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A ROADWAY CONTEXT CLASSIFICATION APPROACH FOR DEVELOPING SAFETY PERFORMANCE FUNCTIONS AND DETERMINING TRAFFIC OPERATIONAL EFFECTS FOR FLORIDA INTERSECTIONS

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Disclaimer Page

Metric Conversion Chart

Symbol	When You Know	Multiply By	To Find	Symbol
Length				
mi	miles	1.61	kilometers	km
km	kilometers	0.621	miles	mi

Technical Report Documentation Page

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16. Abstract

This research developed safety performance functions (SPFs) based on a new Florida Department of Transportation (FDOT) context classification system which contains eight context categories as opposed to the three classifications used in the Highway Safety Manual (HSM). To develop these context-specific SPFs, data were collected for several potential predictor variables, including geometric, traffic, signalization, and other related intersection data based on the Model Inventory of Roadway Elements (MIRE) 2.0, allowing for standard data collection across agencies. Multiple modeling methodologies were utilized and compared to identify the best-performing models and develop a unique context-specific SPF for each intersection group. While some variables, such as major AADT, were common to multiple SPFs, each SPF contained a unique set of variables and different variable coefficients. These unique insights can help FDOT understand crash-influencing factors for different intersection types, identify intersections with high potential for crash reduction, and implement effective countermeasures. The individual group SPFs were also compared to HSM SPFs from the HSM and full context category SPFs. These comparisons showed the improved accuracy and additional insights provided by the individual context-specific SPFs. In addition, departments of transportation from across the United States were surveyed about their current SPF development practices and context classification. Many states (64% of the 42 respondents) use HSM SPFs or SPFs calibrated to their jurisdiction. Although 62% of states had not heard of context classification, 67% of states expressed interest in the system, emphasizing the importance of this research to improve intersection safety across the nation.

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Executive Summary

Safety performance functions (SPFs) are vital tools used by traffic safety analysts to predict the total number of crashes on roadways and intersections. Since SPFs developed in the Highway Safety Manual (HSM) only use data collected from limited states, several states have developed their own region-specific SPFs. However, these SPFs are typically only developed for the three roadway categories used in the HSM. Unlike these previous studies, this research develops SPFs for Florida intersections based on a new context classification system developed by the Florida Department of Transportation (FDOT) which categorizes intersections into eight main categories: C1-Natural, C2-Rural, C2T-Rural Town, C3R-Suburban Residential, C3C-Suburban Commercial, C4-Urban General, C5-Urban Center, and C6-Urban Core. SPFs could theoretically be developed for up to 32 different intersection types using FDOT's context classification system (signalized and unsignalized 3-leg and 4-leg intersections for each of the eight categories), allowing for more accurate SPFs.

To help improve this context classification system and understand what other states think of this system, a survey was developed and conducted on state departments of transportation (DOTs) nationwide. Launched in July 2019, the survey was sent to contacts from 51 DOTs (all 50 states plus District of Columbia). When the survey was ended in May 2020, professionals from 42 DOTs had completed the survey. Out of these 42 states, 62% had not heard about FDOT's context classification system. Most survey respondents (64%) said their states use either SPFs directly from the HSM or SPFs that have been calibrated to their jurisdiction based on the HSM SPFs. Most of the seven respondents whose states do not use the default HSM methodology to develop SPFs said that their models give more accurate results and that the HSM methodology was insufficient or lacked a specific variable or attribute that was important to their state. Overall, this survey showed that most states (67%) are interested in context classification, even if they are not currently planning on implementing such a system. Issues such as lack of data (including incomplete or inaccurate data, as well as a lack of resources to collect the data) and how to properly segment and utilize these data were the main reasons preventing states from developing their own SPFs, while limited applications showing the benefits of context classification were the main reasons agencies were hesitant to implement such a system. By utilizing effective data collection procedures and showcasing the benefits provided by context classification, this research can alleviate these concerns and make other states more willing to follow FDOT's example.

To develop these context-specific SPFs, it is important to have data of sufficient quality and quantity. The University of Central Florida (UCF) research team collected data for over 3,400 intersections throughout Florida provided by FDOT; these included intersections for all 32 types possible based on the FDOT context classification system. These data included geometric, traffic, signalization, and other related intersection data. The Model Inventory for Roadway Elements (MIRE) 2.0 data standard developed by the Federal Highway Administration (FHWA) was used when collecting these data to make it easier for agencies in Florida or other states to collect these data. Some assumptions and modifications had to be made to some variables to make them more applicable to Florida intersections. Florida counties and districts were also contacted regarding data that could not be obtained elsewhere. The resulting database contains

accurate and high-quality data to develop reliable SPF models and assist FDOT in future identification of high-risk intersections and implementation of countermeasures.

Using the collected data, SPFs were developed for 19 of the 32 intersection groups with a sufficient number of intersections and crashes to develop statistically significant models. Similar groups without a sufficient sample size (C6-Urban Core unsignalized 3-leg and 4-leg) were also combined to provide a sufficient sample size for modeling. A minor average annual daily traffic (AADT) model also had to be developed to predict these volumes at intersections without them. For each of the considered intersection groups, multiple modeling techniques were considered as appropriate based on their individual data characteristics. The considered modeling techniques were Poisson, negative binomial (NB), zero-inflated Poisson (ZIP), zero-inflated negative binomial (ZINB), and boosted regression trees (BRTs). The developed models for each group were compared based on their interpretability and various performance measure values to select the best model to use as each group's SPF. Only models that had a functional form which was interpretable and usable by agencies were considered as potential SPFs. Five performance measures were compared for these interpretable models: mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared error (RMSE), Akaike information criterion (AIC), and Bayesian information criterion (BIC). The model which had the lowest values for the majority of these performance measures was selected as the SPF for each intersection group.

Each developed SPF had a unique set of significant variables, demonstrating the importance of developing context-specific SPFs to identify the different influential variables across classification categories. Major AADT was the only variable that was significant and had a positive coefficient in all developed SPF models, indicating that higher major road volumes tend to result in more crashes. Intersection groups in the same context classification often had similar significant variables, but there were differences between each group. The district variable was significant in at least one intersection group per classification category. This variable identifies FDOT districts that have significantly higher (positive coefficient) or lower (negative coefficient) crash frequencies than other districts. District 2 was significant in two C2-Rural intersection groups (negative coefficient), District 3 was significant in two C2T- Rural Town intersection groups (negative coefficient), District 4 was significant in three C3R-Suburban Residential intersection groups (negative coefficient), and District 6 was significant in three C4-Urban General intersection groups (positive coefficient). There were also some common significant variables across context categories for intersection groups with the same signalization or number of legs, such as lighting and minor road speed limit. The SPFs for intersections in the same context classification category (but with a different number of legs and/or signalization) were then compared to identify how the significant factors differed between these groups. Examples of these differences include intersect angle and railroad zone being significant for the C2-Rural unsignalized 3-leg intersection group, but not being significant for any of the other C2 intersection groups, as well as major exclusive left turn length being significant for the C4-Urban General unsignalized 3-leg intersection group, but not for any other C4 intersection groups, and minor exclusive right turn number being significant in the C4 unsignalized 4-leg intersection group, but not for any other C4 groups. By identifying these differences, FDOT will be able to better locate high-risk intersections and determine appropriate treatments to implement at different intersection types, effectively utilizing their resources to best reduce crashes and save lives.

To further show the benefits of the context-specific SPFs, the individual intersection group SPFs developed for the C3R-Suburban Residential and C4-Urban General categories were compared with full SPFs using data from all four intersection groups within each category. For the C3R classification category, the district variable D7 was significant in the signalized 3-leg intersection group, but was not significant in the full model. Additionally, the major median variable was not significant in the full model, but was significant in three of the individual intersection group SPFs. For the C4 classification category, three variables were significant in the individual intersection group SPFs that were not significant in the full SPF: major median, minor exclusive right turn number, and intersect angle. Comparing the individual and full SPFs for both the C3R and C4 categories showed how the individual SPFs better identified significant factors and regional differences. These additional insights will help FDOT effectively direct resources and deploy countermeasures to reduce crash frequencies in high-risk regions. Comparisons were also made between the context-specific SPF for C2T-Rural Town signalized 4-leg intersections and three types of HSM SPFs for rural two-way, two-lane signalized 4-leg intersections: base HSM SPF, base HSM SPF with crash modification factors (CMFs), and calibrated HSM SPF with CMFs. The context-specific SPF outperformed these HSM SPFs for all three considered performance measures (MAPE, MAE, and RMSE), indicating that the context-specific SPF can predict crash frequencies more accurately than the HSM SPFs. Additionally, the base HSM SPF performed better than the HSMs with CMFs, suggesting that the CMF factors included in the HSM might not be accurate for Florida. These comparisons provide FDOT with evidence of the benefits of using context classification over calibrated HSM SPFs.

Based on the results of this study, it is recommended to use the developed context-specific SPFs to improve intersection safety for Florida intersections. These SPFs can be used to identify intersections with high predicted crash frequencies and determine the most effective countermeasures to deploy at these intersections. The methodologies and results of this project address gaps in previous research, including the development of context-specific SPFs based on a classification system which uses more and different categories than those used in the HSM. These context-specific SPFs will allow FDOT to better identify safety-influencing factors for intersection types belonging to different context classification groups. Additionally, no previous research developed SPFs using the national MIRE 2.0 data standard, which allows for easier transferability of data collection practices between states. Other states can use the methodologies developed in this project to collect data and develop context-specific SPFs to improve intersection safety.

While the results of this research provide significant benefits to FDOT, expansions and improvements could be implemented in a phase 2 project to provide additional benefits. Including additional MIRE 2.0 variables that relate to signalized intersections, such as approach traffic control and signal progression, in the modeling process will allow FDOT to understand the impacts of different signalization strategies. The developed SPFs from this project could also be used to identify intersections with high expected crash counts and compare them with similar sister intersections which share traffic and geometric features, but have lower expected crash counts. Comparing these intersections could help FDOT identify the intersections that would benefit the most from geometric modifications and determine the most effective countermeasures to implement at high-risk intersections. Further research could also be conducted on the regional differences identified in this project to identify effective practices used in some FDOT districts that could be applied to other districts and improve intersection safety.

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List of Abbreviations and Acronyms

Abbreviation	Meaning
AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
AGOL	ArcGIS Online
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
BGOP	Bivariate Generalized Ordered Probit
BIC	Bayesian Information Criterion
BOP	Bivariate Ordered Probit
BRT	Boosted Regression Trees
CMF	Crash Modification Factor
DOT	Department of Transportation
EB	Empirical Bayes
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GAM	Generalized Additive Model
GLM	Generalized Linear Model
HSM	Highway Safety Manual
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MIRE	Model Inventory of Roadway Elements
MPB	Mean Prediction Bias
MSE	Mean Squared Error
MSPE	Mean Squared Prediction Error
NB	Negative Binomial
PAG	Pima Association of Governments
PD&E	Project Development and Environment
PDO	Property Damage Only
PennDOT	Pennsylvania Department of Transportation
RCI	Roadway Characteristics Inventory
RMSE	Root Mean Squared Error
RR	Railroad
RTM	Regression-to-the-mean
SDF	Severity Distribution Function
SPF	Safety Performance Function
VMT	Vehicle Miles Traveled
ZINB	Zero-inflated Negative Binomial
ZIP	Zero-Inflated Poisson

Chapter 1: Introduction

1.1 Problem Description

The Florida Department of Transportation (FDOT) has developed a new context classification system for state roadways. This system considers land use characteristics, development patterns, roadway connectivity, and likely user groups to classify roadways into eight main categories: C1-Natural, C2-Rural, C2T-Rural Town, C3R-Suburban Residential, C3C-Suburban Commercial, C4-Urban General, C5-Urban Center, and C6-Urban Core. By implementing this system, FDOT will be able to ensure that all their planning, project development and environment (PD&E), design, construction, and maintenance approaches are suitable, safe, and comfortable for their anticipated users. Due to the newness of this context classification system, no research has been done on using it to evaluate intersection safety in Florida. The data collection requirements and benefits of this system need to be researched so FDOT can effectively utilize this system to improve safety throughout the state. Effective methodologies can also be transferred to other states to allow them to achieve similar benefits.

The primary tools used to evaluate intersection safety are safety performance functions (SPFs). SPFs estimate expected crash frequencies for a specific type of site based on various site characteristics, such as traffic volumes and intersection design. Currently, the Highway Safety Manual (HSM) develops SPFs for three types of roadways: rural two-lane, two-way roads; rural multilane highways; and urban and suburban arterial highways. With the new context classification system, FDOT can develop context-specific SPFs for eight different categories rather than the three categories used in the HSM. This system will allow for development of up to 32 SPFs (unsignalized and signalized 3-leg and 4-leg intersections in each context classification category), which is much more than the 10 intersection SPF types developed in the HSM. No previous research has developed SPFs using this many intersection groups. These SPFs will also be tailored to Florida intersections, allowing FDOT to better identify the unique influential variables and regional differences for the various classification categories and more accurately predict crash frequency for various land uses and intersection types.

1.2 Research Goal, Objectives, and Tasks

The primary goal of this research was to develop context-specific SPFs for different types of Florida intersections based on the FDOT context classification system to help FDOT use this system to improve intersection safety. To achieve this goal, crash and intersection data (traffic volumes, intersection design characteristics, signalization, context classification, and other potential influencing factors) were collected for intersections throughout Florida and modeled using multiple modeling techniques. The Model Inventory of Roadway Elements (MIRE) 2.0 was used when collecting data in this project. This standard allows for the procedures conducted in this research to be easily implemented by local agencies and other states. The developed SPFs were also compared to each other and similar HSM SPFs to show the unique insights provided by these context-specific SPFs. State departments of transportation (DOTs) throughout the United States were also surveyed to understand other states' practices regarding SPFs and context classification and their thoughts and concerns regarding this new classification system.

The following are specific objectives of this research:

- Review previous and current research regarding the use of context classification for roadways and developing regional or jurisdiction-specific intersection SPFs.
- Determine the knowledge and familiarity of other state DOTs with FDOT's context classification system by surveying DOTs across the United States about their current SPF development practices and current or future use of context classification.
- Evaluate and improve data collection practices with the use of MIRE 2.0 as a standard inventory for intersection data collection.
- Develop a statewide intersection database and a geographic information system (GIS) layer containing context classification data for the studied Florida intersections which will help FDOT easily identify context classification and other MIRE 2.0 variable characteristics.
- Use and compare multiple modeling methodologies to develop the best context-specific SPFs for various intersection groups based on various performance measures.
- Compare the developed context-specific SPFs with each other and SPFs developed using the HSM procedures to showcase the beneficial insights that are provided by the context-specific SPFs.

The tasks used to achieve these objectives, including their methodologies and results, are discussed in the remainder of this report. Chapter 2 discusses the thorough literature review on previous studies about SPF development and the current HSM procedures used to develop intersection SPFs. The design, implementation, and results of the state DOT SPF current practices survey are discussed in chapter 3. Chapter 4 discusses the data collection procedures used to develop the statewide intersection database, while chapter 5 details the modeling methodologies used to develop context-specific SPFs and select the best SPF for each intersection group. Results and discussion for each SPF developed in this research are discussed in chapter 6, along with multiple comparisons to illustrate the improved accuracy of these context-specific SPFs. Finally, chapter 7 discusses how these context-specific SPFs can be used to improve intersection safety throughout Florida and provides recommendations on ways to improve and expand this research.

Chapter 2: Literature Review

To assist in developing SPFs for the FDOT context classification system, an extensive literature review was conducted to understand the various methods previously used to develop jurisdiction-specific SPFs. This literature review is organized into three sections. Section 2.1 contains a comprehensive analysis of the conventional HSM procedures and the drawbacks of using these procedures. Section 2.2 describes the methodological frameworks used by previous research to improve on the SPFs developed by HSM. These frameworks consist of two main approaches: calibrating the HSM's SPFs and developing jurisdiction-specific SPFs. Comparisons between the results of these approaches and the HSM's SPFs are also discussed. Section 2.3 provides a summary of the findings from this literature review and identifies some improvements to the existing methods.

2.1 Highway Safety Manual Procedure

This section discusses the conventional HSM methods and procedures that have been previously used to develop SPFs, as well as the drawbacks of using these conventional methods. As discussed previously, crash analysis and crash prediction models are essential tools to assess the safety of intersections as well as determine the sites that would benefit the most from potential improvements. The HSM defines three main elements that are used throughout the process of building a crash prediction model: SPFs, crash modification factors (CMFs), and calibration factors (American Association of State Highway and Transportation Officials [AASHTO], 2010). SPFs are defined as base models which estimate the average crash frequency for specific base conditions of a facility type (AASHTO, 2010). CMFs are defined as the ratio of the number of predicted crashes for one condition compared to another condition (AASHTO, 2010). Calibration factors are factors that are multiplied by the base SPFs to produce calibrated SPFs that are applicable to the region and time period of interest (AASHTO, 2010).

2.1.1 Data Requirements and Limitations

According to the procedure described by HSM, there are some essential data that need to be collected for crash analysis purposes to conduct statistically sound and meaningful analyses (AASHTO, 2010). These data include crash data, facility data, and traffic volume data for the sites under investigation. In general, the level of detail provided by the crash data varies from state to state. However, details such as the location, severity, type, and date and time of the crash, along with information about the roadway and the vehicles and people involved in the crash, are typical basic required details in all crash data (AASHTO, 2010). As an example of the level of details used for crash data in previous research, the Pennsylvania DOT (PennDOT) used eight years of crash data with information on the location, date, and type of crash, along with intersection type, work zone type, and injury severity, to develop SPFs (Donnell, Gayah, & Jovanis, 2014).

The next critical data to be collected are the facility data. These are data regarding the physical characteristics of the roadways and intersections of interest. According to HSM, the basic intersection characteristics needed include number of lanes, presence of medians, shoulder width, area type, and traffic control configurations. Additional useful characteristics to be collected can include the presence of auxiliary lanes and pedestrian crosswalks (Donnell et al., 2014). In the Pennsylvania study, Google Earth was used for the data collection of physical roadway characteristics. Google Earth is said to provide high-quality satellite images of the roads as well as the ability to look at the street view for more details. It also has built-in functions to measure features to scale, such as a protractor to measure intersections angles (Donnell et al., 2014).

Traffic volume data is the final data element needed to develop SPFs. Annual average daily traffic (AADT) volumes are used by the HSM (AASHTO, 2010). AADT values (in vehicles per day) are usually collected by state DOTs. For crash analysis, AADT volumes for a roadway or an intersection leg should be collected for at least 3 consecutive years (Srinivasan & Bauer, 2013). More detailed volume data (pedestrian counts, turning movement counts, etc.) might also be necessary in certain cases (AASHTO, 2010).

After collecting the required data, it is important to acknowledge the natural variations in crash data and account for limitations that are due to the variations in the data (AASHTO, 2010). If these limitations are not considered and accounted for, they can introduce bias that will affect the reliability of the developed SPFs (AASHTO, 2010). These limitations include "natural variability in crash frequency, regression-to-the-mean bias, variations in roadway characteristics, and conflict between crash frequency variability and changing site conditions" (AASHTO, 2010). Natural variation in crash data occurs due to the random nature of crashes, which causes crash frequencies to fluctuate over time at any given site. For this reason, collecting crash data for a short period of time will result in an unreliable estimator of a long-term crash frequency (AASHTO, 2010). Without sufficient data, it is difficult to determine if the estimated crash frequency is considered relatively high, average, or low compared to the typical crash frequency at the site (AASHTO, 2010). The random nature of crashes also makes it difficult to identify if natural fluctuations or changes done to site conditions are the cause of changes in the observed crash frequency (AASHTO, 2010).

The second limitation is the regression-to-the-mean (RTM) bias. This RTM bias is caused by the tendency of a period with high crash frequency to be followed by a period with relatively low crash frequency (AASHTO, 2010). RTM bias occurs when the selection of sites for treatment are based on observed crashes for a short period of time. It is not possible to determine whether any observed reduction in crashes occurred due to the implemented treatments without accounting for potential RTM bias (AASHTO, 2010).

Another limitation is due to variations in roadway characteristics. Traffic volumes, geometric designs, traffic control, and other factors can change over time, making it difficult to determine what exactly caused any identified changes to the crash frequency. This limitation can reduce the time period that can be included in the study, since taking a large study period could include changes in conditions at the site that occurred throughout the years. However, as mentioned before, using a small time period can result in RTM bias. This leads to the last limitation, which is the conflict between crash frequency variability and changing site conditions. Choosing a short period of study could result in RTM bias while choosing a large period of study could cause errors due to site changes. It is important to use careful judgment when balancing these limitations (AASHTO, 2010).

To address these limitations, statistical models using regression analysis have been developed to predict expected crash frequencies. These statistical models address the RTM bias limitation as well as provide reliable estimates of the expected average crash frequency for both existing and changing road conditions. These models improve the reliability of estimated crash frequency by incorporating historic crash data (observed crash data) into the model (AASHTO, 2010). Statistical models which combine predicted estimates of crashes with the observed crash frequencies include the empirical Bayes (EB) method, the hierarchical Bayes method, and the full Bayes method (AASHTO, 2010). In HSM, the EB method is used to develop crash prediction models. The difference between the EB adjusted predicted crash rate and the SPF-predicted number of crashes gives the potential for intersection sites to be upgraded by improvements applied to the site, also known as the potential for safety improvement (Garber & Rivera, 2010). This potential for safety improvement can be used to rank specific intersections and sites where feasible and effective treatments can be undertaken (Garber & Rivera, 2010).

2.1.2 HSM Methodology

In the HSM, the EB method is used to estimate the expected crash frequency by combining developed SPFs with observed crash data. The developed SPFs account for the effects of various treatments through the use of CMFs (AASHTO, 2010). The predictive model estimate of the crash frequency ($N_{predicted}$), is calculated using equation 2-1 (AASHTO, 2010).

$$N_{predicted} = N_{SPF\,x} * \left(CMF_{1x} * CMF_{2x} * \ldots * CMF_{yx}\right) * C_x \qquad (2\text{-}1)$$

Where:
$N_{predicted}$ = predictive model estimate of crash frequency for a specific year on site type x (crashes/year);
$N_{SPF\,x}$ = predicted average crash frequency determined for base conditions from the SPF representing site type x (crashes/year);
CMF_{yx} = CMFs specific to site type x;
y = number of CMFs used for site type x; and
C_x = calibration factor to adjust for local conditions for site type x.

The SPFs developed in the HSM are designed under certain assumptions and for default values referred to as base conditions. If the base conditions are modified, the CMFs should be applied to account for these differences. In addition, the HSM SPFs are developed using data from specific states, so they might not be applicable to all states. Therefore, it is necessary and recommended by the HSM to apply calibration factors which can adjust the SPFs according to the studied region (Mehta & Lou, 2013).

The expected average crash frequency at a site is estimated using the predicted average crash frequency ($N_{predicted}$ from equation 2-1) and observed crash frequency ($N_{observed}$), if available. The EB method is used to combine the predicted estimation using the developed SPFs with the observed crash frequency at a specific site. Then a weighting factor is applied to both estimates; this factor represents the statistical reliability of the model (AASHTO, 2010). It does not depend on the validity of the observed model but rather the variance of the developed SPF (AASHTO, 2010). The EB method combines the observed crash frequency with the predicted crash estimate as shown in equation 2-2 (AASHTO, 2010).

$$N_{expected} = w * N_{predicted} + (1 - w) * N_{observed} \qquad (2\text{-}2)$$

Equation 2-3 below provides the equation for the weighted adjustment factor, w, as a function of the SPF's overdispersion parameter, k (AASHTO, 2010).

$$w = \frac{1}{1+k * \sum_{\substack{all\ study \\ years}} N_{predicted}} \tag{2-3}$$

Note that the EB method does not apply when there is no observed crash data available. For these cases, only the predicted crash frequency from equation 2-1 will be calculated. This predictive method addresses the limitations previously mentioned in section 2.1.1. The SPFs are developed using the negative binomial (NB) distribution due to its ability to better model over-dispersed data compared to the Poisson distribution. This method also focuses on the long term expected crash frequency, which addresses the RTM bias limitation. Additionally, this method incorporates predictive relationships based on data from similar sites, which reduces the reliance on limited crash data from a single site (AASHTO, 2010). Finally, since the relationship between traffic volume and crash frequency is typically nonlinear, this method accounts for that non-linearity by incorporating exposure (Srinivasan & Carter, 2011). The next section discusses the development of HSM SPFs in more detail, including the inclusion of exposure via AADT and the use of CMFs.

2.1.3 Development of SPFs and Use of CMFs and Calibration Factors in HSM

The HSM develops SPFs for the different roadway segment and intersection types shown in table 2-1 (five different roadway segments and 10 different intersection types). These SPFs were developed using multiple regression statistical techniques and several years of crash data (AASHTO, 2010). The Poisson distribution is used in cases where the data's mean and variance are equal. However, for crash data, the variance usually exceeds the mean. This data is called over-dispersed data, so the NB distribution is used since this distribution is suited to modeling over-dispersed data. The overdispersion parameter, which is estimated along with the regression function, is used to determine the value of the weighting factor used in the EB method (see equation 2-3 in previous section). This parameter represents the degree of overdispersion (larger values represent higher variations in the data). An example base SPF for a 3-leg stop-controlled intersection on a rural two-lane, two-way road which is included in the HSM is shown in equation 2-4 (AASHTO, 2010).

Table 2-1: Roadway Segment and Intersection Types with SPFs in HSM (HSM Exhibit 3-9) (AASHTO, 2010)

HSM Chapter	Undivided Roadway Segments	Divided Roadway Segments	Intersections			
			Stop Control on Minor Leg(s)		Signalized	
			3-Leg	4-Leg	3-Leg	4-Leg
10 – Rural Two-Lane Roads	✓	–	✓	✓	–	✓
11 – Rural Multilane Highways	✓	✓	✓	✓	–	✓
12 – Urban and Suburban Arterial Highways	✓	✓	✓	✓	✓	✓

$$N_{spf\ 3ST} = \exp\left[-9.86 + 0.79\ln(AADT_{maj}) + 0.49\ln(AADT_{min})\right] \qquad (2\text{-}4)$$

As shown in equation 2-1 in the previous section, CMFs are also used to determine the predicted crash frequency. CMFs estimate the effect (change in crashes) of various geometric design or roadway features. These CMFs are decimal values that represent how a certain condition is expected to affect the predicted crash frequency. Conditions which are expected to reduce crashes have values less than 1, while conditions which are expected to increase crashes have values greater than 1. The relationships between a CMF and the expected percent change in crash frequency is shown in equations 2-5 (for CMFs less than or equal to 1) and 2-6 (for CMFs greater than 1) (AASHTO, 2010).

