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Improving Freeway Crash Prediction Models Using Disaggregate Flow State Information

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16. Abstract:

Crash analysis methods typically use annual average daily traffic as an exposure measure, which can be too aggregate to capture the safety effects of variations in traffic flow and operations that occur throughout the day. Flow characteristics such as variation in speed and level of congestion play a significant role in crash occurrence and are not currently accounted for in the American Association of State Highway and Transportation Officials' *Highway Safety Manual*. This study developed a methodology for creating crash prediction models using traffic, geometric, and control information that is provided at sub-daily aggregation intervals. Data from 110 rural four-lane segments and 80 urban six-lane segments were used. The volume data used in this study came from detectors that collect data ranging from continuous counts throughout the year to counts from only a couple of weeks every other year (short counts). Speed data were collected from both point sensors and probe data provided by INRIX.

The results showed that models that used data aggregated to an average hourly level reflected the variation in volume and speed throughout the day without compromising model quality. Crash predictions for urban segments underwent a 20% improvement in mean absolute deviation for total crashes and a 9% improvement for injury crashes when models using average hourly volume, geometry, and flow variables were compared to the model based on annual average daily traffic. Corresponding improvements over annual average daily traffic models for rural segments were 11% and 9%. Average hourly speed, standard deviation of hourly speed, and differences between speed limit and average speed had statistically significant relationships with crash frequency. For all models, prediction accuracy was improved across all validation measures of effectiveness when the speed components were added. The positive effect of flow variables was true irrespective of the speed data source. Further investigation revealed that the improvement achieved in model prediction by using a more inclusive and bigger dataset was larger than the effect of accounting for spatial/temporal data correlation. For rural hourly models, mean absolute deviation improved by 52% when short counts were added in comparison to the continuous count station only models. The respective value for urban segments was 58%. This means that using short count stations as a data source does not diminish the quality of the developed models. Thus, a combination of different volume data sources with good quality speed data can lessen the dependency on volume data quality without compromising performance. Although accounting for spatial and temporal correlation improved model performance, it provided smaller benefits than inclusion of the short count data in the models.

This study showed that it is possible to develop a broadly transferable crash prediction methodology using hourly level volume and flow data that are currently widely available to transportation agencies. These models have a broad spectrum of potential applications that involve assessing safety effects of events and countermeasures that create recurring and non-recurring short-term fluctuations in traffic characteristics.

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FINAL REPORT

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ABSTRACT

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This study showed that it is possible to develop a broadly transferable crash prediction methodology using hourly level volume and flow data that are currently widely available to transportation agencies. These models have a broad spectrum of potential applications that involve assessing safety effects of events and countermeasures that create recurring and non-recurring short-term fluctuations in traffic characteristics.

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INTRODUCTION

The 2017-2021 Virginia Strategic Highway Safety Plan set a fatality goal for the state of zero fatalities (Virginia Department of Transportation [VDOT], 2017). To achieve this goal of saving lives and reducing motor vehicle crashes and injuries, Virginia aims to expand the use of data-driven, systemic safety management approaches. Crashes are complicated events that are influenced by multiple factors, including roadway geometry, driver behavior, traffic conditions, and environmental factors. The influence of those factors on traffic crashes cannot be fully understood without detailed information not only on the crash itself but also on its surrounding circumstances. There is a continuing need to evolve and improve analytic methods to increase the understanding of crash causal factors, identify locations with possible safety concerns, and assess the effectiveness of safety improvement alternatives.

The American Association of State Highway and Transportation Officials' (AASHTO) *Highway Safety Manual* (HSM) serves as a national resource that provides standard scientific techniques and knowledge to help transportation officials make informed decisions regarding road safety (AASHTO, 2010; AASHTO, 2014). The core of the predictive methodology used in the HSM is the use of safety performance functions (SPFs). An SPF is a mathematical relationship that models the frequency of crashes by severity and accounts for geometric and traffic control factors that influence crashes on specific types of roads. For practical reasons, base SPFs often use a concise functional form and include only limited numbers of variables (such as annual average daily traffic [AADT] and segment length).

The HSM provides professionals with a much-needed resource in which current knowledge, techniques, and methodologies to estimate future annual crash frequency and severity are presented. Despite that, there are some limitations of using the SPFs recommended in the HSM. One drawback of using AADT for predicting crashes is that it can be interpreted as a quantity measure but it cannot be used to assess the quality of flow. Quality of flow is related to the variation in flow parameters such as speed or density on a much shorter time interval, such as hours or minutes, as compared to the yearly variation in volume used for HSM SPFs. Since AADT is the average number of vehicles per day over an entire year, hourly, daily, and seasonal variations in traffic volume are averaged out. It is generally assumed that crash rates for highways vary with flow state, but the relationship among flow, speed, and crashes is not simple. The customary use of AADT in safety analysis may be too aggregate to capture how variation in the flow affects the occurrence of highway crashes.

A study of the relationship between crashes and flow state requires reliable and detailed information on crashes and disaggregated traffic flow data, which are often complicated by sparse detector coverage and the quality of available data. Volume data are collected by each state from both a limited set of continuous count stations that collect data continuously throughout the year and short count stations that collect data periodically for shorter time intervals. The quality of continuous count data is very high, even though the total number of stations is limited. On the other hand, the short count stations have a broader coverage but the quantity of data available from them is much less. Both of these issues can be crucial since current crash models depend on volume data. One way to address this concern is to add other variables in the modeling process that capture the variation in traffic, such as speed. Private sector probe data theoretically provide 24-hour temporal coverage and broad network coverage spatially. As availability and reliability of observed traffic data significantly affect the accuracy of crash predictions, using probe data, which has better network coverage, might be a useful way to improve the availability of data. Another important consideration in crash modeling is the presence of spatial and temporal correlation in crashes. The HSM-recommended methodology does not acknowledge correlation in data. This issue may be even more acute when disaggregated data are used.

PURPOSE AND SCOPE

Current safety prediction methodologies look only at annual measures of exposure and do not account for changes in traffic flow over the course of a day. As a result, these methods do not do a good job capturing the safety impacts of projects that improve traffic operations but do not change overall exposure, such as incident management programs, dynamic hard shoulder running, or active traffic management. Given VDOT’s recent emphasis on deploying operations projects, there is a need to develop better methods to analyze these projects so that safety impacts can be assessed more accurately and safety performance can be better predicted. The specific objectives of this study were as follows:

1. Determine whether sub-daily crash predictions models can provide better safety predictions than AADT-based models and which time aggregation interval provides the best predictions.

2. Determine if inclusion of traffic state variables improves predictions.

3. Evaluate different sources of speed data and assess the change in quality of crash prediction models based on the data source used. This has implications for how models that rely on speed data can be deployed widely.

4. Investigate whether the data from non-continuous count stations can be used to generate quality predictions. This has implications for whether continuous volume data are required to generate sub-annual predictions, which could affect whether models can be applied widely.

5. Investigate whether accounting for spatial and temporal correlations creates significant improvements in the crash prediction models.

The scope of this study was limited to two common configurations of basic freeway segments in Virginia: two-lane rural freeway directional segments, and three-lane urban freeway directional segments. These cross sections were selected because they are the most common freeway segment type in Virginia and relationships between flow state and safety are expected to be more uniform on limited access freeways than on arterials. It is expected that the models developed in this study will require more data and analytical effort to apply, but they could be used strategically on projects where changes in flow by time of day are expected in order to improve the overall accuracy of safety estimates for those projects.

METHODS

Literature Review

Relevant online databases such as TRID and the VDOT Research Library database were searched to identify relevant literature on disaggregated crash modeling, the relationship between crashes and geometric variables, the relationship between crashes and traffic flow parameters, and statistical methodologies used for crash modeling with and without data correlation.

Data Collection and Preparation

For this task, volume, speed, and geometry data were collected for two-lane directional rural freeway segments and three-lane directional urban freeway segments from 2011-2017 using VDOT data systems. The characteristics of the data sources and how they were processed for use in safety modeling are discussed here.

Volume Data

VDOT's traffic data collection program includes more than 100,000 traffic roadway segments where data are collected and traffic estimates produced. There are more than 400 continuous count stations across the state, 140 of which are on the interstates. The continuous count stations collect data 24 hours a day, 365 days a year. VDOT also has short count stations throughout the state in an effort to ensure that at least some data exist for all roads maintained by VDOT, even if they are not collected continuously in real time. Short count durations range from 48 hours to longer periods less than 1 year. Even though the data derived from continuous count stations are of high quality, the spatial coverage of these stations is limited. Although the short count stations cover a broader area, the quantity of data available from them is less than for the continuous count stations.

First, the locations of traffic detectors were identified using the detector database maintained by VDOT's Traffic Engineering Division (TED) and the VDOT GIS integrator. For rural two-lane segments, 110 count stations were used (31 continuous count, 79 short count); for urban six-lane segments, 80 count stations were used (24 continuous count, 56 short count). For all of the continuous count stations, only the time periods in which volume data met the quality threshold set by VDOT were included in the dataset, resulting in a loss of 16% of data for the rural segments and 9% of data for the urban segments after screening. The short count stations collect data periodically, so average volumes were determined using all data collected at each station, which is less than an entire year's worth of data.

Geometry Data

Geometric and traffic control information was also extracted from several databases. Information such as number of lanes, speed limit, shoulder width, median type, rural/urban designation, etc., was gathered for the study segments. VDOT also provided a database containing horizontal curvature (HC) and vertical curvature (VC) information for each segment. The start and end mile marker positions for these segments were used to match them with the selected freeway segments for this analysis. The VC data were calculated using the difference in slope and length of curve and expressed in the form of percent grade. HC was expressed using length of curve, presence of curve as a percentage of segment length, and radius of curve. Length of curve and radius of curve for each segment were directly available in the dataset.

Identification of Freeway Segments

Only homogeneous basic freeway segments that had volume data and were free from ramps or interchanges were considered for modeling. Endpoints of analysis sections were initially defined such that each freeway segment had no entry/exit ramps within 0.5 miles of the start/end of the segment. Next, it was important to define a segment surrounding each count station so that conditions were homogeneous for the entire length. The number of lanes, lane and shoulder width, speed limit, median type, and median width were used to define the geometric homogeneity of the segment. If the station was on a link with homogeneous characteristics that was greater than 2 miles in length, a buffer of a maximum of 1 mile upstream and 1 mile downstream of the actual location of the detector was created to reduce the likelihood that traffic conditions varied substantially from those of the location of the count station. The product of this task was the identification of a series of basic freeway segments with homogeneous traffic and geometric conditions that contained a detector station.

Speed Data

Speed data were collected from two sources: (1) the available continuous count stations, along with volume data for the entire study period; and (2) INRIX, at 15-minute and hourly intervals. INRIX is a private sector company that processes GPS and fleet probe data to estimate speeds, which are reported spatially using traffic message channel (TMC) links. TMC links are spatial representations developed by digital mapping companies for reporting traffic data and consist of homogeneous segments of roadways. VDOT currently uses INRIX data to support a variety of performance measurement and traveler information applications, and several evaluations have supported the accuracy of the travel time data for freeways (Haghani et al., 2009).

Using the latitude and longitude information of TMCs from INRIX, it was possible to match the location of the identified freeway segments and corresponding TMCs. INRIX provides confidence scores for each 1-minute interval travel time, with a confidence score of 30 representing real-time data and scores of 10 and 20 representing historic data during overnight and daytime periods, respectively. About 73% of the data for rural segments and 71% of the data for urban segments had a confidence score of 30. For the purposes of this analysis, no threshold was set for the confidence scores and both real-time and historic speed data were averaged for use in model development.

Crash Data

Crash data for all segments were obtained from the VDOT Roadway Network System (RNS). The data included detailed information on crash location and date, crash type, severity, number of vehicles involved, etc. For all the segments, crash information was also collected from 2011-2017. For this analysis, the researchers examined total crashes as well as fatal and injury crashes.

Statistical Approach to Crash Prediction Modeling

A range of factors must be considered when developing crash prediction models. Relevant issues include selection of data structure, contributing variables, type of regression method used, technique used for modeling, and model selection and validation. The statistical analysis used to develop the crash prediction models in this study is described here.

Selection of Data Structure

Traditionally, most crash frequency models have used aggregated information with relatively large time scales (e.g., yearly) rather than detailed, time-varying data in smaller time scales (e.g., hourly, daily, or weekly). Because of the adoption of larger time scales, temporal variation of some explanatory variables such as hourly traffic variation or inclement weather is often lost. Depending on how the data are being collected and used, different data formats can be used. Cross-sectional data are observed at a single point of time for several study sites. When this data format is used, the interest lies in modeling how particular sites are performing at a certain point of time (Washington et al., 2010). The problem with this approach is that by analyzing only a "snapshot" of longitudinal data, it is possible to overlook the simultaneous correlation between crashes and their contributing factors. If multiple years of data are available for study sites, it is possible to use a panel data format. The key feature of panel data is that the same sites appear repeatedly. This data structure makes it possible to capture a collective effect of the omitted variables in regression analysis (Washington et al., 2010). If a common correlation pattern in crash frequencies exists across the segments over the analysis period, the pattern can lead to more accurate model estimation compared to the cross-sectional data. Because of these benefits, the crash data used in this study were analyzed as panel data.

Selection of Model Form

Overview

Since crashes are non-negative and characterized by overdispersion (the variance of crashes is greater than the mean), negative binomial regression has become the most common method for developing SPFs and is also the recommended modeling approach in the HSM (AASHTO, 2010; Lord and Mannering, 2010; Milton and Mannering, 1996). In a negative binomial regression model, the probability of roadway entity i having y_i crashes per time period is defined as follows (Washington et al., 2010):

$$P(y_i) = \frac{exp(-\lambda_i) * \lambda_i^{y_i}}{y_i\,!}$$

$$\lambda_i = exp(\beta X_i + \varepsilon_i)$$

where

y_i = the number of crashes for segment i in year t
β = a vector of the estimable parameters
X_i = a vector of the explanatory variables
exp (ε_i) = a gamma-distributed error term with mean 1 and variance α.

It should be noted that λ is an indication of the expected number of crashes on segment i. If one had used a Poisson model and did not have explanatory variables X_i, then λ_i would simply be the estimated mean of crashes observed on the segment. The addition of this term allows the variance to differ from the mean as follows:

$$VAR\ (y_i) = E\ ((y_i)\ [1+ \alpha E(y_i)\ ] = E(y_i)\ + \alpha E(y_i)^{\ 2}$$

Another popular method for modeling disaggregated data is zero inflated models. Zero inflated models have been developed to handle data characterized by a significant number of zeros, or more zeros than one would expect in a traditional Poisson or negative binomial / Poisson-gamma model. These models operate on the principle that the excess zero density that cannot be accommodated by a traditional count structure is accounted for by a splitting regime that models a crash-free versus a crash-prone propensity of a roadway segment (Lord and Mannering, 2010; Washington et al., 2010).

If the probability of a data point being zero is π and the probability of it being non-zero is (1 – π), then the probability distribution of the zero-inflated negative binomial (ZINB) random variable y_i can be written as follows:

$$P_r(y_i = j) = \begin{cases} \pi_i + (1-\ \pi_i)g(y_i = 0) & if\ j = 0 \\ (1-\ \pi_i)g(y_i) & if\ j > 0 \end{cases}$$

where πi is the logistic link function and g(yi) is the negative binomial distribution given by the following:

$$g(y_i) =\ P_r(Y = y_i|\ \mu_i, \alpha) =\ \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i+1)}\left(\frac{1}{1+\ \alpha\mu_i}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu_i}{1+\ \alpha\mu_i}\right)^{y_i}$$

As temporal data aggregation becomes more disaggregate, it is a reasonable expectation to have a larger number of 0 crash observations in each interval. As a result, this study developed crash prediction models using both the negative binomial form and the ZINB form.

