure, the expected number of crashes for a specific intersection in a given year can be estimated directly by the MCMC simulation.

3.2.2. Estimation of safety effectiveness of non-ASCS intersections

To evaluate the performance of the candidate models in estimating the safety effectiveness of ASCS, the authors compute and compare the safety effectiveness of ASCS for non-ASCS intersections among different models since no ASCS effect exists for the non-ASCS intersections. So crash reduction percentage for the non-ASCS intersections (i.e., zero) can be deemed as the ground truth. In the EB procedure, the null hypothesis is that the crash reduction percentage is equal to zero, and the alternative hypothesis is that the crash reduction percentage is not equal to zero. In the FB procedure, the significance of the crash reduction percentage is determined if the 95% BCI does not contain zero. To calculate the crash reduction percentage for the non-ASCS intersections, the authors assume that 2011–2014 is the "before period;" 2015–2017 is the "after period" just for creating a case of evaluating the safety effects for the non-ASCS intersections for both EB and FB procedure.

3.3. Investigation of variation of ASCS safety effects

ASCS safety effects could vary across different intersections with different features. The evaluation results of the safety effectiveness of ASCS are analyzed based on different AADT groups, geometric features, and speed limits of intersections. The evaluation results are aggregated by three groups of AADT at major roads: AADT <= 20,000 vehicles/day, 20,000 vehicles/day < AADT <= 50,000 vehicles/day, and AADT > 50,000 vehicles/day. This grouping of AADT is in line with a previous study (Khattak et al., 2019). The evaluation results are aggregated by two groups based on the number of legs at an intersection (i.e., three-legged and four-legged intersections). The evaluation results are aggregated by six groups based on different speed limits at major roads – 30 mph (13.41 m/s), 35 mph (15.65 m/s), 40 mph (17.88 m/s), 45 mph (20.12 m/s), 50 mph (22.35 m/s), and 55 mph (24.59 m/s). A linear regression model is developed to explore the linear relationship between the ASCS safety effects and each variable (i.e., AADT at major or minor roads, speed limits at major or minor roads, the number of legs at an intersection, the number of exclusive left-turn lanes/right-turn lanes/through lanes on major or minor roads, or the number of access points at an intersection) considered in this study.

4. Data description

As shown in Table 1, reference crash data (i.e., no ASCS is installed) are obtained from similar signalized intersections and corridors (e.g., similar roadway geometrics, the location of proximity, and same functional class of corridors) without ASCS at different locations in South Carolina. Crash data from non-ASCS corridors including US 78 in Berkeley, the segment of US 17A without ASCS in Berkeley, US 1 in Lexington, SC 6 in Lexington, the segment of US 29 without ASCS in Greenville, S-311 in Greenville, SC 146 in Greenville, US 17 in Charleston, SC 171 in Charleston, SC 61 in Charleston, and US 17 in Horry are utilized for the reference crash data. Crash data during before period of ASCS corridors are also utilized for the reference crash data to increase the sample size. The sample size of reference crash data is 680 across different years and different signalized intersections. In the EB procedure, the reference crash data are used for developing the EB models first, and then EB models are combined with the crash data from ASCS corridors to predict EB estimates during after period. Different from the utilization of the crash data in the EB procedure, in the FB procedure, the reference crash data and crash data of ASCS corridors are used directly in the FB models since the FB model prediction and safety effect estimation procedure are conducted in a single step. The South Carolina Department of Transportation (SCDOT) has provided the authors with crash data from 2011 to 2018. The crash data include attributes including the crash type and AADT at intersections (major and minor streets). The following

Table 1
Crash Data Usage and Resource.

Crash Data Type	Crash Data Resource
Reference Crash Data	Similar signalized corridors without ASCS (US 78 in Berkeley, the segment of US 17A without ASCS in Berkeley, US 1 in Lexington, SC 6 in Lexington, another segment of US 29 without ASCS in Greenville, S-311 in Greenville, SC 146 in Greenville, US 17 in Charleston, SC 171 in Charleston, SC 61 in Charleston, and US 17 in Horry), and ASCS corridors (before period crash data of SC 642, US 52, US 17, Roper Mt Rd/Garlington Rd, N Lake Drive, and US 17A)
Crash Data for Validation of EB and FB Models	Non-ASCS corridor (US 29) with 24 intersections
Crash Data for Safety Evaluation for ASCS Corridors	Six ASCS corridors with 65 intersections (crash data of SC 642, US 52, US 17, Roper Mt Rd/Garlington Rd, N Lake Drive, and US 17A)

roadway geometric features are also collected from Google Earth: (a) the number of exclusive left-turn lanes, right-turn lanes and through lanes on major or minor streets, and (b) the number of access points within the influence area of an intersection. In terms of crash type, crash data are aggregated in four categories: total crashes, F + I crashes, rear-end crashes, and angle crashes. In this paper, intersection crashes are investigated for evaluating the ASCS safety effect. According to SCDOT's strategy, intersection crashes are those that happened within 0.05 miles (80.47 m) of the center of the intersection.

ASCS has not been installed in the 24 signalized intersections on US 29 corridor in Greenville, and the corridor could be deemed as a non-ASCS corridor. The crash data of US 29 corridor from 2011 to 2017 during which ASCS is not implemented are used for validating EB and FB models.