Percent Reduction in Crash Frequency = 100 × (1.00 - CMF) (2-5)
Percent Increase in Crash Frequency = 100 × (CMF - 1.00) (2-6)

In the HSM, it is assumed that each CMF is independent, meaning that the combined effects of different CMFs can be estimated by multiplying these CMFs together (AASHTO, 2010). However, this assumed independence does not always exist. In some cases, different conditions could have similar effects on crash frequency, making it possible to overestimate the effect of the combined conditions when the CMFs are multiplied. For example, deploying two different treatments, each with an CMF of 0.8 (20% crash reduction), suggests a combined crash reduction of 100 x [1 - (0.8 x 0.8)] = 36%, but the actual crash reduction could be closer to 20% since most of the benefits of one treatment could have been realized by the other. As there is a lack of research on ways to address the independence of CMFs' elements, users should practice engineering judgement to assess the relationship between different treatments. To account for potential variations in CMFs due to combined treatments or other factors, some CMFs in the HSM include a standard error and confidence interval, indicating the variability of the CMF estimation in relation to sample data values. Confidence intervals for CMFs can be calculated using equation 2-7 and the values shown in table 2-2 (AASHTO, 2010).

$$CI(y\%) = CMF_x \pm SE_x * MSE \qquad (2\text{-}7)$$

Where:
$CI(y\%)$ = the confidence interval for which it is y-percent probable that the true value of the CMF is within the interval;
CMF_x = CMF for condition x;
SE_x = standard error of the CMF_x; and
MSE = multiple of standard error (shown in table 2-2 below).

Table 2-2: MSE Values for Determining Confidence Intervals (HSM Exhibit 3-10) (AASHTO, 2010)

Desired Level of Confidence	**Confidence Interval (Probability that the True Value is Within the Confidence Interval)**	**Multiples of Standard Error (MSE) to Use in Equation 2-7**
Low	65-70%	1
Medium	95%	2
High	99.9%	3

CMF values are provided in the HSM for a specified set of conditions. These values are either presented in the text of the HSM (when there are limited options for a specific treatment), in a formula (when the treatment options are continuous variables), or in tabular form (when the CMF values vary by facility type) (AASHTO, 2010). As an example, table 2-3 shows CMFs for lane width from HSM; these CMFs vary based on lane width and AADT.

Table 2-3: CMFs for Lane Width on Roadway Segments (HSM Exhibit 10-14) (AASHTO, 2010)

Lane Width	**AADT (veh/day)**		
	< 400	**400 to 2000**	**> 2000**
9-ft or less	1.05	$1.05 + 2.81 \times 10^{-4}$(AADT-400)	1.50
10-ft	1.02	$1.02 + 1.75 \times 10^{-4}$(AADT-400)	1.30
11-ft	1.01	$1.01 + 2.5 \times 10^{-5}$(AADT-400)	1.05
12-ft or more	1.00	1.00	1.00

It is important to note that the SPFs developed in the HSM were developed using data from specific states. Since crash frequencies can vary greatly from one jurisdiction to another, the default HSM SPFs might not be reliable for all locations. Therefore, calibration factors are introduced to adjust the HSM SPFs and reflect differences in crash frequencies (AASHTO, 2010).

The calibration procedure is divided into five steps: identifying facility types which require calibration, selecting sites, obtaining data, applying the predictive method for each site, and computing the calibration factor (C_r) per facility type using equation 2-8 (AASHTO, 2010).

$$C_r = \frac{\sum all\ sites\ observed\ crashes}{\sum all\ sites\ predicted\ crashes} \tag{2-8}$$

Calibration factors are greater than 1.0 for intersections that belong to a specific facility type which experience more crashes than the intersections used in developing the HSM SPFs and less than 1.0 for intersections that belong to a specific facility type which experience fewer crashes than those used in developing the HSM SPFs (AASHTO, 2010).

2.1.4 HSM Predictive Method Procedure and Limitations

To help agencies apply the HSM predictive method, the HSM contains an "18-step procedure to estimate the expected average crash frequency (by total crashes, crash severity or collision type) of a roadway network, facility, or site" (AASHTO, 2010). The details of each step are explained thoroughly in the HSM (AASHTO, 2010). While the HSM predictive method can help agencies predict crashes and evaluate various treatments, it does have its limitations. One major limitation is that it does not consider all potential geometric designs and traffic control features which might be of interest. If a CMF is not present in the HSM, it does not mean that the factor has no effect on crashes, but rather that the effect of that factor is unknown or has not yet been considered (AASHTO, 2010). Additionally, the HSM only provides SPFs for ten different intersection types, so there could be a lot of variation amongst intersections in the same group due to different area types that are not differentiated in the HSM.

Another limitation is that driver population and characteristics vary from site to site. The predictive method accounts for the statewide influence of these characteristics by utilizing calibration factors, but does not account for site-specific variations in these characteristics (AASHTO, 2010). It also does not account for weather, daily traffic variations, or the proportions of trucks or motorcycles, as well as potential interactions between influential variables (independence of CMFs assumption discussed previously). Solutions to some of these limitations have been examined in previous research studies (as discussed in section 2.2).

2.2 Studies Which Modified the HSM's SPFs or Developed Jurisdiction-Specific SPFs

The SPFs provided in the HSM can be a good starting point for agencies to predict crashes. However, in order to improve the accuracy of the SPF, modifications can be made to the SPFs based on characteristics specific to the area being studied. This section discusses the approaches used in previous research studies to achieve more accurate SPFs than the SPFs introduced in HSM. These research studies focused on two main approaches: modifying the HSM's SPFs, CMFs, and/or calibration factors; and developing jurisdiction-specific SPFs using alternative modeling techniques to the HSM. Each of these two approaches are discussed in the following subsections.

2.2.1 Modification of the Highway Safety Manual's Safety Performance Functions

One of the major approaches explored in past research to improve the SPFs developed by HSM is to modify the SPFs developed in HSM. This approach involves using CMFs based on local data and/or calculating various calibration factors to use in the SPFs. Studies on this approach still use similar modeling techniques and procedures to the HSM. However, these modifications allow for area types or factors not considered in HSM procedures to be included in the SPFs and can make the SPFs more representative of the study area. Additionally, most of these studies compare the results from their modified SPFs to the default SPFs in HSM to show how these modified SPFs are more accurate.

The city of Edmonton, Alberta, Canada, used HSM predictive methods to assess the safety risks of different proposed complete streets designs. Complete streets is a concept created 35 years ago in order to ensure the safety of all road users and to promote equitable multimodal transportation systems that are effectively integrated with land use developments. In this study, a total of 63 design drafts were proposed and safety indices were computed for each design and compared to alternate options (Barua, El-Basyouny, Islam, & Gargoum, 2014). There were multiple challenges when using the HSM predictive methods in this context. One issue was the lack of baseline models in the HSM for certain site types and roadway categories. Another issue was the lack of appropriate CMFs for some geometric roadway features and the inaccuracy of CMFs due to regional differences. As a whole, the city of Edmonton faced issues using solely HSM calibration data to compare the proposed designs and the involved parties hope that future research will enhance the scope of usability of the HSM (Barua et al., 2014). By developing area-specific SPFs, it is believed that agencies will be better equipped to compare designs of complete streets and more urban conscious spaces.

A good source for finding additional CMFs that are not present in the HSM is the CMF Clearinghouse (University of North Carolina Highway Safety Research Center). This online database contains over 5000 CMFs for various engineering applications. It can be difficult to develop new CMFs, as this requires a significant amount of data and effort compared to using CMFs from the CMF Clearinghouse or developing calibration factors. Therefore, most state DOTs have chosen to calibrate the C_x parameter of equation 2-1, while few state DOTs have developed SPFs based on their own regional data (Xie & Chen, 2016).

A study conducted in Riyadh, Saudi Arabia, compared using HSM default CMFs to using new local CMFs based on fatal and injury crash data (Kaaf & Abdel-Aty, 2015). Roadway segments were randomly chosen and crash counts were collected for these selected segments (Kaaf & Abdel-Aty, 2015). The predicted crashes were then estimated using the SPFs and CMFs provided in the HSM. A calibration factor was then calculated using equation 2-8 provided in section 2.1.3. The calibrated SPFs were then compared to the SPFs developed using the local CMFs. The performance measures used to compare both models were mean absolute deviation (MAD), mean squared prediction error (MSPE), mean prediction bias (MPB), and Bayesian information criterion (BIC). The values for the total fatality and injury (F+I) calibration factors were significantly lower than 1.00 using both default and local CMFs. This indicates that the HSM SPFs overestimated the average crash frequencies in Riyadh (Kaaf & Abdel-Aty, 2015). The results suggest that the SPFs developed using local CMFs for Riyadh outperformed the SPFs using HSM default values for this type of facility. However, since both approaches overestimated the SPFs, the paper developed its own jurisdiction-specific model. This developed SPF model was found to outperform the two previous calibrated models. Therefore, the relationship between crashes and roadway characteristics in Riyadh seems to be different than the assumed relationship in the HSM (Kaaf & Abdel-Aty, 2015).

Another study conducted in Regina, Canada, used five years of collision data and fit several NB regression models for three intersection types; 3-leg unsignalized, 4-leg unsignalized, and 3- and 4-leg signalized (Young & Park, 2012). Calibration factors were then calculated and applied to the default HSM SPFs to model the same data (Young & Park, 2012). Statistical goodness of fit tests were used to determine the best-fitting SPFs for the study region (Young & Park, 2012).

The results showed that for the 3- and 4-leg signalized intersections, the average calibration factors for total collisions and property damage only (PDO) collisions were 2.25 and 2.79, respectively. Therefore, if the HSM SPFs predicted 200 total collisions and 100 PDO collisions, the actual values would be 200 x 2.25 = 450 total collisions and 2.79 x 100 = 279 PDO collisions. This means the HSM SPFs predict (450-200)/450 = 56% fewer total collisions and (279-100)/279 = 64% fewer PDO collisions than what was actually observed during the five-year study period in the city of Regina (Young & Park, 2012). Results also indicated that jurisdiction-specific SPFs were more accurate in predicting crashes at 3- and 4-legged intersections in Regina (Young & Park, 2012).

In Florida, a study was conducted to compare locally calibrated SPFs with default HSM SPFs. Four years of crash data and NB regression were used to develop these SPFs (Lu, 2013). The results indicated that calibrating the HSM SPFs using Florida-specific calibration factors resulted in a better-fitting model than using HSM default values. The tests used to compare the models were Freeman-Tukey R-square and lower MAD and MSPE estimates (Lu, 2013).

In Michigan, SPFs were developed for signalized and unsignalized intersections located on urban and suburban arterials. Databases were developed to integrate traffic crash data, traffic volumes, and roadway geometry data (Savolainen et al., 2015). The default HSM SPFs and state-specific calibrated models were used to model general crash trends. Like previous studies, it was found that the calibrated HSM results were considerably different than the base HSM equation results in terms of the goodness-of-fit across various site types (Savolainen et al., 2015). The Michigan-specific SPFs were estimated by first developing simple models that only considered AADT, similar to the default HSM SPFs. Additional models considering geometric and other factors were then developed. Some of the considered factors included "posted speed limits, number of lanes, presence of medians, intersection lighting, and right-turn-on-red prohibition" (Savolainen et al., 2015). Severity distribution functions (SDFs) were also estimated; these models can be used to estimate crash severity. SDFs include various geometric, operational, and traffic variables that allow them to be applied to individual intersections. Developing these state-specific SPFs and SDFs provides Michigan with highly useful, hyper-calibrated, methodological tools that will allow for efficient planning activity in all seven of Michigan DOT's geographic regions. They also have procedures in place for maintaining and calibrating these SPFs over time (Savolainen et al., 2015).

In 2016, the Pima Association of Governments (PAG) region of Arizona sought to reduce crashes amongst all transportation modes in this rapidly growing region. The crash rate for the PAG region was 7.52 crashes (both incapacitating and fatal crashes) per 100 million vehicle miles traveled (VMT), which was higher than the Arizona statewide average of 7.41 per 100 million VMT. To reduce this crash rate, "SPFs were used to identify locations with safety performance that were better or worse than a typical location based on crash experience, roadway facility characteristics, and average annual daily traffic" (Amec Foster Wheeler, 2016). These SPFs were developed and used to compare segments based on setting (rural vs. urban), number of lanes (2 lanes vs. more than 2 lanes), and presence of median (median vs. no median). Priority ranking tables were developed using 2009-2013 crash data for both urban and rural segments. SPFs were also developed for 3-leg signalized and 4-leg signalized intersections to provide a more sophisticated analysis method than relying solely on priority rankings (Amec Foster Wheeler, 2016).

Instead of using HSM calibration values, some agencies choose to calibrate their state-specific SPFs with SafetyAnalyst or another similar software. SafetyAnalyst is a software package developed by the Federal Highway Administration (FHWA) and multiple state and local agencies which uses HSM procedures to analyze safety (http://www.safetyanalyst.org/). Virginia DOT used SafetyAnalyst to calibrate valid SPFs using appropriate data from the state. However, SafetyAnalyst user's manual suggests four SPFs for two-lane segments which were developed with data from Ohio (Garber, Haas, & Gosse, 2010). A comparative analysis using Freeman-Tukey R^2 coefficient was conducted between the Ohio SPFs suggested in the SafetyAnalyst user's manual and the ones developed specifically for Virginia (Garber et al., 2010). AADT was used as the most significant factor for crashes. Due to the variance in topography in Virginia, three different SPF calibration factors were developed for the state of Virginia (Garber et al., 2010).

Similarly, Florida has utilized SafetyAnalyst, which includes a set of default SPFs with calibration factors, in order to better model the state's safety performance. In this study, Florida-specific SPFs were developed using data from the 2008 roadway characteristics inventory (RCI), as well as fatal and injury crash data and traffic data from 2007-2010 (Lu, 2013). The data were randomly divided so that 70% of the data was used for calibration and 30% of the data was used for validation (Lu, 2013). An NB model was fit on the calibration data to develop Florida-specific SPFs for each type of roadway segment (Lu, 2013). The results of statistical goodness-of-fit tests were validated using the validation data set and then the transferability of the Florida specific SPFs was accessed by comparing the results (Lu, 2013). Local calibration factors were then used to calibrate the default SafetyAnalyst SPFs to Florida data. Comparing these two methods indicated that Florida-specific SPFs outperformed the national default SPFs calibrated to Florida data in terms of prediction accuracy (Lu, 2013). The empirical results support the usage of flow-only SPF models adopted in SafetyAnalyst since they require far less effort to develop compared to full SPFs (Lu, 2013).

The previously mentioned studies addressed modifying HSM's SPFs by using CMFs and calibration factors. However, it is also important to understand the required sample sizes needed to develop accurate SPFs. The HSM recommends a minimum of 30 to 50 sites for any facility type, with each site having at least 100 crashes per year (Shirazi, Lord, & Geedipally, 2016). However, documented studies conducted in Texas tested simulation runs for multiple scenarios with different sample means and variance of the data (Shirazi et al., 2016). The results indicated that as the coefficient of variation of the crash data increases, a sample larger than the HSM recommendations is required to obtain accurate results (Shirazi et al., 2016).

A study was conducted to determine calibration factors for Oregon DOT. This required collecting crash and explanatory data from intersections. Sample sizes ranging from 25 to 200 intersections were used (Dixon et al., 2015). Three years of historical crash frequency data were used to determine the calibration factors. This study suggested that the intersections selected to determine these factors do not need to satisfy the base conditions defined in the HSM and that it is actually more beneficial to use intersections that do not satisfy HSM's base condition when estimating calibration factors (Dixon et al., 2015).

2.2.2 Development of Jurisdiction-Specific Safety Performance Functions

The second approach used by agencies to develop more accurate SPFs is to develop jurisdiction-specific SPFs. The HSM indicates that jurisdiction-specific SPFs "are likely to enhance the reliability of the predictive method" (AASHTO, 2010). They also allow agencies to examine alternative functional forms rather than using the default forms in the HSM and SafetyAnalyst (Srinivasan & Bauer, 2013). A study was conducted which explored fixed- and random-parameter count data models for SPFs, which account for unobserved heterogeneity, and compared them with calibrated and uncalibrated HSM SPFs (Wali, Khattak, Waters, Chimba, & Li, 2018). Crash, traffic and roadway data were collected for two-way, two-lane roads in Tennessee for a five-year period. The calibrated and uncalibrated HSM SPFs were then compared based on prediction accuracy with eight Tennessee-specific SPFs and the results showed the statewide calibration factor was 2.48. This indicates that crashes on rural two-lane, two-way road segments are much more frequent than what HSM SPF predicts and highlights the importance of taking into account unobserved heterogeneity when developing SPFs (Wali et al., 2018). If data are available, it is recommended that agencies develop their own jurisdiction-specific SPFs since they represent the agency's data better than default or calibrated HSM SPFs (Lu, 2013). These jurisdiction-specific SPFs are especially important for agencies in states that experience relatively different crash trends and characteristics than states which had data used in developing the default SPFs (Lu,2013).

PennDOT used the HSM procedures to develop state-specific SPFs which were calibrated by region or district depending on the facility type (Scopatz & Smith, 2016). Critical to their success was the selection of state-relevant CMFs, taken from the CMF Clearinghouse (Scopatz & Smith, 2016). A team of staff members in this project dedicated themselves to reviewing each individual CMF in the CMF Clearinghouse to determine if it was applicable to Pennsylvania. Through consistency in their selection, they were able to come up with parameters and a "Pennsylvania CMF Guide" that includes their selection criteria (Scopatz & Smith, 2016). PennDOT opted to develop region-specific SPFs for two-lane roads after realizing that the statewide SPF was not reliable. As of 2016, PennDOT had developed state-specific SPFs with district-level and county-level calibration factors for rural two-lane and multi-lane roads, urban and suburban arterials, and 18 different intersection types (Scopatz & Smith, 2016).

Various other modeling methodologies have also been explored to improve the SPFs developed by HSM. Previous research has compared existing practices (such as Poisson and NB) with other methodologies such as generalized estimating equations, multilevel, probit, and logit modeling (Dixon et al., 2015). Generalized NB models were shown to rank some sites more hazardous compared to the traditional NB model, but they might not be suitable for EB methods (Lord & Park, 2008). Other comparisons included fitting a bivariate generalized ordered probit (BGOP) and a bivariate ordered probit (BOP) model to two-vehicle crashes at signalized intersections (Chiou, Hwang, Chang, & Fu, 2013). The BGOP was found to more accurately predict crash severity compared to the BOP (Chiou et al., 2013). A study in Toronto, Canada, compared generalized linear models (GLMs) to generalized additive models (GAMs) based on crash data from 59 signalized intersections (Xie & Zhang, 2008). The results indicated that

GAMs offered useful nonlinear modeling techniques compared to GLMs and were also able to generate statistically interpretable results (Xie & Zhang, 2008). To account for correlation in repeated observations, Wang and Abdel-Aty (2007) used generalized estimating equations. Another method that was analyzed was the use of logit models. Random parameter logit models were compared with fixed parameter logit models (Anastasopoulos & Mannering, 2011). The fixed parameters model performed better in predicting crash severity than the random parameters models (Anastasopoulos & Mannering, 2011). A Bayesian hierarchical approach was used to account for the multilevel structure of crash data. The results indicated that Bayesian hierarchical methods can account for heterogeneity between groups, which is important in crash prediction models (Huang, Chin, & Haque, 2008).

Additionally, some recent studies have also tried to address the problems associated with the significant amounts of zeros that can sometimes be present in crash data. In these situations, zero-inflated models and hurdle models have an advantage over conventional GLMs because they can handle data characterized by an excessive number of zeros (Basu & Saha, 2017). Zero-inflated models use a separate process which models the excess zeros independently from the count values (Srinivasan & Bauer, 2013). A study conducted in Malaysia on five years of road accidents showed that zero-inflated negative binomial (ZINB) models performed better than Poisson and NB models based on a lower Akaike information criterion (AIC) value (Prasetijo et al., 2019). Another study of pedestrian-vehicle crashes compared hurdle models to Poisson and NB models and showed that hurdle models outperformed the other models (Shiyuka, 2018). As opposed to the zero inflated Poisson (ZIP) and ZINB approaches, the hurdle model does not assume that the zeros for crash data indicate “safe” conditions or “crash-free” roads; instead, it implies that all segments have crash potential (Shiyuka, 2018). The approach suggested by the hurdle model is to use a logit model to distinguish counts of zeros from large counts, and then using a truncated Poisson model (where zero has been excluded) for the positive counts (Shiyuka, 2018).

The use of boosted regression trees (BRTs) is another modeling technique that could improve SPFs. Compared to traditional GLMs, BRT models can better handle nonlinear data and interaction terms. A study conducted in Alabama compared BRT models to GLM models for 3-leg and 4-leg unsignalized intersections using data collected for 36 safety variables (Wang et al., 2016). Cross validation was used to compare the prediction performance between BRT and GLM models and the results showed that BRT models significantly outperformed the GLM models in predicting crashes for the studied intersections (Wang et al., 2016). One drawback of using BRTs is that they lack a functional form, which makes it difficult to determine the relationship between influential factors and crash frequency. Even without this functional form, SPFs developed using BRTs can still be used for network screening purposes to identify intersections with high crash potential. BRTs could also be used to identify the important variables that local agencies should focus their data collection efforts on, allowing them to save time and money by not collecting data for insignificant variables.

2.3 Summary of Previous Research Findings

The research discussed in this chapter shows that there are many ways to improve the SPFs developed by HSM. These SPFs were only developed for three facility types and specific site types for each facility. Additionally, the HSM’s SPFs were developed using only data from specific states, meaning the results might not be accurate for all states. Some states opted to develop calibration factors and/or their own jurisdiction-specific SPFs to improve the accuracy of these crash prediction models. Most studies used NB models to develop SPFs due to their ability to model over-dispersed data. Alternative models, such as generalized NB, probit, and logit models were also studied as methods to develop SPFs due to their ability to handle the limitations of the NB model (Gamaleldin et al., 2020). Once SPFs were developed using jurisdiction-specific data, these SPFs were often compared to SPFs developed by HSM (either calibrated or uncalibrated). Comparisons were made using several goodness-of-fit statistics, including Freeman-Tukey R^2 coefficient, lower mean absolute deviance, and mean square prediction error estimates. The jurisdiction-specific SPFs often performed much better than the calibrated HSM SPFs, allowing for more accurate determination of geometric, traffic, and other characteristics that influence crashes.

To determine and understand these influencing characteristics when developing the new jurisdiction-specific SPFs, a parameter's coefficient estimate should be assessed based on its magnitude and direction as well as its statistical significance to determine if it should be included in the model and whether it makes sense. For example, if a developed model contains a negative coefficient for the AADT, this model might not have been developed properly, as it indicates that crashes decrease as AADT increases (AASHTO, n.d.). In general, a significance level of 10% is generally used to assess coefficient estimates for AADT on the major road of intersections. For minor road AADT at intersections, a significance level of 20% is usually used (AASHTO, n.d.). The estimate of the dispersion parameter should always be a positive value. If the modeling results give a negative value for the dispersion parameter, this is a good indication that there are problems with the model, even if there are no warnings or errors issued by the statistical software used (AASHTO, n.d.). However, if the value of the dispersion parameter is close to zero, then the model should be remodeled assuming a Poisson distribution (AASHTO, n.d.).

Previous research also suggests that it is a good practice to recalibrate the models after a period of time using data from recent years (Persaud and Lyon, Inc., & Felsburg Holt & Ullevig, 2009). Expected crash frequencies can change over time due to various changes, including changes in reporting practices, demographics, and state-wide safety programs (Persaud and Lyon, Inc., & Felsburg Holt & Ullevig, 2009). Additionally, it could be desirable to recalibrate SPFs for intersection categories for which the SPFs were not originally developed (Persaud and Lyon, Inc., & Felsburg Holt & Ullevig, 2009). When recalibrating SPFs, minimum sample sizes of 30 to 50 sites of the same type and at least 100 observed crashes per year are recommended. However, if the coefficient of variation of the crash data increases, a larger sample is required to obtain accurate results.

This project considers these potential improvements when developing context-specific SPFs. No previous research considered additional roadway categories beyond those listed in the HSM. Using these additional categories allows the developed SPFs to be more accurate and specific to Florida intersections. Utilizing and comparing multiple modeling techniques helps ensure that the best model is selected for each SPF. Comparing the developed context-specific SPFs to base and calibrated HSM SPFs will show the additional insights and improved performance of the context-specific SPFs.

Chapter 3: State DOT Survey Design, Implementation, and Results

To understand the methodologies and opinions of other states regarding SPF development and context classification, a state DOT SPF current practices survey was designed. This online survey was developed by the UCF research team with input from FDOT. Appendix A contains the final version of the survey which was approved by FDOT. The survey contained 16 multiple choice and open-ended questions, but not every respondent answered every question due to the branching nature of the survey. Appendix B shows the various survey paths possible depending on the answer choices selected for certain questions. As shown in this flow chart, the longest possible survey path was ten questions (excluding the participation question) and the shortest possible survey path was five questions. The survey was programmed online by a third-party vendor and extensively tested before it was launched on July 2, 2019.

Once launched, a link to the survey and message describing the survey and overall project were e-mailed to contacts from 51 DOTs (all 50 states plus District of Columbia). These contacts were primarily sourced from two lists of safety engineers: one provided by FDOT and one from FHWA. Additionally, state DOT websites were utilized for states where a listed engineer was not provided, or the contact information was outdated. Some of the contacted engineers forwarded the survey link to other individuals within their agency who were better suited to answer the survey questions. When the survey link was closed on May 20, 2020, state DOT safety engineers or similar professionals (such as state traffic engineers or research coordinators) from the following 42 states had completed the survey:

- Northeast: Connecticut, Maine, Massachusetts, New Hampshire, New York, Pennsylvania, Rhode Island, Vermont
- Midwest: Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, Wisconsin
- South: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia
- West: Alaska, California, Colorado, Idaho, New Mexico, Oregon, Utah, Wyoming

The remaining sections of this chapter discuss the responses to each survey question collected from these 42 states. Section 3.1 discusses the initial questions asked to all respondents (Q1, Q2, and Q3 of the flow chart in appendix B), section 3.2 discusses questions specifically for states which use a non-HSM methodology to develop SPFs (Q4, Q5, and Q6), section 3.3 discusses questions specifically for states which do not develop SPFs (Q7 and Q8), section 3.4 discusses questions for states which do not currently use a context classification system (Q9, Q10, Q11, Q12, and Q13), and section 3.5 discusses questions for states which currently use a context classification or similar system (Q14, Q15, and Q16). Summary of the survey results is given in section 3.6. Summary tables for all of the multiple-choice questions, along with charts for select questions, are shown in appendix C.

