Hot Spot Identification by Modeling Single-Vehicle and Multi-Vehicle Crashes Separately

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ABSTRACT

There has been considerable research conducted on the development of statistical models for predicting motor vehicle crashes on highway facilities. These models have often been employed to estimate the number of crashes per unit of time for an entire highway segment or intersection, without distinguishing the influence different sub-groups have on crash risk. The two most important sub-groups that have been identified in the literature are single- and multi-vehicle crashes. Recently, some researchers have noted that developing two distinct models for these two categories of crashes provides better predicting performance than developing models combining both crash categories together for predicting crashes for an entire facility. Thus, the objective of this study is to determine whether there exists any difference in the identification of hotspots when a single model is applied rather than two distinct models. A hotspot (or blackspot) is a site that has an accident frequency which is significantly higher than expected at some prescribed level of significance. The data used for the comparison analysis were collected on Texas multilane undivided highways for the years 1997-2001. This study shows that modeling single- and multi-vehicle crashes separately predicts slightly fewer false positives and negatives than modeling them together under a single aggregated model in the hotspot identification process. Thus, it is recommended to develop separate models for single- and multi-vehicle crashes for predicting crashes and for the identification of hot spots.
INTRODUCTION

There has been considerable research conducted on the development of statistical models for predicting motor vehicle crashes on highway facilities. These models are most often used for estimating the safety performance of various transportation elements or entities (1-4). In this context, these models have been employed to estimate the number of crashes per unit of time for an entire highway segment or intersection, without distinguishing the influence different sub-groups have on crash risk. From the fundamental crash causation perspective, one of the most important sub-groups is related to the number of vehicles involved in each crash, i.e., single-vehicle (SV) and multi-vehicle (MV) crashes. Some researchers have developed distinct predictive models to estimate the safety performance with respect to the number of vehicles involved in a crash (5-8).

Given the differences observed in the characteristics associated with SV and MV crashes, some transportation safety analysts have proposed that distinct crash prediction models should be developed for these two categories of crashes when the objective of the study consists of estimating the safety performance of highway segments (2, 9-13). These researchers noted that developing two distinct models provides better predicting performance than developing models combining both crash categories together (referred to as ALL model or single aggregated model below). In most cases, the motivation for separating models by the number of vehicles involved in the crash is based on shape of the functional form linking both crash types to the traffic flow variable that has been found to be very different from one another (7, 10).

Since these two categories of models have been used to estimate or predict the number of crashes on highway segments (12-14), there is a need to determine whether there exists differences in the detection of hotspots when a single model is applied rather than two distinct models. A hotspot (or blackspot) is a site that has an accident frequency which is significantly higher than expected at some prescribed level of significance (15). Also, a site can also be considered as a hotspot based on its absolute or relative rank of its safety as compared to other sites having similar characteristics under analysis (16-18). The sites that are properly identified as hot spots and are subsequently selected for treatment should maximize the expected total accident reduction (19).

The primary objective of this paper is to investigate if there is an important difference in the hotspot identification when a unique model is estimated compared to a distinct model for SV and MV crashes. Crash data collected on Texas undivided roads from 1997-2001 were used for this comparison analysis. There are various methods for identifying “sites with promise” or the “hotspot list”. Few methods include the simple ranking of sites (20), the accident reduction potential (21), the classical confidence intervals (22) and the empirical Bayes estimate (23). Once the screening method is defined, hotspot list can be selected on the basis of a threshold or according to the budget constraints (16, 24-25). The threshold-based strategy was used in this study. The threshold-based strategy has been widely used in the hot spot identification in previous studies (see, e.g., 16, 18, 24). This strategy overcomes the limitation of budget-based strategy by not selecting
unnecessarily sites that do not need safety interventions or select only sites that have high accident risk. The threshold-based strategy identifies a list of hazardous sites exceeding a certain threshold value. The limitation of this strategy is related to formally define the thresholds or decision rules for the optimal selection of a hotspot list (16).

