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A full Bayes before-after study accounting for temporal and spatial effects: Evaluating the safety impact of new signal installations

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ABSTRACT

Recently, important advances in road safety statistics have been brought about by methods able to address issues other than the choice of the best error structure for modeling crash data. In particular, accounting for spatial and temporal interdependence, i.e., the notion that the collision occurrence of a site or unit times depend on those of others, has become an important issue that needs further research.

Overall, autoregressive models can be used for this purpose as they can specify that the output variable depends on its own previous values and on a stochastic term. Spatial effects have been investigated and applied mostly in the context of developing safety performance functions (SPFs) to relate crash occurrence to highway characteristics. Hence, there is a need for studies that attempt to estimate the effectiveness of safety countermeasures by including the spatial interdependence of road sites within the context of an observational before-after (BA) study. Moreover, the combination of temporal dynamics and spatial effects on crash frequency has not been explored in depth for SPF development.

Therefore, the main goal of this research was to carry out a BA study accounting for spatial effects and temporal dynamics in evaluating the effectiveness of a road safety treatment. The countermeasure analyzed was the installation of traffic signals at unsignalized urban/suburban intersections in British Columbia (Canada). The full Bayes approach was selected as the statistical framework to develop the models.

The results demonstrated that zone variation was a major component of total crash variability and that spatial effects were alleviated by clustering intersections together. Finally, the methodology used also allowed estimation of the treatment's effectiveness in the form of crash modification factors and functions with time trends.

1. Introduction

A variety of statistical methods have been employed to analyze crash data. Recently, crash data modeling has resorted to increasingly sophisticated statistical techniques to uncover new inferences relating crash occurrence to highway characteristics and to randomness and the unobserved heterogeneity of the data. The main outcome from the modeling process is typically a regression model that produces an estimate of the collision frequency for a location based on the traffic exposure (volume) and site-specific traffic and geometric characteristics (i.e., a safety performance function (SPF)) Traditionally, the techniques used to develop SPFs have accounted for Poisson variation (crashes are random, discrete, non-negative and sporadic events) and extra-Poisson variation due to potential population heterogeneity that leads to over-dispersion (Miaou, 1994).

In addition to the Poisson error structure, other count data distributions have been proposed over the years to deal with specific crash data issues (Lord and Mannering, 2010). Recently, important advances in the field have been brought about by methods able to address issues other than the choice of the best error structure for modeling crashes. In particular, accounting for spatial and temporal effects (dependencies), has become an important issue that needs further research. Overall, autoregressive (AR) models can be used for this purpose as they can specify that the output variable depends on its own previous values and on a stochastic term. In doing so, it is possible to study unobserved factors due to the spatial proximity of road sites or temporal dynamics of crash frequency (Miaou et al., 2003).

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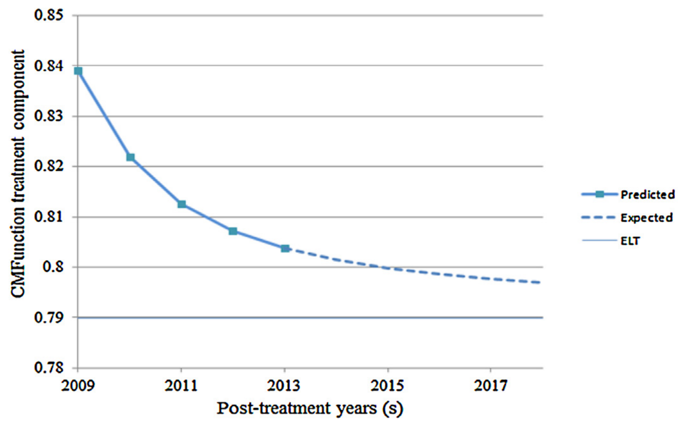

Fig. 1. Estimated and expected profile of the CMFunction treatment component for total collisions.

Regarding unobserved factors, the recent inclusion of spatial effects in the development of SPFs has been gaining considerable attention (Aguero-Valverde and Jovanis, 2008; El-Basyouny and Sayed, 2009). For example, researchers have used the Gaussian conditional autoregressive (CAR) distribution for hierarchical models to account for local spatial dependencies. CAR specifications are introduced through random effects in the mean structure of the data. In the literature, it has been demonstrated that the inclusion of spatial effects can be a surrogate for unknown and relevant covariates, thereby improving model estimation (Dubin, 1988; Cressie, 1992; El-Basyouny and Sayed, 2009).

