Before–After Safety Evaluation Using Full Bayesian Macroscopic Multivariate and Spatial Models

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Many studies have addressed spatial correlation in traffic collision modeling. It has been generally concluded that the inclusion of spatial correlation improves model goodness of fit and the precision of parameter estimates. However, the application in before–after safety evaluation has rarely been documented in the traffic safety literature. The objectives of the presented study were to (*a*) apply both the univariate and multivariate full Bayesian (FB) spatial models in before–after safety evaluation and (*b*) compare the results with those of nonspatial FB models. A reduction of the posted speed limit in urban residential neighborhoods in Edmonton, Alberta, Canada was used as a case study for the before–after safety evaluation. Yearly collision data and other neighborhood characteristics data were collected for a group of treated and reference neighborhoods to develop macroscopic models. The four models considered in this study were (*a*) Poisson–lognormal, (*b*) Poisson–lognormal with conditional autoregressive (CAR) distribution, (*c*) multivariate Poisson–lognormal, and (*d*) multivariate Poisson–lognormal with CAR distribution. The results showed that the multivariate Poisson–lognormal with CAR distribution model for collision severities outperformed the other three models according to the deviance information criteria. Parameter estimates showed slight differences across the models. However, for the current data set, the results of the before–after safety evaluation showed similar findings across the models. Estimated collision reductions were 13%, 24%, and 12% for total, severe, and property-damage-only collisions, respectively.

An important step in the road safety management process is to conduct a before–after safety evaluation of the effects of implemented treatments (*1*). The evaluation results can be used not only for economic justification of the treatments but also for future decision making related to the allocation of funds and selection of treatment.

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The empirical Bayesian (EB) method is the state-of-the-art technique for performing safety evaluations and has been used extensively in the past two decades (*1*). The method proposed by Hauer has several advantages over simple before–after evaluation methods, including that it addresses the regression-to-the-mean bias (*2*).

Recently, several studies have used the full Bayesian (FB) univariate and multivariate methods in before–after safety evaluation (*3–14*). The FB method is reported to have a number of advantages over the EB method, including the ability to account for uncertainty in the data, fewer data requirements, and more flexibility in the selection of collision distributions (*8*). Many previous applications of the FB method used the benefits of this method.

A major advantage of the FB method is its ability to consider spatial correlation in model formulation (*14*). Many cross-sectional studies have included spatial correlation in the FB method and concluded that the inclusion of spatial correlation improves model goodness of fit and the precision of parameter estimates. However, its application in before–after safety evaluation has rarely been documented in the traffic safety literature.

The unit of analysis in most collision models is often either an intersection or a road segment; hence, the unit of analysis for before–after safety evaluation is microscopic. However, for networkwide interventions, such as neighborhood speed limit reduction, application of the same methodology will require a separate evaluation for intersections and road segments, and then they can be combined to obtain the complete evaluation (*1*). This approach requires substantial traffic data, which may not be readily available, especially for low-volume road segments and unsignalized intersections. Therefore, a macroscopic (i.e., area-level or network-level) analysis could be an effective alternative approach to evaluating such safety interventions.

The present study (*a*) applies both univariate and multivariate FB macroscopic spatial models in before–after safety evaluation and (*b*) compares the results with those of nonspatial FB models. A posted speed limit (PSL) reduction in urban residential neighborhoods was used as a case study for a before–after safety evaluation. Yearly collision data and other neighborhood characteristics data (population, dwelling unit, employment distribution, age distribution, etc.) were collected for a group of treated and reference urban residential neighborhoods for the development of macroscopic models. Two spatial models considered in this study were univariate Poisson–lognormal (PLN) with conditional autoregressive (CAR) distribution and multivariate PLN (MVPLN) with multivariate CAR distribution. For nonspatial models, PLN and MVPLN models were used.

LITERATURE REVIEW

The need to consider spatial correlation in collision data analysis was raised by several researchers in the late 1990s (*15–17*). Later, many studies developed advanced statistical models to address spatial correlation in collision data. Studies on collision modeling that considered spatial correlation can be divided into two categories: univariate and multivariate.

Most studies adopted univariate spatial models for analyzing collision data (*18–25*). These studies often compared the univariate spatial model with univariate nonspatial models and found that the spatial model outperformed the nonspatial model. Therefore, it was almost unequivocally concluded that the collision data exhibits spatial correlation and that ignorance of this fact in modeling could result in biased parameter estimation.

A limitation of univariate spatial models is that they do not address the correlations between collision severity levels or types; rather, each collision severity level or type is modeled separately. Earlier studies demonstrated that the collision data of different severity levels or types are correlated (*26*). This correlation reflects that the number of collisions of different severity levels or types at a particular site is likely to rise as a result of the same deficiencies in site design or other unobserved factors or both (*26*).

Few studies focused on a multivariate spatial modeling approach in collision data analysis. Song et al. made four assumptions on spatial correlation for modeling four types of collisions (intersection collisions, intersection-related collisions, driveway-related collisions, and nonintersection-related collisions) (*27*). Using data from 254 counties in Texas, the authors found that the model with multivariate CAR and the univariate model with correlated CAR outperformed the model with univariate CAR. The deviance information criterion (DIC) drop was reported as 13.6 when the multivariate CAR model was compared with the univariate CAR model (*28*).

Aguero-Valverde used univariate and multivariate spatial models to estimate excess collision frequency for 81 cantons (*29*). A variety of canton-level characteristics were included as independent variables in the model. Multivariate spatial models were found to be better fitted to the data, with a DIC drop of 10, compared with the univariate spatial models. However, the variances of the spatial errors were not significant. The author stated that this effect could be related to the small number of spatial units, as only 81 cantons were used. The author also ranked sites by using the models and found that the ranking of sites was similar for both models, but the spatial smoothing related to the multivariate CAR random effects was evident in some extreme values.

Similarly, Wang and Kockelman compared multivariate spatial models with univariate spatial and multivariate nonspatial models for pedestrian collisions (*30*). Using data for 218 zones, the authors concluded that the multivariate CAR model outperformed the other two models with a very large drop in DIC values.

Narayanamoorthy et al. also proposed a spatial multivariate count model to jointly analyze the traffic collision–related counts of pedestrians and bicyclists by injury severity (*31*). Census tract was used as a unit of analysis in the proposed model. The results suggested that ignoring spatial effects can result in substantially biased estimation of the effects of exogenous variables. However, no comparison with univariate spatial models was made.

