A SEGMENT LEVEL ANALYSIS OF MULTI-VEHICLE MOTORCYCLE CRASHES IN OHIO USING BAYESIAN MULTI-LEVEL MIXED EFFECTS MODELS

Thomas Flask  
Graduate Student  
Department of Civil Engineering  
The University of Akron  
302 Buchtel Common  
Akron, OH  
44325-3905  
(330) 972-2426

William H. Schneider IV, Ph.D., P.E. (corresponding author)  
Associate Professor  
Department of Civil Engineering  
The University of Akron  
302 Buchtel Common  
Akron, OH  
44325-3905  
(330) 972-2426

Dominique Lord, Ph.D.  
Associate Professor  
Department of Civil Engineering  
Texas A&M University  
3136 TAMU  
College Station, TX  
77843-3136  
(979) 458-3949
ABSTRACT

Multi-vehicle motorcycle crashes combine elements of design, behavior, and traffic. One challenge with working with motorcycle data are the inherit difficulties associated with missing data – such as motorcycle-specific: vehicle miles traveled (VMT) and average daily traffic (ADT). To address the challenges of the missing data, a random effects Bayesian negative binomial model is developed for the state of Ohio. In this study, the random effect terms improve the general model by describing the spatial correlation with fixed effects, the neighborhood criteria, and the uncorrelated heterogeneity for all the multi-vehicle motorcycle crashes that occurred on the 32,289 state-maintained roadway segments in Ohio. Some key findings from this study include regional data improves the goodness-of-fit, and further improvement of the models may be gained through a distance-based neighborhood specification of conditional autoregressive (CAR). In addition to the model improvement using the random effect terms, key variables such as smaller lane and shoulder widths, increases in the horizontal degree of curvature and increases in the maximum vertical grade will increase the prediction of a crash.

Keywords: Hierarchical Bayes, spatial random effects, uncorrelated random effects, negative binomial model, conditional autoregressive distribution, mixed effects
INTRODUCTION

Motorcycle crashes are known to compose a disproportionately high amount of the overall vehicle fatalities in the United States. Fatalities on motorcycles represented 4,462 deaths of the 30,797 total fatal crashes in the United States in 2009 (FARS, 2012). In that year, when considering the number of fatalities per 100 million VMT (Vehicle Miles Traveled), the motorcycle fatality rate was over 18 times that of passenger car crashes, which was the second highest crash rate for a specific vehicle class (FARS, 2012).

Nationally, 10.1% of the vehicle crash fatalities were motorcycle crashes in 2009 (FARS, 2012). Despite the limited riding season in Ohio due to the weather, the amount of motorcycle involvement in fatalities in the same year was even higher at 16.3%, or 166 fatalities (FARS, 2012). In more recent years, the number of fatal crashes has decreased slightly due to a proactive approach, with 164 fatal crashes in 2010. At the same time, the number of motorcycle crashes (all severities) in Ohio increased from 4,165 in 2009 to 4,381 in 2010 (ODPS, 2012).

A motorcycle crash, as any other vehicle crash, is a complex event with many influential factors and characteristics. Since the mechanisms that lead to each crash may be dramatically different, it is natural to assume that the factors that are behind the two distinct crash types are different as well (Haque et al., 2012; Geedipally and Lord, 2010; Jonsson et al., 2007; Ivan, 2004; Savolainen and Mannering, 2007; Yau, 2004). Therefore, it is reasonable to separate single and multi-vehicle crashes.

Two common approaches to model motorcycle crashes are discrete outcome and negative binomial models (see Savolainen et al., 2011, and Lord and Mannering, 2010, for a review of these models in highway safety research). Some common findings from discrete outcome models show that injury severity is significantly affected by factors such as helmet use, speeding, alcohol use, and operator age (Chang and Yeh, 2006; Savalainen and Mannering, 2007; Haque et al., 2009). While discrete outcome models perform well in estimating the impact of behavioral and crash characteristics on the type of crash that occurs, negative binomial models are more commonly used to estimate or predict the number of crashes based on information such as geometric, demographic, or infrastructural characteristics (Chin and Quddus, 2003; Haque et al., 2010; Harnen et al., 2003; Houston, 2007; Schneider et al., 2010).