3.1 Initial Questions

The initial questions of the survey (Q1, Q2, and Q3) were asked to all 42 survey respondents. These questions asked about the survey respondent's contact information (name, title agency, phone number, and email), their awareness of context classification, and how their state develops SPFs. Based on the response to this third question, respondents were directed to different sections of the survey as shown in appendix B. The contact information provided in Q1 was used to confirm which agencies completed the survey and ensure that follow-up emails were not sent to these agencies. After providing this contact information, respondents were provided with a description of the FDOT context classification system, along with the image shown in figure 3-1 below. In the actual survey, respondents were able to zoom in to see the image and easily read the descriptions of each context classification category. Only 16 of the 42 respondents (38%) had heard about Florida or other states using a context classification system to develop SPFs; the other 26 respondents (62%) had not heard of such a system. Figure 3-2 shows specific state responses to this question.

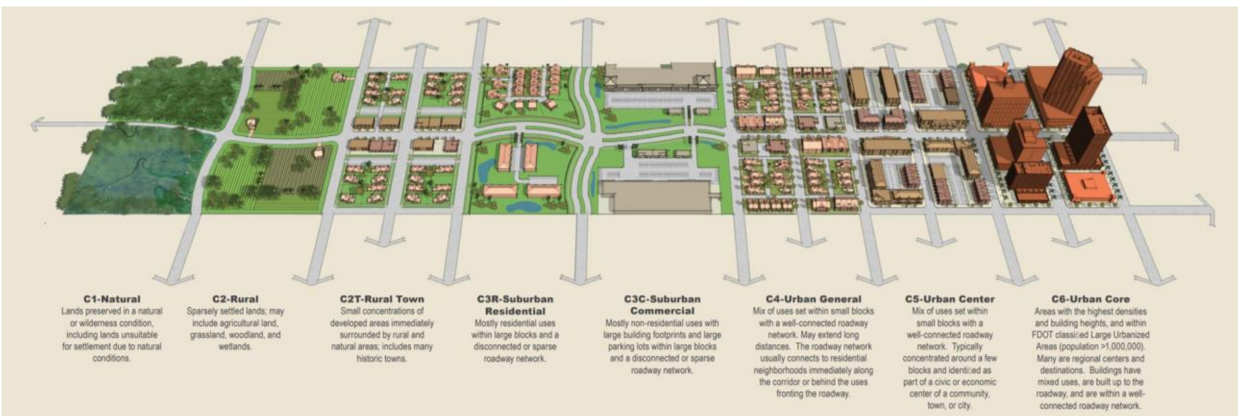

Figure 3-1: FDOT Context Classification Zones (FDOT, 2017)

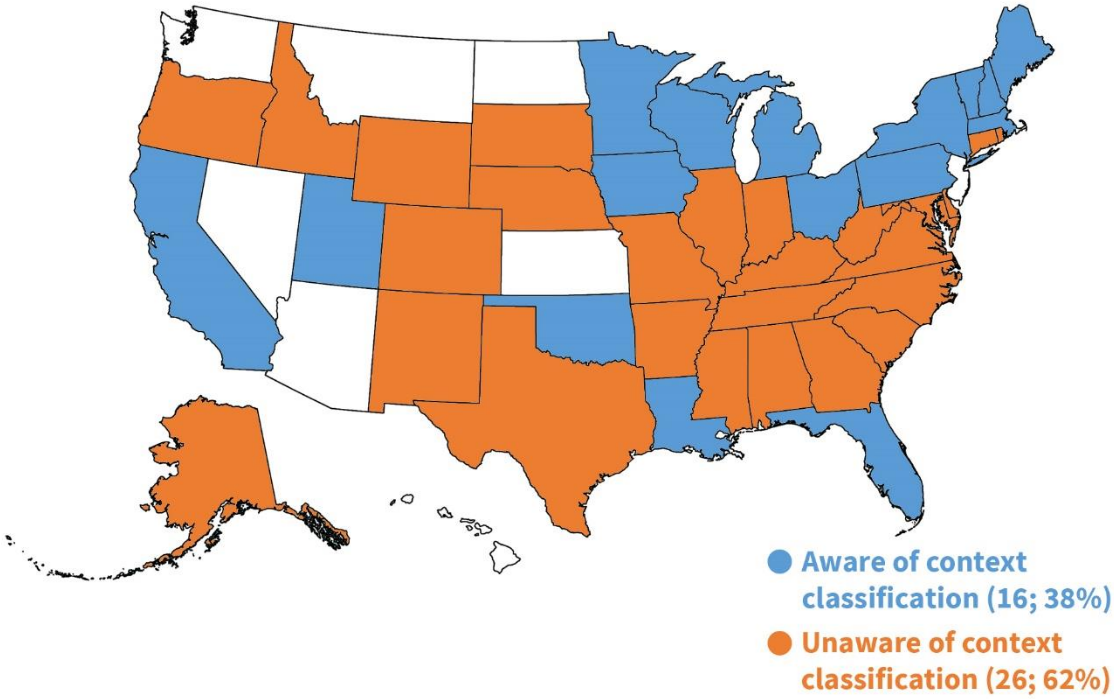

Figure 3-2: State DOT Knowledge of Using Context Classification for SPF Development

The last question in this section asked respondents how their agency currently develops SPFs for intersections. Five answer choices were provided, with all respondents choosing the answer which best corresponded to their agency's SPF development methodology. Nine respondents (21%) use the default SPFs provided in the HSM without modification, 18 (43%) use the HSM methodology to develop jurisdiction-specific SPFs using calibration factors, six (14%) use a non-HSM methodology developed by their own agency, one (2%) uses a non-HSM methodology developed by another agency, and eight (19%) do not develop SPFs for intersections at all. Specific state responses to this question are shown in figure 3-3. Based on these responses, the seven respondents from the yellow and purple states in figure 3-3 were directed to Q4, the eight respondents from the green states in figure 3-3 were directed to Q7, and the 27 respondents from the blue and orange states in figure 3-3 were directed to Q9.

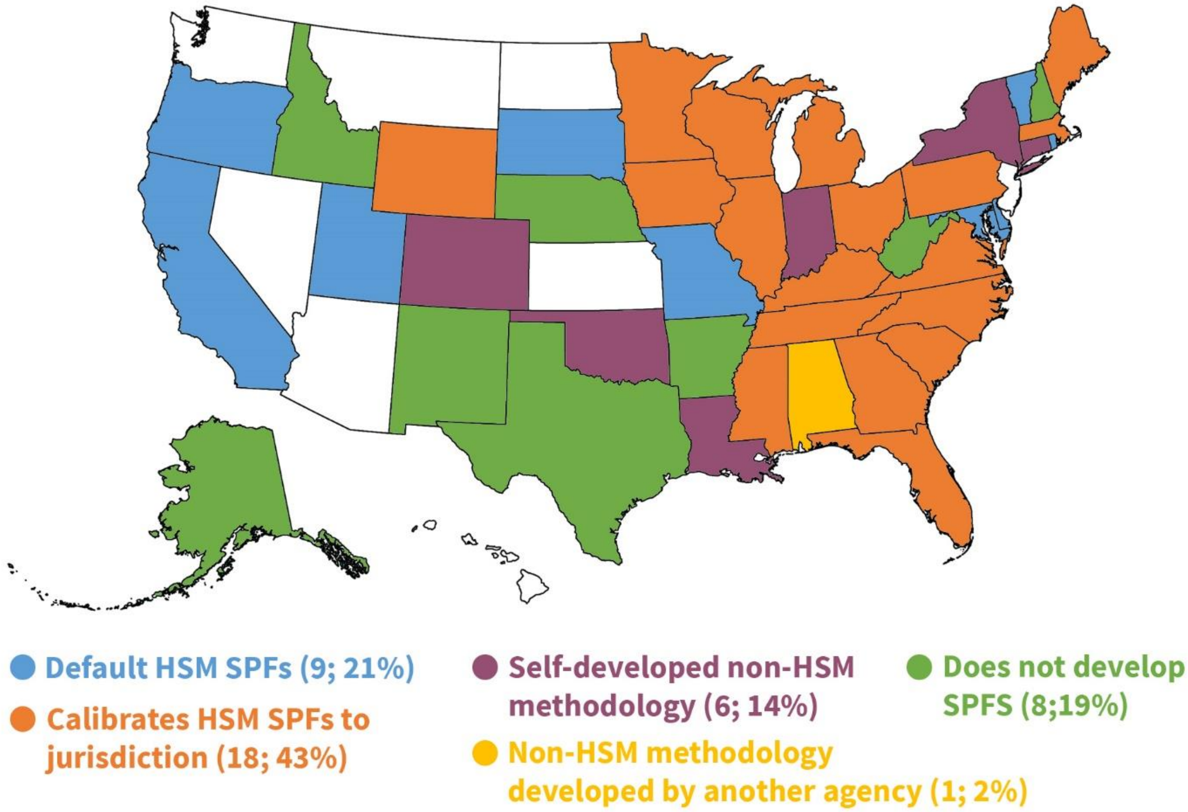

Figure 3-3: Intersection SPF Development of 42 State DOTs

3.2 Questions for States Which Use Non-HSM Methodology

The seven respondents from states which use a non-HSM methodology (yellow and purple states in figure 3-3) were next asked why their state uses a non-HSM methodology to develop their SPFs. Multiple answer choices were provided, with respondents able to select all answer choices that applied. Zero respondents said that the HSM procedures were not rigorous enough, two respondents said the HSM procedures were insufficient, two respondents said their state had specific requirements that the HSM did not account for, and three respondents said that other methods provided more accurate results. Additionally, four respondents specified other reasons why they use a non-HSM method, with the most notable response stating that both planning- and project-level SPFs were needed. Next, these seven respondents were asked if their state uses a system like the FDOT context classification system to develop SPFs. Only the respondent from Oklahoma answered “Yes” to this question, so this respondent was directed to Q14 (discussed in section 3.5). The six respondents who answered “No” were then asked to describe the non-HSM methodology their state uses to develop SPFs. Analysis of the responses to this free-response question showed that these states generally use another form of classification that primarily relies on roadway characteristics, such as functional class of the road, lane count, and whether it is in a rural or urban setting. These six respondents were then directed to Q9 (discussed in section 3.4).

3.3 Questions for States Which Do Not Use SPFs

This section contained questions answered by the eight respondents from states which do not develop SPFs (shown in green in figure 3-3). Respondents were first asked to describe why their state does not use SPFs for intersections. Five respondents answered that their states either lack the resources or the data to accurately create or use SPFs. Two respondents stated that their states are working on developing their SPFs and currently do not use them since they are early in development. The last respondent stated that their state only uses SPFs for network screening. Respondents were next asked if they plan on developing SPFs in the future, of which two answered "No" and the remaining six answered that they plan to use the HSM methodology or a similar approach. No respondent in this section expressed an interest in using a similar approach to the FDOT context classification system. The survey ended for the two respondents who answered "No", while the other six respondents continued to Q10 (discussed in the next section).

3.4 Questions for States Which Do Not Use Context Classification to Develop SPFs

The questions in this section of the survey were asked to respondents who previously said that their state does not use context classification or a similar method. The first question in this section (Q9) was asked to the 27 respondents from the blue and orange states in figure 3-3 who use HSM SPFs or the HSM methodology, along with the six respondents from the purple and yellow states in figure 3-3 (excluding Oklahoma) who use non-HSM methodologies, but do not use a context classification system. These 33 respondents were asked if their state is investigating ways to improve their SPFs; 19 respondents (58%) said "Yes" and 14 respondents (42%) said "No." The 19 respondents who said "Yes" elaborated on what improvements their state is working on, with many focusing on developing/improving calibration factors or finding the optimal ways to segment roadways to get the most accurate SPFs. There were a few notable responses that indicated some states are looking at new data and innovative methods to develop SPFs. Connecticut is planning to use driver and vehicle information, driveway density, and minor roads without AADT in developing SPFs; Louisiana plans to include crash collision manner information in their models; and Virginia is studying the use of artificial intelligence and neural networks to automatically scan roadways to collect data. These responses could help FDOT improve their data collection practices and SPF development and could be researched in a future project.

The next question (Q10) asked respondents if their state has an interest in using context classification to develop SPFs. This question was asked to the 33 respondents who answered Q9, plus the six respondents whose states do not currently develop or use SPFs but plan to develop SPFs in the future using the HSM methodology. Out of these 39 respondents, 26 respondents (67%) expressed an interest in eventually using a system like context classification (individual state responses are shown in figure 3-4). The 13 respondents who did not express an interest in using context classification were then asked why they were not interested in this type of system (Q11). Analysis of these responses showed that common reasons for respondents not being interested in context classification included insufficient evidence of using this system over the current HSM methodology; they are busy developing their own SPFs using HSM or their own methods; issues with unreliable, missing, or unorganized data; and fear that the complexity of rolling out a new system could intimidate their local agencies and prevent widespread adoption. The survey ended for these 13 respondents after completing this question.

Additionally, the survey ended for the five respondents from the states which do not currently develop SPFs who answered "Yes" to Q10.

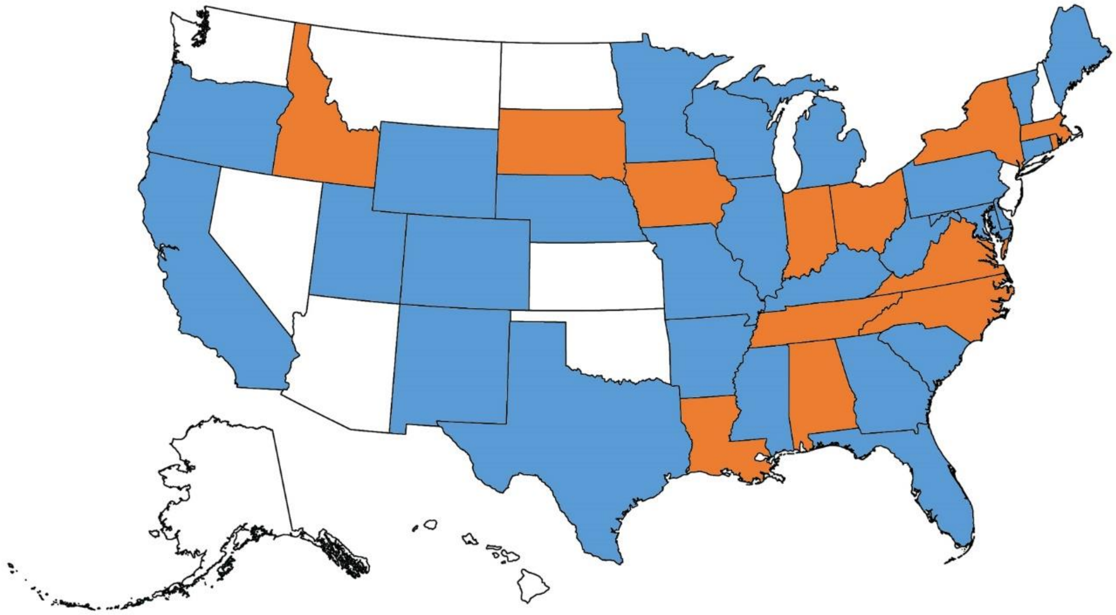

Figure 3-4: State DOT Survey Respondents' Interest in Using Context Classification for SPF Development

The remaining 21 respondents were then asked if their state had any plans to implement context classification (Q12), of which 13 respondents (62%) answered "No." The survey ended for these thirteen respondents, while the eight respondents who answered "Yes" were then asked to explain what kind of system they planned on implementing (Q13). These eight states are shown in blue in figure 3-5 along with Oklahoma (shown in orange), which has already implemented such a system. One notable response was from Pennsylvania's respondent, who stated that Pennsylvania is breaking down SPFs into individual engineering districts and counties. Other respondents noted that their states are studying the use of functional classification or simple context zones to develop SPFs. This was the last survey question for these eight respondents.

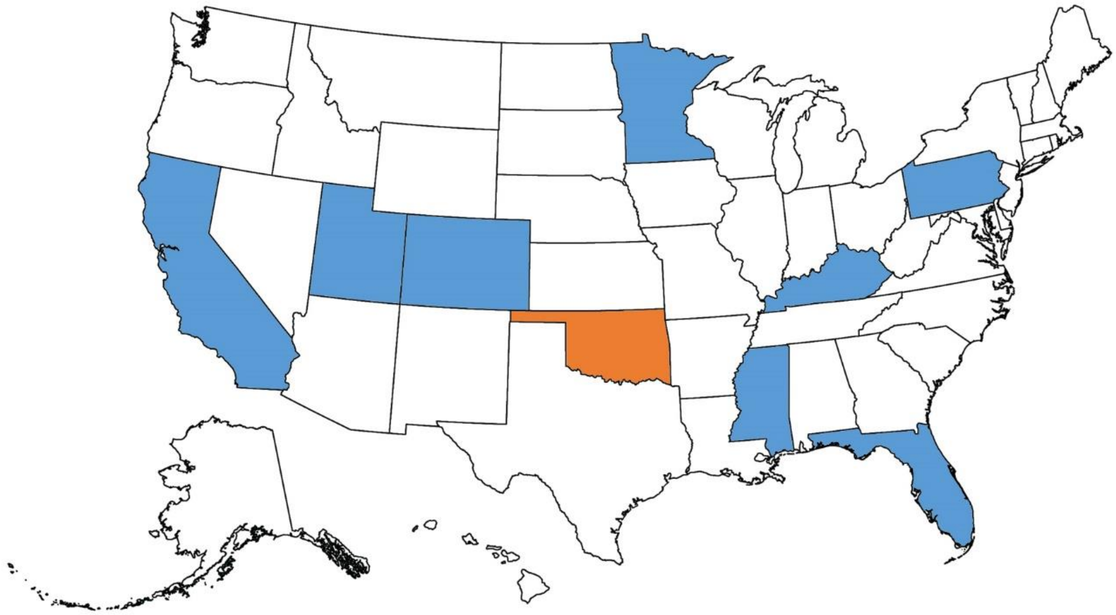

Figure 3-5: State DOT Survey Respondents Who Are Planning to Implement or Have Already Implemented Context Classification or a Similar System

3.5 Questions for States Which Use Context Classification to Develop SPFs

The last set of questions (Q14, Q15, and Q16) was asked to the respondents who said their state currently uses a system similar to FDOT's context classification system. As mentioned in section 3.2, only the respondent from Oklahoma was directed to this section. Oklahoma's context classification system is a terrain-based system that accounts for rolling hills, flat terrain, rock, and various urban classifications. These classifications are used in conjunction with a breakdown of areas into rural or urban. The system was implemented over one year ago, and there has been an improvement in safety measures after implementing this terrain-based classification system. This shows that the use of context classification systems can result in safety improvements, which is a promising indication that FDOT can achieve similar safety improvements using their context classification system.

3.6 Summary of Survey Results

The online survey was developed and tested by the UCF research team and FDOT before being sent by email to DOT contacts in all 50 states plus the District of Columbia. Based on the results from the 42 states who responded to the survey, 62% had not heard about FDOT's context classification system. Although many respondents had not heard of context classification, 26 states expressed interest in eventually adopting a similar system. However, several respondents indicated that they would like to know more about the benefits of using context classification to create SPFs and see how it works for Florida before considering implementing a similar system for their state. Another common concern was the need to collect significantly more data (such as minor road data, number of crashes, and signal timing) to develop these SPFs comparing to using either default or calibrated HSM SPFs. Some respondents said they do not have the resources to collect these data, while others were worried about unreliable or missing data, along with the amount of data overwhelming local agencies.

Most survey respondents (64%) said their states use either an SPF directly from the HSM or an SPF that has been calibrated to their jurisdiction based on the HSM SPFs. Many states are looking at ways to improve their SPFs, typically by calibrating their existing models rather than creating new ones. For the seven respondents whose states do not use the default HSM methodology to develop their SPFs, most said that their models give more accurate results and that the HSM methodology was insufficient or lacked a specific variable or attribute that was important to their state. These non-HSM SPFs tend to focus on functional class, lane count, and if the intersection was in a rural or urban environment.

The free response questions of the survey showed that a few states are using or examining innovative ways to develop SPFs. Oklahoma uses a system similar to context classification but based on the terrain of the landscape (rolling hills, rocky, flat, urban, etc.). This system was implemented over a year ago and has resulted in safety improvements. Other states, like Connecticut and Louisiana, are working on including more data in their SPFs; these data include driver information, vehicle information, and the manner of collision. Virginia is investigating the use of artificial intelligence and neural networks to automatically scan roadways and acquire data for modeling.

Overall, this survey showed that most states (67%) are interested in context classification, even if they are not currently planning on implementing such a system. Issues such as lack of data (including incomplete or inaccurate data, as well as a lack of resources to collect the data) and how to properly segment and utilize this data were the main reasons preventing states from developing their own SPFs. By focusing on their data collection procedures and improving data standardization throughout the state, FDOT can alleviate these concerns and make other states more willing to follow FDOT’s example. The survey results also showed that many states were unaware of context classification and that some respondents wanted to see the benefits of the system before considering it themselves. Oklahoma has a similar system to FDOT which has improved safety, suggesting that FDOT’s system has the potential for similar benefits. FDOT can also consider innovative methods being used by other states, such as the inclusion of driver and vehicle data or the use of neural networks. By improving the data collection procedures and developed context-specific SPFs, FDOT can show other states the benefits of a context classification system while making Florida roadways safer.

Chapter 4: Data Description and Data Collection Procedures

This chapter discusses FDOT's context classification system, describes the data collected for Florida intersections, and details the procedures used to collect these data. In addition, this chapter also discusses issues concerning data quality along with potential improvements that could be implemented to reduce them in the future. FDOT provided the UCF research team with 32 spreadsheets containing 3,653 randomly selected intersections throughout Florida on January 11, 2019, and February 1, 2019. Each spreadsheet contained a specific intersection group based on FDOT's context classification system, the number of crashes at each intersection for the years 2013 to 2015, and variables that data needed to be collected for. Section 4.1 explains FDOT's context classification system and shows the breakdown of the provided intersections by group, while section 4.2 defines and details the variables in the provided spreadsheets, as well as any modifications and additional variables that were included by the UCF research team after consultation with FDOT.

While collecting the intersection data, some issues were encountered concerning data quality and quantity, as well as collecting data for certain variables. Some of these issues were addressed by adding or modifying variables in the provided spreadsheets, as discussed in section 4.2. However, there were additional issues that could not be addressed with changes to the spreadsheets. Section 4.3 focuses on these issues while section 4.4 discusses potential improvements that could be implemented to reduce them in the future. Further research beyond the scope of this project is needed regarding some of these necessary improvements, including the use of ArcGIS Online (AGOL) for data collection, to comprehensively determine their benefits and potential for implementation. This additional research is important to ensure sufficient data is collected and efficient data collection procedures are used so the developed SPFs can be effectively updated and improved in the future.

4.1 FDOT Context Classification System

FDOT's context classification system classifies intersections and roadways into one of eight categories: C1-Natural, C2-Rural, C2T-Rural Town, C3R-Suburban Residential, C3C-Suburban Commercial, C4-Urban General, C5-Urban Center, and C6-Urban Core (FDOT, 2017). This context classification system was developed to better classify intersections and roadways beyond the urban and rural classifications found in the HSM. To correctly identify an intersection or roadway classification, distinguishing characteristics are first identified (FDOT, 2017). Primary measures (such as building height and intersection density) which provide a more detailed assessment of a roadway or intersection, are then determined (Gamaleldin et al., 2020). To be assigned to a certain classification, the majority of the primary measures associated with that classification must be met by an intersection or roadway segment (FDOT, 2017). If needed, secondary measure which provide more detailed characteristics can be utilized to help identify the appropriate context classification; these secondary measures include population density and allowed residential or retail density (Gamaleldin et al., 2020). Figure 3-1 in the previous chapter provides the land area characteristics for each of the eight context classification categories. These classifications are assigned based on as-built conditions or conditions currently present (FDOT, 2018). Future changes to these classifications could be implemented based on new codes or regulations that support the future use of the specific roadways (FDOT, 2018).

One of the main benefits of this context classification system is that it can provide agencies with information on the types and intensity of users in specific classifications (FDOT, 2018). For example, C4, C5, and C6 classifications typically have higher population and intersection densities compared to C1, C2, and C3 classifications. Therefore, C4, C5, and C6 classifications are expected to have more pedestrians, bicyclists, and transit users compared to C1, C2, and C3 classifications (FDOT, 2018). This information can be useful to local and state agencies when determining the geometric features that should be present at intersections within these high-density classifications (such as bike lanes and pedestrian crossings) to reduce the risk of crashes. Other critical information that can be provided by an intersection's context classification is whether there is on-street parking, street trees, and lighting at the intersections (Gamaleldin et al., 2020). Developing context-specific SPFs can help agencies effectively reduce intersection crashes for the distinctive conditions within each context category (Gamaleldin et al., 2020).

Context classification can also be used to identify and provide regional crash characteristics to local agencies, as some counties and Florida districts have more intersections in certain classification groups than in others. To illustrate this, table 4-1 and figure 4-1 show the context classification for all 3,653 Florida intersections provided by FDOT and their distribution by FDOT district. Table 4-1 and figure 4-1 show how the intersections within each context classification category are distributed throughout the FDOT districts. For example, rural classifications (C1, C2, C2T) are more common in D2 and D3, while intersections in suburban and urban classifications (C3R, C3C, and C4) are more common in D5 and D7. Since not all Florida intersections were considered in table 4-1 and figure 4-1 (only the ones provided by FDOT), these distributions and findings will change as more intersections are classified by FDOT.