To accommodate temporal dynamics in crash occurrence, nonlinear intervention models have been recently proposed to account for potential changes in the slope of crash frequency over time at road sites, which might be attributable to a safety treatment (intervention) (El-Basyouny and Sayed, 2012a). They have been successfully applied to longitudinal (before-after) road safety studies. The nonlinear intervention models aim to represent the lagged treatment effects that are distributed over time. They are alternative dynamic regression forms that involve a first-order autoregressive (AR1) SPF based on distributed lags and can accommodate various profiles for the treatment effects. Examples of these advanced SPFs applied to observational before-after (BA) studies can be found in El-Basyouny and Sayed, (2012a) for the evaluation of general intersection improvements, El-Basyouny and Sayed (2012b) for rumble strips, and Sacchi and Sayed (2014) for evaluating signal visibility improvements.

Spatial effects have been investigated and applied mostly in the context of SPF development to relate collision occurrence and highway characteristics. Hence, there is a need for studies that attempt to estimate the effectiveness of safety countermeasures by including the spatial and temporal dependencies of road sites within the context of a BA study. In fact, including spatial effects within a nonlinear intervention model can represent an important contribution to road safety analysis.

Therefore, the main goal of this paper is to conduct an observational before-after study accounting for spatial effects and temporal dynamics in evaluating the safety impact of a road safety countermeasure. The treatments analyzed were traffic signal improvements at urban/suburban intersections in British Columbia (Canada).

The full Bayes (FB) approach was selected as the statistical framework to develop the models. The FB method has several advantages over the well-known empirical Bayes technique, including the ability to allow inference at more than one level for hierarchical (multi-level) models, conduct a multivariate analysis (Park et al., 2010; El-Basyouny and Sayed, 2011), treat each time period as an individual data point, and integrate the estimation of the safety performance function (SPF) and treatment effects in a single step—whereas those are two separate steps in the EB method (Persaud et al., 2010).

Finally, the methodology used can estimate the treatment's effectiveness in the form of a crash modification factor (CMF) and crash modification functions (CMFunction) with temporal trends to analyze how the treatment impact was spread over time (Sacchi et al., 2014).

2. Installation of new traffic signals

A number of treatments can be implemented at intersections to ensure safer and more efficient traffic operations. One of these treatments is the installation of traffic signals. In the literature, several studies have shown that, under appropriate circumstances, traffic signals can lead to safer conditions by separating conflicting movements in time and providing efficiency in traffic operations (HSM, 2010; Chandler et al., 2013). The effects are generally a decrease in severe head-on and angle crashes and an increase in less severe rear-end crashes.

The effectiveness of installing new signals has been the focus of several studies. The earlier studies were carried out using road safety evaluations that did not control for confounding factors. For instance, Short et al. (1982) analyzed the safety impact of signal installations in Wisconsin with a simple before-after approach. They found a significant decrease (34%) in right-angle crashes, a significant increase in rear-end and other crashes, and no or little change in non-severe crashes. More recently, a National Cooperative Highway Research Program (NCHRP) study that aimed to develop the crash experience warrant for traffic signals at four-legged intersections showed that new signal installations cause an overall reduction of 23% for injury crashes, 67% for right-angle crashes, and an increase in rear-end crashes by 38% (McGee et al., 2003). Other studies performed across the United States showed that signal installation could result in a 15% to 20% reduction in overall crashes and an approximate 60% reduction in right-angle crashes (Ermer and Sinha, 1991; Thomas and Smith, 2001; Agent et al., 1996; Gan et al., 2005). Finally, Aul and Davis (2006) analyzed 18 intersections where new signals were installed in Minneapolis–Saint Paul, Minnesota. Even though the reduction/increase in right-angle and rear-end crashes (respectively) were found similar in direction to the NCHRP study, the authors found no change in crash frequency for the total number of intersection-related crashes.

Table 1
Summary descriptive statistics for collision data at study sites.

