Journal of Transportation Technologies, 2025, 15(2), 252-274
https://www.scirp.org/journal/jtts
ISSN Online: 2160-0481
ISSN Print: 2160-0473

Calibration of Highway Safety Manual Crash Prediction Models for Rural Intersections: A Case Study from Delaware

Rodolfo Gomes[1], Abdulkadir Özden[2*], Ardeshir Faghri[1]

[1]Civil Engineering Department, University of Delaware, Newark, Delaware, USA
[2]Department of Civil Engineering, Sakarya University of Applied Sciences, Sakarya, Türkiye
Email: *aozden@subu.edu.tr

How to cite this paper: Gomes, R., Ozden, A. and Faghri, A. (2025) Calibration of Highway Safety Manual Crash Prediction Models for Rural Intersections: A Case Study from Delaware. *Journal of Transportation Technologies*, **15**, 252-274.
https://doi.org/10.4236/jtts.2025.152013

Received: March 23, 2025
Accepted: April 19, 2025
Published: April 22, 2025

Copyright © 2025 by author(s) and Scientific Research Publishing Inc.
This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).
http://creativecommons.org/licenses/by/4.0/
Open Access

Abstract

This study presents a calibration of crash prediction models from the *Highway Safety Manual* (HSM) using localized data for rural intersections in the state of Delaware. The research evaluates six intersection site types under two crash assignment scenarios: (1) a 250-foot circular buffer around all intersections, and (2) a 528-foot buffer applied only to rural multilane divided highways, aligning with DelDOT's methodology. Geographic Information System tools, satellite imagery, and Google Street View were used for data collection, classification, and validation. Calibration factors (CFs) were computed for each site type and assessed using modified R-squared, coefficient of variation, and cumulative residual (CURE) plots. Findings indicate that while the 528-foot scenario produced calibration factors 37% higher on average, it did not lead to improved model fit and may overestimate intersection-related crashes. Therefore, the 250-foot scenario is recommended for future applications. Among the site types analyzed, only RM4STM (rural, multilane, four-legged, stop-controlled) demonstrated an acceptable goodness-of-fit and is suitable for implementation. Delaware-specific crash distributions were also developed to replace default HSM values, including crash severity levels, collision types, and nighttime crash proportions. This study highlights the importance of periodic, data-driven calibration and offers a reproducible methodology for transportation agencies seeking to enhance the accuracy of safety performance models and prioritize roadway safety interventions more effectively.

Keywords

Highway Safety Manual (HSM), Calibration Factors, Rural Intersections, Crash Prediction Models, GIS-Based Safety Analysis

1. Introduction

In recent decades, rapid advancements in transportation systems have significantly transformed mobility, economic development, and societal interaction. Roadway transportation, in particular, has played a central role in facilitating connectivity across regions and supporting economic growth. However, the increasing complexity of road networks and the surge in motor vehicle use have also heightened the risks associated with road traffic, leading to persistent safety challenges. Despite continued efforts in enforcement, education, and engineering, traffic-related injuries and fatalities remain a major public health concern globally and in the United States. This situation necessitates a shift from traditional reactive approaches to more proactive, evidence-based strategies in highway safety management. Against this backdrop, the integration of predictive modeling has emerged as a key approach to understanding and mitigating crash risks on roadways.

1.1. Road Traffic Safety Trends

The US highway system has been the foundation of mobility and economic development in the United States and around the world. It is a lifeline for many people because it gives transportation options, creates jobs, and promotes economic progress [1]. Improved transportation infrastructure not only enhances safety but also drives regional economic growth by facilitating trade and mobility [2]. However, roadway fatalities and injuries have always been a leading safety issue in the US [3]. According to the National Highway Traffic Safety Administration [4], the national roadway fatality rate reached its historic peak in 1972 with 56,278 deaths and had declined consistently for 30 years until it stalled in the early 2010s., as shown in **Figure 1**.

Figure 1. Motor vehicle deaths and rate per 100,000 population [4].

Traffic fatalities in the US have been on the rise since 2013, with a significant increase observed after 2015. In 2021, one of the deadliest years in recent history, 42,939 people lost their lives on roadways, including 7,388 pedestrians and 966 bicyclists in motor vehicle crashes [4]. This alarming trend has been linked to fac-

tors such as distracted driving, speeding, and impaired driving, as well as the disproportionately high fatality rates on rural roads, where higher speeds and weaker enforcement contribute to increased risks [5] [6].

Addressing these challenges requires a comprehensive strategy that integrates improved road safety measures, stronger enforcement, and public awareness campaigns. Traditionally, highway safety decisions have relied on engineering judgment and compliance with standards, but these approaches lack the ability to quantify safety benefits or conduct cost-benefit analyses for different interventions. A data-driven approach is crucial to developing more effective policies and mitigating the ongoing rise in traffic fatalities.

1.2. Predictive Modeling in Highway Safety Management

In the evolving landscape of transportation safety, predictive modeling has emerged as a vital component of modern highway safety management. The conventional approaches often lack the flexibility to incorporate real-time data or account for emerging trends, such as changes in driver behavior, traffic flow, or the integration of new vehicle technologies. In contrast, predictive modeling leverages statistical techniques and machine learning algorithms to analyze complex datasets, uncover patterns, and forecast crash risks under varying roadway and traffic conditions [7].

One of the central tools in this paradigm shift is the Safety Performance Function (SPF), which models the relationship between roadway features (e.g., geometry, control type), traffic volumes, and crash frequency. SPFs allow practitioners to estimate expected crash counts and assess the effectiveness of countermeasures, enabling a proactive and analytical approach to risk reduction [8]. These data-driven methods have proven particularly valuable in conducting cost-benefit analyses, justifying the allocation of resources, and informing the prioritization of safety improvements. As such, predictive modeling serves not only as a technical tool but also as a foundational element of evidence-based policymaking (EBPM) in the transportation sector [9] [10].