Initially, the authors got 13 corridors that have installed ASCS. Original crash data have before period and after period data. The authors only include corridors that have at least two-year after period crash data for this study. ASCS safety effects of six ASCS corridors with a total of 65 signals in South Carolina are evaluated. Only one type of ASCS is investigated in this study. For this specific type of ASCS, there are three main components, including the management system (server), local traffic controller(s), and vehicle detection. The server is responsible for processing data and calculating updated timing plans. The local traffic controller is responsible for gathering detection data, as well as executing the commands received from the server. The interaction between the server and the local traffic controller is performed every few seconds to ensure signal timings are always up-to-date. The primary objective of the algorithm of this type of ASCS is to minimize overall traffic delays of the network while guaranteeing reasonable coordination between intersections. It optimizes the cycle length, splits, and offsets in real-time based on traffic conditions while it does not optimize the phase sequence. By handling conflicting traffic movements and establishing dynamic coordination between intersections in real-time, the ASCS can potentially improve the safety of signalized intersections and corridors while improving the operation of corridors.

US 17A in Summerville includes 12 signalized intersections, which have been installed with ASCS since 2015. SC 642 in Charleston consists of 18 signalized intersections, which have been installed with ASCS since 2015. US 52 in Charleston consists of 17 signalized intersections equipped with ASCS since 2016. US 17 in Pawleys Island consists of six signalized intersections equipped with ASCS since 2016. Roper Mt Rd/Garlington Rd in Greenville includes five signalized intersections with ASCS since 2016. N. Lake Drive in Lexington has been implemented with ASCS at seven signalized intersections since 2015. The study crash data pool for safety evaluation excludes crashes that occurred during the ASCS installation year to minimize evaluation bias caused by construction before activating ASCS and driver's adaption to the new driving environment with ASCS.

In order to properly analyze the crash dataset, the authors collected information from SCDOT regarding whether any other possible safety improvements, in addition to the ASCS, have been made at intersections. Flashing Yellow Arrow (FYA) was installed at some signalized intersections before or after the ASCS was installed. The authors consider FYA as one of the explanatory variables of the model. A categorical variable is considered to distinguish the effects of different numbers of FYA at the intersections on the crash frequency outcomes. Offset improvements for left-turn lanes, which have the potential to reduce crashes and crash severity at signalized intersections, were made on one intersection after the ASCS was installed. To exclude the effect of such safety improvements, crashes that occurred during the period after offset improvements were made are not included in the analysis. An additional signal phase was added to one signal after the ASCS was installed, so the crashes that occurred during the period after such changes were made are not included in the analysis as well.

Table 2 shows a summary of descriptive statistics of the geometric features of intersections and speed limits data. The difference in the geometric features of intersections and speed limits between before period and after period is very small.

Table 3 shows descriptive statistics of the intersection crash frequency (i.e., number of crashes per year) for the before and after period for the ASCS corridors with the maximum number of crashes and minimum number of crashes, respectively. The crash frequency statistics show that crashes are over-dispersed (i.e., variance greater than mean) in the total crash, F + I, rear-end and angle crash for the ASCS corridors.

5. Validation results of candidate models

This section provides comparison results of the FB and EB models in terms of: (a) the potential bias and variance of prediction and (b) the estimation accuracy of safety effectiveness. Based on the comparison results, this section could guide to select the best model for evaluating the safety effectiveness of ASCS.

5.1. Comparison of potential bias and variance of prediction

As shown in Table 4, the FB models have lower RMSE values than that of EB models in all scenarios involving different crash types and predictors. Lower RMSE values indicate lower potential bias and variance of prediction.

5.2. Safety effect estimation comparison

As shown in Fig. 1, Model 6A (AADT + Roadway factor + Year) and Model 6B (AADT + Roadway factor + Year + Spatial effect) have the best estimation because the mean of the crash reduction percentage is quite close to zero (in the "rectangle" box in Fig. 1). This finding indicates that adding the year factor as a covariate into the FB non-spatial model and FB spatial model could improve the accuracy of estimation of the safety effectiveness of ASCS. So safety researchers and practitioners are encouraged to include the year factor in before-and-after evaluation studies.

The difference in the mean of the crash reduction percentage between FB non-spatial models and FB spatial models is small. However, based on the FB spatial model estimation, the spatial effect is statistically significant, which indicates that the spatial effects exist. In addition, DIC is compared between FB non-spatial models and FB spatial models. The difference between the DIC of spatial and non-spatial models is more than 10 in all types of models, which indicates that FB spatial models are preferred over the FB non-spatial models. So safety researchers and practitioners are encouraged to include the spatial effects in FB before-and-after evaluation studies.

6. Safety evaluation results

6.1. Corridor-specific evaluation results

Based on the validation results discussed in Section 5, Model 6B that includes AADT, roadway, year factor, and spatial effect, performs best among all models. Six ASCS corridors at different locations in South Carolina are evaluated using Model 6B. Model parameters are not presented in the paper since model parameters for each corridor vary, and presenting model variables will be cumbersome for the paper. Only significant variables of Model 6B for the total crash for SC 642 are shown in Table 5. All variables presented in this table are statistically significant because 95% BCIs do not include zero. A positive sign of an estimate in Table 5 indicates an increase in the number of crashes, while a negative sign of an estimate indicates a reduction in the number of crashes. As presented in Table 5, the variable, the presence of ASCS, is associated with reductions in the number of crashes at intersections. Other variables, year factor, the number of exclusive left-turn lanes on major streets, the number of through lanes/exclusive right-turn lanes/exclusive left-turn lanes on minor streets, the number of access points on major roads, and AADT of major roads and minor roads, are associated with increases in the number of crashes at intersections. The "sigma.spatial effect" variable is statistically significant, indicating that the spatial effects exist on SC 642 and could be captured by a spatial model. The "sigma.random effect" variable is statistically significant, suggesting that the random effect could capture the variations in the crash frequency across intersections and years.