Sites	Statistics	Annual average collision frequency					
		Before period			After period		
		Total	PDO	F + I	Total	PDO	F + I
All	Mean	30.75	19.29	11.45	27.83	15.96	11.87
	Minimum	1.25	0.50	0.75	1.25	0.75	0.50
	Maximum	131.75	92.25	48.00	123.25	75.00	48.25
	Standard deviation	26.49	17.80	9.24	23.25	14.47	9.46
Treatment (19 sites)	Mean	8.33	5.14	3.18	6.36	3.72	2.63
	Minimum	1.25	0.50	0.75	2.50	1.25	0.50
	Maximum	15.50	9.75	6.50	13.25	8.50	5.50
	Standard deviation	3.81	2.62	1.52	3.14	2.07	1.46
Comparison (107 sites)	Mean	34.73	21.81	12.92	31.64	18.13	13.51
	Minimum	1.75	1.00	0.75	1.25	0.75	0.50
	Maximum	131.75	92.25	48.00	123.25	75.00	48.25
	Standard deviation	26.81	18.18	9.26	23.21	14.64	9.34

3. The evaluation data set

The data set, which was provided by the Insurance Corporation of British Columbia (ICBC), included 19 intersections in Metro Vancouver, Fraser Valley, and Okanagan where new traffic signals were installed between 2008 and 2010. In addition, a total of 107 comparison intersections were carefully selected according to their geographic proximity and similarity in geometric design/traffic control features. Total, fatal-plus-injury (F + I), and property-damage-only (PDO) collision data from 2005 to 2013, as well as traffic volume data in the form of approach average annual daily traffic (AADT), were available. Table 1 shows statistics for collision data at both treatment and comparison sites during the years preceding and following the interventions.

A map was obtained and used to determine the number of neighboring intersections (n_i). Various neighboring structures were considered in previous studies (Aguero-Valverde and Jovanis, 2008). Based on those results as well as others reported in the literature, only first-order neighbors were shown to be worth considering. This study used first-order neighbors to define the neighboring structure, similar to (El-Basyouny and Sayed, 2009). First-order neighbors included all intersections having a direct connection with the treated intersection under consideration. It turned out that the 126 intersections (i.e., 19 + 107) belong to K = 11 zones, where each zone represents the area containing all sites (treatment and comparison) in close proximity to each other and with similar geometric design/traffic control characteristics.

4. Modeling framework

Consider an observational before-after study where collision data are available for a reasonable period of time (3–5 years) before and after the intervention. In addition, a set of collision data for the same period of time is available for a comparison group similar to the treatment sites (time-series cross-sectional modeling). Let Y_{it} denote the collision count recorded at site i (i = 1, 2, . . ., n) during year t (t = 1,2, . . ., m). It is assumed that collisions at the n sites are independent and that

$$Y_{it}|\lambda_{it}\sim Poisson(\lambda_{it}). \quad (1)$$

To address over-dispersion for unobserved or unmeasured heterogeneity, it is assumed that

$$\lambda_{it} = \mu_i \exp(\varepsilon_{it}), \quad (2)$$

where, μ_i is determined by a set of covariates representing site-specific attributes and a corresponding set of unknown regression parameters; whereas, the term $\exp(\varepsilon_i)$ represents a multiplicative random effect.

The negative binomial (Poisson-gamma) model is obtained by the assumption

$$\exp(\varepsilon_i)|k\sim Gamma(k, k) \quad (3a)$$

where, k is the inverse dispersion parameter. Alternatively, the Poisson-lognormal (PLN) regression model is obtained by the assumption

$$\exp(\varepsilon_i)|\sigma_\varepsilon^2\sim \text{Log normal}(0, \sigma_\varepsilon^2) \text{or} \varepsilon_i|\sigma_\varepsilon^2\sim \text{Normal}(0, \sigma_\varepsilon^2). \quad (3b,c)$$

Spatial Poisson models can be defined by incorporating a spatial random effect in Eq. (2) as follows:

$$\lambda_{it} = \mu_{it} \exp(\varepsilon_{it}) \exp(s_{it}). \quad (4)$$

The spatial component s_i suggests that sites closer to each other are likely to have common features affecting their accident occurrence. As noted by Miaou and Lord (2003), random variations across sites may be structured spatially due to the complexity of the traffic interaction around locations. Guided by the results in the literature (e.g., Nicholson, 1999; Aguero-Valverde and Jovanis, 2008), only first-order spatial autocorrelation models were considered.