Moreover, the integration of predictive models enhances the transparency and accountability of safety-related decisions. When safety interventions are supported by quantifiable data, transportation agencies can build stronger cases for funding and regulatory support, even in the face of political or public resistance [7] [10]. This empirically grounded approach ensures that safety policies are not only effective but also equitable and economically defensible, thereby maximizing their long-term impact on reducing roadway fatalities and serious injuries.

1.3. The Highway Safety Manual and the Need for Local Calibration

The *Highway Safety Manual* (HSM) serves as a cornerstone for traffic safety planning in the United States, offering a structured framework for predicting crash frequencies and assessing roadway safety performance. Developed by the American Association of State Highway and Transportation Officials (AASHTO), the

HSM introduces standardized methodologies that integrate engineering principles with statistical modeling to enable evidence-based decision-making. One of its most critical components is the use of SPFs, mathematical models designed to estimate the expected number of crashes at roadway sites based on variables such as traffic volume, geometric design, and control types [11] [12].

While SPFs provide a robust starting point for crash prediction, their default forms are based on national-level datasets, which may not accurately represent the localized conditions of specific jurisdictions. As such, the HSM encourages practitioners to apply a calibration process to align SPFs with local crash and roadway data. This process is essential because regional variations in driving behavior, roadway design standards, and environmental conditions can lead to significant differences in crash occurrence and severity. Without proper calibration, safety predictions may be misleading, potentially resulting in inefficient resource allocation and suboptimal safety interventions [11].

Numerous factors influence the accuracy and relevance of SPFs in local applications. These include roadway geometry (e.g., number of lanes, curvature, shoulder width), traffic control mechanisms, the presence of lighting, and even environmental and temporal variables such as weather conditions and time of day [13] [14]. Moreover, socio-demographic aspects such as vehicle fleet composition and population density further complicate crash prediction modeling. Therefore, localized calibration not only improves model precision but also ensures that the safety countermeasures derived from such models are contextually appropriate and economically justified.

1.4. Rural Intersection Safety in Delaware

Rural intersections in Delaware exhibit distinctive characteristics that pose notable challenges despite experiencing relatively lower traffic volumes than urban roadways. The geometric layout of rural intersections plays a particularly critical role in crash risk. Many rural intersections operate under stop- or yield-control rather than full signalization, which may be insufficient to manage high-speed traffic, especially in the presence of limited sight distances or complex layouts [15] [16]. These conditions are further exacerbated by fluctuating traffic patterns and limited data availability, which complicate safety assessments and hinder the development of tailored countermeasures [17].

To address these challenges, Delaware has aligned its roadway safety strategies with the Strategic Highway Safety Plan (SHSP) framework established by AASHTO. While the first national SHSP was published in 1997 to encourage states to adopt data-driven safety policies, the requirement for state-level SHSPs became mandatory with the 2005 Safe, Accountable, Flexible, Efficient Transportation Equity Act [18]. Delaware responded by releasing its first SHSP in 2006, structured around AASHTO's model implementation process [19]. The latest SHSP, covering the years 2021-2025, adopts the national Toward Zero Deaths strategy and sets a target of reducing roadway fatalities and serious injuries by

15% within the analysis period [20]. As shown in **Figure 2**, Delaware's trend in annual motor vehicle fatalities and serious injuries generally mirrors national patterns, with a troubling plateau and slight increase since the early 2010s.

Figure 2. Annual crash trends in Delaware [20].

A particularly concerning trend involves pedestrian safety. Between 2015 and 2019, pedestrians accounted for 25% of all traffic fatalities and 9% of serious injuries in Delaware, reflecting a notable rise from previous years. As depicted in **Figure 3**, pedestrian fatalities increased by 15% compared to the 2007-2014 period, despite a concurrent 48% decline in serious pedestrian injuries. Alarmingly, 67% of these incidents occurred in low-light conditions, underscoring the need for improved visibility and traffic control at high-risk rural intersections. These findings support the SHSP's emphasis on targeted improvements at rural sites, where contextual risks—such as geometry, visibility, and lighting—require locally adapted solutions [21] [22].

Figure 3. Annual pedestrian fatalities and serious injuries due to motor vehicle accidents [20].

These challenges align with the safety improvement priorities outlined in Delaware's Strategic Highway Safety Plan (SHSP), which emphasizes the need to address systemic risk factors at rural intersections through data-driven planning and resource allocation. The SHSP encourages improvements in intersection design,

the deployment of appropriate traffic control devices, and enhanced data collection efforts aimed at identifying safety deficiencies more effectively [21] [22]. By integrating these strategies, Delaware can advance toward its goal of reducing fatalities and serious injuries, particularly in rural areas that have historically been underrepresented in roadway safety interventions.

This study aims to calibrate the HSM crash prediction models for rural intersections in Delaware to improve their applicability to local conditions. The HSM, published by AASHTO, provides a standardized, data-driven framework for assessing roadway safety. However, national-level models such as SPFs may not reflect regional crash patterns without proper calibration. By adjusting these models using local crash and traffic data, this research enhances their accuracy and relevance for Delaware's rural network.

The calibrated models developed through this study support data-driven decision-making by enabling transportation agencies to better prioritize safety interventions, allocate resources effectively, and evaluate countermeasure impacts. The findings also contribute to Delaware's Strategic Highway Safety Plan (SHSP) by providing a localized tool for identifying high-risk intersections and guiding evidence-based safety improvements.

2. Research Methodology

This study follows the calibration procedure outlined in Part C of the HSM to develop locally adjusted crash prediction models for rural intersections in Delaware. The calibration process ensures that the SPFs, originally derived from national data, reflect the specific roadway, traffic, and crash conditions present in the study area. The methodology involves the following key steps.

2.1. Study Area Definition and Site Selection

The calibration focused on rural intersections within the state of Delaware. Site selection was conducted based on the criteria defined by the HSM, targeting three intersection types:

- Three-legged stop-controlled intersections on two-lane rural roads
- Four-legged stop-controlled intersections on two-lane rural roads
- Signalized intersections with four approaches

It is vital to clarify the HSM distinction between roadway segments and intersections. A roadway segment, according to the manual, is a stretch of continuous traveled way that enables two-way traffic operation; and has uniform geometric design and traffic control features. A segment starts and ends at the center of adjacent intersections or at a change in homogeneous highway characteristics. Meanwhile, an intersection is defined as the junction of two or more road segments.