This paper is divided into five sections. The first section presents a brief background related to SV and MV crashes as well as hotspot identification methods. The second section gives a brief description of data used in this study. The third section describes the methodology utilized for the comparison analysis. The fourth section presents the results of this analysis. The last section provides a summary of the work carried out in this research and recommendation for further work.

BACKGROUND

Many studies dealt with developing separate models for SV and MV crashes. For instance, Shankar et al. (26) analyzed the safety effects of highway design features, weather and other seasonal variables on different crash types. The authors concluded that models predicting crashes for different crash types had a greater explanatory power than a single model that combined all crash types together. Mensah and Hauer (9) developed separate regression models for SV and MV crashes. They reported that using an aggregated model that combine both SV and MV crashes predicts fewer crashes than combining the output of two separate models for the same two categories of crashes.

Ivan et al. (27) investigated differences in causality factors for SV and MV crashes on two-lane rural highways in Connecticut. They found that contributing factors were different for each category of crashes. Ivan (10) modeled crashes using data collected in Connecticut, according to the manner of collision (i.e., number of vehicles involved and their direction of travel). The study showed that the expected number of SV crashes and different types of MV crashes have different effect with the increase in traffic flow. Qin et al. (6) developed zero-inflated Poisson models for different crash types. They noted, for example, that aggregated crash prediction model ignore significant variation in highway crashes. Lord et al. (7) evaluated several functional forms, including distinct models for SV and MV crashes, and one that combined both (referred to as All Model), as a function of traffic flow, vehicle density and volume over capacity (V/C) ratio. Following comparison of the analysis using regression methods, they recommended developing different predictive models for SV and MV crashes rather than developing a common model for both crash categories.

Recently, Geedipally and Lord (8) developed distinct models for SV and MV crashes occurring on undivided segments in Texas. The authors concluded that there exists a difference in the width of confidence intervals when a single model is applied rather than two distinct models.

In summary, numerous studies have shown that MV and SV crashes have vastly different associative relationships with exposure and geometric design features. These differences were noted for various types of highway facilities. Given these observations, some
transportation safety analysts have indicated that distinct models should be estimated for SV and MV crashes when the objective consists of estimated the safety performance of highway segments.

Over the years, several researchers have examined methods, including their strengths and limitations, to identify high risk locations. Hauer and Persaud (28) were the first to examine the performance measures of various methods in identifying high risk locations. Miranda-Moreno (29) documented four different criteria that have been proposed in the literature for hot spot identification. They include the 1) posterior expectation of accident frequency, 2) the posterior probability of excess, 3) the accident reduction potential, and 4) the posterior expectation of ranks. Cheng and Washington (30) compared three commonly implemented techniques: 1) the simple ranking of sites, 2) the classically based confidence intervals and 3) the empirical Bayesian methods using percentage of false negatives (identified as a safe site although unsafe), false positives (identified as an unsafe site although safe), and overall misidentifications (false positives plus false negatives). In a subsequent study, Cheng and Washington (31) proposed four quantitative hotspot identification evaluation tests namely the site consistency test, the method consistency test, the total rank differences test, and the Poisson mean differences test.

Hadayeghi et al. (32) and Miaou and Lord (33) showed that safety performance functions (SPFs) can be useful for assessing the risk of various sites. Miaou and Song (18) suggested ranking locations according to the rates of accident frequency where they suggested using major and minor approach flow in computing the posterior expectation of accident rates. Schluter et al. (16) and Tunaru (17) suggested that if the posterior probability of mean number of accidents at a given site is larger than the means of all the other sites then it is considered as unsafe site. Once the screening criterion is defined, the hotspot list can be selected on the basis of a threshold or according to the budget constraints (16, 24-25).

