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Examination of Features Correlated With Roadway Departure Crashes on Rural Roads

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Roadway departure (RD) crashes are one of the major causes of fatalities on highways. Reducing the number and severity of RD crashes is one of the emphasis areas of the strategic highway safety plan for many state departments of transportation in the United States. Many significant efforts have been aimed at reducing RD crashes, and a continued focus on preventing these crashes is needed. The purpose of this study was to identify roadway geometric design, roadside, and traffic characteristics that are correlated with RD crashes on rural roads. Using data collected in Virginia from 2014-2018, this study analyzed the characteristics of RD crashes on rural roadways and identified how the variation in RD crash frequency and severity is related to roadway, roadside, and traffic features.

The study found a significant correlation between the frequency of RD crashes and annual average daily traffic, shoulder width, and speed limit. The number of RD crashes increased as the annual average daily traffic and speed limit increased and decreased as the shoulder width was increased. Further analysis using more granular data from two fairly recent data sources, SCRIM and iVision, showed promise for further insights into factors influencing RD crashes. In particular, the results showed that these crashes are significantly influenced by roadway geometry (curvature and cross slope) and pavement condition (skid resistance and roughness).

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FINAL REPORT

EXAMINATION OF FEATURES CORRELATED WITH ROADWAY DEPARTURE CRASHES ON RURAL ROADS

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ABSTRACT

Roadway departure (RD) crashes are one of the major causes of fatalities on highways. Reducing the number and severity of RD crashes is one of the emphasis areas of the strategic highway safety plan for many state departments of transportation in the United States. Many significant efforts have been aimed at reducing RD crashes, and a continued focus on preventing these crashes is needed. The purpose of this study was to identify roadway geometric design, roadside, and traffic characteristics that are correlated with RD crashes on rural roads. Using data collected in Virginia from 2014-2018, this study analyzed the characteristics of RD crashes on rural roadways and identified how the variation in RD crash frequency and severity is related to roadway, roadside, and traffic features.

The study found a significant correlation between the frequency of RD crashes and annual average daily traffic, shoulder width, and speed limit. The number of RD crashes increased as the annual average daily traffic and speed limit increased and decreased as the shoulder width was increased. Further analysis using more granular data from two fairly recent data sources, SCRIM and iVision, showed promise for further insights into factors influencing RD crashes. In particular, the results showed that these crashes are significantly influenced by roadway geometry (curvature and cross slope) and pavement condition (skid resistance and roughness).

TABLE OF CONTENTS

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INTRODUCTION

Background

According to the Federal Highway Administration (FHWA), a roadway departure (RD) crash is "a non-intersection crash in which a vehicle crosses an edge line, a centerline, or otherwise leaves the traveled way" (FHWA, 2019a). About 52% of all traffic fatalities in the United States from 2015-2017 were caused by RD crashes. A significant proportion of fatalities on Virginia's roads are the result of RD crashes. From 2014-2019, RD crashes constituted about 52% (2,332 of 4,425) of fatal crashes in Virginia. Reducing the number and severity of RD crashes is one of the eight emphasis areas in the *Virginia 2017-2021 Strategic Highway Safety Plan* (Virginia Department of Transportation [VDOT], 2017).

To improve traffic safety across the nation, transportation agencies and the research community have devoted significant efforts to understand the causes of RD crashes and develop effective countermeasures. Several countermeasures including widening lanes and/or shoulders, modifying shoulder types (paved, gravel, composite, turf), using less rigid barrier types, installing shoulder rumble strips, improving delineation, and changing alignments (grade, horizontal curve radius, etc.) have been shown to reduce the frequency and/or severity of RD crashes (American Association of State Highway and Transportation Officials [AASHTO], 2010; FHWA, 2018).

Based on the literature, the factors associated with RD crashes can be summarized into five categories: traffic-related factors, geometric design and environmental factors, human factors, roadside factors, and other factors (Al-Bdairi and Hernandez, 2017; Das and Sun, 2016; LeBlanc, 2006; Lord et al., 2011). Traffic volume and speed are both important influencing factors. Highway design factors, including lane width, shoulder width and type, roadside design, pavement edge drop-off, horizontal curvature and grades, driveway density, and pavement friction, are associated with RD crashes. Human factors, such as safety belt use, alcohol and drug use, age, and gender, also affect RD crashes; other factors include time of day, vehicle type, etc. These factors have random or fixed effects on roadway departures, and for some roadway and roadside factors, the effects can vary by study site and drivers (Gong and Fan, 2017; Gordon et al., 2013; Kusano and Gabler, 2012; Zou et al., 2014). Therefore, to implement appropriate countermeasures, it is necessary for VDOT to study the characteristics of RD crashes in Virginia and understand the impact of crash-influencing factors on the roadway segments where RD crashes are more prevalent.

Problem Statement

Over the years, VDOT has made significant efforts to reduce RD crashes. Counts of RD crashes are used to identify locations for RD safety improvements, and in 2019, network screening safety performance functions (SPFs) were developed to identify potential locations for RD safety improvements (Kweon and Lim, 2019). Other tools, including the Roadway Departure Safety Implementation Plan (VDOT, 2017) and the Roadway Departure Crash Countermeasure Tool (VDOT, 2016), were developed to provide guidance on selecting countermeasures to mitigate RD crashes. However, even with these tools and improvements, a continued focus on preventing RD crashes is still needed. RD crashes are complex by nature, not only because of the combination of driver, environmental, and roadway factors, but also because of the interaction of multiple elements when only roadway factors are considered. The main strategy to reduce RD crashes is to keep the vehicle on the road; further, a complementary strategy is to minimize the effect of a crash should a vehicle leave the road. Unfortunately, a large number of RD crashes occur on rural roads that have limited or no shoulders and very limited recovery zones.

A thorough understanding of the characteristics of rural RD crashes in Virginia and the factors contributing to these crashes will help VDOT implement countermeasures proactively to improve the safety of rural roads.

PURPOSE AND SCOPE

The purpose of this study was to identify roadway features and traffic characteristics that are correlated with RD crashes on rural roads in Virginia. The main objectives were as follows:

1. Assess the extent of RD crashes on rural roadways in Virginia.

2. Examine how variation in RD crash frequency and severity is related to roadway features and traffic factors.

3. Explore the factors that are currently not included in the VDOT Traffic Engineering Division's (TED) Oracle database (COTEDOP) but may have an effect on RD crashes.

4. Develop recommendations for minimizing the risk of RD crashes.

Specific questions that the study sought to address included the following:

1. Are locations with narrower shoulders more likely to have more RD crashes?

2. Are locations with limited sight distance with a row of trees more likely to have more frequent RD crashes than locations surrounded by grassy fields?

3. Does a certain speed limit combined with other geometric features produce crash hotspots?

4. Should VDOT focus on improving shoulders of certain types of roads or perform selective clearing in certain conditions?

This study focused on examining the impact of roadway geometric design, traffic, and roadway surface condition. Based on discussions with the study's technical review panel, the analysis was limited to two-lane and multi-lane divided and undivided primary and secondary rural highways. The potential impact of rows of trees (Question 2) was not studied because there was an ongoing national research effort at the time of this study—NCHRP 17-72: Update of Crash Modification Factors for the Highway Safety Manual—that sought to address this issue, among others, in a comprehensive manner.

METHODS

To achieve the research objectives, the research team started with an initial review of relevant state roadway network inventory and crash databases, followed by an in-depth review of pertinent crash reports and site characteristics. All analyses were performed using standard statistical methods for estimating potential causal factors.

Literature Review

The literature on the latest developments with regard to RD crash characteristics and potential countermeasures was identified. The Transportation Research International Documentation (TRID) database was used to search the literature. The literature review helped identify factors that are known to contribute to RD crashes and potential countermeasures to reduce crash risk. The literature review also helped identify the common methods used to analyze RD crashes, which provided insights for statistical modeling in later tasks.

A review of RD crash countermeasures was also conducted. The main sources for this information were FHWA and AASHTO publications and the Crash Modification Factors Clearinghouse (FHWA, 2019b). The objective was to identify low-cost treatments for reducing RD crashes on rural roads.

Data Collection and Preparation

Based on the results of the literature review and input from the study's technical review panel and other VDOT staff, the research team identified the data needs and collected crash, roadway, traffic, and other relevant data. All data were screened for quality assurance. Anomalies and incomplete data were identified and removed. The primary sources of data were COTEDOP and the Road Network System (RNS) database; VDOT's iVision system (hereinafter "iVision") and SCRIM (the proprietary truck-based multifunctional roadway survey machine) provided supplemental data. Structured Query Language (SQL) codes were developed to retrieve and process data from COTEDOP, and four categories of data were collected: roadway inventory data, roadway geometry data, traffic volume data, and crash data. iVision and SCRIM were sources of road surface condition data, and they also provided some roadway geometry and roadside data. Each data source is discussed in the following sections.

COTEDOP Roadway and Traffic Data

The scope of this study was limited to two-lane and multi-lane primary and secondary rural highways. The COTEDOP database was first queried to generate an initial list of roadway segments that satisfied this scope. These roadway segments were identified based on the following fields and attributes of the database:

- *Governmentcontrol* = (1. State primary and interstate, 2. State secondary)

- *Functionalclass* = (2. Rural other principal arterial, 3. Rural minor arterial, 4. Rural major collector, 5. Rural minor collector, 6. Rural collector)

- *Facilitytype* = (0. Two-way undivided, 1–3. Divided with no, partial, or full control of access).

Each segment was defined by route name, start milepost, and end milepost. Roadway geo-spatial, geometric, speed limit, and annual average daily traffic (AADT) data for the identified segments were retrieved from the database for the years 2014-2018.

Lane width data were not directly available in COTEDOP; instead, lane widths were calculated by dividing the surface width information by the number of lanes. Segments for which the calculated lane widths were less than 8 ft or greater than 13 ft were excluded from this study. In addition, short segments (less than 0.1 mile long) and those that had either no AADT data available or very low AADT (less than 50 vehicles per day) were excluded from the study. The final dataset consisted of 56,443 segments totaling 35,243 miles of roadway.

iVision Data

iVision is a web application for pavement and asset management. It provides synchronized surface condition data, roadway geometry data, and road and pavement images. Data can be easily exported using the interface shown in Figure 1. iVision data were recorded in

0.1-mile segments, but segments could be shorter if there is any change in geometry or pavement type within 0.1 mile. GPS locations for the start and end points of each segment were recorded.

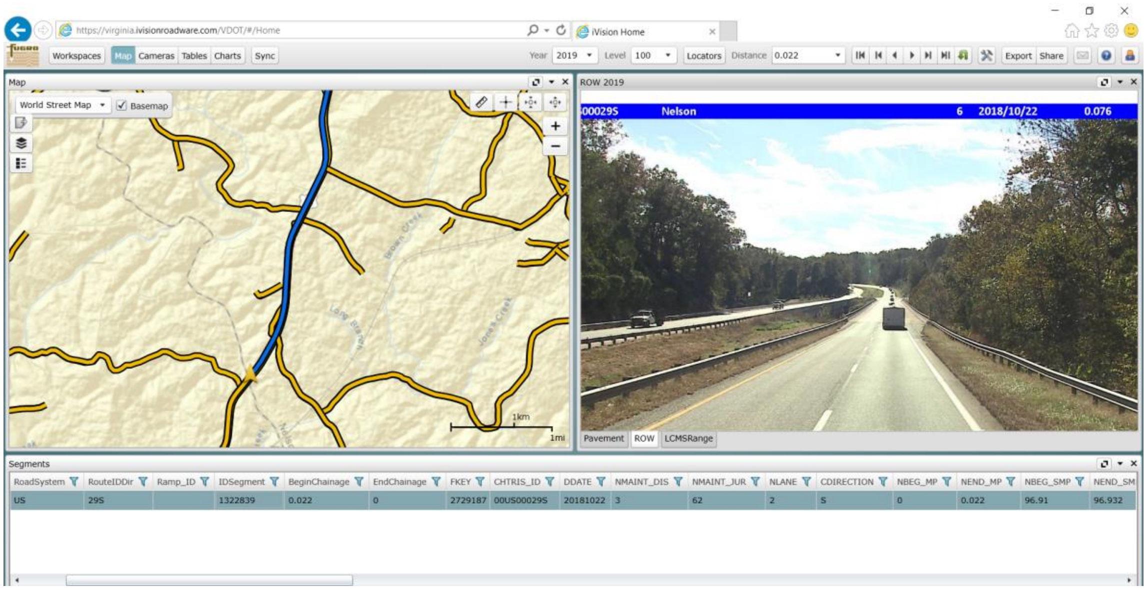

Figure 1. iVision System Interface

iVision data include more than 100 fields. The pavement condition variables collected included the International Roughness Index (IRI) and the year of last rehabilitation. IRI is a standard pavement roughness measure used worldwide, and it indicates ride quality of a vehicle. iVision reported the IRI for both left and right wheel paths, and the average of the two was used to represent the segment IRI in this study. The unit used in iVision is inches per mile.

iVision includes several shoulder condition variables that were not found in COTEDOP. Shoulder condition assessments are generally subjective and made by raters following guidelines specified by VDOT's Maintenance Division (VDOT, 2012). Some of the variables contained in the system are as follows:

- *Shoulder type:* curb, gravel, asphalt, concrete, paved combination (asphalt + concrete), unpaved combination (gravel + turf), or none. Data are recorded for both left and right shoulders.

- *Shoulder length:* total length of shoulder along a segment.

- *Shoulder condition:* the condition rating for shoulder materials (good, fair, poor). The length of shoulder in each of the three conditions is provided. Data are recorded for both left and right shoulders.

- *Drop-off:* the difference in elevation between the traveled surface and the shoulder. Values greater than 3 in are considered high severity, and values between 1.5 and 3 in are considered medium severity. The length of shoulders in each severity category is recorded. Data for both right and left shoulders are available.

- *Deficient slope:* a shoulder slope such that water does not drain away from the roadway. The length of the shoulder with a deficient slope is recorded. Data for both right and left shoulders are available.

- *Build-up:* vegetation growth or debris build-up that adversely affects drainage. The length of shoulder with build-up is recorded. Data for both left and right shoulders are available.

Geometric variables such as lane width, shoulder width, and number of lanes were also collected from iVision. These variables were collected for mainly exploratory purposes. The statistical analysis in this study used geometry data from COTEDOP, as it is the standard database for all kinds of safety analyses for VDOT since the quality of iVision geometry data had not yet been evaluated. The advantage of iVision data is that they are collected on shorter segments than those identified in COTEDOP and therefore might better reflect local conditions.

iVision maintains data for only the past 4 years. iVision data for 2016-2019 were available at the time of this study. The 2016 and 2017 data were for secondary roads only. VDOT collects iVision data for 25% of secondary roads in the state every year, and iVision keeps one set of statewide data for secondary roads in a 4-year period. Currently the 2016 data cover statewide secondary roads. Although the year of data collection was recorded as "2016," 75% of data were actually collected in previous years. This would affect the accuracy of variables, such as the IRI, changing over time. Also, a data completeness check found that the 2016 data did not have data for all secondary roads in the state.

iVision data are directional, but data for lanes in both travel directions may not be available at the same time. Also, the roadway segmentation in both travel directions can be different because of different geometry or other factors (e.g., access points on one side of the road). This makes it challenging to combine data for both travel directions.