The crash prediction models for intersections estimate the average crash frequency at the intersection and intersection-related crashes that occur on the intersection approaches. As shown on the first column of **Table 1**, the HSM uses

repetitive acronyms for site types. As an example, 3ST may refer to three-leg un-signalized intersections on rural two-lane two-way roads or rural multilane highways.

Table 1. SPFs for intersections.

HCM Acronym	Adopted Acronym	Definition
(a) Chapter 10 - Rural Two-Lane, Two-Way Roads		
3ST	R23STM	Un-signalized three-leg (stop control on minor-road approaches)
4ST	R24STM	Un-signalized four-leg (stop control on minor-road approaches)
4SG	R24SG	Signalized four-leg
(b) Chapter 11 - Rural Multilane Highways		
3ST	RM3STM	Un-signalized three-leg (stop control on minor-road approaches)
4ST	RM4STM	Un-signalized four-leg (stop control on minor-road approaches)
4SG	RM4SG	Signalized four-leg

New intuitive acronyms have been adopted by other jurisdictions to avoid misunderstanding the HSM's acronyms. Initially, this research adopted the standard acronyms created and used by other jurisdictions. However, since all-way stop-controlled intersections may be added to future HSM editions, this research innovates by adding the letter M at the end of stop-controlled intersections' acronyms to refer to "stop control on minor roads only". All-way stop-controlled intersections are identified by the letter A at the end. The acronym structure from the beginning to the end is explained below.

To describe the HSM chapter:

- R2: rural two-lane, two-way roads (HSM Chapter 10).
- RM: rural multilane highways (HSM Chapter 11).

Number of legs:

- 3: three leg intersection.
- 4: four leg intersection.

Traffic control device:

- STM: minor-road-only stop controlled intersection.
- STA: all-way stop controlled intersection (not available in the HSM).
- SG: signalized intersection.

For example, RM4SG refers to intersections on rural multilane highways that have four legs and are controlled by a traffic signal.

2.2. Data and Data Preprocessing

Crash data were obtained from the Delaware Department of Transportation (DelDOT) for a five-year period (2015-2019). Corresponding traffic volume data, intersection geometry, and control types were collected using DelDOT's roadway

inventory system and GIS tools. The data were reviewed for consistency, completeness, and correct spatial referencing. Only sites with complete crash and traffic data were included in the analysis.

Table 2 shows required and optional data to develop calibration factors and which one was collected in this research. The software ArcGIS Pro was used to store data.

Table 2. Data requirements for calibration (x: required, o: optional).

Data Element	Related Chapters			Collected	Unit or Range
	10	11	12		
Crash	x	x	x	Yes	-
Number of intersection legs	x	x	x	Yes	3 or 4
Traffic control type	x	x	x	Yes	Traffic light or stop sign
AADT on major road	x	x	x	Yes	Vehicles/day
AADT on minor road	x	x	x	Yes	Vehicles/day
Intersection skew angle	o	o	o	No	Degrees
Approaches with left-turn lanes	x	x	x	Yes	0, 1, 2, 3, 4
Approaches with right-turn lanes	x	x	x	Yes	0, 1, 2, 3, 4
Presence of lighting	x	x	x	Yes	Presence or absence

As recommended by the HSM, crash frequency is likely to change over time, so calibration periods longer than three years are not recommended. All calibration periods should have durations that are multiples of 12 months to avoid seasonal effects. This research considers the years 2017, 2018 and 2019 to develop calibration factors. Since traffic demand in 2020 and 2021 was drastically affected by the COVID pandemic, and crash data were incomplete for 2022, the author decided to analyze data from 2017 to 2019.

2.3. Application of HSM Based SPF Models

The base crash prediction models provided by the HSM were applied to each selected intersection type using standard inputs such as traffic volume (AADT), intersection control type, and geometric characteristics. These models estimate the expected number of crashes under baseline conditions and serve as the reference for calculating calibration factors. For this study, the default SPF values from the HSM spreadsheets were used without additional adjustment for crash modification factors (Equation (1)).

$$N_{predicted} = AADT^{\beta} e^{\alpha} \tag{1}$$

where $N_{predicted}$ is the predicted crash frequency, and superscripts are coefficients provided by the HSM for each intersection type.

2.4. Calibration Factor Calculation

Calibration factors (CFs) were calculated by comparing observed crashes to predicted crashes across all sites using the Equation (2):

$$C_j = \frac{\sum N_{observed}}{\sum N_{predicted}} \tag{2}$$

Separate calibration factors were computed for each intersection type. A CF greater than 1 indicates that the HSM underpredicts crashes for the local conditions, while a CF less than 1 suggests overprediction.

2.5. Crash and Traffic Volume Data Processing

To calculate SPFs, crash and traffic volume data were collected and processed using GIS-based spatial analysis. Since Delaware's crash database does not explicitly identify intersection-related crashes, a spatial buffer approach was adopted. Two scenarios were tested: a 250 ft circular buffer applied to all intersections, and a 528 ft buffer applied only to rural multilane divided intersections. Crashes within these buffers from the 2017-2019 period were considered intersection-related, consistent with HSM practices and DelDOT methodology. Although police-reported crash data may offer more precise location-based classification, the dataset provided by the state did not consistently include an intersection-related flag. Therefore, in alignment with HSM calibration guidance and practices used in similar studies, a spatial buffer method was adopted to assign crashes to intersections.

Annual Average Daily Traffic (AADT) data for the same years were obtained from the "Delaware Traffic Counts 2.0" GIS layer. For most site types, only intersections with available AADT for at least one major and one minor approach were included. Where data were missing on minor approaches, a default value of 500 vehicles/day was used, following DelDOT standards.