4.1. Accounting for temporal dynamics

To investigate the association between crash frequency and covariates, it is necessary to define the term μ_{it}. A way to define μ_{it} is using the so-called "intervention" model, which has been available in the literature for some time (Li et al., 2008; El-Basyouny and Sayed, 2011). An intervention model is a piecewise linear or non-linear function of the covariates designed to accommodate a possible change in the slope of crash frequency over time at treatment sites, which might be attributable to the intervention.

However, it should be noted that in (Li et al., 2008; El-Basyouny and Sayed, 2011), linear slopes were assumed to represent the time and treatment effects across the treated and comparison sites in the regression term μ_{it}. To overcome potential shortcomings of the linear slopes assumption, El-Basyouny and Sayed (2012b) advocated the use of the nonlinear "Koyck" intervention model (Koyck, 1954) to represent the lagged treatment effects that are distributed over time. The Koyck model is an alternative dynamic regression form involving a first-order autoregressive (AR1) SPF that is based on distributed lags. The model affords a rich family of forms (over the parameter space) that can accommodate various profiles for the treatment effects. Therefore, the Koyck model is used as an alternative nonlinear intervention model to estimate the effectiveness of safety treatments in BA designs. Recently, a comparison of several Bayesian evaluation techniques has shown the advantages of using the nonlinear intervention model for BA studies (Sacchi and Sayed, 2015).

Apart from the logarithm of the annual average daily traffic (AADT) at the major and minor approaches (V_{1it} and V_{2it} for intersections) as for baseline SPFs, there are other covariates for crash frequency that can be included in the Koyck model: an indicator of whether the site was an intervention site or a comparison site (a treatment indicator T_i equal to 1 for treated sites, 0 for comparison sites), a time indicator for a sudden drop in crash frequency at the time of the intervention (I_{it} equal to 1 in the after period, 0 in the before period), and a two-way interaction to allow a different intervention slope across the treated and comparison sites. Moreover, the treatment effects can be modeled using distributed lags along with the AR1 model as a proxy for the time effects (Judge et al., 1988; Pankratz, 1991). The regression equation for the rational distributed lag model is given by (El-Basyouny and Sayed, 2012a):

$$\ln(\mu_{it}) = \alpha_0 + \alpha_1 T_i + [\omega/(1-\delta B)]I_{it} + [\omega^*/(1-\delta B)]T_i I_{it} + \beta_1 \ln(V_{1,it}) + \beta_2 \ln(V_{2,it}) + \nu_t, \quad (5)$$

where B denotes the backshift (lag) operator that operates on an element, Z, of a time series to produce the previous element($e.g., BZ_t = Z_{t-1}$), $|\delta| < 1$, and ν_t satisfies the following stationary AR1 equation:

$$\nu_t = \phi \nu_{t-1} + e_t,\ |\phi| < 1,\ e_t \sim \mathrm{N}(0, \sigma_\nu^2),\ \mathrm{t} = 2, 3, \ldots, \mathrm{m}. \quad (6)$$

Consider the expansion $(1-\delta B)^{-1} I_{it} = I_{it} + \delta I_{i,t-1} + \delta^2 I_{i,t-2} + \ldots$, and note that the rational distributed lag model depicts an everlasting treatment effect, as $\ln(\mu_{it})$ is tacitly assumed to be a function of the infinite distributed lags ($I_{it}, I_{i,t-1}, I_{i,t-2}, \ldots$). The parsimonious model (Eq. (5)) is known as the Koyck model (Koyck, 1954), in which the lag weights $\omega\delta^k$ and $\omega^*\delta^k$ decline geometrically for $k = 0, 1, 2, \ldots$. Consequently, the earlier years following the intervention are more heavily weighted than distant years. It should also be noted that although the weights never reach zero, they will eventually become negligible. The two parameters ω and ω^* are impact multipliers, which account for the intervention effects across treated and comparison sites; whereas, δ is a decay parameter controlling the rate at which the weights decline.

An extensive review of the Koyck model applied to road safety and the derivations to implement it in a statistical software can be found in (El-Basyouny and Sayed, 2012b; Sacchi et al., 2014).