SCRIM Data

SCRIM is a truck-based multifunctional roadway monitoring device (Figure 2) that can simultaneously and continuously collect roadway surface condition and geometry data while being driven in the speed range of 25 to 85 km/h (15 to 53 mph). SCRIM has been widely used in European countries for nationwide road surveys. The FHWA first introduced SCRIM to the United States in 2015 to help the states in pavement friction management (Virginia Tech Transportation Institute [VTTI], 2015). VDOT started roadway surveys using SCRIM in 2018 through VTTI. These SCRIM surveys comprise a new source of data for pavement skid resistance, texture, and roadway alignment.

Figure 2. SCRIM. Instrumentation is housed in the truck.

SCRIM data were obtained from VTTI in late 2019. At that time, data were collected on selected routes in four of VDOT's nine districts; however, the majority of data were for interstate highways. Non-interstate data were available for only a few road segments on US 29 in the Lynchburg District; US 460 in the Salem District; and US 11, US 58, and US 460 in the Bristol District. Like iVision data, SCRIM data are directional. The instrument collects data for one direction in each run.

The roadway geometry data collected by SCRIM were horizontal curvature (1/m), vertical gradient (%), and cross slope (%). GPS coordinates were included in the data. The surface condition variables collected by SCRIM included the following:

- *SCRIM reading (SR):* an indicator of skid resistance
- *Mean profile depth (MPD):* an indicator of pavement macrotexture.

RAVCON (Figure 3) and SkidVid (Figure 4), the software from the SCRIM vendor, were used for data processing. RAVCON converted the raw data into a text file, and then SkidVid used the text file as input to visualize data and export data to a spreadsheet. The raw SCRIM data were collected every 100 mm. Using SkidVid, SR, MPD, and geometry data were aggregated by 10 m (33 ft).

The SR collected at different speeds are corrected to a standard speed of 50 km/h (30 mph) based on the *Design Manual for Roads and Bridges*, Volume 7, Section 3, Part 1 (HD 28/15) (Highways England, 2015). The conversion equation is shown in Equation 1:

$$\mathrm{SR50} = \frac{\mathrm{SR(v)} * (-0.0152 * \mathrm{v}^2 + 4.77 * \mathrm{v} + 799)}{1000} \qquad \text{Eq. 1}$$

where v is the testing speed, SR(v) is the SR at speed v, and SR50 is the values of SR(v) corrected to 50 km/h (30 mph).

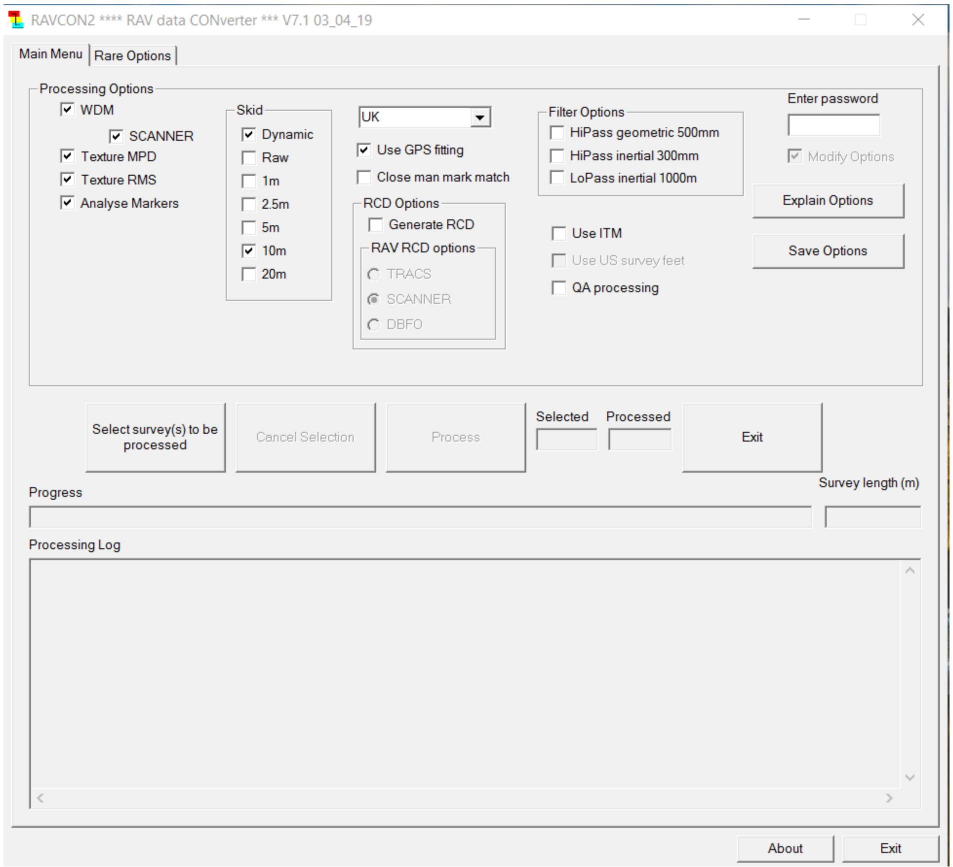

Figure 3. RAVCON Software Layout

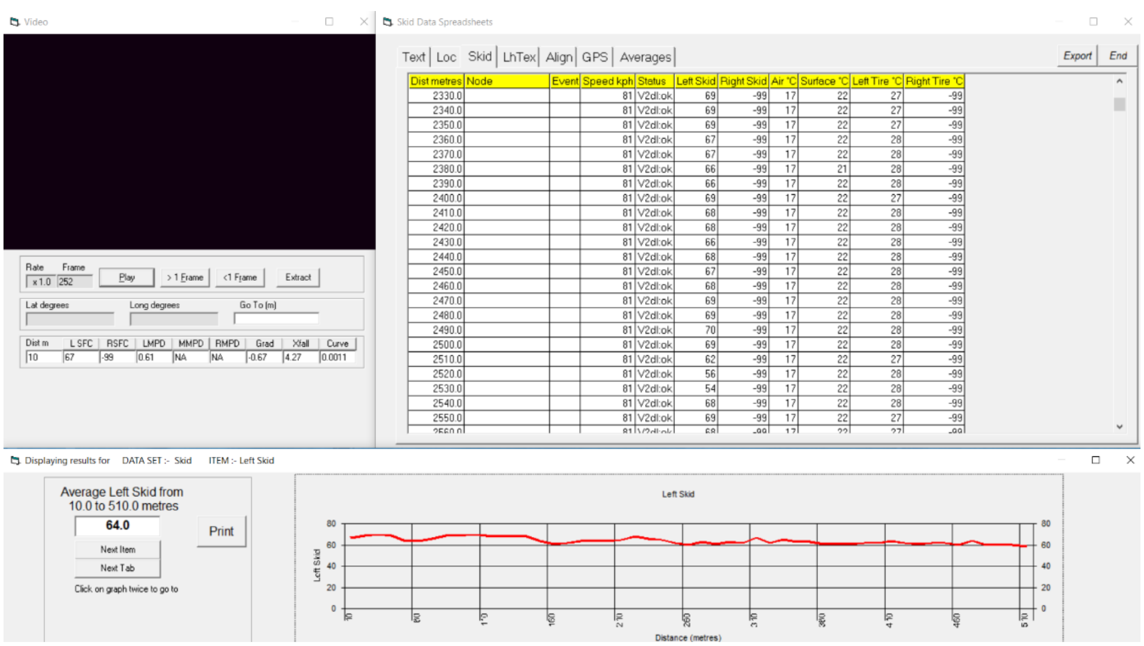

Figure 4. SkidVid Software Layout

SCRIM coefficient (SC) values can be calculated by Equation 2:

$$\mathrm{SR} = \frac{\mathrm{SR}(50)}{10} \times Index\ of\ SFC \qquad \text{Eq. 2}$$

where SC is SR adjusted after any relevant corrections for load, speed, and temperature; the index of SFC (side friction coefficient) is 0.78 (Highways England, 2015).

After a data quality check and the removal of invalid data, a dataset was created for 43 centerline miles of US 29 in the Lynchburg District, 44 centerline miles of US 460 in the Salem District, and 13 centerline miles of US 11 in the Bristol District. Data for US 58 and US 460 in the Bristol District were removed because of incompleteness and errors. The common issues found with the SCRIM data were as follows:

- *Incomplete data:* The number of records for each measure are very different. For example, 125 records were available for alignment measures but more than 6,000 records were available for other measures on US 460 in the Bristol District.

- *Invalid readings:* Data are beyond the normal range for a variable. For example, zeros for GPS readings or negative skid readings were identified as invalid readings.

Crash Data

To account properly for all the crashes to be considered in the study, the research team used a technical definition of *RD crashes* established by VDOT in 2015 (Kweon and Lim, 2019). SQL codes were developed to query the crash data subsystem of VDOT's RNS (RNS_CRASH) database according to the flow diagram in Figure 5. In general, the procedure identifies any crash that involves at least one vehicle leaving the travel lanes as a RD crash unless the crash occurred within 250 ft of an intersection. Crashes that involved pedestrians were excluded from the analyses.

Detailed crash records for RD crashes from 2014-2018 were retrieved. The data were combined with roadway and traffic data from COTEDOP to create a dataset for statistical analysis. The crash records included unique identification, crash types, severity, harmful event, geo-spatial information, route and milepost information, time and date, environmental variables, etc.

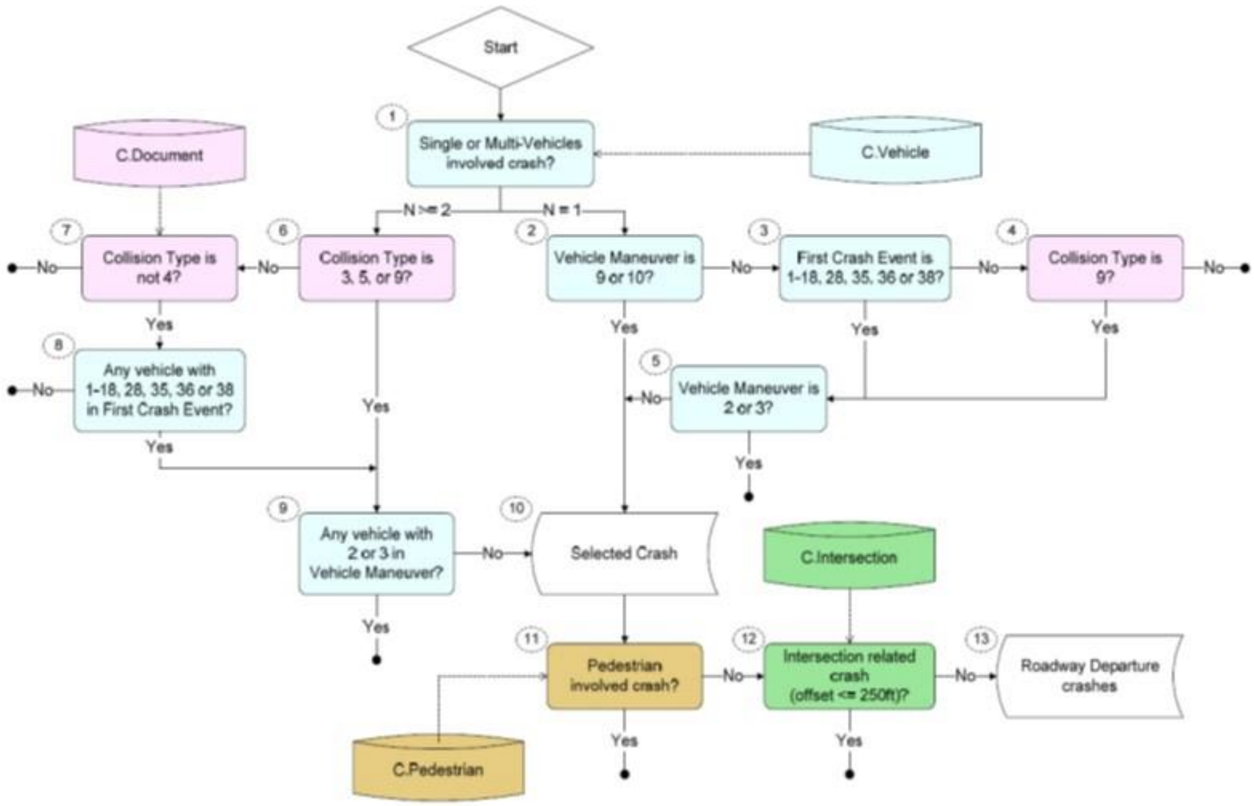

Figure 5. Flow Diagram for Identifying Roadway Departure Crashes (Kweon and Lim, 2019)

Development of Composite Dataset

This task combined RD crash data with COTEDOP, RNS, iVision, and SCRIM data to create the primary and secondary datasets for this study.

Primary Dataset

The RD crashes from RNS and the roadway and traffic data from COTEDOP were linked with unique route information and milepost. RNS and COTEDOP are both Oracle databases. SQL codes were developed to merge the crash data with the roadway and traffic data. This constituted the primary dataset for this study.

Secondary Dataset

RNS crash data were merged with iVision, SCRIM, and COTEDOP data to provide a secondary dataset for this study. The purpose of this dataset was to explore the merits of collecting and archiving data for other variables—with potential for explaining RD crashes—that are not routinely collected or archived as part of current practice.

As SCRIM data were available for only a few sections on US 11, US 29, US 460, crash, roadway geometry, and traffic data for these three routes were selected from the data processed in the previous task. The iVision segment, with an average length of 0.1 miles, was selected as the analysis unit for exploratory analysis. Combining crash data with the other data was challenging as there were no common data fields among those databases and data were stored in different formats. Although iVision, RNS, and COTEDOP data all had route information, they were coded in different formats. The geo-spatial information was the key to combining the data, as shown in Figure 6. Python scripts were developed to create the secondary dataset following three steps.

First, the route information was extracted from COTEDOP roadway data and converted to the iVision route information format. The iVision and COTEDOP roadways were merged based on route information and milepost. This process removed the iVision segments that did not fit the scope of this study (rural two-lane and multi-lane highways) and added roadway and traffic information for the iVision segments left.

Second, based on the SCRIM GPS data (aggregated at 10 m), iVision GPS, route, and milepost information, the combined iVision data created from the previous step were merged with SCRIM data.