Table 4-1: Number of Intersections for Each Context Classification Group per District

Context Classification Category	**District 1**	**District 2**	**District 3**	**District 4**	**District 5**	**District 6**	**District 7**
C1-Natural	16	40	98	36	59	4	12
C2-Rural	126	122	104	7	51	12	29
C2T-Rural Town	76	187	165	0	40	19	48
C3R-Suburban Residential	138	85	74	113	82	32	112
C3C-Suburban Commercial	132	95	119	38	168	20	70
C4-Urban General	44	86	56	145	89	175	49
C5-Urban Center	75	18	14	21	29	89	95
C6-Urban Core	0	102	0	10	1	22	4

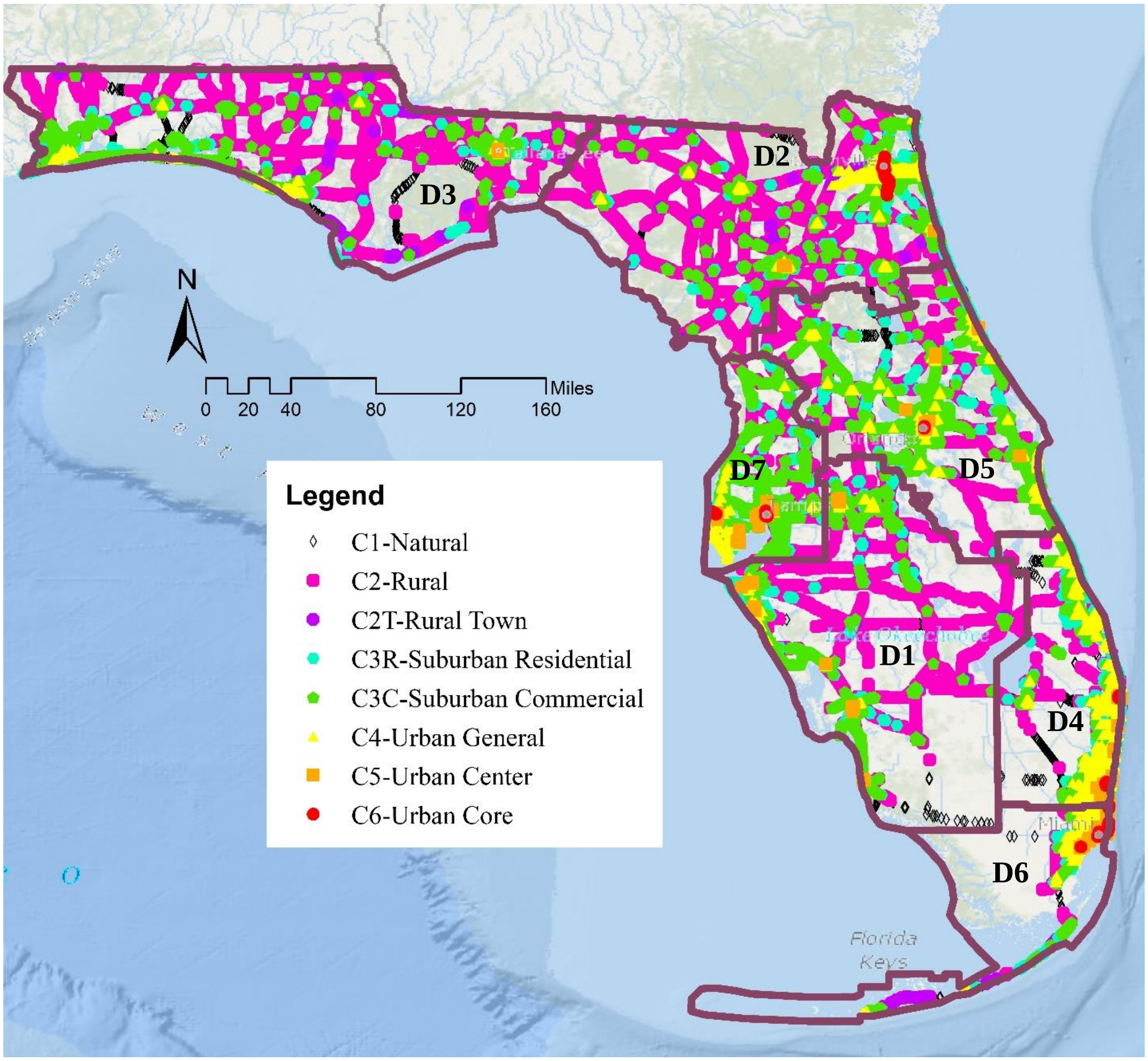

Figure 4-1: Map of Florida Intersections Categorized by Context Classification

In addition to being classified based on FDOT's context classification system, the studied intersections were also grouped based on signalization type (signalized or unsignalized) and number of legs (3-leg or 4-leg intersections). This resulted in 32 intersection groups (unsignalized 3-leg, unsignalized 4-leg, signalized 3-leg, and signalized 4-leg intersections for each of the 8 context classification categories). Separate spreadsheets were provided for each of these groups. SPFs could theoretically be developed for each group individually. However, some of these 32 groups did not have sufficient data to accurately model crashes. According to the HSM, a minimum sample size of 50 intersections is recommended to develop accurate SPFs (AASHTO, 2010). Additionally, all intersections of a specific facility type should have at least 100 crashes per year (AASHTO, 2010).

To estimate how many intersection groups SPFs could be developed for, all 32 intersection groups were reviewed. Any intersections that did not fit in the 32 groups were excluded from the data collection and modeling processes. Before excluding these intersections, the research team checked with FDOT to ensure that it was acceptable to remove these intersections. This review resulted in 241 of the 3,653 intersections being excluded, with section 4.3 discussing these exclusions in more detail. The intersections that were excluded typically had one or more of the following characteristics: contained more than 4 legs, located at an interchange, experienced changes in signalization or number of legs during the crash data period of 2013 to 2015, were continuous green intersections, could not be accurately located based on the provided coordinates, or had unique characteristics that made them unrepresentative of the intersection group. Additionally, some intersections that were misclassified based on signalization type or number of legs were moved to their appropriate groups. No changes were made to the context classification of any intersections as these classifications were finalized by FDOT.

Table 4-2 shows the number of intersections in each intersection group after this review. Based on this distribution of the included 3,412 intersections and the HSM recommended minimum sample size of 50 intersections, SPFs could be developed for 23 different individual intersection groups. These 23 groups with 50 or more intersections are highlighted in gray in table 4-2. Additionally, table 4-3 shows the average number of crashes per year from 2013 through 2015 for all included intersections in each group. The 24 groups highlighted in gray have more than the HSM-recommended 100 crashes per year. Combining the findings from both of these tables results in 21 intersection groups that have a sample size of more than 50 intersections and had 100 or more crashes per year. These 21 groups are discussed further in section 5.1.

Table 4-2: Distribution of Studied Intersections by Intersection Group

Context Classification Category	**Unsignalized 3-Leg**	**Unsignalized 4-Leg**	**Signalized 3-Leg**	**Signalized 4-Leg**
C1-Natural	140	69	3	12
C2-Rural	187	110	45	70
C2T-Rural Town	224	197	11	76
C3R-Suburban Residential	200	134	75	199
C3C-Suburban Commercial	126	132	54	292
C4-Urban General	160	146	74	229
C5-Urban Center	100	103	19	97
C6-Urban Core	48	34	7	39

*Gray highlighted cells are groups with 50 or more intersections.

Table 4-3: Average Intersection Crashes per Year (2013–2015) by Intersection Group

Context Classification Category	Unsignalized 3-Leg	Unsignalized 4-Leg	Signalized 3-Leg	Signalized 4-Leg
C1-Natural	56.7	31.0	21.0	81.0
C2-Rural	114.0	123.0	211.7	609.3
C2T-Rural Town	133.0	146.7	38.3	301.0
C3R-Suburban Residential	165.0	185.7	411.7	2073.0
C3C-Suburban Commercial	223.3	293.0	335.0	3268.7
C4-Urban General	464.0	487.0	599.3	3419.3
C5-Urban Center	208.0	540.3	209.0	1360.7
C6-Urban Core	92.0	91.0	60.7	588.3

*Gray highlighted cells are groups with 100 or more intersection crashes per year.

4.2 Data Description

The provided data spreadsheets contained two main types of data: data for individual intersections and data for individual intersection legs. Some of the data, such as intersection coordinates and number of crashes, were provided by FDOT. FDOT also provided a list of variables for the research team to collect data for, along with lists of possible data options for select variables. Most of these variables were based on the MIRE 2.0 standard developed by FHWA. This MIRE 2.0 standard is discussed next, followed by descriptions of the assumptions made when collecting data for the provided variables, changes made by the UCF research team to the variables and variable values (including the addition of new variables), and the procedures used to collect these data.

4.2.1 MIRE 2.0 Data Standard

The MIRE 2.0 standard, which is detailed by Lefler et al. (2017), “serves as an inventory to support data-driven safety management.” The recommended roadway inventory guidelines and standardized coding provided by MIRE 2.0 are a means to facilitate collaborations between transportation agencies in all states and improve their traffic data inventory (Lefler et al., 2017). MIRE 2.0 contains various data elements for six data types: segment, intersection, intersection leg, interchange/ramp, horizontal curve, and vertical grade (Lefler et al., 2017). Only elements in the intersection and intersection leg data types were considered in this study since they were the types relevant to intersections. The original spreadsheets provided by FDOT contained 11 MIRE 2.0 intersection variables and 30 MIRE 2.0 intersection leg variables to collect data for. Data were collected for these variables (as well for some new variables added by the UCF research team) for each of the 32 different intersection types. All data assumptions, changes, and additions are discussed in the next section.

4.2.2 Data Assumptions, Modifications, and Additions

When starting the data collection process, it was quickly realized that the variables and values included in MIRE 2.0 were insufficient to accurately describe all intersections. Therefore, some modifications had to be made to the provided MIRE 2.0 variables and data values. These modifications included changing some of the specified data values to be more representative of Florida intersections and adding variables to help in the modeling process and improve the data quality. Assumptions also had to be made regarding some variables. All changes to the data were checked and approved by FDOT before being implemented. Any assumptions made by the UCF research team when collecting data were documented to ensure that similar situations were recorded consistently in the data spreadsheets. These modifications and assumptions helped to more clearly define some variables (such as number of through lanes) and made some variables (such as intersection traffic control) more representative of Florida conditions. The following list shows assumptions related to existing variables, while the subsequent list shows changes to existing variables and new variables added to the data spreadsheets.

- Leg Number: The types of approaches counted as intersection legs included roadways, pedestrian/bicycle specific paths, parking areas that provided access to multiple businesses, parking areas for apartment buildings or other large residential areas, schools, churches, warehouses, and other similar approaches. Any approaches that did not fit in these categories were excluded and not counted in the leg number. If an intersection had more than 4 legs or less than 3 legs after excluding any legs, data were not collected for the intersection and it was removed from the spreadsheet. Another assumption regarded how to count unsignalized intersections with offset legs. Intersections with four legs and an offset between two opposing legs of less than 50 feet were counted as 4-leg intersections with no offset. If there were four legs but the offset between two opposing legs was greater than 50 feet, the intersection was counted as two 3-leg intersections (with one of the offset legs at each of the intersections). Intersections with offsets between 50 feet and 250 feet were excluded if it was not possible to tell what intersections the provided coordinates were referring to. Any intersections with offsets greater than 250 feet were always counted as separate intersections. Signalized intersections were counted as 4-leg intersections with offset if the offset legs were handled by the same signal group and 3-leg intersections if the offset legs were not handled by the same signal group.
- Geometry: For 3-leg intersections, it was assumed that the intersection was a T-intersection when two different roads intersected and a Y-intersection when three different roads intersected. The only exceptions to these assumptions were if three separate roads intersected and the angle between one pair of roads was approximately 180 degrees (classified as a T-intersection) and if the minor road bifurcated into two bidirectional approaches at intersections where two roads intersected (classified as a Y-intersection).
- School Zone: Any intersections at a school were considered to be in a school zone, even if there were no roadway markings indicating this. Otherwise, roadway markings were used to determine whether intersections were in a school zone or not.
- Offset Distance: Any offsets of less than 50 feet were counted as 0.
- Approach Identifier: When north-south and east-west orientations were not clear at an intersection, the orientation of a road during its greater course was used to determine the

approach identifiers. Opposing approaches (angle of approximately 180 degrees between them) were then labeled as either north and south or east and west.

- Through Lanes Number: For one-way legs, the number of through lanes was counted as the total number of lanes which were not exclusively left or right turn lanes. For two-way legs, it was counted as the total number of lanes in both directions which were not exclusively left or right turn lanes. Any lanes with multiple movements were counted towards the total number of through lanes. If only one movement type could be made in a given lane, then the lane could still be counted as a through lane even if vehicles could only make a left or right turn as long as the lane was not marked as an exclusive turn lane (this is also discussed in the assumptions for exclusive left turn number and exclusive right turn number). Two-way left turn lanes were not counted as through lanes.
- Left Turn Lane Type: If a leg has (a) lane(s) exclusively for making left turns (and no other movements) at the intersection, then it was labeled as "Conventional left-turn lane(s)." However, if a leg does not have any exclusive left turn lanes or if left turns are to be made somewhere other than the intersection, then it was labeled as "No left-turn lanes." Two-way left turn lanes were counted as conventional left turn lanes (but were not counted as exclusive left turn lanes).
- Exclusive Left Turn Number: A left turn lane was counted as an exclusive left turn lane, only when all of the following criteria were met:
  1. Only left turns are permitted from the lane.
  2. The lane is marked as an exclusive left turn lane.
  3. There is at least one other lane in the same direction on the approach for other movements. If there is only one lane in a direction, that lane was counted as a through lane (even if only left turns are permitted) unless the lane was marked as left turns only.

  Additionally, two-way left turn lanes were not counted as exclusive left turn lanes.
- Left Turn Offset: A value of "N/A" was used for approaches with no exclusive left-turn lanes, no opposing approach, or an opposing approach with no left turn lanes.
- Exclusive Right Turn Number: Like the exclusive left turn number, a right turn lane was counted as an exclusive right turn lane only when all of the following criteria were met:
  1. Only right turns are permitted from the lane.
  2. The lane is marked as an exclusive right turn lane.
  3. There is at least one other lane in the same direction on the approach for other movements. If there is only one lane in a direction, that lane was counted as a through lane (even if only right turns are permitted) unless the lane was marked as right turns only.
- Exclusive Left/Right Turn Length: The values for both the exclusive left and right turn lengths were determined by measuring the distance, in feet, from the stop bar for the exclusive lane to where the exclusive lane began to taper. If there were multiple exclusive left/right turn lanes, then the shortest distance was taken. For cases where the exclusive turn lane did not taper and instead transitioned to a non-exclusive lane, the length was measured as the distance from the stop bar to where the lane ceased to be exclusive. If an exclusive turn lane reached another opening (street, driveway, etc.) before tapering, the length was measured as the distance from the stop bar to this opening. For approaches with no exclusive left or right turn lanes, the value for this variable was set as zero.

- Median Type: Approaches containing grass medians without curbs were counted as “Depressed median.” If an approach had a flush-paved median less than four feet wide, it was counted as “Undivided.”
- Crosswalk Type: This variable was counted as “Pedestrian crossing prohibited” only if there was signage or other markings indicating that pedestrians were prohibited. If these indicators were not present, a value of “Unmarked crosswalk” was used. It was also assumed that all signalized intersections with a pedestrian phase had controlled and marked crosswalks.

The next list shows modifications made to the specified values for existing variables, as well as new variables added to the data collection spreadsheets:

- County: A “County” variable was added to the “Intersection” tab and shows which of the 67 Florida counties the intersection is located in. This variable was added to help the UCF research team contact the appropriate county when requesting data (discussed in section 4.2.3). A list of counties and FDOT districts was added to the “Reference” tab of the data spreadsheets as data values for both this variable and the newly added “District” variable (discussed next).
- District: A “District” variable showing which of the seven FDOT districts the intersection is located in was also added to the “Intersection” tab. This variable was added for use in modeling to determine if there are significant differences in the variability of crashes across FDOT districts, as well as for contacting districts. The district was determined based on the list of counties and districts which was added to the “Reference” tab.
- Excluded Legs: An “ExcludedLegs” variable was added to the “Intersection” tab to indicate the number of approaches at each intersection which were not counted as legs. Examples of excluded legs include single business parking lots, driveways to one or a few homes, dirt roads with minimal traffic volumes, and other similar approaches. If all the approaches were counted as legs, this variable had a value of zero.
- Intersection Traffic Control: The value of “Two-way Stop” for this existing variable was modified to “Two-way Stop/Minor Road Stop” to better represent 3-leg intersections with a stop sign only on the minor road leg.
- Approach Context Classification, Latitude, and Longitude: The three variables “Context Classification”, “Latitude”, and “Longitude” were added to the “IntersectionLeg” tab. These variables were used to develop the GIS layer for the approach data and differentiate between intersections with different classifications in this layer. The value for “Context Classification” was the same as the corresponding value in the “Intersection” tab. The “Latitude” and “Longitude” values were determined for each approach using Google Maps.
- Road Type: A “RoadType” variable was added to the “IntersectionLeg” tab to indicate which approaches were on major roadways and which were on minor roadways. For each intersection, all approaches on the roadway with the higher AADT were counted as “Major”, with “Minor” used for all other approaches. This variable was added to differentiate which characteristics were for major legs and which were for minor legs when modeling.
- Approach Type: An “ApproachType” variable was added to the “IntersectionLeg” tab to indicate whether the approach was a street, commercial or residential parking area,

school, warehouse, or other. "Street" was selected for any approach that was a roadway which continued beyond the intersection. "Commercial Parking Area" was selected for large parking areas at businesses, while "Residential Parking Area" was selected for large parking areas at apartment complexes or other residential areas. "School" and "Warehouse" were selected if an approach ended at a school or warehouse, respectively, before reaching another intersection. If an approach did not fit any of these previous types (such as an entrance to a military base or airport), "Other" was selected.

- Traffic Control Exclusive Right Turn: Two values were added to this existing variable: "No exclusive right-turn lanes" and "No right turns possible." The former value was used for approaches with no exclusive right turns, while the latter value was used for approaches where right turns were not possible due to there being no approach to turn into or other similar constraints. The latter value was added to help differentiate approaches at 3-leg intersections where vehicles cannot physically turn right from approaches where vehicles are not allowed to turn right, but are still physically able to turn right.
- Approach Left Turn Protection: Two values were added to this existing variable: "No left turns allowed" and "No left turns possible." The former value was used for approaches where left turns were prohibited (but physically possible), while the latter value was used for approaches where left turns were not physically possible.
- Crosswalk Type: The values "Marked crosswalk with refuge island" and "Marked with refuge island and supplemental devices" were split to have two values each, one for flush islands (no physical separation between pedestrians and vehicular traffic) and one for raised islands (physical separation between pedestrians and vehicular traffic).
- Bike Lane: A "BikeLane" variable was added to the "IntersectionLeg" tab to indicate if there was a bike lane present on an approach. Only lanes exclusively marked as bike lanes were counted as "Yes." This variable was added to study the effect of bike lane presence on intersection crashes when modeling.

4.2.3 Data Collection Procedures

To collect the intersection data, two main sources were utilized: GIS files provided by FDOT and aerial and street view imagery on Google Maps. The GIS files were used to collect traffic volumes, while Google Maps was used to collect geometric data (number of lanes, median type, crosswalk type, etc.), signalization features (presence of stop signs, turning prohibitions, etc.), and measurements (exclusive left turn and right turn lengths, offset distances, intersection angles, etc.). Some data (such as signalization coordination and turning movement counts) were not available from either of these sources, so data requests were sent to all 67 Florida counties and 7 FDOT districts. The counties were contacted starting on March 24, 2019, with follow-up messages sent every few weeks through August 2019. During these five months, 19 of the 67 counties responded to the data request by either providing some data or saying they were not able to provide the requested data. To improve the response rate, data requests were then sent to all seven FDOT districts on November 22, 2019, with three of the districts responding as of July 2020. Quality control checks were also conducted on all collected data before submission to FDOT to ensure data consistency and accuracy. With the significant amount of data collected for this task, FDOT has a strong database that can be expanded to include more intersections and additional variables in the future.

4.3 Data Collection Issues

The main issues encountered during the data collection process can be classified in two major categories: issues with the quality and quantity of provided data and issues with collecting data for certain intersection characteristics. Each of these categories is discussed in more detail below.

4.3.1 Data Quality and Quantity Issues

The 32 spreadsheets provided by FDOT contained a total of 3,653 intersections. However, some of these intersections had data quality issues which resulted in them being excluded from the data collection process. For some intersections, the provided coordinates were in between two intersections, making it unclear which intersection was being referenced in the data. These intersections were excluded to prevent the wrong intersection from being modeled. Other intersections were excluded because they were not 3-leg or 4-leg intersections or were at interchanges (which have different characteristics than non-interchange intersections). Additionally, continuous green intersections (which can impact traffic differently than traditional signalized intersections) and intersections with unusual characteristics were excluded. After excluding all of these intersections, the total number of intersections in the data was reduced to 3,412.

Out of these 3,412 intersections, about 10% were misclassified and had to be moved to a different group. These misclassifications were mainly due to an incorrect number of legs (such as an intersection being classified as a 3-leg intersection when it was actually a 4-leg intersection) or incorrect signalization (such as being classified as unsignalized when it was actually signalized). Additionally, some intersections seemed to be in the wrong context classification category, as their surrounding areas were different than other intersections in the same context classification. This happened most often for intersections which were categorized as C1-Natural or C2-Rural, but were located in a small town or residential area. Intersections which were misclassified based on the number of legs or signalization were moved to their correct group, but intersections with seemingly incorrect context classifications were not moved since these context classifications were set by FDOT. These latter intersections were noted and data were collected for these intersections, but they were not considered when modeling SPFs. Due to these possible misclassifications, the number of intersections modeled for certain groups was lower than the values shown in table 4-2.

In addition to the mentioned data quality issues, there were also some issues with data quantity. As table 4-2 shows, 9 of the 32 groups have less than 50 intersections, with only 16 groups having 100 or more intersections. Some groups also had a majority of their intersections located in one district or on one roadway. This could bias the developed SPFs toward the conditions of this dominant district/roadway. Since the intersections in these spreadsheets were provided by FDOT and not selected by the UCF research team, it is unclear whether some of these groups could have additional intersections throughout the state which were not included. Having a larger sample size would increase the accuracy of the SPFs and help them better identify any differences between districts. As more intersections are classified, future research could identify and collect data for additional intersections in groups with lower sample sizes or groups biased towards one area to develop context-specific SPFs which are more accurate and more representative of the entire state.

4.3.2 Data Collection Issues

Additional issues caused by limitations of the data collection procedures, ambiguity in descriptions of some of the MIRE 2.0 variables, and a lack of available data for certain variables were encountered. Documenting and understanding these issues are important to improve them in the future and to help other agencies handle these issues. All of these issues are detailed in this section, with potential solutions discussed in section 4.4.

As discussed in section 4.2.3, Google Maps satellite and StreetView images were used to collect data for multiple variables. However, some intersections had discrepancies between the satellite and StreetView images, making it hard to obtain consistent data for these intersections. Since the provided crash data were from 2013-2015, StreetView images from these years were used whenever possible to obtain data on the conditions during this period. However, more recent images had to be used for intersections where images from this period were not available. Some intersections also changed significantly between 2015 and when the satellite images were taken (such as changing from unsignalized to signalized or having more lanes added). For these cases, data obtained from the satellite images (such as turn lane lengths) could not be collected. There were also some blurry or obscured images that made it difficult to collect data for some variables.

Another issue was a lack of clarity for some of the MIRE 2.0 variables and values. The document by Lefler et al. (2017) did provide some basic descriptions of the MIRE 2.0 variables and values, but this information was not enough for some variables. For instance, no information was provided on what lanes should be counted as through lanes. To address this ambiguity in some of the MIRE 2.0 variables, various additions, changes, and assumptions were made, as discussed in section 4.2. Additionally, after a UCF research team member finished collecting data for a specific group, a second team member would check the group to see if there any areas of potential confusion. These quality control checks helped ensure that the collected data were accurate and consistent based on the UCF research team's assumptions. All of the issues mentioned so far presented challenges in the data collection process, but they were overcome by the talents of the UCF research team members. Being able to overcome these issues and collect data for 3,412 intersections in one year was a significant accomplishment which shows UCF's commitment to improving intersection safety in Florida and helping FDOT be an example for other state DOTs to follow.

The last (and most significant) issue was a lack of data for certain variables. Some variables (such as minor AADT) only had data available for a limited number of intersections, while other variables (such as turning movement counts) did not have any data available at all. For example, FDOT GIS files were used to obtain traffic volumes from 2013 to 2015 at the studied intersections. However, many roads were missing AADT values for either one year or all years. This happened for many of the minor roads, but there were even some major roads which lacked these volumes as well. These traffic volumes are very important for modeling SPFs, as traffic volume is one of the main factors affecting crash frequency. To account for these missing minor road volumes, the UCF research team developed a model to predict the minor AADT using the major AADT and other significant roadway factors. This model using data from all 21 groups with sufficient sample sizes is presented in section 6.1. The predicted minor AADT values from this model were used as surrogate minor AADT values when developing the SPFs, but it is recommended to collect actual values in the future to make the developed SPFs more representative of real-world conditions. Once real-world minor AADT data become readily available, the developed SPF models can be updated using these data instead of the modeled minor AADT values.

While minor AADT values were available for some intersections, some data were not available at all. These included turning movement counts and pedestrian counts. As mentioned in section 4.2, data requests were sent to all 67 Florida counties and 7 FDOT districts asking for these otherwise unavailable data. Appropriate contacts for these counties and districts were provided by FDOT, with the UCF research team identifying additional or alternate contacts for some counties. As of July 2020, only 19 of the 67 counties and 3 of the 7 FDOT districts had responded to these requests. From these responses, only 8 counties provided data; these data were very limited and did not include turning movement counts or pedestrian counts, as the counties did not have these data available. Most of the remaining 11 counties who responded said they did not have the requested data or the resources to collect the data, with some indicating that FDOT should have the data.

4.4 Potential Data Collection Improvements

To solve the data issues discussed in this chapter, potential improvements to data collection have been identified. It is expected that implementing these improvements will increase the quantity and quality of traffic data throughout the state. However, additional research is needed to test some of these improvements, determine their various advantages and disadvantages, and effectively implement them.

One potential solution to address the lack of data for certain variables (minor AADT, signalization coordination, turning movements, etc.) is meeting with counties to discuss the needed data. Most counties have not responded to the email requests or phone calls concerning these data. Additionally, most of the responding counties did not have these data or thought that FDOT could provide the requested data. Webinars and presentations for face-to-face meetings could be developed to better educate counties about context classification, and the importance of the requested data and data standardization. Educating the counties on why these data are needed and how to collect these data can improve future data collection and make it easier to update the developed context-specific SPFs.

For data that are not currently available, it might be necessary to make on-site visits to various intersections throughout the state to gather these data. These visits would not only allow for collection of data that are not obtainable otherwise, but would also allow for better understanding of other geometric, traffic, or environmental factors that could affect crash frequency. However, this method of data collection will be very time and resource intensive, so data could not be collected at all intersections in the provided spreadsheets. New data collection techniques, such as the use of AGOL, could be evaluated in a future study to identify any methods that can be more cost-effective, accurate, and efficient than current data collection methods.

Improvements could also be made to the existing data which could make any developed SPFs more accurate. One improvement is the incorporation of additional variables, such as driver demographics or environmental factors. Considering these factors when modeling SPFs could provide additional insights about intersection crashes. Another improvement is collecting data for larger, more diverse samples of intersections. These improvements will reduce any potential bias in the developed SPFs and make them more representative of conditions statewide. The SPFs could also better identify any regional differences between districts. Conducting a future study to make these data improvements, as well as implement the other potential solutions discussed in this chapter, would significantly benefit FDOT by increasing safety. It would also help show other states the benefits of using a context classification system like FDOT's.

4.5 Data Collection Summary

Intersection crashes are a major concern for state and local agencies. To better understand and address the crash risk at Florida intersections, FDOT is developing a data inventory of several geometric and traffic characteristics of intersections. This database is based on the national MIRE 2.0 standard code for data collection, allowing for easier collaboration across agencies. It will also be used to develop accurate SPFs for FDOT's new context classification system. With this system, SPFs could be developed for up to 32 types of intersections (unsignalized and signalized 3-leg and 4-leg intersections in each of the eight context classification categories), which is much more than the 10 groups possible using the HSM methodology.

