

# Risk Factor Identification

**Final Report**  
**December 2016**



Center for Transportation  
Research and Education

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<b>16. Abstract</b> <p>The aim of this study was to provide assistance in the identification of risk factors for traffic crashes on two facility types in Iowa: intersections and horizontal curves. The risk factors were identified through the analysis of a robust database, which combined information from various sources and included traffic volumes, roadway geometry, and other characteristics.</p> <p>For both intersections and horizontal curves, the researchers developed crash trees and regression models, and conducted exploratory visual analytics of Iowa's crash data. The researchers further investigated the effects of skew angle and other factors associated with safety at rural intersections in Iowa through the estimation of safety performance functions (SPFs). The scope on this part of the study was limited to intersections on high-speed (speed limit of 45 mph or higher), rural, two-lane roadways. This analysis provides important results that reinforce the extant research literature as to the relationship between intersection skew angle and crash frequency.</p> <p>The researchers also conducted a more in-depth investigation into safety risk factors for horizontal curves as a part of this study. Crash frequency data for horizontal curves were analyzed using a negative binomial modeling framework, while the crash severity data were analyzed using an ordered probit model. The results demonstrate the relationships between crash frequency/severity and various curve characteristics. Ultimately, the results of this research will allow for more effective network surveillance and identification of high-risk locations.</p>			
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# **RISK FACTOR IDENTIFICATION**

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## **INTRODUCTION AND BACKGROUND**

Traffic fatalities in the US have declined significantly in recent years—from a modern high of 43,510 in 2005 to 32,719 in 2013. Similar declines have occurred in Iowa, where fatalities have declined from 450 to 317 over this same period (NHTSA 2015). These declines are attributable to various factors, including enhanced vehicle safety features, targeted safety-related legislation and enforcement programs, and the introduction of various engineering countermeasures. Intersections and horizontal curves are two high-priority emphasis areas where engineering countermeasures are often applied.

Intersections account for 30 percent of crashes in rural areas and 6 percent of all fatal crashes. Motor vehicle crash injury rates are higher in rural areas, due in part to increased emergency medical services (EMS) response times, reliance on volunteer EMS, and increased transport times (Gonzalez et al. 2009, NHTSA 2006, Zwerling et al. 2005).

Horizontal curves also present heightened crash rates, as the Fatality Analysis Reporting System (FARS) indicates more than 25 percent of fatal crashes in the US occur on horizontal curves (NHTSA 2015, FHWA 2011). The percentage of fatal curve-related crashes is higher on rural roads due to the predominance of horizontal curves, especially on two-lane roadways in rural areas. The average crash rate for horizontal curves is about three times greater than on highway tangents (Torbic et al. 2004).

Consequently, intersections and horizontal curves present two high-priority areas for engineering countermeasures. The implementation of countermeasure programs are generally focused on high-risk locations, which are identified based on extensive historical traffic safety data (i.e., crash history). For example, the Moving Ahead for Progress in the 21st Century (MAP-21) Act requires all states to have in place a Highway Safety Improvement Program (HSIP) that “emphasizes a data-driven, strategic approach to improving highway safety on all public roads that focuses on performance.”

Unfortunately, the identification of candidate locations for engineering countermeasures is often challenging due to the random and rare nature of traffic crashes, as well as related analytical issues such as regression-to-the-mean (RTM). These challenges are particularly pronounced on rural highways, where many potentially high-risk locations may be difficult to identify given lower traffic volumes.

Given the prevailing focus on safety decisions that are data-driven, much research has focused on gaining a more thorough understanding of how various risk factors affect the frequency of traffic crashes, injuries, and fatalities at specific roadway sites. The extant research literature has shown various factors to affect the frequency of traffic crashes, including traffic volume, roadway geometry, type of traffic control, and other factors. Such risk factors are likely to vary across different types of road facilities, such as highway segments, intersections, and interchanges.

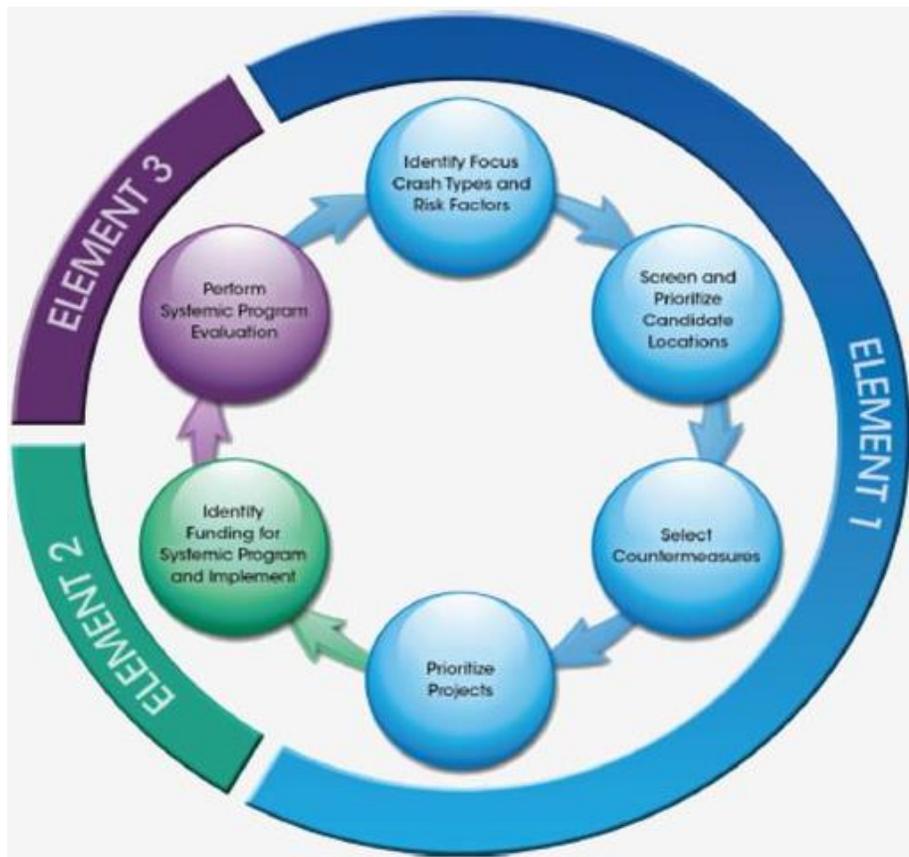
Gaining a better understanding of the complex relationships between crash risk and roadway geometry provides important information to aid in the development of targeted policies and programs to reduce traffic crashes and the resultant injuries and fatalities.

This study aims to provide assistance in the identification of risk factors for traffic crashes on two facility types: intersections and horizontal curves. These risk factors are identified through the analysis of a robust database, which combines data from various sources including traffic volumes, roadway geometry, and other characteristics. Ultimately, the results of this research will allow for more effective network surveillance and identification of high-risk locations.

## LITERATURE REVIEW

The identification of candidate sites for the deployment of specific safety treatments is a critical aspect of any safety improvement program; however, this process can be costly (Hauer et al. 2002). The process of identifying sites candidate sites for safety improvements is critical, while network-wide implementation of counter-measures is only possible under certain staff and budget conditions (Preston et al. 2013a).

One methodology for traffic safety professionals to utilize to identify sites with the potential for safety improvements is to first identify which specific types of crashes need to be mitigated based on network-level data, and then screen and prioritize locations across the roadway system. Recently, the Federal Highway Administration (FHWA) has developed a Systemic Safety Project Selection Tool to aid safety practitioners in the application of this methodology (Preston et al. 2013b). The general process for using this tool is shown in Figure 1.



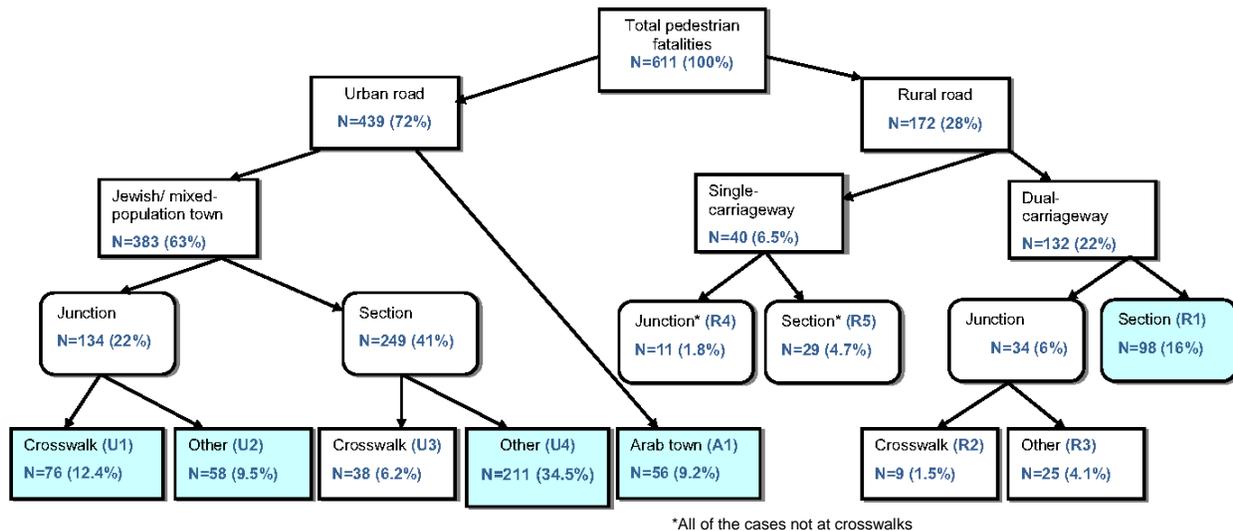
Preston et al. 2013b, FHWA

**Figure 1. FHWA Systemic Safety Project Selection Tool process**

Subsequent research has aimed to apply the tool and other systemic safety tools. Recent research in Iowa examined the Minnesota County Road Safety Plan (CRSP) and the FHWA systemic tool to prioritize roadway segments, horizontal curve sections, and stop-controlled intersections

(Knapp et al. 2014). A similar research project in Kentucky compared the FHWA systemic tool to the US Road Assessment Program (usRAP) and traditional road safety audits in terms of site prioritization and suggested countermeasures (Harwood et al. 2014).

The prioritization of specific network locations for safety improvements is determined by the frequency and severity of various risk factors that are present at a particular site. Risk factors for a particular type of crash or for crashes at a specific facility can be identified for network-specific crash data using a process similar to that presented in Figure 2, where crashes of a particular type are disaggregated into increasingly smaller groups based on certain site characteristics.



Copyright © 2010 Elsevier Ltd. Published by Elsevier Ltd. All rights reserved. Gitelman et al. 2012

**Figure 2. Pedestrian fatality patterns in Israel, 2003–2006**

Statistical algorithms, such as regression trees, can also be utilized to classify crashes based on driver, vehicle, and site characteristics. One study of rural horizontal curves in Wisconsin identified an increase in crash frequency when curve radii are less than 2,500 feet or when traffic volumes exceed 1,300 vehicles per day (Khan et al. 2013). In another Wisconsin study, variables contributing to cross-median-crash (CMC) severity were identified using discrete outcome models (Khan et al. 2015). Regression trees have also been utilized to identify the number of lanes as an important factor in crash severity at signalized intersections (Abdel-Aty and Keller 2005).

A variety of situations are identified in the extant literature where the systemic approach is taken to identify crash types or site characteristics associated with specific crash types. Age-period-cohort (APC) analysis has been applied to fatal crash data from the US for a 30-year period from 1980–2010 to assess which age groups were at risk for specific types of crashes, as well as to identify specific periods of time during which crash trends may have changed (Macinko et al. 2015).

Recent research projects have addressed solo motorcycle, pedestrian-motorcycle, and vehicle-motorcycle crashes (Jimenez et al. 2015), as well as to examine the relationship between the gender of a crashed motorcyclist and the gender of the motorcycle owner (Keall and Newstead 2012).

Two Israeli studies investigated factors contributing to pedestrian crashes. The first study used an intuitive process to identify the location of pedestrian crashes in the context of network elements (in crosswalk, not at intersection, etc.) (Gitelman et al. 2012), while the second used the neural networks to classify pedestrian crashes into clusters sharing similar characteristics (e.g., urban crashes involving the elderly) (Prato et al. 2012).

Several studies have examined site-level risk factors for pedestrian and bicycle crashes (Wang et al. 2016, Bergh et al. 2015). Additionally, studies of low-volume or rural site types have all incorporated a systemic approach to identify crash risk factors (Al-Kaisy et al. 2015, Souleyrette et al. 2005, Preston et al. 2015, Khan et al. 2013).

Collectively, these studies demonstrate the usefulness of the systemic approach to identify factors contributing to crash occurrence in situations where exposure data may be limited or in situations where crashes are extremely rare.

### **Safety at Low-Volume and/or Rural Locations**

The *Manual on Uniform Traffic Control Devices (MUTCD) for Streets and Highways* defines low-volume roads as those located outside of built-up areas with volumes of less than 400 vehicles per day (vpd) annual average daily traffic (AADT) (FHWA 2012). Safety at low-volume locations, and rural locations in general, can be difficult to analyze, especially given the already random nature of crashes. Crash prediction models, commonly referred to as safety performance functions (SPFs), such as those presented in the *Highway Safety Manual (HSM)* (AASHTO 2010), as well as SPFs developed on a project-specific basis, are one type of tool that highway agencies often utilize to quantify safety.

A recent study separately analyzed tangent and curve segments, as well as a combination of two segment types, where volumes were less than 1,000 vpd. This study identified isolated sharp curves as being associated with higher expected crashes in comparison to stretches of road with a series of curves (Avelar et al. 2015).

The industry standard in the development of SPFs has become the negative binomial model; however, a variety of statistical modeling frameworks have been used in SPF estimation for low-volume roads (Polus and Cohen 2012).

In addition, difficulties in assessing safety at low-volume locations have given rise to measures of safety that do not specifically consider crashes. Instead, these measures consider features that are associated with high crash risk, such as the safety risk index (SRI), which uses site

characteristics determined from a safety inspection as well as design consistency to assess the relative safety of a location (Cafiso et al. 2015).

A study in Iowa used an extensive set of descriptive statistics to assess rural road safety, specifically examining the differences between rural primary and secondary roadways, and finding that local roads exhibit a higher frequency of injury crashes than primary roads (Souleyrette et al. 2010).

An Oregon research project attempted to use multivariate linear regression to model the safety effects of geometry and other roadway characteristics on the safety of low-volume roads; however, the regression analysis did not yield any results significant at the 95% confidence interval. To compensate for the shortcomings of the regression analysis, a correlation analysis was performed that revealed crash likelihood increased on low-volume roadways with 10-foot lanes compared to those with 12-foot lanes, on roadways without shoulders or with narrow shoulders compared to those with 4-foot shoulders, and on roadways where the degree of curvature is in excess of 30 degrees compared to those with less than 5-degree curvature (Ewan et al. 2016).

An apparently related report from Oregon utilized a systemic approach to crash classification to find that roadways with 9-foot lanes experienced a smaller percentage of run-off-road (ROR) crashes; however, narrow lanes were associated with higher occurrences of opposite-direction, sideswipe, motorcycle, and truck crashes (Al-Kaisy et al. 2015).

A systemic investigation of rural roadways in Minnesota identified \$232 million worth of road edge, curve delineation, and intersection safety improvements that would not have been identified under traditional site-prioritization methods (Preston et al. 2015).

A recent Hungarian study developed risk factors for specific combinations of roadway geometry and traffic volumes in conjunction with various types of violations as indicated in traffic crash reports (Miletics and Koren 2014). Results showed sites with auxiliary (acceleration/deceleration) lanes tended to experience crashes where the at-fault driver failed to yield or was attempting to pass. Crash rates were also higher at intersections without right turn lanes as drivers would attempt to pass using the left turn lane.

One Iowa study examined criteria for assessing the potential removal of traffic control devices in rural areas. This study showed older and younger drivers are both over-represented in crashes at stop-controlled and uncontrolled intersections while broadside/right-angle crashes were the most prevalent crash type at such locations (Souleyrette et al. 2005). This research also showed that at very low-volume intersections (with daily entering volumes less than 150 vehicles), there were negligible differences in safety performance between stop-controlled and uncontrolled intersections (Souleyrette et al. 2006).

The aforementioned studies show various examples of how systemic safety approaches can be used to assess safety on rural or low-volume roadways and intersections.

## Safety on Horizontal Curves

Substantive research has also been done on the factors affecting safety along horizontal curves on high-speed roadways. Schneider et al. (2009a) examined horizontal curves on rural two-lane highways in Texas and found injuries were more likely to occur on curves with radii between 500 ft. and 2,800 ft. ROR crashes were particularly hazardous for, most notably collisions with roadside objects, on high-speed roads. Khan et al. (2012) evaluated the safety of horizontal curves in light of curve geometric characteristics and sign data collected from the Wisconsin Department of Transportation (WisDOT). Crashes were found to decrease with curve radius and increase with curve length and AADT. Bauer and Harwood (2013) also found crashes to decrease with curve radius, in addition to increasing with vertical grade.