Third, route, direction, and milepost information in crash data were converted to the iVision format and then merged with combined data created from the second step.

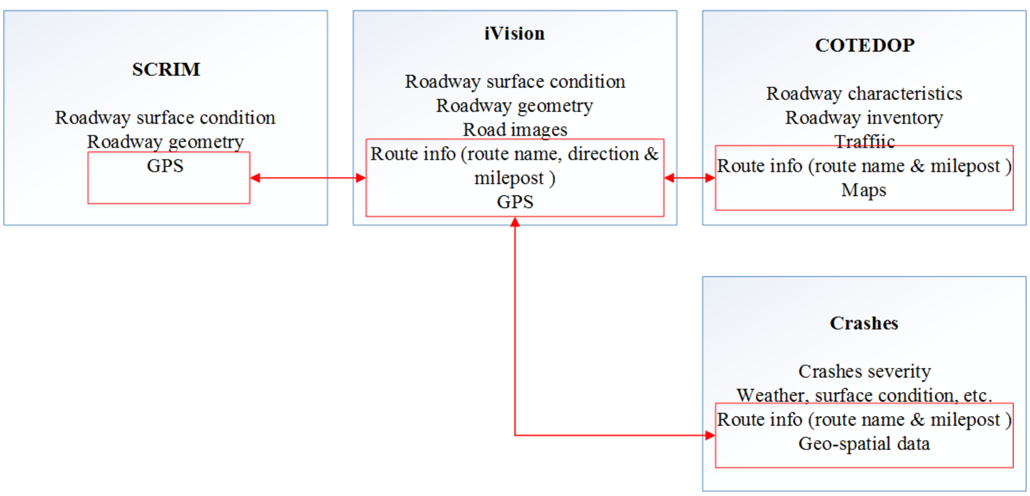

Figure 6. Data Structure for Secondary Dataset

Data Analysis

Standard and advanced statistical methods were used to examine correlations between RD crashes and relevant roadway, roadside, and traffic characteristics. The data analysis included principal component analysis (PCA) to reduce dimensionality of the data; descriptive analysis of variables identified as potentially having the most influence on RD crashes; multinomial logit regression to estimate crash severity; and negative binomial (NB) and zero-inflated Poisson (ZIP) regression models to estimate crash frequency.

The assembled data were split into nine groups depending on roadway type (two-lane, undivided multi-lane, or divided multi-lane) and geographical region (Northern, Eastern, or Western). The three regions and their crash locations are shown in Figure 7. Each region was deemed to have common geometric and driver behavior characteristics (Garber and Rivera, 2010). The northern region was composed of primarily urban and suburban counties near Washington, D.C. The western region consisted of primarily rural roads that often were located in rolling or mountainous terrain; and the eastern region consisted of counties in the central and eastern parts of the state that were primarily flat and had a mixture of urban and rural counties. The specific districts and counties in each of the three regions can be found in Garber and Rivera (2010).

The following sections describe the methodology and the characteristics related to the PCA, NB, multinomial logit, and ZIP models used in this study.

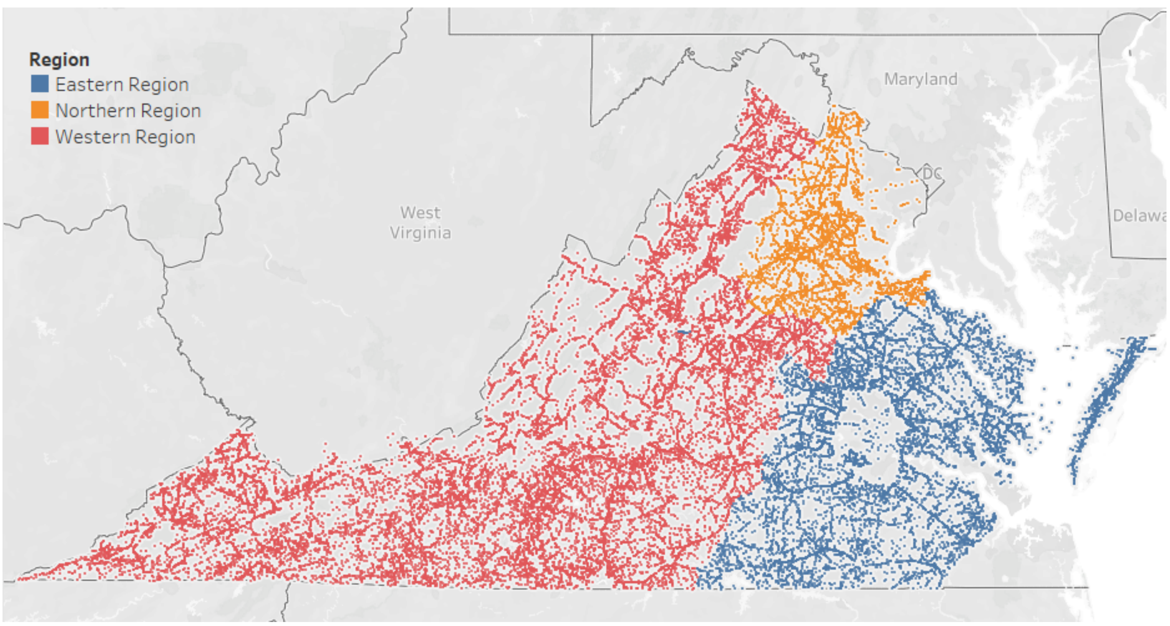

Figure 7. Roadway Departure Crashes in the Three Analysis Regions

Factors Involved in RD Crashes

The primary dataset contained more than 100 variables with possibly complicated correlation patterns. PCA was used to reduce the data to a smaller number of uncorrelated summary variables (principal components) that retained as much of the information in the dataset as possible. The variance accounted for (VAF) by each component (eigenvalue), as well as the correlations between the variables and the principal components (loadings), were estimated using SPSS software. A variable's contribution to the total VAF is reflected in the sum of squared loadings (communality) across all principal components (Linting and Van der Kooij, 2012). There is no clear consensus regarding a good VAF threshold. Linting and van der Kooij (2012) cited Comrey's 1973 advice regarding VAF: 10% is poor, 20% is fair, 30% is good, 40% is very good, and 50% is excellent. Based on this rule of thumb, a minimum VAF criterion of 35% was used in this study.

It is worth noting that standard PCA is based on a matrix of correlations between variables and generally requires interval data and assumptions of linearity between variables. Several of the variables in the dataset used for this study were categorical and therefore not well-suited for standard linear PCA. Therefore, categorical PCA (catPCA), a nonlinear alternative that assigns numerical quantifications to the categories of each variable through optimal scaling, was used (Gifi, 1990; Linting et al., 2007; Meulman et al., 2004). Unlike PCA, which requires numeric variables, catPCA can simultaneously analyze numeric, ordinal, and nominal variables. In situations where all variables are numeric and relationships are linear, catPCA provides the same results as standard PCA.

Nine separate catPCAs were performed using data for each roadway type (two-lane, undivided multi-lane, and divided multi-lane) and geographical region (northern, eastern, western) combination. For each roadway type, variables that contributed substantially to the solution across all three regions (VAF > 0.35) were selected for further consideration as these variables were deemed the ones likely to have the most potential in explaining RD crashes.

Characteristics of Influencing Variables

Characteristics of variables identified through PCA as most likely to influence RD crashes were explored. Crash data were divided into three groups based on severity: no injury (property damage only or no indication of injury); minor injury (possible or non-incapacitating injury); and severe injury (incapacitating or fatal injury). Statistical tests were conducted to examine potential differences in how various factors might affect the severity of RD crashes. For categorical variables, the chi-square contingency test was used. One-way analysis of variance was used for a three-way comparison of means of continuous data. The Kruskal-Wallis test was used for three-way comparison of ordinal data.

Factors Affecting Injury Severity

A multinomial logit model was then formulated with injury severity level as the dependent variable. The explanatory variables used were informed by the literature and the statistical analysis performed earlier. The same three injury severity levels (no injury, minor injury, and severe injury) discussed in the previous section were considered.

To begin, the likelihood that a RD crash will result in injury severity level *j* was expressed as the sum of a deterministic component and a random error component in accordance with Equation 3:

$$U_j = \beta' X_j + \varepsilon_j \qquad \text{Eq. 3}$$

where

U_j = likelihood of crash severity level j
X_j = vector of measurable attributes of each crash severity level
β = vector of coefficients of X_j

ε_j = unobservable factors
$\beta' X_j$ = deterministic component.

The error term was assumed to follow an independent and identically distributed extreme value distribution. The resulting probability of injury severity j, P_j is then given by Equation 4:

$$P_j = \frac{e^{\beta' X_j}}{\sum_{j=1}^{J} e^{\beta' X_j}} \qquad \text{Eq. 4}$$

where J is the total number of crash severity levels to be modeled.

Crash severity level j was considered to be predicted if the calculated value of the severity likelihood function, and by extension the resulting probability, was a maximum among the severity levels being modeled (Peng et al., 2012).

Model parameters were estimated using maximum likelihood methods, which are readily available in many software packages. Emphasis was on identifying variables that may significantly influence the severity of RD crashes, rather than the overall predictive capability of the model. Several functional forms of the regression model (Eq. 3) were tested. Akaike's information criterion (AIC), a goodness-of-fit measure derived from the log-likelihood of the fitted model, the number of predictors, and the number of levels of the dependent variable (crash severity), was used as the primary criterion for comparing models. In comparing two models, the one with the smaller AIC is generally preferable (Cafiso et al., 2010).

Factors Affecting Crash Frequency

An NB model was formulated to investigate further the relationship between RD crash frequency and likely influencing variables derived from PCA. The Poisson and NB models are the most common types of models used by safety analysts. The NB model is especially pertinent to crash frequency variation, as crash data are often overdispersed, with sample variance exceeding the sample mean.

The general form of the model adopted for this study is given in Equation 5:

$$E(Y) = e^{\alpha_0} \cdot n \cdot L \cdot ADT^{\alpha_1} \cdot e^{\sum_{j=1}^{m} \beta_j X_j} \qquad \text{Eq. 5}$$

where

$E(Y)$ = expected RD crash frequency per year
L = length of segment under consideration (mi)
ADT = average daily traffic on the segment (veh/day)
n = years of crash data
X_j = any of m additional variables
α_0, α_1, β_j = model coefficients.

The form of the model specified in Equation 5 is widely accepted partly because it is intuitively appealing; in particular, it logically estimates zero crashes if one of the two exposure variables (ADT or L) equals zero (Cafiso et al., 2010; Peng et al., 2012). As with the multinomial logit model discussed earlier, AIC was used as the primary criterion for comparing competing models, with preference given to models with low AIC values.

Separate models of crash frequency and severity were developed for the three roadway types (two-lane, multi-lane divided, and multi-lane undivided). For each roadway type, three segment location–based subgroups of data were considered for modeling: northern, eastern, and western regions.

A likelihood ratio test was conducted to help assess the need (or otherwise) for a separate model for each subgroup or region (Behnood and Mannering, 2017). The null hypothesis was that parameter estimates were similar between the different subgroups of data. The test statistic was calculated from the log-likelihoods at convergence of models estimated using statewide data and region-specific data as given in Equation 6:

$$\chi^2 = -2\left(LL(\beta) - \sum_{k=1}^{3} LL(\beta_k)\right) \quad \text{Eq. 6}$$

where

$LL(\beta)$ = log-likelihood of model estimated with statewide data
$LL(\beta_k)$ = log-likelihood of model estimated with data from region k (k = 1, 2, 3).

The test statistic shown in Equation 6 is chi-square distributed with degrees of freedom equal to the difference between the total number of parameters estimated in the three subgroup models and the number of parameters estimated in the model using data from all regions. The null hypothesis is rejected (and separate models deemed statistically warranted) if the right-tail probability of the calculated test statistic was less than a pre-specified significance level (e.g., 5%).

Impacts of Roadway Geometry and Pavement Condition

The ZIP model is an alternative to the Poisson and NB models for modeling crash count data. It is suitable for count data that have a much larger than expected number of zeros than assumed by the Poisson model (Hu et al., 2011). This model was considered because the proportion of segments with zero RD crashes in the secondary dataset was approximately 74%. The ZIP model considers the possibility of a two-state process; one a near safe zero-crash state, and the other a normal count process (Poisson) with non-negative integers. The model specification is shown in Equations 7 and 8:

$$E(Y) = (1-\varphi)e^{\sum_{j=1}^{J}\beta_j X_j} \quad \text{Eq. 7}$$

where

$$\varphi = \frac{e^{\sum_{k=1}^{K} \gamma_k Z_k}}{1 + e^{\sum_{k=1}^{K} \gamma_k Z_k}} \qquad \text{Eq. 8}$$

β_j = coefficient for count model covariate j (j = 1,…, J)
X_j = count model covariate j
β_j = coefficient for zero-inflation model covariate k (k = 1,…, K)
Z_k = zero-inflation model covariate k.

RESULTS AND DISCUSSION

Literature Review

Understanding the impact of factors related to rural RD crashes in Virginia is very important for VDOT to implement countermeasures to reduce crash risk; however, because of the complexity of RD crashes, it is challenging to identify factors related to RD crashes and quantify their impacts on crash frequency and severity. The studies in the literature analyzed various categories of factors such as roadway geometry, traffic characteristics, environmental conditions, pavement surface condition, driver behavior, and human factors (Al-Bdairi and Hernandez, 2017; Bahar, 2008; Eustace et al., 2016; Turochy and Ozelim, 2016). Mixed logit models, nested logit models, multinomial logit models, and NB models are the most used models to examine RD crash severity and frequency (Al-Bdairi et al., 2018; Gong and Fan, 2017; Intini et al., 2019; Jurewicz and Ahmed, 2018).

RD Crash Influencing Factors

Well-studied RD crash influencing factors include roadway horizontal curves, lighting/environmental conditions, and human factors such as fatigue and alcohol/drug use. Horizontal curves are well recognized as an important factor for RD crashes on rural roads. An FHWA (2016) study found that approximately three-fourths of curve-related fatal crashes involved single vehicles leaving the travel way and striking fixed objects or overturning. Al-Bdairi et al. (2018) used multinomial logit models, nested logit models, and mixed logit models to analyze RD crash severity involving large trucks and found that driver, traffic flow, roadway geometric features, land use, and time characteristics were the contributing factors to the severity level of these crashes. The study also found a significant difference between lighted and dark conditions and that the level of severity outcomes was highly influenced by “several complex interactions between factors.” Cicchino and Zuby (2017) aimed to “quantify the proportion of drivers involved in unintentional lane drift crashes who would be unable to regain control of their vehicles to inform the design of such systems.” The results showed that 34% of drivers who crashed because they drifted from their lane were sleeping or incapacitated and 13% of these drivers had a medical issue, a blood alcohol concentration over the legal limit, or another factor that compromised vehicle control. Also, when crashes involved serious/fatal injuries, 42% of drivers who drifted were sleeping or otherwise incapacitated. Eustace et al. (2016) studied fatal and injury RD crashes in Ohio using 5 years of data. The results showed that the following were factors in increasing the severity or likelihood of run-off-road crashes: alcohol and drug use, curves/grades, female victims, overturn/rollover crashes, and run-off-road crashes on dry roadway surfaces. Further, buses, trucks, and emergency vehicles that crashed on roads with a posted speed limit higher than 40 mph increased the probability of severity.