Vuong Test

Since both negative binomial and ZINB forms were tested, the model forms needed to be compared to determine which option was superior. The use of the Vuong test statistic (V) has been proposed for non-nested models to compare the fitness of zero inflated models versus that of regular count models (Vuong, 1989). The test statistic is calculated as follows:

$$V = \frac{\overline{m} * \sqrt{N}}{S_m}$$

where

$m_i = log[\frac{f_1\ (y_i)}{f_2\ (y_i)}]$
N = number of observations
$\overline{m}$ = mean of m_i
S_m= standard deviation of m_i
f_1, f_2 = two competing models.

V has a standard normal distribution, and the test has three possible outcomes:

1. If the absolute value of V is less than 1.96 for a 0.95 confidence level, then neither model is preferred by the test result.

2. If V is a large positive value, then Model 1 is preferred.

3. If V is a large negative value, then Model 2 is preferred.

This test was used to select which model form was appropriate for the dataset.

Selection of Modeling Technique

Generalized Linear Models (GLMs)

GLMs are extensions of traditional regression models that allow the mean to depend on the explanatory variables through a link function and the response variable to be any member of a set of distributions called the exponential family (e.g., normal, Poisson, binomial) (McCullagh and Nelder, 1991). In a GLM, each outcome Y of the dependent variables is assumed to be generated from the exponential family. The mean, μ, of the distribution depends on the independent variables, X, through the following:

$$E(Y) = \mu = g^{-(X\beta)}$$

where

E(Y) = the expected value of Y
Xβ = the linear predictor, a linear combination of unknown parameters β
g = the link function.

The unknown parameters, β, are typically estimated using the maximum likelihood method. This method estimates model parameters by selecting those that maximize a likelihood function that describes the underlying statistical distribution assumed for the regression model. For a negative binomial regression model, the likelihood function can be described as follows:

$$L\ (\lambda_i) = \prod_i \frac{\Gamma\ (y_i + \left(\frac{1}{\alpha}\right))}{y_i!\ \Gamma\left(\frac{1}{\alpha}\right)} \cdot \left[\frac{\alpha\lambda_i}{1+\alpha\lambda_i}\right]^{y_i} \cdot \left[\frac{1}{1+\alpha\lambda_i}\right]^{1/\alpha}$$

where

Γ(x) = the gamma function
variance = α
λ = the mean
y_i = the number of crashes per period for roadway segment i.

Models in this study were initially estimated using a GLM.

Spatial and Temporal Correlation and Generalized Linear Mixed Models (GLMMs)

A common phenomenon in crash data is overdispersion, meaning that the variance of the data exceeds the mean. Overdispersion is usually attributed to unobserved heterogeneity. Motor vehicle crashes are highly complex processes influenced by various contributing factors, so it is nearly impossible to collect all the data that describe factors that contribute to a crash and its resulting injury severity. As a result, the impacts of these unobserved factors on the likelihood of a crash cannot be adequately captured solely by the explanatory variables in the model, leading to the unobserved heterogeneity problem (Lord and Mannering, 2010; Mannering and Bhat, 2014).

Traditionally, most crash frequency models have used a cross-sectional data format. Since this format overlooks the correlation between crashes and their contributing factors over time, it is not suitable for studies where multiple years of data are available for each study site. Panel data permit identification of variations across individual roadway segments and variations over time. Accommodation of observation-specific effects also mitigates omitted-variables bias by implicitly recognizing segment-specific attributes that may be correlated with control variables. The time-series nature of multiyear data as used in this study presents serial correlation issues. In a similar vein, there can be spatial correlation space because roadway entities that are in close proximity may share unobserved effects. This again sets up a correlation of disturbances among observations and results in the associated parameter estimation problems.

Both overdispersion and serial correlation needs to be addressed in a modeling framework to produce efficient estimates. Although regular negative binomial models account for overdispersion, they do not allow for location-specific effects or serial correlation over time for clustered crash counts. In recent years, mixed effect models have gained popularity among researchers because of their ability to handle both overdispersion and correlation. They are usually called GLMMs because they use the common distributions associated with the GLM such as Poisson, negative binomial, or zero inflated models and also account for data structures in which observations cluster within larger groups (Hausman et al., 1984). GLMMs were also used in this study to determine whether accounting for spatial and temporal correlation significantly improved crash prediction models.

The dataset for this study was composed of multiple segments for rural and urban highways where data had been collected for 7 years, which introduced correlation in the data that came from a combination of spatial considerations (data from different VDOT districts in Virginia) and temporal considerations (average hourly data for 7 years).

The random effects model can introduce random location-specific or time-specific effects into the relationship between the expected numbers of crashes and the covariates of an observation unit i in a given time period t (Hausman et al., 1984). The GLMM model structure is as follows:

$$y_i|b \approx Distr \left[\mu_i, \frac{\sigma^2}{w_i}\right]$$

$$g(\mu) = \beta X + bZ + \delta$$

where

y_i = dependent variable
b = random effects vector
Distr = a specified conditional distribution of y given b
μ= the conditional mean of y given b, μ_i is its i-th element
σ^2 = the variance or dispersion parameter
w = the effective observation weight vector (w_i = the weight for observation i)
g(μ) = link function that defines the relationship between the mean response μ and the linear combination of the predictors
X = fixed effects design matrix of independent variables
β = fixed-effects vector
Z = random-effects design matrix of independent variables
δ = residuals (Mussone et al., 2017).

The model for the mean response μ is as follows:

$$\mu = g^{-1}(\hat{\eta})$$

where

g^{-1} = inverse of the link function g(μ)
$\hat{\eta}$ = linear predictor of the fixed and random effects of the generalized linear mixed effects model.

In the simplest terms, the mixed effect model used in this study can be defined as follows:

$$Y = \overbrace{\text{Volume} + \text{Geometric Variables} + \text{Flow Variables}}^{\text{Fixed Effect}} + \underbrace{(1|\text{District}) + (1|\text{Year}) + (1|\text{Hour})}_{\text{Random Effect}}$$

Y is the dependent variable (number of crashes); the fixed effect part defines the relationship between different variables and total crashes; and the random effect part clusters data by VDOT districts (to account for spatial correlation) and by year and hour (to account for temporal correlation).

Although VDOT districts are very large, they are reasonably consistent in terms of unobserved factors such as weather and driver behavior. Thus, the spatial correlation is intended to capture these unobserved effects rather than to capture more microscopic correlations between adjacent links. The format "(1|x)" means that the model calculates the variance in intercepts that is different for each group for the random effect "x." This effectively resolves the non-independence that stems from having multiple responses by the same subject. It is also possible to estimate the random effect for each variable separately. For example, Volume|District would essentially estimate the intercept for each district and also a separate random effect parameter for volume for each district. Considering separate parameters for both spatial and temporal effects and for all the correlated variables creates a very complicated model and additional difficulty in interpretation and application. As a result, this study focused on the variances between intercepts for each random effect.

The "glmmTMB" package built for GLMMs using Template Model Builder in R statistical software was used for the modeling. The package fits linear models and GLMMs with various extensions, including zero inflation. The models are fitted using maximum likelihood estimation. Random effects are assumed to be Gaussian on the scale of the linear predictor and are integrated using the Laplace approximation (Bolker, 2019; Brooks et al., 2017).

Differences From the HSM SPF Form

The models developed in this study differ in several significant ways from the HSM freeway models for basic freeway segments (AASHTO, 2014). First, the HSM models are bi-directional and those developed in this study predict crashes only in a single direction of travel. This was done because it was expected that volume, cross section, and flow state would have significant directional differences that should be captured in the crash models. Second, the geometric variables modeled were selected based on their widespread availability in existing VDOT databases. Factors for the lengths, offset, and type of median barrier and outside barrier were not explicitly included in the modeling, although they are used in the HSM, because of the lack of data availability in VDOT sources. Likewise, clear zone width was not included as a factor since it was not widely available in VDOT data sources.

Model Selection and Validation

Model Selection

This study generated a number of potential models, and it was necessary to select the best model based on goodness of fit (GOF) and model efficiency. In order to measure the model fit, the ρ_c^2 statistic was used based on the loglikelihood of the selected model and the constant only model:

$$\rho_c^2 = 1 - \frac{LL(\beta)}{LL(C)}$$

where

(β) = the log-likelihood at convergence
LL(C) = the log-likelihood with the constant only model.

A perfect model has a likelihood equal to 1. The closer the value is to 1, the more variance the estimated model is explaining (Washington et al., 2010).

An analysis of variance (ANOVA) comparing the negative binomial and ZINB models was used to test which distribution fit the model better. ANOVA, which is readily available using R software, gives a list of a number of other GOF measures.

When the models are compared, it is important to have a consistent methodology to select a model from a series of models that have been developed for each technique. A popular method for model selection is the Akaike information criterion (AIC) (Akaike, 1974). The AIC offers an estimate of the relative information lost when a given model is used to represent the process that generated the data and is calculated as follows:

$$AIC = -2LL + 2p$$

where p = the number of estimated parameters included in the model. A lower value of AIC indicates a better model.

The Bayesian information criterion (BIC) is a criterion for model selection among a finite set of models. It is based in part on the likelihood function and is closely related to the AIC. The BIC also uses a penalty term for the number of parameters in the model. The penalty term is larger in the BIC than in the AIC. The BIC is given by the following:

$$BIC = -2ln(L) + k*ln(n)$$

where

n = number of observations
k = the number of free parameters to be estimated

L = the maximized value of the likelihood function for the estimated model (Schwarz, 1978).

Model Validation

An objective assessment of the predictive performance of a particular model can be made only through the evaluation of several GOF criteria. The GOF measures used to conduct external model validation included mean absolute prediction error (MAPE), MAD, and mean squared prediction error (MSPE) (Washington et al., 2010). In addition, cumulative residual (CURE) plots were examined to check the functional form of the model. Residuals are defined as the differences between the observed and fitted values of the response; when plotted cumulatively, they demonstrate the suitability of a regression model. The data in the CURE plot are expected to oscillate about 0. Any large jumps between residuals indicate areas where there may be outliers in the data.

Model building used a random selection of 70% of the available data; the remaining 30% was used for testing and validation. The calculation of the GOF measures was based on the following equations:

$$Mean\ Absolute\ Prediction\ Error\ (MAPE) = \sum_{i=1}^{n}\left|\frac{Y_{model} - Y_{observed}}{Y_{observed}}\right|$$

$$Mean\ Absolute\ Deviation\ (MAD) = \frac{\sum_{i=1}^{n}|Y_{model} - Y_{observed}|}{n}$$

$$Mean\ Squared\ Prediction\ Error\ (MSPE) = \frac{\sum_{i=1}^{n}(Y_{model} - Y_{observed})^2}{n}$$

where

Y_{model} = predicted crash frequency
$Y_{observed}$ = observed crash frequency
n = sample size.

Since AADT-based models predict annual crashes whereas hourly volume models predict hourly crashes, there was a need to look at GOF measures using a consistent time scale. For hourly level predictions, the summation of hourly predictions was used to generate annual predicted numbers of crashes for the GOF calculations so comparisons could be consistent. The average hourly volume data were computed by averaging data for each available hour for each site, so there were always 24 hours of data available for each year and each site for validation. For the validation of raw hourly data, high-quality volume and speed data were not always available for all 24 hours of every single day. To deal with this issue, crash predictions were calculated using all hours with valid data. The hour-by-hour predictions produced by these valid hours were then averaged and multiplied by 365 to convert predictions to an annual value for each hour of the day. This essentially assumed that missing hours are set equal to the value of the average hourly crash prediction for that hour at that site and provides a consistent basis for comparison between the model forms.

Experimental Design for Developing Crash Prediction Models

A three-stage process was used for developing crash prediction models and making decisions about variables and model form using the procedures discussed earlier. The three stages were as follows:

1. initial investigations of data aggregation intervals and influence of flow parameters
2. assessment of the effects of different speed data sources using continuous count stations
3. examination of short count stations and effects of spatial and temporal correlation.

The following sections discuss the major steps in each stage.

Initial Investigations of Data Aggregation Intervals and Influence of Flow State Variables

The first stage involved ascertaining which temporal data aggregation interval produced the best crash prediction models and determining whether inclusion of flow parameters improved the models. Figure 1 provides an overview of how the statistical concepts discussed earlier were applied to investigate these issues. These initial investigations used the four-lane rural freeways to test these concepts since they generally had the most consistent geometric cross sections. Two basic regression model forms were evaluated as part of this stage:

1. models using volume, segment length, and geometric variables
2. models using volume, segment length, geometric variables, and traffic flow parameters.

Each of these model forms was estimated using negative binomial and ZINB models to assess relative performance. Volume was examined at four aggregation intervals:

1. raw hourly volume, as observed each day at the site

2. average 15-minute volume, expressed as an average volume for each 15 minutes of the day for each site over each year

3. average hourly volume, expressed as an average volume for each hour of the day for each site over each year

4. AADT.

Quality of flow variables were summarized at the same time interval as the corresponding volume variable. The models were compared to one another and with the AADT model to determine how the predictions differed from a typical HSM-like model. To be consistent with the HSM, length was used as an offset variable in the models.

Models generated through the process summarized in Figure 1 were compared to assess which combination of data aggregation interval and predictive variables produced the best results. The results of this investigation then informed development of the second stage of model generation.