A parameter (the inverse of the square root of the precision parameter indicated in Eq. (22)) of spatial effect estimation is presented in Table 6. The spatial effects are statistically significant for all corridors and crash types since 95% BCIs do not include zero, which indicates that the spatial effects exist on all corridors and could be captured by the spatial model.

Positive signs of values in Table 7 indicate crash increases, while negative signs of values indicate crash reductions. The 95% BCI of each model is shown in the parentheses in Table 7. The ASCS shows crash reductions for the majority of corridors for different crash types.

As shown in Table 7, the highest safety benefits are noted for angle crash for all corridors except US 17A, possibly because the primary objective of the algorithm of this type of ASCS is to minimize total traffic delays of the intersection, which considers the

Table 2
Descriptive Statistics of Intersection Geometric Features and Speed Limits Data.

Variables	Before Period				After Period			
	Mean	S.D.*	Min	Max	Mean	S.D.*	Min	Max
Number of legs at intersections	3.82	0.38	3	4	3.8	0.4	3	4
Number of through lanes on major streets	5.37	1.44	2	8	5.29	1.28	2	8
Number of the exclusive right-turn lanes on major streets	1.2	0.8	0	2	1.16	0.84	0	2
Number of the exclusive left-turn lanes on major streets	2.28	0.91	0	4	2.22	0.89	0	4
Number of through lanes on minor streets	2.16	1.21	0	5	2.14	1.19	0	5
Number of the exclusive right-turn lanes on minor streets	1.02	0.7	0	2	0.87	0.75	0	2
Number of the exclusive left-turn lanes on minor streets	1.81	0.89	0	4	1.89	0.89	0	4
Number of access points within the influence area of intersection on major streets	3.03	1.75	0	7	3.27	1.8	0	7
Number of access points within the influence area of intersection on minor streets	2.38	1.92	0	7	2.39	1.88	0	7
Speed limit on major streets (mph)	42.64	5	25	55	41.47	5.53	25	55
Speed limit on minor streets (mph)	32.15	4.89	25	50	31.78	4.71	25	50

*S.D.-Standard deviation.

Table 3
Crash Frequency (Number of Crashes per Year) Statistics for ASCS Corridors.

Crash Types	Before period				After period			
	Min	Mean	Max	S.D.*	Min	Mean	Max	S.D.*
US 17A	2011–2014				2016–2018			
Total Crash	5	19.40	52	12.04	7	29.5	86	17.65
F + I	0	4.67	15	3.33	0	5.97	22	4.58
Rear-end	1	9.96	35	8.13	1	14.06	50	10.50
Angle	0	5.88	18	3.76	2	8.06	20	4.16
Roper Mt Rd/Garlington Rd	2011–2015				2017–2018			
Total Crash	0	4.96	23	6.61	0	7.40	28	10.20
F + I	0	0.68	4	1.22	0	0.90	3	1.20
Rear-end	0	3.60	18	4.47	0	5.40	23	7.95
Angle	0	1	8	1.96	0	1.40	7	2.37

*S.D.-Standard deviation.

Table 4
RMSE for EB and FB models.

Model		RMSE			
		Total Crash	F + I	Rear-end	Angle
EB Models	Model 1 (AADT + Annual SPF multipliers)	9.91	5.59	7.07	4.49
	Model 2 (AADT + Road + Annual SPF multipliers)	9.83	5.59	6.92	4.44
	Model 3 (AADT + Road + Year)	9.75	5.54	6.67	4.43
FB Non-spatial Models	Model 4A (AADT)	1.23	1.04	1.31	1.09
	Model 5A (AADT + Road)	1.26	1.01	1.34	1.09
	Model 6A (AADT + Road + Year)	1.15	0.97	1.23	1.01
FB Spatial Models	Model 4B (AADT + Spatial effect)	1.24	0.97	1.30	1.03
	Model 5B (AADT + Road + Spatial effect)	1.31	0.98	1.34	1.05
	Model 6B (AADT + Road + Year + Spatial effect)	1.22	0.91	1.24	0.95