Fitzpatrick et al. (2009) evaluated the safety effects of ramp density and horizontal curvature on freeways in Texas. The study examined the safety of horizontal curves, as well as the adjacent tangent segments. The entire dataset included 561 curve/tangent pairs for a total of 324.3 miles. Crashes on freeway segments were found to increase with average daily traffic (ADT), with on-ramp density, and with degree of curvature. Crashes were also influenced by median width, number of lanes (for urban freeways), and whether the freeway was in an urban area or rural area.

Fitzpatrick et al. (2010) also developed accident modification factors (AMFs) along rural four-lane highways in Texas. Driveway density was found to have slightly different impacts on horizontal curves versus tangents. Fink et al. (1995) analyzed tangent length and sight distance effects on crash rates at horizontal curves on rural two-lane highways. The results suggest that the effect of long tangents becomes more pronounced on sharper curves, and the analysis of sight distance effects suggests that extreme approach conditions (both long and short approach sight distance) may contribute to higher crash rates on sharper curves.

Savolainen et al. (2005) evaluated safety impacts at intersections on super-elevated curved segments, focusing on high-speed four-lane divided highways with two-way stop control in Indiana. Recommendations were presented for curve radius and super-elevation rate when intersections were located on high-speed curves. Results from the same study also indicated that intersections on curves experienced higher percentages of right-angle and single-vehicle crashes. Khan et al. (2013) used regression tree analysis and identified a curve radius of approximately 2,500 feet as a significant point below which there is a marked increase in crashes on horizontal curves.

Findley et al. (2012) studied the spatial relationships among horizontal curves and found that more closely spaced curves have fewer crashes than curves that are more distant to each other. Hauer (1999) found that, for any given deflection angle, the design with the smaller degree of curve (i.e., larger radius) is safer. Results also suggested that the change in crashes is proportional to the change in radius length.

Council (1998) explored differences in the probability of crashes occurring on curve transition areas for level, rolling, and mountainous terrain. The research concluded that spirals can be

beneficial on curves with a degree of curvature more than 3 for level terrain and less than or equal to 8 for rolling terrain. For mountainous areas, it was suggested that spirals should be used only on roads with wider lanes and shoulders.

Persaud et al. (2000) developed an empirical Bayes-based procedure to develop guidelines for applying curve-warning treatments. The procedure recognized the high-crash potential for curves with a small radius (180 m/591 ft) and relatively large AADT (8,700 vpd).

Schneider et al. (2009b) developed a crash prediction model for truck crashes on horizontal curves and found a positive relationship between crashes, ADT, and curve length, and a negative relationship between crashes and curve radius. The radius and length of horizontal curves has also been shown to influence the frequency of motorcycle crashes along rural two-lane highways (Schneider et al. 2010).

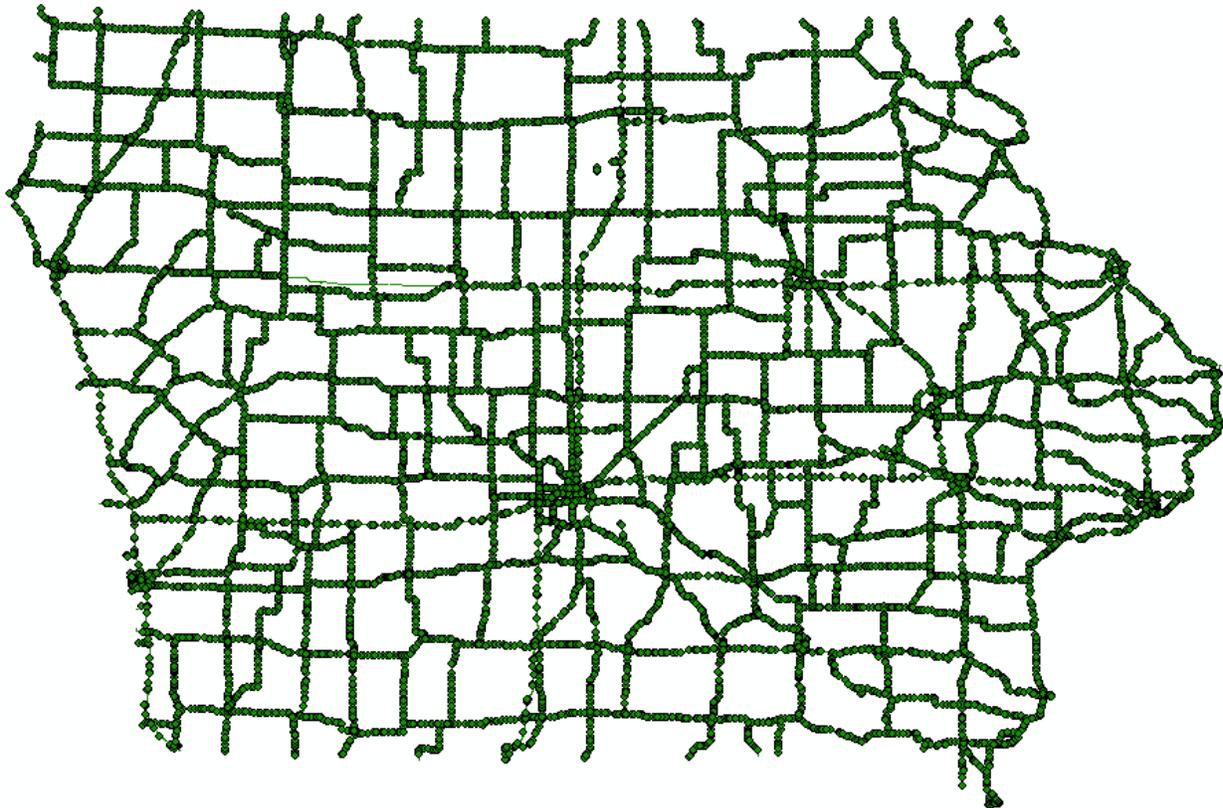
Although various studies have assessed the safety of horizontal curves, changes in the MUTCD with respect to the use of traffic control devices on curves prompts the need for further safety evaluations. When the selection of problem curves for safety improvement is based on crash records, speed-control measures, such as hazard warnings or automated speed enforcement, can be more effective (Persaud et al. 2000). The need exists to examine the effects of other types of signs, as well as factors such as cross slope, pavement friction, and advisory speed, date of installation, sign material, and size (Khan et al. 2012). These are several of the focus areas that are addressed as a part of this study.

## DATA COLLECTION FOR INTERSECTION RISK FACTORS

The researchers constructed the intersection risk factor dataset from the following data sources:

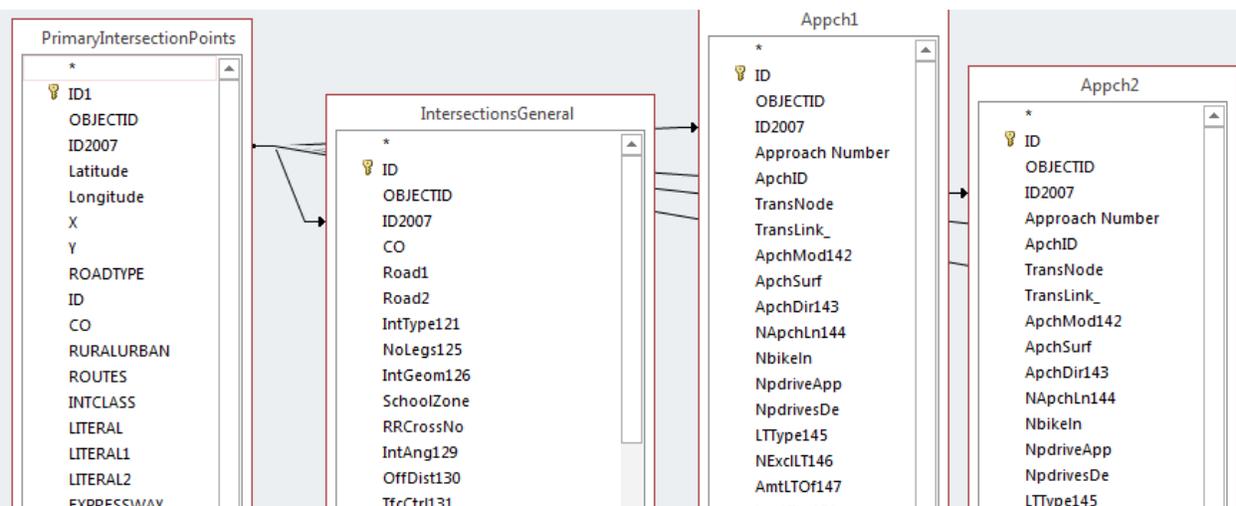
- intersection\_points.shp – A geographic information system (GIS) shapefile containing the location of 173,233 intersections located in Iowa, with a unique identifier of ID2007.
- Intersection\_General.xlsx – An Excel spreadsheet with intersection-level data, including daily entering volume, for the intersection shape file, which could be linked via the ID2007 field.
- Intersection\_Approach.xlsx – An Excel spreadsheet with approach-level data for the intersection shape file, which could be linked via the ID2007 field.
- Statewide crash database – The statewide crash database is maintained by the Iowa DOT's Motor Vehicle Division. The data comes mainly from law enforcement agencies that report at the scene of a crash. A large percentage of these data are collected electronically using the Traffic and Criminal System Software (TraCS). For the purposes of the intersection part of this study, all crashes occurring at Iowa intersections between January 1, 2009 and December 31, 2013 (five years) were extracted.
- Iowa Geographic Information Management System (GIMS) – A series of GIS shapefiles outlining Iowa's roadway network as well as containing geometric and operational information.

First, the researchers imported GIMS and intersection point files into Esri's ArcGIS (mapping software) and selected only the intersections located on the primary roadway network (19,364 intersections), as illustrated in Figure 3. Note that only one of the intersection streets needed to be a primary road to be included.



**Figure 3. Iowa primary roads and associated intersections**

The researchers exported the attribute table of the selected primary road intersections as a database file and joined the table with the Intersection\_General and Intersection\_Approach files using Microsoft Access, as shown in Figure 4.



**Figure 4. Linking of the intersection data sources**

The approach file contained multiple entries for each intersection (one entry per intersection approach). The researchers collected these data manually using Google Earth aerial imagery and Google Streetview imagery. The Intersection\_General file includes the 10 data fields shown in Table 1, while the Intersection\_Approach file includes the 22 fields shown in Table 2.

**Table 1. Intersection characteristic fields**

<ul style="list-style-type: none"> <li>• Number of Legs</li> <li>• Intersection Geometry</li> <li>• School Zone</li> <li>• Intersection Angle</li> <li>• Lighting conditions</li> </ul>	<ul style="list-style-type: none"> <li>• Traffic Control</li> <li>• Signal Type</li> <li>• Offset Distance</li> <li>• Intersection Type</li> <li>• Comments</li> </ul>
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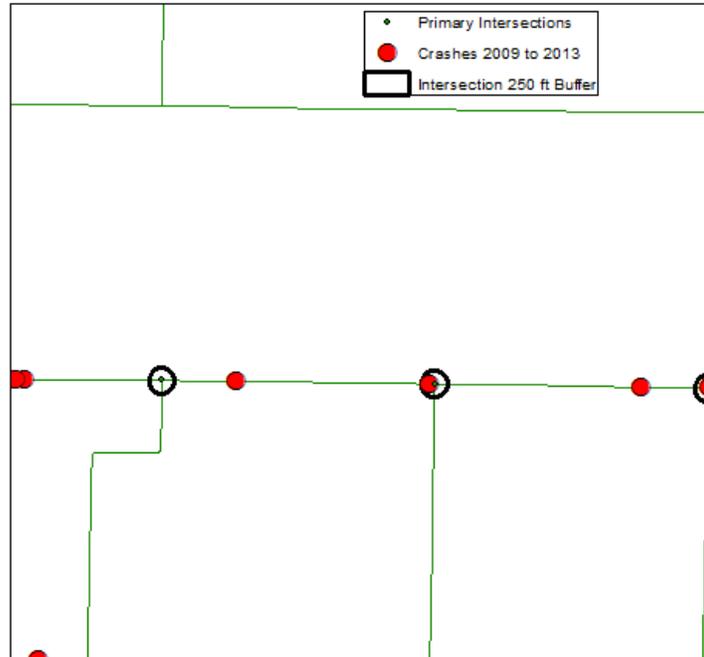
**Table 2. Approach characteristic fields**

<ul style="list-style-type: none"> <li>• Traffic Mode</li> <li>• Pavement Surface type</li> <li>• One- or two-way</li> <li>• Number of bike lanes</li> <li>• Access points within 75 ft</li> <li>• Left-turn type</li> <li>• Left-turn bay length</li> <li>• Number of exclusive LT lanes</li> <li>• Left-turn offset</li> </ul>	<ul style="list-style-type: none"> <li>• Right-turn channelization</li> <li>• Number of exclusive right-turn lanes</li> <li>• Traffic control exclusive right-turn</li> <li>• Right-turn offset</li> <li>• Median type</li> <li>• Traffic Control</li> <li>• Crosswalk type</li> <li>• Transverse Rumble Strips</li> <li>• Comments</li> </ul>
--	--

To accommodate analysis at an intersection level, the researchers reformatted the original approach file into a series of files, with each file containing information on up to one approach of an intersection (intersections were found to have between 0 and 8 approaches, where locations with 0 approaches were generally points that were misidentified as intersections, such as overpasses, while a higher number of approaches was rare and generally indicative of a complex intersection). The ID2007 field is unique for each intersection and, as Figure 4 illustrates, the researchers used the ID2007 field to link each of the separate intersection information files.

The researchers exported the linked intersection files from Access into a single Excel spreadsheet. Further quality assurance/quality control (QA/QC) resulted in the removal of duplicate intersections (40 sites) and of intersections with no general data, and therefore no volume data (4,204 sites). After completion of this QA/QC process, 15,120 intersections were left in the dataset.

Finally, the researchers used ArcGIS to spatially query and join crashes that occurred within 250 feet of one of the 15,120 intersections to the nearest intersection (for the years 2009 through 2013). The spatial query process is illustrated in Figure 5.



**Figure 5. Spatial query of crash data**

Using Excel, the researchers manipulated the exported crash data using pivot tables. For each of the five years of data, the researchers created a separate pivot table. They created binary variables for crash severity from the CSSEVERITY field. The researchers excluded crashes that were specifically coded as non-intersection in the crash database, based on the Non-Intersection Roadway Junction/Feature Type codes 01 through 08 (shown in Figure 6).

99 - Unknown
<b>Type of Roadway Junction/ Feature</b>
<i>Non-intersection:</i>
01 - No special feature
02 - Bridge/overpass/underpass
03 - Railroad crossing
04 - Business drive
05 - Farm/residential drive
06 - Alley intersection
07 - Crossover in median
08 - Other non-intersection (explain in narrative)
<i>Intersection:</i>
11 - Four-way intersection
12 - T - intersection
13 - Y - intersection
14 - Five-leg or more
15 - Offset four-way intersection
16 - Intersection with ramp
17 - On-ramp merge area
18 - Off-ramp diverge area
19 - On-ramp
20 - Off-ramp
21 - With bike/pedestrian path
22 - Other intersection (explain in narrative)
99 - Unknown

**Figure 6. Roadway Junction/Feature Type codes from Iowa DOT Investigating Officer's Report of Motor Vehicle Accident Code Sheet**

## PRELIMINARY ANALYSIS FOR INTERSECTIONS

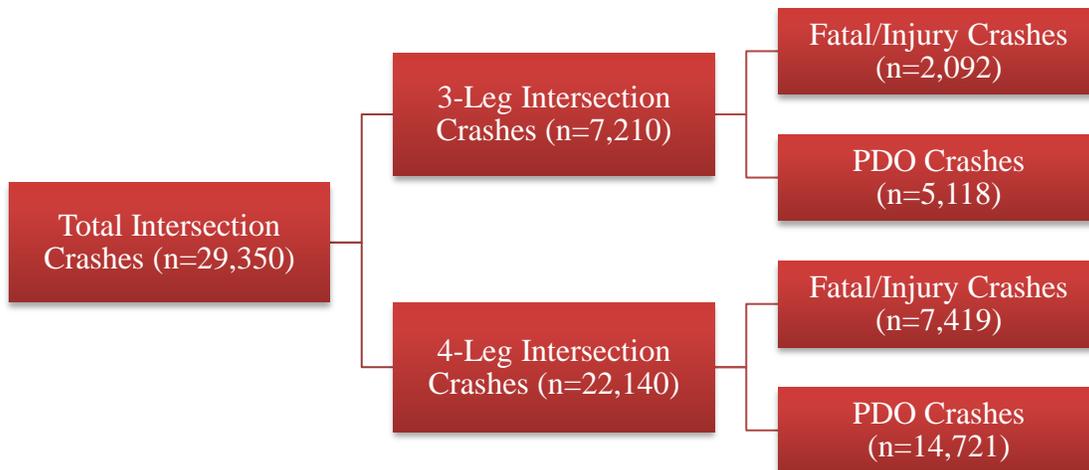
The procedures described in the last chapter resulted in a dataset consisting of 15,120 intersections, which collectively experienced 29,645 crashes over the five-year study period. After removing intersections with more than four legs (30 intersections), the dataset was reduced to 8,006 three-leg intersections and 7,084 four-leg intersections, which experienced 7,120 and 22,140 crashes, respectively.