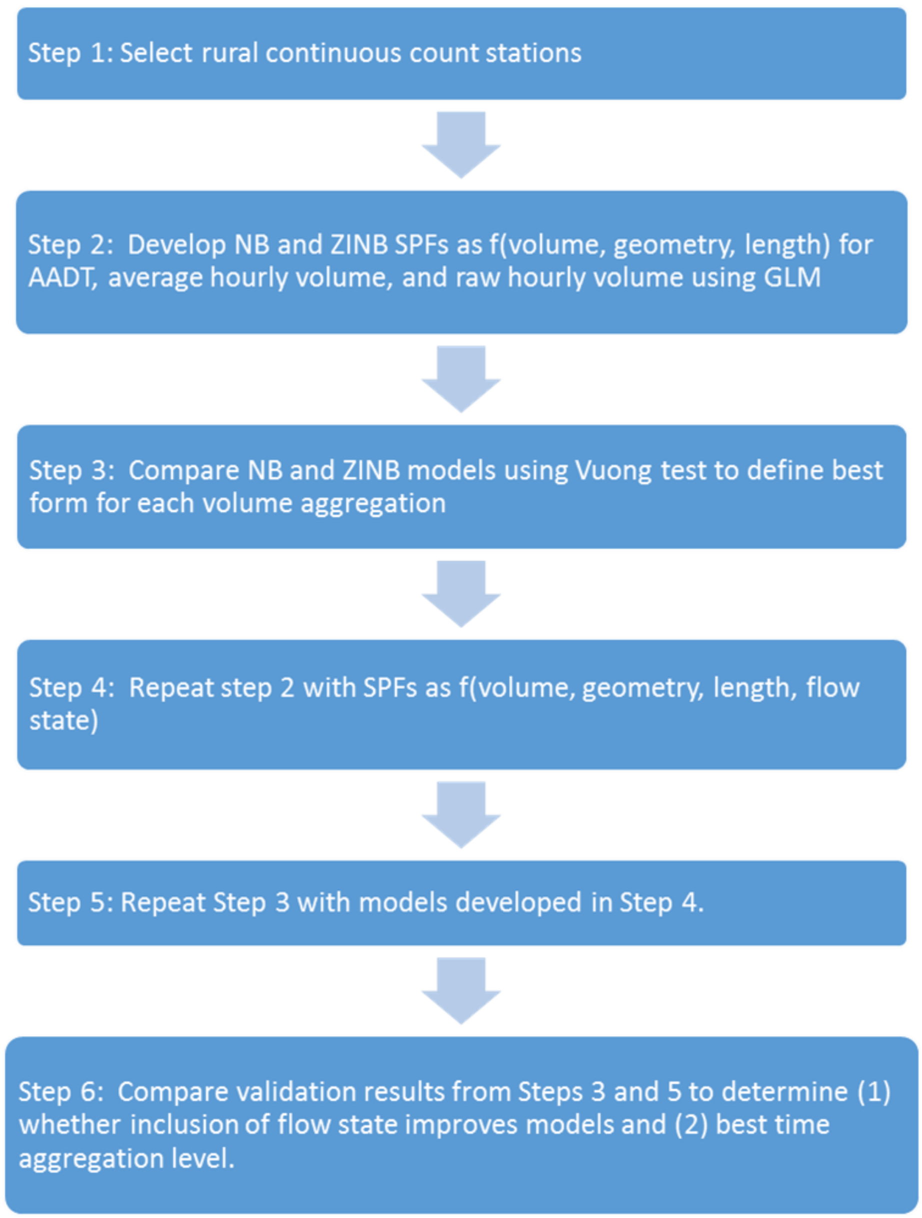


Figure 1. Overview of Stage 1 Modeling to Assess Data Aggregation and Traffic Flow State Effects

Assessment of the Effects of Different Speed Sources Using Continuous Count Stations

After the first stage defined preferred aggregation intervals and assessed the utility of adding flow state variables, the analysis was expanded to examine issues related to the source of speed data. The preferred aggregation interval defined in the first stage was used to construct negative binomial and ZINB models for links spanning both urban and rural continuous count stations. Parallel models were created using speed data from the count station and probe data from INRIX. These models were compared to assess whether probe speed data were an acceptable substitute for point sensor data. Thus, this stage expanded the potential transferability of the models by assessing urban facilities and examining speed data sources. Figure 2 provides an overview of this stage of the analysis.

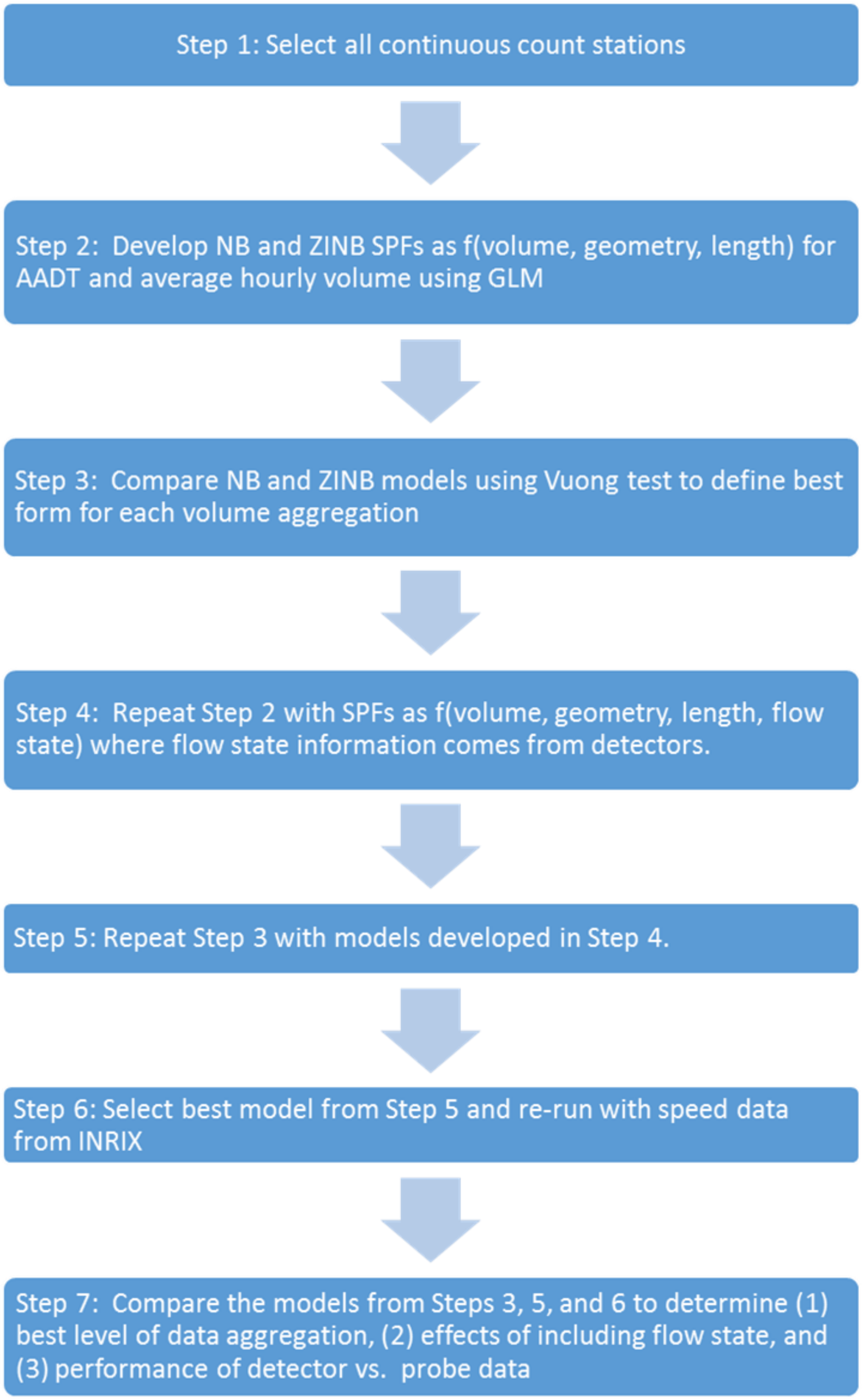


Figure 2. Stage 2 Process for Assessment of Effects of Speed Data Sources for Continuous Count Stations

Examination of Short Count Stations and Effects of Spatial and Temporal Correlation

The third stage of model development built on the previous two stages, with the ultimate goal of developing crash prediction models that could be broadly applied across the state. The preferred source of flow data and temporal aggregation level defined earlier were carried forward to this stage. The previous two stages relied on the use of continuous count stations. Although that data were robust, those stations are present on only a limited portion of the roadway network, which limits the utility of the models to be applied statewide.

In order to expand the application of these models, short count stations were included in the model development process to examine whether model quality suffered from inclusion of sites where continuous volume data were not present. Also, models were developed that accounted for potential spatial and temporal correlation to determine whether inclusion of those terms resulted in significant improvements to the models using the methods discussed earlier. Figure 3 summarizes the modeling process that occurred in this stage.

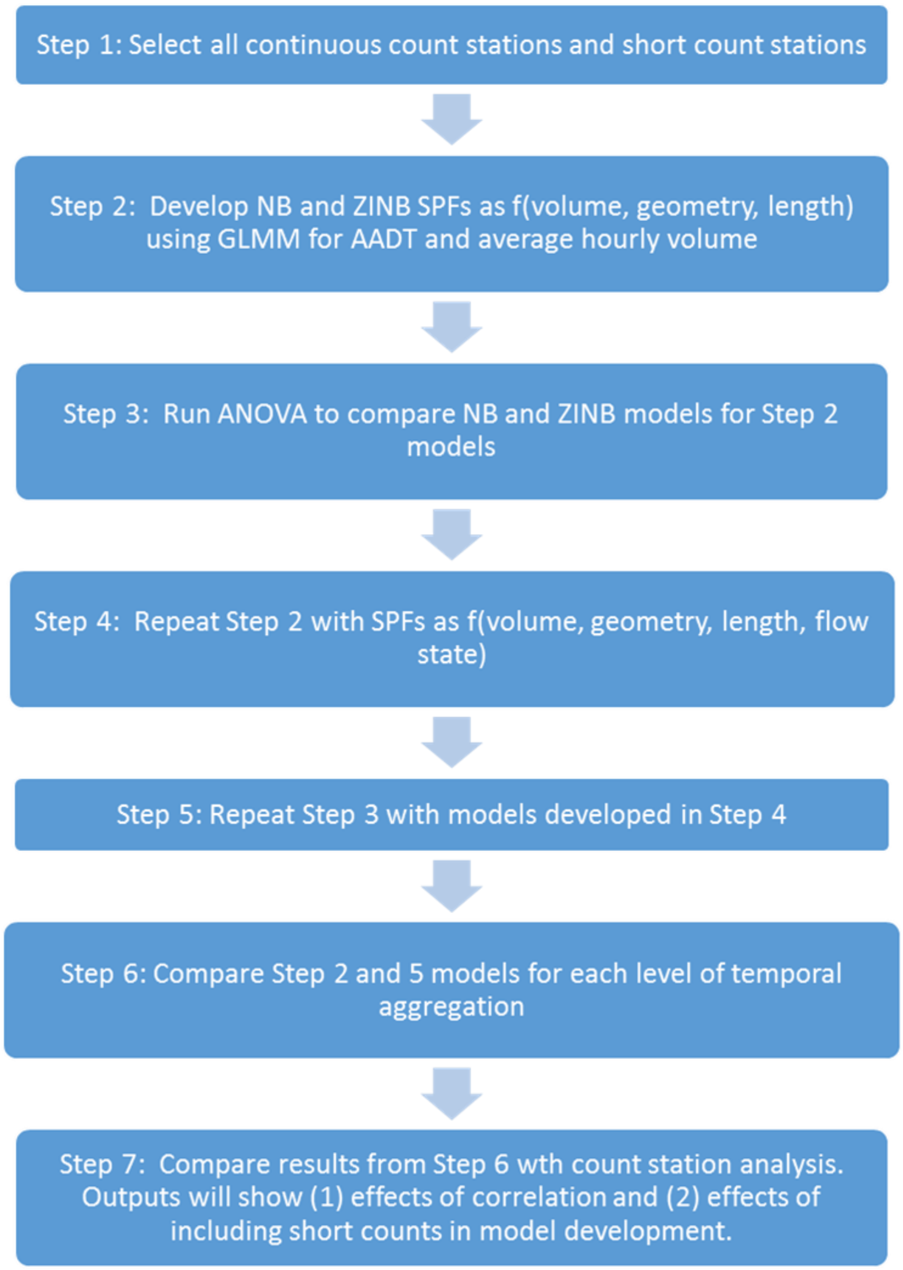


Figure 3. Stage 3 Process for Examination of Short Count Stations and Effects of Spatial and Temporal Correlation

Selection of Preferred Models

Following the completion of the three stages of modeling, preferred models were selected that provided the best predictions accounting for the following:

- level of temporal data aggregation
- inclusion of flow state variables
- use of continuous versus short counts
- use of probe versus continuous count station data
- inclusion of spatial/temporal correlation.

RESULTS AND DISCUSSION

Literature Review

Crash prediction models are very useful tools in highway safety, given their potential for determining both the frequency of crash occurrence and the contributing factors that could be addressed by transportation policies or site interventions. This section highlights existing studies on sub-annual crash trends and discusses the issues associated with data availability and correlation.

Relationship Between Crashes and Hourly Exposure

Studies of relationships between crashes and traffic characteristics can be divided into two categories: aggregated studies, in which the units of analysis represent counts of crashes or crash rates for specific time periods (typically months or years), and disaggregated analysis, where the units of analysis are the crashes themselves and traffic flow is represented by parameters of the traffic flow at the time and place of each crash. Disaggregate models typically use data based on average hourly observations of crash rates and traffic flow.

Ivan et al. (2000) concluded that there was evidence that the hourly volume explains much of the variation in highway crash rates. They focused on using hourly data from 17 rural, two-lane highway segments in Connecticut with varying land use patterns. Single-vehicle and multi-vehicle crashes were modeled separately. Time of day was significant for both types of crashes but in different ways. Single-vehicle crashes occurred most often in the evening and at night. On the other hand, multi-vehicle crashes were more likely to occur during daylight conditions at midday and during the evening peak period.

Persaud and Dzbik (1993) developed crash prediction models at both the macroscopic level (in crashes per unit length per year) and the microscopic level (in crashes per unit length per hour) using the GLM approach with a negative binomial error structure. Crash, road inventory, and traffic data for approximately 500 freeway sections in Ontario, Canada, were obtained for 1988 and 1989. Microscopic models showed a decreasing slope in regression lines as hourly volume increased, perhaps capturing the influence of decreasing speed as congestion formed. This is in contrast to the macroscopic model, which showed increasing slopes.

Perhaps the most extensive evaluation of this subject was an 8-year study of eight sections of four-lane interurban road in Israel (Ceder and Livneh, 1982). Single-vehicle crash rates were very high for flow rates below 250 vehicles per hour (vph). The multiple-vehicle crash rates were more diverse, with one-half of the sites showing a substantial increase in crash rates for flow rates greater than about 900 vph, and the remaining sites showing little change, with increases in hourly traffic volumes. When the two crash types were combined, the results were dominated by the data for multiple-vehicle crashes. More specifically, those study sections that encompassed a broad range of traffic volumes had a U-shaped relationship when crash rates were plotted as a function of hourly volume; the minimum rate occurred near 500 vph. The remaining four sites, three of which did not have hourly volumes in excess of 1,000 vph, did not show an increase in crash rates as hourly volumes increased.

Relationship Between Crashes and Flow Parameters

When the flow of traffic along a freeway is considered, three parameters are of considerable significance: speed and density (which describe the quality of service experienced by the stream) and volume (which measures the quantity of the traffic and the demand on the highway facility). Similar flows could be attributed to different combinations of density and speed, leading to different levels of safety. Speed is an important descriptor of traffic operations that has an effect on crash severity and frequency, but this variable is difficult to capture accurately in aggregate models that use AADT to predict annual crashes. The speed distribution may also play an important role since variance in speed is higher for lower traffic flows than for more congested conditions. By introducing parameters such as speed, density, or volume/capacity (v/c) ratio in addition to traffic volume, crash analysis could take into account the effect of traffic operations on safety.

Solomon (1964) studied the relationship between crashes on two-lane and four-lane roadways and a number of factors. From an analysis of 10,000 crashes, Solomon concluded that crash severity increased rapidly at speeds in excess of 60 mph and the probability of fatal injuries increased sharply above 70 mph. He found a U-shaped relationship between vehicle speed and crash risk, where crash rates were lowest for travel speeds near the mean speed of traffic. Crash risk then increased as a vehicle traveled significantly above or below the mean speed of prevailing traffic. Solomon’s work is often cited as the source of the 85th percentile speed rule for setting speeds.