To start this database, FDOT classified 3,653 intersections throughout Florida. The UCF research team then analyzed these intersections and collected data for several geometric, traffic, signalization, and other intersection and intersection approach variables. Some of these 3,653 intersections were excluded before collecting data as they did not fit in any of the 32 intersection groups. Based on the number of intersections and crashes per group for the remaining 3,412 intersections, there is currently sufficient data to develop SPFs for 21 of the 32 intersection groups. However, as discussed in the next chapter, variance within two of these intersection groups caused them to require a larger sample size and therefore SPFs could not be developed for these two groups in this project.

For each of these 3,412 intersections, data were collected for the 41 variables included in the spreadsheets provided by FDOT, plus additional variables added by the UCF research team to assist in modeling and developing GIS layers of the collected data. While collecting data, various assumptions had to be made regarding certain variables. Modifications also had to be made to some variable values to make them more applicable to Florida intersections. Google Maps and ArcGIS were the main tools used to collect these data, but Florida counties and districts were also contacted regarding data that could not be obtained elsewhere. The end result is a very accurate database that has high-quality data to develop accurate SPF models and assist FDOT in future identification of high-risk intersections and implementation of countermeasures. Issues were encountered during data collection that could have affected the quantity and quality of the data collection. However, the UCF research team was able to either overcome these issues while collecting the data or propose improvements/potential solutions that could be evaluated in a future study. These issues included misclassifications of intersections, overrepresentation of intersections in certain districts or on certain roadways for some groups, lack of a sufficient quantity of data for certain groups, discrepancies between the satellite and StreetView images on Google Maps, low response rate from the Florida counties, and unavailable data for some variables. Studying new data collection techniques (such as AGOL) could allow missing data and data for additional intersections to be collected efficiently. It could also make it easier to collect data for additional variables and remove bias from SPFs for some groups due to the modeled intersections being located in the same area. Educating counties and local agencies on the importance of context classification, safety data collection, and data standardization can improve data collection in the future. This will make it easier for FDOT to update the developed context-specific SPFs.

The developed database is a significant effort that provides a great basis for FDOT to expand upon with additional data from more intersections. It will allow for development of accurate context-specific SPFs based on FDOT's context classification system. These SPFs can then be used to identify sister intersections with similar characteristics, but different crash rates, which have the highest potential for crash reduction. The most effective countermeasures for these locations can then be identified, implemented, and evaluated. To achieve these benefits, it is crucial to establish statewide data standards and determine effective data collection procedures. Future research in these areas will help FDOT overcome data collection issues at a statewide level and cost-effectively improve safety throughout Florida.

Chapter 5: Modeling Methodologies

To develop accurate context-specific SPFs for the intersection groups with sufficient sample sizes, multiple crash prediction modeling methodologies were used and compared to identify the best fitting and most accurate model for each studied intersection group. Section 5.1 discusses the breakdown of the provided intersections by group and which groups had sufficient sample sizes for modeling, while section 5.2 details the considered variables and data preparation performed before starting the modeling process. Section 5.3 then explains the various modeling methodologies that were used and compared to develop the context-specific SPFs, as well as the performance measures and model selection criteria considered to select the best model for each intersection group.

5.1 Intersection Groups Based on FDOT Context Classification System

As mentioned in chapter 4, 21 of the 32 different intersection groups met the HSM recommendations of more than 50 intersections and 100 or more crashes per year. These 21 groups are highlighted in gray in table 5-1, which shows the number of intersections considered for modeling in each group. Even though these 21 groups meet the recommendations, variance within some groups could cause them to require a sample size larger than 50. After preliminary modeling, it was concluded that the C3C signalized 3-leg and C5 unsignalized 3-leg groups need a larger sample size to develop statistically significant and accurate models. Therefore, SPF models were developed for the remaining 19 groups with sufficient sample sizes. Additionally, the C6 unsignalized 3-leg and 4-leg intersection groups (which individually have insufficient sample sizes) were combined to provide a sufficient sample size for modeling. A binary variable was included when modeling this combined group to identify whether the model prediction differs between the individual intersection groups, as discussed in section 6.3.7.

Table 5-1: Distribution of Considered Intersections by Intersection Group

Context Classification Category	Unsignalized 3-Leg	Unsignalized 4-Leg	Signalized 3-Leg	Signalized 4-Leg
C1-Natural	113	61	3	7
C2-Rural	145	98	41	58
C2T-Rural Town	218	188	11	70
C3R-Suburban Residential	186	131	72	192
C3C-Suburban Commercial	120	120	54	288
C4-Urban General	147	140	71	214
C5-Urban Center	94	103	18	97
C6-Urban Core	42	34	7	37

*Gray highlighted cells indicate groups that meet the HSM minimum sample size recommendations for number of intersections (50) and number of crashes (100 per year).

As mentioned in section 4.3.2, a large quantity of intersections did not have available minor AADT volumes. These volumes are important for SPF modeling since traffic volumes are one of the main factors affecting crashes. Table 5-2 shows the number and percentage of intersections with available minor AADT for each of the 21 intersection groups highlighted in gray in table 5-1.

Table 5-2: Number and Percentage of Intersections with Available Minor AADT by Intersection Group

Intersection Group (Signalization, Number of Legs, and Context Classification Category)		**Sample Size**	**Number of Intersections with Available Minor AADT**	**Percentage of Intersections with Available Minor AADT**
Unsignalized 3-Leg	C2-Rural	145	22	15%
	C2T-Rural Town	218	1	0%
	C3R-Suburban Residential	186	5	3%
	C3C-Suburban Commercial	120	3	3%
	C4-Urban General	147	1	1%
	C5-Urban Center	94	3	3%
Unsignalized 4-Leg	C2-Rural	98	20	20%
	C2T-Rural Town	188	13	7%
	C3R-Suburban Residential	131	5	4%
	C3C-Suburban Commercial	120	6	5%
	C4-Urban General	140	3	2%
	C5-Urban Center	103	6	6%
Signalized 3-Leg	C3R-Suburban Residential	72	38	53%
	C3C-Suburban Commercial	54	25	46%
	C4-Urban General	71	29	41%
Signalized 4-Leg	C2-Rural	58	52	90%
	C2T-Rural Town	70	46	66%
	C3R-Suburban Residential	192	138	72%
	C3C-Suburban Commercial	288	155	54%
	C4-Urban General	214	111	52%
	C5-Urban Center	97	37	38%

From table 5-2, it can be seen that unsignalized intersections have a much lower percentage of available minor AADT data than signalized intersections. Combining all 21 groups shows that

719 of the 2,806 intersections in these 21 groups (26%) have available minor AADT. To estimate the minor AADT at the intersections without these volumes, the UCF research team developed a minor AADT prediction model (discussed in section 6.1). While this model provides estimates of minor AADT at intersections without these volumes, it is recommended to collect actual minor AADT volumes in the future to improve the accuracy of the context-specific SPFs.

5.2 Data Preparation

Reliable data are essential for agencies to make accurate and informed decisions regarding the safety and design of intersections since crashes can be influenced by many factors. In this project, several roadway and intersection variables from the MIRE 2.0 data standard (Lefler et al., 2017) were collected for the study intersections as detailed in chapter 4. Not all of these variables were considered for SPF development, as some variables did not have a sufficient quantity of data. The considered variables can be divided into 3 main categories: geometric features, traffic volumes, and general features of the intersection. The variables considered for SPF development in each of these categories are as follows:

- Geometric Features
    - Major/Minor Exclusive Left Turn Number
    - Major/Minor Exclusive Left Turn Length
    - Major/Minor Exclusive Right Turn Number
    - Major/Minor Exclusive Right Turn Length
    - Major/Minor Median
    - Major/Minor Crosswalk
    - Major/Minor Road Width
    - Major/Minor Through Lanes
    - Intersect Angle
- Traffic Volumes
    - Major AADT
    - Minor AADT
- General Features
    - Major/Minor Bike Lane Presence
    - Major/Minor Speed Limit
    - Major/Minor Functional Class
    - Railroad Zone Presence
    - School Zone Presence
    - Lighting Presence
    - FDOT District

Table 5-3 provides more details for each of these variables considered in developing the SPF models (as well as the number of crashes, which is the dependent variable), including the type and category of each variable. 11 of the 18 variables listed above apply to both the major and minor roads (such as exclusive left turn number). These major and minor variables are shown separately in table 5-3, resulting in a total of 30 variables (one dependent variable, 17 geometric variables, two traffic volume variables, and 10 general feature variables). Since the total number of crashes at each intersection during a three-year period (2013 to 2015) was used as the dependent variable, the developed SPF models will predict the number of crashes in a three-year period. Some of these variables (such as road width, speed limit, and functional class) are not listed in the MIRE 2.0 variables for intersections (because they are characteristics of the roadway and not the intersection itself) but are listed in the MIRE 2.0 variables for roadway segments (Lefler et al., 2017). However, they were considered when developing the linear regression model for minor AADT and when modeling the SPFs because they represent roadway characteristics that could influence crashes at the intersection. One variable that was not included in any of the MIRE 2.0 variable categories is the district variable. This variable indicates which FDOT district the intersection is located in. Including this variable can show whether certain districts are expected to have a higher or lower number of crashes compared to other districts for specific intersection groups. Understanding these regional differences could help FDOT identify countermeasures used in districts with lower expected crashes which could be used in other districts to potentially reduce crashes. Other states or agencies could use a similar regional variable to identify differences between regions.

Before modeling, data preparation was needed for some variables to make them more suitable for modeling. Both the major AADT and minor AADT values were logarithmically transformed using the natural logarithm so they better fit a normal distribution. The five categories for the major median and minor median variables (depressed median, raised median with curb, two-way left turn median, undivided, and other divided) were reduced to only two categories; divided (0) and undivided (1). This reduces the number of dummy variables needed in the models and makes it easier to interpret the effects of this variable. Similarly, the number of categories for the major crosswalk and minor crosswalk variables was reduced from five (marked crosswalk, marked crosswalk with refuge island (flush), marked crosswalk with refuge island (raised), prohibited pedestrian crossing, and unmarked) to two: marked crosswalk (0) and unmarked crosswalk (1). Some categorical variables with possible values of “Yes” or “No” were converted to binary variables with “1” for “Yes” and “0” for “No.” Additionally, the continuous variable intersect angle was converted to a binary variable by assigning “1” to intersections with 90-degree angles and a “0” to intersections with angles less than 90 degrees. The information in table 5-3 accounts for all of this data preparation.

Table 5-3: Descriptions of Variables Considered in SPF Development

Variable Name	**Description**	**Type**	**Category**
Total Crashes	Number of crashes at an intersection from 2013-2015 (dependent variable)	Continuous	N/A*
Ln(Major AADT)	Logarithmic transformation of AADT on major roadway	Continuous	N/A
Ln(Minor AADT)	Logarithmic transformation of AADT on minor roadway	Continuous	N/A
District	FDOT district number	Categorical	1-7
School Zone	Indication of whether the intersection is in a school zone	Binary	Yes (1), No (0)
RR Zone	Indication of whether the intersection is in a railroad zone	Binary	Yes (1), No (0)
Intersect Angle	The smallest angle between any two legs of the intersection	Binary	= 90(1), <90 (0)
Lighting	Indication of whether the intersection contains a source of light (lamp post or streetlight)	Binary	Yes (1), No (0)
Major Exclusive Left Turn Number	Number of exclusive left turn lane(s) on the major approach	Continuous	N/A
Major Exclusive Left Turn Length	Storage length of exclusive left-turn lane(s) on the major approach	Continuous	N/A
Major Exclusive Right Turn Number	Number of exclusive right turn lane(s) on the major approach	Continuous	N/A
Major Exclusive Right Turn Length	Storage length of exclusive right-turn lane(s) on the major approach	Continuous	N/A
Minor Exclusive Left Turn Number	Number of exclusive left turn lane(s) on the minor approach	Continuous	N/A
Minor Exclusive Left Turn Length	Storage length of exclusive left-turn lane(s) on the minor approach	Continuous	N/A
Minor Exclusive Right Turn Number	Number of exclusive right turn lane(s) on the minor approach	Binary	Yes (1), No (0)
Minor Exclusive Right Turn Length	Storage length of exclusive right-turn lane(s) on the minor approach	Continuous	N/A
Major Median	Median type separating opposing traffic lanes on the major approach	Binary	Undivided (1), Divided (0)
Minor Median	Median type separating opposing traffic lanes on the minor approach	Binary	Undivided (1), Divided (0)
Major Bike Lane Presence	Presence of a bike lane on the major approach	Binary	Yes (1), No (0)

Table 5-3: Descriptions of Variables Considered in SPF Developments…Continued

Variable Name	Description	Type	Category
Minor Bike Lane Presence	Presence of a bike lane on the minor approach	Binary	Yes (1), No (0)
Major Crosswalk	Type of crosswalk crossing the major approach	Binary	Unmarked (1), Marked (0)
Minor Crosswalk	Type of crosswalk crossing the minor approach	Binary	Unmarked (1), Marked (0)
Major Through Lanes	Total number of through lanes on major approach	Continuous	N/A
Minor Through Lanes	Total number of through lanes on minor approach	Continuous	N/A
Functional Class Major	The functional classification of the major approach	Binary	Collector (1), Arterial (0)
Functional Class Minor	The functional classification of the minor approach	Categorical	Local road (2), Collector (1), Arterial (0)
Speed Limit Major	The posted speed limit on the major approach	Continuous	N/A
Speed Limit Minor	The posted speed limit on the minor approach	Continuous	N/A
Road Width Major	The average paved width of the major approach	Continuous	N/A
Road Width Minor	The average paved width of the minor approach	Continuous	N/A

*N/A stands for "Not Applicable."

5.3 Modeling Methodologies

This section discusses the modeling methodologies and corresponding equations considered to develop the context-specific SPFs, as well as the performance measures and selection criteria used to select the best model. First, the methodology for the minor AADT prediction model is discussed, followed by the various SPF modeling methodologies. Then, the performance measures and selection criteria used to compare between the various SPF models and identify the best model are defined.

5.3.1 Minor AADT Model

Before developing SPFs for each group, a multiple linear regression model of ln(minor AADT) was fit on intersection characteristics which were statistically significant at 5% significance level. This model was developed to predict minor AADT at intersections without this information using available data from all the studied intersection groups. A logarithmic transformation of minor AADT was used to ensure the validity of the statistical assumptions of the regression model. This model has the form shown in equation 5-1. Stepwise selection was used to determine the significant variables in the model, with the final model chosen based on performance diagnostics and best fit statistics.

$$Ln(Minor\ AADT) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (5\text{-}1)$$

Where n = number of significant input variables in the model;
β_0 = intercept;
β_i = variable coefficient (i = 1 to n); and
x_i = significant variable (i = 1 to n).

5.3.2 Poisson Regression Model

The Poisson model is a basic "count data" model that can be used for modeling count data as it is easy to interpret (Srinivasan & Bauer, 2013). In a Poisson regression model, the expected number of crashes at a given site is determined using equation 5-2 (Basu & Saha, 2017).

$$\lambda_i = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n) \quad (5\text{-}2)$$

Where λ_i = the expected number of crashes for site i.

The Poisson distribution restricts the mean and variance to be equal and therefore might not always give accurate results. Due to the assumption of equal mean and variance, Poisson models are not good at modeling over-dispersed data (variance is greater than the mean) (Basu & Saha, 2017). Poisson models are also "negatively influenced by the low sample mean and sample size biases" (Basu & Saha, 2017).

5.3.3 Negative Binomial (NB) Regression Model

One way to account for overdispersion is to model crash counts using an NB regression model. NB models are used in the HSM to develop SPFs. The NB model has the form shown in equation 5-3 (Donnell et al., 2014). Like Poisson models, NB models are easy to interpret, but they can handle data with significant overdispersion (Donnell et al., 2014).

$$\ln\lambda_i = \beta X_i + \varepsilon_i \quad (5\text{-}3)$$

where,
λ_i = expected number of crashes on roadway segment i;
β = vector of estimable regression parameters;
X_i = vector of geometric design, traffic volume, and other site-specific data; and
ε_i = gamma-distributed error term.

5.3.4 Zero-Inflated Poisson (ZIP) and Zero-Inflated Negative Binomial (ZINB) Models

The disadvantage of using GLM models such as Poisson and NB are their inability to account for the excessive zero counts that can be present in crash data (especially for rural areas with lower traffic volumes). To address this issue, ZIP and ZINB models can be used. The ZIP and ZINB models allow for different sets of variables to model the zero state and the count state (Prasetijo et al., 2019). The equations for these models are the same as the equations for the Poisson model (equation 5-2) and NB model (equation 5-3), respectively, with the zero-inflated models having an additional model of the same form for the excess zero counts. These models were considered for the studied groups which had excess zero counts (more than 10% of the intersections in the group had zero crashes), as they are not applicable for groups with low zero counts.

5.3.5 Boosted Regression Trees (BRTs)

The last modeling methodology considered was the use of BRTs. Limited research has been done on using BRTs to develop SPFs. Their advantage over the previous methodologies is that they do not impose a linear relationship between the crash volumes and independent variables. In this study, BRT models were developed using the "gbm" function in R software with the number of trees set to 1000 (R Core Team, 2014). BRTs fit several decision trees to effectively improve the model's accuracy. The BRT methodology consists of taking a random sample of the data for each tree and fitting the model. Then, the used data points are re-entered into the dataset at each iteration and can be used by subsequent trees. These input data are weighted so data which were poorly modeled by earlier trees have a higher chance of being selected for subsequent trees. This allows the model to account for prediction errors of the previous trees when fitting the next tree and therefore the model continues to try to improve its performance. The modeling results show the most influential variables that affect crash frequency, along with the relative influence of each variable on the predicted crashes. This relative influence value is calculated "based on the times a variable is selected for splitting and then weighted by the squared improvement to the model as a result of each split" (Elith et al., 2008). The relative influence of each variable is then averaged over all developed trees and scaled so that the sum of the relative influence of all variables adds to 100. Higher relative influence values indicate stronger influence on the dependent variable, with a relative influence value of zero indicating that the variable has no impact on the dependent variable (Elith et al., 2008).

The major disadvantage that BRTs have compared to the previous models is that BRTs do not provide a model equation showing the signs and coefficients for the influential variables. This makes the BRTs less user friendly for practitioners compared to the previous models, as it is harder to interpret and utilize the BRT results to identify high-risk locations and understand how potential modifications will affect the expected number of crashes. For this project, it is important for the selected SPF models to have a functional form and be interpretable so FDOT can identify effective countermeasures. Therefore, model interpretability was considered the most important model selection criterion, as discussed in section 5.3.7.

5.3.6 Performance Measures

All the models developed using the methodologies described above were evaluated and compared using five performance measures to identify the model that best predicts the total crashes. These measures are:

1. Mean absolute error (MAE)
2. Mean absolute percentage error (MAPE)
3. Root mean squared error (RMSE)
4. Akaike information criterion (AIC)
5. Bayesian information criterion (BIC)

The prediction performance measures, MAE, MAPE, and RMSE are shown in equations 5-4, 5-5, and 5-6, respectively. Lower values of these measures indicate a better performing model.

$$MAE = \frac{1}{n}\sum\left|y_{actual} - y_{pred}\right| \tag{5-4}$$

$$MAPE = \left(\frac{1}{n}\sum\left|\frac{y_{actual}-y_{pred}}{y_{actual}}\right|\right) * 100 \tag{5-5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum\left|y_{actual} - y_{pred}\right|^2} \tag{5-6}$$

Where y_{actual} = observed crash volume,
y_{pred} = estimated crash volume; and
n = number of observations in the intersection group.

The values of AIC and BIC are obtained from the SAS outputs when running NB, Poisson, ZINB, and ZIP models. These AIC and BIC values indicate how well the model fits the data, with lower values indicating a better fit. Both AIC and BIC are not applicable for BRT models since they are non-parametric models.

5.3.7 Model Selection Criteria

Since multiple models were developed for each intersection group (Poisson, NB, and BRT for all 19 studied groups, with ZIP and ZINB for all groups that had zero crashes at more than 10% of their intersections), selection criteria were needed to ensure that the best model was chosen in a consistent manner for each group. Two selection criteria were used to choose the best models: model interpretability and performance measures.

The first criterion, model interpretability, was used to ensure that the model has a functional form and contains coefficient estimates for the influential variables. As mentioned in the discussion of the BRT modeling methodology (section 5.3.5), this interpretability is essential for FDOT to effectively use the developed SPFs. Therefore, a model must meet this criterion before considering the second criterion. The only considered models which do not meet this first criterion are the BRT models. Therefore, BRTs were never selected as SPFs and they were not compared to the other models using the second criterion. For the second criterion, the values of the performance measures mentioned in section 5.3.6 (MAE, MAPE, RMSE, AIC, and BIC) were compared. The model with the lowest values for the majority of these measures (at least three of the five measures) was chosen as the SPF model for the modeled intersection group.

Chapter 6: Developing and Comparing Context-Specific Safety Performance Functions

Using the modeling methodologies identified in chapter 5, SPFs were developed for the 19 modeled intersection groups. As mentioned previously, modeling was initially conducted for the 21 intersection groups shown in gray in table 5-1, but the C3C signalized 3-leg and C5 unsignalized 3-leg groups did not have sufficient sample sizes to develop significant models. Therefore, SPFs were developed for the 19 remaining intersection groups with sufficient sample sizes. This chapter first discusses the linear regression model developed to predict minor AADT volumes for intersections with unavailable minor AADT data. Next, the different models are compared for each intersection group and the best performing model is identified and selected to develop SPFs for each intersection groups based on the model selection criteria defined in the previous section. The developed SPFs for each group are then presented by context classification type along with discussions of the influential variables (sections 6.3.1-6.3.6). Additionally, similar groups without a sufficient sample size (C6 unsignalized 3-leg and 4-leg) were combined to provide a sufficient sample size for modeling. This combined intersection group SPF developed for the C6 classification category is presented in section 6.3.7.

To showcase the benefits of developing context-specific SPFs, three main comparisons were done for this project. First, comparisons of the different sets of significant variables common to different context classification categories are discussed in section 6.4. Then, the eight individual intersection group SPFs that were developed for the C3R-Suburban Residential and C4-Urban General categories (provided in sections 6.3.3 and 6.3.5) were compared with full SPFs for these categories (section 6.5). Each full SPF uses data from all intersections in a category, rather than considering each intersection type separately. Comparing the individual and full SPFs within each category can show how the individual SPFs based on the context classification system better identify significant factors and regional differences. These comparisons illustrate the unique and regional insights that agencies can gain by developing these individual SPFs. Finally, HSM SPFs (baseline, baseline with CMFs, and calibrated with CMFs) for rural two-lane, two-way roads were compared with the developed context-specific SPF for C2T-Rural Town signalized 4-leg intersections (section 6.6).

6.1 Minor Average Annual Daily Traffic (AADT) Model

The 719 intersections shown in table 5-2 (which are from the 21 intersection groups highlighted in gray in table 5-1) were used to develop the minor AADT model. Stepwise selection was used to determine the statistically significant variables by fitting multiple linear regression models in SAS software (SAS 9.4, 2013). Table 6-1 shows the variables included in the final minor AADT model, with the model equation shown in equation 6-1. All included variables were significant at the 5% significance level ($p\text{-value} < 0.05$).

Table 6-1: Minor AADT Model Estimates and Statistical Significance

Variable	Estimate	Standard Error	F-value	P-Value
Intercept	3.059	0.613	42.995	<.0001
Ln(Major AADT)	0.472	0.056	108.24	<.0001
Major Exclusive Left Turn Length	0.00089	0.00024	4.87	0.0005
Minor Exclusive Left Turn Number	0.349	0.063	280.92	<.0001
Minor Exclusive Right Turn Number	0.336	0.073	18.52	<.0001
Minor Through Lanes	0.170	0.036	33.4	<.0001
Speed Limit Major	-0.023	0.004	5.621	<.0001
Speed Limit Minor	0.0095	0.005	4.32	0.0382
Major Median	0.149	0.072	4.87	0.0277
Functional Class Minor = 2	-0.346	0.099	18.52	<.0001
Functional Class Minor = 1	-0.592	0.083	53.49	<.0001

$$Ln(Minor\ AADT) = 3.059 + 0.472\ln(Major\ AADT) + 0.00089(Major\ Exclusive\ Left\ Turn\ Length) + 0.349(Minor\ Exclusive\ Left\ Turn\ Number) + 0.336(Minor\ Exclusive\ Right\ Turn\ Number) + 0.170(Minor\ Through\ Lanes) - 0.023(Speed\ Limit\ Major) + 0.0095(Speed\ Limit\ Minor) + 0.149(Major\ Median) - 0.346(Functional\ Class\ Minor = 2) - 0.592(Functional\ Class\ Minor = 1) \tag{6-1}$$

This model indicates that intersections with higher major AADT, more minor through lanes, higher minor road speed limit, longer major exclusive left turn length, higher number of minor exclusive left turn and right turn lanes, and absence of a dividing median on the major road are expected to have higher minor AADT (keeping all the other variables constant). Conversely, intersections with higher major road speed limits are expected to have lower minor AADT with all other variables held constant. The minor road functional class has a negative coefficient for both local and collector roads, indicating that these roads have lower minor AADT volumes compared to arterial roads, holding all other variables constant.

Most of the relationships between these variables and minor AADT are easy to understand. For example, higher major AADT indicates more traffic in an area, so higher minor AADT is expected. Likewise, longer exclusive left turn lanes on the major roadway indicate a high presence of vehicles turning onto the minor road, suggesting higher minor AADT. Minor roads with more through and turning lanes and higher speed limits are expected to have more traffic (since they were designed to handle more capacity), so the positive signs for these variables' coefficients make sense. The negative sign for the functional class of the minor road is also straightforward, since local and collector roads should have lower volumes than arterials. The relationships between the remaining two variables (major median and speed limit major) and minor AADT are more complicated. If the major roadway has a median, vehicles might only be able to turn right from the minor road onto the major road (if the median continues across the intersection) and they might have limited turning options further along the major road compared to if there was no median. These factors might mean that the minor road is primarily only used by vehicles who need to access their destination using that road and not used by vehicles who want to use the road as an alternate route to avoid traffic on the major road, resulting in lower minor AADT. A higher speed limit on the major road could result in lower minor AADT volumes due to worries about being able to safely turn from the minor road onto the major road at unsignalized intersections or long green phases on the major road causing delays on the minor road at signalized intersections, making these minor roads less appealing.

An analysis of variance (ANOVA) was conducted to determine the significance of the final minor AADT model shown in equation 6-1. The ANOVA had p-value < 0.0001, indicating that the model is highly significant. To test the accuracy and prediction performance of the developed model, the data set was divided into a training set (80% of the data) and a test set (20% of the data). The test MAPE was 6.21%, MAE was 0.505, RMSE was 0.6599, and the adjusted R^2 was 0.62; these results show that the model accurately predicts minor AADT volumes using the significant variables in the model. Therefore, this model was used to determine the missing minor AADT values in all the 19 intersection groups as well as the two combined intersection groups presented in section 6.3.7.