Jalayer et al. (2016) found inattention/fatigue, avoiding something, and driving too fast were common reasons for a driver to leave a travel lane. Roadway and roadside geometric design features play a significant role in whether or not human error results in a crash. Gong and Fan (2017) studied rural RD crashes using a mixed logit model. The likelihood ratio tests indicated that developing separate injury severity models for each age group was statistically superior to estimating a single model using all data. The estimation results showed that the main contributing factor for injury severity varied over different age groups. Inexperience, drug or alcohol involvement, use of a restraint device, and horizontal curves were found to affect the likelihood of crash injuries and fatalities in all age groups. Reckless driving, speeding, distraction, being accompanied by others, and driving an SUV/van had a stronger influence on crash severity for younger/middle-aged drivers than for older drivers. Truck drivers were less likely to have injuries in a large-sized vehicle than drivers in smaller vehicles. Driving on a roadway segment with a lower AADT decreased the likelihood of fatal injury for young drivers. Bahar (2008) found that RD crashes mostly occurred on two-lane local highways and were overrepresented on horizontal curves. Alcohol, fatigue, distraction, and speed were contributing factors. Wang and Wang (2019) studied lane departure behavior using a simulator study. The results showed that there were significant differences between lane departure behavior in the direction of centrifugal force and lane departure behavior against the direction of centrifugal force. Radius, superelevation, and circular curve length of combined curves were significant variables affecting lane departure. Also, the significant effects of geometric design characteristics on lane departure differed by type of combined curve.

Intini et al. (2019) analyzed data taken from run-off-road single-vehicle crashes at rural two-lane road curves in Norway. Logistic regression models were used, and their study found that driver familiarity was a factor associated with dangerous driving behavior such as speeding. Crashes involving unfamiliar drivers were associated with unexpected curves and a combination of horizontal and vertical road curvature. Jurewicz and Ahmed (2018) used Poisson regression modeling to estimate run-off-road crash frequency. The results showed that narrower hazard offsets increased the likelihood of run-off-road casualty crashes. Tight road curvature was a strong and consistent predictor of run-off-road casualty crashes. Freeman et al. (2016) found that RD crashes were often the result of poor driver performance leading up to the crash. Turochy and Ozelim (2016) studied the effects of pavement widening, rumble strips, and rumble stripes on rural highways in Alabama and found that crash modification factors (CMFs) for two-lane roads for the combined effect of paved shoulder and shoulder rumble strips and stripes were 0.79 and 0.82 (reduction in RD crashes of 21% and 18%). Further, CMFs for the combined effect could be as low as 0.7 or as high as 0.81 within the confidence interval. Kuehn et al. (2015) analyzed unintentional car RD crashes and found lane departure to the left happened more often than lane departure to the right. This study also found driver health risks/issues were twice as prevalent as driver distractions. The authors believed lane assist technology was a very important technology for reducing RD crashes.

Pavement friction was found to be linked to RD crashes, as an appropriate level of pavement friction is critical to ensure a vehicle remains in its lane (FHWA, 2019a; Najafi et al., 2015). Skid resistance significantly affects the safety of driving on pavements, especially in wet surface conditions (Mataei et al., 2016). SCRIM road surveys are widely used in European countries to measure skid resistance and identify sites for safety investigation; however, safety analyses using combined SCRIM, roadway, and traffic characteristic data are still limited in the literature. One study conducted in New Zealand found that curvature and skid resistance had strong effects on crashes, but pavement roughness had weaker effects (Cenek and Davies, 2004). But that study used simple analysis methods that could create substantial error for sites with fewer than 25 crashes. It is challenging to quantify the impact of skid resistance on crash risk because the crash event is complicated and involves many factors and the level of skid resistance may vary by vehicle, even at the same location. Studies from Australia found that changing the level of skid resistance can influence crash frequency and severity of wet weather skidding crashes and that the influence of skid resistance as a crash influencing factor decreased as the skid resistance increased (VicRoads, 2018).

Countermeasures

To reduce RD crashes, providing an opportunity to re-enter the travel way safely is a priority (Donnell et al., 2019). Therefore, shoulder, safe pavement edges, and clear zones are recommended as effective countermeasures; countermeasures that keep a vehicle on the travel way and those that reduce crash severity are also recommended (Albin et al., 2016).

AASHTO's *Highway Safety Manual* (HSM) (2010), hereinafter "HSM 2010," provides the following CMFS for RD crash countermeasures:

- Widening lanes on rural two-lane roads and rural multi-lane highways reduces single-vehicle run-off-road crashes and multiple-vehicle head-on, opposite-direction sideswipe, and same-direction sideswipe collisions. The CMFs are presented in Tables 13-2, 13-3, and 13-4 of HSM 2010.

- Widening paved shoulders on rural two-lane roads reduces single-vehicle run-off-road crashes and multi-vehicle head-on, opposite-direction sideswipe, and same-direction sideswipe collisions. The CMFs are provided in Table 13-7 of HSM 2010.

- Modifying shoulder types (paved, gravel, composite, turf) can affect single-vehicle run-off-road crashes on rural two-lane roads. The CMFs are provided in Table 13-9 of HSM 2010.

- Changing barriers along embankments to less rigid types can reduce fatal and injury run-off-road crashes on rural two-lane roads, rural multi-lane highways, freeways, expressways, and urban/suburban arterials. The CMFs are provided in Table 13-22 of HSM 2020.

- Installing continuous milled-in shoulder rumble strips on rural multi-lane divided highways with an AADT of 2,000 to 50,000 and rural freeways can reduce single-vehicle run-off-road crashes. The CMFs are provided in Tables 13-44 and 13-45 of HSM 2010.

- Increasing the clear roadside recovery distance appears to reduce run-off-road crashes, but the effect is uncertain.

- For rural two-lane roads, rural multi-lane highways, freeways, expressways, and urban and suburban arterials, installing roadside barriers along embankments appears to reduce the number of fatal and injury run-off-road crashes and the number of run-off-road crashes of all severities. However, the magnitude of the crash effect is not certain at this time.

A review of the CMF Clearinghouse was conducted to identify countermeasures for RD crashes on rural two-lane and multi-lane highways. The CMF Clearinghouse had more than 1,000 CMFs related to RD crashes, and only those studies specified for RD crashes on rural non-interstate highways and with a quality rating of 4 or 5 stars were reviewed. The results are given in Table 1. The CMFs applicable for "all types" of crashes were excluded to focus on RD crashes only.

The installation of centerline rumble strips and shoulder rumble strips can reduce run-off-road crashes; however, for some countermeasures, such as clear zone width and roadside barriers, CMFs are available, but the studies might lack reliability and applicability (ranked low in the CMF Clearinghouse).

CMFs of 0.58 for run-off-road crashes and 0.60 for all crashes were reported with regard to installing a combination of chevron signs, curve warning signs, and/or sequential flashing beacons. These values applied to principal arterials other than freeways and expressways, and the study area was not specified.

For roadside treatments, CMFs for roadside barriers were found in the CMF Clearinghouse, but these studies were for freeways and expressways only. For pavement friction improvements, the CMFs for RD crashes were 0.306 to 1.566 for all road functional classes.

The CMF Clearinghouse included CMFs for countermeasures that typically comprised a physical change to the infrastructure. Other types of countermeasures such as policy changes and education efforts were not included.

Table 1. Crash Modification Factors (CMFs) for Roadway Departure Crash Countermeasures[a, b]

Category	Countermeasure	CMF	Crash Type	Crash Severity	CMF ID
Alignment	Flatten horizontal curve	0.216	Fixed-object, run-off-road	All	9652
Roadway	Widen narrow pavement	0.643	Run-off-road	All	6863
	Install centerline and shoulder rumble strips	0.6 to 0.92	Run-off-road	All	6852, 6939, 6948, 6970, 6973, 6974
	Install edge line rumble strips at horizontal curve	0.71 to 0.78	Run-off-road	All	9832, 9837, 9839
	Install edge line rumble strips on roadways with a shoulder width of 5 ft or greater	0.34 to 0.57	Run-off-road	K, A, B, C	3404, 3408
Shoulder treatments	Install a combination of shoulder rumble strips, shoulder widening (from 0 to 2 ft), and resurface pavement	0	Head-on, run-off-road	O	9007
		0	Head-on, run-off-road	A, B, C, O	9010, 9012
		0 to 0.877	Head-on, run-off-road	All	9013, 9100
		0.732	Head-on, run-off-road	B, C	9093
		0.743	Head-on, run-off-road	A, B, C	9096
		0.729	Head-on, run-off-road	K, A, B, C	9098
	Install alternative audible lane departure warning treatments	0.79	Head-on, run-off-road	All	9685
	Install safety edge treatment	0.64 to 1, 0.79[c]	Run-off-road	All	(Total of 36 CMFs)
		0.769 to 1.036	Run-off-road	K, A, B, C	4358, 4362, 4364
		0.84 to 0.926	Run-off-road	O	4375, 4379, 4380, 4381, 8663
	Install shoulder rumble strips	0.84,[c] 0.87	Run-off-road	All	3442, 1195
		0.83[c]	Run-off-road	K, A, B, C	3447
	Install shoulder rumble strips and widen shoulder	0.541	Run-off-road	All	6667
	Install shoulder rumble strips on roadways with a shoulder width equal to 5 ft	0.46	Run-off-road	K, A, B, C	3627
	Pave shoulder	0.82 to 0.98	Fixed-object, head-on, run-off-road, sideswipe	A, B, C	6690, 6744
		0.75 to 1.04	Fixed-object, head-on, run-off-road, sideswipe	O	6691, 6745
	Widen shoulder	0.556	Run-off-road, single-vehicle	K, A, B, C	6658
		0.607	Run-off-road, single-vehicle	All	6659
Delineation	Install profiled thermoplastic pavement markings	0.941 to 1.061	Run-off-road	All	9800, 9806, 9813
Sign	Install oversized chevron signs	1.061	Run-off-road	All	8979

[a] This table does not include the CMFs for interstates, freeways, and expressways; the CMFs with no specified roadway type are included.
[b] The study area type is either rural or not specified.
[c] VDOT-preferred CMFs.

VDOT (n.d.) published the Virginia State Preferred CMF List that contains CMFs with high-quality ratings relevant to Virginia. The Virginia State Preferred CMFs specified for run-off-road crashes are included in Table 1. A CMF of 0.79 for all run-off-road crash severities is recommended for adding Safety Edge on rural two-lane undivided highways; the CMF for adding shoulder rumble strips on rural non-freeway segments is 0.84 for property damage only run-off-road crashes and 0.83 for fatal and injury run-off-road crashes.

FHWA's Strategic Approach and Plan for RD crashes includes strategies in three areas: keep vehicles on the roadway, provide for safety recovery, and reduce crash severity (FHWA, 2020). Table 2 provides a list of recommended countermeasures in each area.

The effectiveness of countermeasures in each strategic area has been proven in previous studies. High friction surface treatments were found to reduce total crashes by 24% and wet surface crashes by 52% (FHWA, 2019a). Shoulder rumble strips were proven to reduce single-vehicle run-off-road crashes by about 15% and single-vehicle run-off-road fatal and injury crashes by 29% (Torbic et al., 2017). Installing centerline rumble strips can reduce total crashes by 9% and fatal and injury crashes by 12 % (Torbic et al., 2017). Installing chevron signs on horizontal curves was found to reduce nighttime lane departure crashes by 25% and total crashes by 16%. Regarding the countermeasures to provide safety recovery, Safety Edge was found to reduce fatal and injury crashes by 11% (FHWA, 2017a); increasing the clear zone was found to reduce total crashes by 22%, a change from 3.3 to 16.7 ft, and 44%, a change from 16.7 to 30 ft (FHWA, 2017b), but the effectiveness specified for RD crashes only was not available.

Albin et al. (2016) documented low-cost engineering countermeasures to improve safety on horizontal curves. The information on design, cost, and application guidelines was provided to help agencies understand the available countermeasures and how to select and apply them.

In NCHRP Synthesis 515, McGee (2018) found through a survey of 41 state departments of transportation that the RD crash countermeasures used by most were shoulder rumble strips, centerline rumble strips, flashing beacons on warning signs, tree removal, increased sight distance on curves, superelevation improvement, high friction surface treatment, and cable median barriers. The survey also showed that the countermeasures especially effective for reducing RD crashes were as follows:

- shoulder, edge line, and centerline rumble strips
- safety edge
- high friction surface treatment
- cable median barrier
- increasing the clear zone
- flattening side slopes
- increasing sight distance for curves.

Table 2. FHWA Roadway Departure Crash Strategies and Countermeasures

Countermeasures to Keep Vehicles on Roadway	Countermeasures to Provide for Safety Recovery	Countermeasures to Reduce Crash Severity
• Pavement friction • Rumble strips • Horizontal curve safety • Nighttime visibility	• Safety edge • Clear zones	• Roadside and median barrier

Related VDOT Studies

Several reports closely related to this study have been published by VTRC. Garber and Kassebaum (2008) found that RD crashes were the predominant type of crashes followed by rear-end, angle, and deer crashes on two-lane highways in Virginia. One of the main recommendations was to improve/fix geometric deficiencies of causal factors at RD crash incident locations. Kweon and Lim (2019) developed RD SPFs for 16 types of sites including rural two-lane and multi-lane highways. Variables used in the SPFs were as follows:

- *Rural two-lane highway:* AADT, lane width, shoulder width, median shoulder width, pavement roughness value, pavement condition, surface type, curb gutter, and segment length
- *Rural multi-lane undivided highway:* AADT, shoulder width, segment length
- *Rural multi-lane divided highway:* AADT, lane width, shoulder width, median shoulder width, pavement roughness value, pavement condition, surface type, curb gutter, and segment length.

VDOT's RD crash decision tree tool uses detailed crash records exported from the VDOT TED's Tableau crash tool and additional roadway characteristics data to identify the best countermeasure (VDOT, 2016). This tool includes pavement type and conditions (good or poor) as input but does not include IRI or skid resistance measures.

Data Summary

This section presents crash and roadway characteristics from the primary and secondary datasets. The summary and descriptive statistics of key study variables are also provided.