Harkey et al. (1990) also replicated the U-shaped relationship between speed and crashes on urban roads. The researchers compared the police–estimated travel speed of 532 vehicles involved in crashes over a 3-year period to 24-hr speed data collected on the same section of non–55 mph roads in areas of Colorado and North Carolina. To address partially the concerns of earlier studies and make the crash and speed data more comparable, their analysis was limited to non-intersection, non-alcohol, and weekday crashes.

Empirical examination of the relationship between flow, density, speed, and crash rate on selected freeways in Colorado by Kononov et al. (2011) suggested that as flow-density increases, the crash rate initially remains constant until a certain critical threshold combination of speed and density is reached. Once this threshold is exceeded, the crash rate rises rapidly. The rise in crash rate may be caused by flow compression without a notable reduction in speed; resultant headways are so small that drivers find it difficult or impossible to compensate for errors and avoid a crash. The researchers calibrated SPFs for corridor-specific safety that relate crash rate to hourly volume density and speed.

Zhou and Sisiopiku (1997) examined the general relationships between hourly crash rates and hourly traffic v/c ratios using a 16-mile segment of I-94 in the Detroit area. The v/c ratios were calculated from average hourly traffic volume counts collected in 1993 and 1994 from three permanent count stations. The correlation between v/c ratios and crash rates followed a general U-shaped pattern. The U-shaped models also explained the relationship between v/c ratio and crash rates for weekdays and weekend days, multi-vehicle crashes, and property damage only crashes. On the other hand, single-vehicle crashes and crashes involving an injury or fatality followed a generally decreasing trend with increasing v/c ratios.

Lord et al. (2005) developed predictive models from data collected on freeway segments from Montreal, Quebec, Canada. The study period covered 5 years from 1994-1998. Various traffic flow characteristics were obtained from permanent and temporary count stations. For rural segments, as density and v/c ratio increased, the number of single-vehicle crashes decreased and the number of multi-vehicle crashes increased. The data showed that crashes become less severe with an increasing v/c ratio but did not seem to be affected by density. The results also showed that predictive models that used traffic volume as the only explanatory variable may not adequately characterize the crashes on freeway segments. Functional forms that incorporate density and v/c ratio offered a richer description of crashes occurring on these facilities.

Imprialou et al. (2016) re-examined crash–speed relationships by creating a new crash data aggregation approach that improved representation of road conditions just before crash occurrences. The researchers developed an alternative data aggregation concept that defines the pre-crash traffic and geometric conditions as the crash aggregating factors, termed a condition-based approach. This was tested using data from England's Strategic Road Network in 2012. Compared to approaches that assign crashes into groups based on their spatial relationship with road entities, the new method addresses the inherent problem of overaggregation of time-varying traffic variables and relevant information losses that may affect modelling outcomes. Speed was found to be a significant contributory factor for the number and consequence of crashes when the data were modelled with the condition-based approach. In contrast, the link-based model results showed that speed had a negative relationship with crash occurrences for all severity types. From a methodological point of view, the difference in the results of these approaches reveals that the data aggregation method is an important factor to consider before crash modeling is conducted.

Golob et al. (2004) examined freeway safety as a function of flow. They found that the highest crash rates (6.3 crashes per million vehicle miles traveled) occurred during heavily congested flow, corresponding to low mean speeds and low speed variation. In contrast, the lowest crash rates (0.6 crashes per million vehicle miles traveled) were characterized by high speeds and low speed variation.

Yu and Abdel-Aty (2013) investigated the impacts of data aggregation approaches based on traffic data from Shanghai's urban expressway system. They found that during the congested period, an increase in operating speed would reduce crash likelihood. For medium operating speeds, the changes in operating speed did not have substantial effects on crash occurrence probability. For free-flow periods, increases in operating speed further increased the probability of crashes.

Garber and Ehrhart (2000) analyzed the effect of speed, flow, and geometric characteristics on crash rates for different types of Virginia highways. Based on this study, all of the models showed that under most traffic conditions, the crash rate tends to increase as the standard deviation of speed increases. The effect of the flow per lane and mean speed on the crash rate varied with respect to the type of highway.

Wang et al. (2018) developed different models to estimate crash frequency using annual daily traffic and annual hourly traffic. The study segments were from three expressways in Orlando, Florida, and included basic freeway segments, merging segments, and weaving segments. They found that the logarithm of volume, the standard deviation of speed, the logarithm of segment length, and the existence of a diverge segment were significant variables in the models. Weaving segments had higher daily and hourly crash frequencies than merge and basic freeway segments.

Effect of Correlation on Crash Prediction Models

Statistical methods that incorporate a panel data structure have gained popularity because of their capacity to address both time-series and cross-sectional variations. McCarthy (1999) employed fixed-effects negative binomial models to examine fatal crash counts using 9 years of panel data for 418 cities and 57 areas in the United States. A negative binomial regression with cross-sectional data using the same dataset could not capture the interaction among crashes and variables properly. Noland (2003) used fixed-effects negative binomial and random-effects negative binomial (RENB) models to investigate the effects of roadway improvements on traffic safety using 14 years of data for all 50 U.S. states. A RENB model was found to be more suitable than the conventional negative binomial model. In the RENB model, the joint effects of the unobserved variables are assumed to follow certain distributions along the spatial and temporal dimensions.

Another popular methodology that has been advocated in recent years is a random-parameter negative binomial model. Three years of crash data for two-lane, two-way urban roads in Florida were examined to assess the effect of road-level factors on crash frequency across different regions (Han et al., 2018). A Poisson lognormal model, a hierarchical random intercept model, and a hierarchical random parameter model were compared. The result showed that the hierarchical random parameter model outperformed the Poisson lognormal model and the hierarchical random intercept model. Rather than treating the intercept term as the only random component, as with the RENB model, the random-parameter negative binomial model allows each estimated parameter to vary across individual observations, thus including the unobserved heterogeneity along the spatial and temporal dimensions.

Li et al. (2018) used a mixed effect negative binomial regression model and a back-propagation neural network model to consider bus crashes. The performance of the mixed-effect negative binomial model showed that it is advantageous to use a mixed effects modeling method to predict crash counts in practice because it can take into account the effects of specific factors.

Another analysis using data from an urban road segment in Turin, Italy, also favored the use of mixed effect models (Mussone et al., 2017). Data from 2006-2012 were used, and traffic flows and weather station data were aggregated in 5-minute intervals for 35 minutes across each crash event. Two different approaches, a back-propagation neural network model and a mixed effect model, were used. The researchers concluded that the mixed effect model performed well and was easier to interpret. The mixed effect models combine two popular methodologies for modeling repeated measurements of crash data: fixed effects and random effects models. They are also widely accepted for their ability to handle both spatial and temporal correlation in data.

Data Collection and Preparation

Data Summary

Figure 4 shows the distribution of crashes over the study period by year, severity, and facility type for all study segments. Table 1 provides a summary of the overall traffic, geometric, and crash characteristics of the study segments.

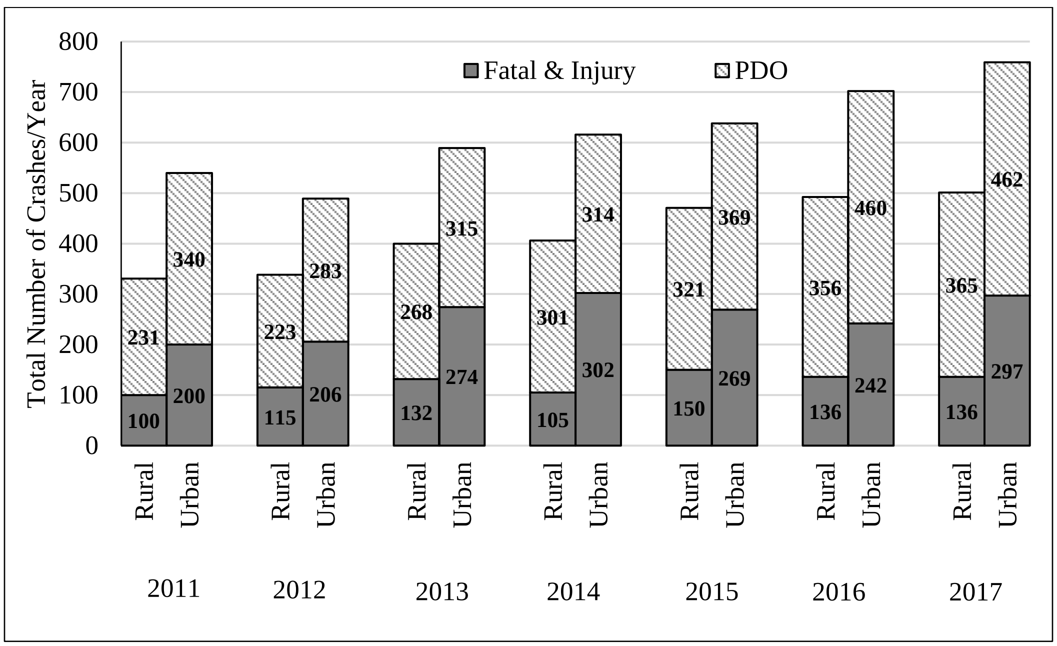


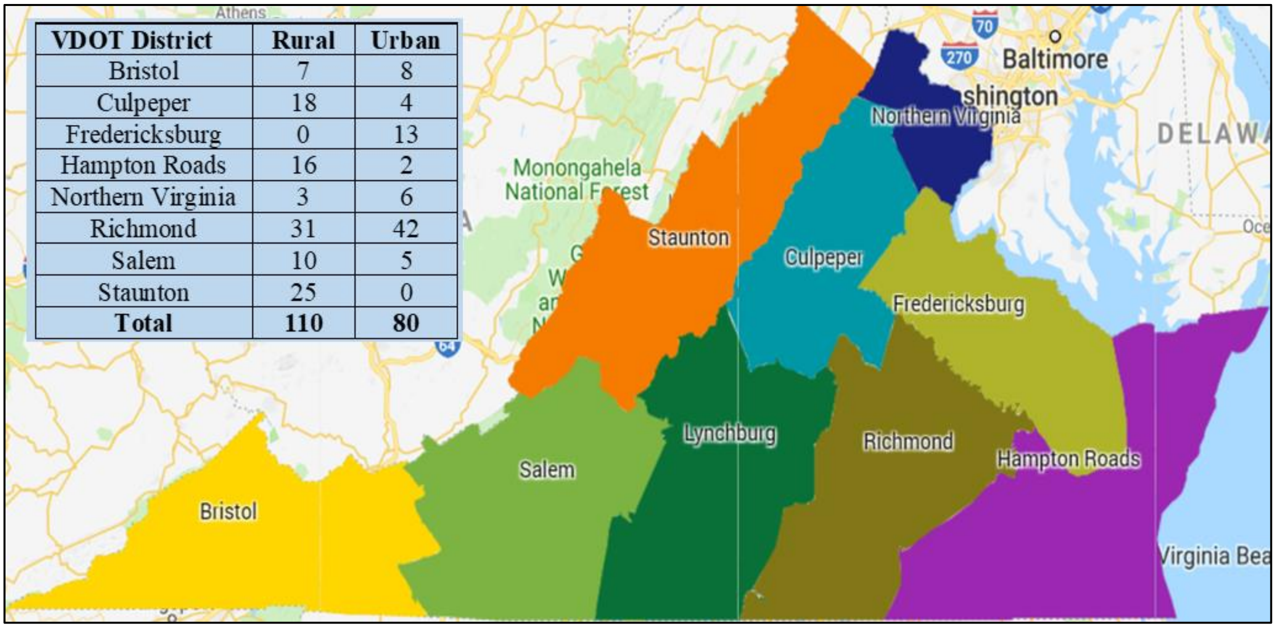
Figure 4. Distribution of Total Number of Crashes for All Study Segments. PDO = property damage only.

Table 1. Descriptive Statistics of Freeway Study Segments

Type of Segment	Total Mileage (mile)	Variable	Mean	Std. Deviation	Min.	Max.
Rural 4-Lane Segments (110 Segments)	195.07	AADT	18702	6225	4059	34728
		Average Hourly Volume (vph)	787.30	530.09	12.00	3064.00
		Average Hourly Speed (mph)	67.83	3.10	48.31	75.72
		Segment Length (mile)	1.79	0.29	1.00	2.00
		Lane Width (ft)	12.00	0.00	12.00	12.00
		Median Shoulder Width (ft)	3.93	2.03	0.00	10.00
		Right Shoulder Width (ft)	5.24	5.08	0.00	12.00
		Median Width (ft)	107.8	59.35	4.00	334.00
		Horizontal Curvature Radius (mile)	2.00	1.58	0.00	5.92
		Horizontal Curvature Length (mile)	0.76	0.59	0.00	2.00
		Grade (%)	-0.26	0.80	-3.17	1.58
		Speed Limit (mph)	69.00	2.64	55.00	70.00
		Annual Total Crashes	5.19	5.13	0	48
		Annual Fatal and Injury Crashes	1.53	1.91	0	19
Urban 6-Lane Segments (80 Segments)	125.42	AADT	40731	17667	10931	76207
		Average Hourly Volume (vph)	1690.71	1186.88	38.75	4960.50
		Average Hourly Speed (mph)	66.13	3.11	40.46	72.60
		Segment Length (mile)	1.60	0.43	0.66	2.00
		Lane Width (ft)	12.00	0.00	12.00	12.00
		Median Shoulder Width (ft)	7.08	3.07	2.00	12.00
		Right Shoulder Width (ft)	4.88	5.12	0.00	12.00
		Median Width (ft)	103.78	86.97	0.00	363
		Horizontal Curvature Radius (mile)	1.83	1.00	0.00	4.62
		Horizontal Curvature Length (mile)	0.93	0.53	0.00	2.00
		Grade (%)	-0.29	0.98	-2.69	2.67
		Speed Limit (mph)	64.42	4.59	55	70
		Annual Total Crashes	12.25	11.47	0	81
		Annual Fatal and Injury Crashes	3.31	2.98	0	19

Std. = standard; Min. = minimum; Max. = maximum; AADT = annual average daily traffic.

VDOT construction districts have been frequently associated with variations in traffic safety because of differences in driving population, terrain, and traffic conditions. For example, interstates in the Salem, Staunton, and Bristol districts are predominantly rural and travel through mountainous terrain whereas the Northern Virginia and Hampton Roads districts have significant recurring congestion. This study used districts as a grouping variable to account for the differences in driving behavior and environment in different parts of Virginia. Figure 5 shows the locations of the districts and the number of study segments in each district.



VDOT District	Rural	Urban
Bristol	7	8
Culpeper	18	4
Fredericksburg	0	13
Hampton Roads	16	2
Northern Virginia	3	6
Richmond	31	42
Salem	10	5
Staunton	25	0
Total	**110**	**80**

Figure 5. VDOT District Map and Number of Study Sites From Each District. The Lynchburg District does not contain any interstates.

Statistical Analysis

Initial Investigations of Data Aggregation Intervals and Influence of Flow State Variables

First, models were developed using data from the rural continuous count stations to investigate the effects of temporal aggregation and flow parameters. Negative binomial and ZINB model forms were investigated first to determine which one was preferred. The Vuong test results supported negative binomial models for all categories except for injury crash models using raw hourly volume. To maintain consistency in model form, negative binomial models were selected for both total and injury crashes.