More recently, negative binomial models have been improved by introducing random effects terms, which offer the prospect of including data and relationships that may be difficult to apply in a standard model configuration. These more advanced models are often referred to as multi-level models, as they introduce data on multiple spatial, temporal, or conceptual levels. Some examples include multi-level random effects that estimate the impact of crashes occurring in the same intersection (Kim et al., 2007), corridor (Guo et al., 2010), region (Yannis et al., 2007), or year (Majumbar et al., 2004). In each case, the multi-level model improves both the model fit and the interpretation of the findings, showing which intersections or regions are more prone to crash occurrence than others. Not only can random effects be used with assigned groups of similar crashes (such as county or time) as shown previously, but they may also be used by comparing the crash frequency of nearby segments or regions (Eksler and Lassarre, 2008; Mitra, 2009; Quddus, 2008; Wang et al., 2009). The researcher may choose
from a variety of methods to define which segments or regions are considered the neighbor of another, such as contiguity or a fixed distance. In this case, conditional autoregressive (CAR) random effects are shown to reduce the model error by adding the prior knowledge of neighboring regions and segments, leading to better parameter estimates. Additionally, CAR random effects are also frequently paired with an uncorrelated random effects term, which quantifies the model error that is not related to the nearby regions or segments, but rather unknown or unmeasured influences (Aguero-Valverde and Jovanis, 2008; Eksler and Lassarre, 2008; Guo et al., 2010; Mitra, 2009).

Ultimately, random effect terms may be used to reduce model error that is caused by unavailable or unrecorded data such as motorcycle specific vehicle miles traveled or ADT. The models within this paper will utilize the previous demonstration of the random effect terms used in other areas of traffic safety and apply these statistical methodologies directly to motorcycle specific models. This application will improve the key parameters that influence multi-vehicle motorcycle crashes. While the use of random effects in negative binomial models is relatively new in the field of safety, this application is new to motorcycle specific crashes.

MATERIALS AND METHODS

Three datasets (ODOT, 2011; ODPS, 2011; US Census Bureau, 2011) were used in this multi-level study. The first dataset is provided by the Ohio Department of Transportation (ODOT) and is composed of 32,289 interstate, US route, and state route segments. The segments are predominantly classified as principal and minor arterial routes. This dataset, shown in Table 1, includes the following: pavement type, lane width, shoulder width, number of lanes, median presence, horizontal and vertical curve related statistics, the overall vehicle ADT, and the length of the segment. Secondary information may be extracted from the initial dataset to calculate the number of horizontal curves per segment, horizontal curves per mile, maximum degree of curve, and percent of the segment that is a horizontal curve. Similarly, the number of vertical curves, vertical curves per mile, maximum grade, and the percent of the segment that is a vertical curve are extracted from the vertical curve data. In addition to the roadway segments, township information from the ODOT dataset, including the number of lane miles, area of the township, and the urban status of the township, is used to capture information about the 1,459 townships in Ohio. Of the 1,459 townships, 940 are considered urban townships in this study. A township is designated as urban if an incorporated city, based on the city boundaries provided by ODOT, is located inside the region (ODOT, 2011). All the variables listed above are considered as fixed effects parameters with the exception of the ADT and segment length, which are entered into the model as an offset as shown in order to measure exposure as a rate (see Miaou and Song, 2005, or Lord et al., 2005):

$$e_h = \frac{(ADT_h \times L_h)}{10^6}$$

(1)

where $ADT_h$ is the ADT of segment $h$, $L_h$ is the segment length, and $e_h$ is the value of the offset for the segment. The offset accounts for the exposure of each segment to multi-vehicle motorcycle crashes. Although the data in this study are missing specific measures of motorcycle travel, these two means of exposure along with each random effects term reduce the error due to the lack of available data.
US Census data (US Census Bureau, 2011) were used to include demographic information that described the different regions of Ohio in a manner similar to Aguero-Valverde and Jovanis (2006). Knowledge about the household demographics—such as the percent of residents over age 65, percentage of residents under the poverty level, and the mean travel time to work—was included in the model. In addition to demographic information, the county population, number of motorcycle endorsements (motorcycle licenses), and number of registered motorcycles are used as measures of motorcycle and motor vehicle traffic and are compiled at a regional level.

The number of multi-vehicle motorcycle crashes that occur between 2006 and the summer of 2011 on each segment is determined by combining Ohio crash data as reported by the Ohio Department of Public Safety (ODPS) with the ODOT geographic locations of each roadway segment (ODPS, 2011; ODOT, 2011). A total of 3,804 non-intersection related multi-vehicle motorcycle crashes are found to have occurred on state-maintained roadways from 2006 through the summer of 2011; this total includes 68 fatal crashes and 1,163 injury crashes. Geographic coordinates, which are used to identify the segment on which each crash occurred, are available for 3,379 crashes (ODPS, 2011). Segments with no geographic coordinates and those having unrealistic characteristics (such as excessive lane widths) are removed, and the remaining 3,119 multi-vehicle motorcycle crashes are considered in this study.