### Crash Trees

Preliminary risk factor analyses were conducted on all three- and four-leg intersections located on the primary (state-maintained) roadway network. As noted previously, for each intersection included in the study, five years (2009–2013) of crash data were obtained from the statewide crash database. Using ArcGIS, the researchers identified crashes located within 250 feet of an intersection. The team constructed a series of crash trees to examine general trends in traffic crashes and injuries/fatalities by intersection type. This process involved aggregating the sites into homogeneous subgroups based on the following screening criteria:

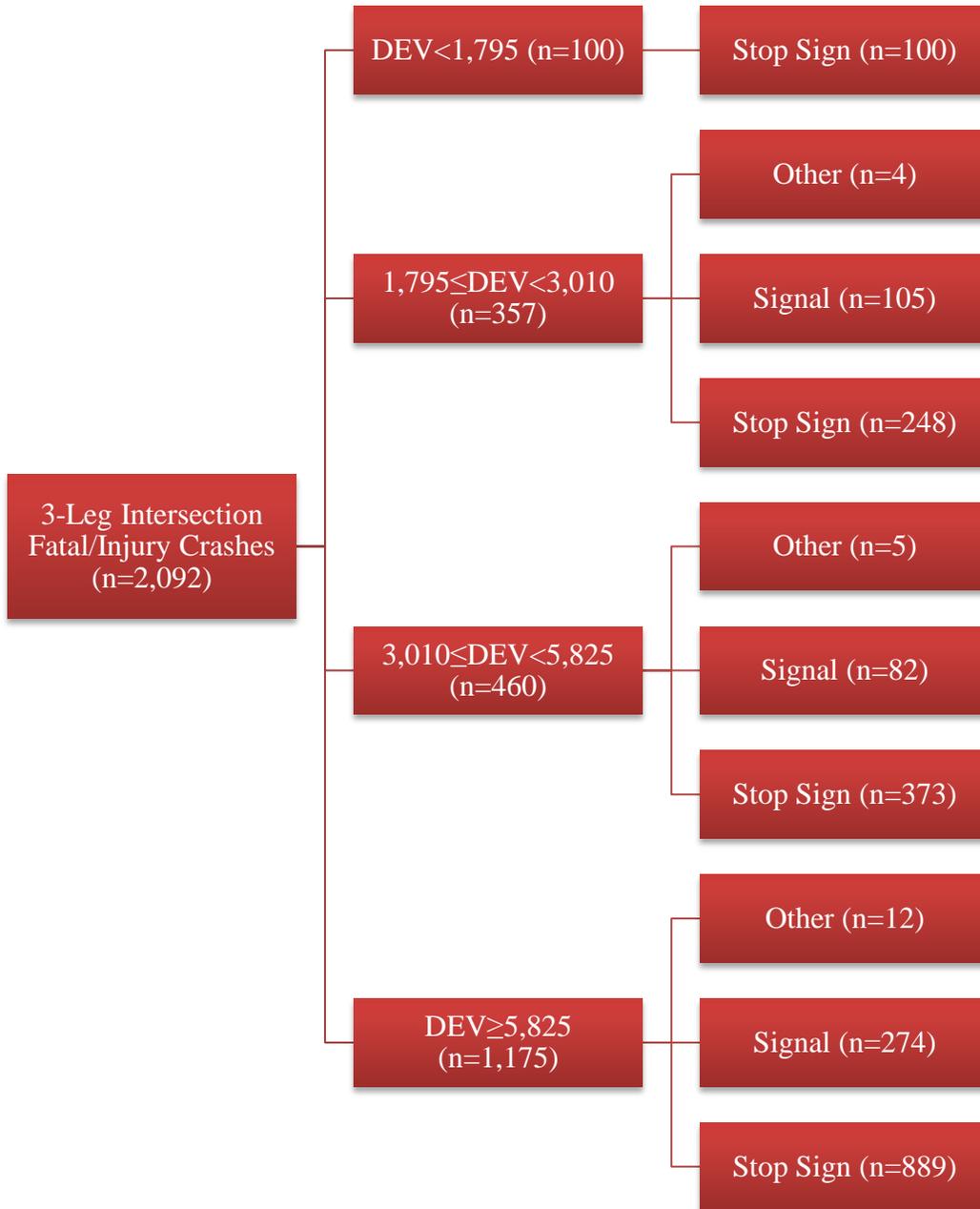
- Number of intersection legs (3 versus 4)
- Injury severity categories (fatal/injury versus property damage only)
- Average daily traffic (based upon quartiles of total daily entering volume)
- Type of traffic control present at the intersection (signalized, stop-control, other)

Figures 7–11 illustrate how many crashes occurred within each of these subcategories. Figure 7 provides a general overview of crashes among three- and four-leg intersections.



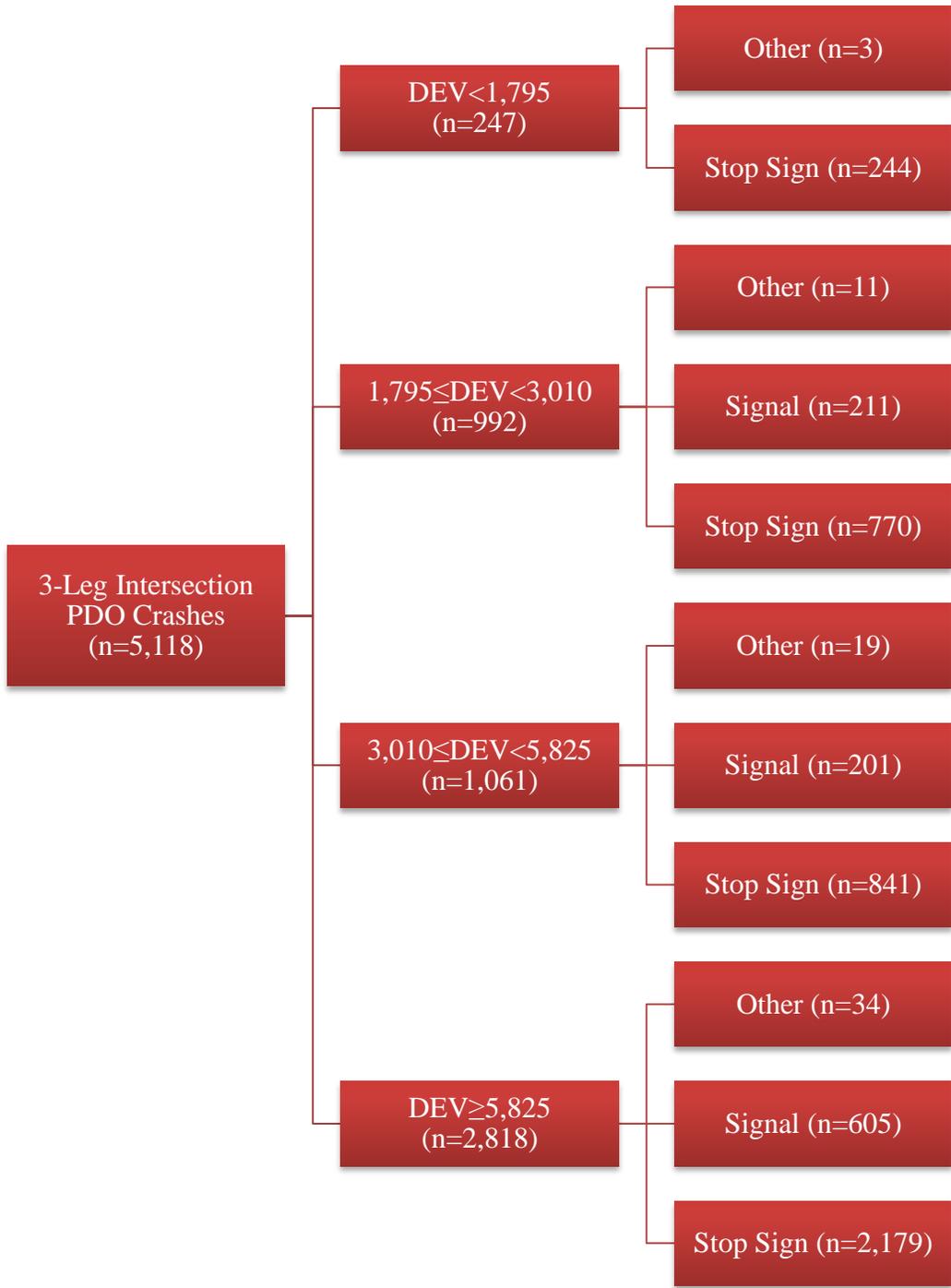
**Figure 7. Three- versus four-leg intersections by crash injury severity**

Figures 8 and 9 provide further details for the three-leg locations and Figures 10 and 11 detail four-leg intersections.



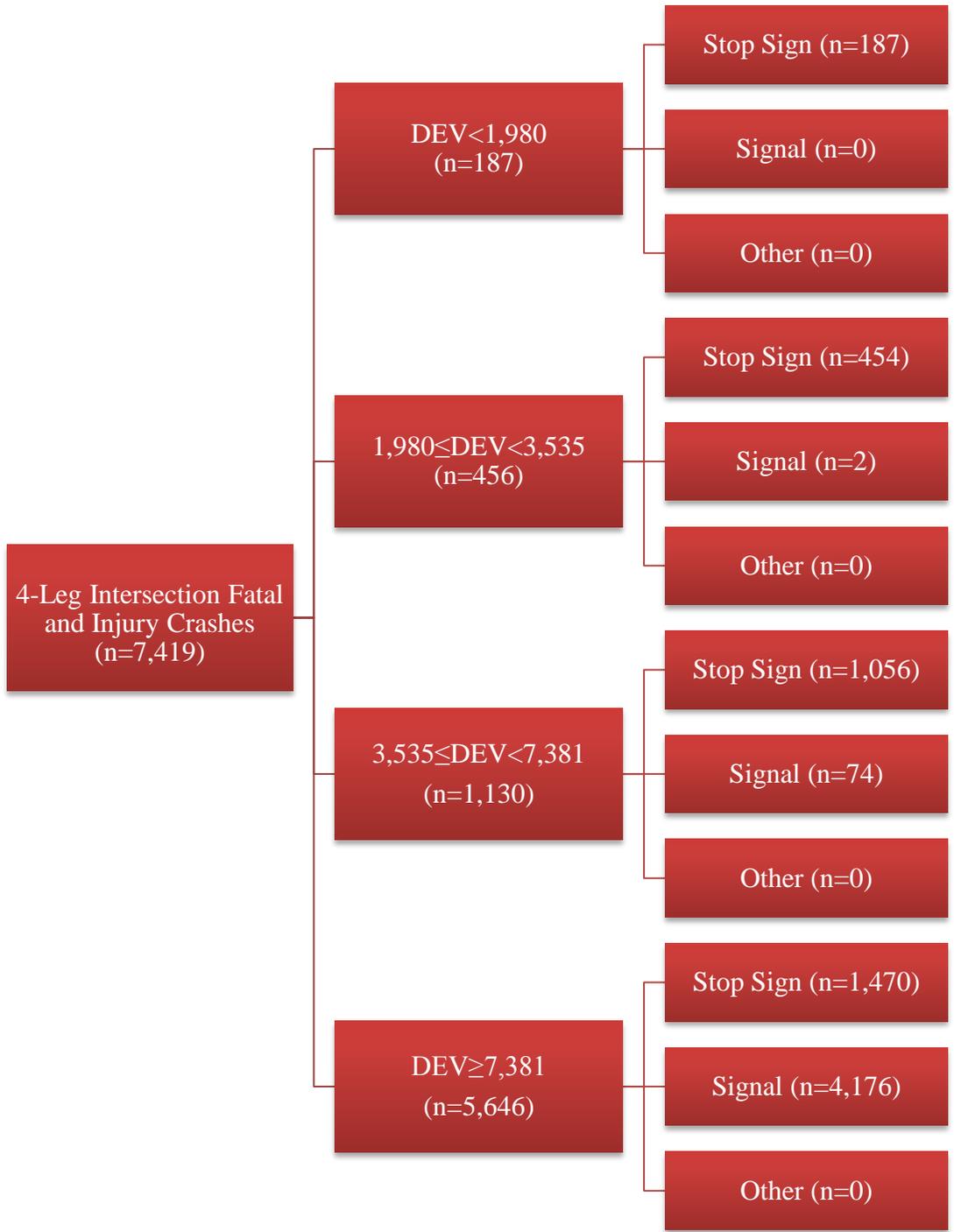
DEV=daily entering vehicles

**Figure 8. Three-leg intersection fatal/injury crashes**



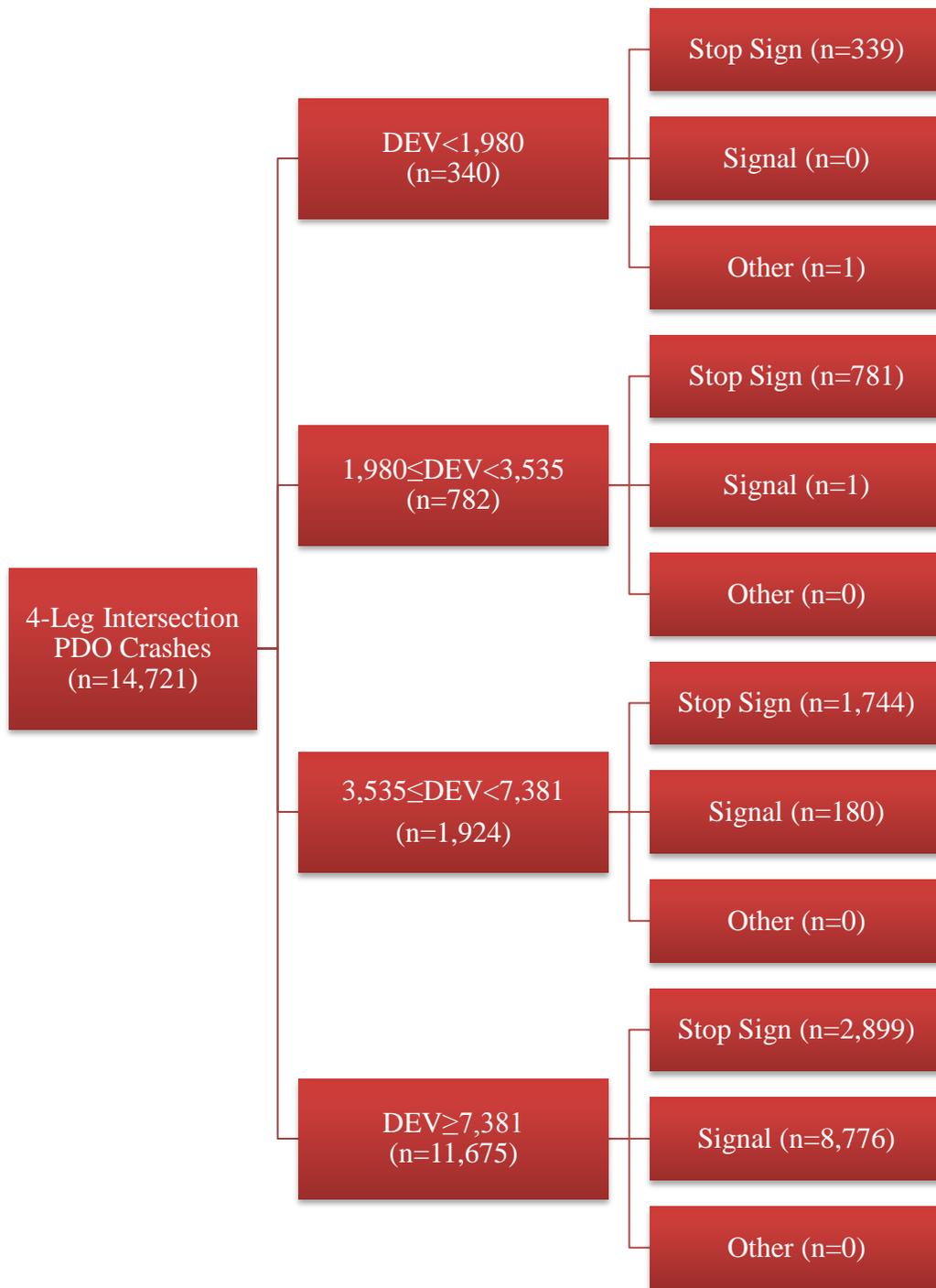
PDO=property damage only, DEV=daily entering vehicles

**Figure 9. Three-leg intersection PDO crashes**



DEV=daily entering vehicles

**Figure 10. Four-leg intersection fatal/injury crashes**



PDO=property damage only, DEV=daily entering vehicles

**Figure 11. Four-leg intersection PDO crashes**

When examining these figures, each box indicates a sample size (denoted by n=), which details how many crashes occurred within each site type. These results generally show that the majority of the crashes occurred at stop-controlled intersections.

While stop-controlled locations comprise the majority of these intersection crashes, note that the annual number of crashes on a per site basis tends to be relatively low due to lower traffic volumes. Consequently, these types of locations provide good candidates for large-scale systemic safety analyses.

### Regression Models

In addition to the crash trees, a series of basic crash prediction models were estimated from a subset of the original 15,120 intersections. After removing intersections with more than four legs (30 intersections), as well as those with missing traffic volume or crash data (258 intersections), 14,832 intersections remained in the analysis dataset. Summary statistics for the 3-leg and 4-leg intersections within this sample are provided in Tables 3 and 4.