Primary Dataset

The primary dataset used for this study was obtained by merging data from two VDOT databases: (1) crash records from the RNSCRASH database, and (2) locational, geometric, and AADT data from the COTEDOP database. The dataset included 48,340 RD crashes on 56,443 roadway segments (totaling 35,243 miles of roadway) from 2014-2018.

Table 3 summarizes the relative distribution of segments over the three geographical regions of the state—northern, western, and eastern—each of which was deemed to have common geometric and driver behavior characteristics (Garber and Rivera, 2010). A majority of segments (58.5% of the total mileage) were in the western part of the state. Approximately 31% of the total mileage was in the eastern region, and the remaining 10.5% was in the northern part of the state.

Table 3. Summary of Study Segments

Region	Roadway Type	Number of Segments	Length (mi)	Total Travel (10^6 veh-mi)
Northern	Two-Lane	5,314	2,869	8,385
	Multi-Lane, Divided	499	203	6,073
	Multi-Lane, Undivided	103	24	332
	All Types	5,916	3,096	14,790
Western	Two-Lane	30,711	20,149	29,395
	Multi-Lane, Divided	1,941	856	14,876
	Multi-Lane, Undivided	339	117	1,033
	All Types	32,991	21,121	45,305
Eastern	Two-Lane	16,176	10,384	14,863
	Multi-Lane, Divided	1,119	533	10,998
	Multi-Lane, Undivided	241	108	1,557
	All Types	17,536	11,025	27,418
All Regions	Two-Lane	52,201	33,401	52,644
	Multi-Lane, Divided	3,559	1,592	31,947
	Multi-Lane, Undivided	683	249	2,922
	All Types	56,443	35,243	87,513

Also shown in Table 3 is total travel (in million vehicle-miles) on study segments during the 5-year analysis period. Relative to its percentage of the total mileage (10.5%), the northern region had a disproportionately high percentage (17%) of the total travel during the 5-year analysis period, which was not surprising. Conversely, the western region had a disproportionately lower percentage of travel (52%) relative to its percentage of the total mileage (58.5%). The proportions of roadway mileage and the amount of travel were similar, at approximately 31%, for the eastern region.

Table 4 shows the distribution of crashes by roadway type and geographical region. For the segments in this study, a majority of RD crashes (approximately 60%) occurred in the western part of the state. The lowest percentage (approximately 13%) was recorded in the northern region, and the remaining 27% was in the eastern region. The table also shows that a majority of crashes were non-injury crashes, with fatal and injury crashes constituting approximately 43% of the total number of RD crashes during the analysis period. The number of RD crashes that resulted in an injury or a fatality ranged from 40% to 50% across all regions and roadway types.

Approximately 52% of all crashes occurred on a tangent (or straight) section (see Table 5). Proportionally more crashes occurred on tangents than on horizontal curves for all roadway types and regions except for two-lane roadway segments in the western part of the state where approximately 57% of crashes were on horizontal curves. Overall, approximately 53% of all RD crashes on two-lane roadway segments occurred on a horizontal curve. The relative distribution of fatal and injury crashes among the various roadway type and region combinations was generally similar to the relative distribution of total RD crashes. Approximately 54% of all fatal and injury crashes on two-lane segments were on a horizontal curve.

Table 4. Summary Characteristics of Roadway Departure Crash Data

Region	Roadway Type	Fatal and Injury Crashes		All Crash Severities	
		Count	Percentage[a]	Count	Percentage[b]
Northern	Two-Lane	2,143	40.4	5,299	13.2
	Multi-Lane, Divided	461	43.1	1,069	14.3
	Multi-Lane, Undivided	22	50.0	44	5.6
	All Types	2,626	41.0	6,412	13.3
Western	Two-Lane	10,527	43.4	24,280	60.6
	Multi-Lane, Divided	1,856	42.8	4,334	57.8
	Multi-Lane, Undivided	185	47.6	389	49.5
	All Types	12,568	43.3	29,003	60.0
Eastern	Two-Lane	4,502	43.0	10,475	26.2
	Multi-Lane, Divided	873	41.6	2,097	28.0
	Multi-Lane, Undivided	148	41.9	353	44.9
	All Types	5,523	42.7	12,925	26.7
All Regions	Two-Lane	17,172	42.9	40,054	
	Multi-Lane, Divided	3,190	42.5	7,500	
	Multi-Lane, Undivided	355	45.2	786	
	All Types	20,717	42.9	48,340	

[a] Percentage of total crashes (all severities) for applicable region and roadway type.
[b] Percentage of applicable statewide crash count totals.

Table 5. Roadway Departure Crashes on Tangent Sections

Region	Roadway Type	Fatal and Injury Crashes		All Crash Severities	
		Count	Percentage[a]	Count	Percentage[a]
Northern	Two-Lane	1,091	50.9	2,778	52.4
	Multi-Lane, Divided	377	81.7	877	82.1
	Multi-Lane, Undivided	19	86.4	39	88.6
	All Types	1,487	56.6	3,694	57.6
Western	Two-Lane	4,473	42.5	10,441	43.0
	Multi-Lane, Divided	1,252	67.4	2,951	68.1
	Multi-Lane, Undivided	174	93.9	355	91.2
	All Types	5,807	46.2	13,560	46.8
Eastern	Two-Lane	2,383	52.9	5,735	54.7
	Multi-Lane, Divided	697	79.8	1,701	81.1
	Multi-Lane, Undivided	139	93.9	322	91.2
	All Types	3,219	58.3	7,758	60.0
All Regions	Two-Lane	7,946	46.3	18,954	47.3
	Multi-Lane, Divided	2,326	72.9	5,530	73.7
	Multi-Lane, Undivided	241	67.9	530	67.4
	All Types	10,512	50.7	25,012	51.7

[a] Percentage of applicable region and roadway type crash count.

A breakdown of crash counts by year is provided in Table 6. With the exception of the year 2018 where RD crashes were slightly elevated—between 6% and 9% more crashes than the previous 4-year average—in each of the three regions, there was a general downward trend in crashes.

Also shown in Table 6 is an estimate of the average crash rate for each roadway type and region combination for the entire study period. Crash rates were calculated as the ratio of total crashes to total vehicle-miles traveled (see Tables 4 and 5). It may be seen that the highest rates were for two-lane roadways. RD crash rates were comparable for divided and undivided multi-lane lane study segments for the 5-year analysis period. The western region had crash rates higher than the statewide average for all roadway types.

Table 6. Trends in Roadway Departure Crashes

Region	Roadway Type	Crash Count					Crash Rate (per 10^6 veh-mi)[a]
		2014	2015	2016	2017	2018	
Northern	Two-Lane	1,065	1,101	990	987	1,156	0.63
	Multi-Lane, Divided	231	239	220	178	201	0.18
	Multi-Lane, Undivided	9	8	9	8	10	0.13
	All Types	1,305	1,348	1,219	1,173	1,367	0.43
Western	Two-Lane	4,824	4,908	4,815	4,731	5,002	0.83
	Multi-Lane, Divided	877	784	785	893	995	0.29
	Multi-Lane, Undivided	80	68	81	84	76	0.38
	All Types	5,781	5,760	5,681	5,708	6,073	0.64
Eastern	Two-Lane	2,023	2,157	2,015	2,023	2,257	0.70
	Multi-Lane, Divided	395	409	461	397	435	0.19
	Multi-Lane, Undivided	47	67	74	86	79	0.23
	All Types	2,465	2,633	2,550	2,506	2,771	0.47
All Regions	Two-Lane	7,912	8,166	7,820	7,741	8,415	0.76
	Multi-Lane, Divided	1,503	1,432	1,466	1,468	1,631	0.23
	Multi-Lane, Undivided	136	143	164	178	165	0.27
	All Types	9,551	9,741	9,450	9,387	10,211	0.55

[a] Average over all years (2014-2018) and study segments.

Secondary Dataset

The secondary dataset for this study was constructed with the COTEDOP, RNS, iVision, and SCRIM data. The purpose of this dataset was to explore potential impacts of roadway geometry and pavement (including shoulder) condition on RD crash frequency. Table 7 provides summary characteristics of salient variables in the secondary dataset. These variables were later considered in RD crash frequency model specifications.

After invalid and incomplete readings were removed, the SCRIM data were available only for limited segments on US 29 in the Lynchburg District, US 460 in the Salem District, and US 11 in the Bristol District. All segments on US 11 were excluded during data conflation as they were not on the selected COTEDOP segments. Even though a majority of iVision segments were approximately 0.1 mile long, there were some shorter segments. Segments that were less than 0.02 mile long were excluded from this study; this ensured that each segment had a minimum of three SCRIM measurements. In addition, segments were excluded from analysis if they had received significant maintenance (rehabilitation) in any of the years from 2014-2018, for which crash data were used.

The final dataset included 903 iVision segments on US 29 in the Lynchburg District and US 460 in the Salem District. The total length was 86 miles (two-direction total). There were 364 RD crashes during the 5-year analysis period; 211 (58%) were on dry pavement, and 114 (31%) were on wet pavement. Approximately 29% of all crashes were in the Salem District.

Table 7. Salient Variables in Secondary Dataset

Variable	Mean	Min.	Max.
Exposure			
Segment length (mi)	0.09	0.02	0.10
Average daily traffic (veh/day)	6773	3722	8422
Roadway Geometry			
Average gradient within segment (%)	0.02	-22.48	6.83
Average of absolute gradient values within segment (%)	2.44	0.08	6.83
Minimum gradient within segment (%)	-0.78	-7.36	6.63
Maximum gradient within segment (%)	0.86	-6.46	7.67
Maximum of absolute gradient values within segment (%)	3.16	0.14	7.67
Average cross slope within segment (%)	-1.53	-11.30	26.04
Average of absolute slope values within segment (%)	3.02	0.19	11.30
Minimum cross slope within segment (%)	-3.08	-13.59	9.51
Maximum cross slope within segment (%)	-0.04	-10.70	11.41
Maximum of absolute cross slope values within segment (%)	4.31	0.27	13.59
Average curvature within segment (1/mi)	-0.02	-6.64	15.21
Average of absolute curvature values within segment (1/mi)	1.15	0.16	7.07
Minimum curvature within segment (1/mi)	-1.02	-16.25	4.67
Maximum curvature within segment (1/mi)	0.96	-4.35	10.46
Maximum of absolute curvature values within segment (1/mi)	2.00	0.16	16.25
Lane width (ft)	10.99	9.60	12.40
Right shoulder width (ft)	1.74	0	8
Roadside/Shoulder Condition			
Right shoulder is paved (1 = paved)	0.75	0	1
Right shoulder is not paved (1 = not paved)	0.21	0	1
Left shoulder is paved (1 = paved)	0.25	0	1
Left shoulder is not paved (1 = not paved)	0.61	0	1
Proportion of right shoulder material in relatively good condition	0.63	0.00	1.00
Proportion of right shoulder material in fair condition	0.08	0.00	1.00
Proportion of right shoulder with vegetation growth or debris build-up	0.00	0.00	0.87
Proportion of shoulder experiencing a drop-off greater than 3 in	0.00	0.00	0.07
Proportion of shoulder experiencing a drop-off between 1.5 in and 3 in	0.03	0.00	1.00
Proportion of shoulder experiencing a drop-off greater than 1.5 in	0.14	0.00	1.00
Proportion of right shoulder in relatively good or fair condition	0.71	0.00	1.00
Proportion of left shoulder material in relatively good condition	0.23	0.00	1.00
Proportion of left shoulder with vegetation growth or debris build-up	0.02	0.00	1.00
Roadway Surface Condition			
Skid resistance / SCRIM coefficient	63.03	9.64	87.37
Mean profile depth (x 0.0394 in)	0.73	0.25	1.71
Pavement roughness (in/mi)	81.65	38	255
Operational Variables			
Speed limit (mph)	58.57	40	65
Change in speed limit from adjacent segment (mph)	0.23	0	15
Crash Counts			
All crashes / 5 years (2014-2018)	0.40	0	11
Dry-pavement crashes / 5 years (2014-2018)	0.23	0	4
Wet-pavement crashes / 5 years (2014-2018)	0.13	0	11

The SCRIM surveys for US 460 and US 29 were conducted in 2018 and 2019, respectively. The SCRIM data for these 2 years were combined into a small dataset to explore the pavement condition variables before further modeling with the secondary data. The skid resistance indicator (SC) and pavement macrotexture indicator (MPD) are compared in Figure 8; the wet condition crash rate per million vehicle-miles and the wet condition crash ratio (total wet condition crashes / total crashes in wet and dry conditions) are also plotted. The wet condition crash ratio is used to identify elevated wet condition crash locations, and segments with a ratio greater than a threshold value (usually between 0.25 and 0.5) need to be investigated (FHWA, 2010; Najafi, Flintsch, and Medina, 2017). Although the average wet condition crash ratio varied by facility type, the average SC was not very different across facility type and road. All SC readings were grouped to represent three different levels of skid resistance.

Figure 9 shows that the wet crash rate per million vehicle-miles decreased as skid resistance increased from SC Level 1 (SC < 0.4) to Level 2 (SC between 0.4 and 0.5) as expected. From SC Level 2 to Level 3, the level of skid resistance increased and the crash rate slightly increased for the segments on US 460. This might be because the influence of skid resistance on crashes decreases as skid resistance increases (VicRoads, 2018).