**THEORY AND CALCULATION**

Negative binomial modeling with Bayesian inference is commonly used to predict crashes. Within this practice, Bayesian inference differs from traditional statistics in that the parameters are estimated using prior knowledge, as shown in Bayes Theorem:

\[
p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)}
\]

where \(p(y|\theta)\) represents the posterior density, \(p(y|\theta)\) denotes the model likelihood, \(p(\theta)\) is the known background information, and \(p(y)\) represents the unconditional density of the data. Guo et al. (2010) and Congdon (2010) present a detailed description of Bayes’ theorem, and the application of Bayesian negative binomial models may be found in examples such as Haque et al. (2010), Mitra (2009), Noland and Quddus (2004), or Quddus (2008).

Within the last few years, researchers such as Aguero-Valverde and Jovanis (2010) and Wang et al. (2009) have been introducing random effects into models so as to include information that may be either unavailable or may be difficult to express in the form of fixed effects. This form of modeling is particularly advantageous in studies such as this, since motorcycle-specific ADT and VMT are difficult to measure. In order to measure the impact of the random effects, three types of Bayesian negative binomial models are considered in this study:

- Uncorrelated heterogeneity model (UH model)
- County and township level random effects model (CT model)
- Spatially correlated random effects models (SC models).
In the UH model, only fixed effects and one random effects term for uncorrelated heterogeneity is specified. In the CT and SC models, full Bayesian negative binomial models are specified with normally distributed random effects terms at the county and township levels. These models are selected to improve the estimate of the multi-vehicle motorcycle crash parameters by acknowledging that some of the variation in crash frequency may be attributed to regional characteristics. To maximize the potential model improvement, multiple SC models are specified, each controlling the amount of information about nearby segments by changing the radius at which segments are considered neighbors: the neighborhood radius. This will allow comparisons to be made between each model type.

**Uncorrelated Heterogeneity Model:**

The fixed effects terms of the UH model are measured on the segment level. The predictors describe characteristics of the roadway, such as lane width or horizontal and vertical alignment.

\[
\rho_h = \frac{\mu_h}{\kappa}, \quad \lambda_h \sim \text{Gamma}(\kappa, \rho_h) \quad (3)
\]

\[
y_h \sim \text{Poisson}(\lambda_h) \quad (4)
\]

\[
\ln \mu_h = \sum_{h=1} \ln(e_h) + \alpha_0 + \alpha_k(x_h - \bar{x}_k) + v_h \quad (5)
\]

where: 
- \( h \): segment level index 
- \( x_h \): segment level predictors
- \( \lambda_h \): expected number of crashes per segment
- \( \mu_h \): segment level mean between iterations
- \( \kappa \): mean of gamma distribution
- \( \alpha_k \): segment level parameters 
- \( k \): predictor index
- \( e_h \): model offset
- \( v_h \): uncorrelated random effects
- \( \rho_h \): precision of gamma distribution

The uncorrelated random effects term also describes error that is caused by uncorrelated heterogeneity. The uncorrelated random effects term in this study is defined as follows:

\[
v_h \sim \text{Normal}(0, \tau_v) \quad (8)
\]

where \( v_h \) represents the normally distributed uncorrelated random effects term and \( \tau_v \) is the precision, or inverse variance, of the uncorrelated random effects, which is given an uninformative gamma prior distribution:

\[
\tau_v \sim \text{Gamma}(0.5, 5 \times 10^{-4}) \quad (9)
\]

similar to that used in Wang et al. (2009) or Quddus (2008). The uncorrelated heterogeneity term prevents the other random effects terms from inferring undue correlation, and therefore improves the parameter estimates. In turn, the Bayesian credible interval (BCI) for each parameter is narrower after removing some of the model error. For more information on UH models, consider Quddus (2008) and Congdon (2003).
County and Township Random Effects Model:

Township and county random effects terms were added to the UH model. Each term was composed of demographic and infrastructural data describing the region in which the segment exists. Each term was specified as follows:

\[ b_i \sim \text{Normal} (\bar{b}_i, \sigma_b), \quad \bar{b}_i = \sum_{i=1}^{\beta_k} \left( z_i - \bar{z}_k \right) \]  

(10)

\[ c_j \sim \text{Normal} (\bar{c}_j, \sigma_c), \quad \bar{c}_j = \sum_{j=1}^{\gamma_k} \left( w_j - \bar{w}_k \right) \]  

(11)

where:

\( i \): township level index  
\( j \): county level index  
\( \beta_k \): township level parameters  
\( \gamma_k \): county level parameters  
\( z_i \): township level predictors  
\( w_j \): county level predictors  
\( \bar{b}_i \): mean of township level random effects  
\( \bar{c}_j \): mean of county level random effects  
\( \sigma_b \): standard deviation of township means  
\( \sigma_c \): standard deviation of county means

The values of the random effects terms for each township and county also give insight into the magnitude and sign of the regional influence. These random effects terms help to interpret models developed using large statewide datasets. For more information on multi-level models, consider Congdon (2003), Hauer (2004) and Yannaz-Tuzel and Ozbay (2010).