Higle and Hecht (34), Cheng and Washington (30), and Maher and Mountain (35) used a simulation-based approach to evaluate and compare techniques for the identification of hazardous locations. Richardson et al. (36) criticized that the use of the point estimate for hot spot identification does not make full use of the posterior distribution of crash mean. In sum, there is no shortage of work that has been preformed for identifying high risk locations.

**METHODOLOGY**

This section describes the probabilistic structure of the Poisson-gamma model, the functional form linking single-vehicle crashes and multi-vehicle crashes to traffic flow, the performance evaluation criteria for hot spot identification and the procedure used to for simulation.
Probabilistic Structure of Poisson-Gamma Models

Poisson and Poisson-gamma models belong to the family of generalized linear models (GLMs). Poisson-gamma models in highway safety applications have been shown to have the following probabilistic structure: the number of crashes at the \( i \)-th entity (road section, intersections, etc.) and \( t \)-th time period, \( Y_{it} \), when conditional on its mean \( \theta_{it} \), is assumed to be Poisson distributed and independent over all entities and time periods as:

\[
Y_{it} | \theta_{it} \sim Po(\theta_{it}) \quad i = 1, 2, \ldots, I \text{ and } t = 1, 2, \ldots, T
\]  

(1)

The mean of the Poisson is structured as:

\[
\theta_{it} = \mu_{it} \exp(\epsilon_{it})
\]  

(2)

where,
- \( \mu_{it} \) is a function of the covariates (\( X \));
- \( \beta \) is a vector of unknown coefficients; and,
- \( \epsilon_{it} \) is a the model error independent of all the covariates.

It is usually assumed that \( \exp(\epsilon_{it}) \) is independent and gamma distributed with a mean equal to 1 and a variance \( 1 / \phi \) for all \( i \) and \( t \) (here \( \phi \) is the inverse dispersion parameter, with \( \phi > 0 \)). With this characteristic, it can be shown that \( Y_{it} \), conditional on \( \mu_{it} \) and \( \phi \), is distributed as a Poisson-gamma random variable with a mean \( \mu_{it} \) and a variance \( \mu_{it}(1 + \mu_{it} / \phi) \) respectively.

Functional Form

The segment length was assumed to be directly proportional to the crash frequency, meaning that the segment length has linear relation with the crash occurrence. Thus, the segment length is considered to be an offset rather than considering it as a covariate. The statistical model considered in this study is similar to that used elsewhere in the safety literature (see 37), except that there is only one independent variable, namely Average Daily Traffic (ADT). These models are often referred to as flow-only models. These models are the most popular type of models developed and used by transportation safety analysts (38, 39). They are often preferred over models that include several covariates because they can be easily re-calibrated when they are developed in one jurisdiction and applied to another (40, 41). Although such models will suffer from an omitted variables bias (because many non-flow related factors are known to affect the frequency of crashes), the empirical assessment carried out in this work still provides valuable information for the development of SV and MV predictive models.

The mean of the crashes per year for segment \( i \) can be calculated by
\[ \mu_i = \beta_0 L_i F_i^{\beta_1} \]  

where,

\( L_i = \) length (in miles) of segment \( i \),

\( F_i = \) Average Daily Traffic (ADT),

\( \beta_0 = \) intercept (to be estimated),

\( \beta_1 = \) coefficient (to be estimated) associated with ADT.

It is usually assumed that the total number of crashes increases at a decreasing rate as the traffic volume increases. This relationship is characterized in predictive models with the coefficient for the traffic volume parameter (\( \beta_1 \)) to be below 1.

**Performance Evaluation Criteria**

Table 1 shows the classification of outcomes (such as type I errors, type II errors, number of detected and non-detected sites as hotspots) according to a given hotspot identification method. These outcomes are used for evaluating the performance of different methods in identifying the true hotspots.