Appendix A shows the preferred models that were developed for models using raw hourly data, average hourly data, AADT, and geometric variables. It should be noted that the AIC and BIC values shown in the tables in this report cannot be directly compared across different temporal resolutions since different numbers of data points are used in each of these models. For example, a single link would have 1 observation per year for an annual model, 24 for an average hourly volume model, and 8,760 for a raw hourly model. Variables representing median width, HC, and VC were all found to be significant. For total crashes, the results indicated that wider medians generally had more crashes. For VC, positive grades did not have any significant effect on crash frequency based on this dataset. These relationships may be based on the specific characteristics of the rural study sites used and may not be widely transferable, however. The radius of HC had a negative parameter, indicating that larger radii are associated with fewer crashes. For injury crashes, only volume and segment length were significant for raw hourly volume models and no relationship between geometric variables and crash frequency was present.

Next, models were created by adding flow parameters such as v/c ratio, speed, and density to the models selected in the previous step. The parameters for the preferred models with flow parameters included are shown in Appendix B. The percentage of heavy vehicles was also considered a variable, but it did not have any significant effect on crash frequency in this dataset. Initially, speed, density, and v/c ratio were all tested in the model. While the models were being developed, it was found that the v/c ratio was often an unreliable indicator of traffic flow state since incidents, work zones, or other events might restrict flow at the site. This created a situation where observed speeds might be low but the corresponding v/c ratio was also low. Inclusion of the v/c ratio often resulted in counterintuitive parameter signs, so it was removed from further consideration. After different combinations of volume, speed, and density variables were examined, it was observed that only speed and density had a logical and statistically significant relationship when they were used one at a time with volume or when they were both used in the same model without a volume component. This finding is not surprising since traffic flow theory indicates that all three variables are related, so their presence in the same model violates assumptions of parameter independence. Since volume was deemed an important measure of exposure and speed is more widely available than density, models that used volume in conjunction with speed were selected as the best alternative.

For all models developed, speed was negatively related to crashes, meaning that lower average speed was correlated with higher crash frequency. Lower average speeds indicated the presence of congestion, so this relationship was intuitive. The negative relationship with speed and injury crashes seems counterintuitive since higher speeds are generally associated with more severe injuries. This result could be due to how injury was defined and the type of data used for modeling. Fatal and injury crashes were combined in this category and ranged from a crash being fatal to a minor injury that did not require any physician or hospital visit. Disaggregating the injury crash data further by injury severity was not feasible because of the impact on sample sizes available at each injury level, however. This relationship also might be specific to this particular dataset. This analysis was based on rural continuous count station data where the maximum hourly volume observed was 3,822 vph across two lanes. Thus, these results may be driven by the fact that this dataset was dominated by locations that often experienced speeds near free flow and a broader variation in traffic speeds was not expected.

Model Comparison

The performance of the preferred raw hourly and average hourly models was contrasted to the AADT-based models to determine if more disaggregate models improved crash predictions. For all models, data from 2016 and 2017 were used as the validation dataset. Table 2 shows the comparison among these models. The AADT models did not include speed as a variable because averaging speed data over 1 year did not capture the effect of speed on traffic conditions and crashes on an hourly level. For comparison purposes, the volume, flow, and geometry models were compared to the AADT-based volume and geometry models.

Table 2. Comparison of Model Performance

	Total Crashes								
	Raw Hourly Volume			Average Hourly Volume			AADT		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume, length, and geometry models	3.87 (+2.0%)[a]	69% (-9.0%)	31.46 (+3.0%)	3.31 (-12.0%)	58% (-20.0%)	24.28 (-21.0%)	3.78	78%	30.60
Volume, length, geometry, and flow state models[b]	3.77 (-0.3%)	61% (-17.0%)	28.98 (-5.3%)	3.29 (-13.0%)	47% (-31.0%)	18.98 (-38.0%)	---	---	---
	Fatal and Injury Crashes								
	Raw Hourly Volume			**Average Hourly Volume**			**AADT**		
	MAD	**MAPE**	**MSPE**	**MAD**	**MAPE**	**MSPE**	**MAD**	**MAPE**	**MSPE**
Volume, length, and geometry models	2.15 (+85.3%)	53% (-6.0%)	2.53 (+3.3%)	1.04 (-10.3%)	47% (-12.0%)	2.12 (-13.5%)	1.16	59%	2.45
Volume, length, geometry, and flow state models[b]	1.14 (-1.7%)	52% (+9.0%)	2.04 (+16.7%)	1.04 (-10.3%)	43% (-16.0%)	1.84 (24.9%)	---	---	---

AADT = annual average daily traffic; MAD = mean absolute deviation; MAPE = mean absolute percentage error; MSPE = mean squared prediction error; --- = models were not generated.

[a] Values in parentheses represent the change compared to the respective AADT-based models.

[b] These models were compared to the AADT-based volume, length, and geometry models.

For both the raw and average hourly volume models for total crashes, prediction accuracy improved as speed variables were added, but the raw hourly models for fatal and injury crashes gave a mixed result in comparison to the AADT-based model. For these models, the raw hourly volume and geometry model performed worse than the AADT model in terms of MAD and MSPE. Results were similar for injury crashes for raw hourly models as well. This result was likely influenced by the missing data in the raw volume dataset. Ideally, all sites would have 100% hourly data availability. Unfortunately, 23% of the raw hourly data in the validation dataset did not meet quality control standards and thus were not used to generate predictions.

The prediction accuracy improved significantly for both total and injury crashes when average hourly data were used. In this case, the average volume calculation helped to smooth out the discrepancies created by missing raw hourly data. This model consistently performed better than the AADT-based model for all measures of effectiveness (MOEs). The flow parameter models showed the highest improvement for all MOEs compared to the AADT-based model with volume, length, and geometric variables. MAD, MAPE, and MSPE decreased by 13%, 31%, and 38%, respectively, for total crashes and 10%, 16%, and 25%, respectively, for injury crashes.

Based on the results of preliminary analysis, raw data models were discarded from further consideration. Gaps in data availability created problems with model predictions, which worsened performance relative to AADT models. As a result, the next step focused on the use of average hourly data. The preliminary analysis also showed that inclusion of flow state in crash prediction models had a beneficial effect, so those variables were subjected to further examination in the next step.

Assessment of the Effects of Different Speed Sources Using Continuous Count Stations

In the second stage of analysis, the dataset was expanded to include both the rural four-lane and urban six-lane segments with continuous count station data. In this case, average 15-minute and average hourly volumes were compared to AADT models, and the quality of predictions generated using point sensor and INRIX data was compared.

As with the previous stage of the analysis, initial investigations focused on whether negative binomial or ZINB model forms were preferred. The Vuong test results showed that in general, negative binomial models performed better than the zero inflated models with respect to AIC value, variable significance, and sign of estimated coefficients. Appendix C documents the results from the Vuong test. For the average 15-minute dataset, the volume and geometry model for fatal and injury crashes for rural segments was the only category where the Vuong test results preferred the zero inflated model over the negative binomial form. For average hourly data, negative binomial models outperformed the zero inflated models for both rural and urban segments, irrespective of crash type. To maintain consistency in model form, negative binomial models were used for both total and injury crashes.

Volume and Geometry Models

Appendix D shows the model parameters for the volume and geometry models for all levels of temporal aggregation. For urban segments, the only statistically significant geometric variable was median width for all levels of aggregation and crash type. The segments with curve presence were mostly composed of long, gentle horizontal curves that almost resembled a tangent section. There was little variability in vertical grades for these segments as well. Median width was negatively associated with crash frequency, indicating that wider medians in urban segments reduce the total number of crashes. Previous research indicated that median width between 20 and 30 ft generally shows a mixed effect on crashes and median width of 60 to 80 ft has a decreasing effect on crashes (Chang and Xiang, 2003; Knuiman et al., 1993). About 55% of the urban dataset had median widths within this range, so the negative relationship between median width and crashes is intuitive.

For rural segments, 71% of the data came from segments with median widths greater than 80 ft and no median barrier. The results indicated that wider medians generally had more crashes for the rural segments. This counterintuitive finding is likely related to the relatively small sample used and the homogeneity of that sample. For VC, presence of grade (both positive and negative) increases the probability of any type of crash. This was not tied to a specific grade threshold value or length. For injury crashes and single-vehicle crashes, only negative grades had a statistically significant effect. These findings were similar irrespective of the volume disaggregation level and aligned with the results of previous research (Graham et al., 2014; Shankar et al., 2004; Watson et al., 2014).

Volume, Geometry, and Flow State Models

Multiple ways to represent speed were evaluated, including average speed, standard deviation of speed, and the difference between the posted speed limit and average speed (hereinafter "delta speed"). These models were developed twice: first with speed data from the continuous count stations and then repeating the same model with speed data from INRIX. This was done to compare how the data source affects the model fit. Table 3 shows the parameters for the rural models that include speed parameters. For total crashes, speed was negatively related to crashes, meaning that lower average speed was correlated with higher crash frequency. Lower average speeds indicated the presence of congestion, so this relationship is intuitive for rural sites. These models also showed that as the standard deviation of hourly average speeds or 15-minute average speed increases, the frequency of crashes also increases. This is also intuitive since it shows that variability in flow is correlated with reduced safety.

For rural models, it was found that standard deviation was positively related to crashes involving injury. The variable delta speed had a negative relationship with injury crashes. A positive value of delta speed would have meant that the average speed was lower than the speed limit, indicating congestion. A negative value, on the other hand, would represent free flow conditions. The negative relationship between delta speed and injury crashes seems counterintuitive since higher speeds are generally associated with more severe injuries. As explained previously, this result could be due to the sites used for modeling and the fact that they tended to operate at free flow speeds.

Table 4 shows that the speed parameters showed consistent results for urban segments as well. Standard deviation of speed always had an increasing effect on crash frequency for all crash types. For total crashes, another significant flow parameter was delta speed. The models showed that crashes on urban segments increased as congestion increased. For injury models, only standard deviation of speed was a statistically significant flow parameter.

Table 3. Parameter Estimates for Models Based on Volume, Geometry, and Flow for Rural Segments

	Models With Detector Speed						**Models With INRIX Speed**					
	Average 15-Minute Volume			**Average Hourly Volume**			**Average 15-Minute Volume**			**Average Hourly Volume**		
Total Crashes	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-1.31	1.770	<2E-16	-6.91	0.394	<2E-16	-1.66	1.760	<2E-16	-5.95	0.413	<2E-16
log (Volume)	0.42	0.052	6E-16	0.45	0.054	<2E-16	0.36	0.058	3E-10	0.34	0.061	2E-08
Grade of VC												
Negative	0.31	0.098	0.0016	0.33	0.098	0.0003	0.24	0.096	0.014	0.36	0.094	0.0002
Positive	0.17	0.137	0.2164	0.07	0.149	0.3004	0.09	0.139	0.476	0.03	0.135	0.8272
Percent of HC	0.05	0.008	2E-10	0.04	0.009	1E-09	0.05	0.007	3E-09	0.04	0.007	2E-06
Length of HC	-2.66	0.496	8E-08	-2.21	0.463	7E-09	-2.21	0.471	2E-06	-2.13	0.439	1E-06
Average Speed	-0.09	0.026	0.0001	0.06	0.012	3E-05	-0.09	0.026	8E-04	0.07	0.017	2E-05
Std. Dev. of Speed	0.13	0.022	2E-09	0.17	0.024	3E-10	0.15	0.022	2E-11	0.17	0.021	3E-07
AIC	5805			3708			5903			3826		
	Average 15-Minute Volume			**Average Hourly Volume**			**Average 15-Minute Volume**			**Average Hourly Volume**		
Injury Crashes	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-5.15	0.678	<2E-16	-7.25	0.612	0.0002	-8.19	0.902	<2E-16	-6.33	0.691	<2E-16
log (Volume)	0.37	0.086	2E-05	0.36	0.093	0.0001	0.32	0.097	9E-04	0.26	0.101	0.001
Percent of HC	0.04	0.015	0.0033	0.17	0.057	0.0618	0.04	0.014	0.006	0.21	0.053	0.001
Length of HC	-1.88	0.826	0.0023	-0.59	0.334	0.0066	-1.60	0.797	0.045	-0.68	0.329	0.037
Std. Dev. of Speed	0.11	0.039	0.0035	0.19	0.042	7E-07	0.12	0.041	0.004	0.17	0.035	3E-06
Delta Speed	0.15	0.044	0.0002	0.07	0.024	0.0003	0.16	0.039	6E-05	0.07	0.029	0.011
AIC	2368			1681			2399			1741		

Std. = standard; VC = vertical curve; HC = horizontal curve; Std. Dev. = standard deviation; AIC = Akaike information criterion.

Table 4. Parameter Estimates for Models Based on Volume, Geometry, and Flow for Urban Segments

	Models With Detector Speed						Models With INRIX Speed					
	Average 15-Minute Volume			Average Hourly Volume			Average 15-Minute Volume			Average Hourly Volume		
Total Crashes	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-10.59	0.755	<2E-16	-4.87	0.347	<2E-16	-7.64	0.665	<2E-16	-4.81	0.338	<2E-16
log (Volume)	0.55	0.051	<2E-16	0.34	0.048	9E-13	0.58	0.052	<2E-16	0.32	0.048	9E-12
Median Width	-0.21	0.167	<2E-16	-0.22	0.366	<2E-16	-0.15	0.208	<2E-16	-0.28	0.278	<2E-16
Std. Dev. of Speed	0.08	0.009	<2E-16	0.13	0.012	<2E-16	0.11	0.013	<2E-16	0.16	0.111	<2E-16
Delta Speed	0.11	0.013	<2E-16	0.05	0.006	<2E-16	0.03	0.011	0.0002	0.02	0.009	1.4E-05
AIC	7709			4264			8407			4887		
	Average 15-Minute Volume			**Average Hourly Volume**			**Average 15-Minute Volume**			**Average Hourly Volume**		
Injury Crashes	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-11.14	1.34	<2E-16	-6.62	0.594	<2E-16	-8.07	1.16	<2E-16	-6.07	0.539	<2E-16
log (Volume)	0.51	0.089	1E-08	0.36	0.079	6E-07	0.44	0.088	6E-07	0.32	0.072	8E-06
Median Width	-0.13	0.128	1E-10	-0.25	0.123	<2E-16	-0.17	0.146	2E-06	-0.19	0.135	<2E-16
Std. Dev. of Speed	0.07	0.017	2E-05	0.17	0.013	<2E-16	0.12	0.018	3E-10	0.15	0.009	<2E-16
AIC	3274			2059			3515			2328		

Std. = standard; Std. Dev. = standard deviation; AIC = Akaike information criterion.

Model Comparison

Next, the developed models were compared. Model comparisons provide a check on whether flow parameters improve model performance as expected. They also show how different levels of data aggregation affect the performance. Finally, they show whether the model performance is significantly different depending on the source of speed data. For all models, irrespective of type of facility, type of crash, or level of data aggregation, the highest prediction accuracy was achieved across all validation MOEs when speed components were added to the model.

Tables 5 and 6 show the comparison of performance among the models developed for rural and urban sites, respectively. Even though the average 15-minute volume models performed better than the AADT-based model most of the time, there were certain models (injury models for urban segments) that were worse than the AADT models. It is possible that at a 15-minute level, data are too noisy to capture the true relationship between crashes and flow parameters. Likewise, inaccuracies in time stamps of crash reports could influence results at that level. The prediction accuracy improved significantly for all models when average hourly data were used. In this case, the aggregation interval was neither too disaggregated to capture the random nature of crashes nor too aggregated to lose the variation in traffic.