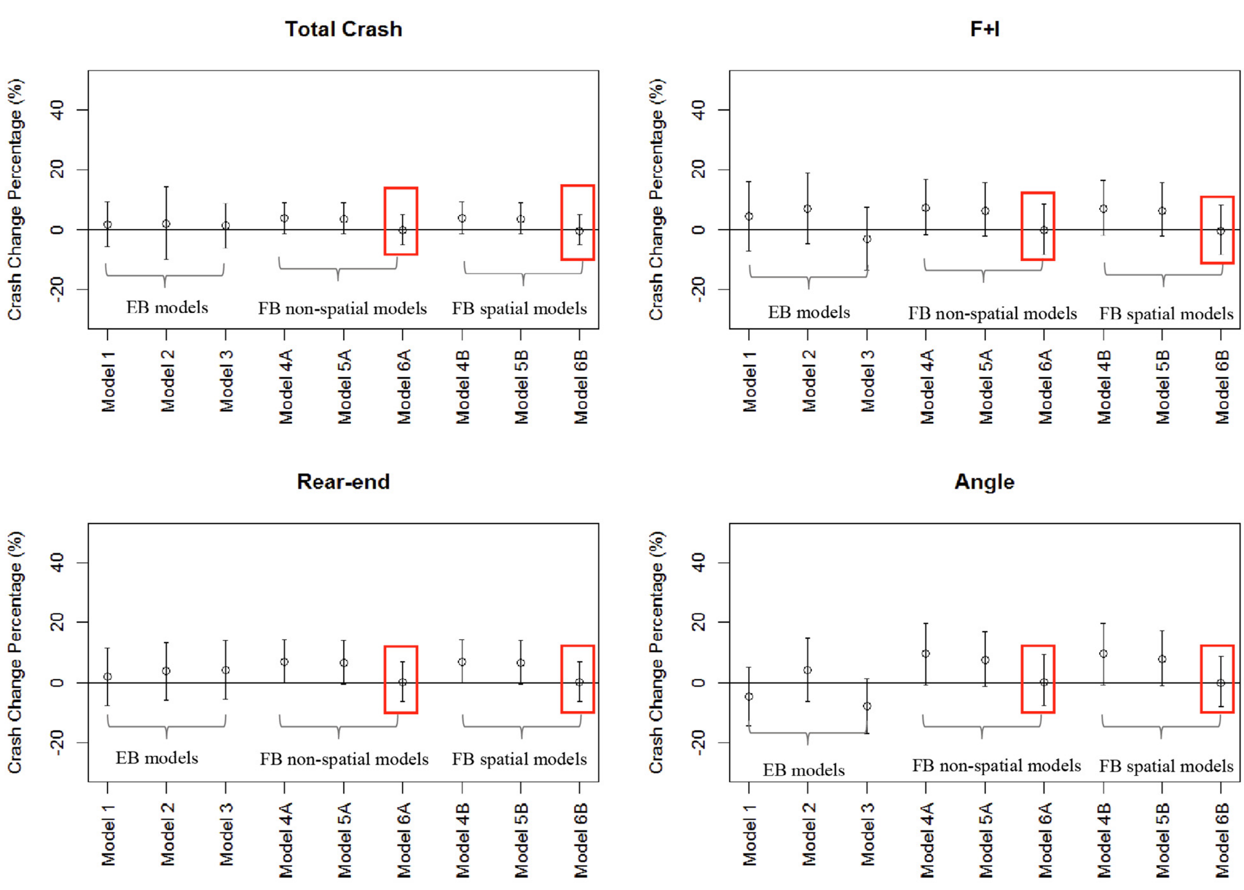

Fig. 1. Crash Change Percentage with 95% CI among EB Models and with 95% BCI among FB Models.

Table 5
Model estimates for the total crash evaluation for SC 642.

Variable	Estimate	95% BCI
The presence of ASCS	−0.40	(−0.61, −0.18)
Year factor	0.12	(0.10, 0.15)
The number of exclusive left-turn lanes on major streets	0.07	(0.001, 0.13)
The number of through lanes on minor streets	0.08	(0.03, 0.12)
The number of exclusive right-turn lanes on minor streets	0.22	(0.14, 0.30)
The number of exclusive left-turn lanes on minor streets	0.28	(0.21, 0.35)
The number of access points on major roads	0.06	(0.04, 0.09)
Log (AADT of major roads)	0.75	(0.63, 0.87)
Log (AADT of minor roads)	0.22	(0.18, 0.26)
Intercept	−8.34	(-9.61, −7.08)
sigma.spatial effect[a]	0.65	(0.35, 1.06)
sigma.random effect[b]	0.60	(0.56, 0.64)

a: the inverse of the square root of the precision parameter indicated in Eq. (22).
b: the square root of the variance in Eq. (14).

traffic demand from side streets. The algorithm of the ASCS potentially decreases the number of angle conflicts.

For rear-end crashes, three corridors (i.e., US 52, N. Lake Drive, and US 17A) shows ASCS increases in rear-end crashes, possibly because ASCS deployed on these corridors tends to achieve balanced service for all vehicle movements, thus minimizing number of stops along corridors (fewer stops may lead to fewer rear-end crashes) tends to be of lower priority than minimizing delay. In addition, the side traffic demand is relatively high among these corridors; thus it may interrupt the major traffic flow.

For US 52, ASCS shows a crash increase in F + I, possibly because the speed limit difference between major streets and minor streets at intersections is relatively high (over 14 mph), which leads to higher crash severity levels.

6.2. Intersection-specific evaluation results

The safety effectiveness of ASCS is also evaluated for each intersection. As shown in Fig. 2, a negative value means that ASCS reduces crashes. The figure shows that most of the intersections with ASCS show crash reductions for all crash types except the rear-end crash. The ASCS increases in rear-end crashes, possibly because ASCS deployed on these intersections tends to achieve balanced service for all vehicle movements, and minimizing the number of stops at intersections (fewer stops may lead to fewer rear-end crashes) tends to be of lower priority than minimizing delay.