**Table 1 here**

The following six measures are used to evaluate the comparative performance of the “SV+MV” and “ALL” models in terms of the power to detect the “true” hotspots:

**False Discovery Rate (FDR):** FDR is the proportion of Type I errors among the “detected” hotspots. The method with a smaller FDR is considered to be the best among all available methods (29).

\[ FDR = \frac{V}{D} \]  

**False Negative Rate (FNR):** FNR is the proportion of Type II errors among the “detected” non-hotspots. It is expected that the FNR is relatively small if the method performs well (29).

\[ FNR = \frac{R}{(n - D)} \]  

Sensitivity (SENS): SENS is the proportion of sites that have been correctly detected as hotspots. This criterion is interpreted as the capacity of the method to detect a “true” hotspot in a group under analysis. This value should be closer to one if the method performs well (29).
Specificity (SPEC): SPEC represents the proportion of non-hotspots that have been correctly classified as “true” non-hotspots. This criterion gives the capacity of a method to detect “true” non-hotspots in a group under analysis. This value should be closer to one if the method performs well (29).

\[ SPEC = \frac{U}{n_0} \]  

Risk (RISK): RISK is the proportion of total number of errors (Type I and II) and the number of sites under analysis. The RISK values close to 0 are expected when a method or a model performs well (29).

\[ RISK = \frac{(V + R)}{n} \]  

Poisson mean differences (PMD): PMD gives different weight for each falsely identified site. More precisely, it is used to differentiate various false identifications and to quantify more clearly the adverse consequences that result from erroneous identifications of unequal importance (31). It is the sum of the absolute difference of True Poisson Means (TPMs) associated with the falsely identified sites and critical TPMs (for more details about this test, the reader is referred to 31). The model with larger value of PMD is less desirable.

Simulation Design

Simulation is usually preferred to empirical data because the sites which are true hotspots are not known before hand with the empirical data (29, 30). Using simulation, we can establish sites that are a priori hazardous and can assess if the proposed methods are working well for identifying these locations. This in turn helps in counting the number of false positives and negatives.

The simulation design was accomplished using the following process:

1. Generate the traffic flow and segment length from a log normal distribution with a given mean and variance. The mean and variance are calculated from the Texas dataset described in the next section. Random values are generated for 1,000 sites.

2. Generate the “true” mean for SV and MV crashes at each site using \( \mu_i = \beta_0 L_i \beta_i^{\beta} \). The parameters \( \beta_0 \) and \( \beta_i \) are defined prior to the simulation. These parameters are directly taken from Table 3 for SV and MV
crashes. The “true” crash mean at each site is calculated by summing the true mean of SV and MV crashes.

3. Specify a threshold value \( k \) and all sites which have crash mean above this value are considered as hotspots. In this study, the threshold value \( k \) is set to the mean of all sites in the Texas data. The following selection rule is applied for identifying the hotspots:

\[
\text{If } \mu_i^{true} > k \text{ set } h_i = 1 \text{ and site } i \text{ is defined as “true” hotspot}
\]

\[
\text{Else set } h_i = 0, \text{ and site } i \text{ is defined as “non-true” hotspot}
\]

Then, the total “true” number of hotspots is calculated as:

\[
n_1 = \sum_{i=1}^{n} h_i
\]

4. Generate the error \( \varepsilon_i \) at each site for SV and MV crashes. It is usually assumed that \( \exp(\varepsilon_i) \) is independent and gamma distributed with a mean equal to 1 and a variance \( 1 / \phi \) for all \( i \), where \( \phi \) is the inverse dispersion parameter which is taken directly from table 3.

5. Simulate SV and MV crash counts for each site. It is assumed that crash counts at a site follow a Poisson distribution with known \( \theta_i \). The total crashes (referred as ALL crashes) are calculating by taking the sum of SV and MV crashes.

\[
Y_{i, sim} | \theta_i \sim Po(\theta_i)
\]

Where, \( \theta_i = \mu_i^{true} \exp(\varepsilon_i) \)

6. The parameters \( \hat{\beta}_0 \) and \( \hat{\beta}_1 \) are re-estimated for SV, MV and ALL crashes by modeling crashes and site attributes given in step 1.