Spatially Correlated Random Effects Model:

By drawing inference from the structure of the model error, spatial random effects allow information from neighboring segments to reduce the model error. Additionally, transportation safety researchers often consider spatial correlation in order to reduce model error due to omitted or unavailable crash predictors (Quddus, 2008). There is a potential drawback of using this modeling technique: the spatial random effects term might assume that spatial correlation is present in situations where it may not be. To account for this, an uncorrelated random effects term is added to help prevent undue inference of spatial correlation by explaining model error caused by uncorrelated heterogeneity between segments or regions (Mitra, 2009; Wang et al., 2009).

The spatial correlation in this study is structured as a Gaussian conditional autoregressive (CAR) prior distribution, such that:

\[ P(u|r) \propto \frac{1}{\gamma^m} \exp \left( -\frac{1}{2} \sum_{i} \sum_{j \in \delta_h} (u_i - u_j)^2 \right), h \neq j \]  

(12)

where \( m \) is the index of the number of neighbors in the adjacency matrix, \( \delta_h \) is the neighborhood of the segment \( h \), \( r \) is the prior knowledge of the segment, and \( j \) denotes the neighbor of region \( h \) (Lawson, 2009). This yields a normally distributed spatially correlated error term as proposed by Besag (1974):
\[ u_h \sim \text{Normal} \left( \frac{\sum_j u_j w_{hj}}{\sum_j w_{hj}}, \frac{\tau_u}{\sum_j w_{hj}} \right), h \neq j \]

where \( u_h \) is the spatial random effects term for segment \( h \), \( u_j \) is the neighbor of region \( h \) given index \( j \), \( w_{ij} \) is the weight of the neighbor (in this case 1 for neighbors, 0 otherwise), and \( \tau_u \) the precision of \( u_h \), given an uninformative gamma prior distribution, as applied in a study of London crash data by Quddus (2008) or used in Wang et al. (2009).

In this study, neighborship is defined at the segment level and is based on the distance between two segments in any direction. To assess the effect of changing the neighborhood radius, 10 radii are chosen between 0 and 7 miles.

**Model Evaluation**

The deviance information criterion (DIC) is often used to assess the goodness-of-fit of hierarchical Bayesian models (Aguero-Valverde and Jovanis, 2008; Guo et al, 2010; Mitra, 2009; Carter et al., 2012). The DIC is derived from deviance-based model statistics:

\[ DIC = \bar{D} + p_D = D(\bar{\theta}) + 2p_D \]

where \( \theta \) is the parameter set, \( \bar{D} = E_{\theta\mid y}(D) \), or the average of the deviance, \( p_D \) is the effective number of parameters for a hierarchical model, and \( D(\bar{\theta}) = D[E_{\theta\mid y}(\bar{\theta})] \), which is the deviance at the posterior means of the parameters (Aguero-Valverde and Jovanis, 2010; Congdon, 2010; Spiegelhalter, 2002). Since the DIC increases as model deviance and complexity grow, a model that shows a significant reduction in DIC, typically considered 7 to 10 points or more, performs better than the model with a greater DIC (Spiegelhalter, 2002). Ultimately, the lower the DIC, the more efficient the model will be.

**RESULTS AND DISCUSSION**

Using IBM SPSS Statistics V. 19, an initial model is run to assess the statistical significance (p-value less than 0.05) of each predictor. WinBUGS V. 1.4.3 is used to run subsequent analyses of each of the 12 models with neighborhood radii between 0.25 and 7 miles. Changing the neighborhood radius caused significant changes in the DIC, as shown in Table 2. The rationale behind considering multiple models is to explore the impact of changing the amount of spatial knowledge included in the spatial random effects term’s neighborhood. In each of the models, convergence is verified through the Gelman-Rubin statistic (Lawson, 2009). The analysis of each of the models included 20,000 iterations after convergence. In each of the 12 models, the covariates are the same and are statistically significant. The neighborhood radius has a significant impact on the goodness-of-fit of each model, as measured through the DIC, which is shown in Table 2. All models showed significant improvement in goodness-of-fit over the UH, and almost all models with radii over 0.75 miles are significantly improved from the CT model. The CT model provided the largest improvement over the UH model, showing the regional information adds value in interpretation and model improvement. Specifying 10 SC models showed
that for smaller radii, such as those less than 0.5 miles, the DIC is not improved, but rather the model error is increased, showing that small neighborhood radii may constrict the knowledge regarding spatial correlation between the segments and may not deliver an entirely representative picture about the way that the segments are related spatially. The DIC is less reduced for 2 mile radii and larger. Simultaneously, the cost in terms of computational power and data preparation increases at an exponential rate as its radius increases. Therefore, since the 1.75 mile radius achieves the largest reduction in DIC with the greatest efficiency, Model 5 is selected.