Additionally, Crash Modification Factors (CMFs) were calculated using field-verified data. The number of approaches with right and left turn lanes was identified through manual review of satellite imagery and Google Street View. Similarly, the presence of street lighting was assessed using street-level imagery to support geometric and operational assessments relevant to crash risk.

2.6. Evaluation of Calibration Quality

The accuracy and reliability of the calibrated models were evaluated using multiple statistical techniques:

- **CURE Plots** (Cumulative Residuals): To examine the fit between observed and predicted crash frequencies.
- **Modified R^2 Values**: To assess model explanatory power post-calibration.
- **Coefficient of Variation (CV)**: To evaluate the variability in crash data across sites.

CURE plots are simply graphical representation of the cumulative residuals (observed minus predicted crashes) compared to the variable of interest. In this

study, CURE plots are compared to AADT, as recommended by The Calibrator's guide [23]. As an example, **Figure 4** shows the CURE plot developed for RM3STM in this research. The solid line indicates the cumulative residual, while the upper and lower dotted lines indicate the 95th percentile confidence limits. According to Lyon *et al.* [23], the area exceeding the 95th percentile confidence limits indicate the amount of bias in the model.

Figure 4. An example of CURE plots.

The goodness-of-fit measure "modified R-squared" (also known as modified R^2 or adjusted R^2) addresses a limitation of the popular R-squared (or R^2) for multiple regression analysis. While R-squared tends to increase as more variables are added to the model (even if they do not improve the model significantly), modified R-squared penalizes the addition of unnecessary variables [24]. Both measures, commonly called coefficient of determination, answer the question, "To what extent does the model explain the variation in crash frequency?".

$$Modified\ R^2 = m * R^2 = \frac{\sum_i (y_i - y)^2 - \sum_i U_i^2}{\sum_i (y_i - y)^2 - \sum_i Y_i^2} \tag{3}$$

where,

y_i = observed counts.

Y_i = predicted values from SPFs.

y = sample average.

$U_i = y_i - Y_i$.

In this calculation, modified R-square = 0.5 indicates that half of the variation is explained by the model, where 0 indicates that the variation is not explained by the model and 1 infers the model explains all the variation. Modified R-squared values closer to one indicate a better fit model and, therefore, the independent variable (AADT) is likely to predict the dependent variable (crash frequency). These methods provided both visual and quantitative insight into the calibration model's performance.

On the other hand, CV indicates how closely grouped a particular data set is. In other words, it measures variation against the mean. However, since it is based on

the sample mean and standard deviation, outliers can adversely affect it. The Calibrator's guide suggests that a reasonable threshold for the CV is between 0.10 and 0.15. Users of the calibration tool can apply this threshold to assess whether the SPF, and the estimated calibration factor based on the calibration dataset, are recommended [23].

3. Data Collection Methods

Data collection represented the most time-intensive aspect of this research, involving integration of spatial data, field verification, and agency records to support the calibration of HSM predictive models for rural intersections in Delaware. The data were collected for six intersection site types, consistent with HSM Chapter 10 (Rural Two-Lane, Two-Way Roads) and Chapter 11 (Rural Multilane Highways). All data were stored and processed using ArcGIS Pro, in combination with Google Street View and satellite imagery for manual validation.

Table 3 shows the data collected in this research and its sources. The column "Purpose" shows the reason why each data element was collected. As listed in the first column, the "Intersection classification" and "Intersection approaches classification" data were collected to classify intersections into the six HSM site types.

Table 3. Collected data types and collection sources.

Data Purpose	Data Element	Collection Source
Intersection classification	Traffic Control Type	DelDOT Google Street View
	Number of intersection legs	First Map (Delaware Road Inventory 2.0) First Map (Delaware Traffic Counts 2.0) Satellite Imagery
Intersection approach classifications	Urban vs. Rural	Google Street View FirstMap (Urban Areas 2020)
	Number of lanes and functional roadway classification	First Map (Delaware Road Inventory 2.0) First Map (Delaware Traffic Counts 2.0) Satellite Imagery
Calculations of SPFs	Crash	Google Street View FirstMap (Public Crash Data)
	AADT on major road	First Map (Delaware Traffic Counts 2.0)
	AADT on minor road	First Map (Delaware Traffic Counts 2.0)
Calculations of CMFs	Intersection skew angle	Not collected
	Number of approaches with left-turn lanes	Satellite Imagery Google Street View
	Number of approaches with right-turn lanes	Satellite Google Street View
	Presence of street lighting	Google Street View

3.1. Intersection and Approach Classification

The intersection classification data were used to identify whether intersections

were signalized or controlled only by stop signs on minor roads, and whether they had three or four legs. Additionally, information about the major and minor roads at each intersection was used to determine whether the sites fell under Chapter 10 (rural two-lane, two-way roads) or Chapter 11 (rural multilane highways) of HSM. Most of the spatial data used in this study were obtained from FirstMap, Delaware's public GIS platform maintained by DelDOT. Spatial analysis and data storage were conducted using ArcGIS Pro. To verify the accuracy of intersection classifications and roadway characteristics, satellite imagery and Google Street View were frequently used throughout the data collection process. The following sections describe the remaining steps in the data collection process in more detail.

3.2. Dataset Preparation and Sampling

The intersection data were initially provided by DelDOT in XML format, with separate spreadsheets for signalized and unsignalized intersections. These files included geographic coordinates, road names, and links to Google Street View. The spreadsheets were imported into ArcGIS Pro using standard tools, and geolocated to create spatial layers for further analysis.

DelDOT's unsignalized dataset contained multiple intersection types (e.g., roundabouts, all-way stops, yield-controlled), but only minor-road-only stop-controlled intersections were relevant for this study. OpenStreetMap was evaluated as a potential source for identifying traffic control types, but was found to be unreliable. As a result, all relevant intersections were manually identified and verified using Google Street View and satellite imagery.

