Spatial Correlation in Multilevel Crash Frequency Models

Effects of Different Neighboring Structures

Jonathan Aguero-Valverde and Paul P. Jovanis

Recent research has shown the importance of spatial correlation in road crash models. Because many different spatial correlation structures are possible, however, this study tested several segment neighboring structures to establish the most promising one to model crash frequency in road networks. A multilevel approach was also used to account for the spatial correlation between road segments of different functional types, which are usually analyzed separately. The study employed a full Bayes hierarchical approach with conditional autoregressive effects for the spatial correlation terms. Analyses of crash, traffic, and roadway inventory data from rural engineering districts in Pennsylvania and Washington affirmed the importance of spatial correlation in road crash models. Pure distance-based neighboring models (i.e., exponential decay) performed poorly compared with adjacency-based or distance order models. The results also suggest that spatial correlation is more important in distances of 1 mi or less. The inclusion of spatially correlated random effects significantly improved the precision of the estimates of the expected crash frequency for all segments by pooling strength from their neighbors and thus reducing their standard deviation. Results from Pennsylvania and Washington showed that spatial correlation substantially increased the random effects. There was a consistent indication that 70% to 90% of the variation explained by the random effects resulted from spatial correlation. This suggests that spatial models offer a significant advantage, since poor estimates that result from small sample sizes and low sample means are a frequent issue in highway safety analysis. Application of spatial correlation to the identification of sites with promise indicated that more sites were identified because of a reduction in the variance of the estimates, which would allow for greater confidence in the selection of sites for treatment.

Recent research has shown the importance of spatial correlation in road crash models at the segment and intersection level (*1–4*). Many different spatial correlation structures are possible, yet most correlation structures used in highway safety are based on conditional autoregressive (CAR) terms (*5*) where units are considered correlated only if they are adjacent (*1–2, 6–9*).

J. Aguero-Valverde, Programa de Investigación en Desarrollo Urbano Sostenible, Universidad de Costa Rica, Barrio Los Profesores, Calle B, No 11, Mercedes, San Pedro, San José, 11503 Costa Rica. P. P. Jovanis, Department of Civil and Environmental Engineering and Pennsylvania Transportation Institute, Pennsylvania State University, 212 Sackett Building, University Park, PA 16802-1408. Corresponding author: J. Aguero-Valverde, jaguero@produs.ucr.ac.cr.

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Conditional models of spatial correlation can accommodate different correlation structures through the weights that are given to each neighbor. Aguero-Valverde and Jovanis proposed the use of the inverse of the order (as defined by proximity) as weight in a segment level model (*1*). Guo et al. proposed weights that are equal to the inverse of the (aerial) distance for an intersection model (*4*). Aerial distances in road safety network models, (e.g., those of intersections) can be quite different, however, from the distances that should be measured (i.e., the distance that a vehicle has to cover to go from Point A to Point B, or network distance). To calculate those network distances, a topological model of the road network has to be created by using geographic information system (GIS) tools.

To better account for spatial correlation in highway safety models, a topological model of the road network should include the different functional classes and road types, since users travel through different classes of roads in any given trip. Users are one of the sources of spatial correlation. As they travel through different road classes, they carry spatial correlation with them. Furthermore, when roads of different functional classes intersect, they share a geographical space that is also a source of spatial correlation. A multilevel approach is needed in order to include different road classes in a single model and to estimate different coefficients for each road type. A multilevel model is also needed to account for spatial correlation across road classes.

Multilevel models are fairly new in highway safety literature (*10–14*). The first two deal with the hierarchical occupant-car-crash structure in order to control the correlation between units in the same groups (occupants in the same car or cars in the same crash) (*10–11*). This hierarchy is observed in models of crash severity where occupant, vehicle, and crash characteristics are modeled as independent variables. Others have modeled the outcome of a crash (level 1) within an intersection (level 2) (*13*). In the final group, crash counts have been modeled at level 1 by county (*12, 14*). These units have been aggregated at level 2 by geographic region. In the study reported here, crash counts by road segment were modeled at the first level of the hierarchy while the segments were aggregated by road functional class at the second level to estimate coefficients for the independent variables by road class.

The purpose of this research was to explore the effect of spatial dependence in multilevel models of road crash frequency at the segment level. Different segment neighboring structures were explored to establish the most promising one to model crash frequency in road segment networks. Coefficients for the covariates were estimated by road type in a single network model. This facilitated the analysis of the spatial correlation structures in the whole network simultaneously rather than in separate models by road type (as is common in highway safety practice). Spatial dependency was modeled in terms of network distances and relationships such as in a directed graph.

METHODOLOGY

Multilevel models were implemented by using a full Bayes hierarchical approach. At the first level of the hierarchy, the units of analysis were the road segments. At the second level, the segments were grouped by road type into six classes: (*a*) urban, two-lane roads; (*b*) urban interstates and other principal arterials; (*c*) other urban, multilane roads; (*d*) rural, two-lane roads; (*e*) rural interstates and other principal arterials; and (*f*) other rural, multilane roads. The crash counts were assumed to be Poisson distributed:

$$y_{ilt} \sim \text{Poisson}\left(\theta_{ilt}\right) \tag{1}$$

where y_{ilt} was the observed number of crashes in segment i of the road type l at time t (in years), and θ_{ilt} was the expected Poisson rate for segment i of the road type l at time t. The Poisson rate was modeled as a function of the covariates by following a log-normal distribution as shown in Equation 2:

$$\log\left(\theta_{ilt}\right) = \beta_{0l} + \sum_k \beta_{kl} x_{iltk} + v_i + u_i \tag{2}$$

where

- β_{0l} = intercept for road type l,
- β_{kl} = coefficient for the kth covariate for the road type l,
- x_{iltk} = value of the kth covariate for segment i of the road class l at time t,
- v_i = heterogeneity among segments, and
- u_i = spatially correlated random effect for segment i.

The heterogeneity random effects were assumed to follow a normal distribution:

$$v_i \sim N\left(0, \tau_v\right) \tag{3}$$

where τ_v was the precision (inverse of the variance), which controlled the Poisson extravariation as the result of heterogeneity.

This model provided different coefficient estimates across road types and allowed spatial correlation between neighboring road segments even if they belonged to different road types. This spatially correlated effect was modeled by using a Gaussian CAR prior (*5*):

$$u_i \,|\, u_{-i} \sim N\left(\frac{\sum_{j\sim i} w_{ij} u_j}{w_{i+}}, \frac{1}{w_{i+}\tau_u}\right) \tag{4}$$

where

- u_{-i} = all neighbors of i,
- τ_u controls Poisson extravariation because of clustering or spatial correlation,
- $j \sim i$ denotes that segment j is a neighbor of segment i,
- w_{ij} = weight of jth neighbor of ith segment, and
- w_{i+} = sum of weights of neighbors of segment i.

Random effects were pooled over time to improve model estimation. The assumption of constant random effects over time was not restrictive, provided that the covariates explained most variation over time.