A study conducted in Oregon also developed a linear regression model to predict the minor AADT volumes when these volumes are unavailable (Dixon et al., 2015). This Oregon model had four significant variables: log(major AADT), major through lanes, functional class major, and functional class minor. The log(major AADT) estimate had a positive coefficient and the functional class minor variable had a negative coefficient (Dixon et al., 2015); these signs are consistent with the developed minor AADT model shown in equation 6-1. However, the adjusted R^2 for the Oregon developed model was 0.5658 and the MAPE was 52.4% (Dixon et al., 2015), which indicate that the minor AADT model shown in equation 6-1 performs significantly better than the Oregon model at predicting the missing minor AADT volumes. It is important to note that only 66 intersections were used to develop the Oregon minor AADT model, while the minor AADT model developed in this project used a much larger sample of 719 intersections.

6.2 SPF Model Development and Selection for Each Modeled Intersection Group

With the missing minor AADT values estimated using the model in equation 6-1, the data for each of the 19 intersection groups was ready to be modeled. Poisson, NB, and BRT models were considered for all 19 groups. Since the ZINB and ZIP models are only appropriate for data with an excessive number of zeros, each group was analyzed to determine the number and percentage of interchanges with zero crashes. Table 6-2 shows these values for each of the 19 intersection groups. The eight groups with more than 10% of their intersections having zero crashes were considered to have excessive zero counts (value of “Yes” in last column of table 6-2), so ZIP and ZINB models were only considered for these eight groups. Even though the ZIP and ZINB models are appropriate for these groups, they are not guaranteed to outperform the regular

Poisson or NB models, as the characteristics of the individual data sets will determine which model performs the best.

Table 6-2: Number and Percentage of Intersections with Zero Crashes for Each Intersection Group

Intersection Group (Signalization, Number of Legs, and Context Classification Category)		Sample Size	Number of Intersections with Zero Crashes	Percentage of Intersections with Zero Crashes	Excessive Zeros (>10%)
Unsignalized 3-Leg	C2-Rural	145	66	46%	Yes
	C2T-Rural Town	218	92	42%	Yes
	C3R-Suburban Residential	186	62	33%	Yes
	C3C-Suburban Commercial	120	20	17%	Yes
	C4-Urban General	147	8	5%	No
Unsignalized 4-Leg	C2-Rural	98	26	27%	Yes
	C2T-Rural Town	188	65	35%	Yes
	C3R-Suburban Residential	131	29	22%	Yes
	C3C-Suburban Commercial	120	13	10%	Yes
	C4-Urban General	140	5	4%	No
	C5-Urban Center	103	3	3%	No
Signalized 3-Leg	C3R-Suburban Residential	72	3	4%	No
	C4-Urban General	71	1	1%	No
Signalized 4-Leg	C2-Rural	58	0	0%	No
	C2T-Rural Town	70	6	9%	No
	C3R-Suburban Residential	192	1	1%	No
	C3C-Suburban Commercial	288	3	1%	No
	C4-Urban General	214	2	1%	No
	C5-Urban Center	97	0	0%	No

To determine the SPF model which best predicted the number of crashes in a three-year period for each classification group, the Poisson, NB, and BRT models (plus ZIP and ZINB for the eight groups with excessive zeros) were compared using the model selection criteria discussed in section 5.3.7. Table 6-3 shows the five considered performance measures and model interpretability for the eight intersection groups with excessive zeros, while table 6-4 shows these values for the remaining eleven groups. Values highlighted in gray indicate the lowest value for that performance measure for the intersection group. For the eight groups with excessive zeros (table 6-3), ZINB models were selected for two groups (C2-Rural unsignalized 3-leg and C3C-Suburban Commercial unsignalized 3-leg), and NB models were selected for the remaining six groups, based on the previously defined model selection criteria (model is easily interpretable and has the lowest values for at least three of the five performance measures). For all eleven groups without excessive zeros, NB models were selected. In both tables 6-3 and 6-4, BRT models often outperformed the other models. However, since BRTs do not have a functional form that can be easily used to identify locations with high crashes and see how changes to various factors will affect the predicted crashes, they did not meet the first model selection criteria (model interpretability) and were therefore not considered as possible SPF models or compared with the other models for the second model selection criterion (performance measures). The code used to develop and run the BRT models was provided to FDOT; this code can be used in R software to run the BRT models and obtain predictions. Details of the selected SPF models (indicated in the last rows of tables 6-3 and 6-4) are discussed in section 6.3.

Table 6-3: Performance Measures for Intersection Groups with Excessive Zero Crash Data

Model	Performance Measure	C2-Rural Unsignalized 3-Leg	C2-Rural Unsignalized 4-Leg	C2T-Rural Town Unsignalized 3-Leg	C2T-Rural Town Unsignalized 4-Leg	C3R-Suburban Residential Unsignalized 3-Leg	C3R-Suburban Residential Unsignalized 4-Leg	C3C-Suburban Commercial Unsignalized 3-Leg	C3C-Suburban Commercial Unsignalized 4-Leg
Poisson	***MAE***	2.56	2.38	1.74	1.57	1.55	3.24	4.38	4.39
	MAPE	104.0%	90.4%	58.3%	67.4%	68.6%	93.3%	195.1%	94.3%
	RMSE	5.09	3.92	2.81	2.52	2.22	4.77	6.09	5.55
	AIC	281.9	295.5	483.4	547.4	492.3	443.8	546.0	536.1
	BIC	305.4	308.7	495.4	558.9	520.8	456.3	562.6	550.3
	Model Interpretability	Yes	Yes	yes	Yes	Yes	Yes	Yes	Yes
NB	***MAE***	1.93	1.68	1.71	1.56	1.54	3.26	3.73	4.36
	MAPE	86.7%	54.7%	52.1%	63.2%	58.6%	81.9%	157.3%	91.4%
	RMSE	3.31	2.31	2.81	2.53	2.26	3.14	5.29	5.71
	AIC	282.9	267.3	447.7	456.4	464.4	392.6	413.7	437.2
	BIC	311.5	278.3	462.7	470.7	481.5	407.7	428.0	453.8
	Model Interpretability	Yes	Yes	Yes	yes	Yes	Yes	Yes	Yes
ZINB	***MAE***	1.63	1.94	1.70	1.86	1.64	2.96	4.33	4.68
	MAPE	78.3%	82.5%	53.6%	67.2%	80.2%	89.9%	136.0%	101.0%
	RMSE	2.72	2.76	2.82	3.33	2.42	4.12	5.74	5.83
	AIC	279.9	271.2	447.9	459.4	464.5	404.5	408.2	437.5
	BIC	308.6	286.6	468.5	479.3	493.0	419.5	427.3	458.1
	Model Interpretability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ZIP	***MAE***	2.07	1.95	1.71	1.93	2.09	3.14	4.58	4.51
	MAPE	80.4%	82.5%	59.5%	72.1%	68.2%	90.1%	205.2%	96.0%
	RMSE	4.46	2.69	2.84	3.56	5.12	4.47	6.41	5.65
	AIC	289.9	294.7	458.8	515.6	489.6	429.9	520.7	509.5
	BIC	315.9	310.1	482.8	535.6	506.7	445.1	541.6	530.8
	Model Interpretability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6-3: Performance Measures for Intersection Groups with Excessive Zero Crash Data…Continued

Model	***Performance Measure***	C2-Rural Unsignalized 3-Leg	C2-Rural Unsignalized 4-Leg	C2T-Rural Town Unsignalized 3-Leg	C2T-Rural Town Unsignalized 4-Leg	C3R-Suburban Residential Unsignalized 3-Leg	C3R-Suburban Residential Unsignalized 4-Leg	C3C-Suburban Commercial Unsignalized 3-Leg	C3C-Suburban Commercial Unsignalized 4-Leg
BRT	***MAE***	2.32	1.07	2.34	1.75	1.84	1.75	1.28	2.28
	MAPE	59.4%	36.4%	57.4%	55.1%	66.2%	50.0%	42.8%	55.1%
	RMSE	3.53	1.67	3.3	2.59	2.93	2.44	2.28	3.25
	AIC	N/A*	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	BIC	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Model Interpretability	No	No	No	No	No	No	No	No
SELECTED SPF MODEL		ZINB	NB	NB	NB	NB	NB	ZINB	NB

*N/A stands for not applicable.

Table 6-4: Performance Measures for Intersection Groups without Excessive Zero Crash Data

Model	Performance Measure	C2-Rural Signalized 4-Leg	C2T-Rural Town Signalized 4-Leg	C3R-Suburban Residential Signalized 3-Leg	C3R-Suburban Residential Signalized 4-Leg	C3C-Suburban Commercial Signalized 4-Leg	C4-Urban General Unsignalized 3-Leg	C4-Urban General Unsignalized 4-Leg	C4-Urban General Signalized 3-Leg	C4-Urban General Signalized 4-Leg	C5-Urban Center Unsignalized 4-Leg	C5-Urban Center Signalized 4-Leg
Poisson	***MAE***	12.13	6.54	6.98	8.62	13.40	4.72	5.34	12.47	21.23	9.95	18.89
	MAPE	87.3%	54.1%	66.2%	93.4%	70.6%	78.6%	104.1%	88.4%	89.4%	195.0%	76.6%
	RMSE	14.56	10.30	8.91	12.69	18.28	6.70	7.21	16.00	31.86	14.76	28.97
	AIC	415.4	331.6	391.5	1811.5	3609.1	751.5	747.1	534.8	2079.9	653.3	1167.4
	BIC	428.7	344.5	404.7	1828.8	3635.4	767.2	762.5	547.5	2106.9	669.3	1182.7
	Model Interpretability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NB	***MAE***	10.13	5.89	6.43	13.82	14.12	4.40	5.21	11.98	17.54	9.91	16.67
	MAPE	80.6%	39.6%	64.2%	82.7%	68.5%	89.5%	100.6%	96.4%	70.6%	162.3%	61.5%
	RMSE	14.63	11.03	8.38	20.06	18.76	6.43	7.36	15.49	25.92	13.96	25.85
	AIC	308.1	279.7	336.9	1076.2	1669.1	582.5	592.4	368.6	1260.9	493.3	571.5
	BIC	316.4	290.8	350.1	1090.6	1692.1	595.6	607.8	377.7	1284.7	504.6	582.4
	Model Interpretability	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BRT	***MAE***	4.46	10.01	5.92	9.27	10.07	3.05	3.38	12.22	11.72	5.3	14.01
	MAPE	46.1%	60.4%	58.6%	49.9%	49.1%	60.4%	72.4%	50.2%	57.8%	75.1%	59.2%
	RMSE	5.56	17.5	7.58	12.94	13.85	4.89	4.68	18.53	17.95	7.21	21.47
	AIC	N/A*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	BIC	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Model Interpretability	No	No	No	No	No	No	No	No	No	No	No
SELECTED SPF MODEL		NB	NB	NB	NB	NB	NB	NB	NB	NB	NB	NB

*N/A stands for not applicable.

6.3 Safety Performance Functions (SPFs) for Each Context Classification Group

This section provides the SPFs for the 19 intersection groups shown in tables 6-3 and 6-4, including significant variables, coefficients, and p-values. SPFs for intersection groups with the same context classification category are presented in the same section (C2-Rural in 6.3.1, C2T-Rural Town in 6.3.2, C3R-Suburban Residential in 6.3.3, C3C-Suburban Commercial in 6.3.4, C4-Urban General in 6.3.5, and C5-Urban Center in 6.3.6). An additional SPF model was developed for the C6 context classification category by combining intersection groups that did not have sufficient data and including a variable to distinguish between each intersection group. This combined SPF model was developed using the intersections in the C6 unsignalized 3-leg and C6 unsignalized 4-leg intersection groups and is presented in section 6.3.7.

6.3.1 C2-Rural

6.3.1.1 C2-Rural Unsignalized 3-Leg

The C2-Rural unsignalized 3-leg intersection group was one of the intersection groups with excessive zeros. As shown in table 6-3, the ZINB model outperformed the other models for this group. Table 6-5 shows the significant variables, coefficient estimates, and p-values for the ZINB model, with the SPF shown in equation 6-2 and the zero-state model shown in equation 6-3. All variables were significant at a 5% significance level (p-value < 0.05). For the zero-state model, the only significant variable was the major AADT variable, which had a negative coefficient. This indicates that an increase in major AADT volume reduces the probability of an intersection having zero crashes.

In this SPF, major AADT, intersect angle, speed limit minor and railroad (RR) zone variables have a positive relationship with the total crash data. This means that intersections in this group with more traffic on the major road, a higher minor road speed limit, and which are located in a railroad zone are expected to have more crashes. All these variables and their impact on the number of crashes make sense (roadways with more traffic and higher speeds are expected to have more crashes, while the presence of railroad crossings could result in increased rear-end crashes due to drivers suddenly stopping for the railroad gates). Additionally, the intersect angle variable indicates that intersections with angles less than 90 degrees tend to have less crashes than 90-degree angled intersections. One possible reason for this is that drivers might be more cautious and travel at lower speeds while turning at intersections with smaller angles (due to reduced sight distances), thereby reducing the chances of a crash. The lighting variable also had a negative coefficient, indicating that the presence of lighting at an intersection reduces the crashes at that intersection (which makes sense). The final significant variable was the district variable, which was significant for FDOT D2 and D7. Since these were the only districts with statistically significant coefficients, they were compared to all other districts. The negative estimate for D2 indicates that intersections from this group located in D2 are expected to have fewer crashes than intersections from this group located in other districts. Similarly, the positive estimate for D7 indicates that intersections from this group located in D7 are expected to have higher crashes than intersections from this group located in other districts. These differences could be due to driver characteristics, signalization, or other factors which vary between districts, but were not considered in the SPF model. A future research project could examine the intersections from this group (and other groups with statistically significant district variables) in the identified districts in more detail to better understand these differences.

Table 6-5: Zero-Inflated Negative Binomial SPF Model for C2-Rural Unsignalized 3-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-4.493	1.521	10.52	0.0012
District = 2	-1.141	0.349	10.70	0.0011
District = 7	1.183	0.274	18.60	<0.0001
Ln(Major AADT)	0.396	0.169	5.46	0.0195
Intersect Angle	0.813	0.239	11.48	0.0007
Speed Limit Minor	0.056	0.009	33.60	<0.0001
Lighting	-0.902	0.274	10.83	0.0010
RR Zone	1.644	0.379	18.85	<0.0001

$$N_{pred} = \exp\left(-4.493 - 1.141(District = 2) + 1.183(District = 7) + 0.396\ln(Major\ AADT) + 0.813(Intersect\ Angle) + 0.056(Speed\ Limit\ Minor) - 0.902(Lighting) + 1.644(RR\ Zone)\right) \quad (6\text{-}2)$$

$$N_{pred} = \exp\left(9.327 - 1.706\ln(MajorAADT)\right) \quad (6\text{-}3)$$

Where N_{pred} is the number of predicted total crashes for a specific site.

The SPF shown in equation 6-2 was compared to a Florida-specific SPF for rural 3-leg intersections from previous literature (Lu, 2013). The mean squared error (MSE) for the developed C2 unsignalized 3-leg intersection SPF was 20.3, while the MSE for the rural 3-leg intersection SPF developed in previous research was 192.47. Since a lower MSE value is better, this comparison shows that the context-specific SPF developed for this project performed much better than the previously developed SPF which only classified intersections into rural and urban classifications.

6.3.1.2 C2-Rural Unsignalized 4-Leg

The C2-Rural unsignalized 4-leg intersection group was one of the intersection groups with excessive zeros. As shown in table 6-3, the NB model outperformed the other models for this group. Table 6-6 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-4. All variables were significant at a 5% significance level (p-value < 0.05). Like the SPF for the previous group, major AADT and speed limit minor have positive coefficients while D2 has a negative coefficient.

Table 6-6: Negative Binomial SPF Model for C2-Rural Unsignalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-5.929	1.619	13.41	0.0003
District = 2	-0.617	0.303	4.16	0.0413
Ln(Major AADT)	0.662	0.170	15.09	0.0001
Speed Limit Minor	0.713	0.014	6.34	0.0118

$$N_{pred} = \exp\left(-5.929 - 0.617(District = 2) + 0.662\ln(Major\ AADT) + +0.713(Speed\ Limit\ Minor)\right) \tag{6-4}$$

6.3.1.3 C2-Rural Signalized 4-Leg

The C2-Rural signalized 4-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-7 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF equation shown in equation 6-5. All variables were significant at a 5% significance level (p-value < 0.05) except for lighting, which had a p-value of 0.051 (significant at a 10% significance level). The signs of the major AADT and lighting variables are consistent with previous groups. This is the first group where minor AADT was a significant variable; the positive sign indicates that intersections in this group with more traffic on the minor road are expected to have more crashes (which makes sense and agrees with the positive sign for the major AADT). Unlike the previous groups, the district variable was not a significant predictor in this intersection group, indicating that there is no significant difference in the number of crashes between districts for intersections in this group.

Table 6-7: Negative Binomial SPF Model for C2-Rural Signalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-6.976	2.049	11.59	0.0007
Ln(Major AADT)	0.735	0.184	15.96	<0.0001
Ln(Minor AADT)	0.383	0.151	6.42	0.0113
Lighting	-0.448	0.229	3.80	0.051

$$N_{pred} = \exp\left(-6.976 + 0.735\ln(Major\ AADT) + 0.383\ln(Minor\ AADT) - 0.448(Lighting)\right) \tag{6-5}$$

6.3.2 C2T-Rural Town

6.3.2.1 C2T-Rural Town Unsignalized 3-Leg

The C2T-Rural Town unsignalized 3-leg intersection group was one of the intersection groups with excessive zeros. As shown in table 6-3, the NB model outperformed the other models for this group. Table 6-8 shows the significant variables, coefficient estimates, and p-values for the

NB model, with the SPF shown in equation 6-6. All variables were significant at a 5% significance level (p-value < 0.05). Only one variable in this model, major AADT, was common to the developed SPFs for the C2-Rural context classification intersection groups. This shows that different factors affect the number of intersection crashes for different context classifications. Like the previous SPFs, major AADT has a positive coefficient. The district variable was significant for D3 and had a negative coefficient, indicating that intersections from this group located in D3 are expected to have fewer crashes than intersection from this group located in any other district. Road width of the minor road was the final significant variable, with the positive coefficient indicating that intersections in this group with wider minor roads are expected to have more crashes. This makes sense because wider roads typically have more traffic and a higher tendency for drivers to speed, which leads to more crashes.

Table 6-8: Negative Binomial SPF Model for C2T-Rural Town Unsignalized 3-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-10.376	1.839	31.81	<0.0001
District = 3	-0.871	0.234	13.81	0.0002
Ln(Major AADT)	1.119	0.199	31.63	<0.0001
Road Width Minor	0.034	0.014	6.40	0.0114

$$N_{pred} = \exp\left(-10.376 - 0.871(District = 3) + 1.119\ln(Major\ AADT) + +0.034(Road\ Width\ Minor)\right) \quad (6\text{-}6)$$

6.3.2.2 C2T-Rural Town Unsignalized 4-Leg

The C2T-Rural Town unsignalized 4-leg intersection group was one of the intersection groups with excessive zeros. As shown in table 6-3, the NB model outperformed the other models for this group. Table 6-9 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-7. All variables were significant at a 5% significance level (p-value < 0.05). Both the major and minor AADT had positive coefficients (similar to previous groups), while the district variable had a positive coefficient for D7. This means that intersections from this group located in D7 are expected to have more crashes than intersections from this group located in any other district.

Table 6-9: Negative Binomial SPF Model for C2T-Rural Town Unsignalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-13.957	2.107	43.88	<0.0001
District = 7	0.942	0.391	5.81	0.0159
Ln(Major AADT)	1.092	0.214	26.11	<0.0001
Ln(Minor AADT)	0.690	0.349	3.89	0.0486

$$N_{pred} = \exp\left(-13.957 + 0.942(District = 7) + 1.092 \ln(Major\ AADT) + +0.690 \ln(Minor\ AADT)\right) \quad (6\text{-}7)$$

6.3.2.3 C2T-Rural Town Signalized 4-Leg

The C2T-Rural Town signalized 4-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-10 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-8. All variables were significant at a 5% significance level (p-value < 0.05) except for major AADT (p-value of 0.0731) and lighting (p-value of 0.0685), which were both significant at a 10% significance level. The significant variables in this model were all included in one or more previous SPFs with their coefficients having the same sign. This consistency indicates that there are similarities between the different intersection groups, but only developing one model for each context classification category would not show the different significant variables, variable combinations, and coefficient magnitudes for each individual intersection group.

Table 6-10: Negative Binomial SPF Model for C2T-Rural Town Signalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-3.939	2.015	3.82	0.0506
District = 3	-1.472	0.326	20.42	<0.0001
Ln(Major AADT)	0.396	0.221	3.21	0.0731
Ln(Minor AADT)	0.413	0.124	11.14	0.0008
Lighting	-0.814	0.447	3.32	0.0685

$$N_{pred} = \exp\left(-3.939 - 1.472(District = 3) + 0.396 \ln(Major\ AADT) + +0.413 \ln(Minor\ AADT) - 0.814(Lighting)\right) \quad (6\text{-}8)$$

6.3.3 C3R-Suburban Residential

6.3.3.1 C3R-Suburban Residential Unsignalized 3-Leg

The C3R-Suburban Residential unsignalized 3-leg intersection group was one of the intersection groups with excessive zeros. As shown in table 6-3, the NB model outperformed the other models for this group. Table 6-11 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-9. All variables were significant at a 5% significance level (p-value < 0.05) except for major AADT (p-value of 0.0739) and minor AADT (p-value of 0.0569), which were both significant at a 10% significance level. Like previous groups, the major and minor AADT variables have positive coefficients, while the remaining variables were not present in the SPFs for any previous groups. The functional class of minor road variable has a negative coefficient for a value of 1. This variable contained three categories: arterial (0), collector (1) or a local road (2), so the negative estimate for functional class (1) indicates that less crashes are expected to occur on collector roads as opposed to arterial roads, since a value of 0 was used as the base category for this variable. This relationship makes sense, since collector roads in this intersection group are likely to be around residential areas where people might drive more cautiously compared to higher-speed arterials. D4 was the only significant district in this intersection group, with the negative coefficient indicating that intersections from this group located in D4 are expected to have less crashes than intersections from this group located in any other district.

Table 6-11: Negative Binomial SPF Model for C3R-Suburban Residential Unsignalized 3-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-8.873	1.973	20.23	<0.0001
District = 4	-1.953	0.587	11.09	0.0009
Ln(Major AADT)	0.521	0.292	3.19	0.0739
Ln(Minor AADT)	0.938	0.492	3.62	0.0569
Functional Class Minor = 1	-1.508	0.706	4.57	0.0326

$$N_{pred} = \exp\left(-8.873 - 1.953(District = 4) + 0.521\ln(Major\ AADT) + \right.$$
$$\left. +0.938\ln(Minor\ AADT) - 1.508\ (Functional\ Class\ Minor = 1)\right) \quad (6\text{-}9)$$

6.3.3.2 C3R-Suburban Residential Unsignalized 4-Leg

The C3R-Suburban Residential unsignalized 4-leg intersection group was one of the intersection groups with excessive zeros. As shown in table 6-3, the NB model outperformed the other models for this group. Table 6-12 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-10. All variables were significant at a 5% significance level (p-value < 0.05). The major AADT, minor AADT, and D4 coefficients had the same signs as the previous group. A new variable is the major median variable. This variable has a positive coefficient, indicating that intersections with an undivided major road are expected to have more crashes than intersections where the major road is divided, which makes sense since vehicles have a higher chance of crashing into vehicles on the opposite side of the road or vehicles turning left across traffic without the presence of divided medians.

Table 6-12: Negative Binomial SPF Model for C3R-Suburban Residential Unsignalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-14.297	2.156	43.99	<0.0001
District = 4	-1.071	0.375	8.18	0.0042
Ln(Major AADT)	0.991	0.292	11.52	0.0007
Ln(Minor AADT)	0.858	0.369	5.41	0.0200
Major Median	0.646	0.283	5.20	0.0226

$$N_{pred} = \exp\left(-14.297 - 1.071(District = 4) + 0.991 \ln(Major\ AADT) + +0.858 \ln(Minor\ AADT) + 0.646(Major\ Median)\right) \quad (6\text{-}10)$$

6.3.3.3 C3R-Suburban Residential Signalized 3-Leg

The C3R-Suburban Residential signalized 3-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-13 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-11. All variables were significant at a 5% significance level (p-value < 0.05) except for district = 7, which had a p-value of 0.0679 (significant at a 10% significance level). The four significant variables from the previous group are also significant for this group, with their coefficients having the same signs for both groups. In addition to these variables, the D7 variable was also significant and had a negative coefficient. The negative coefficients for both D4 and D7 indicate that intersections from this group located in either of these districts are expected to have less crashes than intersections from this group in any of the other districts.

Table 6-13: Negative Binomial SPF Model for C3R-Suburban Residential Signalized 3-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-11.153	1.869	35.62	<0.0001
District = 4	-0.583	0.218	7.15	0.0075
District = 7	-0.423	0.232	3.33	0.0679
Ln(Major AADT)	1.169	0.174	45.42	<0.0001
Ln(Minor AADT)	0.249	0.086	8.39	0.0038
Major Median	0.416	0.187	4.94	0.0263

$$N_{pred} = \exp\left(-11.153 - 0.583(District = 4) - 0.423(District = 7) + 1.169 \ln(Major\ AADT) + 0.249 \ln(Minor\ AADT) + 0.416(Major\ Median)\right) \quad (6\text{-}11)$$

6.3.3.4 C3R-Suburban Residential Signalized 4-Leg

The C3R-Suburban Residential signalized 4-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-14 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-12. All variables were significant at a 5% significance level (p-value < 0.05). The three significant variables were also significant in the SPFs for the previous two groups and their coefficients had the same signs for all three groups.