**Table 3. Primary three-leg intersection summary statistics**

Variable	Min	Max	Mean	Std Dev
Daily Entering Vehicles	45	37,776	4,899	5,200.7
Total Annual Crashes	0	72	0.348	5.0
Annual Fatal/Injury Crashes	0	17	0.102	1.3
Annual PDO Crashes	0	57	0.246	3.8

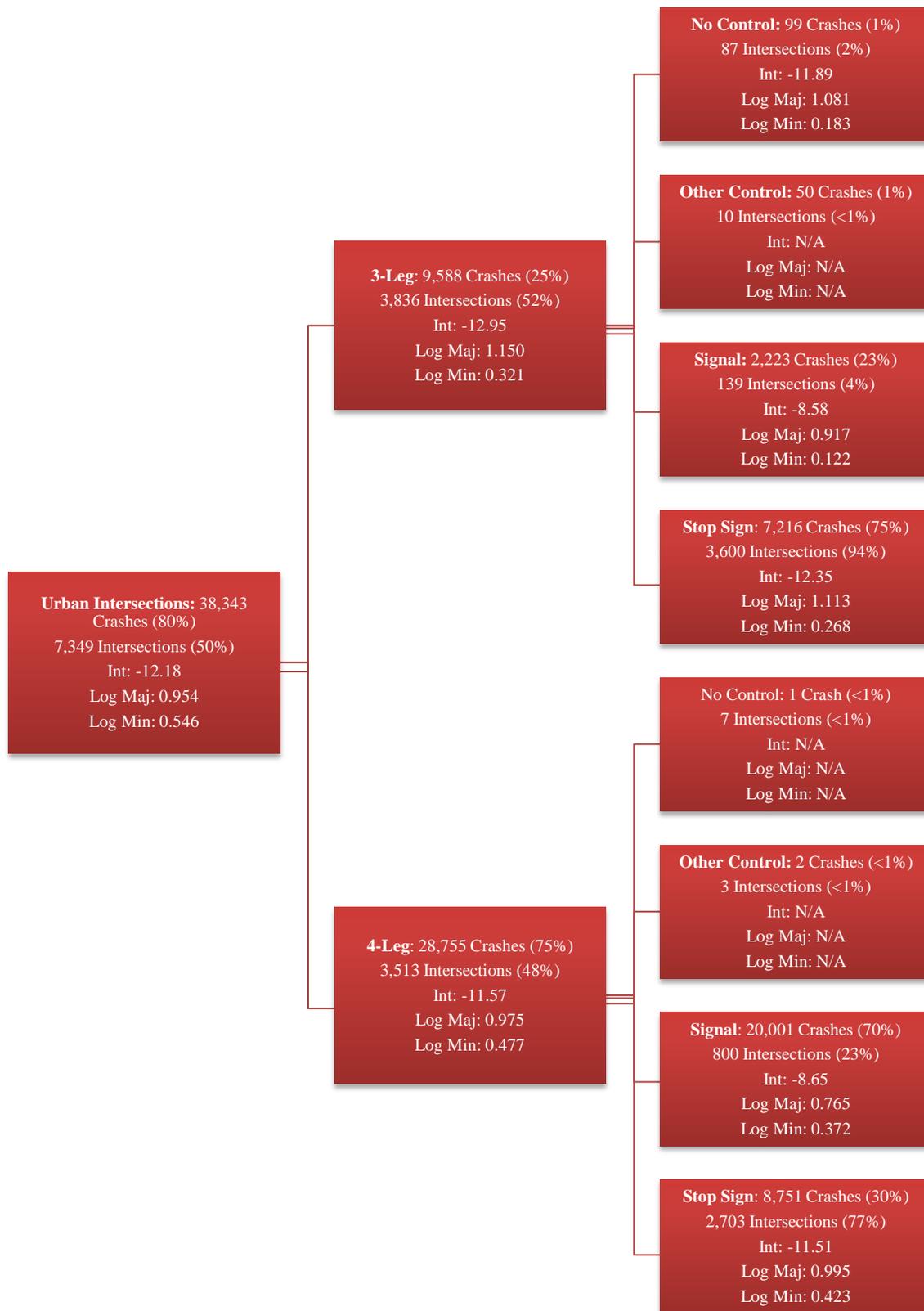
**Table 4. Primary four-leg intersection summary statistics**

Variable	Min	Max	Mean	Std Dev
Daily Entering Vehicles	100	49,250	5,874	6,288.3
Total Annual Crashes	0	145	0.298	11.0
Annual Fatal/Injury Crashes	0	55	0.098	3.5
Annual PDO Crashes	0	96	0.201	7.9

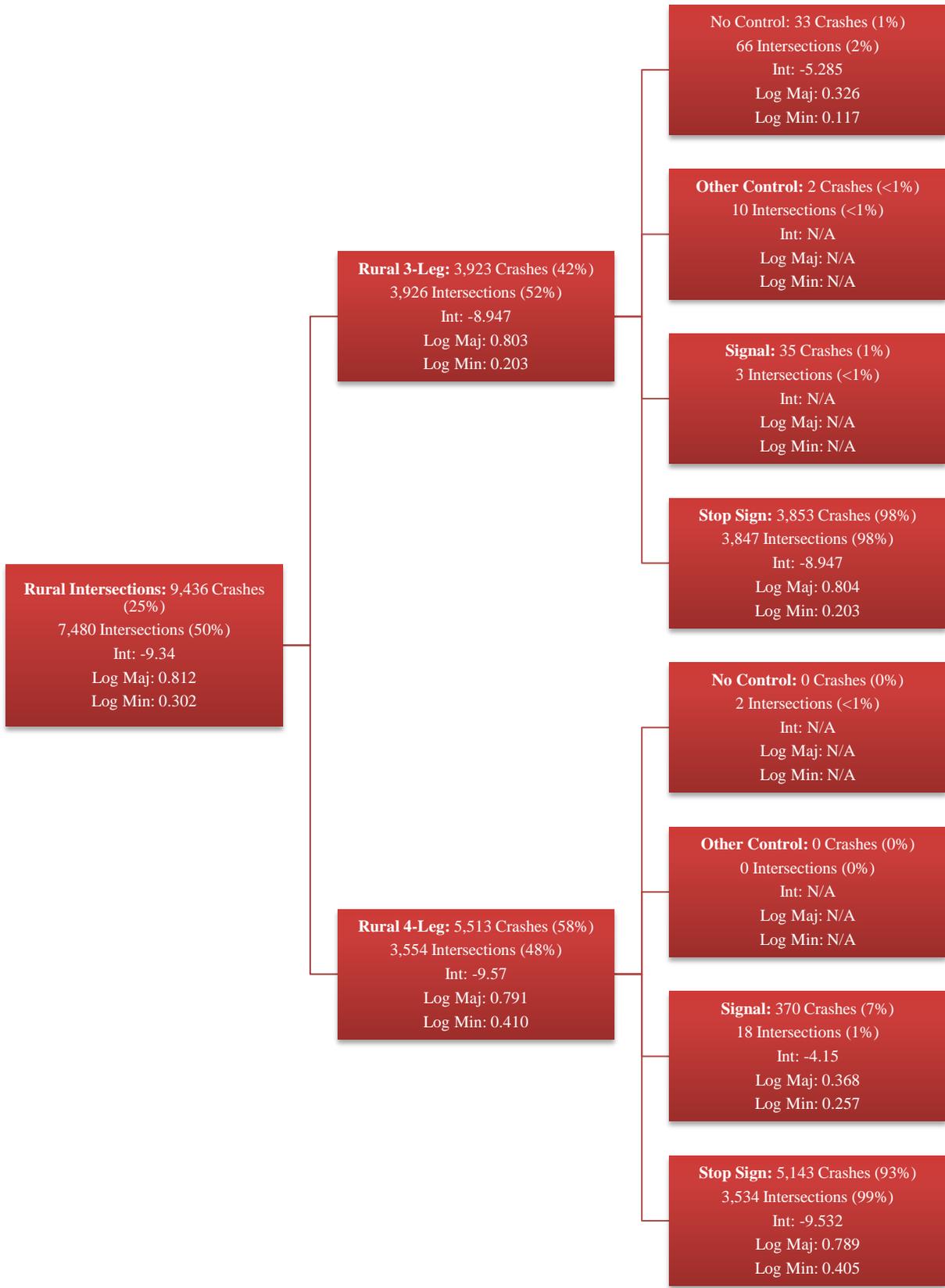
Figures 12 and 13 provide the following information for various site type categories:

- The number of intersections within that site type
- The number of crashes within that site type
- Crash prediction model results, including parameter estimates for the constant term, as well as the major and minor road traffic volumes

Models were estimated for all site types with a minimum of 30 intersections. The ADT values were transformed by the natural logarithm function. As such, these results provide elasticities; that is, the coefficient reflects the percent increase in crashes associated with a 1 percent increase in ADT on the major or minor road.



**Figure 12. Parameter crash estimates for urban intersections**



**Figure 13. Parameter crash estimates for rural intersections**

The number of intersections in rural and urban areas along primary roads in Iowa are approximately equal. However, urban intersections account for 75 percent of all crashes, which is largely reflective of the traffic volume at these intersections. Note that crashes also tended to increase at a higher rate at urban intersections as compared to rural intersections. This may suggest greater caution on the part of motorists at rural intersections, or it may reflect general differences in the geometry at such locations. Note that this is somewhat in contrast with the broader research literature, which suggests the effects of volume tend to be dampened at higher volumes.

Turning to traffic control type, differences were significant with respect to volume trends among signalized and stop-controlled intersections. In general, the ADT for the major (i.e., higher-volume) roads tended to have a more pronounced impact than the ADT of the minor roads at stop-controlled intersections. The differences in model results across various intersection facility types provides motivation for a more detailed investigation of specific risk factors.

### **Exploratory Visual Analytics of Intersection Crash Data**

In addition to the more traditional methods described previously, this research also sought to conduct exploratory visual analytics of Iowa's intersection crash data over this same 5-year period (2009–2013). The researchers used Tableau (software) as a visual analytics tool to filter, highlight, cross-filter, and visualize the datasets with relative ease. (Visual exploratory analysis helps researchers to design and execute queries on the fly, thus leading to an organic exploration of datasets as the interesting facts are uncovered. This is in contrast to the data graphing techniques that are usually used where the graphs are plotted from pre-defined hypotheses and are usually static.)

The researchers conducted a spatial correlation analysis prior to visualization. The aim of this analysis was to find any spatial clusters in the crash data. The intersections were classified as five clusters:

1. High-High (HH) cluster denotes an intersection with a high number of crashes surrounded by other intersections with a high number of crashes. Such clusters are expected around urban areas.
2. High-Low (HL) cluster denotes a high-crash intersection surrounded by low-crash intersections. These clusters may represent locations that would be good candidates for site-specific safety improvements.
3. Low-High (LH) cluster denotes a low-crash intersection surrounded by high-crash intersections.
4. Low-Low (LL) cluster denotes a low-crash intersection surrounded by low-crash intersections. Such a cluster might exist in low exposure areas.
5. None denotes a cluster of intersections where no significant correlation was found spatially.

## Methodology

The researchers analyzed the spatial autocorrelation of traffic crashes using the Local Moran's I method, which is also called Anselin Local Moran's I, or local indicators of spatial association (LISA). Given a set of weighted features, the LISA method is used to identify spatial clusters of features with attribute values that are similar in magnitude. The method is also used to identify spatial outliers. To realize this, LISA calculates a Local Moran's I value, a z-score, a p-value, and a code representing the cluster type for each observation. Based on these parameters, spatial clusters or outliers can be identified. The equation for calculating the Local Moran's I value of each observation is shown in Equation 1:

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j \neq i}^n w_{i,j} (x_j - \bar{X}) \quad (1)$$

where  $I_i$  is local Moran's I index,  $x_i$  is the observation  $i$ ,  $\bar{X}$  is the mean of the observations,  $w_{i,j}$  is the spatial weight between feature  $i$  and  $j$ ,  $n$  is the total number of observations, and,

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^n w_{i,j}^2}{n-1} - \bar{X}^2 \quad (2)$$

Based on the calculated parameters, the Local Moran's I method classified observations into the five categories: HH, HL, LH, LL, and insignificant data.

After identifying the clusters, the researchers visualized the data as shown in Figure 14. Chart A in Figure 14 shows squares with each representing a single intersection with the size of each proportional to the crash rate at the intersection, in proportion to the surrogate crash rate (total crashes/approach volume). Chart B in Figure 14 is a bubble chart with each bubble representing an intersection with the size of each proportional to the total number of crashes during the study period. Chart C shows the scatter plot between surrogate crash rate and total crashes. Chart D presents the geospatial locations of the intersections on the map of Iowa.

Also, Tableau provides an ability to filter and explore the data in multiple ways. The selection can be made either geographically, by selecting the area of interest on the map, or by checking the filters on the side panel on or off.

Figure 15 shows all of the clusters identified using LISA. It shows that HH clusters, despite their high crash numbers, have relatively lower crash rates compared to the HL clusters. This implies HH clusters are usually high-volume intersections. Figure 16 exclusively shows the HH clusters. These clusters are primarily concentrated in the metropolitan areas of Iowa. LH clusters representing both low crash numbers as well as very low crash rates are shown in Figure 17. These represent intersections with a low number of crashes surrounded by high-crash locations. Further exploration of these sites will elucidate the characteristics of sites that make them safer even with higher exposure rates. HL clusters are high-crash locations surrounded by low-crash locations, as shown in Figure 18. These sites show high crashes despite low exposure.