At the third stage, hyperpriors were given for τ_v and τ_u. To make these priors "fair" (i.e., equal prior emphasis on heterogeneity and clustering) the approximation suggested by Bernardinelli et al. was used (*15*):

$$\text{sd}\left(v_i\right) = \frac{1}{\sqrt{\tau_v}} \approx \frac{1}{0.7\sqrt{\bar{w}_+ \tau_u}} \approx \text{sd}\left(u_i\right) \tag{5}$$

where sd(.) was the standard deviation, and $\bar{w}_+$ was the average sum of the weight of neighbors. This was important to guarantee that the posterior proportion of variation explained by the spatial correlation term (η) (defined in Equation 6) was obtained mainly from the data.

$$\eta = \frac{\text{sd}\left(\mathbf{u}\right)}{\text{sd}\left(\mathbf{u}\right) + \text{sd}\left(\mathbf{v}\right)} \tag{6}$$

One of the study's most important tasks was to analyze the effect of neighboring structure specifications on the fit of the model to the data. Neighboring structures were tested from the simple to the more complex by beginning with adjacency-based structures.

Adjacency-Based Models

The simplest neighboring structure is that of adjacency-based, first-order neighbors. First-order neighbors are shown in Figure 1*a*, and they are defined as all segments that connect directly with the segment in question. The schematic road network depicted in Figure 1*a* shows the second- and third-order neighbors for segment *i*. As shown, second-order neighbors are those connected directly to first-order neighbors, and third-order neighbors are connected to second-order neighbors. This hierarchical definition of adjacency is strictly based on network topology, but it ignores distances between segments. As shown in Equation 3, different neighbors can have different weights. For adjacency-based neighbors, the weights assigned were equal to the inverse of the order (i.e., 1, ½, and ⅓), as proposed previously (*1*).

Distance Order Models

Neighboring structures based on network distances between segments were explored also. The adjacency hierarchy was defined in terms of distances (i.e., first-order neighbors were within a half-mile of the segment of interest; second order neighbors were between ½ and 1 mi; and third-order neighbors were between 1 and 1½ mi). Here the distance used was the traveled or network distance from midpoint to midpoint, as opposed to the Euclidian distance. This can be considered a hybrid adjacency model, where the order is distance-based, but the weights are still the inverse of the order.

Distance Exponential Decay Models

Full distance-based models were also tested. The weights were estimated by using an exponential decay function of the network distance. This approach was inspired by the work of Best et al., who considered the distance to be the Euclidian between the geographic centroids of the districts (*16*). Equation 7 shows the definition of distance-based weights for the model:

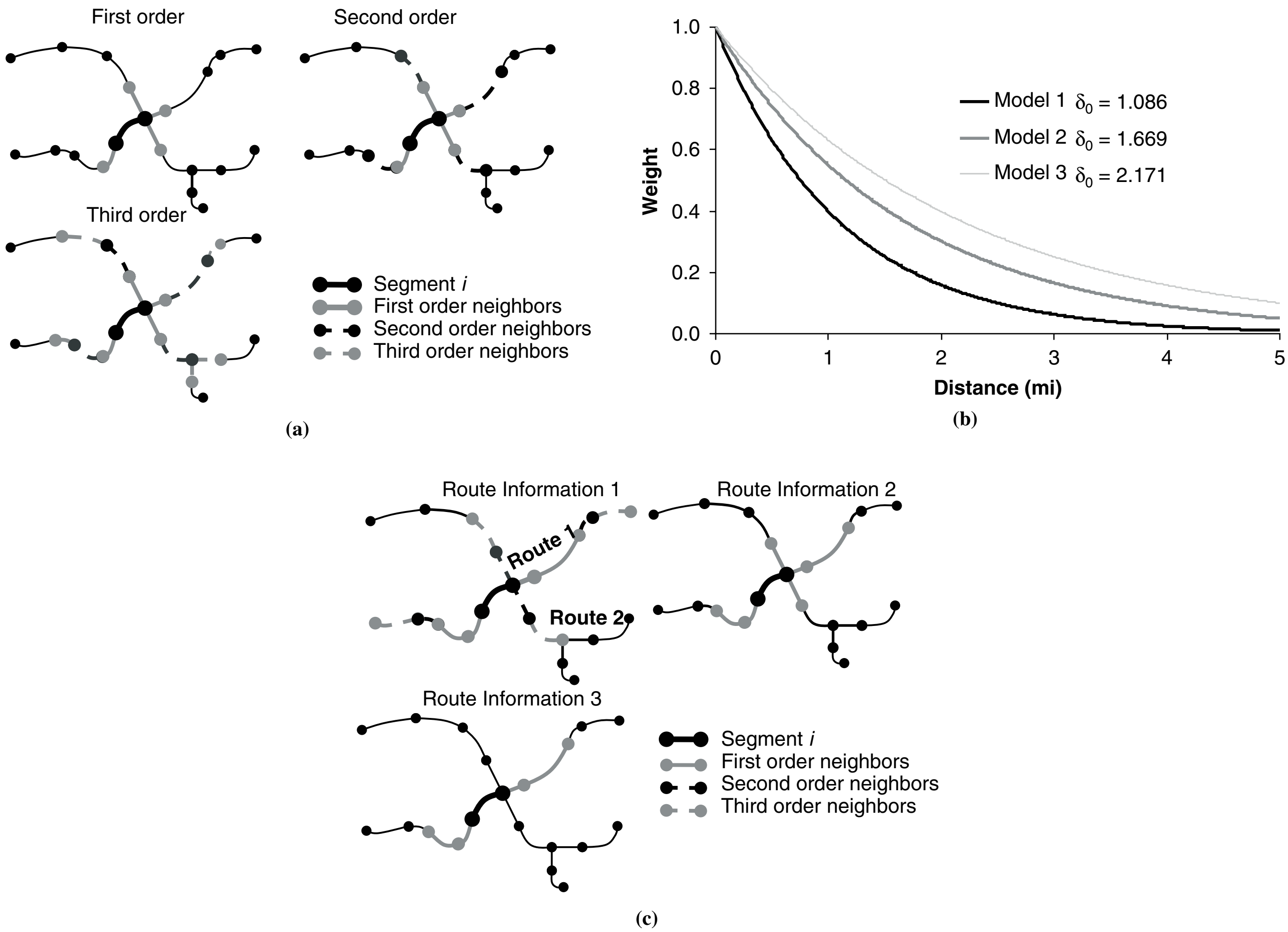

FIGURE 1 Proposed neighboring structures: (*a*) adjacency-based neighbors definition, (*b*) exponential decay weight functions for different values of δ_0, and (*c*) adjacency-route information neighbors definition.

$$w_{ij} = e^{\frac{-d_{ij}}{\delta_0}} \tag{7}$$

where

w_{ij} = weight of the *j*th neighbor of the *i*th segment,
d_{ij} = network distance between segments *i* and *j*, and
δ_0 = a constant.

This approach was computationally feasible for only a few hundred observations since it would imply the calculation of millions of shortest path distances (traveled distances). To overcome this, and as a first approximation to the problem, an arbitrary maximum distance of 5 mi was selected; any segment whose distance was greater than this threshold had a weight of zero. Since the average segment length was less than half a mile, this distance included approximately more than 10 segments.