The evaluation results are aggregated by three groups of AADT at major roads: AADT less than or equal to 20,000 vehicles/day (sample size = 14), AADT between 20,000 vehicles/day and 50,000 vehicles/day (sample size = 48), and AADT greater than 50,000 vehicles/day (sample size = 3). This grouping of AADT is in line with a previous study (Khattak et al., 2019). As shown in Fig. 3 (b), for F + I cashes, there is a linear relationship between the crash change due to the ASCS and different AADT groups based on the regression analysis. Higher AADT decreases ASCS safety benefits in reducing the F + I crashes. The possible reason could be that higher traffic volume may be associated with more severe crashes. As shown in Fig. 3 (a), (c), and (d), for the total crash, rear-end crash, and angle crash, crash changes due to the ASCS are not statistically different between different AADT groups based on the regression analysis.

Table 6
Spatial Effect Estimation for Each Corridor.

Corridor-specific Model	Spatial Effect Estimation (95% BCI)			
	Total Crash	F + I	Rear-end	Angle
SC 642	0.65 (0.35∼1.06)	0.30 (0.03∼0.89)	0.49 (0.22∼0.87)	0.39 (0.09∼0.85)
Roper Mt Rd	1.24 (0.15∼3.3)	0.67 (0.03∼2.81)	0.59 (0.03∼2.21)	4.75 (1.15∼15.11)
US 17 Pawleys Island	0.28 (0.03∼0.92)	0.18 (0.03∼0.68)	0.45 (0.05∼1.24)	0.18 (0.03∼0.67)
US 52	0.31 (0.06∼0.71)	0.12 (0.03∼0.36)	0.36 (0.06∼0.84)	0.48 (0.13∼0.96)
N. Lake Drive	0.56 (0.14∼1.25)	0.92 (0.19∼2.10)	0.27 (0.03∼0.81)	0.87 (0.32∼1.89)
US 17A	0.33 (0.03∼0.84)	0.21 (0.03∼0.63)	0.29 (0.03∼0.79)	0.45 (0.05∼1.01)

Table 7
Corridor-specific Safety Effect Estimation.

Location	Crash Change Percentage (95% BCI)			
	Total Crash	F + I	Rear-end	Angle
SC 642	−32.2%* (−45.0%∼−17.4%)	−16.3% (−36.7%∼8.5%)	−16.7% (−34.3%∼5.1%)	−41.7%* (−55.8%∼−24.8%)
Roper Mt Rd	−41.1%* (−64.9%∼−8.1%)	−73.7%* (−88.7%∼−52.6%)	−3.4% (−45.5%∼54.3%)	−92.0%* (−99.4%∼−75.3%)
US 17 Pawleys Island	−49.8%* (−66.8%∼−27.2%)	−46.7%* (−68.2%∼−16.3%)	−39.4%* (−61.1%∼−9.8%)	−57.4%* (−73.3%∼−35.2%)
US 52	−4.6% (−25.7%∼20.8%)	+16.2% (−15.7%∼55.9%)	+0.4% (−24.4%∼30.5%)	−15.6% (−37.8%∼11.8%)
N. Lake Drive	−6.5% (−31.2%∼24.4%)	−26.8% (−52.1%∼6.4%)	+3.2% (−25.8%∼39.5%)	−28.0% (−51.0%∼1.8%)
US 17A	+19.7% (−5.7%∼19.8%)	−31.8%* (−49.8%∼−10.0%)	+17.1% (−9.7%∼49.4%)	+10.8% (−15.4%∼42.8%)

*: statistically significant in terms of 95% BCI (FB).