7. Steps 5 and 6 are repeated for 25 times to obtain statistically reliable estimates. The average values for the parameters are finally used. The crash mean for SV, MV and ALL crashes is calculated using \( \hat{\mu}_i = \hat{\beta}_0 L_i F_i^{\hat{\beta}_1} \). Once \( \hat{\mu}_i \) is obtained for each site and based on a given model (SV+MV and ALL), The following selection rule is applied for identifying the “detected” hotspots:

\[
\text{If } \hat{\mu}_i > k \text{ set } d_i = 1, \text{ the site } i \text{ is a “detected” hotspot}
\]

\[
\text{Else set } d_i = 0, \text{ the site } i \text{ is a “non-detected” hotspot}
\]

Then, the total “detected” number of hotspots is calculated as:
\[ D = \sum_{i=1}^{n} d_i \]

8. The error measures FDR, FNR, SENS, SPEC, RISK and PMD given in the above section are calculated for SV+MV crashes and ALL crashes.

DATA DESCRIPTION

The statistical models were developed using crash data collected at 1,499 Texas undivided four-lane highway segments. The data were obtained from the Texas Department of Public Safety and the Texas Department of Transportation (TxDOT) for the years 1997 to 2001. The data included information on segment length, AADT, number of intersections, number of horizontal curves and other variables that influence the crash rate. The crash data provided details about the severity as well as the number of vehicles involved in the collision. Only segment related crashes were considered in this study. A total of 2,559 SV crashes and 1,694 MV crashes were extracted, respectively. Table 2 provides relevant descriptive statistics for key explanatory variables and crash data.

Table 2 here

Figure 1 shows the percent frequency of crash severities for SV, MV and ALL crashes. As seen in this figure, MV crashes have a much larger percentage of fatalities and serious injuries than SV crashes. This is expected since MV (head-on) crashes on average have a greater transfer of energy than SV crashes.

Figure 1 here

RESULTS

This section describes the results of the comparison analysis between SV, MV and ALL crash models.

Table 3 provides the parameter estimates with their associated standard errors. All the model parameters were statistically significant at the 5% level.

Table 3 here

Figure 2 illustrates the relationship between crashes and traffic flow for the SV, MV, ALL and SV+MV, respectively. From this figure, the crash-flow relationships indicate that the SV crashes increases at a decreasing rate as traffic flow increases. This relationship basically means that there are proportionally less crashes per passing vehicles as the traffic flow increases (\( \beta_1 < 1 \)) and thus the crash risk per vehicle diminishes when traffic flow increases. The total number of crashes (ALL) increases linearly with traffic flow (since \( \beta_1 \) is almost equal to 1). However, for MV crashes, we observed a different relationship, in which the crash rate increases as traffic flow
increases ($\beta_1 > 1$). In other words, the likelihood of being involved in a MV crash increases as the traffic flow increases. This is not uncommon and has been observed before ($Z, II$). Figure 2 also shows that the combined model (SV+MV) always predicts more crashes than the ALL crash model, as documented in Mensah and Hauer ($\Omega$). It is worth noting that the number of crashes increases with an increasing rate with the traffic flow when the SV+MV model is used, whereas the crashes increases linearly as traffic flow increases with the ALL crash model.

**Figure 2 here**

Table 4 shows the outcomes of hotspot identification by ALL and SV+MV models. Out of 731 true hotspots, the ALL model detected 723 sites as hotspots whereas SV+MV detected all 731 sites as hotspots. In other words, the type I errors (false positives) are 8 with ALL model and no type I errors with SV+MV model. There were 4 type II errors (false negatives) with ALL model and 3 type II errors with SV+MV model. In total, there were 12 sites that were detected wrongly by the ALL model, whereas only 3 sites by SV+MV model.