A recent study by Barua et al. used two data sets to compare the performance of multivariate CAR models with univariate CAR models (*32*). It was reported that the multivariate spatial models provided a superior fit over the univariate spatial models with a significant drop in the DIC value (35.3 for one data set and 116 for the other).

From the methodological standpoint on including spatial correlation in collision modeling, various approaches have been used in the literature. However, the most frequently used approach is CAR distribution for modeling spatial correlation. Quddus compared several distributions to address spatial correlation and found that CAR distribution under a Bayesian framework can provide more appropriate and better inference over classical spatial models (*21*). El-Basyouny and Sayed compared three spatial models [CAR, multiple membership (MM), and extended MM (EMM)] with a nonspatial PLN model (*22*). The authors found that the EMM and CAR models provided similar goodness of fit and outperformed the PLN and MM models.

Many univariate studies were found in the literature but only a few multivariate studies with spatial correlation. These few studies suggest the importance of including multivariate spatial correlation in collision modeling. However, to what extent these advanced statistical models affect the before–after safety evaluation results is not known. This paper discusses the use of both univariate and multivariate macroscopic spatial models in a before–after safety evaluation of urban residential PSL reduction and compares the results with those of nonspatial models. The findings from this study will enhance the current understanding of before–after safety evaluation methodology.

DATA DESCRIPTION

The study applied the proposed before–after safety evaluation methodology for an urban residential PSL reduction pilot program in the city of Edmonton, Alberta, Canada. The PSL reduction process began in October 2009, the final implementation starting on May 1, 2010. Eight neighborhoods were selected for reduction of the PSL from 50 to 40 km/h. The PSL in five neighborhoods reverted to 50 km/h in October 2011, while it remained at 40 km/h for the other three neighborhoods. Islam et al. provided detailed information on the reasons for the PSL reduction initiative, as well as the neighborhood selection process (*33*).

The *Highway Safety Manual* (HSM) recommends use of 3 years of collision data for both the before and after periods and even multiples of 12 months to perform the before–after safety evaluation (*1*). Moreover, it is recommended to exclude the entire year during which the safety intervention is implemented.

According to the time line of the pilot program and the HSM recommendation, the study defined the calendar year as October to September, using October 2006 to September 2009 as the before period and October 2010 to September 2013 as the after period to perform the safety evaluation. For three of the treated neighborhoods, 3 years of after period data were available for the analysis, while for five neighborhoods, only 1 year of after period data were available.

In addition to the eight treated urban residential neighborhoods, another 210 urban residential neighborhoods with the PSL remaining at 50 km/h were selected as a reference group. To avoid substantial changes in neighborhood characteristics during the analysis period, it was ensured from census data that none of these neighborhoods were undergoing major development.

Collision data obtained from the Motor Vehicle Collision Information System maintained by the City of Edmonton were processed and aggregated by neighborhood for each of the 6 years with a geographic information system. Because the PSL reduction was limited to the roads within the neighborhood and excluded the neighborhood boundary roads, the collision data aggregated by neighborhood also excluded boundary collisions. The data were recorded as one of three severity types: fatal, injury, and property damage only (PDO). Because of the small number of fatal collisions, fatal and injury collisions were combined into a new category, referred to as severe collisions.

In addition to the yearly collision data gathered, exposures, road and traffic characteristics, and sociodemographic data were collected for both the treated and reference neighborhoods to develop the macroscopic model. These data were collected from various databases with both manual and automatic processes. The City of Edmonton's Spatial Land Inventory Management database was used to obtain some of the geometric variables, such as area of the neighborhood and total lane kilometers. The sociodemographic variables were obtained from the available 2008, 2009, 2012, and 2013 municipal census data. The neighborhood vehicle kilometers traveled (VKT) data were obtained from the planning model. Tables 1 and 2 present the summary statistics of the data for reference and treated neighborhoods, respectively. As shown in these tables, a comprehensive set of data was collected to conduct this study.

METHODOLOGY

Four models were developed in the study for performing a before–after safety evaluation: (*a*) PLN, (*b*) MVPLN, (*c*) PLN with CAR distribution (PLN-CAR), and (*d*) MVPLN with multivariate CAR distribution (MVPLN-CAR).

PLN Model

Let Y_{it}^{k} denote the observed collision count at neighborhood i ($i = 1, 2, \ldots, n$) during time period t for a severity level k ($k = 1, 2, \ldots, K$).

TABLE 1 Summary Statistics of Reference Group Data

Variable	Mean	SD	Minimum	Maximum
Before (October 2006–September 2009)				
Total collisions/year	29.15	30.87	0	215
Severe collisions/year	3.43	5.51	0	37
PDO collisions/year	25.72	26.03	0	184
log (VKT)	7.66	0.94	4.09	9.28
Population/year	3,125	1,438	385	8,923
Proportion of students/year	0.24	0.06	0.07	0.43
Proportion of part-time employees/year	0.05	0.01	0.02	0.08
Proportion of full-time employees/year	0.44	0.06	0.14	0.57
Proportion of unemployed/year	0.02	0.01	0.00	0.07
Proportion of retired persons/year	0.12	0.06	0.02	0.38
Dwelling unit/year	1,245	659	118	5,162
Proportion of males/year	0.50	0.02	0.39	0.63
Proportion of population age ≤ 15	0.15	0.04	0.00	0.28
Proportion of population age ≤ 65	0.11	0.06	0.01	0.40
Proportion of households with 0 cars	0.09	0.08	0.00	0.41
Proportion of households with ≥ 2 cars	0.49	0.17	0.08	0.86
After (October 2010–September 2013)				
Total collisions/year	24.11	25.95	0	178
Severe collisions/year	2.47	3.78	0	23
PDO collisions/year	21.64	22.66	0	158
log (VKT)	7.68	0.94	4.13	9.29
Population/year	3,279	1,654	332	10,659
Proportion of students/year	0.23	0.05	0.07	0.42
Proportion of part-time employees/year	0.06	0.01	0.01	0.12
Proportion of full-time employees/year	0.40	0.06	0.14	0.53
Proportion of unemployed/year	0.02	0.01	0.001	0.07
Proportion of retired persons/year	0.12	0.05	0.02	0.32
Dwelling unit/year	1,323	716	116	5,214
Proportion of males/year	0.50	0.02	0.40	0.59
Proportion of population age ≤ 15	0.14	0.04	0.03	0.26
Proportion of population age ≤ 65	0.11	0.05	0.02	0.36
Proportion of households with 0 cars	0.09	0.08	0.00	0.41
Proportion of household with ≥ 2 cars	0.49	0.17	0.08	0.86
Number of traffic signals	0.58	1.38	0	8
Collector road length (km)	2.17	1.39	0	11.05
Local road length (km)	8.06	4.00	0	21.08
Total road length (km)	10.23	4.76	1.38	32.14
Old neighborhood (1 for yes, 0 for no)	0.23	0.42	0	1
Grid neighborhood (1 for yes, 0 for no)	0.12	0.32	0	1
New neighborhood (1 for yes, 0 for no)	0.52	0.50	0	1