4.2. Accounting for spatial effects

The Gaussian CAR models proposed by Besag et al. (1991) are among the most commonly used for modeling spatial effects. Let $C(i)$ and s_{-i} represent the set of neighbors of site i and the set of all spatial effects except s_i, respectively. The Gaussian CAR model is given by Eq. (7):

$$s_i | s_{-i} \sim Normal(\bar{s}_i, \sigma_s^2/n_i),\ \bar{s}_i = \sum\nolimits_{j \in C(i)} s_j/n_i \quad (7)$$

Eq. (7) is based on an adjacency-based proximity measure: $w_{ij} = 1$ if sites i and j are neighboring sites and $w_{ij} = 0$ otherwise. The conditional mean is the mean of adjacent special effects, while the conditional variance is inversely proportional to the number of neighbors.

5. Estimating crash modification factors and functions

CMFs and CMFunctions can be employed to measure the effectiveness of a safety treatment. Let L_{TBi} and L_{TAi} denote the averages of $\ln(\mu_{it})$ for the treated sites over the appropriate years during the before and after periods, respectively, and let L_{CBi} and L_{CAi} denote the averages of $\ln(\mu_{it})$ for the comparison sites, where $\ln(\mu_{it})$ are averaged over the appropriate sites (all sites in the matching comparison group) and years. Therefore, by averaging the predicted collisions on the log-scale, a set of treatment effectiveness indices can be obtained from

$$\ln(\theta_i) = L_{TAi} + L_{CBi} - L_{TBi} - L_{CAi}. \quad (8a)$$

and

$$\ln(\theta) = (1/n)\sum\nolimits_{i=1}^{n} \ln(\theta_i). \quad (8b)$$

Although the estimate of θ is subject to a small amount of bias, it is typically negligible (Ezra, 1997). Hence, the overall CMF is equivalent to θ, while the overall percentage of reduction in predicted collision counts is given by $(1-\theta) \times 100$.

The indices in Eq. (8a) and (8b) were developed in parallel to Park et al. (2010). The difference is that they average μ_{it} first and then take the logarithm, but we here propose to compute $\ln(\mu_{it})$ first and then average. However, the non-linear logarithmic function $\ln(x)$ is approximately linear for a large value of x, in which case the difference would be negligible. Thus, it is conjectured that the difference between the two approaches would be fairly small in most of the before-after traffic safety studies carried out in practice unless the observed collision counts are fairly small.

The following subsection presents the mathematical steps that lead to the estimation of the CMFunction with time trends.

5.1. CMFunction with time trends

It has been demonstrated in previous research (El-Basyouny and Sayed, 2012a, 2012b) that the components of the CMFunction for the *ith* treated site after s post-intervention years can be written:

$$\theta_{is} = K_1(i,s) K_2(i,s) K_3(i,s) K_4(i,s), \quad (12)$$

where,

$$K_1(i,s) = [\theta_{i,s-1}]^{\phi} = [\theta_{i1}]^{\phi^{s-1}}, \quad (13a)$$

$$K_2(i,s) = \exp\{c + d(1-\delta^s)/s\},\ \mathrm{c} = \omega^*(1-\phi)/(1-\delta),\ \mathrm{d} = \omega^*(\phi-\delta)/(1-\delta)^2, \quad (13b)$$

$$K_3(i,s) = [\theta(V_{1is})]^{\beta_1} / [\theta(V_{1i,s-1})]^{\phi\beta_1}, \quad (13c)$$

$$K_4(i,s) = [\theta(V_{2is})]^{\beta_2} / [\theta(V_{2i,s-1})]^{\phi\beta_2}, \quad (13d)$$

The component $K_1(i,s)$ corresponds to the time (novelty) effects. After the first year of the intervention, the subsequent novelty component will either grow or decline exponentially at a rate of ϕ according to whether $\theta_{i1} < 1$ or $\theta_{i1} > 1$. In both cases, $K_1(i,s)$ converges to 1 (since $|\phi| < 1$).

The treatment component of the CMFunction (Eq. (13b)) describes a non-linear relation of s involving the impact multiplier ω^* along with the AR1 parameter ϕ and the decay parameter δ. In the long run, $K_2(i,s)$ converges to $\exp\{c\}$, which corresponds to the everlasting (permanent) treatment (ELT) impact.