**Table 4 here**

As discussed above, if FDR, FNR, RISK and PMD values are smaller and SENS and SPEC values are higher in one model than the other then it is said to be superior. All the error measures suggest that the SV+MV crash model is superior to the ALL crash model, although the difference is not high. The summary results are shown in Table 5.

**Table 5 here**

Figure 3 gives the comparison between the true mean and the predicted number of crashes for ALL and SV+MV models. The shape of the curve predicted by SV+MV model is similar to the true mean curve. The predicted values estimated by the SV+MV model are also much closer to true mean. The values predicted by ALL model are almost the same as true mean until the AADT reaches 15,000 but starts to deviate a lot at higher traffic flows.

**Figure 3 here**

In summary, the results show that identifying hot stops using two distinct models provided a slightly better performance compared to using one single aggregated model. This small disparity is probably attributed to the differences in the predicted values, as observed in Figures 2 and 3. In the light of this research, it is therefore suggested to use SV and MV models for identifying high risk locations. However, using a single aggregated model should be adequate when SV and MV models are not available, since there was only a 1% difference in the identification process between the two.
SUMMARY AND CONCLUSIONS

The objective of this research was to examine the potential differences in the hotspot identification when SV and MV crashes are modeled separately and together (ALL model). Recently, some transportation safety analysts have recommended modeling both categories of crashes independently for estimating the safety performance of highway segments. To accomplish the comparison analysis, crash data were collected on rural four-lane highways in Texas. The error measures documented in Miranda-Moreno (29) and Cheng and Washington (31) were used in this study to evaluate the performance of ALL model and SV+MV model for the hotspot identification.

The following results were obtained from the analysis:

1. There is a clear difference in the prediction of crash mean values between aggregated crash prediction (ALL) and the summation of distinct models (SV and MV). This confirms previous work done by Mensah and Hauer (9) on this topic.
2. The SV+MV model gives slightly fewer false positives and negatives than the ALL model in the hotspot identification process. Given the research done by others and supported by the results documented in this paper, it is recommended to develop SV and MV models separately for predicting crashes (see 8) and for hot spot identification.

Since this research was applied to a single dataset, it is suggested to confirm the results using additional datasets, such as those collected on freeway and rural two-lane highways. With the recent application of multivariate models (43-45), the same kind of comparison analysis should be undertaken for crash data modeling involving the severity of the collision.

REFERENCES


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TABLE 2 Descriptive Statistics of Independent Variables and Crash Data
TABLE 3 Estimates of Model Coefficients (and Standard Errors)
TABLE 4 Classification of Outcomes
TABLE 5 Error Measures

FIGURE 1 Percent frequencies of crash severities
FIGURE 2 Crash-flow relationship for total crashes
FIGURE 3 Prediction of crash mean by two models
### TABLE 1 Outcomes Classified According to a Given Hotspot Identification Method (42)

<table>
<thead>
<tr>
<th></th>
<th>Number of sites “detected” as non-hotspots</th>
<th>Number of sites “detected” as hotspots</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of “true” non-hotspots</td>
<td>U</td>
<td>V</td>
</tr>
<tr>
<td>Number of “true” hotspots</td>
<td>R</td>
<td>S</td>
</tr>
</tbody>
</table>