NOTE: Sample size = 210.

TABLE 2 Summary Statistics of Treated Group Data

Variable	Mean	SD	Minimum	Maximum
Before (October 2006–September 2009)				
Total collisions/year	33.92	23.78	4	93
Severe collisions/year	4.33	4.23	0	14
PDO collisions/year	29.58	20.37	4	82
log (VKT)	7.48	0.97	6.07	8.59
Population/year	3,786	1,661	1,415	6,694
Proportion of students/year	0.24	0.06	0.14	0.31
Proportion of part-time employees/year	0.05	0.02	0.03	0.08
Proportion of full-time employees/year	0.41	0.03	0.37	0.47
Proportion of unemployed/year	0.02	0.01	0.005	0.04
Proportion of retired persons/year	0.17	0.08	0.09	0.32
Dwelling unit/year	1,569	672	485	2,612
Proportion of males/year	0.49	0.02	0.44	0.53
Proportion of population age ≤ 15	0.14	0.04	0.09	0.22
Proportion of population age ≤ 65	0.16	0.08	0.08	0.30
Proportion of households with 0 cars	0.12	0.11	0.006	0.33
Proportion of households with ≥ 2 cars	0.51	0.22	0.22	0.79
After (October 2010–September 2013 for 3 neighborhoods; Oct 2010–Sep 2011 for 5 neighborhoods)				
Total collisions/year	31.07	22.87	6	82
Severe collisions/year	2.71	2.70	0	8
PDO collisions/year	28.36	21.23	6	77
log (VKT)	7.50	0.97	6.11	8.60
Population/year	3,975	1,564	1,356	6,521
Proportion of students/year	0.21	0.04	0.15	0.29
Proportion of part-time employees/year	0.06	0.01	0.04	0.08
Proportion of full-time employees/year	0.38	0.03	0.35	0.43
Proportion of unemployed/year	0.02	0.01	0.004	0.05
Proportion of retired persons/year	0.18	0.07	0.09	0.27
Dwelling unit/year	1,736	646	486	2,581
Proportion of males/year	0.49	0.03	0.45	0.53
Proportion of population age ≤ 15	0.13	0.03	0.09	0.20
Proportion of population age ≤ 65	0.16	0.07	0.08	0.26
Proportion of households with 0 cars	0.15	0.12	0.006	0.33
Proportion of households with ≥ 2 cars	0.43	0.20	0.22	0.79
Number of traffic signals	0.63	0.74	0	2
Collector road length (km)	3.48	1.86	1.27	6.84
Local road length (km)	11.98	5.74	5.41	20.78
Total road length (km)	15.47	7.30	6.68	26.42
Old neighborhood (1 for yes, 0 for no)	0.25	0.46	0	1
Grid neighborhood (1 for yes, 0 for no)	0.25	0.46	0	1
New neighborhood (1 for yes, 0 for no)	0.50	0.53	0	1

Collision data are count data that are rare, random, discrete, and nonnegative. It is assumed that collisions at the n neighborhood are independent and that

$$Y_{it}^{k} \mid \theta_{it}^{k} \sim \text{Poisson}\left(\theta_{it}^{k}\right) \tag{1}$$

where θ_{it}^{k} is the Poisson parameter. Because of the overdispersion of the collision data, it is common to incorporate an error term in the Poisson parameter to capture the unobserved or unmeasured heterogeneity, such as

$$\theta_{it}^{k} = \mu_{it}^{k} \exp\left(u_{i}^{k}\right) \tag{2}$$

where μ_{it}^{k} is the systematic component of the model, determined by a set of covariates representing neighborhood attributes and a corresponding set of unknown regression parameters, and the term u_{i}^{k} represents heterogeneous random effects; μ_{it}^{k} can be expressed as

$$\ln\left(\mu_{it}^{k}\right) = \beta_{0t}^{k} + \beta_{1}^{k} \ln\left(\text{VKT}_{i}\right) + \beta_{2t}^{k} T + \sum_{j=3}^{J} \beta_{j}^{k} X_{jit} \tag{3}$$

where

β_{0t}^{k} = intercept for year t (the yearly trend of collisions was addressed by taking this random intercept across the years);
VKT_i = vehicle kilometers traveled for neighborhood i;
T = indicator variable, with $T = 1$ indicating a treated neighborhood and $T = 0$ a reference neighborhood;
β_{1}^{k}, β_{2t}^{k} = regression parameters for VKT and indicator variable T(Treated), respectively;
X_{jit} = set of covariates; and
β_{j}^{k} = corresponding regression parameters.

For variable T, a random parameter is considered across the years, as shown by the subscript t for the corresponding regression parameter.

Therefore, no separate indicator variable to differentiate the before versus the after period is needed. For model estimation, the vague prior $\beta \sim N(0, 100^2)$ is used.

In the univariate PLN model, for each collision severity, k,

$$\exp(u_i)\big|\sigma_u^2 \sim \text{ lognormal}\left(0, \sigma_u^2\right)$$

or

$$u_i\big|\sigma_u^2 \sim \text{normal}\left(0, \sigma_u^2\right) \tag{4}$$

where σ_u^2 represents the within-neighborhood (extra) variation. For σ_u^{-2}, the following prior is used: gamma(ε, ε), where ε is a small number (e.g., 0.01 or 0.001).