3.3. Urban-Rural Classification

The classification of intersections as urban, suburban, or rural was based on the definitions provided by the Federal Highway Administration (FHWA) and implemented using the "Urban Areas 2020" GIS layer from FirstMap. Urban areas were defined as those with populations over 5,000 or more than 2,000 housing units. Using ArcGIS Pro's spatial tools, intersections located within urban polygons were labeled as urban or suburban, while the remainder were classified as rural. This classification was necessary to ensure consistency with the HSM's site type framework and SPF applicability.

3.4. Number of Legs, Lanes, and Functional Classification

The number of intersection legs, lanes, and roadway functional classifications were obtained from the "Delaware Road Inventory 2.0" and "Traffic Counts Last 10 Years" GIS layers. These datasets provided geometric attributes and AADT values for 2017–2019. However, due to missing data and the way divided and undivided roads are represented differently in GIS, manual verification using satellite imagery and Google Street View was necessary to ensure accuracy, especially in distinguishing multilane and two-lane roads.

3.5. Site Type Classification

After random sampling, each intersection was reviewed and classified into one of six HSM site types based on geometry and control type. The classification was recorded in the GIS attribute table using standardized acronyms (e.g., RM3STM). Intersections that did not match any site type were labeled "Null" and excluded from the analysis.

3.6. Sample Size

To meet HSM requirements, at least 30 intersections were sampled per site type. For site types with fewer than 100 crashes annually, more intersections were added. Where fewer than 30 intersections existed statewide (e.g., RM4SG), all available sites were included. Final outputs included six GIS layers, each representing one calibrated intersection category.

4. Analysis and Results

As detailed in the previous section, extensive data were collected and processed for six intersection site types. The final output of this data preparation phase included the following GIS products for each site type:

- A GIS layer containing Crash Modification Factor (CMF) attributes.
- A GIS layer containing crash data within 250 feet of the intersection center (Scenario 1).
- For rural multilane highways, an additional layer containing crashes within 1/10 mile (528 ft) of the intersection center (Scenario 2).
- A GIS layer including AADT values for major and minor approaches.

All GIS attribute tables were exported to Microsoft Excel for further analysis. While CMF-related attributes required no additional filtering, crash and traffic volume data were aggregated and summarized using the PivotTable tool to support calibration factor calculations.

4.1. Calibration Factor Results

Calibration factors (CFs) were computed by comparing the observed number of crashes to the HSM-predicted values for each site type. In the first scenario, intersection-related crashes were defined as those occurring within a 250-foot radius from the intersection center. Table 4 presents the calibration results under this assumption.

Table 4. Calibration factors based on the 250-ft intersection influence area.

Site Type	Sample Size	Nobserved	Npredicted	Calibration Factor	Severity
R23STM	312	332	416.32	0.79	KABCO
R24STM	90	311	366.87	0.85	KABCO
R24SG	21	383	318.28	1.20	KABCO
RM3STM	40	250	170.69	1.46	KABCO
RM4STM	35	314	225.97	1.39	KABCO
RM4SG	14	509	773.87	0.66	KABCO

In the second scenario, which applies only to intersections located on rural multilane highways, crashes occurring within 528 feet (approximately 1/10 mile) of the center were considered intersection-related, following DelDOT's standard for high-speed roads. Table 5 shows the calibration factors calculated using this expanded buffer.

Table 5. Calibration factors based on the 528-ft intersection influence area for multilane highways.

Site Type	Sample Size	Nobserved	Npredicted	Calibration Factor	Severity
RM3STM	40	352	170.69	2.06	KABCO
RM4STM	35	446	225.97	1.97	KABCO
RM4SG	14	660	773.87	0.85	KABCO

The calibration factors ranged from 0.66 to 2.06 across all site types. The highest values were observed for four-legged, signalized intersections (e.g., RM3STM and RM4STM), suggesting that the HSM may substantially underpredict crash frequencies at these complex intersections in Delaware. Notably, the second scenario—using the larger buffer for rural multilane sites—produced calibration factors that were, on average, 37% higher than those from the first scenario. This indicates the sensitivity of CF values to the spatial criteria used for defining intersection-related crashes. Figure 5 and Figure 6 display the geographical distribution of analyzed intersections across the state, categorized by site type.

Figure 5. Locations of R23STM, R24STM, and R24SG intersections.

Figure 6. Locations of RM3STM, RM4STM, and RM4SG intersections.

4.2. Validation of the Results

To assess the reliability and applicability of the calibrated SPFs, statistical goodness-of-fit measures were calculated using the FHWA Calibrator Tool, as described in Section 2.6, Cumulative Residuals, Modified *R*-squared, Coefficient of Variations were used for both calibration scenarios. Table 6 and Table 7 present the Modified R^2 and CV values for the first and second crash assignment scenarios, respectively.

Table 6. Goodness-of-fit measures for the first scenario (250-ft buffer).

Site Type	Calibration Factor	Modified *R*-squared	Coefficient of Variation
R23STM	0.79	0.00	0.20
R24STM	0.85	0.00	0.27
R24SG	1.20	0.03	0.16
RM3STM	1.46	0.20	0.12
RM4STM	1.39	0.00	0.13
RM4SG	0.66	0.02	0.13

In the second scenario, which applies only to intersections located on rural multilane highways, crashes occurring within 528 feet of the center were considered intersection-related, following DelDOT's standard for high-speed roads. Table 5 shows the calibration factors calculated using this expanded buffer.

Table 7. Goodness-of-fit measures for the second scenario (528-ft buffer for rural multilane highways).

Site Type	Calibration Factor	Modified *R*-squared	Coefficient of Variation
RM3STM	2.06	0.12	0.13
RM4STM	1.97	0.00	0.13
RM4SG	0.85	0.02	0.13

For intersections located on rural two-lane, two-way roads (R23STM, R24STM, R24SG), the Modified R^2 values were near zero, and the coefficients of variation ranged between 0.16 and 0.27, indicating poor model fit under both calibration scenarios. These results suggest that SPFs for these intersection types may require further refinement or segmentation to improve predictive accuracy.