The selection of the constant δ_0 was also somewhat arbitrary. A sensitivity analysis was performed for different δ_0 s. Figure 1*b* shows the functions with the three values selected. The values of δ_0 were selected so that the values of the function at the 5-mi mark were 0.01 (1%), 0.05, and 0.10. Those values were 1.086, 1.669, and 2.171, respectively.

Adjacency–Route Information Models

Another important element in the adjacency hierarchy is traffic flow continuity. The flow of traffic through several segments of corridors or routes is a source of spatial correlation. Consequently, models are tested with higher weights assigned to segments that belong to the same route. Three neighboring structures were tested here. First, adjacency-based, second-order neighbors were promoted to first-order neighbors if they belonged to the same route of the segment of interest *i*; third- and fourth-order neighbors were promoted to second and third order, respectively. Conversely, first-, second-, and third-order neighbors were demoted to second-, third-, and fourth-order neighbors, respectively, if they belonged to different routes. Fourth-order neighbors were dropped in the final neighboring structure. First-order neighbors were used only in the second model. For this, segments adjacent to first-order neighbors were also considered first-order neighbors if they belonged to the same route; segments adjacent to the segment of interest were also considered first-order neighbors even if they belonged to a different route. The third model was based on the second model, but only segments in the same route were included in the neighboring structure. Figure 1*c* presents a schematic of the neighboring structures.

For the calculation of network distances and adjacencies, a stack of open-source GIS software was used. A spatial–relational database was assembled by using the open-source software PostgreSQL/PostGIS. This combination was used to calculate the adjacencies between segments. For the network distance calculations, the open-source GIS GRASS was used (*17*).

Ranking of Sites for Engineering Improvement

The effect of the inclusion of spatially correlated random effects on the ranking of sites for engineering improvement was also analyzed. To better assess the effect of spatial correlation on the ranking of sites, its effect was also explored on the estimates of the expected crash frequency in each particular segment. Two frequently used methods to rank sites are (*a*) by expected crash frequency and (*b*) by expected excess crash frequency (*18*). Here the expected excess crash frequency was defined as the difference between the crash frequency expectation at the site and the expectation at similar sites; the expectation at similar sites was estimated by using the safety performance function. When using full Bayes hierarchical models, this difference is measured by the random effects; hence the importance of the effect of spatially correlated random effects on ranking of sites. Equation 8 shows the expression for excess crash frequency (Δ_{ilt}) (*19*):

$$\Delta_{ilt} = \exp\left(\beta_{0l} + \sum_k \beta_{kl} x_{iltk}\right) * \left(\exp\left(v_i + u_i\right) - 1\right) \tag{8}$$

Model Comparison

Three different goodness-of-fit (GOF) measures were used for model comparison and selection: posterior mean deviance, deviance information criterion (DIC), and Bayesian information (Schwarz) criterion (BIC). The posterior mean deviance ($\bar{D}$) can be taken as a Bayesian measure of fit or adequacy (*20*). To account for model complexity, the DIC was proposed (*20*). The DIC is considered the Bayesian equivalent of the Akaike Information Criterion (AIC). DIC is defined as an estimate of fit plus twice the effective number of parameters, as shown in Equation 9:

$$\text{DIC} = D\left(\bar{\theta}\right) + 2p_D = \bar{D} + p_D \tag{9}$$

where

$D(\bar{\theta})$ = deviance evaluated at $\bar{\theta}$, the posterior means of the parameters of interest;
p_D = effective number of parameters in the model; and
$\bar{D}$ = posterior mean of the deviance statistic $D(\theta)$.

As with AIC, models with lower DIC values are preferred.

The BIC is another penalized likelihood criterion, which can be approximated as described by Carlin and Louis (*21*) and shown below:

$$\text{BIC} = 2\hat{l} - p \log n \tag{10}$$

where

p = number of parameters in the model,
n = number of data points, and
$2\hat{l}$ = negative of the posterior deviance.

Since hierarchical models with random effects are used, the exact number of parameters and data points is unknown. To overcome this problem, the effective number of parameters p_D was used in place of the total number of parameters, and the total number of data points was used for n. For more details on the GOF measures, see Carlin and Louis (*21*), Congdon (*22–23*), and Gelman et al. (*24*).

DATA DESCRIPTION

The effect of spatial correlation was tested by using crash and roadway inventory data from two primarily rural regions in Pennsylvania and Washington. The Pennsylvania area of study was PennDOT Engineering District 2-0, which includes the nine counties that cover the north-central part of the state. Data for 2003 through 2006 included 7,968 road segments, of which 566 were urban, two-lane roads; 216 were urban interstates and other principal arterials; 78 were other urban, multilane roads; 6,353 were rural, two-lane roads; 680 were rural interstates and other principal arterials; and 75 were other rural, multilane roads. Crash data were obtained from the Pennsylvania Department of Transportation (PennDOT) crash reporting system. Road data were obtained from the Pennsylvania Road Management System for each year of analysis. The digital map of state roads from Pennsylvania Spatial Data Access enabled the geolocation of crashes (*25*).

Most variables were included in categorical form, and the categories were created in such a way that the baseline represented the typical road design condition for PennDOT (e.g., lane width 12 ft; outside shoulder width 10 ft). In other circumstances, the baseline was selected so that the supposedly better design elements were compared against the deficient or inferior baseline (e.g., divisor width 0 ft). Other values were divided in as many categories as practical so that the minimum number of observations in any category was more than 30.

The Washington State Department of Transportation (WSDOT) Engineering District 6 included eight counties, which covered the northeast part of the state. Highway Safety Information System data were used for crash, roadway inventory, and traffic volume data (*26*). All of this information was georeferenced by using a GIS Linear Reference System file provided by the WSDOT through the Geodata Distribution Catalog (*27*). WSDOT data included vertical and horizontal alignment information not included in the PennDOT data set. Data for calendar years 2003 through 2005 included 4,643 road segments, of which 152 were urban, two-lane roads; 360 were urban interstates and other principal arterials; 485 were other urban, multilane roads; 3,067 were rural, two-lane roads; 275 were rural interstates and other principal arterials; and 304 were other rural, multilane roads.

RESULTS

Models were estimated by using OpenBUGS 2.2 (*28*). OpenBUGS makes use of the Metropolis-Hastings algorithm to sample from the full, unnormalized, posterior distribution of interest by producing Markov Chain Monte Carlo runs for each parameter. Quantities of interest such as means and variances were then estimated from these samples. In general, the last values of the Markov Chains in a previous model were used as initial values for the next model. Between 1,000 and 5,000 iterations were discarded as burn-in for each model to make sure that the chains had converged to the target distribution before sampling from the posterior. After that, 100,000 iterations were saved to produce summary statistics for each parameter in the model. This sample size guaranteed that Monte Carlo errors were small compared with the variance of the parameter estimates (lower than 6% of the standard deviation of the parameter for all of the estimates).