MVPLN Model

For the MVPLN model, u_i^k denotes multivariate normal error distribution:

$$\exp\left(u_i^k\right)\Big| \sim \text{lognormal}\left(0, \sum\right)$$

or

$$u_i^k \sim \text{Normal}\left(0, \sum\right), \sum = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1K} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2K} \\ \cdots & \cdots & \cdots & \cdots \\ \sigma_{K1} & \sigma_{K2} & \cdots & \sigma_{KK} \end{pmatrix} \tag{5}$$

The diagonal elements of the variance–covariance matrix $\sum$ represent the variances, and the off-diagonal elements, σ_{hk}, represent the covariance of u_i^h and u_i^k. For model estimation, the following prior is used: $\sum^{-1} \sim$ Wishart (I, K), where I is the $K \times K$ identity matrix.

PLN-CAR Model

Spatial correlation can be accounted for by incorporating a spatial random effect (also known as spatial correlation, structured variation, or structured error), as follows:

$$\theta_{it}^k = \mu_{it}^k \exp\left(u_i^k\right) \exp\left(s_i^k\right)$$

or

$$\ln\left(\theta_{it}^k\right) = \ln\left(\mu_{it}^k\right) + u_i^k + s_i^k \tag{6}$$

where the spatial component s_i^k suggests that sites closer to each other are likely to have common features affecting collision occurrence. According to the literature, the most commonly used first-order CAR prior distribution is for s_i^k.

For the univariate CAR spatial correlation (S_i), the joint conditional distribution can be expressed as follows:

$$S_i\big|S_{-i} \sim \text{Normal}\left(\vartheta_i + \sum_{j=1}^{n} S_d C_{ij}\left(S_j - \vartheta_i\right), \phi D_{ii}\right) \tag{7}$$

where S_{-i} denotes all the elements except S_i, and ϕ is the correlation parameter. $D_{ii} = 1/n_i$, where n_i is the number of neighborhoods that are adjacent to neighborhood i. $S_d = S_{d(\max)}$, which equals one with the particular choice of C_{ij} and D_{ii}. C_{ij} is the element of the weight matrix and can be expressed as follows:

$$C_{ij} = \frac{W_{ij}}{W_{i+}}$$

where

$$W_{i+} = \Sigma_{j=1}^{n} W_{ij}$$

$$W_{ij} = \begin{cases} 1 & \text{if neighborhood } i \text{ and } j \text{ are adjacent} \\ 0 & \text{otherwise} \end{cases}$$

The specification of C, D, and S_d leads to the conditional distribution, as follows:

$$S_i\big|S_{-i} \sim \text{Normal}\left(\frac{\overline{S}_i, \sigma_s^2}{n_i}\right) \tag{8}$$

where $\overline{S}_i = \sum_{j \in C(i)} S_j / n_i$, $C(i)$, is the set of neighbors for neighborhood i, and σ_s^2 is the variance for spatial correlation. For model estimation, it is assumed that $\sigma_s^{-2} \sim$ gamma(ε, ε), where ε is a small number (e.g., 0.01 or 0.001).

MVPLN-CAR Model

For the multivariate k-dimensional CAR model, the vector of spatially correlated i neighborhood is

$$S_{ki} = \left(S_{1i}, S_{2i}, \ldots, S_{ki}\right), S_{ki}\Big|\left(S_{1(-i)}, \ldots, S_{k(-i)}\right) \sim \quad MN\left(\overline{S_{(k)i}}, \frac{\Omega}{n_i}\right)$$

$$\Omega = \begin{pmatrix} \sigma_{s11}^2 & \sigma_{s12}^2 & \cdots & \sigma_{s1K}^2 \\ \sigma_{s21}^2 & \sigma_{s22}^2 & \cdots & \sigma_{s2K}^2 \\ \cdots & \cdots & \cdots & \cdots \\ \sigma_{sK1}^2 & \sigma_{sK2}^2 & \cdots & \sigma_{sKK}^2 \end{pmatrix} \tag{9}$$

Here, $(S_{1(-i)}, \ldots, S_{k(-i)})$ denotes the neighborhoods of the $k \times n$ matrix S_{ki}, excluding the ith neighborhood; Ω is the variance–covariance matrix for spatial correlation.

The diagonal elements of the covariance matrix (Ω) represent spatial variance. The off-diagonal elements represent the spatial covariance of different severity levels. For model estimation, it is assumed that $\Omega^{-1} \sim$ Wishart (I, K), where I is the $K \times K$ identity matrix.

Model Estimation

The posterior distributions required in the FB approach were obtained with Markov chain Monte Carlo sampling techniques available in WinBUGS (*34*). Monitoring convergence is critical because it ensures that the posterior distribution is found, indicating when parameter sampling should begin. To check convergence, two parallel chains with diverse starting values were tracked to ensure full coverage of the sample space. Convergence of multiple chains was assessed with the Brooks–Gelman–Rubin (BGR) statistic (*35*). A value of less than 1.2

of the BGR statistic indicates convergence. Convergence was also assessed by visual inspection of the Markov chain Monte Carlo trace plots for the model parameters, as well as by monitoring the ratios of the Monte Carlo errors relative to the respective standard deviations of the estimates; as a rule, these ratios should be less than 0.05.

Model Comparison and Goodness of Fit

When different modeling approaches are used, it is important to compare the performance of the models and find the best-fitting model. This study adopted the DIC for model comparison (*28*). As a goodness-of-fit measure, DIC is a Bayesian generalization of the Akaike information criterion (AIC) that penalizes larger-parameter models. Similarly to the AIC, the model with the smallest DIC is estimated to be the model that would best predict a replicate data set of the same structure as that currently observed (*28*). According to Spiegelhalter et al., it is difficult to determine what would constitute an important difference in DIC (*28*). Very roughly, differences of more than 10 might definitely rule out the model with the higher DIC. Differences between 5 and 10 are considered substantial. However, if the difference in DIC is less than 5, and the models make very different inferences, it could be misleading to report only the model with the lowest DIC. El-Basyouny and Sayed showed that the DIC is additive under independent models (*26*). Therefore, DIC values of the univariate models were added for comparing with the corresponding multivariate models.