The components $K_3(i,s)$ and $K_4(i,s)$ represent the effects of major and minor traffic volumes, respectively. The numerator is the current traffic volume index raised to a fractional power (β_1 and β_2) and thereby would be close to 1. Yet, the denominator would be even closer to 1, as the power of the previous year's index is much smaller ($\phi\beta_1 < \beta_1$ and $\phi\beta_2 < \beta_2$). Thus, unless the traffic volumes are subject to significant annual fluctuations, these components are expected to be near 1. $K_3(i,s)$ and $K_4(i,s)$ are inversely related to the indirect (through traffic volumes) local impact under the Koyck model.

6. Results

6.1. Parameters used for posterior estimates

The statistical software WinBUGS (Spiegelhalter et al., 2005) was chosen as the modeling platform to obtain the FB estimates. The models in Eqs. (1)–(7) were fitted assuming the whole set of regression parameters to be non-informative with zero mean and a large variance, i.e., Normal(0, 10^3), to reflect the lack of precise knowledge of their value (prior distribution). Variances (i.e., ${\sigma_e}^2$ and ${\sigma_v}^2$) were assumed as Inverse-Gamma (0.001, 0.001), the AR1 parameter φ as Normal(0,1) (not to impose stationarity), and the decay parameter δ as Uniform(-1, 1).

For the Gaussian CAR model, it was shown (Breslow and Clayton, 1993) that Eq. (7) is equivalent to $f(s_{1,\ldots,}s_n|\sigma_s^2) \propto \sigma_s^{-n}\exp\{-\sum n_i s_i(s_i-\bar{s}_i)/2\sigma_s^2\}$, which provides the correct likelihood function for σ_s^2. The term contributed by each site is $\ell_i = n_i s_i(s_i-\bar{s}_i)$. A proper prior $Gamma(1+\sum \ell_i/2, 1+n/2)$ is assumed for σ_s^{-2}. It was also shown (Bernardinelli et al., 1995) that the marginal variance σ_{sm}^2 of the spatial effects is approximated by $\sigma_{sm}^2 \approx 2\sigma_s^2/\bar{n}$, where $\bar{n} = \sum n_i/n$. Following Congdon (2006), it is assumed that $\sigma_u^2 = c^2\sigma_{sm}^2$, where c is a discrete random variable having a discrete uniform prior over the 19 values {0.1, 0.2, . . . 0.9, 1, 2, . . ., 10}.

The impact of spatial correlation is assessed by computing the proportion of total variation that is due to spatial variation:

$$\Psi_s = \frac{\mathrm{var}(s)}{\mathrm{var}(s)+\sigma_\varepsilon^2} \tag{14}$$

where, var(s) represents the marginal variance of s. For the CAR model, var(s) can be estimated directly from the posterior distribution of s.

The BUGS code produced draws from the posterior distribution of the parameters, and given those draws, MCMC techniques were used to approximate the posterior mean and standard deviation of the parameters. Hence, the posterior summaries were computed by running 40,000 iterations of two independent Markov chains for each of the parameters in the models. Chains were thinned using a factor of 10 and the first 10,000 iterations in each chain were discarded as burn-in runs. The convergence was monitored by reaching ratios of the Monte Carlo errors relative to the standard deviations for each parameter smaller than 5%, using the BGR statistics of WinBUGS (Gelman et al., 2004) and also visual approaches such as observing trace plots.

6.2. Model parameter and CMF estimate

The results of applying the modeling framework for the proposed case study are presented below. F+I, PDO and total collision models were implemented individually, and therefore, three sets of parameters were obtained for each model. Table 2 lists the mean values and standard deviations of the coefficients.

The magnitude and sign of the parameters were found in line with the ones observed in other similar studies (El-Basyouny and Sayed, 2012b. In the results, the treatment site indicator ($_{\alpha 1}$) was found significantly negative for all severity types, indicating a lower collision frequency at treatment sites. The slopes due to the intervention (ω) as well as the combined intervention-time effects across sites (ω^*) showed a different mix of signs for each severity type. The decay and AR1 parameters showed positive and negative signs, for total/F+I and PDO respectively, indicating different slopes for the treatment component $K_2(i, s)$ (see next section). Finally, the traffic volume coefficients (β_1 and β_2) were found to be significantly positive, confirming the direct effect of exposure on the increase of collision frequency.