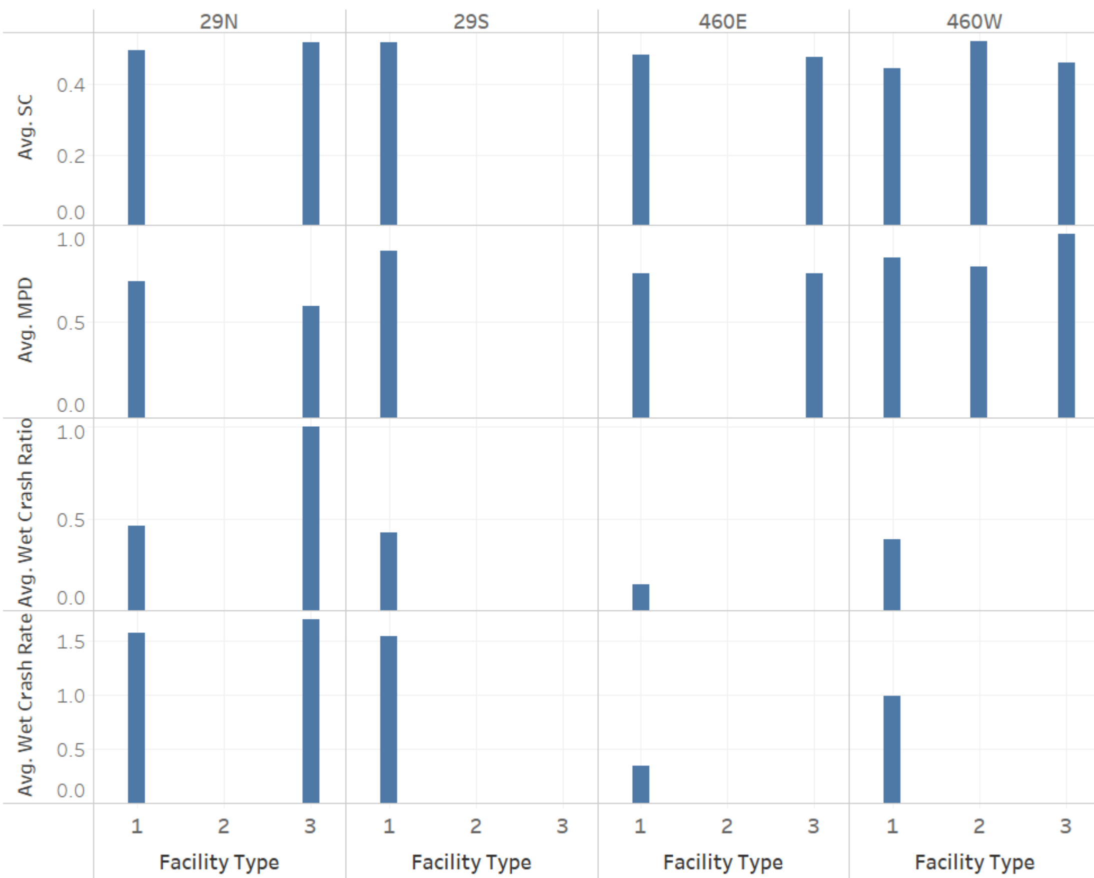

Figure 8. SCRIM Coefficients: Average Mean Profile Depth (MPD), Average Wet Condition Crash Ratios, and Average Rate of Wet Condition Crashes by Route and Facility Type. Facility type: 1 = divided, no access control; 2 = divided, partial access control; 3 = divided, full access control.

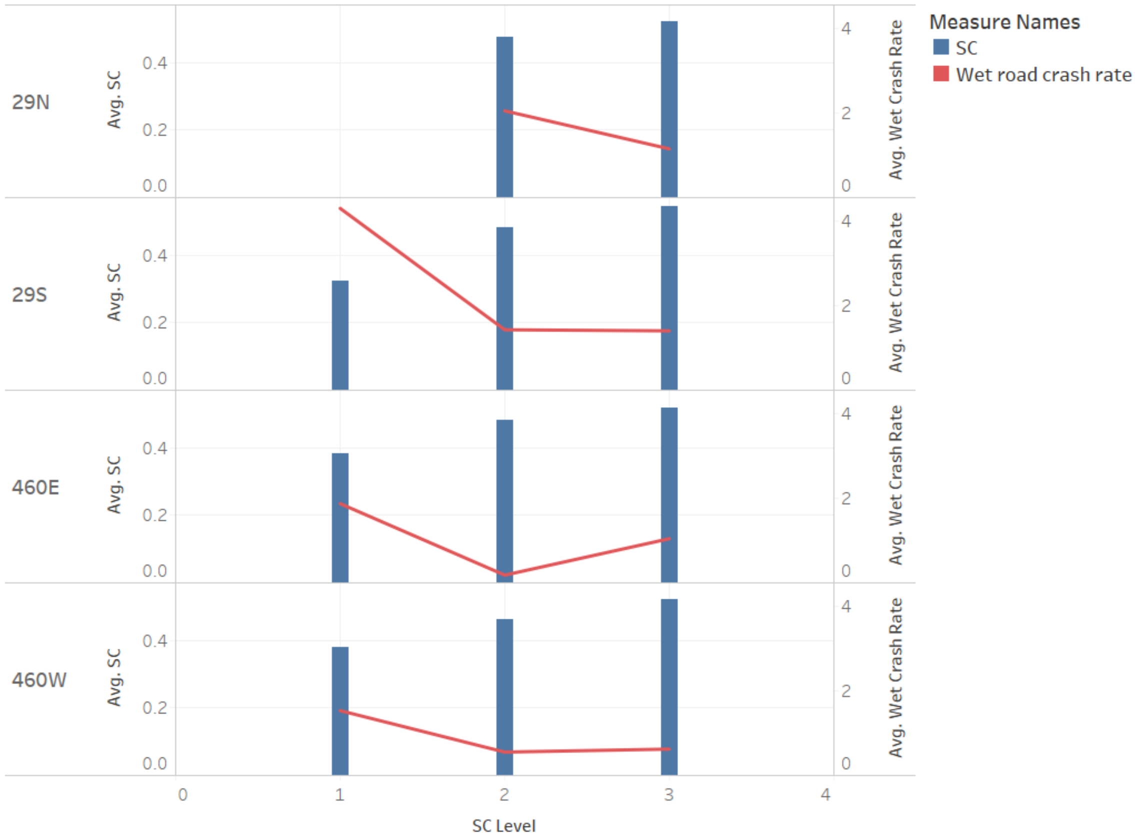

Figure 9. Wet Condition Crash Ratio by SCRIM Coefficient (SC) Level. SC levels are defined as 1 = SC < 0.4; 2 = 0.4 ≤ SC < 0.5; 3= SC ≥ 0.5.

Data Analysis

Factors Involved in RD Crashes

This section provides information regarding the analysis of the primary dataset for a general overview of factors that might influence RD crashes. Nonlinear principal components analysis was undertaken to reduce dimensionality in the dataset and to identify variables that might be involved in RD crashes.

The data were split into nine groups depending on roadway type (two-lane, undivided multi-lane, divided multi-lane) and region (northern, eastern, western). Separate analyses were performed using data from each group. All analyses were done using the program CATPCA from the "Categories" module in SPSS. In each case, a five- or six-dimension solution was found to explain between 57% and 86% of the variance in the respective datasets. A summary of the results showing variable contributions for the "most important" variables identified through PCA is shown in Table 8. Variables that contributed substantially (VAF > 0.35) to the solution across all nine data groups were considered "important" and selected for further consideration.

Table 9 provides descriptive statistics and analysis of the 10 variables identified through PCA. Statistical tests were conducted to examine potential differences in how these variables might affect the severity of RD crashes. The results suggested a statistically significant association between roadway functional class, speed limit, shoulder width, pavement roughness, traffic control, weather, roadway surface condition, and crash severity. However, there were no statistically significant differences in AADT, median width, and the presence (or absence) of a curb among the three severity groups. Although studies in the literature found that traffic volume was associated with severity outcomes, some found that roads with lower AADTs decreased the likelihood of fatal crashes for young drivers, and others found that injury severity was high during dark hours although the traffic volume was low (Al-Bdairi et al., 2018; Eustace et al., 2016; Gong and Fan, 2017).

Crashes in wintry conditions tended to result in non-injury outcomes rather than injury outcomes. A plausible explanation is that drivers may exercise more caution when driving in wintry conditions and travel at lower speeds. A similar observation pertained to crash outcomes in rainy conditions. In addition, approximately 47% of all crashes occurred on segments with marked traffic lanes (as opposed to other traffic control types). These crashes tended to result in minor or no injury outcomes rather than severe injuries.

RD crashes on minor arterials tended to result in severe injury outcomes rather than non-injury outcomes whereas the converse was true for crashes on local roadway segments. A plausible reason for this could be a general difference in speed limits on the two facility types. This seems consistent with the observation that the speed limit was on average higher in the severe crash outcome group than the non-injury outcome group. Similarly, general differences in characteristics of different roadway functional groups may partly explain the observation that there were more severe injury than non-injury crashes on segments with wider shoulders (6 to 9 ft) whereas the opposite was true on segments with narrower shoulders (1 to 3 ft).

Factors Affecting Injury Severity

This section presents the statistical analysis results for evaluating the relationship between RD crash severity and various risk factors. A multinomial logit model was used to investigate the potential impact of the roadway and its environment on crash severity. Three injury severity levels (no injury, minor injury, and severe injury) were considered. For model calibration, “no injury” was set as the base scenario with all of its coefficients set equal to zero. The explanatory variables considered for model development (based on the results of the PCA) are shown in Table 10.

All variables shown in Table 10 were used for initial model development. However, only those variables that were significant at the 5% level were retained in the final model. Models were estimated using the statistical software SAS. Tables 11 and 12 show summary results for two-lane roadways and divided multi-lane roadways. The concordance statistic (Hand and Till, 2001), an *R*-square-like measure used for logistic regression, suggested fairly weak predictive ability; nevertheless, the likelihood ratio chi-square statistic indicated good model fit overall (p-value ≈ 0).

Table 8. Variable Contribution[a] to Nonlinear Principal Component Analysis Solution

Variable	Two-Lane Roadways			Multi-Lane, Undivided Roadways			Multi-Lane, Divided Roadways		
	Northern	**Western**	**Eastern**	**Northern**	**Western**	**Eastern**	**Northern**	**Western**	**Eastern**
Functional class	0.802	0.830	0.779	0.912	0.725	0.768	0.585	0.842	0.367
Speed limit	0.605	0.599	0.658	0.937	0.660	0.543	0.641	0.440	0.605
Annual average daily traffic	0.703	0.713	0.762	0.948	0.640	0.837	0.750	0.421	0.522
Average shoulder width	0.494	0.393	0.417	0.834	0.915	0.867	0.820	0.507	0.844
Average median width	N/A	N/A	N/A	N/A	N/A	N/A	0.871	0.731	0.638
Curb or gutter	0.780	0.840	0.795	0.947	0.896	0.890	0.856	0.997	0.870
Traffic control	0.910	0.599	0.799	0.825	0.864	0.735	0.944	0.821	0.880
Pavement roughness	0.809	0.840	0.791	0.964	0.708	0.842	0.938	0.444	0.637
Weather condition	0.815	0.846	0.845	0.970	0.817	0.888	0.838	0.866	0.871
Road surface condition	0.851	0.864	0.874	0.868	0.834	0.908	0.891	0.881	0.890
Number of components	6	6	6	5	6	6	6	6	6
Variance-accounted-for	68.5%	65.1%	69.0%	86.1%	74.6%	77.5%	70.0%	57.2%	58.3%

N/A = not applicable.

[a] Total variance accounted for (sum of communalities) across all components.

Table 9. Characteristics of Potential Influencing Variables

Variable	Injury Severity Level (% Crashes in Each Category)			
	No Injury (N = 7,623)	**Minor Injury (N = 13,831)**	**Severe Injury (N = 6,886)**	**All Crashes (N = 48,340)**
Roadway Functional Class*				
Other principal arterial	16.3	16.3	16.6	16.4
Minor arterial*	18.4	19.3	22.1	19.2
Major collector	31.5	32.1	30.8	31.5
Minor collector*	12.5	12.2	11.4	12.3
Local*	21.3	20.1	19.0	20.7
Average Annual Daily Traffic[a]	4,071	4,187	4,079	4,105
Speed Limit (mph)[a]*	48.4	48.8	49.6	48.7
Shoulder Width (ft)*				
0 to 1	1.0	1.0	0.9	1.0
1 to 3*	23.7	23.0	20.1	23.0
3 to 6	47.6	48.0	47.5	47.7
6 to 9*	23.5	23.7	27.6	24.1
Greater than 9	4.2	4.4	3.9	4.2
Median Width[a,b]	54.6	56.6	57.0	55.5
Curb or Gutter				
Absent	99.5	99.5	99.4	99.5
Present	0.5	0.5	0.6	0.5
Pavement Roughness (in/mi)*				
Less than 95 (or Good)*	81.1	79.7	78.4	80.3
95 to 170 (or Fair)*	18.3	19.6	21.0	19.0
Greater than 170 (or Poor)	0.6	0.7	0.6	0.6
Traffic Control				
No traffic control*	25.8	24.3	21.9	24.8
Slow or warning sign	1.9	2.0	1.8	1.9
Traffic lanes marked*	47.6	46.7	45.6	47.0
No passing lanes*	24.7	27.0	30.6	26.2
Weather Condition				
No adverse condition*	70.1	75.9	83.8	73.7
Fog or mist*	3.9	3.9	3.1	3.8
Rain*	16.6	14.3	10.6	15.1
Snow, sleet, or hail*	9.4	5.8	2.5	7.4
Roadway Surface Condition				
Dry*	64.4	70.0	79.2	68.1
Wet*	22.4	20.8	16.3	21.1
Wintry*	12.7	8.6	4.0	10.3
Debris	0.6	0.6	0.5	0.6

[*] Significant difference (at the 0.05 level) between groups.
[a] These entries represent mean values (not percentages).
[b] Divided multi-lane roadways only.

Table 10. Definitions and Summary Characteristics of Explanatory Variables Used in Logit Model

Variable	Mean	Min.	Max.
Average shoulder width (ft)	4.31	0	33
Speed limit (mi/h)	48.80	15	70
Pavement roughness (in/mi)	40.44	0	272
Curb (1 if no curb or gutter; 0 otherwise)	0.99	0	1
Traffic control (1 if traffic lanes marked; 0 otherwise)	0.47	0	1
Wintry condition (1 if Yes; 0 if No)	0.10	0	1
Average median width (ft)[a]	57.25	2	249

[a] Divided multi-lane roadways only.

No statistically meaningful results were obtained using data for undivided multi-lane roadways at a regional analysis level because of the lack of an adequate sample size. For example, there were only 42 valid observations in the attempt to calibrate a model for the eastern region. Less than 2% of all crashes were on undivided multi-lane segments. Analysis using statewide data was not particularly informative either as the only statistically significant variable was "wintry condition" (odds ratio 0.117; CI [0.028, 0.485]).

For two-lane roadways, the results indicated that shoulder width, speed limit, lane marking, and wintry conditions are significantly associated with injury severity. The positive signs for shoulder width and speed limit indicated that as their values increased, the likelihood for injury outcomes also increased. RD crash frequency analysis performed later in the study found that crash frequency decreased as shoulder width increased. That is, although wider shoulders may reduce the likelihood for a RD crash, the outcome may be severe once the crash occurs. These may suggest possible correlations with other factors such as (higher) operating speed, speed limit, and lane width (Boodlal et al., 2015). Figure 10 shows the relationships among RD crash frequency, average shoulder width, and speed limit on two-lane roadway segments.