Before–After Evaluation

A conventional way of expressing the overall safety effect of a treatment is to use the odds ratio (*1*). For the current application, the odds ratio, also referred to as the crash modification factor, is expressed as $OR_{overall} = \theta_{TA}\theta_{CB}/\theta_{TB}\theta_{CA}$, where θ_{TB} and θ_{TA} denote the predicted collision counts for the treated sites, averaged over the appropriate number of years during the before and after periods, respectively, and θ_{CB} and θ_{CA} represent the predicted collision counts for the reference sites averaged over the appropriate number of years in the before and after periods, respectively. To make the analysis consistent, average predicted collision for the reference group was used for the years for which the after period is applicable for treated neighborhoods. The overall safety effectiveness as a percentage change in collision frequency across all sites can be expressed as safety effectiveness = $100 \times (1 - OR_{overall})$.

RESULTS AND DISCUSSION

Model Comparison and Goodness of Fit

For each model, the posterior estimates were obtained via two chains with 50,000 iterations, 10,000 of which were excluded as a burn-in sample with WinBUGS. The BGR statistics were less than 1.2, the ratios of the Monte Carlo errors relative to the standard deviations of the estimates were less than 0.05, and trace plots for all the model parameters indicated convergence.

The model selection criteria are presented in Table 3. The differences in DIC values are significant among the four models (*28*). The best-performing model is the MVPLN-CAR model, and the worst is the PLN model. This finding is intuitive, as the former model accounts for the correlation between collision severity levels, as well as spatial correlation, while the latter ignores them. Of the PLN-CAR and the MVPLN model, the latter is better fitted. Thus, for the current data set, the effect of heterogeneous correlation between the collision severity levels is more influential than spatial correlation.

TABLE 3 Model Comparison with DIC

Model	DIC	Model	DIC
PLN	12,349	MVPLN	12,270
PLN-CAR	12,297	MVPLN-CAR	12,230

The model estimation results are presented in Table 4. The models differ a little in terms of the significant variables and their estimates. In general, the variables found to be statistically significant and associated with both severe and PDO collisions are vehicle kilometers traveled, number of traffic signals, grid network pattern, dwelling units, proportion of population age 15 or younger, proportion of population age 65 or older, and proportion of households with two or more cars. For indicator variables related to treated neighborhoods, all are insignificant, except for Year 1. Other variables listed in Table 1 were also found to be statistically insignificant.

The parameter estimate for the log transformation of vehicle kilometers traveled was highly significant and positively associated with both severe and PDO collisions. Across the models, the estimates varied from 0.416 to 0.525 for severe collisions and from 0.243 to 0.358 for PDO collisions. The higher value of the estimate for severe collisions denotes that the effect of vehicle kilometers traveled on collision frequency is higher for severe collisions than for PDO collisions.

The number of traffic signals within the neighborhood was significant and positively associated with both severe and PDO collisions. Moreover, the effect of the number of traffic signals was higher for severe collisions than for PDO collisions.

The road network pattern was found to be significant only in nonspatial models. The results show that neighborhoods with grid pattern road networks are associated with fewer collisions compared with other road network patterns.

The dwelling unit number for the neighborhood was significant and positively associated with both severe and PDO collisions, irrespective of the models. The parameter estimates varied from 0.206 to 0.352 for severe collisions and from 0.350 to 0.367 for PDO collisions. The study attempted to include neighborhood population in the model. However, because of the high correlation between population and dwelling units, both variables could not be included in the same model. When only population was included, the resulting models had a higher DIC value than the models with dwelling unit. Therefore, in the final models, dwelling unit was used.

With respect to population age distribution, the proportion of the population age 15 or older was significant and negatively associated with PDO collisions in the spatial model. This finding was not unexpected, as the higher proportion of this age group indirectly represents fewer drivers and, therefore, less exposure in the neighborhood. The proportion of the population age 65 or older was also significant and negatively associated with both severe and PDO collisions. This finding is consistent with previous research (*21, 24*).

The proportion of households with zero cars, households with two or more cars, and household income were found to be highly correlated. Therefore, one of these variables was included at a time, and the DIC values were compared. The model including the number of households with two or more cars as a variable was found to yield the lowest DIC

TABLE 4 Summary of Model Estimation Results

	PLN Model				PLN-CAR Model				MVPLN Model				MVPLN-CAR Model			
	Severe		PDO		Severe		PDO		Severe		PDO		Severe		PDO	
Variable	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD
Intercept1	−2.434	0.438	0.193	0.314	−3.047	0.628	−2.164	1.799	−2.626	0.496	0.147	0.322	−2.234	0.474	0.742	0.312
Intercept2	−2.468	0.436	0.213	0.313	−3.081	0.627	−2.146	1.799	−2.646	0.494	0.170	0.321	−2.258	0.473	0.761	0.311
Intercept3	−2.578	0.439	0.234	0.315	−3.193	0.629	−2.116	1.799	−2.752	0.498	0.193	0.323	−2.361	0.477	0.790	0.313
Intercept4	−2.759	0.440	0.107	0.316	−3.375	0.630	−2.247	1.799	−2.936	0.498	0.062	0.323	−2.547	0.478	0.660	0.313
Intercept5	−2.882	0.439	−0.140	0.315	−3.499	0.629	−2.499	1.799	−3.056	0.497	−0.186	0.322	−2.673	0.476	0.409	0.312
Intercept6	−2.972	0.441	−0.015	0.316	−3.589	0.631	−2.375	1.800	−3.149	0.498	−0.063	0.323	−2.765	0.477	0.534	0.313
Log(VKT)	0.433	0.052	0.345	0.036	0.416	0.056	0.243	0.034	0.525	0.057	0.358	0.037	0.432	0.055	0.264	0.036
Signal no.	0.255	0.031	0.161	0.026	0.247	0.034	0.169	0.022	0.244	0.039	0.152	0.029	0.246	0.032	0.170	0.022
Grid			−0.318	0.102					−0.438	0.157	−0.355	0.105	−0.163	0.136	−0.140	0.085
Dwelling	0.325	0.060	0.362	0.031	0.352	0.063	0.367	0.029	0.206	0.051	0.356	0.030	0.266	0.048	0.350	0.029
Pop. ≤ 15							−0.841	0.411					−1.255	0.832	*−0.802*	*0.398*
Pop. ≥ 65			−1.040	0.332			−1.112	0.314	−1.208	0.559	−0.881	0.308	−1.233	0.549	−0.944	0.305
Car ≥ 2	−1.448	0.279	−0.669	0.196	−1.290	0.325	−0.522	0.219	−1.532	0.335	−0.588	0.213	−1.327	0.333	−0.621	0.208
Treated1	0.638	0.257	0.249	0.174	0.499	0.263	0.221	0.155	0.710	0.279	0.214	0.185	0.577	0.261	0.251	0.163
Treated2	0.413	0.268	0.140	0.175	0.275	0.273	0.114	0.156	0.475	0.292	0.107	0.186	0.341	0.273	0.145	0.164
Treated3	0.068	0.295	0.210	0.173	−0.066	0.300	0.186	0.154	0.117	0.314	0.179	0.184	−0.007	0.300	0.218	0.163
Treated4	0.159	0.301	0.097	0.176	0.025	0.306	0.072	0.158	0.191	0.320	0.064	0.187	0.065	0.308	0.102	0.165
Treated5	−0.281	0.362	−0.030	0.181	−0.413	0.367	−0.056	0.166	−0.258	0.378	−0.061	0.192	−0.378	0.364	−0.025	0.172
Treated6	0.469	0.296	0.206	0.176	0.336	0.302	0.179	0.158	0.483	0.315	0.172	0.187	0.364	0.299	0.209	0.166