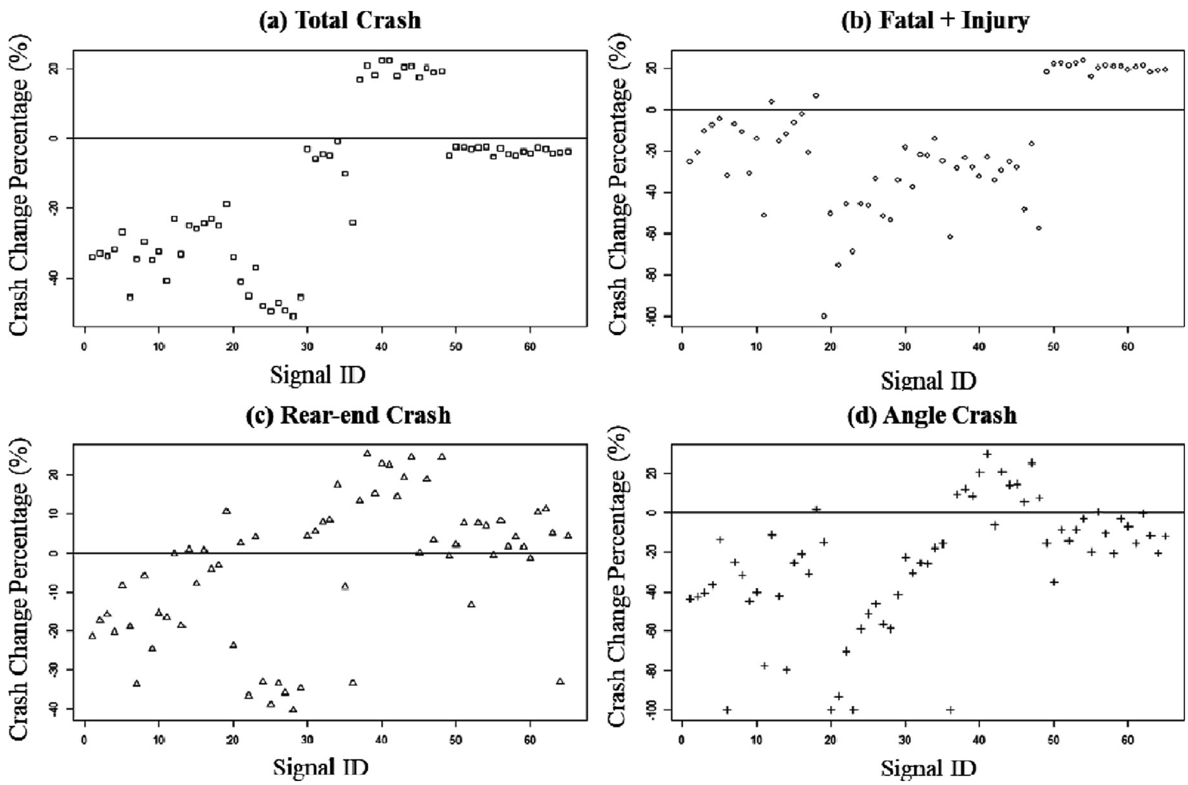

Fig. 2. Percent Change of Crashes due to ASCS at Each Intersection for Different Crash Types.

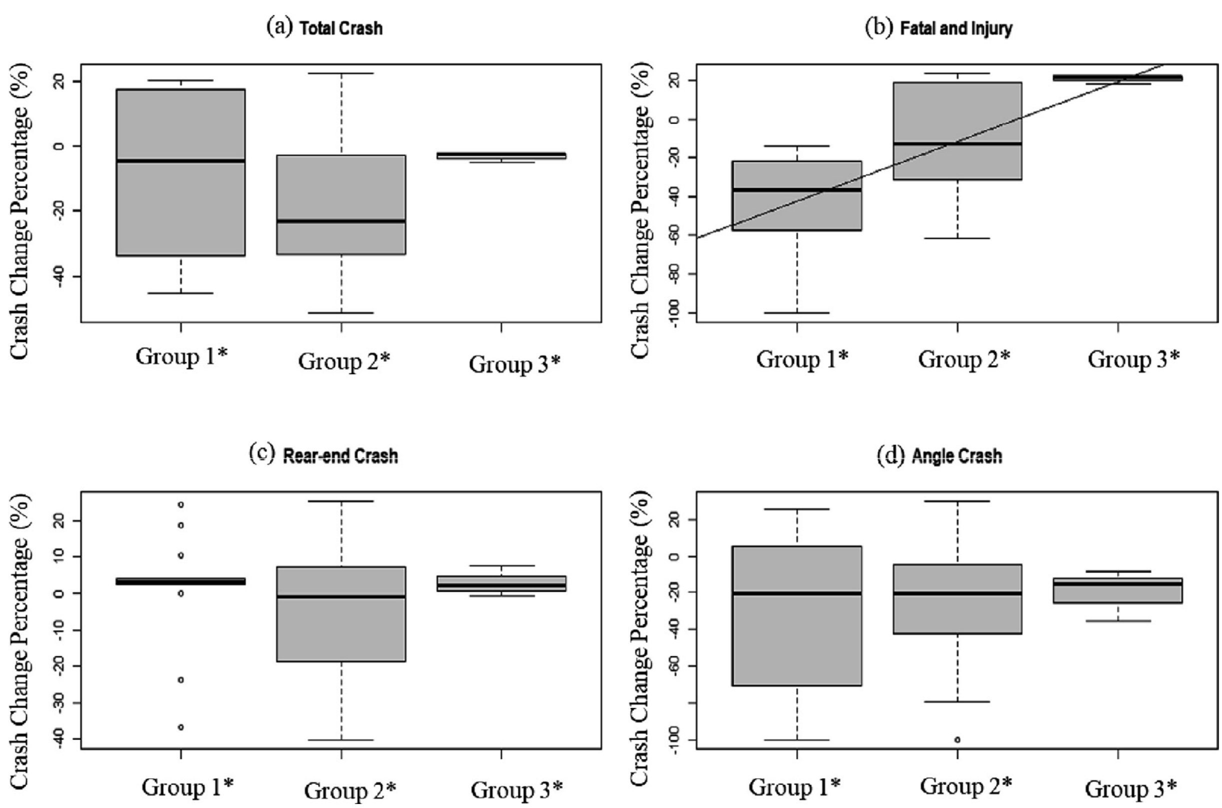

Fig. 3. Evaluation results aggregated by AADT of major roads *: Group 1 (sample size = 14): AADT <= 20,000 vehicles/day; Group 2 (sample size = 48): 20,000 vehicles/day < AADT <= 50,000 vehicles/day; Group 3 (sample size = 3): AADT > 50,000 vehicles/day.

The evaluation results are aggregated by two groups based on the number of legs at an intersection, that is, three-legged (sample size = 16) and four-legged intersections (sample size = 49). As shown in Fig. 4 (b), for F + I crashes, the crash reduction due to the ASCS is more considerable in the four-legged intersection compared to the three-legged intersection and the crash reduction due to the ASCS is statistically different between the four-legged intersection and three-legged intersection based on the regression analysis. As shown in Fig. 4 (a), (c), and (d), for the total crash, rear-end crash, and angle crash, crash changes due to the ASCS are not statistically different between four-legged intersections and three-legged intersections based on the regression analysis.