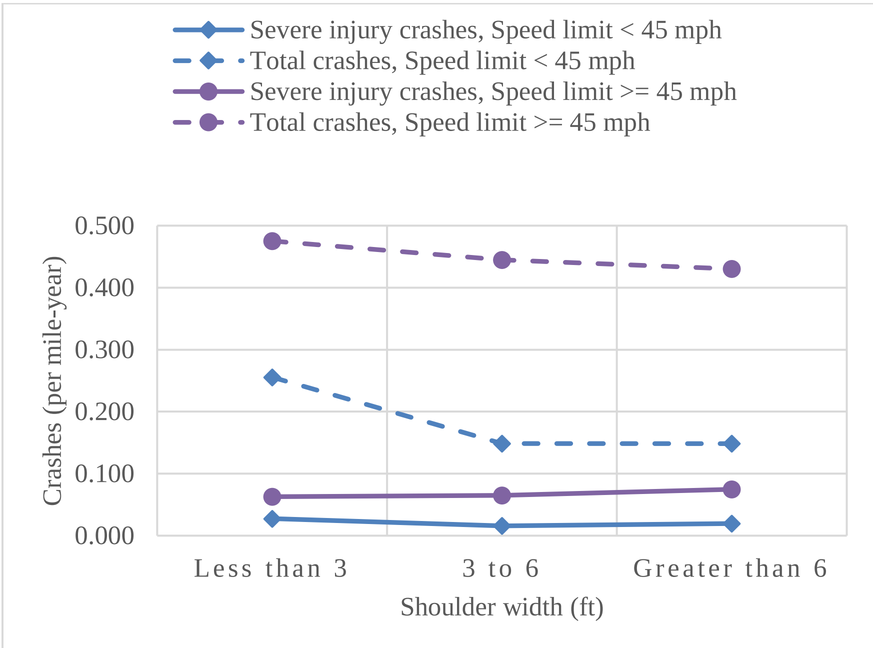

Figure 10. Relationships Among Speed, Shoulder Width, and Roadway Departure Crash Frequency

It may be seen that total crash frequency was highest on segments for which the average shoulder width was less than 3 ft and decreased as shoulder width increased. However, there was a general increase in severe injury crashes as shoulder width increased on segments with speed limits greater than 45 mph. Although the increase in severe injury crashes was statistically significant, the magnitude of the increase appears practically marginal and unlikely to offset the overall RD crash reduction benefits associated with a wider shoulder. The effect of shoulder width on injury severity was not significant in the northern and eastern parts of the state.

The negative values for marked traffic lanes and wintry conditions (Table 11) suggest that the likelihood of injury is decreased with those conditions. The effect of lane markings on injury severity was not statistically significant in the eastern region. These differences may be a reflection of general differences in roadway and driver behavior characteristics between the analysis regions (Garber and Rivera, 2010).

In addition to the four variables identified for two-lane roadways, average median width was found to be associated with RD crash severity on divided multi-lane roadways (Table 12). The likelihood ratio test was used to test for similarity in parameter values based on using the entire dataset (for a given roadway type) vs. data for the different subgroups or regions. The null hypothesis of similar parameter values was rejected with high confidence (over 99.99%), suggesting that the estimation of separate models for the regional subgroups was statistically warranted (Behnood and Mannering, 2017).

Factors Affecting Crash Frequency

An NB regression model was used to investigate further factors significantly associated with RD crash frequency. SAS software was used to model RD crash frequency as a function of roadway characteristics. A subset of the variables from Table 7 (shoulder width, speed limit, pavement roughness, curb, and median width) were used as explanatory variables. These were supplemented by the exposure variables: ADT in vehicles per day (mean of 1,731, minimum of 50, maximum of 53,584), segment length in miles (mean of 0.64, minimum of 0.10, maximum of 10.35), and the number of years of crash data ($n = 5$ years). The analysis was restricted to roadway segments that were continuously present in the COTEDOP database for the 5-year analysis period from 2014-2018. A total of 50,656 segments were used.

All variables were used for model development; however, only those that were significant at the 5% level were included in the final model. Summaries of the modeling results are provided in Tables 13 through 15. Performance of the models was assessed by comparing the sample probability distribution (relative frequencies) of the data to the average probability distributions predicted using the estimated models across the full range of crash counts in the data (Hilbe, 2014). In general, the models appear to underestimate the proportion of zero crash counts but perform well predicting the non-zero crashes.

Table 11. Logit Model Results of Roadway Departure Crash Severity for Two-Lane Roadways

Variable	Estimate (Standard Error)[a]			
	Northern Region	**Western Region**	**Eastern Region**	**Statewide**
Intercept [Severe]	-2.8984 (0.3453)	-2.5662 (0.1458)	-2.4392 (0.2450)	-2.5764 (0.1158)
Intercept [Minor]	-1.1812 (0.2353)	-0.8455 (0.1033)	-1.3101 (0.1925)	-0.9833 (0.0838)
Average shoulder width (ft) [Severe]		0.0541 (0.0154)		0.0416 (0.0113)
Average shoulder width (ft) [Minor]		0.0026 (0.0120)*		0.0051 (0.0088)*
Speed limit (mi/h) [Severe]	0.0335 (0.0076)	0.0247 (0.0031)	0.0261 (0.0051)	0.0257 (0.0026)
Speed limit (mi/h) [Minor]	0.0107 (0.0053)	0.0063 (0.0023)	0.0132 (0.0041)	0.0083 (0.0019)
Marked traffic lanes (1 if Yes; 0 otherwise) [Severe]	-0.2114 (0.0994)	-0.2789 (0.0538)		-0.2041 (0.0386)
Marked traffic lanes (1 if Yes; 0 otherwise) [Minor]	0.0438 (0.0721)*	-0.1642 (0.0403)		-0.1156 (0.0294)
Wintry condition (1 if Yes; 0 if No) [Severe]	-1.3460 (0.2300)	-1.1796 (0.1166)	-1.0268 (0.1603)	-1.1672 (0.0871)
Wintry condition (1 if Yes; 0 if No) [Minor]	-0.6229 (0.1187)	-0.3270 (0.0629)	-0.5054 (0.1061)	-0.4167 (0.0491)
Model Statistics				
Number of observations	4,482	14,520	5,966	24,968
Likelihood ratio chi-square	89.56	270.49	89.04	444.20
Degrees of freedom	6	8	4	8
Concordance statistic (AUC)	0.554	0.555	0.543	0.551
Akaike information criterion (AIC)	8,152	27,695	11,420	47,290

[a] Parameter defined for "severe injury" [Severe]; "minor injury" [Minor].
*Not significant at the 5% significance level.

Table 12. Logit Model Results of Roadway Departure Crash Severity for Divided Multi-Lane Roadways

Variable	Estimate (Standard Error)[a]			
	Northern Region	**Western Region**	**Eastern Region**	**Statewide**
Intercept [Severe]	-1.9901(0.2819)	-1.8663 (0.2063)	-2.8326 (0.9588)	-1.8458 (0.1625)
Intercept [Minor]	-0.5696 (0.1786)	-0.7210(0.1282)	-3.5370 (0.8048)	-0.7511 (0.1044)
Average shoulder width (ft) [Severe]	0.0921 (0.0364)		-0.1391 (0.0421)	
Average shoulder width (ft) [Minor]	0.0034 (0.0243)*		-0.0655 (0.0352)*	
Speed limit (mi/h) [Severe]			0.0463 (0.0178)	
Speed limit (mi/h) [Minor]			0.0571 (0.0147)	
Marked traffic lanes (1 if Yes; 0 otherwise) [Severe]		0.6022 (0.2112)		0.5451 (0.1592)
Marked traffic lanes (1 if Yes; 0 otherwise) [Minor]		0.1065 (0.1325)*		0.0339 (0.1011)*
Wintry condition (1 if Yes; 0 if No) [Severe]	-1.7592 (0.4686)	-1.3301 (0.2123)	-1.7268 (0.3486)	-1.4939 (0.1688)
Wintry condition (1 if Yes; 0 if No) [Minor]	-0.5724 (0.2086)	-0.5424 (0.1157)	-0.4283 (0.1687)	-0.5068 (0.0863)
Average median width (ft) [Severe]				0.0009 (0.0008)*
Average median width (ft) [Minor]				0.0013 (0.0006)
Model Statistics				
Number of observations	1,069	4,334	2,054	7,500
Likelihood ratio chi-square	32.48	76.48	68.42	150.55
Degrees of freedom	4	4	6	6
Concordance statistic (AUC)	0.559	0.531	0.561	0.541
Akaike information criterion (AIC)	2,000	8,197	3,871	14,157

[a] Parameter defined for "severe injury" [Severe]; "minor injury" [Minor].
*Not significant at the 5% significance level.

The results suggest that RD crash frequency on two-lane roadways (Table 13) is significantly influenced by ADT, shoulder width, speed limit, pavement roughness, and curb. The positive coefficients for the ADT and speed limit variables indicate that as those values increased, the number of crashes also increased. The negative values for the shoulder width and pavement roughness variables indicate that the number of crashes decreased as those variables increased. Figure 11 shows the predicted number of RD crashes as shoulder width and speed limit change at different traffic flow levels. It may be seen that RD crashes can be expected to be most frequent on high speed–high volume segments with narrow shoulders. The figure also shows that widening the shoulder, lowering the speed limit, or both would reduce the predicted number of crashes at all traffic flow levels; however, the magnitude of change would decrease slightly as shoulder width progressively increased. Figure 11 can be helpful in determining the speed limit–shoulder width combination needed to attain a target RD crash frequency.

The absence of a curb (or gutter) was also significantly associated with increased crash frequencies, as shown by a positive coefficient for the curb variable (Table 13). This variable was not found to have a significant influence on RD crashes in the northern region.

RD crash frequency on divided multi-lane roadways (Table 14) was significantly influenced by ADT, shoulder width, speed limit, and median width. The coefficient for median width was positive, suggesting that the number of crashes increased as the median width increased. This might be because of higher operating speeds on roads with wider medians. The other variables influenced crash frequency in a manner similar (positive or negative) to how they influenced crash frequency on two-lane roadways. For undivided multi-lane roadways (Table 15), only ADT and speed limit were found to influence crash frequency. Analysis for undivided multi-lane roadways was not done for the northern region because there were insufficient data (only 24 valid observations) for reliable statistical analysis.

Table 13. Negative Binomial Model Results of Roadway Departure Crash Frequency for Two-Lane Roadways

Variable	Estimate (Standard Error)			
	Northern Region	**Western Region**	**Eastern Region**	**Statewide**
Intercept	-5.7556 (0.3401)	-5.7838 (0.17)	-6.6989 (0.2866)	-6.0276 (0.1334)
log(ADT)	0.6688 (0.0271)	0.5773 (0.0127)	0.6149 (0.0208)	0.6043 (0.0098)
Average shoulder width (ft)	-0.1226 (0.0134)	-0.118 (0.0073)	-0.1526 (0.0109)	-0.1294 (0.0055)
Speed limit (mph)	0.0129 (0.0036)	0.0143 (0.0017)	0.0272 (0.0029)	0.0165 (0.0013)
Pavement roughness (in/mi)	-0.0026 (0.0006)	-0.001 (0.0003)	-0.0033 (0.0005)	-0.0016 (0.0002)
Curb (1 if no curb or gutter; 0 otherwise)		0.5719 (0.1464)	0.6316 (0.2509)	0.5237 (0.1159)
Dispersion parameter	0.4613 (.0359)	0.3863 (0.0181)	0.4383 (0.0314)	0.4253 (0.0147)
Model Statistics				
Number of observations	2,929	11,841	6,400	21,170
Log-likelihood	-3535	-13248	-5996	-22859
Akaike information criterion (AIC)	7,084	26,510	12,007	45,733
Predicted (observed) counts:				
0	53% (62%)	55% (65%)	63% (71%)	57% (67%)
1	20% (17%)	22% (18%)	19% (15%)	21% (17%)

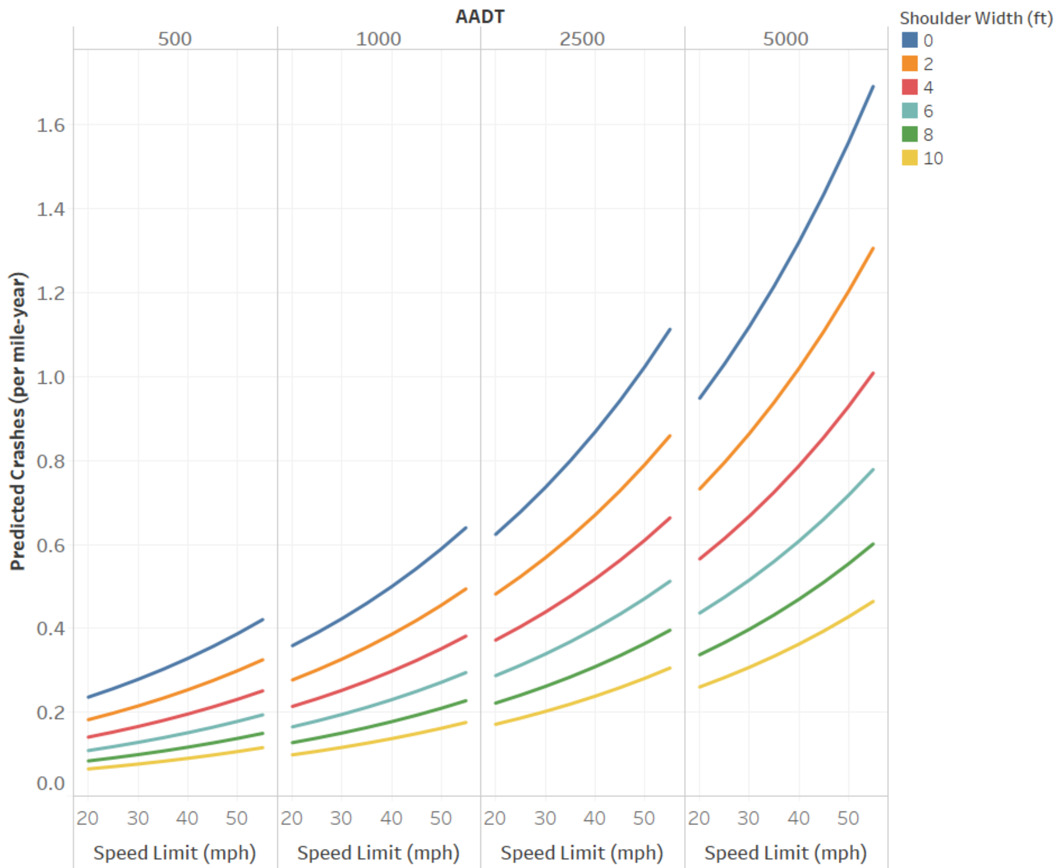

Figure 11. Change in Roadway Departure Crash Frequency With Change in Speed Limit and Shoulder Width. AADT = annual average daily traffic.