NOTE: Shading indicates nonsignificant; italics indicate significant at 90% credible interval; estimates for other variables (except treated) significant at 95% credible interval. Pop. = population.

TABLE 5 Variance–Covariance Estimate for Error Components for MVPLN Model

Collision Type	Severe	PDO
Severe	0.34 (0.05)	0.91 (0.02)
PDO	0.23 (0.03)	0.19 (0.02)

NOTE: Shading indicates correlation; parentheses indicate standard deviation.

TABLE 7 Variance–Covariance Matrix for MVPLN-CAR Model

Collision Type	For Heterogeneous Error		For Spatial Error	
	Severe	PDO	Severe	PDO
Severe	0.19 (0.06)	0.93 (0.12)	0.15 (0.16)	0.65 (0.53)
PDO	0.12 (0.05)	0.08 (0.04)	0.14 (0.14)	0.15 (0.12)

NOTE: Shading indicates correlation; parentheses indicate standard deviation.

value and hence was included in the final models. The parameter estimates show that households with two or more cars are associated with lower collision frequency for both collision severity levels. This variable can be interpreted as an inverse of neighborhood poverty. To this end, this finding is in line with previous studies (*21, 24*).

The parameter for variable *T*(Treated) was allowed to vary by year to capture the differences in yearly collision trend between treated and reference neighborhoods. This is important in before–after evaluation for adjusting for the time trend effect. Therefore, a separate parameter estimate was found for each of the 6 years of collision data. However, as shown in Table 4, only for Year 1 (Treated1), the parameter is significant at the 95% credible interval. Few other estimates are significant at lower credible intervals. Because few treated sites were available for the study and a random-parameter assumption was made for this variable, they were kept in the models despite their nonsignificance.

Variance estimates for the PLN model are as follows (parentheses indicate standard deviation):

Collision Type	*Heterogeneous Error*
Total	0.20 (0.02)
Severe	0.27 (0.04)
PDO	0.19 (0.02)

Variance estimates for the MVPLN model are presented in Table 5.

Variance estimates for error components of the models are presented for the PLN-CAR model in Table 6 and in Table 7 for the MVPLN-CAR model. Regardless of the model type, variances for heterogeneous error were always statistically significant and indicated the need to incorporate a heterogeneous error term in the model. Moreover, the value of heterogeneous variance was higher for severe collisions than PDO collisions, which denotes that severe collisions exhibit more randomness than PDO collisions. Furthermore, for both the MVPLN and PLN-CAR models, the covariance between severe and PDO collisions for heterogeneous error was statistically significant, indicating the appropriateness of the use of multivariate models for collision severity. In the univariate model, this covariance between the severity levels is ignored.

The correlation between severe and PDO collisions for the heterogeneous error was statistically significant and very high. The MVPLN model estimated the correlation as 91%, while the MVPLN-CAR model estimated it as 0.93%. This high correlation indicates that a higher number of PDO collisions is associated with a higher number of severe collisions, as the numbers of both types are likely to rise because of the same deficiencies in neighborhood design or other unobserved factors or both (*26*).

For the univariate spatial model, the variance of the spatial error was statistically significant for PDO collisions but was insignificant for severe collisions, indicating that the proximate neighborhoods are more closely related to PDO collisions than severe collisions for the current data. Therefore, including spatial error is more likely to improve model prediction significantly only for the PDO collisions rather than severe collisions.

For spatial error, the correlation between severe and PDO collisions, as found for the MVPLN-CAR model, was estimated as 65%; however, it was not statistically significant. A possible reason for the spatial correlation not being significant is that the boundary collisions were excluded from the analysis. With boundary collisions distributed among the adjacent neighborhoods, a higher spatial correlation could have been expected. Another reason could be that the model has two random error components, the heterogeneous component accounting for a substantial portion of the random effect (*29*).

TABLE 6 Variance for PLN-CAR Model

Collision Type	For Heterogeneous Error	For Spatial Error
Total	0.08 (0.04)	0.19 (0.11)
Severe	0.23 (0.04)	0.05 (0.06)
PDO	0.06 (0.03)	0.21 (0.09)

Evaluation Results

The models presented in the preceding section were used to evaluate the safety effects of reducing the urban residential PSL. Table 8 presents the results of the before–after safety evaluation for the various models. As shown in the table, the estimated collision reductions and the precision are almost the same across the models. According to the DIC value of the models, the recommended collision reduction estimates are 13%, 24%, and 12% for total, severe, and PDO collisions, respectively. Whereas the total and PDO collision reductions are statistically significant at the 95% credible interval, the severe collision reduction is significant at the 90% credible interval.