For the rural hourly volume, geometry, and flow models, MAD, MAPE, and MSPE improved by 11%, 33%, and 29%, respectively, when continuous count stations were used as the speed data source and 10%, 28%, and 17%, respectively, when INRIX speed data were used. For the urban models, similar trends were observed where MAD, MAPE, and MSPE improved by 20%, 22%, and 38%, respectively, for detector data and 20%, 19%, and 32% for INRIX data. In both cases, these models were compared to AADT-based volume and geometry models. Even though models using INRIX data performed slightly worse than the models based on continuous count data, they were still far better than AADT-based models.

Because of the random nature of crash occurrence, the 15-minute data had too much variability to generate useful models. Similarly, aggregated models that rely on AADT may fail to capture variations in traffic flow that could influence safety. Another very important finding was that speed variables played a significant role in model performance irrespective of their source. Since current models rely only on volume, quality of volume data dictates the quality of the model. This step showed that INRIX data can be used as an alternate source for speed data without reducing the quality of crash prediction models. Models developed using INRIX data performed similarly to the models using speeds from continuous count stations during model validation. For all crash types and model categories, INRIX models consistently outperformed AADT models. This provided a strong basis for using INRIX data along with historic volume distributions from short count stations in the next step.

Table 5. Model Comparison for Rural Segments[a]

	Total Crashes								
	Average 15-min Volume			Average Hourly Volume			AADT		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume, length, and geometry models	3.47	58%	27.88	3.45	58%	25.24	3.62	76%	28.18
	(-4%)	(-18%)	(-1%)	(-5%)	(-18%)	(-10%)			
Volume, length, geometry, and flow state models[b]	3.37	54%	23.77	3.21	43%	20.11	—	—	—
	(-7%)	(-22%)	(-16%)	(-11%)	(-33%)	(-29%)			
Volume, length, geometry, and flow state models (INRIX)[b]	3.35	59%	22.07	3.24	48%	23.5	—	—	—
	(-7%)	(-17%)	(-22%)	(-10%)	(-28%)	(-17%)			
	Fatal and Injury Crashes								
	Average 15-min Volume			**Average Hourly Volume**			**AADT**		
	MAD	**MAPE**	**MSPE**	**MAD**	**MAPE**	**MSPE**	**MAD**	**MAPE**	**MSPE**
Volume, length, and geometry models	1.31	41%	2.86	1.13	40%	2.23	1.2	55%	2.94
	(+9%)	(-14%)	(-3%)	(-6%)	(-15%)	(-24%)			
Volume, length, geometry, and flow state models[b]	1.17	39%	2.47	1.09	33%	1.72	—	—	—
	(-3%)	(-16%)	(-16%)	(-9%)	(-22%)	(-41%)			
Volume, length, geometry, and flow state models (INRIX)[b]	1.17	37%	2.83	1.1	38%	1.85	—	—	—
	(-3%)	(-18%)	(-4%)	(-8%)	(-17%)	(-37%)			

AADT = annual average daily traffic; MAD = mean absolute deviation; MAPE = mean absolute percentage error; MSPE = mean squared prediction error; --- = models were not generated.

[a] Values in parentheses represent the change compared to the respective AADT-based models.

[b] These models were compared to the AADT-based volume, length, and geometry models.

Table 6. Model Comparison for Urban Segments[a]

<table>
<tr><td rowspan="3"></td><td colspan="9">Total Crashes</td></tr>
<tr><td colspan="3">Average 15-min Volume</td><td colspan="3">Average Hourly Volume</td><td colspan="3">AADT</td></tr>
<tr><td>MAD</td><td>MAPE</td><td>MSPE</td><td>MAD</td><td>MAPE</td><td>MSPE</td><td>MAD</td><td>MAPE</td><td>MSPE</td></tr>
<tr><td rowspan="2">Volume, length, and geometry models</td><td>8.13</td><td>52%</td><td>140.56</td><td>7.72</td><td>40%</td><td>120.92</td><td rowspan="2">8.52</td><td rowspan="2">52%</td><td rowspan="2">181.91</td></tr>
<tr><td>(-5%)</td><td>(0%)</td><td>(-23%)</td><td>(-9%)</td><td>(-12%)</td><td>(-34%)</td></tr>
<tr><td rowspan="2">Volume, length, geometry, and flow state models[b]</td><td>7.87</td><td>45%</td><td>129.97</td><td>6.81</td><td>30%</td><td>112.47</td><td rowspan="2">—</td><td rowspan="2">—</td><td rowspan="2">—</td></tr>
<tr><td>(-8%)</td><td>(-7%)</td><td>(-29%)</td><td>(-20%)</td><td>(-22%)</td><td>(-38%)</td></tr>
<tr><td rowspan="2">Volume, length, geometry, and flow state models (INRIX)[b]</td><td>8.11</td><td>40%</td><td>138.81</td><td>6.82</td><td>33%</td><td>124.35</td><td rowspan="2">—</td><td rowspan="2">—</td><td rowspan="2">—</td></tr>
<tr><td>(-5%)</td><td>(-12%)</td><td>(-24%)</td><td>(-20%)</td><td>(-19%)</td><td>(-32%)</td></tr>
<tr><td rowspan="3"></td><td colspan="9">Fatal and Injury Crashes</td></tr>
<tr><td colspan="3">Average 15-min Volume</td><td colspan="3">Average Hourly Volume</td><td colspan="3">AADT</td></tr>
<tr><td>MAD</td><td>MAPE</td><td>MSPE</td><td>MAD</td><td>MAPE</td><td>MSPE</td><td>MAD</td><td>MAPE</td><td>MSPE</td></tr>
<tr><td rowspan="2">Volume, length, and geometry models</td><td>2.77</td><td>36%</td><td>15.14</td><td>2.56</td><td>21%</td><td>10.83</td><td rowspan="2">2.68</td><td rowspan="2">29%</td><td rowspan="2">14.94</td></tr>
<tr><td>(+3%)</td><td>(+7%)</td><td>(+1%)</td><td>(-4%)</td><td>(-8%)</td><td>(-28%)</td></tr>
<tr><td rowspan="2">Volume, length, geometry, and flow state models[b]</td><td>2.53</td><td>29%</td><td>12.68</td><td>2.44</td><td>19%</td><td>8.61</td><td rowspan="2">—</td><td rowspan="2">—</td><td rowspan="2">—</td></tr>
<tr><td>(-6%)</td><td>(0%)</td><td>(-15%)</td><td>(-9%)</td><td>(-10%)</td><td>(-42%)</td></tr>
<tr><td rowspan="2">Volume, length, geometry, and flow state models (INRIX)[b]</td><td>2.67</td><td>31%</td><td>12.73</td><td>2.34</td><td>24%</td><td>9.71</td><td rowspan="2">—</td><td rowspan="2">—</td><td rowspan="2">—</td></tr>
<tr><td>(0%)</td><td>(+2%)</td><td>(-15%)</td><td>(-13%)</td><td>(-5%)</td><td>(-35%)</td></tr>
</table>

AADT = annual average daily traffic; MAD = mean absolute deviation; MAPE = mean absolute percentage error; MSPE = mean squared prediction error; --- = models were not generated.

[a] Values in parentheses represent the change compared to the respective AADT-based models.

[b] These models were compared to the AADT-based volume, length, and geometry models.

Examination of Short Count Stations and Effects of Spatial and Temporal Correlation

Given the findings of the prior step, the next step focused on expanding the usability of the models by using average hourly volumes from short count stations (where data were not available continuously), along with attempting to correct for spatial and temporal correlation. Once again, initial steps involved comparing negative binomial and ZINB distribution models. The results again showed that negative binomial models performed better with respect to the AIC value, BIC value, variable significance, and ANOVA. Appendix E summarizes the comparison results.

The interpretation of GLMMs is similar to that of GLMs; however, there is an added complexity because of the role of random effects. The output of a mixed effect model lists parameter estimates for the fixed effect part and the variance between groups for the random effect part. If the variance is indistinguishable from zero, then the correlation within a group is not strong. In the mixed effect model, one or more random effects are added to the fixed effects. These random effects essentially give structure to the error term "ε." For this study, random effects for "district," "year," and "hour" were considered.

Volume, Length, and Geometry Models

For total and injury crashes, the radius of horizontal curve was negatively associated with crash frequency. A larger radius indicates a flatter curve, so this relationship is intuitive. Vertical grade, which ranges from -3% to +3% (negative grade means downgrade, and positive grade means upgrade), was found to be significant for total crashes, but only negative grades had a statistically significant relationship. This result indicates that for total crashes, steeper negative grade causes more crashes. Since speed usually increases in downhill driving, this finding is logical. Median width showed that wider medians in urban segments reduce the total number of crashes but are correlated with more crashes for rural segments. Appendix F documents the results for these models.

Volume, Geometry, and Flow Parameter Models

Table 7 shows the rural models that include speed parameters. Average hourly speed was positively related to total crashes, meaning that higher average speed is correlated with higher crash frequency. Standard deviation of speed was significant for all crash types and indicated that crash frequency increases as more variation in hourly speeds is observed over a year. The variable delta speed that represents the difference between speed limit and average speed was significant for all crash types as well. It was observed that injury crashes increased during free flow conditions (Delta Speed 1) and decreased during congestion (Delta Speed 2). This is a logical relationship given the relative velocities during collisions that occur during these flow states.

Table 8 shows that the speed parameters showed consistent results for urban segments as well. Standard deviation of average speed always had an increasing effect on crash frequency for all crash types. The variable delta speed was significant for all crash types for urban segments as well. During free flow conditions (Delta Speed 1), total crashes and injury crashes increased. This relationship is intuitive and consistent with rural segments.

Table 7. Parameter Estimates for Models Based on Volume, Geometry, and Flow for Rural Segments

	Total Crashes			Injury Crashes		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-8.61	0.971	<2E-16	-6.73	0.375	<2E-16
log (Volume)	0.54	0.076	1.5E-12	0.41	0.055	4.0E-14
Radius of Horizontal Curve (mile)	-0.06	0.019	0.00443	—	—	—
% of Horizontal Curve Length						
Less than 25%	0.53	0.107	6.60E-07	—	—	—
>25% ~ ≤50%	0.11	0.096	0.000025	—	—	—
>50% ~ ≤ 75%	0.41	0.093	1.20E-05	—	—	—
>75%	0.13	0.099	0.19522	—	—	—
Speed	0.03	0.012	0.00974	—	—	—
Standard Deviation	0.17	0.017	<2E-16	0.16	0.024	2.0E-11
Delta Speed						
Delta Speed 1	0.31	0.068	9.05E-06	1.29	0.095	<2E-16
Delta Speed 2	0.04	0.067	0.57048	-0.29	0.117	0.0014
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.182 (0.017)			0.174 (0.035)		
Year	0.212 (0.045)			0.111 (0.013)		
Hour	0.508 (0.003)			0.263 (0.092)		
AIC	10679			5716.8		
BIC	10795.1			5782.1		
ρ^2_c	0.29			0.18		

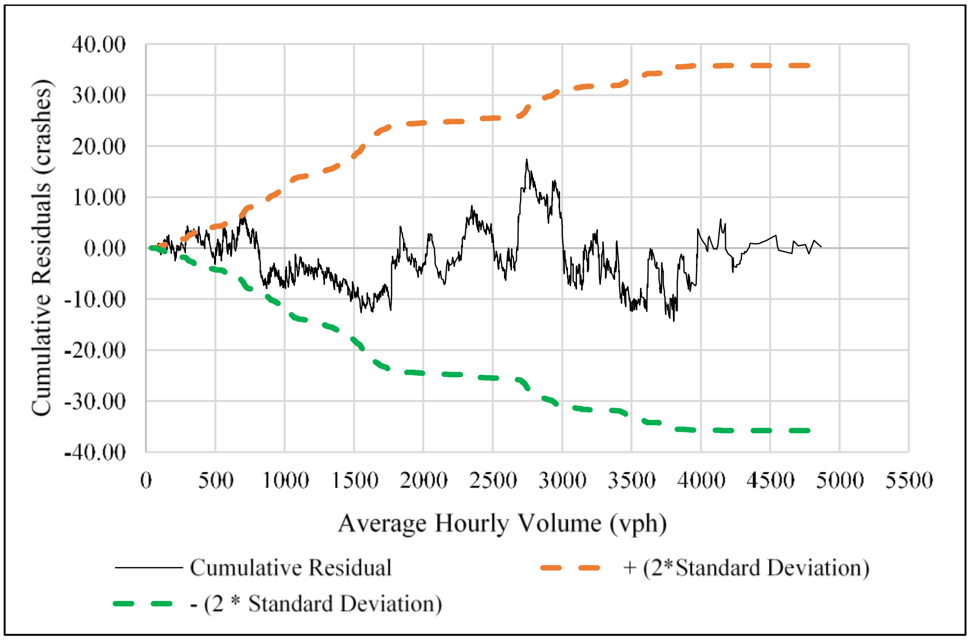
Std. = standard; --- = parameter not used in model; AIC = Akaike information criterion, BIC = Bayesian information criterion.

Table 8. Parameter Estimates for Models Based on Volume, Geometry, and Flow for Urban Segments

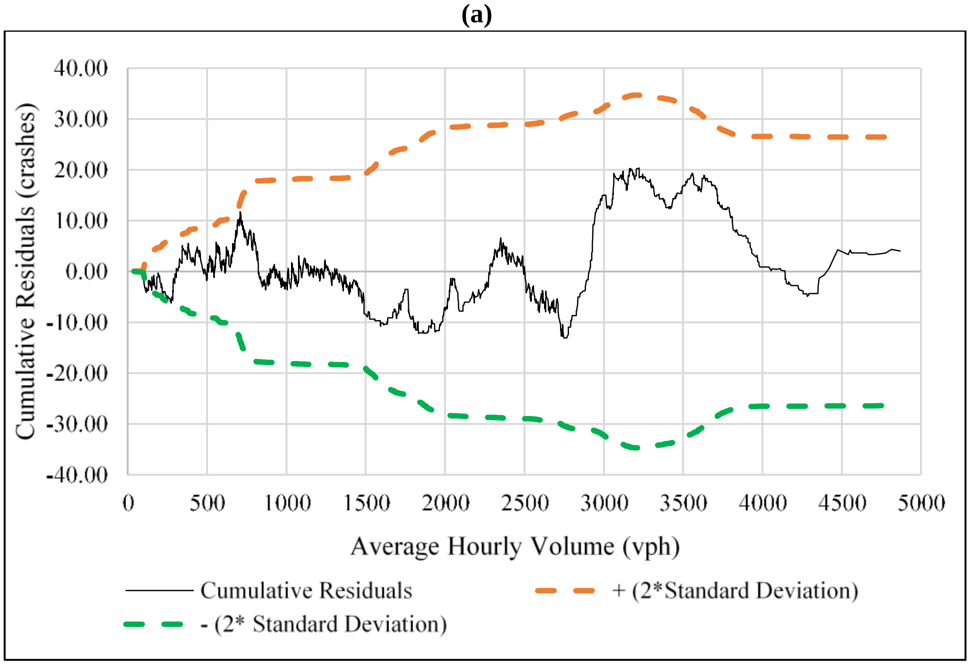
	Total Crashes			Injury Crashes		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-5.8	0.351	<2E-16	-6.79	0.459	<2E-16
log (Volume)	0.44	0.044	<2E-16	0.37	0.057	3.9E-11
Radius of Horizontal Curve (mile)	-0.08	0.029	0.00563	-0.09	0.043	0.00408
Length of Horizontal Curve						
≤ 0.5	0.76	0.174	1.4E-05	0.89	0.233	0.00013
>0.5 ~ ≤1.0	1.06	0.171	6.4E-10	1.2	0.229	1.5E-07
>1.0 ~ ≤1.5	1.16	0.175	3.6E-11	1.34	0.244	4.4E-08
>1.5	0.75	0.177	2.1E-05	0.85	0.236	0.00034
Standard Deviation	0.11	0.007	<2E-16	0.12	0.011	<2E-16
Delta Speed						
Delta Speed 1	0.14	0.059	2.1E-04	0.98	0.088	<2E-16
Delta Speed 2	0.03	0.058	0.58262	-0.21	0.103	0.00438
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.137 (0.007)			0.152 (0.022)		
Year	0.326 (0.181)			0.254 (0.159)		
Hour	0.546 (0.032)			0.324 (0.092)		
AIC	10185.9			6025.2		
BIC	10293.1			6119.2		
$\boldsymbol{\rho_c^2}$	0.23			-0.24		

Std. = standard; AIC = Akaike information criterion, BIC = Bayesian information criterion.