Table 6-14: Negative Binomial SPF Model for C3R-Suburban Residential Signalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-6.488	1.044	38.62	<0.0001
Ln(Major AADT)	0.618	0.103	35.69	<0.0001
Ln(Minor AADT)	0.395	0.063	38.80	<0.0001
Major Median	0.259	0.112	5.33	0.0210

$$N_{pred} = \exp\left(-6.488 + 0.618 \ln(Major\ AADT) + 0.395 \ln(Minor\ AADT) + 0.259(Major\ Median)\right) \quad (6\text{-}12)$$

6.3.4 C3C-Suburban Commercial

6.3.4.1 C3C-Suburban Commercial Unsignalized 3-Leg

The C3C-Suburban Commercial unsignalized 3-leg intersection group was one of the intersection groups with excessive zeros. As shown in table 6-3, the ZINB model outperformed the other models for this group. Table 6-15 shows the significant variables, coefficient estimates, and p-values for the ZINB model, with the SPF shown in equation 6-13 and the zero-state model shown in equation 6-14. All variables were significant at a 5% significance level (p-value < 0.05). Like the C2-Rural unsignalized 3-leg intersection group, the only significant variable in the zero-state model was the major AADT variable, which had a negative coefficient. This indicates that an increase in major AADT volume reduces the probability of an intersection having zero crashes. In the SPF model, the major AADT and lighting variables have coefficients with the same signs as in previous groups. The functional class minor = 2 (local roads) has a negative coefficient, indicating that intersections in this group with local minor roads are expected to have less crashes than intersections in this group with arterial minor roads. This makes sense because local roads have lower traffic volumes, lower speeds, and other characteristics that make vehicles less likely to crash on them. The district variable has a positive coefficient for D2 indicating that intersections from this group located in D2 are expected to have more crashes than intersections from this group located in any other district.

Table 6-15: Zero-Inflated Negative Binomial SPF Model for C3C-Suburban Commercial Unsignalized 3-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-9.493	1.869	25.78	<0.0001
District = 2	1.193	0.361	10.90	0.0010
Ln(Major AADT)	1.182	0.191	38.25	<0.0001
Lighting	-0.426	0.214	3.96	0.0467
Functional Class Minor = 2	-0.577	0.267	4.68	0.0304

$$N_{pred} = \exp\left(-9.493 + 1.193(District = 2) + 1.182\ln(Major\ AADT) - 0.426(Lighting) - 0.577(Functional\ Class\ Minor = 2)\right) \quad (6\text{-}13)$$

$$N_{pred} = \exp\left(26.98 - 3.1210\ln(MajorAADT)\right) \quad (6\text{-}14)$$

6.3.4.2 C3C-Suburban Commercial Unsignalized 4-Leg

The C3C-Suburban Commercial unsignalized 4-leg intersection group was one of the intersection groups with excessive zeros. As shown in table 6-3, the NB model outperformed the other models for this group. Table 6-16 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-15. All variables were significant at a 5% significance level (p-value < 0.05). The coefficient signs for the major AADT, intersect angle, and major median variables all agree with previous groups. Both D1 and D3 have negative coefficients, indicating that intersections from this group located in either of these districts are expected to have less crashes than intersections from this group in any of the other districts.

Table 6-16: Negative Binomial SPF Model for C3C-Suburban Commercial Unsignalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-9.886	2.151	21.12	<0.0001
District = 1	-0.526	0.231	5.19	0.0228
District = 3	-0.689	0.255	7.30	0.0069
Ln(Major AADT)	1.135	0.211	28.97	<0.0001
Intersect Angle	0.636	0.207	9.44	0.0021
Major Median	0.505	0.237	4.55	0.0329

$$N_{pred} = \exp\left(-9.886 - 0.526(District = 1) - 0.689(District = 3) + 1.135\ln(Major\ AADT) + 0.636\,(Intersect\ Angle) + 0.505(Major\ Median)\right) \quad (6\text{-}15)$$

6.3.4.3 C3C-Suburban Commercial Signalized 4-Leg

The C3C-Suburban Commercial signalized 4-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-17 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-16. All variables were significant at a 5% significance level (p-value < 0.05). Similar to previous groups, major AADT, minor AADT, and major median all had positive coefficients. Also, lighting and functional class minor = 2 (local roads) have negative coefficients, which agree with the C3C-Suburban Commercial unsignalized 3-leg intersection group.

Table 6-17: Negative Binomial SPF Model for C3C-Suburban Commercial Signalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-9.146	1.091	70.24	<0.0001
Ln(Major AADT)	0.899	0.102	78.43	<0.0001
Ln(Minor AADT)	0.425	0.046	87.28	<0.0001
Lighting	-0.301	0.132	5.24	0.0221
Functional Class Minor (= 2)	-0.389	0.123	9.98	0.0016
Major Median	0.204	0.099	4.19	0.0405

$$N_{pred} = \exp\left(-9.146 + 0.899\ln(Major\ AADT) + 0.425\ln(Minor\ AADT) - 0.301(Lighting) - 0.389(Functional\ Class\ Minor = 2) + 0.204(Major\ Median)\right) \quad (6\text{-}16)$$

6.3.5 C4-Urban General

6.3.5.1 C4-Urban General Unsignalized 3-Leg

The C4-Urban General unsignalized 3-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-18 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-17. All variables were significant at a 5% significance level (p-value < 0.05). The major AADT has a positive coefficient (like all previous groups), while the major exclusive left turn length has a negative coefficient, meaning that intersections in this group with longer exclusive left turn lanes on the major roadway are expected to have less crashes. This makes sense, as longer left turn lanes could prevent the left turn queue from exceeding the storage length of the left turn lane and extending into the through lanes, therefore reducing crashes due to drivers in the through lanes trying to go around the left turn queue. The D6 variable also has a positive coefficient, indicating that intersections from this group located in D6 are expected to have more crashes than intersections from this group located in any other district.

Table 6-18: Negative Binomial SPF Model for C4-Urban General Unsignalized 3-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-6.761	1.499	20.35	<0.0001
District = 6	0.676	0.167	16.46	<0.0001
Ln(Major AADT)	0.872	0.151	33.20	<0.0001
Major Exclusive Left Turn Length	-0.008	0.002	10.87	0.0010

$$N_{pred} = \exp\left(-6.761 + 0.676(District = 6) + 0.872\ln(Major\ AADT) - 0.008\ (Major\ Exclusive\ Left\ Turn\ Length)\right) \quad (6\text{-}17)$$

6.3.5.2 C4-Urban General Unsignalized 4-Leg

The C4-Urban General unsignalized 4-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-19 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-18. All variables were significant at a 5% significance level (p-value < 0.05). Like the previous group, the major AADT and D6 variables had positive coefficients. The speed limit minor variable also had a positive coefficient, which agrees with previous groups where this variable was significant. A new variable is the minor exclusive right turn number. This variable has a positive coefficient, which means that intersections with an exclusive right turn lane on the minor road are expected to have more crashes than intersections without an exclusive right turn lane on the minor road. Since exclusive turn lanes are typically used where there is a high number of turning vehicles, this increase in expected crashes could be due to the increased number of right-turning vehicles and associated increase in traffic conflicts.

Table 6-19: Negative Binomial SPF Model for C4-Urban General Unsignalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-5.469	1.607	11.58	0.0007
District = 6	0.887	0.166	28.70	<0.0001
Ln(Major AADT)	0.544	0.138	15.33	<0.0001
Minor Exclusive Right Turn Number	0.934	0.385	5.88	0.0153
Speed Limit Minor	0.066	0.023	8.41	0.0037

$$N_{pred} = \exp\left(-5.469 + 0.887(District = 6) + 0.544\ln(Major\ AADT) + 0.934\ (Minor\ Exclusive\ Right\ Turn\ Number) + 0.066\ (Speed\ Limit\ Minor)\right) \quad (6\text{-}18)$$

6.3.5.3 C4-Urban General Signalized 3-Leg

The C4-Urban General signalized 3-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-20 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-19. All variables were significant at a 5% significance level (p-value < 0.05). The positive coefficients for the three significant variables (major AADT, minor AADT, and major median) agree with previous groups where these variables were significant. The district variable was not significant, indicating there is no significant difference in the expected crashes between districts for this intersection group.

Table 6-20: Negative Binomial SPF Model for C4-Urban General Signalized 3-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-11.437	3.278	12.18	0.0005
Ln(Major AADT)	1.120	0.316	12.54	0.0004
Ln(Minor AADT)	0.322	0.122	6.94	0.0084
Major Median	0.552	0.273	4.09	0.0431

$$N_{pred} = \exp\left(-11.437 + 1.120\ln(Major\ AADT) + 0.322\ln(Minor\ AADT) + 0.552(Major\ Median)\right) \tag{6-19}$$

6.3.5.4 C4-Urban General Signalized 4-Leg

The C4-Urban General signalized 4-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-21 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-20. All variables were significant at a 5% significance level (p-value < 0.05). The positive coefficient for the D6 variable agrees with the SPFs for the C4 unsignalized intersection groups, while the positive coefficients for the other variables agree with multiple previous groups.

Table 6-21: Negative Binomial SPF Model for C4-Urban General Signalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-7.680	0.986	60.68	<0.0001
District = 6	0.449	0.107	17.70	<0.0001
Ln(Major AADT)	0.728	0.102	51.39	<0.0001
Ln(Minor AADT)	0.297	0.064	21.58	<0.0001
Intersect Angle	0.226	0.114	3.96	0.0466
Speed Limit Minor	0.031	0.011	7.34	0.0068
RR Zone	0.623	0.213	8.60	0.0034

$N_{pred} = \exp\,(-7.680 + 0.449(District = 6) + 0.728\ln(Major\ AADT) +$
$+\ 0.297\ln(Minor\ AADT) + 0.226(Intersect\ Angle) + 0.031(Speed\ Limit\ Minor) +$
$0.623(RR\ Zone))$ (6-20)

6.3.6 C5-Urban Center

6.3.6.1 C5-Urban Center Unsignalized 4-Leg

The C5-Urban Center unsignalized 4-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-22 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-21. All variables were significant at a 5% significance level (p-value < 0.05). Like all previous groups, the major AADT variable had a positive coefficient. The only other significant variables were the district variables for D1 and D7. Both of these coefficients had negative signs, indicating that intersections from this group located in either one of these districts are expected to have fewer crashes than intersections from this group located in any of the other districts.

Table 6-22: Negative Binomial SPF Model for C5-Urban Center Unsignalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-0.832	1.851	0.20	0.6531
District = 1	-1.061	0.239	19.58	<0.0001
District = 7	-0.783	0.208	14.20	0.0002
Ln(Major AADT)	0.377	0.182	4.30	0.0381

$N_{pred} = \exp\,(-0.832 - 1.061(District = 1) - 0.783(District = 7) +$
$0.377\ln(Major\ AADT))$ (6-21)

6.3.6.2 C5-Urban Center Signalized 4-Leg

The C5-Urban Center signalized 4-leg intersection group did not have excessive zeros, so the NB model was the best model. Table 6-23 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-22. All variables were significant at a 5% significance level (p-value < 0.05) except for major AADT, which had a p-value of 0.0657 (significant at a 10% significance level). All the significant variables had positive coefficients, which agree with multiple previous groups. The district variable was significant for D6, which was also the case for three of the four C4 intersection groups.

Table 6-23: Negative Binomial SPF Model for C5-Urban Center Signalized 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-3.448	1.712	4.06	0.044
District = 6	0.812	0.175	21.51	<0.0001
Ln(Major AADT)	0.341	0.186	3.39	0.0657
Ln(Minor AADT)	0.388	0.082	22.09	<0.0001

$$N_{pred} = \exp\left(-3.448 + 0.812(District = 6) + 0.341\ln(Major\ AADT) + 0.388\ln(Minor\ AADT)\right) \quad (6\text{-}22)$$

6.3.7 C6-Urban Core

6.3.7.1 C6-Urban Core Unsignalized 3-Leg and 4-Leg

Due to the insufficient sample sizes for the individual C6 intersection groups, similar groups were combined to provide a sufficient sample size for modeling. The two groups that were combined were the C6-Urban Core unsignalized 3-leg intersection group and unsignalized 4-leg intersection group. A binary leg number variable was added for this combined group to distinguish between 3-leg (0) and 4-leg (1) intersections in this group. Less than 10% of the intersections in this combined group had zero crashes, so ZINB and ZIP models were not appropriate models for this group. The NB model was the best performing model for this group with the following performance measure results: MAPE = 65.1%, MAE = 6.79, and RMSE = 11.29. Table 6-24 shows the significant variables, coefficient estimates, and p-values for the NB model, with the SPF shown in equation 6-23. All variables were significant at a 5% significance level (p-value < 0.05). Like previous SPFs, the major AADT and the intersect angle variables had positive coefficients. The major bike lane presence variable was significant in this SPF, but was not significant in any other SPF. The negative coefficient indicates that intersections in this combined group with an exclusive bike lane on the major road are expected to have fewer crashes than intersections in this group without an exclusive bike lane. This makes sense, as drivers tend to drive more cautiously when there are vulnerable road users on the road. The leg number variable had a positive coefficient, indicating that C6 4-leg intersections are expected to have more crashes than C6 3-leg intersections. This could be due to the higher traffic volumes at 4-leg intersections compared to 3-leg intersections.

Table 6-24: Negative Binomial SPF Model for C6-Urban Core Unsignalized 3-Leg and 4-Leg Intersections

Variable	Estimate	Standard Error	Chi-Square	p-value
Intercept	-3.552	2.444	2.11	0.1462
Ln(Major AADT)	0.477	0.233	4.18	0.0408
Intersect Angle	0.643	0.282	5.21	0.0224
Major Bike Lane Presence	-0.892	0.223	16.01	<0.0001
Leg Number	0.641	0.230	7.74	0.0054

$$N_{pred} = \exp\left(-3.552 + 0.477\ln(Major\ AADT) + 0.643(Intersect\ Angle) - 0.892(Major\ Bike\ Lane\ Presence\ ) + 0.641(Leg\ Number)\right) \quad (6\text{-}23)$$

6.4 Comparisons Between Developed Context-Specific SPFs

To better understand the findings from the developed context-specific SPFs and the similarities and differences between them, table 6-25 provides a summary of the significant variable coefficients for the developed SPFs. This table does not include the SPF model that was developed by combining two intersection groups in the C6 context classification category. The table is split into six sections based on context classification category, as two context classification categories (C1-Natural and C6-Urban Core) did not have any individual intersection groups with sufficient intersection and crash sample sizes. Values of “N/A” (not applicable) in the table indicate that a variable was not statistically significant in that group’s SPF and therefore did not have an estimated coefficient. Table 6-25 shows that different context classification categories had different sets of significant variables common to their intersection groups. For example, the D2 variable was common to two C2-Rural intersection groups while the D4 variable was common to three C3R-Suburban Residential intersection groups. The signs of the coefficients for these common variables were the same, indicating these factors had similar effects for intersection groups within the same context classification. There were also some common variables which were significant for intersection groups with the same signalization and number of legs, but different context classifications. Two examples of these are the lighting variable, which was significant for unsignalized 3-leg and signalized 4-leg intersections, and the speed limit minor variable, which was mainly significant for 4-leg intersections. Major AADT was significant and had a positive coefficient in all models, which agrees with previous research. Each model had a unique set of significant variables, which demonstrates that FDOT’s context classification system allows FDOT to more easily identify differences between intersection groups than the HSM, which uses fewer intersection groups. For context classification categories that have similar variables for all their intersection groups (such as C3R-Suburban Residential and C4-Urban General), a full model could be developed. This model could be then applied to all intersections in the context classification category and the results compared to the individual group SPFs. These full models were developed for these two context classification categories and compared with the individual SPFs to show the improved performance of the individual group SPFs, as discussed in the next section.

Table 6-25: Summary of Significant Variable Coefficients in the SPF Models for Each Context Classification Intersection Group

C2- Rural			
Variable	**Unsignalized 3-leg**	**Unsignalized 4-leg**	**Signalized 4-leg**
Intercept	-4.493	-5.929	-6.976
District = 2	-1.141	-0.617	N/A*
District = 7	1.183	N/A	N/A
Ln(Minor AADT)	N/A	N/A	0.383
Ln(Major AADT)	0.396	0.662	0.735
Intersect Angle	0.813	N/A	N/A
Speed Limit Minor	0.056	0.713	N/A
Lighting	-0.902	N/A	-0.448
RR Zone	1.644	N/A	N/A

C2T – Rural Town			
Variable	**Unsignalized 3-leg**	**Unsignalized 4-leg**	**Signalized 4-leg**
Intercept	-10.376	-13.957	-3.939
District = 3	-0.871	N/A	-1.472
District = 7	N/A	0.942	N/A
Ln(Minor AADT)	N/A	0.690	0.413
Ln(Major AADT)	1.119	1.092	0.396
Road Width Minor	0.034	N/A	N/A
Lighting	N/A	N/A	-0.814

C3R – Suburban Residential				
Variable	**Unsignalized 3-leg**	**Unsignalized 4-leg**	**Signalized 3-leg**	**Signalized 4-leg**
Intercept	-8.873	-14.297	-11.153	-6.488
District = 4	-1.953	-1.071	-0.583	N/A
District = 7	N/A	N/A	-0.423	N/A
Ln(Minor AADT)	0.938	0.858	0.249	0.395
Ln(Major AADT)	0.521	0.991	1.169	0.618
Functional Class Minor = 1	-1.508	N/A	N/A	N/A
Major Median	N/A	0.646	0.416	0.259

Table 6-25: Summary of Significant Variable Coefficients in the SPF Models for Each Context Classification Intersection Group… Continued

C3C – Suburban Commercial				
Variable	**Unsignalized 3-leg**	**Unsignalized 4-leg**	**Signalized 4-leg**	
Intercept	-9.493	-9.886	-9.146	
District = 1	N/A	-0.526	N/A	
District = 2	1.193	N/A	N/A	
District = 3	N/A	-0.689	N/A	
Ln(Minor AADT)	N/A	N/A	0.425	
Ln(Major AADT)	1.182	1.135	0.899	
Lighting	-0.426	N/A	-0.301	
Functional Class Minor = 2	-0.577	N/A	-0.389	
Intersect Angle	N/A	0.636	N/A	
Major Median	N/A	0.505	0.204	
C4- Urban General				
Variable	**Unsignalized 3-leg**	**Unsignalized 4-leg**	**Signalized 3-leg**	**Signalized 4-leg**
Intercept	-6.761	-5.469	-11.437	-7.680
District = 6	0.676	0.887	N/A	0.449
Ln(Minor AADT)	N/A	N/A	0.322	0.297
Ln(Major AADT)	0.872	0.544	1.120	0.728
Major Exclusive Left Turn Length	-0.008	N/A	N/A	N/A
Minor Exclusive Right Turn Number	N/A	0.934	N/A	N/A
Speed Limit Minor	N/A	0.066	N/A	0.031
Major Median	N/A	N/A	0.552	N/A
Intersect Angle	N/A	N/A	N/A	0.226
RR Zone	N/A	N/A	N/A	0.623
C5- Urban Center				
Variable	**Unsignalized 4-leg**	**Signalized 4-leg**		
Intercept	-0.832	-3.448		
District = 1	-1.061	N/A		
District = 6	N/A	0.812		
District = 7	-0.783	N/A		
Ln(Minor AADT)	N/A	0.388		
Ln(Major AADT)	0.377	0.341		

*N/A stands for "Not Applicable."

6.5 Comparison of Full SPF Models and Individual Context-Specific SPFs

The individual SPFs for the C3R-Suburban Residential and C4-Urban General context classification categories (presented in sections 6.3.3 and 6.3.5, respectively) were compared to the full SPFs developed for both categories. These were the only categories which had sufficient sample sizes for SPFs to be developed for all four intersection types. Each full SPF uses data from all intersections in a category, rather than considering each intersection type separately. Comparing the individual and full SPFs within each category can show how the individual SPFs based on the context classification system better identify significant factors and regional differences.

6.5.1 Full SPF Model Comparisons for C3R-Suburban Residential Context Classification

Table 6-26 shows the summary of the significant variables for all four C3R individual intersection group SPFs and the full SPF. A full SPF model for this context category was developed using data from all intersections in this category using the same methodology discussed in chapter 5. An NB model was chosen as the best SPF model using the model selection criteria presented in section 5.3.7. The significant variables for the full model are presented in the last column of table 6-26. All variables were significant at a 5% significance level (p-value < 0.05) except for those noted in table 6-26, which were significant at a 10% significance level. The major and minor AADT variables had positive coefficients and were significant in all of the C3R SPFs. The minor road functional class variable was significant for the unsignalized 3-leg intersection group and the full group and had a negative coefficient for collector roads. The major median variable was significant for all groups except unsignalized 3-leg intersections and the full group.

Table 6-26: Summary of Significant Variable Coefficients in the SPF Models for C3R-Suburban Residential Context Classification Group

Variable	Unsignalized 3-leg	Unsignalized 4-leg	Signalized 3-leg	Signalized 4-leg	Full Model
Intercept	-8.873	-14.297	-11.153	-6.488	-10.014
Ln(Major AADT)	0.521*	0.991	1.169	0.618	0.793
Ln(Minor AADT)	0.938*	0.858	0.249	0.395	0.629
Functional Class Minor = Collector Road	-1.508	N/A**	N/A	N/A	-0.649
Major Median	N/A	0.646	0.416	0.259	N/A
District = 4	-1.953	-1.071	-0.583	N/A	-0.413
District = 7	N/A	N/A	-0.423*	N/A	N/A

* Significant at a 10% significance level.
** N/A stands for "Not Applicable."

The last two significant variables were regional district variables. District 4, which contains Palm Beach and southeast Florida, was significant in three SPFs, with a negative coefficient in all these SPFs. This shows that intersections in D4 are expected to have fewer crashes than intersections from the same group in other districts. District 7, which contains Tampa and west central Florida, was only significant in the signalized 3-leg SPF and had a negative coefficient. This means that C3R signalized 3-leg intersections located in D7 are expected to have fewer crashes than C3R signalized 3-leg intersections in other districts (except D4 since it was also significant in this SPF).

Comparing the full SPF to the individual intersection group SPFs shows that some insights obtained from the individual SPFs would not be obtained by only considering the full SPF. D7 was not significant in the full model, so the lower expected crash frequencies in this district for signalized 3-leg intersections would not be identified. Losing this regional insight means that FDOT might not examine D7 for potential improvements that could be applied to other regions. The major median variable was also not significant in the full model. This variable was significant in three of the four individual intersection group SPFs, but FDOT would not see the impact of the major median on crash frequency if they only used the full SPF. This comparison demonstrates the importance of developing context-specific SPFs for each intersection group rather than only developing a full SPF for an entire context category.

6.5.2 Full SPF Model Comparisons for C4-Urban General Context Classification

Table 6-27 shows the summary of the significant variables for all four C4 individual intersection group SPFs and the full SPF. A full SPF model for this context category was developed using data from all intersections in this category using the same methodology discussed in chapter 5. An NB model was chosen as the best SPF model using the model selection criteria presented in section 5.3.7. All variables were significant at a 5% significance level (p-value < 0.05). Like the C3R SPFs, the major AADT, minor AADT, and major median have positive coefficients for the groups they are significant in, with the major AADT significant in all five SPFs. The remaining six variables were not significant in any of the C3R SPFs, showing the differences in crash factors between context classifications. The major exclusive left turn length was only significant for the unsignalized 3-leg and full SPFs, with a negative coefficient in both these SPFs. The minor road speed limit variable was significant for the unsignalized 4-leg, signalized 4-leg, and full SPFs, with a positive coefficient in all three of these SPFs (higher speed limit results in more crashes). The minor exclusive right turn number variable was only significant for the signalized 3-leg SPF and had a positive coefficient. Both the RR zone and intersect angle variables were significant in the signalized 4-leg SPF, with the RR zone variable also significant in the full SPF. The only significant regional variable in the C4 SPFs was the variable for district 6; this district was significant for all groups except signalized 3-leg intersections. District 6, which contains Miami and the Florida Keys, had a positive coefficient, indicating that intersections in D6 are expected to have more crashes than similar intersections in other districts.

Table 6-27: Summary of Significant Variable Coefficients in the SPF Models for C4-Urban General Context Classification Group

Variable	Unsignalized 3-leg	Unsignalized 4-leg	Signalized 3-leg	Signalized 4-leg	Full Model
Intercept	-6.761	-5.469	-11.437	-7.680	-8.104
Ln(Major AADT)	0.872	0.544	1.120	0.728	0.626
Ln(Minor AADT)	N/A*	N/A	0.322	0.297	0.449
Major Median	N/A	N/A	0.552	N/A	N/A
Major Exclusive Left Turn Length	-0.008	N/A	N/A	N/A	-0.0016
Speed Limit Minor	N/A	0.066	N/A	0.031	0.028
Minor Exclusive Right Turn Number	N/A	0.934	N/A	N/A	N/A
Intersect Angle	N/A	N/A	N/A	0.226	N/A
Railroad Zone	N/A	N/A	N/A	0.623	0.786
District = 6	0.676	0.887	N/A	0.449	0.616

* N/A stands for "Not Applicable."

Three variables that were significant in the individual intersection group SPFs were not significant in the full SPF: major median, minor exclusive right turn number, and intersect angle. If only the full SPF was used, the impacts of these variables would not be identified, which could make it harder for FDOT to identify reasons for higher crash frequencies and effective treatments to reduce crashes. The comparisons with the full SPFs for both the C3R and C4 categories show that developing SPFs for individual intersection types within each context classification can provide more insights into regional differences and crash factors than only considering full SPFs. These additional insights will help FDOT effectively direct resources and deploy countermeasures to reduce crash frequencies in high-risk regions.

6.6 Comparisons of HSM SPFs with a Context-Specific SPF

To illustrate the benefits of using a context classification system for SPF development, comparisons were made between the context-specific SPF for C2T-Rural Town signalized 4-leg intersections (presented in section 6.3.2.3) and three types of HSM SPFs for rural two-way, two-lane signalized 4-leg intersections: the base HSM SPF, the base HSM SPF with CMFs, and a calibrated HSM SPFs with CMFs. All 70 intersections in C2T-Rural Town signalized 4-leg were used for modeling the context-specific SPF, but only two-way, two-lane intersections in the intersection group were considered when calculating the performance measures to allow for accurate comparisons with the HSM SPFs.

The base HSM SPF for 4-leg signalized intersections on rural two-lane, two-way roads is shown in equation 6-25 (AASHTO, 2010). This base SPF is used to predict the expected crash frequency for each studied intersection. These predicted values can then be multiplied by various CMFs to account for the individual intersection characteristics. The HSM outlines four CMFs that can be used for this specific SPF: intersection skew angle, intersection left-turn lanes, intersection right-turn lanes, and lighting. For the first three CMFs, the values and procedures outlined in the HSM were used. The lighting CMF required calculation of the proportion of crashes at unlit intersections which occurred at night. This calculated proportion of 0.274 was used instead of the HSM's default value of 0.286. With values for all four CMFs calculated for each intersection, a new set of predicted crash frequencies was determined.

$$N = \exp\left(-5.13 + 0.60 \ln AADT_{maj} + 0.20 \ln AADT_{min}\right) \quad (6\text{-}25)$$

Where $N =$ SPF estimate of intersection-related predicted average crash frequency for base conditions.

The final HSM SPF considered was a calibrated SPF with CMFs. For the base SPF with CMFs, the total predicted crash frequency for all 31 intersections was 379.02, while the actual number of crashes was 331. This resulted in a calibration factor of 0.87. Multiplying this calibration factor to each intersection's predicted crash frequency provided a third set of prediction values. While the CMFs and calibration factor do account for some intersection and data characteristics not considered in the base SPF, they do not account for regional variation across Florida. This regional variation, along with other factors not considered in the CMFs, is captured by the context-specific SPF. The crash predictions for the HSM SPFs and the context-specific SPF are shown in table 6-28 alongside their respective performance measures.