Adjacency-based and distance-based models were analyzed as well as combinations of those two structures and the inclusion of route information. The base models included heterogeneity random effects only. All of the following models included the heterogeneity random effects, as well as the CAR spatially correlated random effects with different neighboring structures. Altogether, 25 models were estimated for PennDOT and WSDOT data. GOF measures of these models were presented in Table 1. Detailed models are presented in Tables 2 and 3. All model specifications were identical within each region except for the spatial correlation term.

For PennDOT data, all of the spatial models had the same or better fit to the data than the model with heterogeneity only (PAAB0), as measured by the posterior deviance. Furthermore, several spatial models had $\bar{D}$s of 50 or more points lower than PAAB0. In particular, the distance first-order model (PADO1) had a posterior deviance more than 200 points lower than PAAB0. The DIC and BIC statistics showed similar results, with PADO1 presenting the lowest DIC overall; again, more than 200 points lower than PAAB0.

The Washington models presented similar results in terms of the DIC and BIC statistics with lower values for all spatial models. The distance first-order model (WSDO1) was not estimated because of neighboring structure problems. Several segments were longer than 1 mi, particularly on rural roads, which implied that they had no neighbors within half a mile. This produced an unstable model that did not converge and was discarded. Nevertheless, the distance second-order model did converge and showed the lowest DIC—more than 200 points lower than the heterogeneity only model (WSAB0). For WSDOT models, however, WSAB0 was one of the best in terms of $\bar{D}$, surpassed only by the distance order models.

Adjacency-Based Models

As shown in Table 1, all of the adjacency-based models for Pennsylvania had DICs that were more than 150 points better than PAAB0. The differences among them, however, in terms of DIC or $\bar{D}$ were modest. In any case, the best model was the first-order model (PAAB1). For brevity, only the best overall models for Pennsylvania (PADO1) and Washington (WSDO2) are presented here. The rest can be seen in the Aguero-Valverde dissertation (*29*). The Washington state data showed a different picture with respect to the adjacency-based models. The third-order model (WSAB3) was the best in terms of DIC and $\bar{D}$, but the differences were modest.

Distance Order Models

As was the case with the Pennsylvania adjacency-based models, the Pennsylvania model for first-order neighbors was the best in terms of DIC, but the differences among distance order models were far bigger. In fact, the first-order model was the best overall for Pennsylvania data in terms of DIC and $\bar{D}$. Table 2 shows the estimates for the distance first-order model (PADO1).

As explained previously, the distance-based, first-order neighbors' model for WSDOT data was not estimated because of neighboring

TABLE 1 Goodness-of-Fit Measures for Neighboring Structure Models: PennDOT and WSDOT Data

Model	Neighboring Structure	$\bar{D}$	$D(\bar{\theta})$	p_D	DIC	BIC	η
PAAB0 uncorrelated effects	None	34,901	33,196	1,705	36,606	−52,580	—
PAAB1 first order	Adjacency-based	34,897	33,379	1,518	36,415	−50,636	0.71
PAAB2 second order		34,891	33,356	1,536	36,427	−50,814	0.73
PAAB3 third order		34,888	33,351	1,538	36,426	−50,833	0.87
PADO1 first order	Distance order	34,677	33,039	1,638	36,315	−51,663	0.86
PADO2 second order		34,902	33,221	1,681	36,583	−52,338	0.75
PADO3 third order		34,895	33,376	1,518	36,413	−50,640	0.89
PAED1 Exponential Decay 1	Exponential decay	34,869	33,289	1,580	36,449	−51,252	0.83
PAED2 Exponential Decay 2		34,847	33,228	1,618	36,465	−51,630	0.84
PAED3 Exponential Decay 3		34,847	33,230	1,617	36,464	−51,618	0.84
PARI1 Route Information 1	Adjacency–route information	34,879	33,338	1,541	36,419	−50,857	0.85
PARI2 Route Information 2		34,886	33,353	1,533	36,418	−50,779	0.64
PARI3 Route Information 3		34,710	33,040	1,670	36,379	−52,024	0.97
WSAB0 uncorrelated effects	None	13,503	12,781	722	14,225	−20,393	—
WSAB1 first order	Adjacency-based	13,518	12,923	596	14,114	−19,202	0.888
WSAB2 second order		13,513	12,915	597	14,110	−19,213	0.904
WSAB3 third order		13,509	12,910	600	14,109	−19,230	0.904
WSDO1 first order[a]	Distance order						
WSDO2 second order		13,345	12,677	668	14,013	−19,719	0.947
WSDO3 third order		13,491	12,960	531	14,022	−18,559	0.914
WSED1 Exponential Decay 1	Exponential decay	13,510	12,870	640	14,150	−19,618	0.878
WSED2 Exponential Decay 2		13,507	12,862	645	14,152	−19,659	0.938
WSED3 Exponential Decay 3		13,507	12,860	647	14,154	−19,682	0.937
WSRI1 Route Information 1	Adjacency–route information	13,513	12,917	596	14,109	−19,200	0.912
WSRI2 Route Information 2		13,518	12,921	596	14,114	−19,206	0.937
WSRI3 Route Information 3		13,505	12,916	590	14,095	−19,132	0.902

[a]Model could not be estimated because of neighboring structure problems.

TABLE 2 Model PAD01 Distance First-Order Neighbors: PennDOT Data

Variable	Mean	SD	MC Error
Urban Two-Lane			
Intercept	–4.92	0.62	0.011
AADT	0.51	0.06	0.001
Length (mi)	1.14	0.12	0.002
Lane wd < 11 ft	–0.04	0.17	0.003
Lane wd ≥ 11 and < 12 ft	–0.12	0.15	0.003
Lane wd = 12 ft			
Lane wd > 12 and < 16 ft	0.32	0.19	0.003
Lane wd ≥ 16 ft	0.29	0.16	0.003
Speed limit < 30 mph			
Speed limit ≥ 30 and < 40 mph	0.07	0.14	0.003
Speed limit ≥ 40 and < 50 mph	0.10	0.17	0.004
Speed limit ≥ 50 mph	0.31	0.26	0.005
Mean shoulder wd < 2 ft	–0.03	0.21	0.003
Mean shoulder wd ≥ 2 and < 4 ft	–0.11	0.19	0.003
Mean shoulder wd ≥ 4 and < 6 ft	–0.10	0.19	0.003
Mean shoulder wd = 6 ft			
Mean shoulder wd > 6 ft	–0.43	0.23	0.003
Urban Interstates			
Intercept	–6.47	1.82	0.099
AADT	0.77	0.19	0.010
Length (mi)	1.07	0.19	0.004
Lane wd < 12 ft	–0.15	0.26	0.005
Lane wd = 12 ft			
Lane wd > 12 and < 16 ft	–0.34	0.33	0.006
Lane wd ≥ 16 ft	0.29	0.25	0.005
Barrier	0.41	0.20	0.004
Speed limit < 30 mph			
Speed limit ≥ 30 and < 40 mph	–1.66	0.29	0.007
Speed limit ≥ 50 mph	–1.02	0.41	0.012
Right shoulder wd < 3ft	0.07	0.30	0.008
Right shoulder wd ≥ 3 and < 6 ft	0.40	0.24	0.006
Right shoulder wd ≥ 6 and < 10 ft	0.61	0.25	0.006
Right shoulder wd = 10 ft			
Right shoulder wd > 10 ft	–0.38	0.56	0.009
Left shoulder wd < 3 ft	0.23	0.27	0.006
Left shoulder wd ≥ 3 and < 6 ft	0.41	0.24	0.005
Left shoulder wd ≥ 6 and <10 ft	0.68	0.23	0.005
Left shoulder wd > 10 ft			
Divisor wd = 0 ft			
Divisor wd > 0 and < 30 ft	–0.49	0.37	0.013
Divisor wd ≥ 30 and ≤ 50 ft	–0.94	0.49	0.015
Divisor wd > 50 ft	–1.20	0.43	0.014
Urban Other Multilanes			
Intercept	–2.85	2.86	0.054
AADT	0.23	0.30	0.005
Length (mi)	1.66	0.29	0.004
Lane wd < 12 ft	0.72	0.48	0.009
Lane wd = 12 ft			
Lane wd > 12 and < 16 ft	0.77	0.42	0.006
Lane wd ≥ 16 ft	0.95	0.42	0.007