Figure 6 shows the CURE plots for average hourly volume for the volume, flow, and geometry models. CURE plots are a reflection of not only the functional form of the particular explanatory variable but also of whether other relevant explanatory factors have been included in the model in an appropriate form. For both rural and urban segments, the CURE plot for hourly volumes were within the limit of 2 standard deviations. These plots reinforce the suitability of volume, flow, and geometry models and show that inclusion of volume in average hourly level form is appropriate.



(a)



(b)

Figure 6. Hourly Volume Cumulative Residual Plots: (a) rural segments; (b) urban segments

Model Comparison Between GLMMs, Volume Sources, and Effects of Correlation

Tables 9 and 10 show the comparison of performance among the model forms. For both rural and urban segments and for both crash types, prediction accuracy improved when speed variables were added. Models using average hourly data showed better predictive capability compared to AADT models. When hourly data were used, data were not too disaggregated to capture the random nature of crashes or to lose the variation in traffic. The inclusion of the short count stations also appeared to improve the models further. For the rural hourly volume, geometry, and flow models, MAD, MAPE, and MSPE improved by 64%, 26% and 62%, respectively, for total crashes and 39%, 20%, and 40%, respectively, for injury crashes as compared to AADT models. For the urban models, similar trends were observed where MAD, MAPE, and MSPE improved by 51%, 18%, and 53%, respectively, for total crashes and 45%, 18%, and 59% for injury crashes as compared to AADT models.

Next, models were developed that had both spatial and temporal random effect variables. The spatial correlation was represented by "District." For all models, the intercept and standard deviation for this group revealed that even though a correlation was present between segments that belonged to same district, in general, the spatial correlation was weaker than the temporal one. For all categories, the variance was much smaller for districts than it was for year or hour. This may be because the sample sizes among districts were not equally distributed, as seen in Figure 5.

Table 9. Model Comparison for Rural Segments[a]

	Total Crashes					
	Average Hourly Volume			**AADT**		
	MAD	**MAPE**	**MSPE**	**MAD**	**MAPE**	**MSPE**
Volume, length, and geometry models	1.16 (-63%)	55% (-14%)	2.92 (-57%)	3.1	69%	6.87
Volume, length, geometry, and flow state models[b]	1.11 (-64%)	43% (-26%)	2.59 (-62%)	–	–	–
	Fatal and Injury Crashes					
	Average Hourly Volume			**AADT**		
	MAD	**MAPE**	**MSPE**	**MAD**	**MAPE**	**MSPE**
Volume, length, and geometry models	0.73 (-33%)	33% (-15%)	1.58 (-32%)	1.09	48%	2.33
Volume, length, geometry, and flow state models[b]	0.66 (-39%)	28% (-20%)	1.39 (-40%)	–	–	–

AADT = annual average daily traffic; MAD = mean absolute deviation; MAPE = mean absolute percentage error; MSPE = mean squared prediction error; --- = models were not generated.
[a] Values in parentheses represent the change compared to the respective AADT-based models.
[b] These models were compared to the AADT-based volume, length, and geometry models.

Table 10. Model Comparison for Urban Segments[a]

	Total Crashes					
	Average Hourly Volume			AADT		
	MAD	MAPE	MSPE	MAD	MAPE	MSPE
Volume, length, and geometry models	1.92	35%	47.92	2.98	47%	79.43
	(-36%)	(-12%)	(-40%)			
Volume, length, geometry, and flow state models[b]	1.45	29%	36.95	—	—	—
	(-51%)	(-18%)	(-53%)			
	Fatal and Injury Crashes					
	Average Hourly Volume			**AADT**		
	MAD	**MAPE**	**MSPE**	**MAD**	**MAPE**	**MSPE**
Volume, length, and geometry models	1.09	12%	4.58	1.69	26%	8.82
	(-36%)	(-14%)	(-48%)			
Volume, length, geometry, and flow state models[b]	0.93	8%	3.63	—	—	—
	(-45%)	(-18%)	(-59%)			

AADT = annual average daily traffic; MAD = mean absolute deviation; MAPE = mean absolute percentage error; MSPE = mean squared prediction error; --- = models were not generated.

[a] Values in parentheses represent the change compared to the respective AADT-based models.

[b] These models were compared to the AADT-based volume, length, and geometry models.

This step used a larger dataset that came from both continuous count and short count stations. Although the quantity of data available for modeling increased overall, the availability and quality of data at the short count stations were lower than for those used in the models that relied only on continuous count stations. This new dataset was more broadly representative of average data quality and availability for freeway facilities nationally. The model comparison in Tables 9 and 10 showed that the best models for this dataset were the volume, geometry, and flow models. To isolate the effects of using the broader dataset composed of continuous count stations and short count stations and the effect of correlation, three types of volume, geometry, and flow models were compared. Model 1 reflects the initial models developed using only continuous count station data (31 rural segments, 23 urban segments) and negative binomial regression. Model 3 consists of the earlier models developed using a combination of short and continuous count data (110 rural segments, 80 urban segments) and mixed effect generalized linear models. Model 2 was developed by re-running Model 3 without any spatial or temporal correlation. This model used data from Model 3 and negative binomial regression from Model 1. A comparison of all three models is shown in Table 11 based on total crashes. It shows how performance changed from using the smaller dataset without correlation to using the broader dataset with correlation. In each case, Model 1 was used as the base model for comparison.

The results show that for both rural and urban segments, inclusion of the short count stations in Model 2 had a large beneficial impact on model performance compared to Model 1. Including consideration of data correlation also had a positive effect, as seen in the MOEs for Model 3, although the incremental improvement was lower than that from the inclusion of the short count stations. For rural hourly models, MAD and MSPE improved by 52% and 72%, respectively, for Model 2 in comparison to Model 1. The improvement in model performance can be attributed to the size of the dataset. MAD and MSPE further improved by 66% and 89% between Model 1 and Model 3. The improved performance for Model 3 was due to the more appropriate methodology incorporating spatial and temporal correlation and the use of a broader dataset. The urban segments showed similar results as well.

Table 11. Model Comparison to Check for Data Quality and Correlation[a]

	Rural Segments			
	Data Source	**Correlation**	**MAD**	**MSPE**
Model 1	Continuous Count Only	No	3.24	23.5
Model 2	Continuous and Short Count	No	1.56	6.63
			(-52%)	(-72%)
Model 3	Continuous and Short Count	Yes	1.11	2.59
			(-66%)	(-89%)
	Urban Segments			
	Data Source	**Correlation**	**MAD**	**MSPE**
Model 1	Continuous Count Only	No	6.82	124.35
Model 2	Continuous and Short Count	No	2.89	90.54
			(-58%)	(-27%)
Model 3	Continuous and Short Count	Yes	1.45	36.95
			(-79%)	(-70%)

MAD = mean absolute deviation; MSPE = mean squared prediction error.
[a] Values in parentheses represent the change compared to Model 1.

Since current models such as those in the HSM rely only on volume, the quality of volume data dictates the quality of the model. The analysis showed that using short count stations as a data source does not diminish the quality of developed models if speed-related variables are also used in the model. This means that a combination of different volume data sources with good quality speed data can lessen the dependency on the quality of the volume data without compromising performance. Since short count stations are more common, this finding also indicates that this approach can be applied broadly across transportation networks.

CONCLUSIONS

- *Models that incorporated speed along with volume provided better performance than models that used other combinations of flow variables.* Multiple flow parameters were investigated, including heavy vehicle percentage, v/c ratio, speed, and density. Only speed and density had a logical and statistically significant relationship when they were combined with volume. Since speed is more widely available than density, models that used volume in conjunction with speed were selected as the best alternatives.

- *For all models, prediction accuracy was improved across all validation MOEs when the speed components were added vs. when the speed components were not added.* Speeds from both continuous count stations and probe data provided similar results.

- *Models using raw hourly data were inferior to models using other levels of aggregation.* The raw hourly models were influenced by the missing data in the dataset. About 23% of the raw hourly data in the validation dataset did not meet quality control standards and thus could not be used to generate predictions. These models did not have a better prediction capability in comparison to AADT models.

- *Using averages of available data in each hour improved the model performance significantly over AADT models.* The average volume calculation helped to smooth out the discrepancies created by missing raw hourly data. Models based on average 15-minute data did not always perform better than AADT models. For both rural and urban segments, models based on average hourly data outperformed the AADT-based models across all MOEs. For total crashes on urban segments, models using hourly volume, geometry, and flow variables showed 20%, 22%, and 38% improvement in MAD, MAPE, and MSPE, respectively, as compared to the AADT-based model. Corresponding improvements for rural segments were 11%, 33%, and 29%. The added benefit is that average values are more easily predicted for future conditions than the distributions of data.

- *Models developed using both short count and continuous count station data outperformed those using only continuous count stations.* For rural hourly models, MAD and MSPE improved by 52% and 72%, respectively, when short counts were added in comparison to continuous count only models. The respective values for urban segments were 58% and 27%.

- *Inclusion of spatial and temporal correlation improves model fit, but the district-level spatial correlation effect is weaker than the temporal one.* For all categories, the variance is much smaller for districts than it is for year or hour. Although the temporal correlation was stronger than the spatial one, the variance in data explained by yearly correlation was smaller than the hourly correlation. When the models that accounted for correlation were compared to the models that used the same dataset but no correlation, MAD and MSPE improved by 14% and 17%, respectively, for rural segments and 21% and 43%, respectively, for urban segments. Although accounting for correlation improved model performance, it provided smaller benefits than inclusion of the short count data in the models for rural sites. Spatial correlation benefits were larger for urban locations.

RECOMMENDATIONS

1. *VDOT's TED should begin pilot testing the models developed in this study to analyze two-lane rural and three-lane urban freeway segments where projects are expected to impact the quality of traffic flow*. The models created in this study can be immediately applied to any potential rural two-lane or urban three-lane freeway segment projects. As an initial pilot, the TED could begin using these models to compare alternatives on freeway segments that are expected to influence speeds or hourly volume distributions. In cases where little variation in flow is expected, analysts should weigh the tradeoffs between the level of effort to conduct the analysis and the anticipated improvement in accuracy of predictions for a specific application. Comparisons between predictions made using the hourly models and AADT models should be made to assess whether conclusions would change if the hourly models were used.

2. *The Virginia Transportation Research Council (VTRC), in conjunction with VDOT's TED, should expand this research effort to examine other freeway facility types.* This study examined only basic freeway segments for three-lane urban freeways and two-lane rural freeways. Given the positive results found in this study, additional models should be developed for freeway interchange areas and other freeway cross sections. Expansion to those other facilities may be more complex and require additional data elements. For example, interchange analysis will require additional data on merging and diverging traffic and ramp configuration.

IMPLEMENTATION AND BENEFITS

Implementation

For Recommendation 1, VDOT's TED will apply the models shown in Tables 7 and 8 when a safety analysis of hourly level data on freeway segments is required. This will occur upon publication of this report. Since these models are applicable only for two-lane rural and three-lane urban freeway segments, the potential pilot testing may be limited in scope. Findings from these pilot tests will be compiled by the TED and VTRC and used to inform future research conducted as part of Recommendation 2.

For Recommendation 2, VTRC and the TED will discuss relative need, availability of data, and potential applications of the models for various freeway cross sections and elements. Based on this discussion, VTRC would initiate a second phase of research if the results from Recommendation 1 merited further development of this technique.

Benefits

The benefit of implementing Recommendation 1 is to gain more field experience with the applications of the models developed in this study. Since the models proposed in this study will require more effort to apply on the part of the analyst, there is a potential that more time would be required to perform an analysis than to use traditional SPFs. Lessons learned about applications and projects where these techniques were beneficial will help further define use cases where this more detailed level of analysis is appropriate.

The benefits of implementing Recommendation 2 will be an ability to improve the quality of freeway crash predictions by including operational characteristics in the analysis over the entire freeway system. Although it is difficult to quantify the monetary benefit of this improvement, better crash predictions should result in better evaluations of countermeasures and more accurate identification of locations where operational improvements could improve safety.

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APPENDIX A

PARAMETER ESTIMATES FOR MODELS BASED ON VOLUME AND GEOMETRY FOR RURAL FOUR-LANE FREEWAY SEGMENTS USING CONTINUOUS COUNT STATION LOCATIONS

	Total Crashes								
	Raw Hourly Volume			**Average Hourly Volume**			**AADT**		
	Estimate	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-12.53	0.452	<2E-16	-7.75	0.501	<2E-16	-5.78	1.803	0.001348
log (Volume)	0.31	0.046	1.07e-11	0.50	0.057	<2E-16	0.49	0.186	8.07e-04
Median Width									
≤60 ft	0.67	0.251	0.0941	0.45	0.265	0.0895	0.55	0.237	0.1210
>60 ft to ≤120 ft	1.04	0.251	3.34e-05	0.79	0.257	0.0019	1.11	0.229	1.27e-06
>120 ft to ≤180 ft	1.05	0.239	1.04e-05	1.06	0.246	1.78e-05	0.83	0.209	7.23e-05
>180 ft	0.76	0.232	0.0011	0.81	0.239	7.96e-04	0.74	0.206	3.13e-04
Grade of VC									
≤-1.0%	0.31	0.309	0.3272	0.08	0.317	0.8039	0.27	0.348	0.4387
≥-1.0% to <-0.5%	0.59	0.292	0.0437	0.42	0.302	0.0163	0.40	0.349	0.2471
≥-0.5% to <0%	0.87	0.289	0.0027	0.55	0.297	0.0063	0.42	0.338	0.2156
≥0% to <0.5%	0.16	0.297	0.5815	0.11	0.308	0.7154	0.28	0.344	0.4201
≥0.5%	0.22	0.302	0.4599	0.35	0.311	0.2567	0.12	0.389	0.7564
Radius of HC	-0.06	0.029	0.0243	-0.007	0.047	0.0087	-0.03	0.039	0.0042
AIC	12170			3563			838		
	Fatal and Injury Crashes								
	Raw Hourly Volume			**Average Hourly Volume**			**AADT**		
	Estimate	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-12.21	1.023	<2E-16	-7.71	0.783	<2E-16	-7.29	2.720	7.30e-06
log (Volume)	0.19	0.117	8.89e-04	0.42	0.090	3.43e-06	0.54	0.282	4.68e-04
Median Width									
≤60 ft	0.34	0.571	0.5439	0.31	0.435	0.4747	0.64	0.358	0.0717
>60 ft to ≤120 ft	0.73	0.567	0.1968	0.55	0.418	0.1898	0.38	0.362	0.2970
>120 ft to ≤180 ft	0.67	0.531	0.2071	1.04	0.392	0.0023	0.95	0.293	0.0012
>180 ft	0.52	0.518	0.3183	0.82	0.379	0.0034	0.78	0.283	0.0055
Grade of VC									
≤ -1.0%	-0.22	0.676	0.7504	-0.68	0.488	0.1612	-0.34	0.509	0.5011
≥-1.0% to <-0.5%	0.14	0.625	0.8277	0.17	0.455	0.7074	0.22	0.501	0.6625
≥-0.5% to < 0%	0.46	0.621	0.4531	0.09	0.443	0.8359	0.43	0.486	0.3781
≥ 0% to <0.5%	-0.59	0.629	0.3501	-0.76	0.486	0.1182	-0.22	0.506	0.6646
≥0.5%	-0.34	0.633	0.5941	-0.32	0.476	0.4962	-0.04	0.572	0.7005
Radius of HC	-0.29	0.115	0.7251	-0.07	0.081	0.9350	-0.04	0.056	0.5136
AIC	4735			1623			551		

AADT= annual average daily traffic; Std. = standard; VC = vertical curve; HC = horizontal curve; AIC = Akaike information criterion.