Although the model parameter estimates differ a little among various models, the collision reduction estimates show no noticeable

TABLE 8 Effect of PSL Reduction on Collision Frequency

Model	Collision Reduction in Percentage[a]		
	Total	Severe	PDO
PLN	12.95 (4.91)	24.9 (13.05)	11.28 (5.28)
PLN-CAR	13.39 (4.93)	24.50 (13.17)	11.72 (5.27)
MVPLN		24.05 (13.13)	12.00 (5.24)
MVPLN-CAR		23.97 (13.27)	11.88 (5.25)

NOTE: All are significant at 95%, except shaded cells, which are significant at 90% credible interval.
[a]Standard deviation in parentheses.

differences. A possible reason could be related to the data used in the current study. As shown in Table 2, the changes in explanatory variables between the before and the after period for the treated group are minimal. Therefore, differences in model parameter estimates had little impact on the before–after evaluation results. However, such might not be the case for all safety treatments. If a treatment affects other factors (e.g., traffic volume) in addition to the number of collisions, it may be possible that different models estimate significantly different collision reductions. Moreover, the study used only eight treated neighborhoods; analysis with more treated sites could yield different results.

The PSL was reduced for all roads within the boundaries (excluding boundary roads) of the treated residential neighborhoods, including collector and local road segments and the associated intersections. To conduct a model-based microscopic (i.e., intersection and road segment level) safety evaluation for the entire study area, it is necessary to collect exposure data (i.e., traffic volume) for all road segments and intersections. However, the data were not available, as road agencies often do not collect traffic volume data for low-volume residential collector and local road segments and intersections. An earlier study evaluated the safety effect of the same PSL reduction by using microscopic collector road segments only (*7*). With this subgroup safety evaluation, the total, severe, and PDO collision reductions were estimated as 26%, 50%, and 18%, respectively. These collision reduction estimates are substantially different from the findings of the present study, especially for severe collisions.

The differences in results between the earlier microscopic (i.e., collector road segments) and the current macroscopic (i.e., neighborhoods) safety evaluation of the same PSL reduction are intuitive and reasonable. This PSL reduction resulted in a mean free-flow speed change from 51.1 to 47.7 km/h (3.4 km/h reduction) for collector roads and from 43.8 to 41.8 km/h (2.0 km/h reduction) for local roads (*33*). Given the higher impact of PSL reduction on speed for collector roads, it is expected that the overall reduction of collisions—and specifically severe collisions—will be higher for collector roads than local roads. Therefore, when both collector and local roads are combined in the safety evaluation—which is the case for macroscopic evaluation—the resulting collision reduction will be less than that for only collector roads.

Finally, the estimated collision reductions are quite high, given that the current PSL reduction program did not include any costly infrastructure or geometrical changes. Rather, the program included only changes in PSL signs, together with an educational campaign and enforcement. Therefore, according to the results, the PSL reduction integrated with education and enforcement could be an effective countermeasure to improve safety on urban residential roads.

CONCLUSIONS AND FUTURE RESEARCH

This study used univariate and multivariate FB macroscopic spatial models for a before–after evaluation of urban residential PSL reduction. The before–after evaluation results were compared with that of nonspatial models. The four modeling formulations considered were PLN, PLN-CAR, MVPLN, and MVPLN-CAR. Yearly collision data and other neighborhood characteristics data were collected for eight treated and 210 reference urban residential neighborhoods to develop macroscopic models. The PSL on all roads within the treated neighborhoods (excluding boundary roads) was reduced from 50 to 40 km/h. The data set used in the study included 3 years of before data and 3 years of after data for before–after safety evaluation.

The MVPLN-CAR model outperformed the other models for the DIC. Vehicle kilometers traveled, number of traffic signals, road pattern, dwelling unit, proportion of population age 15 or younger, proportion of population age 65 or older, and households with two or more cars were found to be statistically significantly associated with neighborhood collisions. The parameter estimates vary a little across different models, although their signs are consistent.

The before–after safety evaluation results showed that the differences in collision reduction estimated under various models were negligible. This result could be related to the small number of treated sites in the study or a result of excluding boundary collisions from the analysis. Further studies with more treated sites could be conducted to justify the findings. In general, the PSL reduction was estimated to reduce total, severe, and PDO collisions by 13%, 24%, and 12%, respectively. From this evaluation, it is recommended that PSL on urban residential roads be reduced to improve traffic safety. The study found significant safety benefits from reduction of the PSL from 50 to 40 km/h; future studies could evaluate the safety benefits of further reducing the PSL on residential roads to 30 km/h.

Although the study addressed heterogeneous and spatial correlation in the modeling formulation, it could be extended by considering random parameters across neighborhoods. The random parameters model can provide better inference than the fixed-parameters model and can account for heterogeneity across neighborhoods caused by unobserved factors.

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REFERENCES

1. *Highway Safety Manual.* AASHTO, Washington, D.C., 2010.
2. Hauer, E. *Observational Before/After Studies in Road Safety Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety.* Pergamon Press, Oxford, United Kingdom, 1997.
3. El-Basyouny, K., and T. Sayed. Full Bayes Approach to Before-and-After Safety Evaluation with Matched Comparisons: Case Study of Stop-Sign In-Fill Program. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2148,* Transportation Research Board of the National Academies, Washington, D.C., 2010, pp. 1–8.
4. El-Basyouny, K., and T. Sayed. A Full Bayes Multivariate Intervention Model with Random Parameters Among Matched Pairs for Before–After Safety Evaluation. *Accident Analysis and Prevention,* Vol. 43, No. 1, 2011, pp. 87–94.
5. El-Basyouny, K., and T. Sayed. Measuring Safety Treatment Effects Using Full Bayes Non-Linear Safety Performance Intervention Functions. *Accident Analysis and Prevention,* Vol. 45, 2012, pp. 152–163.
6. El-Basyouny, K., and T. Sayed. Evaluating the Signal Head Upgrade Program in the City of Surrey. *Accident Analysis and Prevention,* Vol. 50, 2013, pp. 1236–1243.
7. Islam, M.T., and K. El-Basyouny. Full Bayesian Evaluation of the Safety Effects of Reducing the Posted Speed Limit in Urban Residential Area. *Accident Analysis and Prevention,* Vol. 80, 2015, pp. 18–25.
8. Lan, B., B. Persaud, C. Lyon, and R. Bhim. Validation of a Full Bayes Methodology for Observational Before–After Road Safety Studies and Application to Evaluation of Rural Signal Conversions. *Accident Analysis and Prevention,* Vol. 41, No. 3, 2009, pp. 574–580.
9. Lan, B., and B. Persaud. Evaluation of Multivariate Poisson Lognormal Bayesian Methods for Before–After Safety Evaluations. *Journal of Safety and Security,* Vol. 4, No. 3, 2012, pp. 193–210.