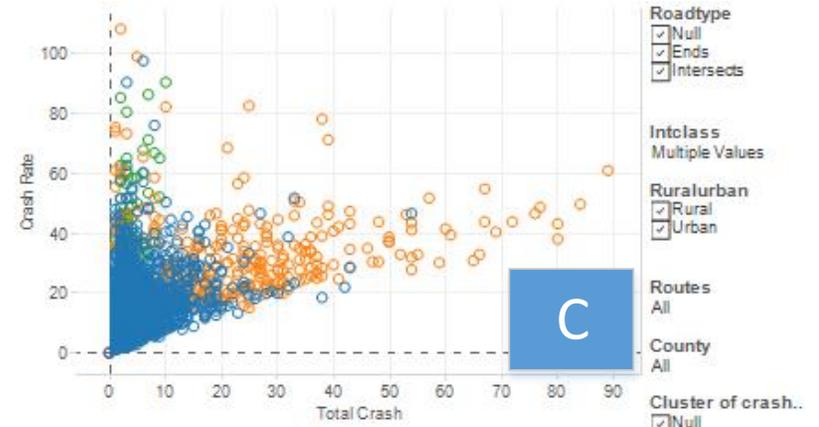
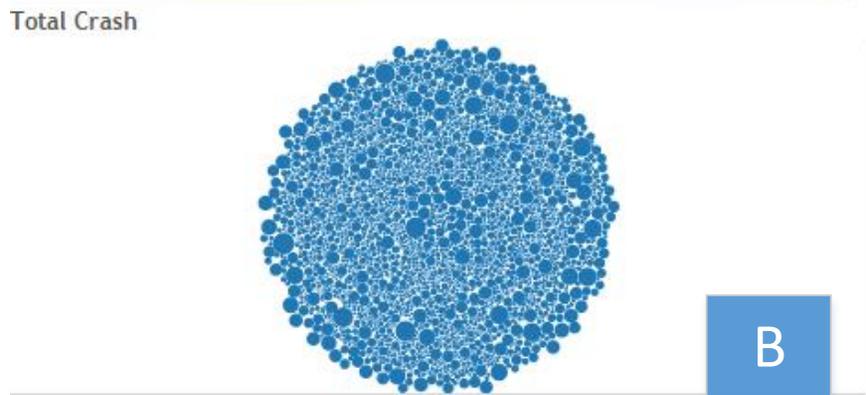
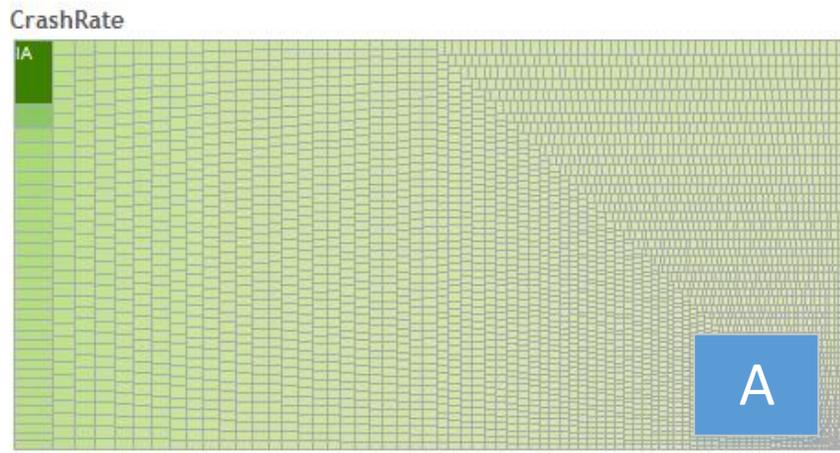
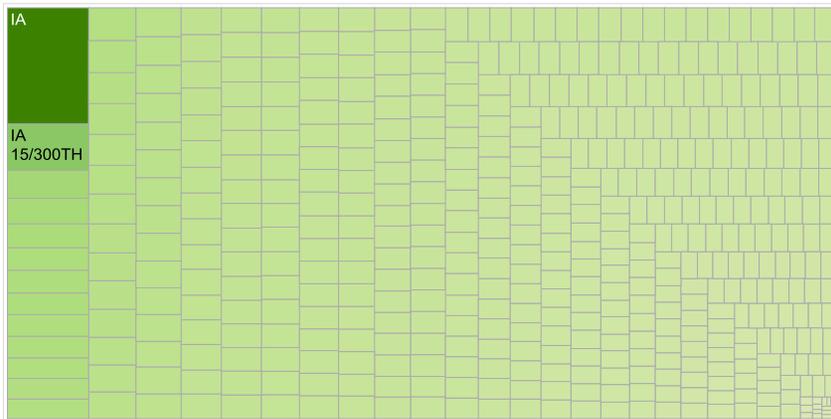
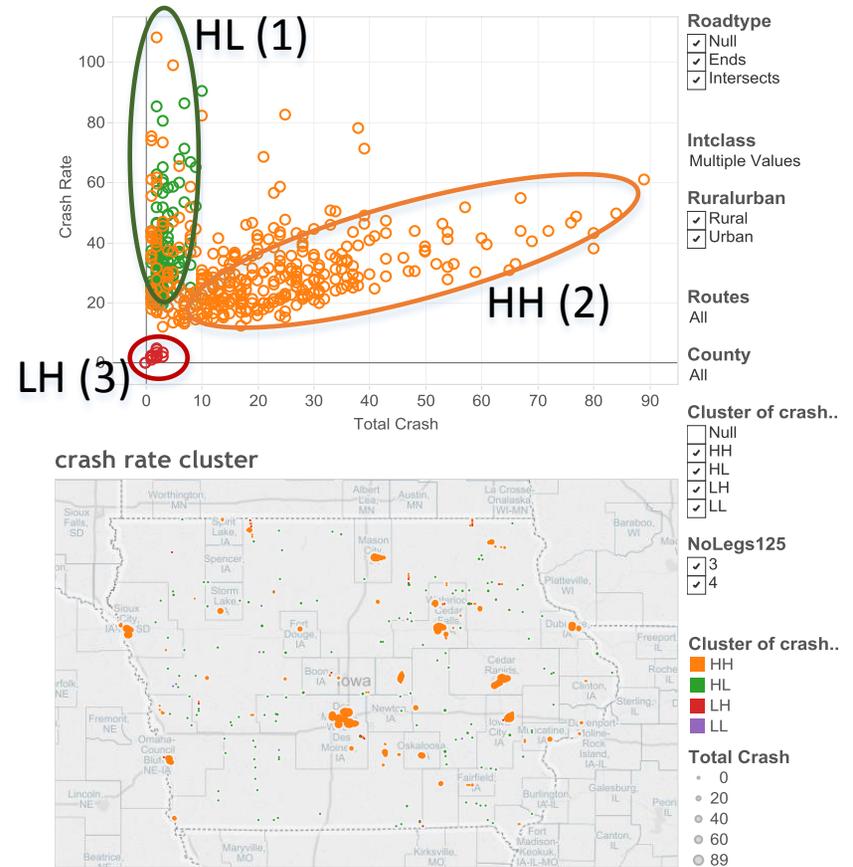
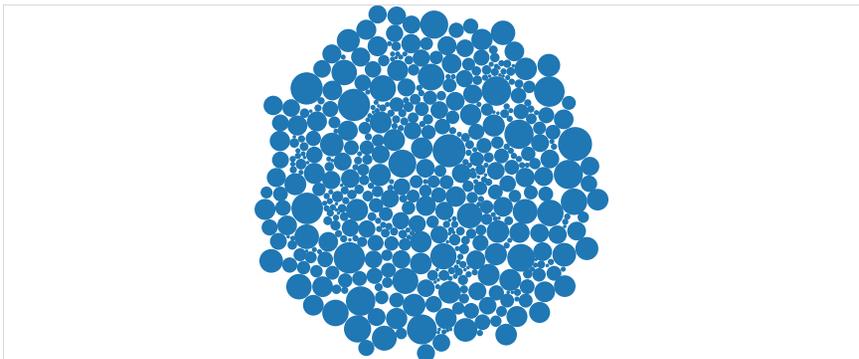


Figure 14. Graphical exploration of intersection crashes

### CrashRate



### Total Crash



**Figure 15. Significant clusters in intersection crash dataset**

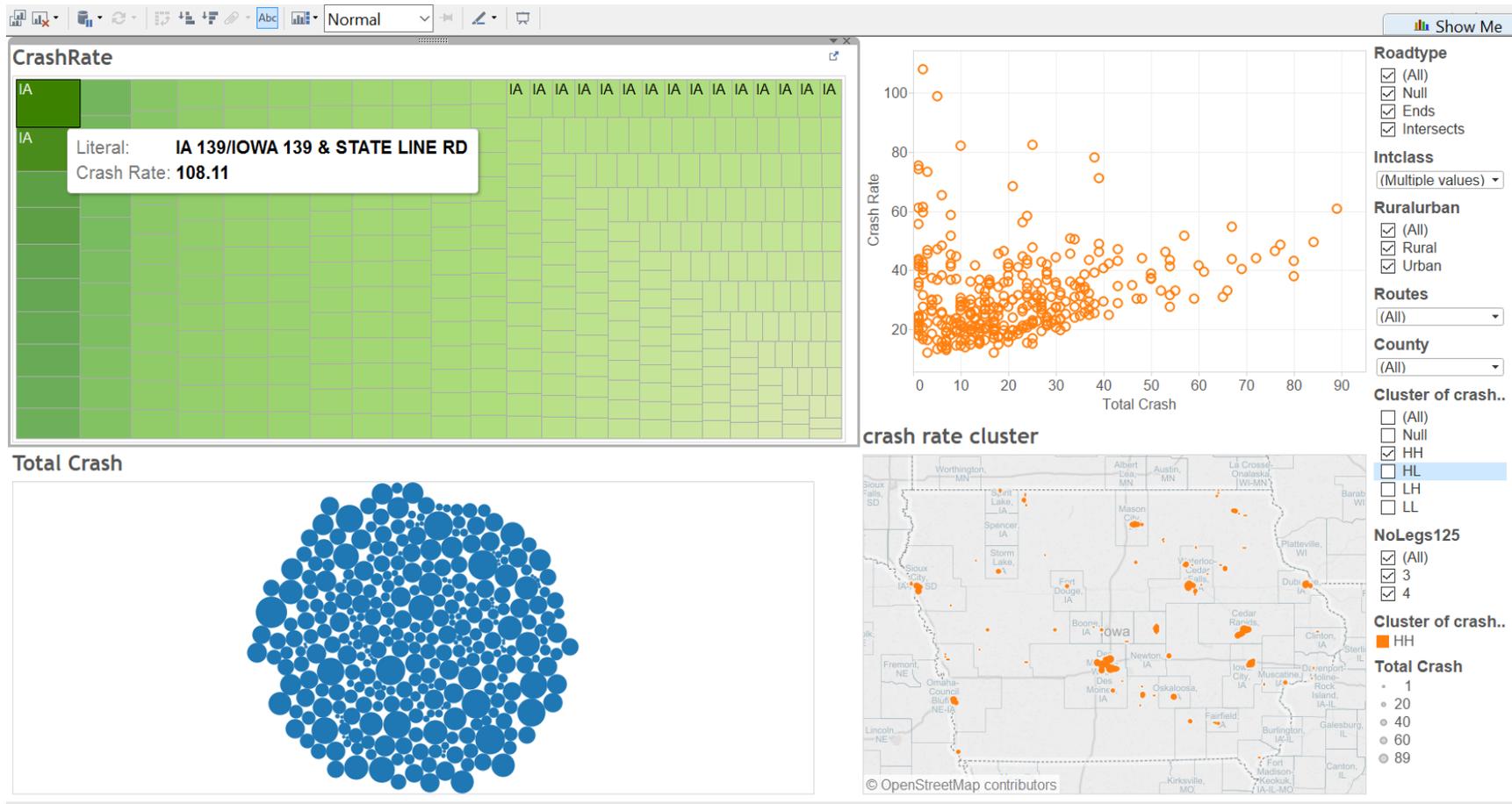
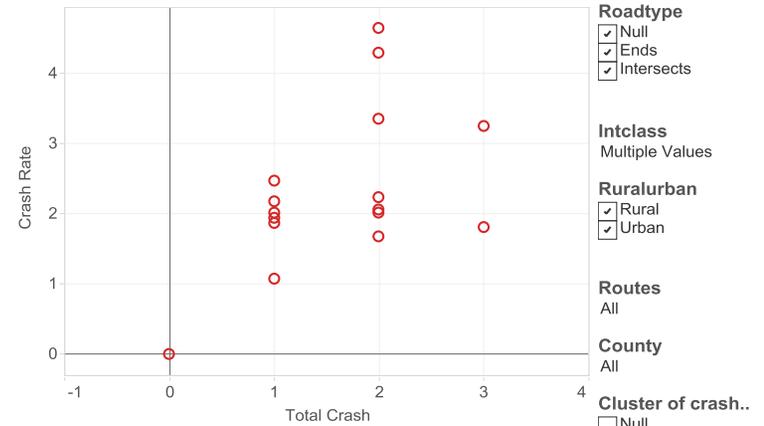
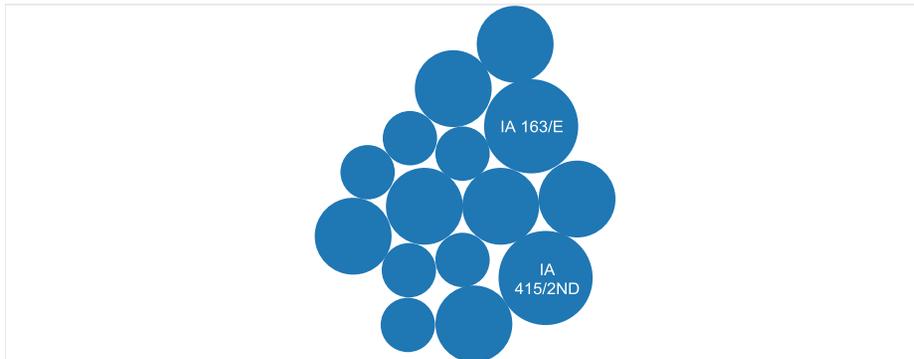


Figure 16. HH cluster representation

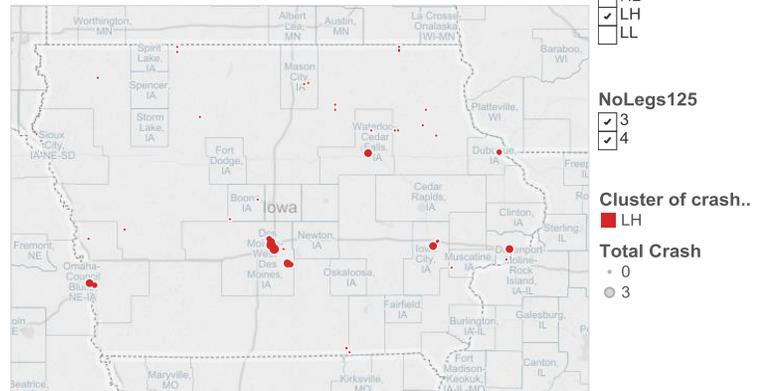
**CrashRate**

IA 5/IOWA 5 & 205TH AVE 4.640	IA 130/NEW LIBERTY RD & W 76TH ST 3.347	IA 165/ABBOTT DR & OWEN PKWY 2.233	IA 192/S 7TH ST & 7TH AVE 2.015	IA 415/SW ORALABOR RD & SW EDGEWOOD LN 1.932
		IA 5/IOWA 5 & CARTER ST 2.173		
	IA 415/2ND AVE & NW 43 PL 3.241		IA 163/E UNIVERSITY AVE & SAMPSON ST 1.864	IA 415/2ND AVE & NW 57 PL 1.674
IA 1/IOWA 1 & KITTY LEE RD 4.287		IA 934/UNIVERSITY AVE/NW RAMP CURV & S HACKETT RD 2.057		
	IA 5/IOWA 5 & DUBUQUE ST 2.462	IA 415/2ND AVE & NW 46 PL 2.016	IA 163/E UNIVERSITY AVE & HUBBELL AVE & E 21ST CT 1.804	IA

**Total Crash**



**crash rate cluster**



**Figure 17. LH cluster representation**



## **INVESTIGATION OF INTERSECTION SKEW ANGLE, HEAVY-TRUCK VOLUME, AND LIGHTING**

Ideally, intersections are oriented such that roadways intersect at a 90-degree angle where possible. However, due to existing road alignments, location and right-of-way constraints, and various other factors, intersections cannot always be designed to this preferred configuration, resulting in a skewed intersection.

*A Policy on Geometric Design of Streets and Highways* recommends that four-legged, rural intersection angles “should not be more than 30 degrees from perpendicular” (i.e., should not be less than 60 degrees or more than 120 degrees) (AASHTO 2011). The *Highway Safety Manual* highlights the impact of road design on drivers, citing that “improper lookout” is the greatest human factor for crashes at intersections (AASHTO 2010). In fact, 74 percent of crashes at intersections are caused by this particular issue. With the additional burden of an unusual angle for a driver to see around, this may cause additional risk.

As a part of this study, an investigation was conducted to assess the effects of skew angle and other factors associated with the safety performance of rural intersections in Iowa. The scope was limited to intersections located on high-speed (speed limit of 45 mph or higher), rural, two-lane roadways. This analysis provides important results that reinforce the extant research literature as to the relationship between intersection skew angle and crash frequency.

### **Skew-Angle Research Literature**

“Skewness” or skew angle is defined as the angle at which an intersection diverges from 90 degrees. It is widely agreed upon in the highway design field that intersections should be aligned at a 90-degree angle, resulting in a skew angle of zero degrees. However, due to physical constraints, this is not always possible (Harkey 2013).

Geometrically, skewed intersection designs have longer curb lines and larger intersection areas. A vehicle traveling at an angle travels a longer distance with a longer travel time than one traveling perpendicularly through the intersection. Having a larger intersection area results in a larger conflict area, which reduces the safety of the intersection (Kaluva 2013). Keeping in mind this geometric characteristic, drivers are required to fully scan an intersection in a generally short amount of time, and must decide how to maneuver. With limited time and a large number of factors to consider, drivers are less likely to see or judge oncoming traffic in situations where the intersection is difficult to scan (Harkey 2013).

Skew may also introduce issues for traffic operations as traffic flow can be disrupted when approaches to an intersection are skewed. When the right-turn intersection angle is less than 90 degrees, drivers travel through the intersection slower than normal. The same happens for drivers of left-turning vehicles when the left intersection angle is acute. Conversely, turns made on obtuse intersection angles tend to be made at higher speeds (AASHTO 2011).

According to Kaluva (2013), skewed intersections are considered to have two main safety issues: a large conflict area and poor sight distance. As stated previously, a skewed intersection has a larger intersection area, which increases the conflict area. As a result, vehicles are exposed to conflicting traffic for a longer span of time (Kaluva 2013, Neuman 1985, Gattis and Low 1997, Walker 1993). A driver's sight distance may be reduced due to the skew of the intersection (Kaluva 2013). At skewed intersections, a driver's lateral sight distance may be reduced due to difficulty in a driver's ability to turn their head to completely view a conflicting approach. Drivers have an approximate field of vision of 220 degrees, which means that blind spots may exist for drivers who are stopped at either right- or left-skewed intersections. These issues become more severe for older drivers, or drivers with physical limitations who commonly have issues with turning their heads adequately enough at a skewed intersection (Kaluva 2013, García and Belda-Esplugues 2007).

At intersections with a smaller right-turn angle, drivers making right turns might intrude into the oncoming lane of traffic in an effort to see conflicting traffic. Whereas, at intersections with smaller left-turn angles, drivers making left turns may speed up and use unsafe gaps in turning (Gattis and Low 1997).

Drivers have also been shown to react differently to skewed intersections compared to right-angle intersections. Lack of familiarity in driving through skewed intersections may result in driver confusion (Kaluva 2013). In a 2007 study by Libreros and García (2007), recording devices were used to study driver behavior as drivers were approaching a skewed intersection to make a right turn. The study found that drivers approach the skewed intersection in various ways, which may include remaining in the center of the travel lane, hugging the centerline of the road, cutting across the right shoulder, or approaching as close to perpendicular as possible to the crossroad.

Historically, sight distances have been addressed as an intersection safety consideration. David and Norman (1975) found sight distance obstruction as one of the six intersection design features that affect crashes. Hanna et al. (1976) investigated characteristics of intersection accidents in rural municipalities and concluded that intersections with poor driver sight distance on one or more traffic approaches tend to have a higher than normal crash rate.

Harwood et al. (2000) found that a skew angle diverting 10 degrees from the typical 90-degree orientation showed a 4 percent increase in crash frequency, and a 45-degree diversion increased the number of crashes by 20 percent at three-leg stop-controlled intersections. A higher increase in crash frequency was seen for four-leg stop-controlled locations, where a 10-degree skew angle result in a 5.4 percent higher frequency, and a 45-degree skew was associated with a 28 percent increase. The findings of this study are used in the current edition of the *Highway Safety Manual* (HSM) as the coefficients in skewed intersection crash modification factors (CMFs) (AASHTO 2010).