APPENDIX B

PARAMETER ESTIMATES FOR MODELS BASED ON VOLUME, GEOMETRY, AND FLOW FOR RURAL FOUR-LANE FREEWAY SEGMENTS USING CONTINUOUS COUNT STATION DATA

	Total Crashes					
	Raw Hourly Volume			**Average Hourly Volume**		
	Estimate	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-2.63	0.512	2.8e-07	-2.09	0.875	<2E-16
log (Volume)	0.44	0.045	<2E-16	0.53	0.054	<2E-16
Median Width						
≤60 ft	0.62	0.237	0.1685	0.15	0.244	0.5398
>60 ft to ≤120 ft	0.31	0.223	0.0086	0.02	0.222	0.9426
>120 ft to ≤180 ft	0.28	0.210	0.0183	0.63	0.208	0.0026
>180 ft	0.26	0.198	0.1929	0.48	0.197	0.0014
Grade of VC						
≤-1.0%	0.02	0.324	0.9475	0.44	0.315	0.1603
≥-1.0% to <-0.5%	0.15	0.318	0.6313	0.09	0.308	0.7705
≥-0.5% to <0%	0.28	0.307	0.3546	0.03	0.300	0.9236
≥0% to <0.5%	0.25	0.323	0.4337	0.09	0.317	0.7758
≥0.5%	0.11	0.327	0.7568	0.09	0.302	0.7635
Radius of HC	-0.01	0.047	0.8115	-0.07	0.047	0.4172
Speed	-0.14	0.004	<2E-16	-0.07	0.009	1.41e-13
AIC	11166			3399		
	Fatal and Injury Crashes					
	Raw Hourly Volume			**Average Hourly Volume**		
	Estimate	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-0.32	2.408	0.0098	-1.89	1.164	0.0013
log (Volume)	0.38	0.141	0.0071	0.46	0.082	1.68e-08
Median Width						
≤60 ft	0.49	0.733	0.4983	0.58	0.411	0.1538
>60 ft to ≤120 ft	0.41	0.679	0.5478	0.31	0.362	0.3872
>120 ft to ≤180 ft	0.24	0.659	0.7115	0.38	0.341	0.2643
>180 ft	0.43	0.666	0.5182	0.45	0.337	0.1833
Speed	-0.19	0.033	1.94e-08	-0.084	0.013	1.05e-10
AIC	4529			1527		

Std. = standard; VC = vertical curve; HC = horizontal curve; AIC = Akaike information criterion.

APPENDIX C

VUONG TEST RESULTS FOR RURAL FOUR-LANE FREEWAY AND URBAN SIX-LANE FREEWAY CRASH PREDICTION MODELS USING CONTINUOUS COUNT STATION DATA

Rural Segments				
Total Crashes				
	Model	**AIC Corrected**	**BIC Corrected**	**Result**
Average 15-Minute	Volume, length, and geometry models	0.387	2.511	Model 1 > Model 2
	Volume, length, geometry, and flow state models	3.273	4.009	Model 1 > Model 2
Average Hourly	Volume, length, and geometry models	1.997	2.292	Model 1 > Model 2
	Volume, length, geometry, and flow state models	1.868	4.816	Model 1 > Model 2
Injury Crashes				
	Model	**AIC Corrected**	**BIC Corrected**	**Result**
Average 15-Minute	Volume, length, and geometry models	-8.596	-6.877	Model 2 > Model 1
	Volume, length, geometry, and flow state models	1.465	2.367	Model 1 > Model 2
Average Hourly	Volume, length, and geometry models	0.341	8.041	Model 1 > Model 2
	Volume, length, geometry, and flow state models	1.267	4.925	Model 1 > Model 2
Urban Segments				
Total Crashes				
	Model	**AIC Corrected**	**BIC Corrected**	**Result**
Average 15-Minute	Volume, length, and geometry models	5.734	6.775	Model 1 > Model 2
	Volume, length, geometry, and flow state models	6.005	6.657	Model 1 > Model 2
Average Hourly	Volume, length, and geometry models	4.710	5.252	Model 1 > Model 2
	Volume, length, geometry, and flow state models	6.498	7.107	Model 1 > Model 2
Injury Crashes				
	Model	**AIC Corrected**	**BIC Corrected**	**Result**
Average 15-Minute	Volume, length, and geometry models	2.781	1.292	Model 1 > Model 2
	Volume, length, geometry, and flow state models	3.427	4.088	Model 1 > Model 2
Average Hourly	Volume, length, and geometry models	3.425	3.735	Model 1 > Model 2
	Volume, length, geometry, and flow state models	0.578	2.839	Model 1 > Model 2

Model 1 = negative binomial; Model 2 = zero-inflated negative binomial; AIC = Akaike information criterion; BIC = Bayesian information criterion.

APPENDIX D

PARAMETER ESTIMATES FOR VOLUME AND GEOMETRY MODEL FOR RURAL FOUR-LANE FREEWAY AND URBAN SIX-LANE FREEWAY CRASH PREDICTION MODELS USING CONTINUOUS COUNT STATIONS

Rural Segments									
	Total Crashes								
	Average 15-Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-8.41	0.307	<2E-16	-8.04	0.385	<2E-16	-9.04	1.289	2E-12
log (Volume)	0.56	0.051	<2E-16	0.57	0.0524	<2E-16	0.87	0.131	2E-11
Median Width	0.43	0.138	5E-06	0.51	0.315	3E-09	0.65	0.902	0.0153
Grade of VC									
Negative	0.42	0.092	5.E-06	0.48	0.098	8.E-07	0.55	0.106	3E-07
Positive	0.38	0.133	0.00465	0.33	0.143	2E-02	0.41	0.161	0.0102
Percent of HC	0.05	0.001	6E-11	0.06	0.009	9E-11	0.06	0.008	3E-14
Length of HC	-2.74	0.472	4E-09	-3.15	0.515	8E-10	-3.82	0.476	1E-15
AIC	5977			3864			796		
	Injury Crashes								
	Average 15-Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-9.29	0.532	<2E-16	-8.46	0.629	<2E-16	-11.07	2.125	2E-07
log (Volume)	0.51	0.087	8E-09	0.47	0.086	3E-08	0.95	0.216	1E-05
Median Width	0.24	0.711	1E-03	0.36	0.667	2E-05	0.29	0.201	0.0255
Grade of VC									
Negative	0.35	0.161	3E-02	0.36	0.161	0.0248	0.49	0.167	3E-03
Positive	0.16	0.243	0.4989	0.03	0.255	0.8909	0.36	0.267	0.1784
Percent of HC	0.05	0.015	8E-04	0.04	0.016	9E-03	0.041	0.014	4E-03
Length of HC	-2.59	0.855	2E-03	-2.61	0.936	5E-03	-2.70	0.807	8E-04
AIC	2416			1745			544		

AADT = annual average daily traffic; Std. = standard; VC = vertical curve; HC = horizontal curve; AIC = Akaike information criterion.

Urban Segments									
	Total Crashes								
	Average 15-Minute Volume			Average Hourly Volume			AADT		
	Estimate	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-9.65	0.301	<2E-16	-6.91	0.359	<2E-16	-17.36	2.401	5E-13
log (Volume)	0.97	0.051	<2E-16	0.70	0.048	<2E-16	1.75	0.236	1E-13
Median Width	-0.13	0.032	4E-09	-0.11	0.063	<2E-16	-0.21	0.001	0.0043
AIC	8868			5520			742		
	Injury Crashes								
	Average 15-Minute Volume			**Average Hourly Volume**			**AADT**		
	Estimate	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(> |z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-9.99	0.499	<2E-16	-8.56	0.563	<2E-16	-23.12	2.805	<2E-16
log (Volume)	0.82	0.083	<2E-16	0.75	0.073	<2E-16	2.19	0.272	8E-16
Median Width	-0.11	0.541	6E-06	-0.32	0.423	1E-09	-0.15	0.001	6E-07
AIC	3964			2559			469		

AADT = annual average daily traffic; Std. = standard; VC = vertical curve; HC = horizontal curve; AIC = Akaike information criterion.

APPENDIX E

NEGATIVE BINOMIAL AND ZERO-INFLATED NEGATIVE BINOMIAL COMPARISON FOR RURAL FOUR-LANE FREEWAY AND URBAN SIX-LANE FREEWAY CRASH PREDICTION MODELS USING SHORT COUNT AND CONTINUOUS COUNT STATIONS

	Rural Segments						
	AIC		**BIC**		**ANOVA (NB, ZINB)**	**Critical Chi-Square**	**Preferred Model**
	NB	**ZINB**	**NB**	**ZINB**			
Volume, length, and geometry models	10783	10833	10870	10895	4.77	7.79	NB
Volume, length, geometry, and flow models	10679	10687	10795	10811	2.46	4.61	NB
	Urban Segments						
	AIC		**BIC**		**ANOVA (NB, ZINB)**	**Critical Chi-Square**	**Preferred Model**
	NB	**ZINB**	**NB**	**ZINB**			
Volume, length, and geometry models	10218	10229	10312	10333	5.08	6.25	NB
Volume, length, geometry, and flow models	10186	10199	10293	10311	6.87	7.79	NB

AIC = Akaike information criterion; BIC = Bayesian information criterion; ANOVA = analysis of variance; NB = negative binomial; ZINB = zero-inflated negative binomial.

APPENDIX F

PARAMETER ESTIMATES FOR VOLUME AND GEOMETRY MODEL FOR RURAL FOUR-LANE FREEWAY AND URBAN SIX-LANE FREEWAY CRASH PREDICTION MODELS INCLUDING SPATIAL AND TEMPORAL CORRELATION USING CONTINUOUS AND SHORT COUNT STATIONS

Rural Segments						
	Total Crashes					
	Average Hourly Volume			**AADT**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-7.04	0.401	<2E-16	-9.98	1.14	<2E-16
log (Volume)	0.67	0.062	<2E-16	1.11	0.11	<2E-16
Radius of Horizontal Curve (mile)	-0.05	0.019	0.00875	—	—	—
Median Width (ft)	0.21	0.005	2.72E-05	—	—	—
% of Horizontal Curve Length						
Less than 25%	0.53	0.111	1.39E-06	0.28	0.106	0.0077
>25% ~ ≤50%	0.24	0.092	0.009	0.13	0.094	0.0028
>50% ~ ≤75%	0.46	0.088	2.02E-07	0.27	0.099	0.0065
>75%	0.09	0.099	0.338	0.16	0.104	0.8737
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.182 (0.047)			0.198 (0.028)		
Year	0.465 (0.105)			0.317 (0.049)		
Hour	0.538 (0.241)			—		
AIC	10782.9			2324.3		
BIC	10870.1			2361.3		
ρ^2_c	0.21			0.19		
	Injury Crashes					
	Average Hourly Volume			**AADT**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-7.13	0.464	<2E-16	-11.81	1.46	4.9E-16
log (Volume)	0.54	0.069	1.80E-14	0.67	0.114	7.7E-16
Median Width	0.14	0.001	9.90E-03	—	—	—
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.132 (0.055)			0.065 (0.048)		
Year	0.297 (0.017)			0.193 (0.025)		
Hour	0.419 (0.047)			—		
AIC	4777.3			1485		
BIC	4828.2			1505.5		
ρ^2_c	0.11			0.07		

AADT = annual average daily traffic; Std. = standard; --- = parameter not used; AIC = Akaike information criterion; BIC = Bayesian information criterion.

Urban Segments						
	Total Crashes					
	Average Hourly Volume			**AADT**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-6.68	0.372	<2E-16	-5.55	0.919	1.5E-09
log (Volume)	0.67	0.047	<2E-16	0.65	0.085	4.5E-15
Radius of Horizontal Curve (mile)	-0.09	0.033	0.0032	-0.14	0.044	1.1E-03
Grade						
Positive Grade	-0.04	0.052	0.39928	—	—	—
Negative Grade	0.22	0.071	0.00173	—	—	—
Length of Horizontal Curve						
≤0.5	0.04	0.179	0.8147	0.26	0.245	3.0E-01
>0.5 ~ ≤1.0	0.45	0.177	0.0112	0.6	0.243	1.3E-02
>1.0 ~ ≤1.5	0.61	0.181	0.0007	0.94	0.253	2.2E-04
1.5	0.26	0.182	0.0154	0.44	0.249	7.7E-02
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.129 (0.071)			0.173 (0.054)		
Year	0.576 (0.087)			0.215 (0.083)		
Hour	0.618 (0.145)			—		
AIC	10217.9			1538		
BIC	10311.7			1576.8		
$\boldsymbol{\rho^2_c}$	0.15			0.10		
	Injury Crashes					
	Average Hourly Volume			**AADT**		
Fixed Effect	**Estimate**	**Std. Error**	**Pr(>|z|)**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Intercept	-8.62	0.587	<2E-16	-7.75	1.422	4.8E-09
log (Volume)	0.71	0.058	<2E-16	0.71	0.129	3.6E-09
Radius of Horizontal Curve (mile)	-0.12	0.051	0.01971	—	—	—
Length of Horizontal Curve						
≤0.5	0.94	0.393	0.01707	0.72	0.358	4.3E-02
>0.5 ~ ≤ 1.0	1.32	0.388	0.0007	0.93	0.35	7.7E-03
>1.0 ~ ≤1.5	1.46	0.4	0.0003	1.15	0.37	9.0E-04
1.5	1.13	0.398	0.0046	0.81	0.35	2.2E-02
Random Effect	**Intercept (Standard Deviation)**			**Intercept (Standard Deviation)**		
District	0.132 (0.053)			0.137 (0.256)		
Year	0.242 (0.085)			0.267 (0.032)		
Hour	0.529 (0.057)			—		
AIC	4600.3			1015.5		
BIC	4687.4			1054.2		
$\boldsymbol{\rho^2_c}$	0.14			0.10		

AADT = annual average daily traffic; --- = parameter not used; AIC = Akaike information criterion; BIC = Bayesian information criterion.