While motorcycle ADT is not available, total ADT is commonly considered as an offset, such as in Wang and Abdel-Aty (2008), Aguero-Valverde and Jovanis (2006), or Eksler and Lassarre (2008). Segment length was also considered as an offset as suggested in Lord et al. (2005) and Ma et al. (2008). The parameter of the offset is fixed to one in order to acknowledge that the variables account for exposure to crashes and are not causative factors.

The standard deviation of each random effects term, as shown in Table 3, shows its relative influence on the frequency of motorcycle crashes on a segment. The county and township standard deviations are similar in value, implying that the influence of the terms that compose the random effect for each segment is nearly equal. The standard deviation of the uncorrelated random effects term has the greatest value, showing the important influence of this term, as well as reflecting the difficulty of capturing all terms that describe the frequency of motorcycle crashes. The standard deviation of the uncorrelated random effect standard deviation is the greater than that of the other terms as well. This implies that the amount of error between segments varies in this respect more in some segments than others. This result should be expected, as the number and impact of unexplained factors varies between segments as well.

The type of pavement on a roadway affects vehicular dynamics during a crash event. For example, the coefficient of friction may vary between pavement types. Concrete paved segments are found to have lower crash rates than segments paved with asphalts in this study, similar to general motor vehicle findings shown in Geedipally et al. (2012). While the width of a roadway has an impact on the number of crashes, the lane use may influence segments with the same width to have different crash frequencies. Segments with six or more lanes are found to experience lower crash rates, such as in Wang et al. (2009). This result may be explained by the increased possibility of changing lanes to avoid a crash, as well as higher design standards. Other findings show that narrower shoulders may offer fewer chances to move away from a dangerous situation. Smaller lane widths are associated with an increase in the frequency of multi-vehicle crashes in each model. Similar to shoulder widths, narrower lanes suggest that there may not be sufficient space for a motor vehicle or motorcycle to find an escape route. The results for the lane width and shoulder width are consistent with current non-motorcycle research, such as Aguero-Valverde and Jovanis (2010). In general, wider roadways tend to have fewer multi-vehicle motorcycle crashes, although the lane use impacts the effectiveness of increased pavement width. This type of model could be employed by practitioners who desire to assess the safety impacts of a roadway improvement for a specific type of segment. For example, this model shows that in this dataset, there is no statistically significant difference between eleven- and twelve-foot lanes. Therefore, for a four-lane road, the more effective safety improvement would be increasing
the shoulder width rather than increasing each of the four lanes by one-foot each.

Divided highways tend to have fewer multi-vehicle motorcycle crashes, and reduce the frequency of multi-vehicle motorcycle crashes, again suggesting that more available space in this area allows the motorcyclist and the driver the ability to escape a crash. This finding is similar to general multi-vehicle crashes shown by Ahmed et al. (2011), which found wider medians tended to reduce the frequency of crashes. A practitioner using this type of model with this dataset would determine that a divided highway should reduce the frequency of multi-vehicle motorcycle crashes.

In regard to horizontal and vertical curves, the model results for motorcycles are found to be consistent with general crashes as seen in Ma et al. (2008), showing an increasing correlation between the maximum degree of curvature and the frequency of crashes. An analysis such as this would show a practitioner the impact of designing a sharper curve on the crash type chosen for the dataset. Reducing the degree of curve in this case would tend to have a statistically significant impact on the number of multi-vehicle motorcycle crashes, which may play a part in justifying a proposed design change or segment improvement. Likewise, the results show that the maximum grade, which is the highest absolute value of the grade, is associated with an increase in the frequency of motorcycle crashes which again is consistent with general crashes as seen in Wang (2009). The percentage of the segment that is considered a vertical curve is found to be significantly associated with multi-vehicle motorcycle crashes. There is an inverse relationship between the topography and the number of multi-vehicle crashes; one possible explanation for this finding may be related to the reduced sight distances, as drivers and riders may consider these segments to be inherently dangerous and will, in turn, travel more conservatively.

The posterior distribution of the township and county level random effects show whether fewer or more multi-vehicle motorcycle crashes occur in the region. For segments where the parameters cause the mean of the posterior distribution for the county or township random effects to be positive, the combined influence of the included factors anticipated to predict fewer crashes. The standard deviations also provide a measure of how much the regional influence varies across the state of Ohio. In this case, the county and townships have standard deviations relatively close in value suggesting a homogeneous sample. If the values are significantly different from each other, it would suggest that the townships, on average, were more diverse.