Haleem and Abdel-Aty (2010) used discrete outcome models to analyze data from three- and four-leg unsignalized intersections in Florida. One of several factors affecting crash severity was the intersection angle being less than or equal to 75 degrees, which increased fatal injury

probability by 0.4 percent compared to intersection angles greater than 75 degrees at four-leg intersections.

Oh et al. (2004) developed macro-level crash prediction models for signalized intersections and multi-lane stop-controlled intersections in rural areas. Negative binomial regression models were fit to intersection crash data from California, Georgia, and Michigan, with the results showing that an intersection angle that departs from a 90-degree angle is, in accordance with expectation, detrimental to safety at three-leg stop-controlled multi-lane intersections. The results also showed that intersection angle has a relatively smaller effect at signalized intersections as compared to stop-controlled locations. This is due to the traffic signal managing conflicting vehicles, limiting the amount of decision-making the driver must perform. The lessened influence of roadway geometry at signalized intersections compared to stop-controlled intersections has been seen in other studies, as well (Oh et al. 2004, Hutton et al. 2015).

## Statistical Methods

To ascertain the effects of skew angle and other pertinent factors, a series of safety performance functions (SPFs) were estimated as a part of this study. The HSM provides a series of SPFs for intersections located along rural two-lane highways (AASHTO 2010). These SPFs can be used to predict average annual crash frequencies based on AADT on the major and minor roads under base conditions. These base conditions include a skew angle of zero, no left-turn or right-turn lanes on the stop-controlled approaches, and no lighting. For instances where these base conditions are not met, the basic SPF can be adjusted using CMFs (AASHTO 2010). Within the context of this study, the research team estimated SPFs in consideration of each of these base conditions.

Consistent with the state-of-the-art research literature, the researchers estimated SPFs following a count data framework. As a starting point, a Poisson regression model was estimated, wherein the probability of intersection  $i$  experiencing  $y_i$  crashes during the five-year analysis period is:

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!} \quad (3)$$

where  $\lambda_i$  is the Poisson parameter for intersection  $i$ , which is equal to the expected number of crashes at that intersection during the analysis period,  $E[y_i]$ . Poisson regression models are estimated by specifying the Poisson parameter  $\lambda_i$  as a function of explanatory variables, with the most common functional form being:

$$\lambda_i = EXP(\beta X_i) \quad (4)$$

where  $X_i$  is a vector of explanatory variables and  $\beta$  is a vector of estimable parameters (e.g., AADT, skew angle, presence of lighting and turn lanes). To account for the fact that crash data tend to be overdispersed (i.e., the variance of crash counts is generally greater than the mean), the negative binomial model has emerged as a preferred alternative to the Poisson model. The

negative binomial model is derived by rewriting this Poisson parameter for each segment  $i$  as follows:

$$\lambda_i = EXP(\beta X_i + \varepsilon_i) \tag{5}$$

where  $EXP(\varepsilon_i)$  is a gamma-distributed error term with mean of one and variance  $\alpha$ . The  $\alpha$  term is also known as the over-dispersion parameter, which is reflective of the additional variation in crash counts beyond the Poisson model (where  $\alpha$  is assumed to equal zero). The addition of this term allows the variance to differ from the mean as follows:

$$VAR[y_i] = E[y_i] + \alpha E[y_i]^2 \tag{6}$$

### Intersection Investigation Results and Discussion

The researchers conducted separate analyses for three-leg and four-leg intersections. While the extant research literature has generally examined total crashes, an additional model was developed for broadside and angle crashes at four-leg intersections. Results of the negative binomial model for three-leg intersections are shown in Table 5, while Table 6 presents model results for total crashes and broadside/angle crashes at four-leg intersections. Each table provides parameter estimates, standard errors, and p-values for each variable, along with goodness-of-fit statistics.

**Table 5. Negative binomial model results for three-leg intersections**

<b>Parameter</b>	<b>Coefficient (Std Error)</b>	<b>p-value</b>
Intercept	-6.626 (0.170)	<0.001
LN(Major Road AADT)	0.681(0.023)	<0.001
LN(Minor Road AADT)	0.311 (0.014)	<0.001
Skewness	0.003 (0.001)	<0.001
Heavy-vehicle AADT percentage	-0.012 (0.002)	<0.001
Three paved approaches	Base condition	N/A
Overdispersion parameter	0.539 (0.044)	<0.001
<b>Goodness of Fit</b>		
Sample size	9711	
Log-likelihood	-7687.876	
AIC	15387.752	

N/A=not applicable, AIC=Akaike's Information Criterion

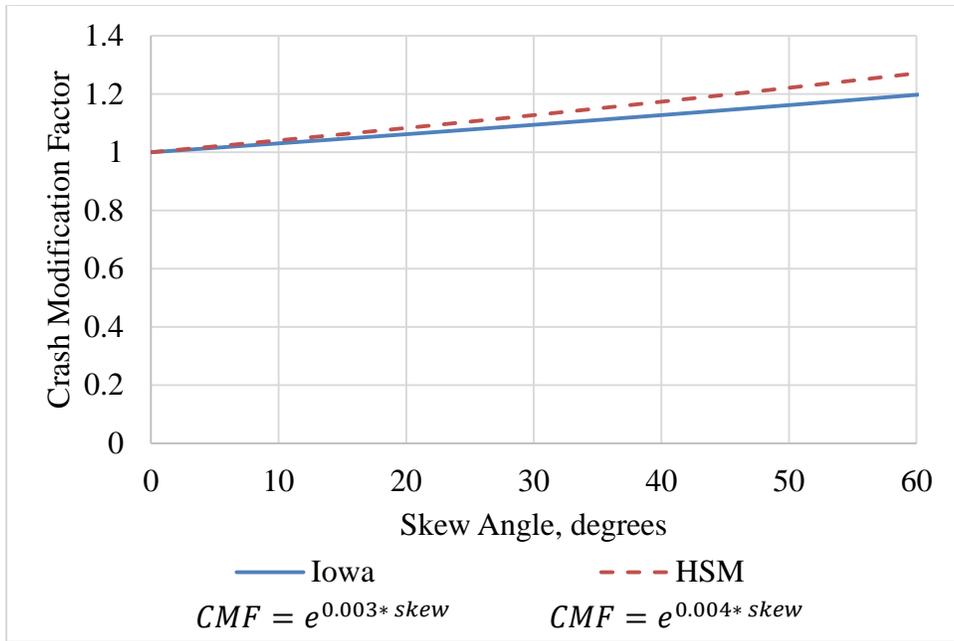
**Table 6. Negative binomial model results for four-leg intersections by crash type subset**

<b>Parameter</b>	<b>Total Crashes</b>		<b>Broadside and Angle Crashes</b>	
	<b>Coefficient (Std Error)</b>	<b>p-value</b>	<b>Coefficient (Std Error)</b>	<b>p-value</b>
Intercept	-7.575 (0.1941)	<0.001	-7.924(.302)	<0.001
LN(Major Road AADT)	0.663 (0.0233)	<0.001	.320(.042)	<0.001
LN(Minor Road AADT)	0.555 (0.0248)	<0.001	0.939(0.043)	<0.001
Skewness	0.004 (0.002)	0.010	0.005(.0029)	0.073
Heavy-vehicle AADT percentage	-0.009(0.002)	<0.001	-0.009(0.0033)	0.006
No lighting present	0.090 (0.0538)	0.125	N/S	N/S
Two paved approaches	-0.105 (0.0678)	0.122	-0.306(0.110)	0.005
Three paved approaches	-0.268 (0.053)	<0.001	-0.532(0.080)	<0.001
Four paved approaches	Base	-		-
<b>Goodness of Fit</b>				
Overdispersion parameter	0.246		0.412	
Sample size	8344		8344	
Log-likelihood	-6805.504		-3177.384	
AIC	13629.008		6370.769	

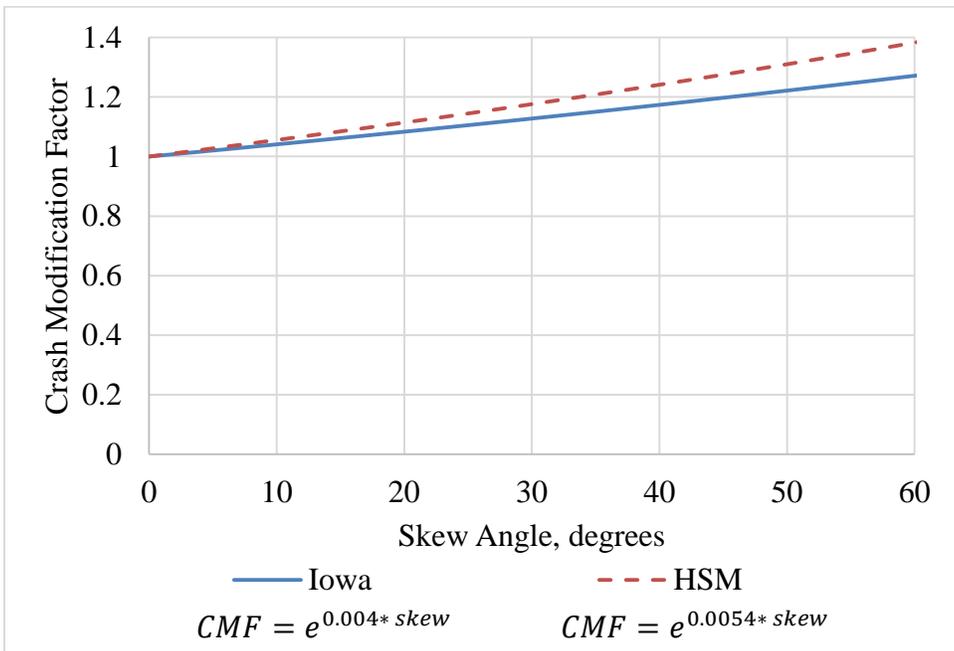
AIC=Akaike's Information Criterion

In each analysis, crashes were found to increase consistently with traffic volumes on both the major and minor roads. In general, the effect of major road AADT was quite consistent across the two samples, while minor road AADT was found to exhibit a larger influence among four-leg intersections.

Turning to the primary factor of interest, crashes were shown to increase with skew angle at both three-leg and four-leg intersections. These results are generally consistent with the estimates provided in the HSM (AASHTO 2010), although the effects are slightly less pronounced for the Iowa intersections in both instances, as shown in Figure 19.



**Three-leg intersections**



**Four-leg intersections**

**Figure 19. CMFs by skew angle for three-leg (top) and four-leg (bottom) intersections in Iowa versus the HSM**

For three-leg intersections, if the skew angle were to be 10 degrees from 90, the overall effect would be an increase of 3 percent in crashes. For four-leg intersections, a skew angle of 10 degrees would result in a 4 percent increase. This more pronounced effect is reasonable as the number of conflict points increases at four-leg locations, requiring drivers to more extensively scan the intersection.

Continuing on this point, crashes were less frequent if one or more of the intersection approaches were unpaved at four-leg intersections. This is likely a reflection of the disaggregate-level turning movement counts at these intersections. When the minor roadway is paved, the number of left-turn movements from the major road is likely to be greater, as well as the number of crossing movements, because paved approaches generally have higher traffic volumes (larger AADT). For this study, average AADT for three-leg intersections was 45 vpd for minor unpaved roads and 337 vpd for three-leg intersections with all approaches paved.

Interestingly, crashes were less frequent at intersections where heavy-truck volumes were higher. This finding may be due, in part, to the fact that those highways with larger heavy-truck volumes tend to be of a higher functional class, which would be correlated with other roadway features. In general, heavy-truck volumes are significantly higher on roadways of higher functional classification. Such roadways generally have wider lanes and shoulders, larger clear zones, and other higher design standards that may lead to fewer crashes than similar, lower functional class facilities. Continuing on this point, during preliminary investigations of the three-leg intersection dataset, the presence of lighting and the number of paved approach surfaces were both found to have a statistically significant association with fewer crashes. However, when the heavy-truck percentage variable was added, neither factor was found to be significant.

The presence of intersection lighting was also shown to be associated with fewer crashes at four-leg intersections, although the effect was not statistically significant for four-leg intersections. This finding is also consistent with prior research, such as a study by Kim and Washington (2006) of 155 rural intersections on two-lane highways in Georgia. Sasidharan and Donnell (2013) found the presence of roadway lighting resulted in 6 percent fewer nighttime crashes. According to the HSM, intersections with lighting would decrease the crashes depending on the proportion of total crashes for unlighted intersections that occur at night (AASHTO 2010).

## **DATA COLLECTION FOR HORIZONTAL CURVE RISK FACTORS**

The researchers used the following data sources for this part of the project to study horizontal curve risk factors in Iowa.

- Two-lane horizontal paved curves dataset (developed by researchers at InTrans)
- Primary curves dataset (provided by the Iowa DOT)
- Iowa GIMS database (provided by the Iowa DOT)
- Sign inventory dataset (provided by the Iowa DOT)
- Driveways dataset (developed and provided by InTrans)
- Intersection database (developed by InTrans)
- Statewide crash database (provided by the Iowa DOT Motor Vehicle Division)

### **Two-Lane Horizontal Paved Curves Dataset**

Researchers from the Institute of Transportation (InTrans) at Iowa State University developed a database detailing horizontal curves along paved, two-lane highways in Iowa. This dataset provided information about 11,748 curves. The dataset included information on curve locations, as well as other key characteristics such as curve radius, curve length, and degree of curve. Curves for which radius was not available (94) were excluded from the analyses, resulting in the remaining 11,654 curves on two-lane roads.

### **Primary Curves Dataset**

Two inventory databases were created detailing the locations and characteristics of horizontal curves on the primary and secondary roadway networks throughout the state. These databases were developed in collaboration with researchers from the Wisconsin Traffic Operations and Safety (TOPS) Laboratory. This study utilized the database created for the primary routes.

The researchers used Curve Finder to extract curve information for Iowa. Curve Finder is a tool that the Wisconsin TOPS Laboratory developed to automatically extract horizontal curve location and geometric information from GIS roadway maps. It is a fully automated method for extraction of horizontal curve data that the researchers implemented as a customized add-in tool in Esri's ArcMap. In addition, the length, radius, and central angle of the curves were automatically computed at the same time in the dataset. Figure 20 shows a graphical overview of the research team's implementation of Curve Finder.

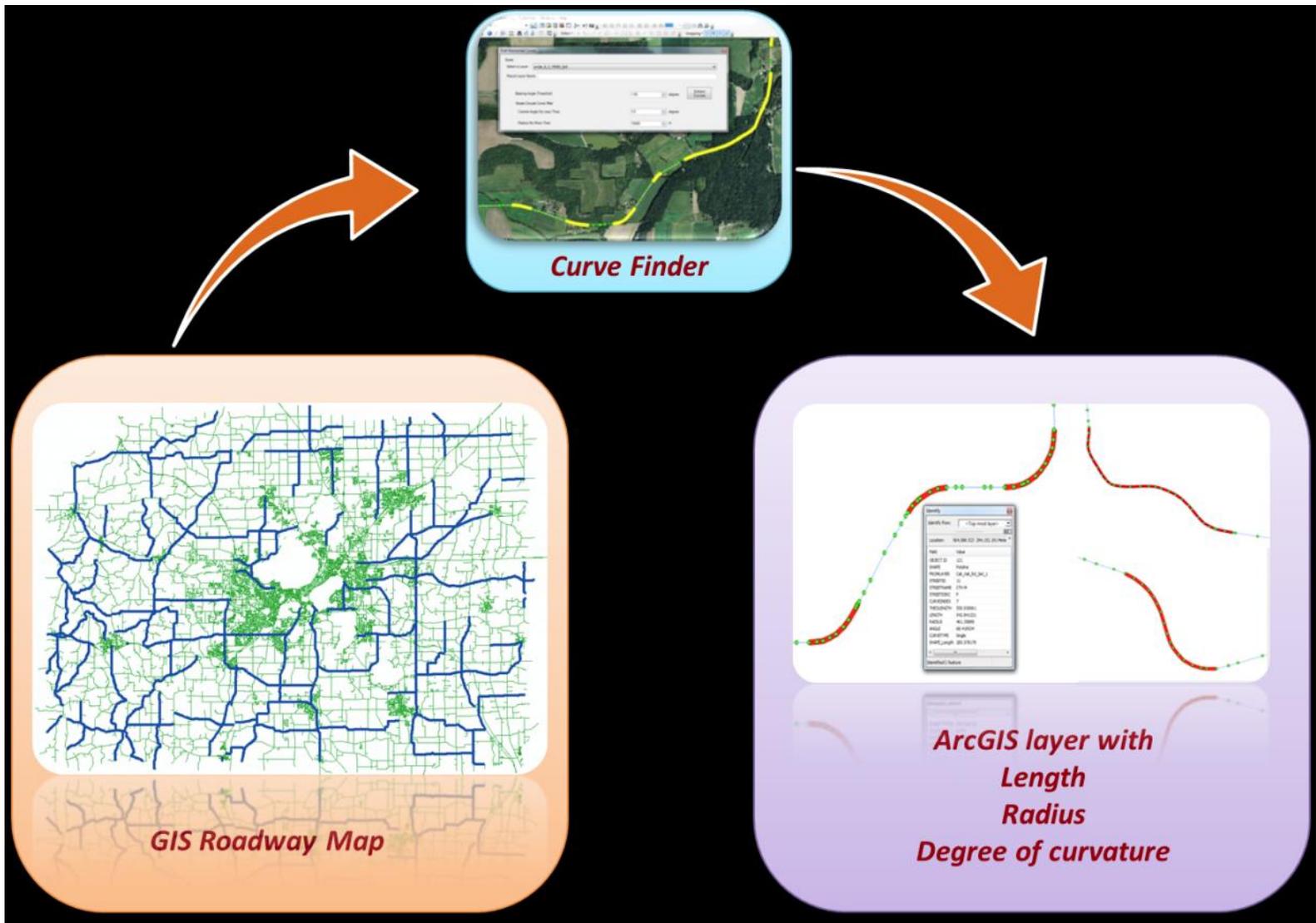


Figure 20. Curve Finder implementation

This research has been some of the first to make use of the Curve Finder data, which is still undergoing a thorough vetting process by researchers at InTrans. Prior to utilizing the curve database for this research, several QA/QC measures were taken to maximize the usefulness of the data. A team of undergraduate researchers at InTrans combed through the entire primary network and identified roadway segments coded as curves that were not actually curves. Several other issues with the data have been identified, which, although believed to have a minimal effect on the curve data for the primary network, may affect the results of this research:

- Tangent sections included as a portion of curves
- Single curves split into multiple shorter curves
- Reverse curves indicated, when a tangent section exists between curves
- Over- and under-estimation of curve radius

Efforts are currently underway to assess the extent to which these issues are present in the data; however, that work has not been completed at the time of this publication.