Variable	Mean	SD	MC Error
Rural Two-Lane			
Intercept	–5.89	0.28	0.014
AADT	0.63	0.03	0.001
Length (mi)	1.28	0.08	0.003
Lane wd < 10 ft	–0.37	0.10	0.003
Lane wd ≥ 10 and < 11 ft	0.06	0.07	0.002
Lane wd ≥ 11 and < 12 ft	0.10	0.06	0.002
Lane wd = 12 ft			
Lane wd > 12 ft	0.15	0.09	0.002
Speed limit < 35 mph			
Speed limit ≥ 35 and < 45 mph	0.12	0.11	0.004
Speed limit ≥ 45 and < 55 mph	0.07	0.11	0.004
Speed limit ≥ 55 mph	–0.01	0.11	0.004
Mean shoulder wd < 3 ft	0.08	0.09	0.003
Mean shoulder wd ≥ 3 and < 4 ft	0.07	0.09	0.003
Mean shoulder wd ≥ 4 and < 6 ft	0.00	0.08	0.002
Mean shoulder wd = 6 ft			
Mean shoulder wd > 6 ft	0.02	0.09	0.002
Rural Interstates			
Intercept	–6.00	1.75	0.098
AADT	0.63	0.18	0.010
Length (mi)	1.55	0.25	0.008
Lane wd < 12 ft	–0.04	0.27	0.007
Lane wd = 12 ft			
Lane wd > 12 ft	–0.61	0.26	0.006
Barrier	0.17	0.10	0.002
Speed limit < 55 mph			
Speed limit = 55 mph	–0.38	0.28	0.012
Speed limit = 65 mph	0.07	0.32	0.015
Right shoulder wd < 6 ft	0.36	0.20	0.008
Right shoulder wd ≥ 6 and < 10 ft	0.51	0.19	0.007
Right shoulder wd = 10 ft			
Right shoulder wd > 10 ft	0.10	0.14	0.004
Left shoulder wd < 6 ft	0.25	0.21	0.008
Left shoulder wd ≥ 6 and < 10 ft	0.47	0.20	0.007
Left shoulder wd = 10 ft			
Left shoulder wd > 10 ft	0.75	0.22	0.005
Divisor wd = 0 ft			
Divisor wd > 0 and < 30 ft	–0.39	0.31	0.013
Divisor wd ≥ 30 and ≤ 50 ft	–0.30	0.35	0.015
Divisor wd > 50 ft	–0.15	0.31	0.014
Rural Other Multilanes			
Intercept	–5.88	2.53	0.130
AADT	0.63	0.32	0.016
Length (mi)	1.49	0.53	0.009
Lane wd < 12 ft	–0.07	0.65	0.014
Lane wd = 12 ft			
Lane wd > 12 ft	0.34	0.58	0.010
Barrier	–0.95	0.99	0.009
Speed limit < 50 mph			
Speed limit ≥ 50 mph	–0.53	0.47	0.011

(continued)

TABLE 2 *(continued)* **Model PADO1 Distance First-Order Neighbors: PennDOT Data**

Variable	Mean	SD	MC Error	Variable	Mean	SD	MC Error
Barrier	–0.13	0.76	0.008	Right shoulder wd = 0 ft	–0.65	0.79	0.017
Speed limit < 35 mph				Right shoulder wd > 0 and < 6 ft	0.31	0.65	0.012
Speed limit ≥ 35 and < 45 mph	0.24	0.60	0.014	Right shoulder wd = 6 ft			
Speed limit ≥ 45	0.08	0.84	0.020	Right shoulder wd > 6 ft	–0.23	0.64	0.014
Right shoulder wd = 0 ft				Left shoulder wd = 0 ft	1.62	0.90	0.021
Right shoulder wd < 0 ft	–0.03	0.50	0.008	Left shoulder wd > 0 and < 6 ft	0.43	0.83	0.019
Left shoulder wd = 0 ft				Left shoulder wd = 6 ft			
Left shoulder wd > 0 and <10 ft	0.30	0.55	0.009	Left shoulder wd > 6 ft	0.50	0.76	0.018
Left shoulder wd ≥ 10 ft	–0.54	0.53	0.009	Divisor wd = 0 ft			
Divisor wd = 0 ft				Divisor wd > 0 and < 30 ft	–1.29	0.73	0.016
Divisor wd > 0 and < 30 ft	0.09	0.56	0.014	Divisor wd ≥ 30 ft	–0.50	0.76	0.016
Divisor wd ≥ 30	–0.04	0.82	0.021	eta	0.86	0.01	0.001
				sd.u	3.29	0.31	0.017
				sd.v	0.51	0.02	0.001

NOTE: wd = width, $\bar{D}$ = 34,676.7, $D(\bar{\theta})$ = 33,038.6, DIC = 36,314.8, pD = 1,638.1, and BIC = –51,663.3. Gray cells indicate significance at 97.5% level.

structure instabilities. The second- and third-order models presented several differences, beginning with the posterior deviances, where the WSDO2 had a value almost 150 points lower than WSDO3 but had DICs that were only 9 points apart. Table 3 presents the results for model WSDO2.

Distance Exponential Decay Models

The three Pennsylvania models in this group presented few differences among them or with the previous adjacency-based models. The model with the fastest rate of decay (PAED1) was marginally better in terms of DIC, but the other two models had better $\bar{D}$. Similarly, WS models presented only small differences in GOF, and WSED1 was marginally better. In any case, these models were the middle-of-the-pack in GOF measures.

Adjacency–Route Information Models

The first two Pennsylvania models (PARI1 and PARI2) included neighbors that did not belong to the same route. They presented virtually the same values for coefficient estimates and were similar to previous adjacency-based and exponential models. PARI3 was different from any previous model, however, and presented the best fit of this group and the second best overall. Washington data presented similar results, with WSRI3 having the best DIC of the group and the third best overall.