At the township level, the frequency of multi-vehicle motorcycle crashes is found to increase with the number of lane miles, suggesting that multi-vehicle motorcycle crashes tend to occur more frequently in areas with a larger amount of developed infrastructure. Urban townships are found to have fewer multi-vehicle motorcycle crashes. This may be a result of the higher design standards generally in place in urban road segments as well as lower average speeds in urban areas.

At the county level, three covariates are found to be significant: number of motorcycle endorsements (motorcycle licenses), county population, and mean travel time to work for residents. The findings suggest that counties with more endorsed riders tend to have lower motorcycle crash rates. The parameter for county population, which is positive, complements this value. The findings show that multi-vehicle motorcycle crashes tend to occur more often in regions that are more densely
populated. Finally, the mean travel time to work for residents of a county is found to have a positive-valued parameter in terms of the frequency of multi-vehicle motorcycle crashes.

**CONCLUSION**

The models in this study estimate the frequency of multi-vehicle motorcycle crashes across the state of Ohio. The parameters show the impact of various factors describing social, infrastructural, and geometric factors. The effect of considering spatial relationships between roadway segments is also evaluated. In this study, consideration of spatial random effects in a multi-level model improved the estimates of multi-vehicle motorcycle crashes at the segment level. In general, the inclusion of random effects reduced the standard deviation of the parameters. The analysis of motorcycle crashes at the segment level is found to be useful for estimating the impacts of many geometric factors of roadways on the number of crashes. Hierarchical Bayesian modeling provides more confident estimates of the impact of geometric properties, especially with spatial correlation.

In practice, engineers and public officials constantly seek to improve the safety of their roadways. However, with limited budgets, improvements must be weighed against each other to achieve the maximum effectiveness with the resources available. The model utilized in this study is an effective tool in making these difficult decisions, especially where a specific type of crash is overrepresented and a practitioner is tasked with proposing a single safety improvement that will reduce the frequency of that crash type. For example, if multi-vehicle motorcycle crashes are overrepresented in an area, this model could be used to find what geometric improvements are the most effective improvements. Other data, such as spatial correlation and demographic statistics would serve to improve the estimates by removing unexplained variation where possible. In this case, an engineer or public official would find that there is no statistical significance between segments with two and four lanes, implying that widening shoulders up to eight-feet or widening lanes up to 11-feet may be a more justifiable approach for crash mitigation.

The predicted crash frequency results may also be usefully interpreted. A researcher may apply ranking by sorting predicted crash frequencies or assessing the impact of safety improvements. Analysis at the segment level may also improve the ability of safety professionals to plan and optimize safety campaigns that are directed at multi-vehicle motorcycle crashes by demonstrating the factors involved in motorcycle crashes. Although the results presented in this paper provided useful information, further work is needed. Given the latest advancements in statistical modeling (Lord and Mannering, 2010; Mannering and Bhat, 2014), researchers should examine how models, such as the negative binomial-Lindley (Geedipally et al., 2012), latent-class/finite mixture/Markov switching (Malyshkina et al., 2009); Park and Lord, 2010; Zou et al., 2014), random parameters (Anastasopoulos and Mannering, 2009), the Sichel (Zou et al., 2013) or generalized ordered-response (Castro et al., 2012) may be used for refining the estimates and therefore obtaining a better understanding of risk factors. Non-linear responses between the number of crashes and the explanatory variables should also be investigated (Hauer, 2004; Bonneson et al., 2012) as well as the latest models in spatial statistics (Wang and Kockelman, 2013).
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Table 1: A summary of the descriptive statistics of covariates of potential predictors for multi-vehicle motorcycle crashes in Ohio at the segment level