Conversely, rural multilane intersections (RM3STM, RM4STM, RM4SG) demonstrated better performance in terms of coefficient of variation, with values consistently around 0.13 across both scenarios. However, Modified R^2 values remained low (< 0.20), indicating that while prediction variability is low, the proportion of explained variance in observed crashes remains limited. This is consistent with prior findings in the literature, where SPF models often show weak correlation for specific site types but still offer useful calibration for safety planning.

No substantial differences were observed between the two scenarios in terms of goodness-of-fit metrics. As discussed further in Section 5.1, the first scenario—which assigns intersection-related crashes within a 250-ft buffer—offers a simpler and more widely accepted approach and is therefore recommended for implementation. To illustrate the model fit visually, CURE plots for selected site types under the first scenario are presented in **Figures 7**.

The CURE plots for R23STM and R24STM exhibit clear signs of model bias. In both cases, the cumulative residuals deviate substantially from the 95% confidence bands, indicating that the calibration factors applied to these site types fail to adequately capture the underlying crash trends. This suggests a misalignment between observed crash patterns and the predictive assumptions embedded in the original SPFs, which may be due to unaccounted contextual variables such as driver behavior, roadway geometry, or enforcement conditions specific to Delaware's rural two-lane intersections. In contrast, the CURE plots for the remaining four site types display residuals that fluctuate within acceptable confidence limits, suggesting no significant systematic bias. These results reinforce the conclusion that, while the HSM SPFs may require further refinement for simpler rural two-lane intersections, their application—once calibrated—is more reliable for more complex intersections such as those on rural multilane highways or signalized junctions.

Figure 7. CURE plots for selected site types under the first scenario (250-ft buffer).

4.3. Replacement of Crash Default Distribution to Local Conditions

The HSM provides default crash distribution values for severity levels, collision types, and crash conditions (e.g., lighting, pedestrians, driveway crashes), which vary across facility types. However, these defaults are based on datasets from other U.S. states and may not accurately reflect local crash patterns in Delaware. Therefore, this study developed Delaware-specific crash distributions using observed data from calibrated intersections, focusing on Scenario 1, which assigns crashes within 250 ft of the intersection center as intersection-related.

Following Figure 8 and Figure 9 visualize the distribution of crash severity for intersections located on rural two-lane roads and rural multilane highways respectively. In both facility types, the proportion of Property Damage Only crashes was highest, especially for three-legged intersections. Fatal crashes constituted a very small portion (below 2%), while personal injury crashes represented approximately one-fourth to one-third of all crashes, depending on the site type.

Figure 8. Crash severity distribution for rural two-lane roads.

Figure 9. Crash severity distribution for rural multilane roads.

Tables 8 presents the detailed distribution of collision types for each site category. Across all site types, multiple-vehicle crashes were more frequent than single-vehicle crashes. Notably:

- Rear-end collisions were dominant in signalized and four-legged intersections (e.g., RM4SG), often accounting for over 40% of total crashes.
- Angle collisions were prominent in unsignalized sites, especially in R24STM and RM4STM.
- Head-on and sideswipe collisions were less frequent but varied slightly by geometry and control type.

Single-vehicle crashes were more frequent in three-legged intersections and involved common crash types such as collisions with animals or running off the road.

Table 8. Distribution of collision types by facility and crash severity.

Rural Two-Lane Two-Way Roads (HSM Chapter 10)									
	R23STM			R24STM			R24SG		
Collision Type	FI	PDO	Total	FI	PDO	Total	FI	PDO	Total
Single-Vehicle Crashes									
Collision with animal	1.3%	22.5%	17.1%	1.1%	13.1%	9.3%	0.0%	4.8%	3.7%
Collision with bicycle	1.3%	0.0%	0.3%	0.0%	0.5%	0.3%	1.4%	0.8%	0.9%
Collision with pedestrian	2.6%	0.0%	0.7%	0.0%	0.0%	0.0%	7.0%	0.4%	1.9%
Overturned	Data not available								
Ran off road	Data not available								
Other single-vehicle crashes	5.3%	22.5%	18.1%	1.1%	13.6%	9.6%	5.3%	22.5%	18.1%
Total single-vehicle crashes	46.1%	59.9%	56.4%	6.5%	27.3%	20.6%	7.0%	14.7%	13.0%
Nultiple-Vehicle Crashes									
Angle collision	19.7%	12.6%	14.4%	65.6%	43.4%	50.5%	42.3%	22.3%	26.7%
Head-on collision	6.6%	1.8%	3.0%	7.5%	2.5%	4.1%	14.1%	4.0%	6.2%
Rear-end collision	23.7%	18.5%	19.8%	10.8%	17.2%	15.1%	28.2%	45.0%	41.3%
Sideswipe collision	23.7%	18.5%	19.8%	10.8%	17.2%	15.1%	28.2%	45.0%	41.3%
Other multiple-vehicle collision	0.0%	5.9%	4.4%	4.3%	6.1%	5.5%	4.2%	11.2%	9.6%
Total multiple-vehicle crashes	53.9%	40.1%	43.6%	93.5%	72.7%	79.4%	93.0%	85.3%	87.0%
Total Crashes	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Rural Multilane Highways (HSM Chapter 11)									
	R23STM			R24STM			R24SG		

Continued

Collision Type	FI	PDO	Total	FI	PDO	Total	FI	PDO	Total
Single-Vehicle Crashes									
Collision with animal	1.8%	19.1%	14.5%	1.0%	11.2%	7.8%	0.0%	4.2%	3.2%
Collision with bicycle	0.0%	0.6%	0.5%	1.0%	0.0%	0.3%	0.0%	0.0%	0.0%
Collision with pedestrian	0.0%	0.0%	0.0%	2.0%	0.0%	0.7%	1.0%	0.0%	0.2%
Overturned	Data not available								
Ran off road	Data not available								
Other single-vehicle crashes	1.8%	19.7%	15.0%	4.0%	11.2%	8.8%	1.0%	4.2%	3.4%
Total single-vehicle crashes	22.8%	37.6%	33.6%	6.9%	28.8%	21.6%	5.0%	12.8%	11.0%
Nultiple-Vehicle Crashes									
Angle collision	45.6%	19.7%	26.6%	67.3%	33.2%	44.4%	46.5%	24.3%	29.5%
Head-on collision	3.5%	1.9%	2.3%	6.9%	1.0%	2.9%	7.9%	2.7%	3.9%
Rear-end collision	24.6%	28.7%	27.6%	12.9%	22.0%	19.0%	32.7%	49.3%	45.4%
Sideswipe collision	1.8%	12.1%	9.3%	2.0%	9.8%	7.2%	3.0%	9.2%	7.8%
Other multiple-vehicle collision	1.8%	0.0%	0.5%	4.0%	5.4%	4.9%	5.0%	1.8%	2.5%
Total multiple-vehicle crashes	77.2%	62.4%	66.4%	93.1%	71.2%	78.4%	95.0%	87.2%	89.0%
Total Crashes	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