The Curve Finder tool was implemented on a route basis (e.g., I-80, US 30) providing coverage over the entire primary and secondary network; however, due to the frequency of concurrent routes (e.g., I-80 and I-35 in the Des Moines metro area), there were several redundancies in the dataset. The researchers used Microsoft Excel to apply logic functions to sort the data by latitude and longitude and remove the duplicates.

### **GIMS Database**

The curves dataset contained spatial locations that did not always correspond well to data from the GIMS. Curves were mapped to the extent possible using the 2014 GIMS database. The researchers extracted volume and other characteristics. A study period of five years (2010–2014) was selected for the purposes of the risk factor analysis for horizontal curves. When assembling the database, the researchers extracted AADT for the middle year (2012) of the study period.

Since the curves dataset did not correspond exactly with the GIMS segments, the researchers used the near table function of Esri's ArcGIS to create a NEAR\_FID column in the curves dataset for each of the curves, and, then, used the FID column in the GIMS database to join the traffic-volume data. The researchers found that 93 sites were devoid of AADT information, and they deleted these curves from the curves dataset leaving 11,561 curves in the dataset. Summary statistics for the curves dataset are provided in Table 7.

**Table 7. Summary statistics for horizontal curve segments**

<b>Statistic</b>	<b>AADT</b>	<b>Radius</b>	<b>Length</b>
Mean	870	1,297	631
Min	2.00	51.75	68
Max	95,500	10,146.79	3,818
Std Dev	1,744	939.27	403.69
1stQ	120.00	690.39	360.01
2ndQ	390.00	1,046.16	522.84
3rdQ	1,000.00	1,670.56	788.7

The GIMS database provided characteristics such as number of lanes, median type, median width, functional class, access control, and whether the location was in a rural or urban area. Only 1,019 curves of the 11,561 curves were in urban areas, which means about 91 percent of the curves were classified as rural.

The researchers used the direct lane dataset of the GIMS data to obtain information about most of the geometric and cross-sectional characteristics of each of the curves. Unlike the other GIMS datasets, the direct lane fields provide details separately for each direction of travel. Thus, the attributes in the direct lane dataset were for each direction bound (northbound, eastbound, etc.), but the other GIMS datasets had attribute values that were the total for all directions bound together.

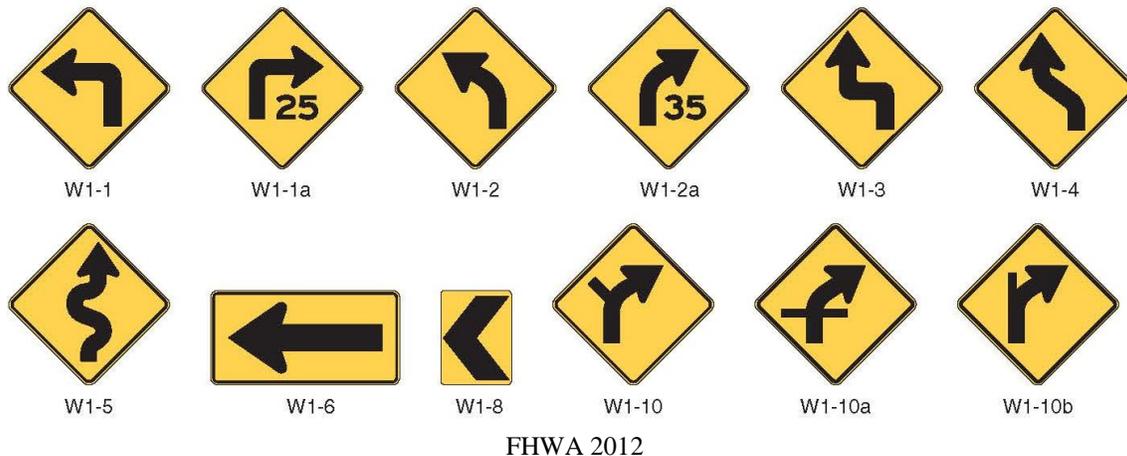
In order to join other GIMS datasets to the direct lane dataset, the numerical attributes for both bounds in the direct lane dataset were either averaged or summed with the categorical attributes concatenated (so that categories for each bound could be identified later) using Excel, as shown in Table 8. Table 8 also provides summary statistics for the GIMS dataset that the researchers created.

**Table 8. Summary statistics for GIMS segments**

Attribute Name	Description (codes in GIMS manual)	Operation to combine bounds	Mean	Min	Max	Std Dev
SURFWIDTH	Total width of road surface	Average	23.21	16	80	3.03
SURFTYPE	Type of surface	Concatenate	63.19	0	92	13.53
SHDTYPEPR	Right shoulder type	Concatenate	2.00	0	9	1.94
SHDWIDTHR	Right shoulder width	Average	4.84	0	28	2.81
RUMBLER	Presence of rumble strips	Concatenate	0.02	0	1	0.14
CURBEDR	Whether right side has a curb	Concatenate	0.01	0	1	0.12
SHDTYPEL	Left shoulder type	Concatenate	1.99	0	9	1.94
SHDWIDTHL	Left shoulder width	Average	4.82	0	17	2.79
RUMBLEL	Presence of rumble strips	Concatenate	0.02	0	1	0.13
CURBEDL	Whether left side has a curb	Concatenate	0.01	0	1	0.11
LIMITMPH	Speed limit	Average	52.64	15	55	6.30

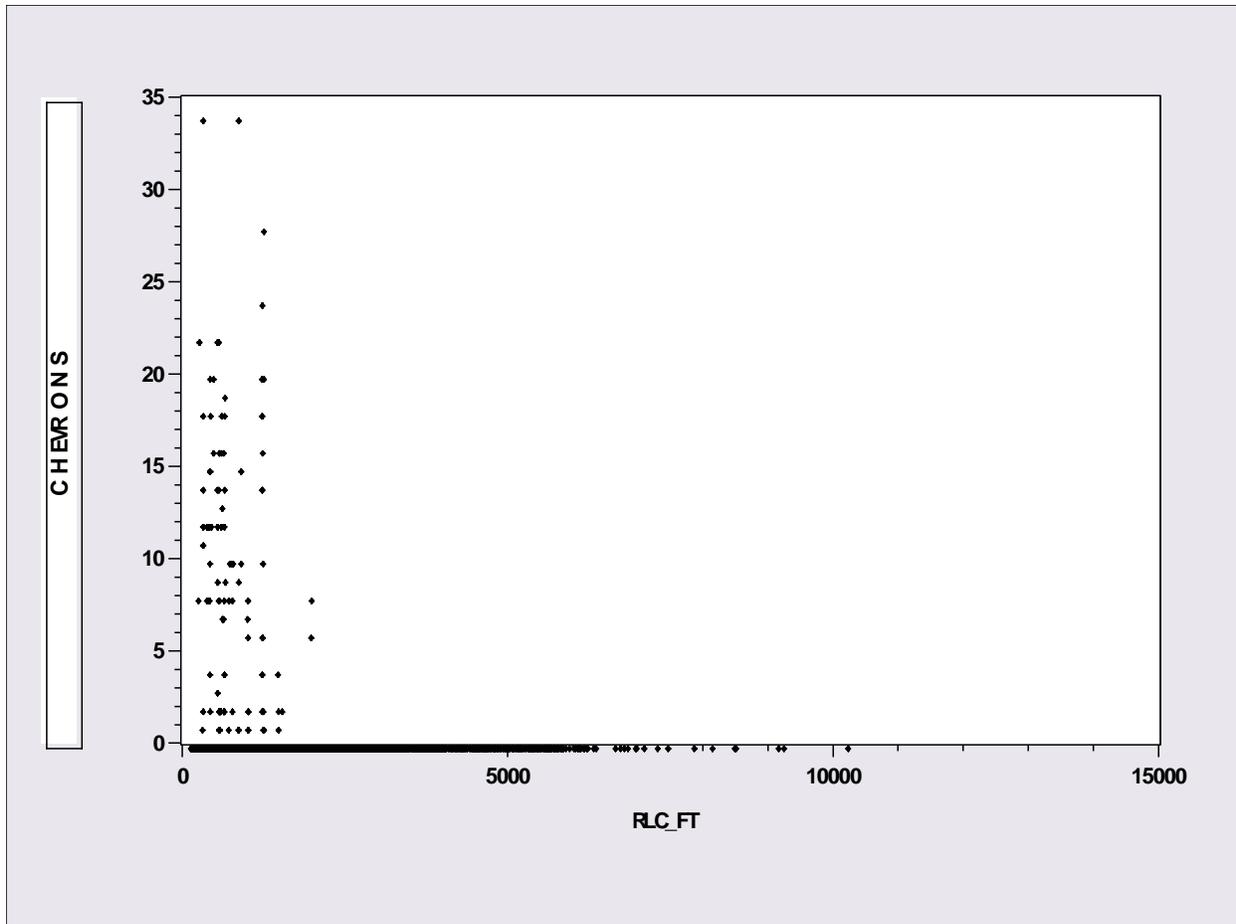
**Sign Inventory Dataset**

The Iowa DOT developed a sign dataset that provided locations of various signs on the study curves. The researchers created a query in ArcGIS to spatially select the curves that contained chevron alignment signs (W1-8). They also created an attribute with the counts of chevrons on those curves. Similarly, the researchers selected other alignment signs (W1-1 and W1-13, shown in Figure 21) to incorporate related data in this study.



**Figure 21. Curve sign images**

A total of 144 curves in the dataset had chevron installations. To ascertain the relationship of radius and spacing and quantity of chevrons on any curve, the researchers plotted number of chevrons against radius of curves (as shown in the Figure 22). The researchers noted that sharper curves had more chevrons with shorter spacing between them. W1-1 and W1-3 signs were found on 21 and 17 curves, respectively.



**Figure 22. Chevrons versus curve radius**

### **Driveways Dataset**

InTrans researchers created a driveways dataset. Due to the incomplete nature of the public road crossing (PRC) information in the access management file and the inconsistent identification and categorization of PRCs, as well as the availability of PRC information via the `prelim_intersection_database_20150608.mdb` file, the research team removed PRCs contained within the access point dataset (using a two-step process). Ultimately, the PRC information was redundant with the intersection database described subsequently.

First, driveways labeled as being PRCs were removed. After this process, it was clear that intersection points were still present in the driveway data but misidentified as driveways, so a second step was used to remove the intersections. The researchers used ArcGIS to identify and remove driveway points located within 5 feet of an intersection in the `prelim_intersection_database_20150608.mdb` file. This process removed additional intersections from the driveways dataset. The researchers used the final dataset that had all of the PRCs removed to spatially locate the curves that contained driveways on them. Then, they did a spatial join to calculate the number of driveways on each of the curves. This information was stored as a separate attribute.

## **Intersection Database**

InTrans created an intersection database as part of a prior project for the Iowa DOT. This database includes a shapefile providing an extensive inventory of intersection characteristics throughout the state. The database currently includes information for more than 170,000 intersections. For this study, the researchers spatially located curves that included intersections using this shapefile. They did a spatial join to calculate the number of intersections on each of the curves and stored this information as a separate attribute.

## **Statewide Crash Database**

For the purposes of the horizontal curve risk factor analysis, the researchers extracted crash data from the beginning of 2010 through the end of 2014. The researchers summed the total crashes over this five-year period for each curve and broke the data down for crashes by each injury severity level (based on the most severe injury sustained in each crash). For the purposes of this study, the researchers extracted two samples of crash data:

1. Data for curves located on Iowa's paved two-lane highway system. The researchers used these data as part of a preliminary crash-tree analysis to discern general trends in crashes with respect to traffic volume and curve radius.
2. Data for horizontal curves located along multi-lane highways on the Iowa primary road network. Using these data, the researchers conducted a more detailed analysis of various curve characteristics, which included the estimation of safety performance functions (SPFs), to examine the relationship between crashes and curve characteristics.

## PRELIMINARY ANALYSIS FOR PAVED TWO-LANE HORIZONTAL CURVES

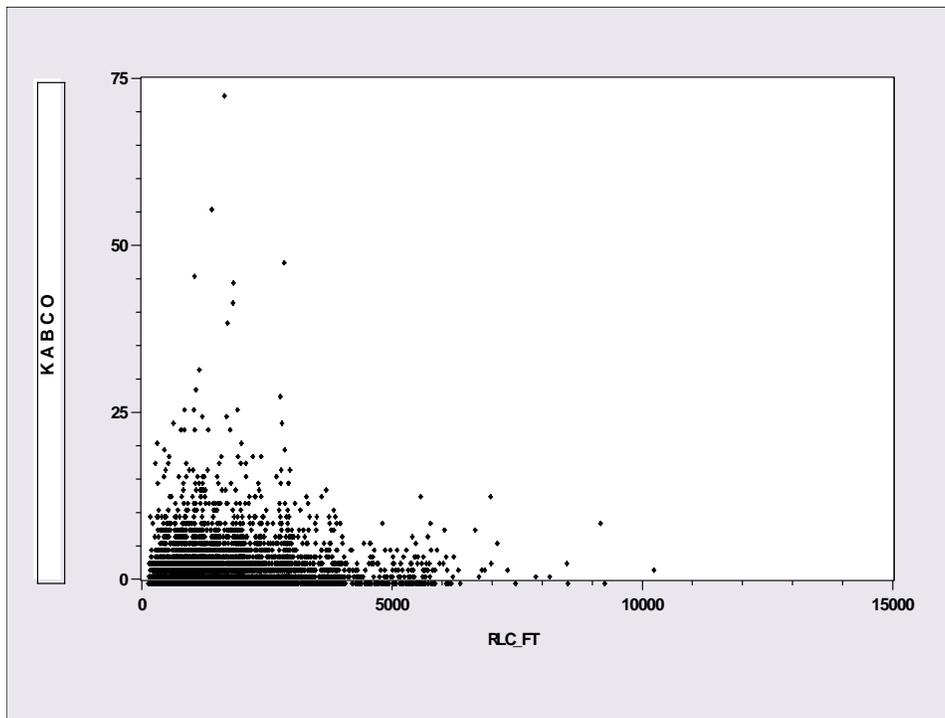
The research team conducted a high-level analysis to examine general trends among the horizontal curves located on paved two-lane highways across Iowa. Summary statistics from the crash data for these curves are provided in Table 9.

**Table 9. Summary crash type statistics for GIMS segments**

Crash Type	Mean	Min	Max	Total	Std Dev
K	0.02	0	2	254	0.15
A	0.07	0	4	787	0.29
B	0.16	0	7	1,851	0.48
C	0.20	0	15	2,316	0.61
KABC	0.45	0	20	5,208	1.04
O	0.86	0	53	9,962	1.93
KABCO	1.31	0	73	15,170	2.67

K=Fatality, A=Disabling Injury, B=Evident Injury, C=Possible Injury, O=Property Damage Only

Turning to one of the primary characteristics of interest, Figure 23 shows the distribution of total crashes when plotted against radius. The total crashes are clustered between radii of 60 to 5,000 feet.