Ranking of Sites for Engineering Improvement

One application of spatial correlation is in the identification of sites with promise. Table 4 presents the top 40 sites ranked by excess crash frequency (Δ) by using distance first-order model for Pennsylvania (PADO1). The table shows also the respective ranking for those sites when using the heterogeneity only model (PAAB0). From the table it is evident that, for the top sites, the estimates of the excess crash frequency (and consequently the expected crash frequency for each site) were consistently higher for the spatial than for the nonspatial model. This was the result of the better fit of the spatial model, as the deviance of the PADO1 model was more than 200 points lower than the PAAB0 model. This means that the expected crash frequency (and therefore the excess crash frequency) of the spatial model was closer to the observed counts than the nonspatial model.

By comparing the ranks, it becomes clear that several top 40 segments in the spatial model were not even in the top 150 for the heterogeneity only model. Clearly the ranks differed significantly. This—plus the increase in the estimates for excess and expected crash frequencies for each segment—has important consequences for the selection of sites for further safety analysis and benefit–cost calculations. Clearly, different sites would be selected for potential treatment with the spatial correlation models rather than for heterogeneity only. Higher excess estimates also generally mean higher estimated crash reductions and economic benefit.

Another effect of the inclusion of spatial correlation in crash frequency models is the increase in the precision of the estimates of the excess and expected crash frequency for each segment. Figure 2 shows the segments where the excess crash frequency was significantly different from zero for both PADO1 and PAAB0 models. As the map clearly shows, there were many more segments with significant estimated excess crash frequency with the spatial model than with the nonspatial model. Indeed for Pennsylvania data, there were 1,022 significant segments for PADO1 and only 110 significant segments for PAAB0. Because a spatially correlated term was included, site estimates pooled strength from their neighbors, which improved the precision of the estimates and reduced the standard deviation. The clustering of segments with significant Δ was also evident from the figure, especially on Routes 80, 322, 45, and 220. All of the segments with significant Δ in the PAAB0 model were also significant in the PADO1 model. Significant segments of the spatial model connected otherwise disconnected significant segments in the nonspatial model, particularly for the clusters on the routes mentioned above.

TABLE 3 Model WSDO2 Distance Second-Order Neighbors: WSDOT Data

Variable	Mean	SD	MC Error
Urban Two-Lane Roads			
Intercept	–10.414	3.111	0.161
AADT	1.165	0.351	0.018
Length (mi)	1.325	0.263	0.006
Lane wd < 12 ft	0.304	0.829	0.013
Lane wd = 12 ft			
Lane wd > 12 and ≤16 ft	–1.319	1.115	0.018
Lane wd > 16 ft	–0.170	0.790	0.019
Speed limit ≥ 40 mph	–0.815	0.525	0.008
Average shoulder wd = 0 ft			
Average shoulder wd > 0 and < 5 ft	–2.724	1.292	0.018
Average shoulder wd ≥ 5 and < 8 ft	–0.574	0.802	0.019
Average shoulder wd = 8 ft	–0.758	0.830	0.019
Number of vertical curves	–0.265	0.151	0.002
Maximum percentage grade	0.040	0.108	0.002
Number of horizontal curves	–0.131	0.366	0.005
Maximum degree of curve	0.075	0.055	0.001
Urban Interstates			
Intercept	–11.500	1.752	0.097
AADT	0.988	0.135	0.007
Length (mi)	0.904	0.061	0.002
Lane wd = 12 ft			
Lane wd > 12 and < 16 ft	0.370	0.814	0.042
Lane wd ≥ 16 ft	0.647	0.759	0.038
Median barrier	–0.161	0.331	0.013
Speed limit < 60 mph			
Speed limit = 60 mph	0.357	0.250	0.009
Speed limit = 70 mph	0.028	0.270	0.009
Right shoulder wd 1 = 0 ft			
Right shoulder wd 1 > 0 and ≤ 10 ft	0.280	0.474	0.022
Right shoulder wd 1 = 12 ft	0.857	0.656	0.025
Right shoulder wd 2 = 0 ft			
Right shoulder wd 2 > 0 and ≤ 10 ft	–0.205	0.787	0.041
Right shoulder wd 2 = 12 ft	–0.825	0.896	0.042
Left shoulder wd 1 = 0 ft			
Left shoulder wd 1 > 0 and < 8 ft	–0.302	0.822	0.041
Left shoulder wd 1 ≥ 8 ft	–0.022	0.782	0.038
Left shoulder wd 2 > 0 ft	0.203	0.853	0.042
Divisor wd ≥ 0 and < 18 ft			
Divisor wd ≥ 18 and ≤ 22 ft	–0.091	0.157	0.003
Divisor wd > 22 ft	0.231	0.300	0.009
Number of vertical curves	0.043	0.085	0.002
Maximum percentage grade	–0.004	0.046	0.001
Number of horizontal curves	–0.061	0.165	0.003
Maximum degree of curve	0.067	0.094	0.002
Urban Other Multilane Roads			
Intercept	–11.985	1.782	0.097
AADT	1.072	0.185	0.010
Length (mi)	0.837	0.089	0.002
Lane wd < 12 ft	–0.705	0.303	0.006
Lane wd = 12 ft			

Variable	Mean	SD	MC Error
Rural Two-Lane Roads			
Intercept	–4.993	0.623	0.033
AADT	0.368	0.098	0.005
Length (mi)	1.213	0.060	0.003
Lane wd < 12 ft	0.027	0.108	0.004
Lane wd = 12 ft			
Lane wd > 12 and ≤16 ft	0.862	0.267	0.006
Lane wd > 16 ft	0.736	0.281	0.008
Speed limit < 35 mph			
Speed limit ≥ 35 and < 55 mph	–0.079	0.226	0.007
Speed limit ≥ 55 mph	0.359	0.208	0.007
Average shoulder wd < 2 ft			
Average shoulder wd ≥ 2 and < 4 ft	–0.102	0.179	0.005
Average shoulder wd ≥ 4 and < 8 ft	0.193	0.193	0.006
Average shoulder wd ≥ 8 ft	0.203	0.204	0.007
Number of vertical curves	0.003	0.009	0.000
Maximum percentage grade	0.033	0.021	0.001
Number of horizontal curves	–0.016	0.016	0.000
Maximum degree of curve	0.024	0.005	0.000
Rural Interstates			
Intercept	14.061	6.932	0.389
AADT	–0.674	0.466	0.026
Length (mi)	1.119	0.093	0.002
Lane wd >12 ft	–6.186	4.524	0.252
Median barrier	–5.029	5.115	0.287
Right shoulder wd 1 = 10 ft	–1.586	3.513	0.196
Right shoulder wd 2 = 10 ft	3.630	7.388	0.415
Left shoulder wd 1 > 0 ft	–1.590	4.075	0.228
Left shoulder wd 2 > 0 ft	–3.051	4.398	0.246
Divisor wd ≥ 100 ft	0.099	0.302	0.013
Number of vertical curves	–0.129	0.116	0.004
Maximum percentage grade	0.168	0.104	0.003
Number of horizontal curves	0.112	0.199	0.006
Maximum degree of curve	0.138	0.271	0.008
Rural Other Multilane Roads			
Intercept	–7.524	4.146	0.232
AADT	0.679	0.448	0.025
Length (mi)	0.984	0.102	0.003
Lane wd ≤ 12 ft			
Lane wd > 12 and ≤ 16 ft	–0.012	0.519	0.018
Lane wd > 16 ft	–1.706	0.848	0.025
Median barrier	0.441	1.637	0.086
Speed limit < 35 mph			
Speed limit ≥ 35 and < 55 mph	1.090	0.421	0.012
Speed limit ≥ 55 mph	2.520	0.741	0.034
Right shoulder wd 1 = 0 ft			
Right shoulder wd 1 > 0 and < 10 ft	–0.616	1.014	0.048
Right shoulder wd 1 = 10 ft	–1.427	0.822	0.037
Right shoulder wd 2 > 0 ft	–1.949	1.986	0.107
Left shoulder wd 1 = 0 ft			