<table>
<thead>
<tr>
<th>Covariates</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
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<tbody>
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<td>0.4</td>
<td>0</td>
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</tr>
<tr>
<td>ADT (veh/day) b</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>0 to 1,000</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>1,001 to 5,000</td>
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<td>5,001 to 10,000</td>
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<td>≥30,000</td>
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<td>Overall ADT</td>
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<td>0.6</td>
<td>0.9</td>
<td>0.01</td>
<td>8.2</td>
</tr>
<tr>
<td>Concrete Pavement (0 for asphalt)</td>
<td>0.03</td>
<td>0.17</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of Lanes b</td>
<td>2.8</td>
<td>1.3</td>
<td>2</td>
<td>11</td>
</tr>
<tr>
<td>Shoulder Width (ft.) b</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;4 ft.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 to 8 ft.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥8 ft.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divided Highway (ft.) b</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Undivided</td>
<td>77.8%</td>
<td>25,129</td>
<td>7.6%</td>
<td>4,710</td>
</tr>
<tr>
<td>0 to 30 ft. (divided)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥30 ft. (divided)</td>
<td>14.6%</td>
<td>4,710</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Lane Width (ft.) b</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9 to 11 ft.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥11 ft.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed Limit (mph) b</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;35 mph</td>
<td>5.0%</td>
<td>1,618</td>
<td>0</td>
<td>1,618</td>
</tr>
<tr>
<td>35 to 45 mph</td>
<td>25.3%</td>
<td>8,156</td>
<td>0</td>
<td>8,156</td>
</tr>
<tr>
<td>≥45 mph</td>
<td>69.7%</td>
<td>22,515</td>
<td>0</td>
<td>22,515</td>
</tr>
<tr>
<td>Number of Horizontal Curves b</td>
<td>1.6</td>
<td>9.4</td>
<td>0</td>
<td>327</td>
</tr>
<tr>
<td>Maximum Degree of Curve b</td>
<td>2.5</td>
<td>6.7</td>
<td>0</td>
<td>158</td>
</tr>
<tr>
<td>Horizontal Curves/mile b</td>
<td>1.0</td>
<td>3.8</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Percent Horizontal Curve b</td>
<td>5.5%</td>
<td>16.713%</td>
<td>0%</td>
<td>100%</td>
</tr>
<tr>
<td>Number of Vertical Curves b</td>
<td>1.6</td>
<td>8.3</td>
<td>0</td>
<td>294</td>
</tr>
<tr>
<td>Maximum Grade (+/-) b</td>
<td>1.5</td>
<td>3.3</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Vertical Curve/mile b</td>
<td>1.1</td>
<td>3.7</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Percent Vertical Curve b</td>
<td>9.9%</td>
<td>24.8%</td>
<td>0%</td>
<td>100%</td>
</tr>
<tr>
<td>Lane Miles (ln*mi.) b, c</td>
<td>127.6</td>
<td>79.8</td>
<td>.01</td>
<td>813.2</td>
</tr>
<tr>
<td>Area (mi2) c</td>
<td>28.3</td>
<td>11.2</td>
<td>.01</td>
<td>86.9</td>
</tr>
<tr>
<td>Road Density(ln*mi/mi2) b</td>
<td>3.6</td>
<td>1.5</td>
<td>2.2</td>
<td>9.2</td>
</tr>
<tr>
<td>% Over 65 d</td>
<td>14.6%</td>
<td>2.1%</td>
<td>8.8%</td>
<td>19.1%</td>
</tr>
<tr>
<td>Travel Time to Work (min) d</td>
<td>23.6</td>
<td>3.8</td>
<td>17.4</td>
<td>34.1</td>
</tr>
<tr>
<td>Motorcycle Registration a</td>
<td>4,371</td>
<td>4,839</td>
<td>417</td>
<td>27,100</td>
</tr>
<tr>
<td>Motorcycle Endorsements a</td>
<td>8,253</td>
<td>9,179</td>
<td>982</td>
<td>47,003</td>
</tr>
<tr>
<td>Population d</td>
<td>140,353</td>
<td>230,136</td>
<td>13,435</td>
<td>1,280,122</td>
</tr>
</tbody>
</table>

aData from the Ohio Department of Public Safety (ODPS, 2011)
bData from the Ohio Department of Transportation (ODOT, 2011)
cData from the Public Utilities Commission of Ohio (PUCO, 2011)
dData from the US Census Bureau (US Census Bureau, 2011)
Table 2: A comparison of model goodness-of-fit for different neighborhood radii through the DIC

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Neighborhood Radius</th>
<th>$\bar{D}$</th>
<th>$D(\bar{\theta})$</th>
<th>$p_D$</th>
<th>DIC$^a$</th>
<th>DIC Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>UH$^b$</td>
<td>0</td>
<td>20,702</td>
<td>19,146</td>
<td>1,557</td>
<td>22,259</td>
<td>-</td>
</tr>
<tr>
<td>CT$^c$</td>
<td>0</td>
<td>17,320</td>
<td>16,831</td>
<td>488</td>
<td>17,808</td>
<td>4,451</td>
</tr>
<tr>
<td>1</td>
<td>0.5</td>
<td>16,292</td>
<td>14,671</td>
<td>1621</td>
<td>17,913</td>
<td>4,346</td>
</tr>
<tr>
<td>2</td>
<td>0.75</td>
<td>15,899</td>
<td>13,997</td>
<td>1902</td>
<td>17,802</td>
<td>4,457</td>
</tr>
<tr>
<td>3</td>
<td>1.25</td>
<td>17,088</td>
<td>16,382</td>
<td>706</td>
<td>17,795</td>
<td>4,464</td>
</tr>
<tr>
<td>4</td>
<td>1.5</td>
<td>16,243</td>
<td>14,744</td>
<td>1,499</td>
<td>17,741</td>
<td>4,518</td>
</tr>
<tr>
<td>5</td>
<td>1.75</td>
<td>16,422</td>
<td>15,103</td>
<td>1,319</td>
<td>17,741</td>
<td>4,519</td>
</tr>
<tr>
<td>6</td>
<td>2</td>
<td>17,134</td>
<td>16,477</td>
<td>657</td>
<td>17,792</td>
<td>4,467</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>16,944</td>
<td>16,058</td>
<td>886</td>
<td>17,830</td>
<td>4,429</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>17,129</td>
<td>16,468</td>
<td>661</td>
<td>17,791</td>
<td>4,468</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>17,069</td>
<td>16,364</td>
<td>705</td>
<td>17,774</td>
<td>4,485</td>
</tr>
<tr>
<td>10</td>
<td>7</td>
<td>17,059</td>
<td>16,331</td>
<td>729</td>
<td>17,788</td>
<td>4,471</td>
</tr>
</tbody>
</table>