The HSM SPFs were compared to the context-specific SPF for the C2T signalized 4-leg intersection group given in equation 6-8. The context-specific SPF shows that both the major and minor AADT have a positive relationship with the number of crashes which agrees with the base HSM SPF. The lighting variable has a negative relationship with crash frequency, which agrees with the lighting CMF in the HSM. The final significant variable in the context-specific SPF is the district variable, which has a negative coefficient for FDOT D3. District 3 contains 21 of the 70 modeled intersections for this group, with 12 of these being two-way, two-lane intersections. This regional aspect of the context-specific SPF suggests that the HSM SPFs would overestimate the crashes experienced in D3. Using the context-specific SPF allows for more accurate predictions of D3 intersection crash frequency, helping safety engineers better determine which intersections need treatments to reduce its crash frequency.

MAE, RMSE, and MAPE were used to compare the prediction performance of the three developed HSM SPFs with the context-specific SPF for the studied intersections. The results of these comparisons are shown in table 6-28. Based on these comparisons, the context-specific SPF outperformed each of the HSM SPFs in all three performance measures. This indicates that the context-specific SPF was able to predict crash frequencies more accurately than the HSM SPFs. Additionally, the base HSM SPF performed better than the HSMs with CMFs, suggesting that the CMF factors included in the HSM might not be accurate for Florida. These comparisons provide FDOT with evidence of the benefits of using context classification over calibrated HSM SPFs.

Table 6-28: Crash Predictions and Performance Measures of HSM SPFs and C2T Signalized 4-Leg Context-Specific SPF

Safety Performance Function	**Total Predicted Crashes**	**MAE**	**RMSE**	**MAPE**
Base HSM SPF	209.677	7.169	12.560	92.6%
HSM SPF with CMFs	379.020	9.445	12.500	197.3%
Calibrated HSM SPF with CMFs	331	8.887	12.401	168.5%
C2T Signalized 4-Leg Context-Specific SPF	296.489	5.410	10.372	70.2%

Chapter 7: Conclusions and Recommendations

FDOT's innovative context classification system can help FDOT better understand the factors that influence crashes for different contexts. In this project, intersection data were collected for over 3,400 Florida intersections in 32 different intersection groups within the eight context classification categories in FDOT's context classification system. These data were used to develop SPFs for 19 of these 32 groups which had sufficient samples of intersections and crashes. Two groups from the C6 classification category with insufficient sample sizes were also combined to develop an additional SPF. Multiple modeling methodologies were examined to select the most appropriate and accurate model for each group. Each developed context-specific SPF had a unique set of variables and coefficients, but was often similar to SPFs for other intersection groups in the same context classification or that had the same signalization or number of legs. These SPFs included many variables that were not considered in the HSM SPFs, such as the regional district variable and the functional class. Many of these SPFs also contained district variables which identified certain FDOT districts that were expected to have either more crashes (positive coefficient) or less crashes (negative coefficient) than other FDOT districts. The coefficient signs for the significant variables were consistent across intersection groups and made practical sense, validating the accuracy of the models.

Multiple comparisons were made between the developed context-specific SPFs and other similar SPFs to illustrate the benefits of using FDOT's context classification system to develop SPFs. The individual SPFs for the C3R-Suburban Residential and C4-Urban General context classification categories were compared to the full SPFs developed for both categories. Several variables were significant in the individual SPFs that were not significant in the full model for the same category (D7 and major median for the C3R classification category and major median, minor exclusive right turn number, and intersect angle for the C4 classification category). In addition, comparisons were made between the context-specific SPF for C2T-Rural Town signalized 4-leg intersections and three types of HSM SPFs for rural two-way, two-lane signalized 4-leg intersections: the base HSM SPF, the base HSM SPF with CMFs, and a calibrated HSM SPFs with CMFs. All three performance measures calculated (MAPE, MAE, and RMSE) were lower for the context specific SPF as compared to the HSM SPFs. This indicates that context-specific SPF can predict crash frequencies more accurately than the HSM SPFs.

In addition to developing SPFs, state DOTs were surveyed on the methods they use to develop SPFs and their opinions regarding context classification. This survey showed that many states are interested in the use of context classification to develop SPFs, even if they are not currently planning on implementing such a system. However, some states wanted more evidence of the benefits of context classification before considering such a system. States were also concerned about collecting data for this system. Creating easy-to-use models based on context classification and showing the benefits of these context-specific SPFs compared to HSM SPFs can encourage adoption by local agencies. Increased usage of context classification systems could improve the accuracy of SPFs and allow for development of regionalized models, improving safety throughout the United States.

The comparisons discussed in this report provide evidence of the benefits of using context classification to develop SPFs. These developed context-specific SPFs provide FDOT with essential insights on the different influential variables for intersection types across context classification groups and regions. The results of this study address gaps in previous research as no study previously developed intersection SPFs based on FDOT's context classification system. Previous research that developed jurisdiction-specific SPFs only developed them for the three categories used in the HSM. Using the additional categories provided by FDOT's context classification system allows the developed SPFs to be more accurate and specific to Florida intersections while helping FDOT more accurately identify significant factors that influence crashes at different intersection types. Additionally, no previous research developed SPFs using the national MIRE 2.0 data standard, which allows other states to apply the data collection practices used in this project to develop their own context-specific SPFs.

Future expansions and improvements to the modeling processes and methodologies discussed in this project could occur as more data becomes available. These expansions and improvements could be studied and implemented as part of a new research project or phase 2 of this project. One improvement is including additional MIRE 2.0 variables related to signalized intersections, such as approach traffic control and signal progression. These variables could potentially show the impacts of signal control and progression on the safety and operations of signalized intersections and how these impacts vary for different context classification categories. Sufficient data for these variables are required before these improvements could be tested. The methodologies of this project can also be expanded to develop context-specific SPFs for the 13 intersection groups that had insufficient sample sizes in this project. While this project took a major undertaking by developing context-specific SPFs for the first time, these context-specific SPFs were only developed for 19 out of the 32 possible intersection groups due to data limitations in the intersections provided by FDOT. By including additional Florida intersections as they are classified, a complete and whole set of context-specific based SPFs can be developed for all intersection groups in Florida, serving as a showcase for other states to follow. Another potential expansion of this research is using the context-specific SPFs to identify the intersections in different classification groups which would benefit the most from geometric modifications and/or changes to traffic features. The developed SPFs could be used to identify intersections with high expected crash counts and similar sister intersections with low expected crash counts. Studying the differences between these intersections could help FDOT determine the most effective countermeasures to implement at the intersections with the most potential for crash reduction, providing the most benefits for the lowest cost and saving lives.

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APPENDIX A: STATE DOT SPF CURRENT PRACTICES SURVEY

The University of Central Florida (UCF), in conjunction with the Florida Department of Transportation (FDOT), is conducting a survey of State DOTs' current practices to develop Safety Performance Functions (SPFs). The results of this survey will help FDOT understand various methodologies and current practices used to develop SPFs throughout the nation. This survey asks about the methods your agency currently uses to develop SPFs and will only take a few minutes of your time. If you have any questions about this survey, please contact Haitham Al-Deek, Ph.D., P.E. (the UCF Principal Investigator of this project) at Haitham.Al-Deek@ucf.edu or Alan El-Urfali (FDOT Project Manager) at Alan.El-Urfali@dot.state.fl.us.

Would you like to participate in this survey?

- ☐ Yes
- ☐ No **(If No, END SURVEY)**

1. Please provide the following information:
   Name:
   Title:
   Agency:
   Phone number:
   E-mail:

Figure 1 shows the context classification system that the Florida Department of Transportation (FDOT) is currently implementing to develop their Safety Performance Functions (SPFs). This system classifies an area and its roadways into one of eight categories based on land use, development patterns, and other characteristics.

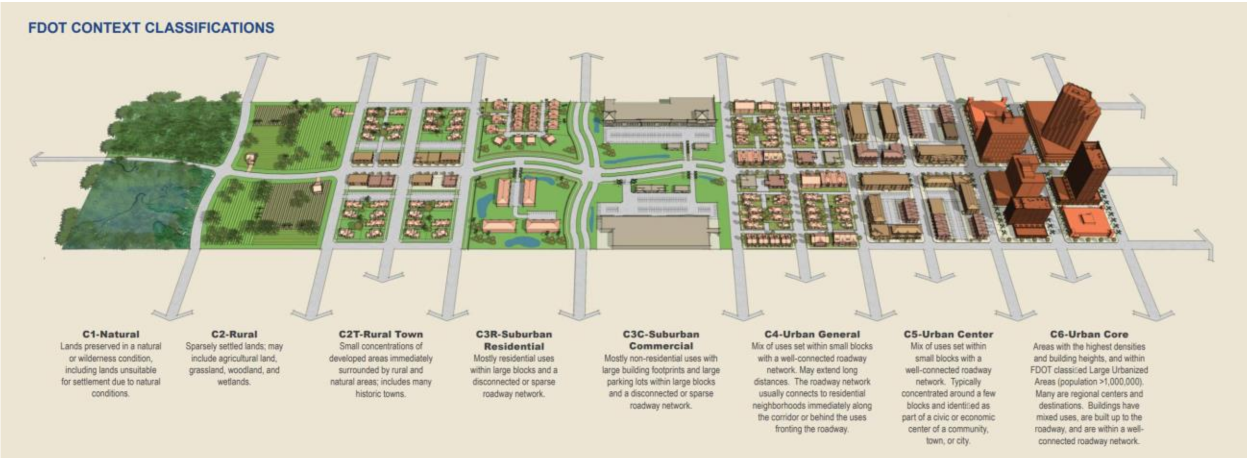

Figure 1: FDOT Context Classification Zones (FDOT Context Classification, August 2017)

2. Prior to this survey, had you heard about Florida or other states using context classification (like the FDOT context classification system shown in Figure 1) to develop SPFs?
   ☐ Yes
   ☐ No

3. Please select one of the following options which best describes how your agency currently develops SPFs for intersections.
   ☐ Uses default SPFs provided in the Highway Safety Manual (HSM).
   (Proceed to Question 9)
   ☐ Uses the HSM methodology to develop jurisdiction-specific SPFs for your agency using calibration factors. **(Proceed to Question 9)**
   ☐ Uses a non-HSM methodology developed by your agency.
   (Proceed to Question 4)
   ☐ Uses a non-HSM methodology developed by another agency.
   (Proceed to Question 4)
   ☐ Does not develop SPFs for intersections. **(Proceed to Question 7)**

<u>Section 1: Agency Uses Non-HSM Methodology</u>

4. Why does your agency use a non-HSM methodology to develop SPFs? Please select all that apply.
   ☐ HSM procedures were not rigorous enough.
   ☐ HSM procedures were insufficient.
   ☐ State had specific requirements that HSM did not account for.
   ☐ Other methods provided more accurate results.
   ☐ Other: Please specify

Figure 1: FDOT Context Classification Zones (FDOT Context Classification, August 2017)

5. Does your agency currently use a system similar to the FDOT Context Classification system (shown in Figure 1) to develop SPFs?
   ☐ Yes **(Proceed to Question 14)**
   ☐ No **(Proceed to Question 6)**

6. Please describe the methodology your agency uses to develop SPFs:
   Free Response

(Proceed to Question 9)

Section 2: Agency Does Not Use SPFs

7. Why does your agency not develop SPFs for intersections?:
   Free Response

Figure 1: FDOT Context Classification Zones (FDOT Context Classification, August 2017)

8. Is your agency currently planning to develop SPFs in the future?
   ☐ Yes, using a similar approach to the FDOT Context Classification System shown in Figure 1. **(Proceed to Question 13)**
   ☐ Yes, using the Highway Safety Manual (HSM) methodology or similar approach. **(Proceed to Question 10)**
   ☐ No. **(END SURVEY)**

Section 3: Agency Does Not Use Context Classification or Similar

9. Is your agency currently investigating ways to improve its methodology to develop SPFs? If yes, please specify what improvements are being considered.
   ☐ Yes: Please Specify
   ☐ No

10. Does your agency have any interest in using context classification or a similar system to develop SPFs?
   ☐ Yes **(If respondent answered "Yes, using the Highway Safety Manual (HSM) methodology or similar approach" to Question 8, END SURVEY. Otherwise, proceed to Question 12)**
   ☐ No **(Proceed to Question 11)**

11. Please explain why your agency does not have any interest in using context classification or a similar system to develop SPFs:
   Free Response

   END SURVEY

12. Does your agency currently have any plans to implement context classification or a similar system in the future?
   ☐ Yes **(Proceed to Question 13)**
   ☐ No **END SURVEY**

13. Please describe the context classification or similar system that your agency is considering for future implementation:
   Free Response

   END SURVEY

<u>Section 4: Agency Uses Context Classification</u>

14. When did your agency first start using context classification or a similar system for the development of SPFs?
    - ☐ 1 – 6 months ago
    - ☐ 6 months – 1 year ago
    - ☐ More than 1 year ago

15. Please describe the context classification or similar system that your agency is currently using:
    Free Response

16. Has your agency witnessed an improvement in safety measures after the implementation of this system?
    - ☐ Yes
    - ☐ No
    - ☐ Unknown

END SURVEY

APPENDIX B: SURVEY PATHS

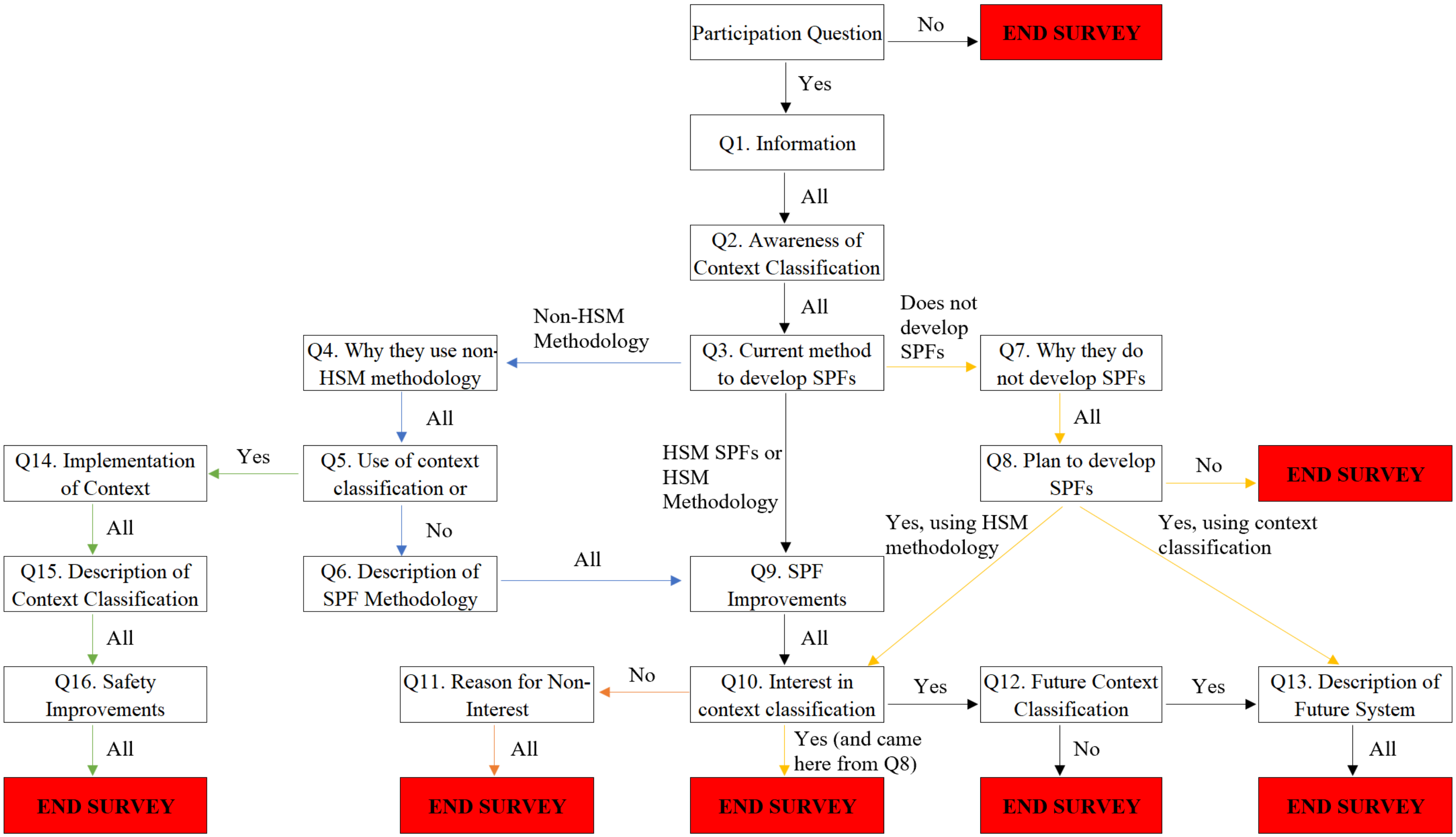

Figure B-1: State DOT Survey Paths

APPENDIX C: SUMMARY OF SURVEY RESPONSES

Table C-1: Awareness of Context Classification

Prior to this survey, had you heard about Florida or other states using context classification to develop SPFs?

Response	Total Frequency	Total Percentage
Yes	16	38%
No	26	62%
Total	**42**	**100%**

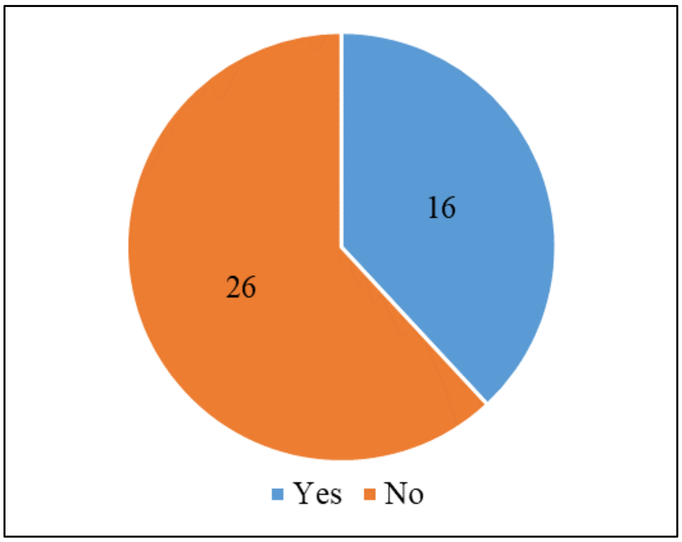

Figure C-1: State DOT Knowledge of Using Context Classification for SPF Development

Table C-2: Current Method to Develop SPFs

Please select one of the following options which best describes how your agency currently develops SPFs for intersections.

Response	Total Frequency	Total Percentage
Uses default SPFs provided in the Highway Safety Manual (HSM).	9	21%*
Uses the HSM methodology to develop jurisdiction-specific SPFs for your agency using calibration factors.	18	43%*
Uses a non-HSM methodology developed by your agency.	6	14%*
Uses a non-HSM methodology developed by another agency.	1	2%*
Does not develop SPFs for intersections.	8	19%*
Total	**40**	**100%***

*Unrounded percentages sum to 100%

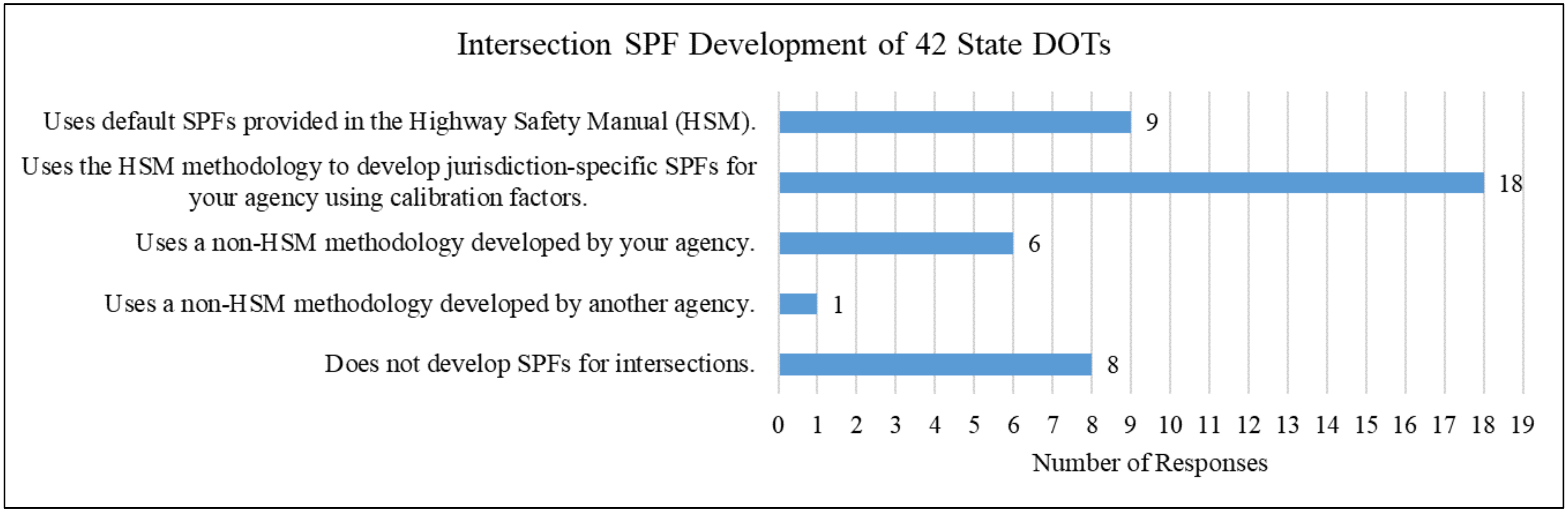

Figure C-2: Intersection SPF Development of 42 State DOTs

Table C-3: Reasons for Use of Non-HSM Methodology to Develop SPFs

Why does your agency use a non-HSM methodology to develop SPFs?

Response	Total Frequency	Total Percentage
HSM procedures were not rigorous enough.*	0	0%
HSM procedures were insufficient.*	2	29%
State had specific requirements that HSM did not account for.*	2	29%
Other methods provided more accurate results.*	3	43%
Other: Please specify*	4	57%

*Respondents could select more than one of the indicated responses.

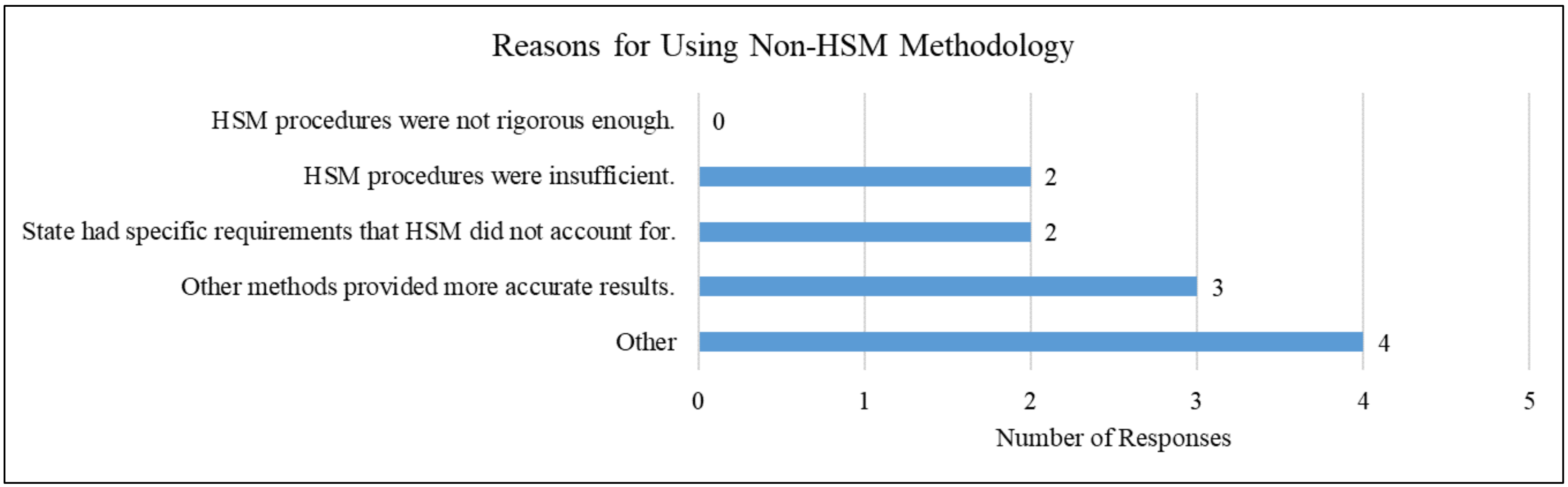

Figure C-3: State DOT Reasons for Using a Non-HSM Methodology to Develop SPFs

Table C-4: Current Use of a Context Classification System to Develop SPFs

Does your agency currently use a system similar to the FDOT Context Classification system to develop SPFs?

Response	Total Frequency	Total Percentage
Yes	1	14%
No	6	86%
Total	**7**	**100%**

Table C-5: Future Plans to Develop SPFs

Is your agency currently planning to develop SPFs in the future?

Response	Total Frequency	Total Percentage
Yes, using a similar approach to the FDOT Context Classification System.	0	0%
Yes, using the HSM methodology or similar approach.	6	75%
No	2	25%
Total	**8**	**100%**

Table C-6: Investigation of Ways to Improve SPF Development

Is your agency currently investigating ways to improve its methodology to develop SPFs?

Response	Total Frequency	Total Percentage
Yes	19	58%
No	14	42%
Total	**33**	**100%**

Table C-7: Interest in Using Context Classification to Develop SPFs

Does your agency have any interest in using context classification or a similar system to develop SPFs?

Response	Total Frequency	Total Percentage
Yes	26	67%
No	13	33%
Total	**39**	**100%**

Table C-8: Future Plans on Implementation of Context Classification

Does your agency currently have any plans to implement context classification or a similar system in the future?

Response	Total Frequency	Total Percentage
Yes	8	38%
No	13	62%
Total	**21**	**100%**

Table C-9: First Use of Context Classification for SPF Development

When did your agency first start using context classification or a similar system for the development of SPFs?

Response	Total Frequency	Total Percentage
1 – 6 months ago	0	0%
6 months – 1 year ago	0	0%
More than 1 year ago	1	100%
Total	**1**	**100%**

Table C-10: Safety Improvements due to Context Classification Implementation

Has your agency witnessed an improvement in safety measures after the implementation of this system?

Response	Total Frequency	Total Percentage
Yes	1	100%
No	0	0%
Unknown	0	0%
Total	**1**	**100%**