With regards to the extra-Poisson variation, the magnitudes of ${\sigma^2}_\varepsilon$ demonstrated the presence of over-dispersion in the data. The proportions of total variability due to spatial variation (Ψ_s) were overwhelming, with magnitudes equal to 0.988, 0.987, and 0.856 for total, PDO, and F+I collisions, respectively. In addition, the goodness of fit of this model was compared to the one of a parsimonious model without spatial and temporal effect components. This was done by means of the deviance information criteria (DIC). The DIC is a Bayesian generalization of Akaike's information criterion (AIC) that penalizes larger parameter models. According to the DIC guidelines, deviations of more than 10 units might definitely rule out the model with the higher DIC (El-Basyouny and Sayed, 2009). Overall, the DIC for the model for total crashes was 7272 compared to 7327 for the parsimonious model (a difference of 55). This indicates the superior fit of the model with the spatial and temporal effects. Similar results were also obtained for F + I and PDO models.

Table 3 shows the resulting treatment effectiveness indexes (i.e., the CMFs) for all sites. Overall, the signal improvements reduced markedly severe (F + I) collisions by 21.8%. PDO collisions were reduced by 10.2% and total collisions by 16%, which were found in agreement with the percentages reported in the literature.

It is also interesting to note that the reductions were more marked for severe than non-severe crashes. This is in good agreement with the results presented in the literature review that indicated a decrease in severe (head-on and angle) crashes and an increase in less severe (rear-end) crashes. For this study, the reduction of PDO crashes for new signal only is, in fact, not statistically significant at the 95% confidence level.

7. Discussion

Overall, the results showed that zone variation was a major component of total variability and that spatial effects were alleviated by clustering intersections together, as demonstrated by the spatial correlation indicator (Ψ_s).

From a statistical point, the model framework made it possible to ascertain whether variation remained after accounting for known and measured covariate effects, and whether the residual effects suggested spatial patterns or clusters. The presence of residual effects can also be seen as a surrogate for unknown and geo-demographics covariates. For this reason, from a more transportation engineering perspective, the model framework suggested that neighboring regions may share common infrastructures (network features) and present similar demographic/socio-economic characteristics. As a result, similar road and traffic environments and similar road users' behavior can eventually lead to similar road safety levels.

The use of demographic/socio-economic characteristics to analyze road safety is actually not new in the field. Different research has linked socio-economic variables, such as unemployment, low income, area of residence, educational level, to road safety. See for instance Abdalla et al. (1997), Noland and Quddus (2004), and Lovegrove and Sayed, (2006).

7.1. CMFunction estimates

As shown in Table 3, the treatment effectiveness was estimated as a constant that did not change in the post-treatment period. However, a CMFunction with time trend can be estimated by means of Eq. (12) to analyze how the implemented countermeasure affected safety over time.

Table 2
Parameter estimates for all severity models.

Variable	Parameter	Mean ± Standard Deviation		
		Total	PDO	F + I
Intercept	α_0	−6.276 ± 0.955	−7.548 ± 1.282	−7.870 ± 1.152
Treatment site indicator	α_1	−0.813 ± 0.150	−0.719 ± 0.168	−0.518 ± 0.158
Major AADT	β_1	0.557 ± 0.078	0.590 ± 0.094	0.750 ± 0.094
Minor AADT	β_2	0.120 ± 0.051	0.210 ± 0.073	0.258 ± 0.064
Decay parameter	δ	0.312 ± 0.380	0.661 ± 0.245	−0.127 ± 0.370
AR1 parameter	φ	0.075 ± 0.079	−0.044 ± 0.278	0.009 ± 0.060
Impact	ω	−0.030 ± 0.024	−0.073 ± 0.034	0.050 ± 0.033
mul-	ω^*	−0.175 ± 0.102	−0.081 ± 0.057	−0.358 ± 0.150
St. deviation of e_t	σ_v	0.055 ± 0.020	0.056 ± 0.020	0.058 ± 0.021
Extra-Poisson variation	$\sigma^2{}_\varepsilon$	0.192 ± 0.028	0.180 ± 0.031	0.153 ± 0.034
Structured/unstructured spatial effect relation	c	0.968 ± 0.055	0.942 ± 0.074	0.873 ± 0.097
Spatial variation	$\sigma^2{}_s$	1.097 ± 0.155	1.082 ± 0.159	1.069 ± 0.163
Spatial correlation	Ψ_s	0.988 ± 0.006	0.987 ± 0.007	0.856 ± 0.193

Table 3
CMF estimates for total and severity types.