Table 14. Negative Binomial Model Results of Road Department Crash Frequency for Divided Multi-Lane Roadways

Variable	**Estimate (Standard Error)**			
	Northern Region	**Western Region**	**Eastern Region**	**Statewide**
Intercept	-8.2780 (0.9355)	-8.1896 (0.5632)	-6.964 (0.6703)	-7.2455 (0.4057)
log(ADT)	0.8618 (0.0906)	0.7536 (0.0508)	0.5463 (0.0540)	0.6095 (0.0327)
Average shoulder width (ft)	-0.0513 (0.0161)	-0.0254 (0.0109)		
Speed limit (mph)		0.0273 (0.0063)	0.0234 (0.0079)	0.0253 (0.0047)
Average median width (ft)	0.0081 (0.0024)		0.0063 (0.0011)	0.0027 (0.0005)
Dispersion parameter	0.1973 (0.0460)	0.4126 (0.0358)	0.3091 (0.0439)	0.4029 (0.0268)
Model Statistics				
Number of observations	359	1,470	953	2775
Log-likelihood	-632	-2,612	-1,436	-4,734
Akaike information criterion (AIC)	1,274	5,233	2,882	9,478
Predicted (observed) counts:				
0	27% (29%)	31% (35%)	38% (42%)	33% (37%)
1	23% (21%)	23% (19%)	24% (23%)	23% (21%)

Table 15. Negative Binomial Model Results of Roadway Departure Crash Frequency for Undivided Multi-Lane Roadways[a]

Variable	Estimate (Standard Error)		
	Western Region	**Eastern Region***	**Statewide**
Intercept	-3.7033 (1.3277)	-8.9931 (1.0465)	-6.5465 (0.9098)
log(ADT)	0.3913 (0.1541)	0.6916 (0.0853)	0.5293 (0.0849)
Speed limit (mph)		0.0466 (0.0109)	0.0298 (0.0084)
Dispersion parameter	0.8107 (0.1679)		0.5134 (0.0927)
Model Statistics			
Number of observations	230	221	468
Log-likelihood	-319	-266	-622
Akaike information criterion (AIC)	643	537	1,252
Predicted (observed) counts:			
0	49% (50%)	46% (51%)	47% (50%)
1	23% (24%)	25% (22%)	24% (23%)

[a] A separate model was not estimated for the northern region because the sample size was too small (only 24 valid observations).
[*]Estimates are based on a Poisson regression model as dispersion parameter of negative binomial model was not significant at a 5% significance level.

The likelihood ratio test for similarity of regional subgroup model parameter values was rejected with high confidence (greater than 99.99%), indicating that the use of separate models for the different regions was statistically warranted.

Impacts of Roadway Geometry and Pavement Condition

This part of the study explored potential impacts of roadway geometry and pavement (including shoulder) condition on RD crash frequency using the secondary dataset that was constructed by supplementing data from standard VDOT Oracle databases with iVision and recently available SCRIM data. Data were aggregated based on the iVision segments. Since these segments are relatively short (mean length 0.09 miles for this study), most segments had zero crashes. The proportion of zero counts in terms of all crash types was approximately 74%. As for dry- and wet-pavement crashes, the percentages of zero counts were 82% and 91%, respectively. Therefore, the ZIP model was used to analyze this dataset.

The ZIP model was used to relate crash frequency to the roadway geometry and pavement condition variables described in Table 7. Several combinations of the variables were tested using stepwise regression methods. Table 16 provides a summary of the modeling results obtained using SAS software. Separate models were estimated for total crashes (all types) and for dry-pavement crashes. Both models showed good agreement between the observed probability distribution and the average probability distributions predicted using the estimated models. No statistically reliable results were obtained for wet-pavement crashes because of the small sample size.

Table 16. ZIP Model Results of Roadway Departure Crash Frequency

Variable	Estimate (t-statistic)	
	All Crashes	**Dry-Pavement Crashes**
Count Model		
Intercept	-3.078 (-0.85)	-5.136 (-1.11)
Average daily traffic (veh/day)	0.662 (1.59)	0.952 (1.79)
Change in speed limit from adjacent segment (mph)	0.06 (1.69)	0.082 (2.1)
Average gradient within segment (%)	-0.035 (-1.92)	-0.046 (-1.91)
Average cross slope within segment (%)	0.097 (2.34)	0.032 (0.59)
Average curvature within segment (1/mi)	0.186 (2.00)	0.082 (0.72)
Skid resistance / SCRIM coefficient	-0.042 (-3.4)	-0.059 (-3.47)
Right shoulder width (ft)	-0.196 (-2.17)	-0.289 (-1.96)
Right shoulder is paved (1 = paved)	-0.136 (-0.16)	0.856 (0.86)
Left shoulder is paved (1 = paved)	-0.46 (-0.56)	-0.328 (-0.32)
Proportion of right shoulder material in relatively good condition	1.003 (1.18)	0.104 (0.11)
Proportion of right shoulder material in fair condition	0.576 (0.63)	-0.148 (-0.14)
Proportion of shoulder experiencing a drop-off greater than 3 in	7.669 (0.33)	
Proportion of left shoulder material in relatively good condition	1.184 (1.38)	0.977 (0.89)
Zero-inflation Model		
Intercept	-6.885 (-1.86)	-13.376 (-2.43)
Mean profile depth (x 0.0394 in)	1.761 (2.13)	1.433 (1.45)
Pavement roughness (in/mi)	0.02 (3.55)	0.034 (3.81)
Lane width (ft)	0.587 (1.83)	1.059 (2.26)
Model Statistics		
Log likelihood	-709	-496
Akaike information criterion (AIC)	1454	1026
Bayesian information criterion (BIC)	1540	1107
Predicted (observed) counts		
0	74% (74%)	82% (82%)
1	17% (17%)	14% (13%)

ZIP = Zero-inflated Poisson.

The positive coefficients for MPD, pavement roughness, and lane width in the zero-inflation model indicate that the odds of being in the near-zero crash state increased as those variables were increased. The count model results suggest that crash frequency is statistically significantly influenced by cross slope, curvature, shoulder width, and skid resistance. The signs of the coefficients indicate that the number of crashes increased as the average cross slope and curvature increased and decreased as the shoulder width and skid resistance increased. The number of dry-pavement crashes also decreased as shoulder width and skid resistance increased.

Table 17 compares observed crash counts to predictions of the ZIP and NB models. The comparisons were based only on study segments for which SCRIM and iVision data were available. Predictions for the ZIP model, which were based on iVision segments, were aggregated over their corresponding segments from the primary database before comparisons were made.

Table 17. Comparison of ZIP Model and Negative Binomial Model Predictions for Select Segments

Model	Metric			
	Predicted Crashes (Observed = 278)	**Mean Square Error**	**Mean Bias**	**Mean Absolute Deviation**
Negative binomial	236	21.9	-0.480	1.94
Zero-inflated Poisson	280	16.8	0.028	1.93

ZIP = zero-inflated Poisson.

The mean absolute deviation estimates were nearly identical for the two models. However, the NB model seemed to have underestimated systematically the overall average crash count. The total crash count predicted by the ZIP model over all segments was nearly equal to the sum of observed counts; the NB model predicted approximately 15% fewer crashes.

Summary and Discussion

This study examined the factors related to RD crashes on rural highways in Virginia. A review of archived data for the years 2014-2018 showed a general downward trend in RD crashes except for 2018 where, for the segments studied, RD crashes increased by an average of 7% compared to the previous 4-year average. A majority of crashes were non-injury crashes, with fatal and injury crashes constituting approximately 43% of the total number of RD crashes during the analysis period. Approximately 52% of all crashes occurred on a tangent section. However, for two-lane roadway segments, proportionally more crashes (approximately 54%) were on horizontal curves.

An initial exploratory analysis identified 10 factors with high potential for explaining RD crashes including roadway functional class, speed limit, AADT, shoulder and median widths, traffic control (e.g., lane markings), pavement roughness, and road surface conditions. Further analysis of how these factors might affect crash frequency and severity indicated that shoulder width, speed limit, lane markings, and wintry conditions were all significantly associated with injury severity levels. The study also found a significant association between the frequency of RD crashes and AADT, shoulder width, speed limit, and pavement roughness. In general, these factors did not affect RD crashes similarly across the state. For example, the effect of shoulder width on injury severity was not significant in the northern and eastern parts of the state.

The results suggested that widening roadway shoulders can provide significant reductions in RD crash frequency with a statistically significant but practically marginal increase in the number of severe injury crashes, especially on two-lane segments with speed limits greater than 45 mph. Neuner et al. (2016) found more than one-half of speeding-related RD fatal crashes occurred on roadways with a posted speed limit between 40 and 55 mph and that addressing curves was the major aspect of preventing speeding-related RD crashes. In the western region, where there are more curvature interactions with speed, about 58% of fatal and injury RD crashes on two-lane roadway segments occurred on curves; the numbers for the northern and eastern regions were 49% and 47%, respectively.

This study also explored safety analysis using iVision and SCRIM data. Both systems can provide synchronization of surface condition and roadway geometry data. The factors collected by iVision and SCRIM but not existing in the RNS and COTEDOP databases provided a new opportunity to identify high-risk locations where the current RD SPFs may underestimate the risk because of the new factors not included in the models. Statewide road surveys using iVision and SCRIM, in addition to hotspots analysis and project-based study, would make it possible to conduct safety analyses on a large scale. Analysis of a sample of such data in this study found a statistically significant association between RD crash frequency and geometric characteristics such as cross slope and curvature. A significant association was also found between crash frequency and pavement skid resistance, a variable that is at present collected on a routine basis.

Ideally, the skid resistance from the SCRIM survey for the crash year should be used as the level of skid resistance changes over time. Because of very limited data availability, this study used data collected in 1 year as an indicator for a 5-year period for the segments without any major maintenance. Further study with more data and a larger sample size is needed. A comparison of predictions from the analysis involving SCRIM and iVision data (ZIP model) with analysis based only on the primary dataset (NB model) for identical segments suggested moderately superior performance by the former. However, the NB model predictions seemed generally acceptable (approximately 15% error in total crash count estimate). It is also unclear how much of the differences in predictions are the result of differences in the underlying data or the types of models used for the predictions. Although the newly available SCRIM data holds promise for deriving further insights into factors correlated with RD crashes, there can be significant challenges to mainstreaming it for analysis. For example, data conflation was a very time-consuming task in this study. Geo-spatial information and roadway inventory (unique route name, direction, and milepost) comprise the key for connecting these databases. However, the key information is coded in different formats, making it very difficult to establish a connection, especially for the secondary roads and business roads. Standardizing those key data fields is very valuable. Collecting and synthesizing these data at the statewide level could be challenging. Nevertheless, where available, they could be used to enhance crash data analysis at the project level.

A review of FHWA publications, state strategies, and the CMF Clearinghouse was conducted to identify low-cost treatments for RD crashes on rural two-lane and multi-lane highways. The low-cost engineering countermeasures with proven CMFs specified for RD crashes included the following:

- Install centerline and shoulder rumble strips.
- Install edge line rumble strips.
- Install shoulder safety edge treatment.

The analysis of the secondary data found that many segments on US 29 Northbound had a high wet crash ratio. Further investigation is needed for those segments, and some may benefit from high friction surface treatment, which was found to reduce wet-condition crashes by 52%. The cost of this treatment is moderate.

CONCLUSIONS

- *Locations with narrower shoulders are more likely to have more RD crashes.* Multi-faceted analyses in this study consistently indicated that shoulder width is significantly associated with RD crash frequency, decreasing as shoulder width increased.

- *Locations with horizontal curves are more likely to have frequent RD crashes.* The study found a significant association between RD crash frequency and roadway curvature, with crash frequency increasing as curvature increased.

- *Locations with narrow shoulders and high speed limits are more prone to RD crashes.* A plot of the predicted number of RD crashes on two-lane roadways as a function of shoulder width and speed limit (Figure 11) showed that RD crashes are more likely at locations with high speed limit–narrow shoulder combinations.

- *Roadway geometry and pavement condition affect the frequency of RD crashes.* Analysis in this study using SCRIM and iVision data found a significant association between roadway geometry (curvature, cross slope) and pavement surface condition (skid resistance, roughness).

- *The various factors do not affect all parts of the state evenly.* In several cases in this study, potential influencing factors, even for the same roadway type, were found to be significant in one region of the state and not significant in others.

RECOMMENDATIONS

1. *VDOT's TED should prioritize systemic countermeasure deployment on horizontal curves on rural two-lane roadway segments with shoulder widths less than 3 ft.* RD crash frequency was highest on segments for which the average shoulder width was less than 3 ft and decreased as shoulder width increased. Also, proportionally more crashes occurred on horizontal curves of two-lane roadway segments than on tangent sections. There is the potential to derive substantial safety benefits by implementing low-cost countermeasures.

2. *VDOT's TED should utilize the findings of this study to assess safety tradeoffs between speed limits and shoulder width when assessing RD crashes on rural two-lane roadways.*

3. *VTRC should conduct a pilot study to study further the use of SCRIM and iVision data for safety studies; identify standard procedures for data processing; and conduct case studies.* Early results from this study are promising, but additional data need to be acquired to determine if predictive benefits justify the additional effort required to use these datasets.

IMPLEMENTATION AND BENEFITS

Implementation

For Recommendation 1, VDOT's TED should focus on rural two-lane segments with the stated features during the next round of Highway Safety Improvement Program systemic improvement projects. A summary of potential engineering countermeasures is provided in Table 1 and in the Virginia State Preferred CMF List (VDOT, n.d.). Specific countermeasures from these resources with proven effectiveness include installing horizontal curve warning signs, safety edge treatments, and rumble strips. In addition, the results of an ongoing VTRC study, Development of a Systemic Safety Improvement Plan for Two-Lane Rural Roads in Virginia, should assist with this. TED is already implementing some of these measures as part of an ongoing process to comply with curve signing requirements in the *Manual on Uniform Traffic Control Devices for Streets and Highways* (MUTCD).

With regard to Recommendation 2, within 3 months of the publication of this report, VDOT's TED will encourage and promote the use of Figure 11 in VDOT's regions to help determine the speed limit–shoulder width combination needed to mitigate RD crashes on two-lane roadways.

For Recommendation 3, within 2 years of at least two SCRIM surveys becoming available for statewide locations, VTRC's Traffic and Safety Research Advisory Committee will assess the need for a more extensive study to evaluate the opportunities and challenges of using SCRIM and iVision data for VDOT safety studies. The SCRIM surveys should cover rural two-lane and multi-lane highways. At least 3 years need to elapse to accumulate enough crash data to construct robust models. At this point, this project idea will be discussed and balloted within the research advisory committee.

Benefits

The implementation of Recommendation 1 will help VDOT maximize the effectiveness of efforts to reduce the frequency and severity of rural RD crashes. The study found that horizontal curves have a high incidence of RD crashes, so low-cost systemic countermeasures have a high potential to produce significant crash reductions.

The implementation of Recommendation 2 will encourage more informed, defendable decision making regarding speed setting and facilitate consistent engineering judgment across the state regardless of location. This will allow speed limit and shoulder width tradeoffs to be considered explicitly.

The implementation of Recommendation 3 will support the decisions regarding the need for wide application of SCRIM and iVision data and the establishment of a standard procedure for long-term data collection and data processing.

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