On the other hand, lighting conditions can significantly affect crash risk, particularly at rural intersections lacking illumination. Table 9 presents the proportion of crashes that occurred at unlighted intersections during nighttime. For rural two-lane intersections, nighttime crash rates ranged from 10.2% to 29.8%, while rural multilane intersections ranged from 9.8% to 25.4%. These figures can be used to adjust default nighttime crash proportions in future local safety analyses, especially when evaluating lighting countermeasures.

Table 9. Proportion of nighttime crashes at unlighted intersections.

Rural Two-Lane Two-Way Roads (HSM Chapter 10)	
Intersection Type	**Proportion of crashes that occur at night**
R23STM	29.8%
R24STM	20.6%
R24SG	10.2%
Rural Multilane Highways (HSM Chapter 11)	
Intersection Type	**Proportion of crashes that occur at night**
RM3STM	25.4%
RM4STM	21.3%
RM4SG	9.8%

5. Discussion

This study investigated the applicability of HSM crash prediction models for rural intersections in Delaware through local calibration efforts. By analyzing six site types and utilizing GIS-based spatial techniques, the study explored how calibration factors vary across intersection configurations and how crash assignment assumptions can influence model performance.

The comparative analysis of two spatial scenarios for assigning intersection-related crashes revealed the sensitivity of CFs to buffer distance assumptions. While

the 528-foot buffer scenario, applied to rural multilane highways, produced higher CFs, it also introduced the risk of misclassifying unrelated crashes—especially in high-speed areas. The commonly accepted 250-foot buffer offered greater methodological consistency, aligning better with HSM recommendations and minimizing potential bias.

Calibration performance varied across site types, revealing limitations of the national SPFs when applied to specific intersection categories. Notably, two unsignalized two-lane intersection types (R23STM and R24STM) exhibited poor model fit across all evaluation metrics, suggesting that national models may not sufficiently capture crash dynamics in these settings. Other types lacked sufficient data to meet HSM sampling thresholds, limiting their calibration potential.

This research also demonstrates the practical value of integrating public GIS platforms and high-resolution imagery for spatial data analysis and validation. The database developed offers a replicable framework for future calibration efforts and can be updated with new data as roadway conditions evolve. However, limitations such as variable data quality, inconsistencies in crash geolocation, and underrepresentation of some site types point to the need for continued investment in data collection and maintenance to enhance model reliability.

While the calibration process followed the standard methodology outlined in the Highway Safety Manual, focusing on AADT, geometric configurations, and control type, other variables known to influence crash risk—such as posted speed limits, pedestrian and bicyclist activity, and weather conditions—were not included in this study. However, future research aimed at developing new local SPFs may benefit from the integration of these additional factors, provided that reliable and consistent data sources are available. Their inclusion could enhance model accuracy, particularly in complex urban or multimodal traffic environments.

6. Conclusions

By developing localized calibration factors for rural intersection types in Delaware, this study offers actionable insights for transportation safety planning. Among the six site types analyzed, only RM4STM (Rural Multilane, Four-Legged, Stop-Controlled Intersections) satisfied both the statistical validation and HSM minimum data requirements. The recommended calibration factor of 1.39 for this site type can be directly implemented by the DelDOT to adjust predicted crash frequencies, thereby improving project prioritization and investment efficiency.

The findings also led to the development of Delaware-specific distributions for crash severity, collision types, and nighttime crash proportions, enabling state agencies to replace generic national defaults with locally representative data. These improvements contribute to more accurate safety evaluations and support the formulation of evidence-based safety policies.

To ensure continued effectiveness, DelDOT is encouraged to periodically update calibration values using current crash records and traffic volumes. The GIS-based methodology used in this study provides a scalable foundation that can be

extended to additional site types and facility classes. As such, this research not only improves the alignment between predictive models and local roadway conditions but also supports long-term, data-driven traffic safety management across the state.

Acknowledgements

The authors would like to thank the Delaware Department of Transportation (DelDOT) for providing access to intersection and traffic volume datasets, which were essential to the success of this study. The support of ArcGIS Pro under an academic license provided by Esri Inc. is also gratefully acknowledged.

Author Contribution

Rodolfo Gomes de Oliveira led the study design, data collection, GIS-based spatial analysis, calibration computations, and preparation of the initial manuscript draft. Ardeshir Faghri supervised the research, provided methodological guidance, and contributed to the critical revision of the manuscript. Abdulkadir Ozden supported the development figures, assisted with the interpretation of statistical outputs, and contributed to the refinement of the discussion and final writing. All authors reviewed and approved the final version of the manuscript. During the writing and editing process, the authors made use of artificial intelligence tools to support language refinement and improve clarity; all intellectual contributions and final content were reviewed and approved by the authors.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] U.S. Department of Transportation, Federal Highway Administration (2024) Highway Statistics (Washington, DC: Annual Issues), Table VM-202. http://www.fhwa.dot.gov/policyinformation/statistics.cfm

[2] Kopits, E. and Cropper, M. (2003) Traffic Fatalities and Economic Growth. World Bank Policy Research Working Paper. https://doi.org/10.1596/1813-9450-3035