	CMF	Mean ± Standard Deviation		
		Total	PDO	F + I
All sites	θ	0.840 ± 0.054	0.898 ± 0.070[a]	0.782 ± 0.073
	$(1-\theta)\times 100$	16%	10.2%	21.8%

[a] CMF < 1.0 not significant at the 95% confidence level.

Given that there were no significant traffic volume changes for treatment sites from the before to the after period, the indexes defined in terms of the major and minor AADT, $\theta(V_{is})$ (see Eqs. (13c) and (13d)), were equal to 1.0. Therefore, the only relevant components of the CMFunction were the treatment element and the time (novelty) effects, $K_2(i, s)$ and $K_1(i, s)$ respectively. It was found that $K_1(i, s)$ ranged between 0.99 and 1 at almost all sites, in different post-treatment years, for all the severity levels (except F+I values for the first post-treatment year only, which ranged between 1 and 1.03). This indicates that the $K_1(i, s)$ value has a negligible impact on the treatment's effectiveness.

For all these reasons, it was possible to show how the safety countermeasure affected collision frequency over time by analyzing only the CMFunction treatment component, $K_2(i, s)$. Fig. 1 illustrates its profile during the post-treatment period for total collisions (bold blue line). Similar graphs can also be obtained for F+I and PDO collisions. Overall, the treatment component has slightly decreased over time, with a consequent improvement in safety. Moreover, the CMFunction treatment component can be projected onto a future time period (i.e., not included in the data set), as in the long term $K_2(i, s)$ converges to $\exp\{c\}$. This latter term corresponds to the everlasting treatment (ELT) impact. Therefore, it is reasonable to plot the expected CMFunction reduction components also for the post-treatment years not included in the data set (dashed line in Fig. 1).

This plot represents a powerful and valuable tool especially since it can have a significant impact on the economic evaluation of safety programs and countermeasures, as current evaluation techniques assume constant CMFs over time.

8. Conclusions

This research focused on including spatial effects and temporal dynamics in evaluating the effectiveness of new traffic signal installations at urban/suburban intersections in British Columbia, Canada.

With regards to the treatment itself, the results showed that traffic signal improvements led to a reduction of collision frequency. These reductions were more marked for severe (−21.8%) than non-severe crashes (−10.2%). These trends were in agreement with the results found in the literature that indicated a more marked reduction of severe (head-on and angle) crashes than non-severe (rear-end) crashes.

The use of the proposed modeling framework also demonstrated that: (1) zone variation was a major component of crash variability and that spatial effects were alleviated by clustering intersections together; (2) the methodology used allowed the estimation of the treatment effectiveness in the form of CMFs and time-varying CMFunctions. For instance, the resulting CMFunction for total crashes indicated that the treatment component has slightly increased over time, with a consequent improvement in safety.

Overall, the results of this paper strongly support the incorporation of spatial effects and temporal trends in BA studies. However, there is a need to further investigate some important issues. First, this study used first-order neighbors to define the neighboring structure, where first-order neighbors included all intersections having a direct connection with the treated intersections; however, it might be argued that a first-order definition might produce different results when urban or rural setting are considered. In fact, the distance of first-order neighbors in rural or suburban setting can be potentially larger than the distances between first-order neighbors in urban areas. Similarly, it is also important to further investigate if different characteristics in terms of geometric design and traffic control features can have an impact on spatial variation as this study focused only on signalized intersections. Finally, for this study the number of treatment and comparison sites was selected by the government insurance agency "ICBC" and was fixed. Hence, it would be interesting to explore how the variation of number of sites, especially in terms of ratio of treatment versus comparison sites, can affect the outcome on spatial effects.

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