Additionally, the evaluation results are aggregated by six groups based on different speed limits at major roads – 30 mph (13.41 m/s), 35 mph (15.65 m/s), 40 mph (17.88 m/s), 45 mph (20.12 m/s), 50 mph (22.35 m/s), and 55 mph (24.59 m/s). As shown in Fig. 5 (a) and (c), for the total crash and rear-end crash, there is a linear relationship between the ASCS safety benefits and different speed limits based on the regression analysis. The ASCS safety benefit in reducing the total crash and rear-end crash increases as the speed limit increases. As shown in Fig. 5 (b), the ASCS safety benefit in lowering F + I crashes decreases as the speed limit increases based on the regression analysis. It is expected that the higher average speed may be associated with higher severe crashes. As shown in Fig. 5 (d), for the angle crash, it is found that there is no linear relationship between the crash change due to the ASCS and different speed limits based on the regression analysis.

A linear regression model is developed to explore the linear relationship between the ASCS safety effects and each continuous variable (i.e., the number of exclusive left-turn lanes/right-turn lanes/through lanes on major or minor streets, or the number of access points at an intersection) considered in this study. Based on our analysis, for F + I crashes, as the number of through lanes on major streets increases, the ASCS safety benefit decreases. More number of through lanes on major streets are associated with higher traffic volume, so the ASCS safety benefit decreases with the increasing traffic volume. For the total crash, rear-end crash, and the angle crash, there is no linear relationship between the safety effectiveness of the ASCS and the number of through lanes on major streets. For the F + I crashes, as the number of access points on minor streets increases, the ASCS safety benefit increases. The possible reason could be that the average speed of the traffic is lower due to the interruption of traffic from/to the access points, so the severe crashes are reduced. For the total crash, rear-end crash, and the angle crash, there is no linear relationship between the safety effectiveness of the ASCS and the number of access points on minor streets.

For all crash types (i.e., total crash, F + I, rear-end crash, and angle crash) considered in this paper, based on the regression analysis, there is no linear relationship between the safety effectiveness of ASCS and AADT of minor roads, the number of the exclusive right-turn lanes on major streets, the number of the exclusive left-turn lanes on major streets, the number of through lanes at minor streets, the number of the exclusive right-turn lanes on minor streets, the number of the exclusive left-turn lanes on minor streets, the number of access points on major streets, and the speed limit at minor streets.

7. Conclusions

This paper develops a series of models, including the Poisson-Lognormal models, Poisson-Gamma models, and spatial models that are implemented in the EB and FB before-and-after studies. Different EB and FB models are validated using real-world non-ASCS intersections. The uniqueness of this paper is that it investigates how model variations would affect: (a) potential bias (e.g., bias due to regression-to-the-mean, traffic volume changes, and roadway geometric feature changes) and variance of prediction and (b) estimation accuracy of safety effectiveness. The findings would provide useful guidance for determining appropriate mod-