\[
\begin{align*}
\text{n} & \quad - \text{Total number of sites in the set under analysis} \\
\text{n}_0 & \quad - \text{Number of “true” non-hotspots} \\
\text{n}_1 & \quad - \text{Number of “true” hotspots} \\
\text{U} & \quad - \text{Number of sites correctly classified as non-hotspots} \\
\text{V} & \quad - \text{Number of false positives or Type I errors} \\
\text{R} & \quad - \text{Number of false negatives or Type II errors} \\
\text{S} & \quad - \text{Number of sites correctly classified as hotspots} \\
\text{D} & \quad - \text{Number of sites detected hotspots as hotspots}
\end{align*}
\]
# TABLE 2 Descriptive Statistics of Independent Variables And Crash Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean (Std. dev)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Segment length (Miles)</td>
<td>0.1</td>
<td>6.275</td>
<td>0.55 (0.67)</td>
<td>830.5</td>
</tr>
<tr>
<td>AADT (Vehicles/day)</td>
<td>42</td>
<td>24800</td>
<td>6613.6 (4010.1)</td>
<td>--</td>
</tr>
<tr>
<td><strong>SV</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incapacitating Injury (A)</td>
<td>0</td>
<td>5</td>
<td>0.17 (0.54)</td>
<td>252</td>
</tr>
<tr>
<td>Non-Incapacitating Injury (B)</td>
<td>0</td>
<td>16</td>
<td>0.41 (1.14)</td>
<td>617</td>
</tr>
<tr>
<td>Possible Injury (C)</td>
<td>0</td>
<td>10</td>
<td>0.30 (0.81)</td>
<td>452</td>
</tr>
<tr>
<td>Fatal (K)</td>
<td>0</td>
<td>3</td>
<td>0.05 (0.24)</td>
<td>73</td>
</tr>
<tr>
<td>Non-Injury (O)</td>
<td>0</td>
<td>29</td>
<td>0.78 (1.89)</td>
<td>1165</td>
</tr>
<tr>
<td>Total Crashes</td>
<td>0</td>
<td>56</td>
<td>1.71 (3.80)</td>
<td>2559</td>
</tr>
<tr>
<td><strong>MV</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incapacitating Injury (A)</td>
<td>0</td>
<td>5</td>
<td>0.12 (0.43)</td>
<td>177</td>
</tr>
<tr>
<td>Non-Incapacitating Injury (B)</td>
<td>0</td>
<td>14</td>
<td>0.23 (0.69)</td>
<td>343</td>
</tr>
<tr>
<td>Possible Injury (C)</td>
<td>0</td>
<td>15</td>
<td>0.37 (0.99)</td>
<td>556</td>
</tr>
<tr>
<td>Fatal (K)</td>
<td>0</td>
<td>4</td>
<td>0.06 (0.28)</td>
<td>85</td>
</tr>
<tr>
<td>Non-Injury (O)</td>
<td>0</td>
<td>12</td>
<td>0.36 (0.95)</td>
<td>533</td>
</tr>
<tr>
<td>Total Crashes</td>
<td>0</td>
<td>41</td>
<td>1.13 (2.52)</td>
<td>1694</td>
</tr>
<tr>
<td><strong>ALL</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incapacitating Injury (A)</td>
<td>0</td>
<td>7</td>
<td>0.29 (0.79)</td>
<td>429</td>
</tr>
<tr>
<td>Non-Incapacitating Injury (B)</td>
<td>0</td>
<td>29</td>
<td>0.64 (1.61)</td>
<td>960</td>
</tr>
<tr>
<td>Possible Injury (C)</td>
<td>0</td>
<td>17</td>
<td>0.67 (1.46)</td>
<td>1008</td>
</tr>
<tr>
<td>Fatal (K)</td>
<td>0</td>
<td>7</td>
<td>0.11 (0.42)</td>
<td>158</td>
</tr>
<tr>
<td>Non-Injury (O)</td>
<td>0</td>
<td>41</td>
<td>1.13 (2.48)</td>
<td>1698</td>
</tr>
<tr>
<td>Total Crashes</td>
<td>0</td>
<td>97</td>
<td>2.84 (5.69)</td>
<td>4253</td>
</tr>
<tr>
<td>Crash type</td>
<td>$\ln \beta_0$</td>
<td>$\beta_1$</td>
<td>$\alpha$ (1/$\phi$)</td>
<td></td>
</tr>
<tr>
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<td>-------------</td>
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### TABLE 5 Error Measures

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FIGURE 1 Percent frequencies of crash severities.
FIGURE 2 Crash-flow relationship for total crashes.
FIGURE 3 Prediction of crash mean by two models.