10. Lan, B., and R. Srinivasan. Safety Evaluation of Discontinuing Late Nighttime Flash Operations at Signalized Intersections. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2398,* Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 1–9.
11. Li, W., A. Carriquiry, M. D. Pawlovich, and T. Welch. The Choice of Statistical Models in Road Safety Countermeasure Effectiveness Studies In Iowa. *Accident Analysis and Prevention,* Vol. 40, No. 4, 2008, pp. 1531–1542.
12. Park, E. S., J. Park, and T. J. Lomax. A Fully Bayesian Multivariate Approach to Before–After Safety Evaluation. *Accident Analysis and Prevention,* Vol. 42, No. 4, 2010, pp. 1118–1127.
13. Pawlovich, M. D., W. Li, A. Carriquiry, and T. Welch. Iowa's Experience with Road Diet Measures: Use of Bayesian Approach to Assess Impacts on Collision Frequencies and Collision Rates. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1953,* Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 163–171.
14. Persaud, B., B. Lan, C. Lyon, and R. Bhim. Comparison of Empirical Bayes and Full Bayes Approaches for Before–After Road Safety Evaluations. *Accident Analysis and Prevention,* Vol. 42, No. 1, 2010, pp. 38–43.
15. Levine, N., K. E. Kim, and L. H. Nitz. Spatial Analysis of Honolulu Motor Vehicle Crashes (I): Spatial Patterns. *Accident Analysis and Prevention,* Vol. 27, No. 5, 1995, pp. 663–674.
16. Black, W. R., and I. Thomas. Accidents on Belgium's Motorways: A Network Autocorrelation Analysis. *Journal of Transport Geography,* Vol. 6, No. 1, 1998, pp. 23–31.
17. Nicholson, A. Analysis of Spatial Distributions of Accidents. *Safety Science,* Vol. 31, No. 1, 1999, pp. 71–91.
18. Miaou, S.-P., J. J. Song, and B. K. Mallick. Roadway Traffic Collision Mapping: A Space–Time Modeling Approach. *Journal of Transportation and Statistics,* Vol. 6, No. 1, 2003, pp. 33–57.
19. MacNab, Y. C. Bayesian Spatial and Ecological Models for Small–Area Accident and Injury Analysis. *Accident Analysis and Prevention,* Vol. 36, No. 6, 2004, pp. 1019–1028.
20. Aguero-Valverde, J., and P. Jovanis. Spatial Analysis of Fatal and Injury Crashes in Pennsylvania. *Accident Analysis and Prevention,* Vol. 38, No. 3, 2006, pp. 618–625.
21. Quddus, M. A. Modelling Area-Wide Count Outcomes with Spatial Correlation and Heterogeneity: An Analysis of London Collision Data. *Accident Analysis and Prevention,* Vol. 40, No. 4, 2008, pp. 1486–1497.
22. El-Basyouny, K., and T. Sayed. Urban Arterial Accident Prediction Models with Spatial Effects. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2102,* Transportation Research Board of the National Academies, Washington, D.C., 2009, pp. 27–33.
23. Mitra, S. Spatial Autocorrelation and Bayesian Spatial Statistical Method for Analyzing Intersections Prone to Injury Crashes. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2136,* Transportation Research Board of the National Academies, Washington, D.C., 2009, pp. 92–100.
24. Huang, H., M. A. Abdel-Aty, and A. L. Darwiche. County-Level Collision Risk Analysis in Florida: Bayesian Spatial Modeling. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2148,* Transportation Research Board of the National Academies, Washington, D.C., 2010, pp. 27–37.
25. Ahmed, M., H. Huang, M. Abdel-Aty, and B. Guevara. Exploring a Bayesian Hierarchical Approach for Developing Safety Performance Functions for a Mountainous Freeway. *Accident Analysis and Prevention,* Vol. 43, No. 4, 2011, pp. 1581–1589.
26. El-Basyouny, K., and T. Sayed. Collision Prediction Models Using Multivariate Poisson–Lognormal Regression. *Accident Analysis and Prevention,* Vol. 41, No. 4, 2009, pp. 820–828.
27. Song, J., M. Ghosh, S. Miaou, and B. Mallick. Bayesian Multivariate Spatial Models for Roadway Traffic Collision Mapping. *Journal of Multivariate Analysis,* Vol. 97, No. 1, 2006, pp. 246–273.
28. Spiegelhalter, D., A. Thomas, N. Best, and D. Lunn. *WinBUGS User Manual.* MRC Biostatistics Unit, Cambridge, United Kingdom, 2005.
29. Aguero-Valverde, J. Multivariate Spatial Models of Excess Collision Frequency at Area Level: Case Of Costa Rica. *Accident Analysis and Prevention,* Vol. 59, 2013, pp. 365–373.
30. Wang, Y., and K. M. Kockelman. A Poisson–Lognormal Conditional–Autoregressive Model for Multivariate Spatial Analysis of Pedestrian Collision Counts Across Neighborhoods. *Accident Analysis and Prevention,* Vol. 60, 2013, pp. 71–84.
31. Narayanamoorthy, S., R. Paleti, and C. R. Bhat. On Accommodating Spatial Dependence in Bicycle and Pedestrian Injury Counts by Severity Level. *Transportation Research Part B,* Vol. 55, 2013, pp. 245–264.
32. Barua, S., K. El-Basyouny, and M. T. Islam A Full Bayesian Multivariate Count–Data Model of Collision Severity with Spatial Correlation. *Analytic Methods in Accident Research,* Vol. 3–4, 2014, pp. 28–43.
33. Islam, M. T., K. El-Basyouny, and S. E. Ibrahim. The Impact of Lowered Residential Speed Limits on Vehicle Speed Behavior. *Safety Science,* Vol. 62, 2014, pp. 483–494.
34. Lunn, D. J., A. Thomas, N. Best, and D. Spiegelhalter. WinBUGS: A Bayesian Modelling Framework: Concepts, Structure, and Extensibility. *Statistics and Computing,* Vol. 10, No. 4, 2000, pp. 325–337.
35. Brooks, S. P., and A. Gelman. Alternative Methods for Monitoring Convergence of Iterative Simulations. *Journal of Computational and Graphical Statistics,* Vol. 7, No. 4, 1998, pp. 434–455.

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