[3] Ozbay, K., Nassif, H., Bartın, B., Xu, C. and Bhattacharyya, A. (2019) Calibration/Development of Safety Performance Functions for New Jersey. National Transportation Library. https://rosap.ntl.bts.gov/view/dot/56146

[4] NHTSA (2023) Overview of Motor Vehicle Traffic Crashes in 2021. NHTSA. https://rosap.ntl.bts.gov/view/dot/78769

[5] Mohammed, A.A., Ambak, K., Mosa, A.M. and Syamsunur, D. (2019) A Review of the Traffic Accidents and Related Practices Worldwide. *The Open Transportation Journal*, **13**, 65-83. https://doi.org/10.2174/1874447801913010065

[6] Abrams, M.Z. and Bass, C.R. (2024) Female Vs. Male Relative Fatality Risk in Fatal Motor Vehicle Crashes in the US, 1975-2020. *PLOS ONE*, **19**, e0297211. https://doi.org/10.1371/journal.pone.0297211

[7] Gössling, S. (2017) Police Perspectives on Road Safety and Transport Politics in Ger-

many. *Sustainability*, **9**, Article 1771. https://doi.org/10.3390/su9101771

[8] Hyder, A.A., Allen, K.A., Di Pietro, G., Adriazola, C.A., Sobel, R., Larson, K., *et al.* (2012) Addressing the Implementation Gap in Global Road Safety: Exploring Features of an Effective Response and Introducing a 10-Country Program. *American Journal of Public Health*, **102**, 1061-1067. https://doi.org/10.2105/ajph.2011.300563

[9] De Marchi, G., Lucertini, G. and Tsoukiàs, A. (2014) From Evidence-Based Policy Making to Policy Analytics. *Annals of Operations Research*, **236**, 15-38. https://doi.org/10.1007/s10479-014-1578-6

[10] Bax, C., De Jong, M. and Koppenjan, J. (2010) Implementing Evidence-Based Policy in a Network Setting: Road Safety Policy in the Netherlands. *Public Administration*, **88**, 871-884. https://doi.org/10.1111/j.1467-9299.2010.01843.x

[11] Dadvar, S., Lee, Y. and Shin, H. (2020) Improving Crash Predictability of the Highway Safety Manual through Optimizing Local Calibration Process. *Accident Analysis & Prevention*, **136**, Article ID: 105393. https://doi.org/10.1016/j.aap.2019.105393

[12] Miaou, S. (2013) Some Limitations of the Models in the Highway Safety Manual to Predict Run-off-Road Crashes. *Transportation Research Record*: *Journal of the Transportation Research Board*, **2377**, 38-48. https://doi.org/10.3141/2377-05

[13] Faden, A., Abdel-Aty, M., Mahmoud, N., Hasan, T. and Rim, H. (2023) Multivariate Poisson-Lognormal Models for Predicting Peak-Period Crash Frequency of Joint On-Ramp and Merge Segments on Freeways. *Transportation Research Record*: *Journal of the Transportation Research Board*, **2678**, 133-147. https://doi.org/10.1177/03611981231178797

[14] Li, D. and Al-Mahamda, M.F.M. (2020) Collective Risk Ranking of Highway Segments on the Basis of Severity-Weighted Crash Rates. *Journal of Advanced Transportation*, **2020**, Article ID: 8837762. https://doi.org/10.1155/2020/8837762

[15] Tawfeek, M.H. and El-Basyouny, K. (2019) Estimating Traffic Volume on Minor Roads at Rural Stop-Controlled Intersections Using Deep Learning. *Transportation Research Record*: *Journal of the Transportation Research Board*, **2673**, 108-116. https://doi.org/10.1177/0361198119837236

[16] Peiris, S., Corben, B., Nieuwesteeg, M., Gabler, H.C., Morris, A., Bowman, D., *et al.* (2018) Evaluation of Alternative Intersection Treatments at Rural Crossroads Using Simulation Software. *Traffic Injury Prevention*, **19**, S1-S7. https://doi.org/10.1080/15389588.2018.1528357

[17] Oneyear, N., Hallmark, S., Goswamy, A., Thapa, R. and Basulto-Elias, G. (2023) Analysis of Stopping Behavior at Rural T-Intersections Using Naturalistic Driving Study Data. *Journal of Transportation Technologies*, **13**, 208-221. https://doi.org/10.4236/jtts.2023.132010

[18] Federal Highway Administration (2024) SHSP IMP Overview. United States Department of Transportation. https://highways.dot.gov/safety/hsip/shsp/strategic-highway-safety-plan-implementation-process-model/shsp-imp-overview

[19] Delaware Department of Transportation (2006) Delaware's Strategic Highway Safety Plan. https://deldot.gov/Programs/DSHSP/

[20] Delaware Department of Transportation (2020) Delaware 2021-2025 Strategic Highway Safety Plan: Toward Zero Deaths. https://deldot.gov/Programs/DSHSP/pdfs/2021-2025%20SHSP%20Emphasis%20Area%20Statistics.pdf?cache=1744740754544

[21] Goswamy, A., Hallmark, S., Litteral, T. and Pawlovich, M. (2018) Safety Evaluation of Destination Lighting Treatment at Stop Controlled Cross-Intersections. *Transpor-*

tation Research Record: *Journal of the Transportation Research Board*, **2672**, 113-121. https://doi.org/10.1177/0361198118774747

[22] Ai, Q., Zhang, J. and Ye, Y. (2024) Strategies to Enhance the Level of Service and Safety of Rural Roads: A Case Study. *PLOS ONE*, **19**, e0300525. https://doi.org/10.1371/journal.pone.0300525

[23] Lyon, C., Persaud, B.N. and Gross, F.B. (2016) The Calibrator—An SPF Calibration and Assessment Tool User Guide. United States. Federal Highway Administration. Office of Safety. https://rosap.ntl.bts.gov/view/dot/50484

[24] Bhandari, A. (2025) Key Difference between R-Squared and Adjusted R-Squared for Regression Analysis. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2020/07/difference-between-r-squared-and-adjusted-r-squared/