(continued)

TABLE 3 *(continued)* **Model WSDO2 Distance Second-Order Neighbors: WSDOT Data**

Variable	Mean	SD	MC Error	Variable	Mean	SD	MC Error
Lane wd > 12 and < 16 ft	−0.427	0.178	0.003	Left shoulder wd 1 > 0 and < 8 ft	−0.481	0.991	0.050
Lane wd ≥ 16 ft	−0.135	0.196	0.003	Left shoulder wd 1 ≥ 8 ft	−1.486	1.145	0.038
Median barrier	1.392	1.227	0.052	Left shoulder wd 2 > 0 ft	0.975	1.442	0.075
Speed limit < 35 mph				Divisor wd = 0 ft			
Speed limit ≥ 35 and < 55 mph	−0.256	0.198	0.003	Divisor wd > 0 and < 60 ft	0.689	1.025	0.050
Speed limit ≥ 55 mph	−0.568	0.233	0.004	Divisor wd ≥ 60 ft	0.604	1.029	0.050
Right shoulder wd 1 = 0 ft				Number of vertical curves	−0.005	0.051	0.001
Right shoulder wd 1 > 0 and ≤ 8 ft	−0.003	0.375	0.006	Maximum percentage grade	0.074	0.066	0.001
Right shoulder wd 1 > 8 ft	−0.603	0.548	0.008	Number of horizontal curves	0.229	0.123	0.003
Right shoulder wd 2 > 0 ft	−0.573	0.524	0.008	Maximum degree of curve	0.062	0.034	0.001
Left shoulder wd 1 = 0 ft				eta	0.947	0.010	0.001
Left shoulder wd 1 > 0 and < 8 ft	−0.550	0.555	0.006	sd.u	10.466	2.559	0.144
Left shoulder wd 1 ≥ 8 ft	0.039	0.345	0.005	sd.v	0.565	0.051	0.002
Divisor wd = 0 ft							
Divisor wd > 0 and < 18 ft	−1.316	1.213	0.052				
Divisor wd ≥ 18 ft	−0.188	1.157	0.044				
Number of vertical curves	−0.013	0.055	0.001				
Maximum percentage grade	0.018	0.035	0.000				
Number of horizontal curves	0.294	0.194	0.002				
Maximum degree of curve	−0.015	0.032	0.000				

NOTE: wd = width, $\bar{D}$ = 13,345, $D(\bar{\theta})$ = 12,677, DIC = 14,013, pD = 668.0, and BIC = −19,719. Gray cells indicate significance at 97.5% level.

CONCLUSIONS AND RECOMMENDATIONS

In general, the inclusion of spatial correlation has an important impact on the estimation of crash frequency models. Inclusion of spatial correlation explains a significantly bigger proportion of the extra-Poisson variability present in the data, producing better fitting models. The precision of the crash frequency and excess crash frequency estimates are also improved compared with models with heterogeneity-only random effects.

In terms of the effect of spatial correlation on model fit, all of the PennDOT data models with spatial correlation had the same or better fit than the heterogeneity-only model, as measured by the posterior deviance. PennDOT spatial models were also better in terms of DIC and BIC statistics. WSDOT models presented similar results in terms of the DIC and BIC statistics, with lower values for all of the spatial models. The WSDOT model with heterogeneity-only, however, was one of the best in terms of posterior deviance, surpassed only by the distance order models. These results clearly indicate the importance of including spatial correlation in road crash models. Furthermore, the proportion of Poisson extra-variation, explained by the spatially correlated random effect, was significantly higher than the variation explained by the heterogeneity (not spatially correlated) random effect. In fact, this proportion (η) was higher than 70% for all Pennsylvania models and higher than 87% for all Washington models.

The extent of spatial correlation was also explored. Pure distance-based neighboring models (i.e., exponential decay) performed poorly compared with adjacency-based or distance order models. Exponential decay models included neighbors up to 5 mi apart. Distance order models with neighbors only 1 mi apart, however, performed better. In fact, the best model for Pennsylvania included neighbors only a half-mile apart, and the best Washington model included neighbors 1 mi apart. These results suggest that spatial correlation is more important in distances of 1 mi or less.

The inclusion of route information in the neighboring structure significantly improved the models especially when a simple neighboring structure was used. The best route information models included only neighbors directly adjacent to the segment and adjacent to this first neighbor if they shared the same route number. This was also the second best overall model and hence supported the hypothesis that spatial correlation was stronger between segments that belonged to the same route. Serial correlation cannot be thought of alone, however, because the best models overall included any segment within a half-mile or 1 mi for Pennsylvania and Washington data, respectively.

The inclusion of spatially correlated random effects significantly improves the precision of crash frequency estimates by pooling strength from their neighbors, thus reducing their standard deviation. This gives spatial models an important advantage since poor estimates that result from small sample sizes and low sample means are a frequent issue in highway safety analysis.

Although exponential decay models did perform worse than distance-order or adjacency-based models, some other pure distance-based models might perform better. In particular, weights that are inversely proportional to the distance or the square distance can be explored. Given the current evidence, lower distances of about 1 mi might be a good threshold point to consider segments correlated. Another variation might be the use of different decay functions for neighbors when they belonged to the same route. Two different functions could be used: (*a*) one rapid-decay function for different route neighbors and (*b*) one slower decay function for same route neighbors.