$^a$DIC = $\bar{D} + p_D = D(\bar{\theta}) + 2p_D$

$^b$Only uncorrelated random effects (base model)

$^c$Uncorrelated, county, and township random effects

Note: A significant change in DIC may be considered to be 7 to 10 points or more (Spiegelhalter, 2002). The bold values are statistically different from the base model.
Table 3: A summary of the results of the segment level multi-vehicle motorcycle crash model where the neighborhood radius equals 1.75 miles

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean</th>
<th>S.D.</th>
<th>95% BCI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Lower</td>
</tr>
<tr>
<td>Geometry</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-3.45</td>
<td>0.11</td>
<td>-3.69</td>
</tr>
<tr>
<td>Concrete</td>
<td>-0.08</td>
<td>0.12</td>
<td>-0.33</td>
</tr>
<tr>
<td>Lanes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥6 lanes</td>
<td>-0.24</td>
<td>0.08</td>
<td>-0.39</td>
</tr>
<tr>
<td>Shoulder Width</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;4 ft.</td>
<td>0.47</td>
<td>0.08</td>
<td>0.35</td>
</tr>
<tr>
<td>4 to 8 ft.</td>
<td>0.38</td>
<td>0.06</td>
<td>0.27</td>
</tr>
<tr>
<td>≥8 ft.</td>
<td>Base</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lane Width</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9 to 10 ft.</td>
<td>0.56</td>
<td>0.09</td>
<td>0.40</td>
</tr>
<tr>
<td>10 to 11 ft.</td>
<td>0.37</td>
<td>0.06</td>
<td>0.26</td>
</tr>
<tr>
<td>≥11 ft.</td>
<td>Base</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divided Highway</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Undivided</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 to 30 ft.</td>
<td>-0.51</td>
<td>0.11</td>
<td>-0.74</td>
</tr>
<tr>
<td>≥30 ft.</td>
<td>-0.94</td>
<td>0.07</td>
<td>-1.09</td>
</tr>
<tr>
<td>Base</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Horizontal Curves</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max Degree</td>
<td>0.03</td>
<td>0.003</td>
<td>0.02</td>
</tr>
<tr>
<td>Vertical Curves</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max Grade (+/-)</td>
<td>0.05</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>Percent Vertical Curve</td>
<td>-0.21</td>
<td>0.12</td>
<td>-0.42</td>
</tr>
<tr>
<td>Township Level</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lane Miles (ln*mi.)</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Urban</td>
<td>-0.004</td>
<td>0.06</td>
<td>-0.12</td>
</tr>
<tr>
<td>County Level</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Endorsements</td>
<td>-0.01</td>
<td>0.02</td>
<td>-0.06</td>
</tr>
<tr>
<td>County Population</td>
<td>0.04</td>
<td>0.10</td>
<td>-0.15</td>
</tr>
<tr>
<td>Travel Time to Work</td>
<td>0.02</td>
<td>0.02</td>
<td>-0.01</td>
</tr>
<tr>
<td>Random Effects</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>S.D. of CAR</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>S.D. of Uncorrelated</td>
<td>0.49</td>
<td>0.29</td>
<td>0.05</td>
</tr>
<tr>
<td>S.D. of County</td>
<td>0.28</td>
<td>0.04</td>
<td>0.20</td>
</tr>
<tr>
<td>S.D. of Township</td>
<td>0.27</td>
<td>0.09</td>
<td>0.11</td>
</tr>
<tr>
<td>Dispersion Parameter (k)</td>
<td>20.27</td>
<td>0.50</td>
<td>19.25</td>
</tr>
</tbody>
</table>