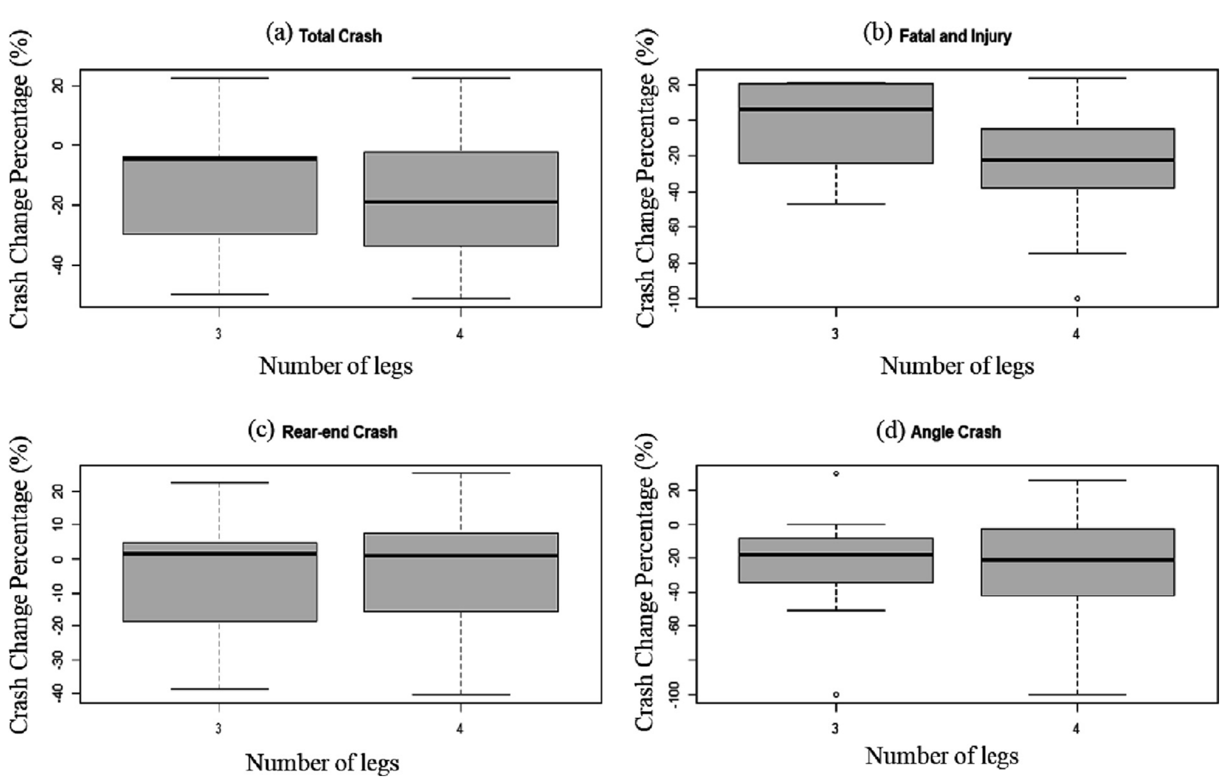

Fig. 4. Evaluation results aggregated by number of legs at an intersection.

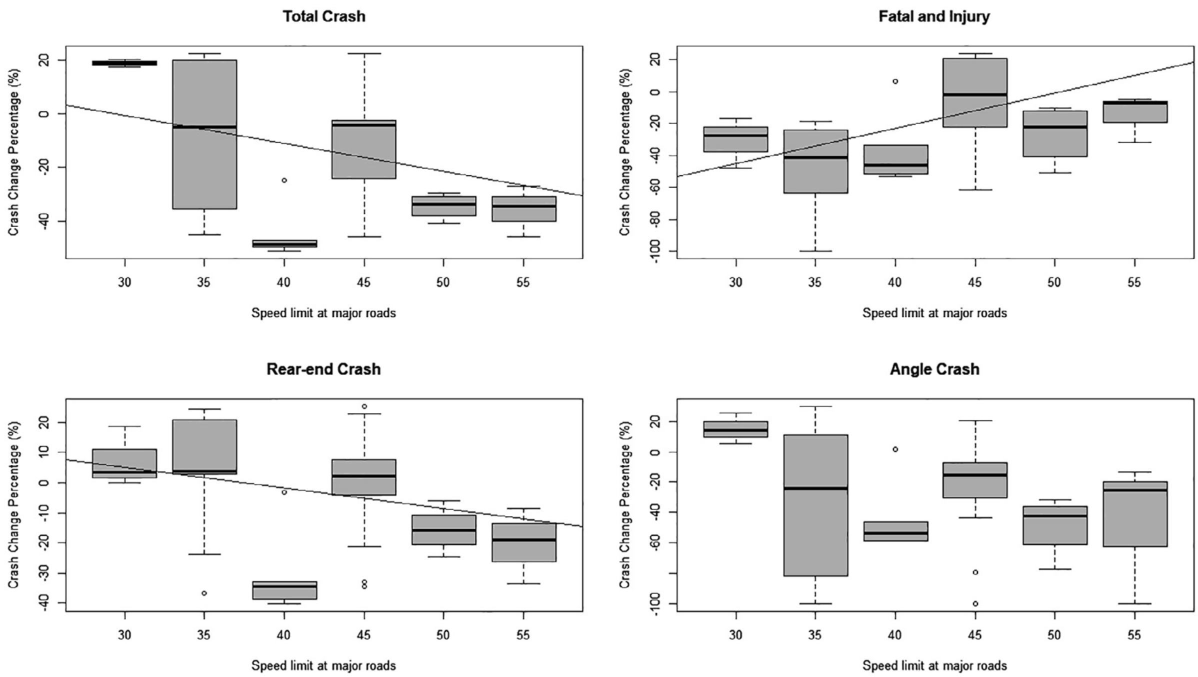

Fig. 5. Evaluation results aggregated by speed limits at major streets**. Sample size for each speed limit: 30 mph: 3; 35 mph: 12; 40 mph: 6; 45 mph: 37; 50 mph: 4, 55 mph: 3.

els for before-and-after safety studies. The FB model that accounts for traffic volume, roadway geometric features, year factor, and spatial effects shows the best performance in reducing potential bias and variance of prediction and improving the accuracy of safety effect estimation.

This paper then applies the best FB model to the safety evaluation of ASCS and evaluates the safety effectiveness of ASCS at six corridors with a total of 65 signalized intersections. ASCS shows crash reductions for most of corridors and intersections. It is also found that the safety effectiveness of ASCS varies across the intersections with different features (i.e., AADT at major streets, number of legs at an intersection, the number of through lanes on major streets, the number of access points on minor streets, and the speed limit at major streets).

Although this paper discusses different explanatory variables such as AADT, roadway geometric features, and year factor, other possible explanatory variables such as weather conditions, socio-economic factors may be accounted for in developing the crash prediction model. Gaussian CAR distribution is used in the spatial model. However, other distributions of spatial models, such as double exponential distribution and multivariable Gaussian distribution, could be implemented in the spatial model. The effect of neighboring weight matrix structures, such as distance-based weights and exponential decay-based weights on spatial models, may be evaluated in future work.

8. Practical applications

The association between ASCS and crash reductions encourages more ASCS deployments. The variation of the safety effectiveness of ASCS with different intersection features provides insights into selecting ASCS deployment sites for reducing crashes.

9. Declarations of Interest

None.

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