Other neighboring structures that combined distance order models and route information models could be tested as well. For example, segments within 1 mi are considered neighbors, if they belong

TABLE 4 Comparison of Rankings by Excess Crash Frequency: Models PADO1 and PAAB0

Rank PADO1	Segment Number	Δ PADO1	Δ PAAB0	Rank PAAB0	Observed Crash Frequency per Year	Average μ (SPF)	Obs. Crash Freq. Minus Average μ
1	532	3.11	2.48	1	4.5	0.492	4.01
2	3,518	2.76	2.15	5	4	0.504	3.50
3	6,630	2.71	2.16	3	3.75	0.745	3.01
4	916	2.47	1.82	9	3.5	0.466	3.03
5	3,744	2.45	1.51	25	3.5	0.728	2.77
6	813	2.40	1.72	11	3.75	0.730	3.02
7	1,847	2.36	1.66	19	3.25	0.489	2.76
8	802	2.31	1.22	51	2.75	0.501	2.25
9	540	2.28	1.69	15	3.5	0.371	3.13
10	2,144	2.17	2.00	7	3.75	0.550	3.20
11	1,880	2.14	1.71	13	3.25	0.543	2.71
12	264	2.10	1.56	21	3.75	0.809	2.94
13	3,743	2.04	1.31	43	3	0.531	2.47
14	3,481	1.97	1.51	23	3.25	0.389	2.86
15	1,797	1.94	1.32	39	2.5	0.424	2.08
16	265	1.91	1.69	17	3.5	0.503	3.00
17	6,594	1.86	1.22	53	2.75	0.279	2.47
18	542	1.84	1.16	59	2.75	0.498	2.25
19	803	1.80	0.93	89	2.25	0.278	1.97
20	2,141	1.69	1.17	57	2.5	0.418	2.08
21	1,883	1.67	0.71	163	1.75	0.799	0.95
22	1,875	1.67	1.25	47	2.75	0.595	2.15
23	527	1.65	1.34	31	3	0.504	2.50
24	3,533	1.63	1.32	37	3	0.534	2.47
25	943	1.62	1.33	35	3	0.593	2.41
26	3,745	1.61	1.08	63	2.5	0.351	2.15
27	804	1.58	0.59	231	1.75	0.443	1.31
28	816	1.58	1.02	75	2.75	0.879	1.87
29	6,769	1.58	0.96	79	2.75	0.779	1.97
30	528	1.57	0.99	77	2.25	0.416	1.83
31	500	1.55	0.94	87	2.25	0.430	1.82
32	3,411	1.54	0.73	157	2.25	0.583	1.67
33	3,722	1.54	1.20	55	2.75	0.523	2.23
34	3,801	1.54	0.77	133	2.25	0.624	1.63
35	466	1.52	1.07	67	2.5	0.480	2.02
36	397	1.51	0.65	177	1.75	0.270	1.48
37	396	1.50	0.66	173	1.75	0.328	1.42
38	801	1.49	0.89	97	2.25	0.454	1.80
39	2,142	1.48	0.83	107	2	0.406	1.59
40	1,881	1.47	0.64	189	1.5	0.583	0.92

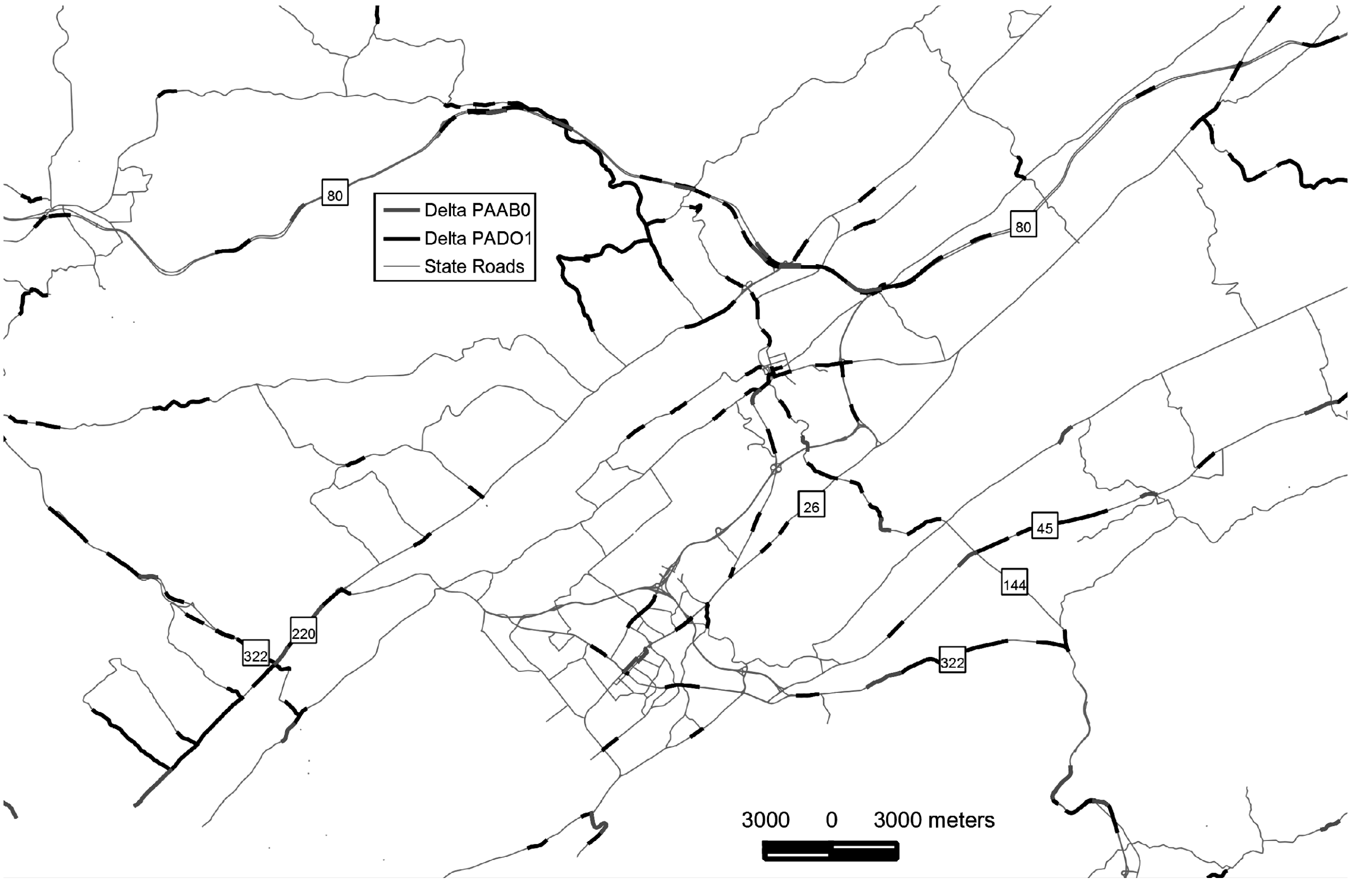

FIGURE 2 Road segments with significant excess crash frequency for Models PADO1 and PAAB0, State College area.

to the same route, and segments within a half-mile are considered neighbors irrespective of route membership. Several other combinations could be tested. The analysis reported here, however, suggests that simpler models perform better.

Pure distance-based models could be extended to include direct spatial dependency structures rather than conditional spatial structures such as the ones presented in this work. These models offer the advantage of directly modeling spatial dependency through the variogram–covariogram functions. They therefore offer straightforward measures of dependency as a function of the (transformed) distance.

Full Bayes methods offer the flexibility to accommodate road segments, intersections, and ramps in a single, full-network model. A complete model would further advance understanding of the interactions of these transportation facilities by accounting for those shared spatial unobservables. Multilevel models could be used: At the first level, individual sites could be analyzed. At the second level, these sites could be aggregated in groups of different facilities (i.e., four-legged intersections, three-legged intersections, two-lane roads, multilane roads, and freeways).

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