**Figure 23. Crashes versus radius**

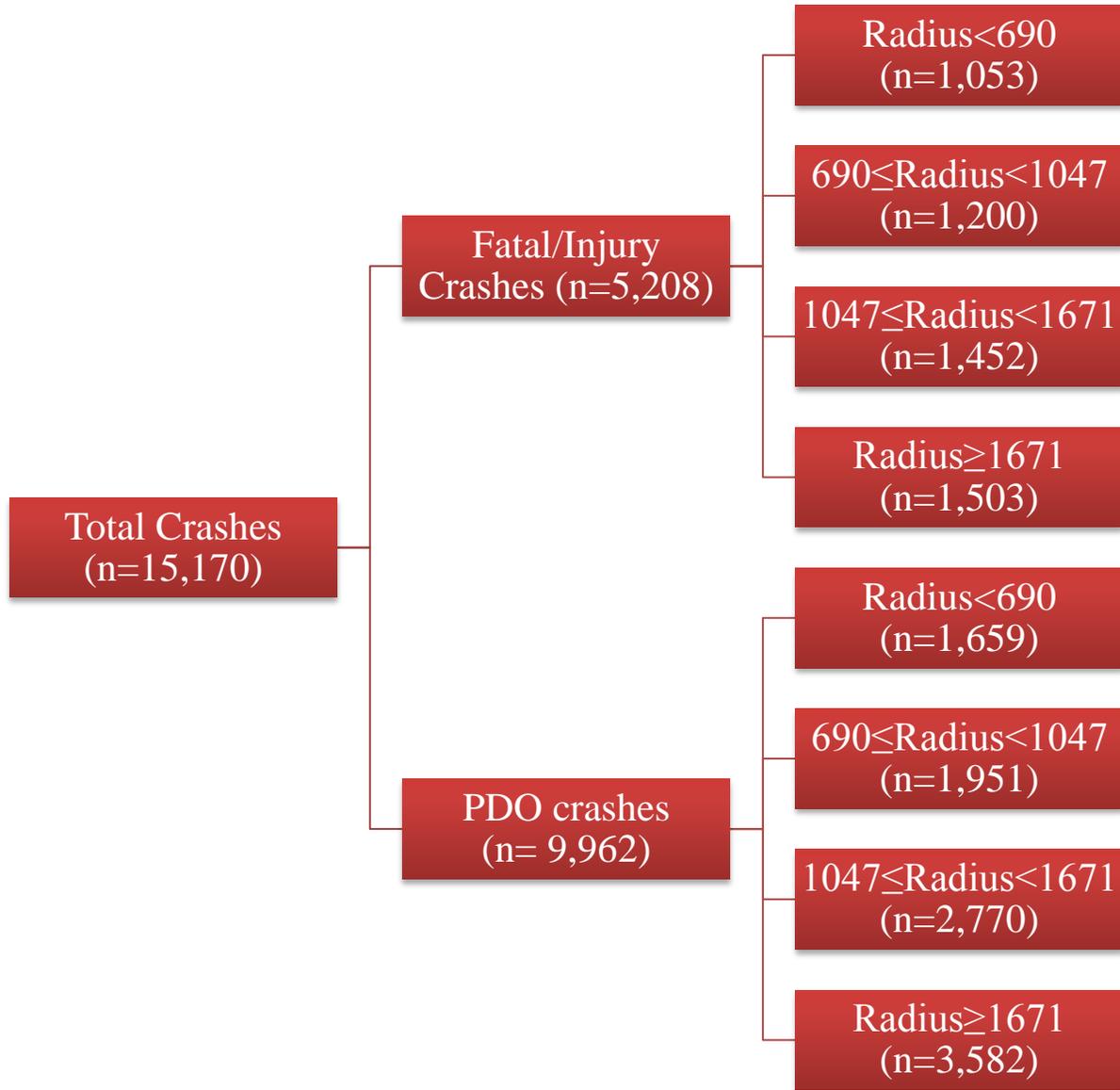
Using Excel, the researchers manipulated the exported crash data using pivot tables. They excluded crashes that were specifically coded as intersection-related within the crash database from the dataset based on the Intersection Roadway Junction/Feature Type codes 11 through 22 (shown in Figure 24).

99 - Unknown
<b>Type of Roadway Junction/ Feature</b>
<i>Non-intersection:</i>
01 - No special feature
02 - Bridge/overpass/underpass
03 - Railroad crossing
04 - Business drive
05 - Farm/residential drive
06 - Alley intersection
07 - Crossover in median
08 - Other non-intersection (explain in narrative)
<i>Intersection:</i>
11 - Four-way intersection
12 - T - intersection
13 - Y - intersection
14 - Five-leg or more
15 - Offset four-way intersection
16 - Intersection with ramp
17 - On-ramp merge area
18 - Off-ramp diverge area
19 - On-ramp
20 - Off-ramp
21 - With bike/pedestrian path
22 - Other intersection (explain in narrative)
99 - Unknown

**Figure 24. Roadway Junction/Feature Type codes from Iowa DOT Investigating Officer’s Report of Motor Vehicle Accident Code Sheet**

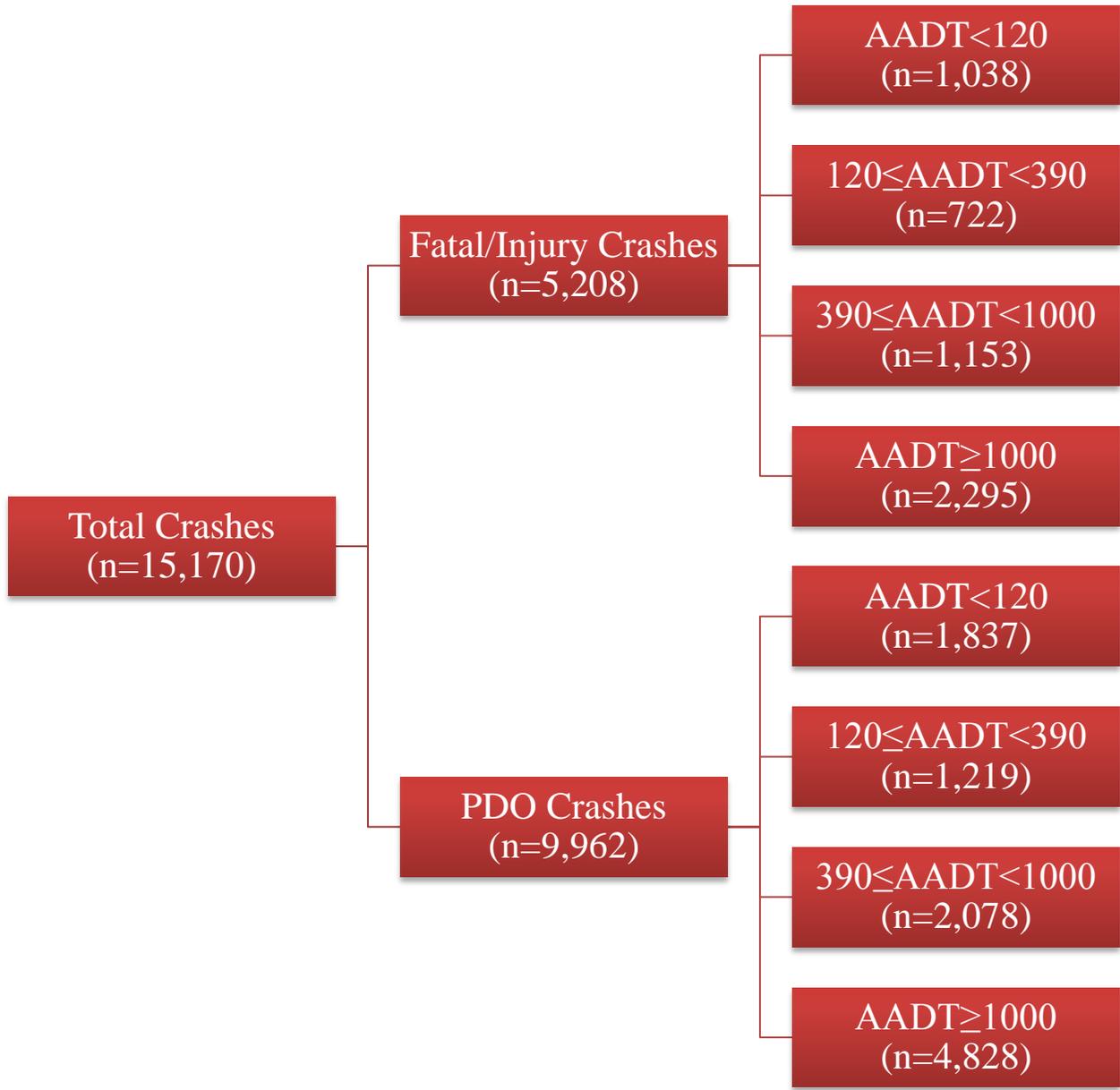
For each of the five years of data (including and excluding intersection-related crashes), the researchers created a separate pivot table. They also created binary variables for crash severity from the CSEVERITY field.

Once the researchers assembled these data, they conducted a crash-tree analysis to examine some preliminary trends in the horizontal curve database. The researchers constructed trees by considering all crashes occurring on two-lane horizontal curves in Iowa during the five-year study period (2010–2014 for this part of the study), aggregated between fatal/injury and PDO crashes. The next split grouped crashes of each injury severity by quartiles of curve radius, as shown in Figure 25.



**Figure 25. Fatal/injury versus PDO crashes on horizontal curves based on curve radius**

Another tree was created by splitting the two crash injury severity levels (fatal/injury and PDO) by the quartile of daily entering volume (dev). Figure 25 shows the results of this tree analysis.



**Figure 26. Fatal/injury versus PDO crashes on horizontal curves based AADT ranges**

## DETAILED INVESTIGATION OF DIVIDED HIGHWAY HORIZONTAL CURVE RISK FACTORS

The research team conducted an in-depth investigation of the safety of horizontal curves on divided highways for this study. They aggregated the data into two groups: freeway and non-freeway segments. About 53 percent of the curves in the dataset were located on limited access facilities (i.e., freeways), while the remainder were comprised of high-speed non-freeways, including expressways. Table 10 shows the descriptive statistics for the data used as part of the horizontal curve crash frequency analysis.

**Table 10. Descriptive statistics for horizontal curve crash frequency dataset**

Variable	Freeway (n=251)				Non-Freeway (n=220)			
	Average	Std Dev	Min	Max	Average	Std Dev	Min	Max
Directional AADT	9,974	5,413	1,390	2,4870	4,726	2,006	1,395	11,960
Curve radius (ft)	3,329	1,015	1,420	5,257	2,781	969	678	5,176
Curve length (ft)	1,223	760	121	4,407	1,197	701	116	3,535
55 MPH speed limit	0.072	0.258	0	1	0.418	0.493	0	1
65 MPH speed limit	0.311	0.463	0	1	0.582	0.493	0	1
70 MPH speed limit	0.618	0.486	0	1	0.000	0.000	0	0
Surface width	24.080	0.732	24	32	24.018	0.929	16	30
Rural area	0.729	0.444	0	1	0.786	0.410	0	1
Median width (ft)	56.876	26.105	2	380	60.195	21.498	9	140
Cable median years	0.797	1.503	0	5	0.000	0.000	0	0
Independent curve	0.717	0.450	0	1	0.750	0.433	0	1
Reverse curve	0.112	0.315	0	1	0.091	0.287	0	1
Compound curve	0.171	0.377	0	1	0.159	0.366	0	1
Left curve	0.494	0.500	0	1	0.486	0.500	0	1
Paved outside shoulder	0.944	0.229	0	1	0.627	0.484	0	1
Outside shoulder width	10.000	0.605	8	15	9.727	1.039	3	12
Outside rumble strip	0.853	0.355	0	1	0.464	0.499	0	1
Paved inside shoulder	0.829	0.377	0	1	0.314	0.464	0	1
No inside shoulder	0.004	0.063	0	1	0.068	0.252	0	1
Inside shoulder width	6.048	0.817	0	10	5.791	1.957	0	10
Inside rumble strip	0.080	0.271	0	1	0.136	0.343	0	1
<b>Total Crashes (2010–2014)</b>	<b>2.267</b>	<b>2.171</b>	<b>0</b>	<b>11</b>	<b>1.423</b>	<b>1.433</b>	<b>0</b>	<b>7</b>

For these curves, the researchers identified non-intersection crashes, as well as crashes that occurred in the merge or diverge area, using the roadway type. They used a spatial query in ArcMAP to identify crashes that were within 150 feet of the curves. Given that the curve database was developed on a directional basis (northbound, southbound, etc.), the researchers were able to match crashes to specific curves using directional coding. The researchers excluded crashes that did not have directional coding, as well as curves adjacent to said crashes, from their analyses to ensure that the data used is as complete and accurate as possible.

Separate summaries are provided for freeways and non-freeways in the table. Similar data are provided in Table 11 for the crash severity dataset. While the frequency dataset included 471 horizontal curves, 953 crashes were reported on these segments during the five-year analysis period.

**Table 11. Descriptive statistics for horizontal curve crash severity dataset**

Variable	Freeway (n=666)				Non-Freeway (n=287)			
	Mean	Std Dev.	Min	Max	Mean	Std Dev.	Min	Max
K or A	0.024	0.153	0	1	0.038	0.192	0	1
B	0.089	0.284	0	1	0.122	0.327	0	1
C	0.111	0.314	0	1	0.192	0.394	0	1
PDO	0.776	0.417	0	1	0.648	0.478	0	1
Driver not protected	0.024	0.153	0	1	0.038	0.192	0	1
Driver not ejected	0.980	0.138	0	1	0.965	0.183	0	1
Airbag deployed	0.101	0.301	0	1	0.160	0.367	0	1
Driver age	39.977	16.321	15	99	38.091	17.837	16	90
Male driver	0.667	0.471	0	1	0.578	0.494	0	1
Alcohol, drug, or medication	0.030	0.171	0	1	0.031	0.174	0	1
Single-vehicle, no fixed object	0.219	0.414	0	1	0.286	0.452	0	1
Single-vehicle, fixed object	0.267	0.443	0	1	0.247	0.431	0	1
Head-on	0.014	0.115	0	1	0.010	0.102	0	1
Rear-end	0.215	0.411	0	1	0.251	0.434	0	1
Angle-left	0.000	0.000	0	0	0.028	0.165	0	1
Broadside	0.011	0.102	0	1	0.017	0.131	0	1
Sideswipe same	0.264	0.441	0	1	0.150	0.357	0	1
Sideswipe opposite	0.011	0.102	0	1	0.010	0.102	0	1
Dusk	0.033	0.179	0	1	0.014	0.117	0	1
Dawn	0.024	0.153	0	1	0.031	0.174	0	1
Ice, snow, or slush	0.320	0.466	0	1	0.328	0.469	0	1
Concrete barrier	0.054	0.226	0	1	0.000	0.000	0	0
Paved median	0.000	0.000	0	0	0.031	0.174	0	1
Grass median	0.637	0.481	0	1	0.948	0.223	0	1
Curbed median	0.000	0.000	0	0	0.021	0.143	0	1
Curbed grass median	0.309	0.462	0	1	0.000	0.000	0	0
Compound curve	0.075	0.264	0	1	0.105	0.306	0	1
Reverse curve	0.065	0.246	0	1	0.073	0.260	0	1
Independent curve	0.860	0.347	0	1	0.822	0.382	0	1
Left curve	0.545	0.498	0	1	0.484	0.500	0	1
Curve length (ft)	1,392	707	158	4,407	1,480	935	142	4,919
Curve radius (ft)	3,343	932	1,645	5,279	2,677	1,014	678	5,119
55 MPH speed limit	0.078	0.268	0	1	0.540	0.498	0	1
65 MPH speed limit	0.293	0.455	0	1	0.460	0.498	0	1
70 MPH speed limit	0.629	0.483	0	1	0.000	0.000	0	0
AADT	12,514	5,600	1,795	25,850	6,199	3,127	1,700	12,750
Urban	0.338	0.473	0	1	0.436	0.496	0	1

K=Fatality, A=Disabling Injury, B=Evident Injury, C=Possible Injury, PDO=Property Damage Only

## Statistical Methods

Once the researchers compiled the datasets, they conducted a series of statistical analyses to ascertain how crashes were affected by curve radius, curve type, and other geometric and site characteristics. They considered various count data model frameworks in the development of crash prediction models. Ultimately, they assessed frequency data using a negative binomial modeling framework. This is similar to the approach utilized for the intersection risk factor analysis for this study. Within the context of the horizontal curve analysis, the probability of a specific horizontal curve  $i$  experiencing  $y_i$  crashes during the five-year analysis period is as follows:

$$P(y_i) = \left( \frac{1/\alpha}{\left(\frac{1}{\alpha} + \lambda_i\right)} \right)^{1/\alpha} \frac{[(1/\alpha) + y_i]}{[(1/\alpha) y_i!]} \left( \frac{\lambda_i}{\left(\frac{1}{\alpha} + \lambda_i\right)} \right)^{y_i} \quad (7)$$

where  $\lambda_i$  is equal to the expected number of crashes at curve  $i$  during the analysis period,  $E[y_i]$ . The parameter  $\lambda_i$  is specified as a function of explanatory variables:

$$\lambda_i = EXP(\beta X_i) \quad (8)$$

where  $X_i$  is a vector of explanatory variables and  $\beta$  is a vector of estimable parameters (e.g., AADT, curve radius). To account for the fact that crash data tend to be over dispersed (i.e., the variance of crash counts is generally greater than the mean), the parameter  $\lambda_i$  is allowed to vary as follows:

$$\lambda_i = EXP(\beta X_i + \varepsilon_i) \quad (9)$$

where  $EXP(\varepsilon_i)$  is a gamma-distributed error term with mean of one and variance  $\alpha$ .

In contrast to the crash frequency data, the crash severity data are of a discrete, ordinal nature, with crashes classified on a five-point scale ranging from no injury to fatal injury. Due to a limited number of fatal (K) crashes, the researchers used a combined fatal and incapacitating injury category in this study (K+A). Consequently, these data are well suited for analysis using an ordered probit model. Ordered probit models are derived by defining a latent variable  $z$ , which can be specified as a linear function for each observation such that:

$$z = \beta X + \varepsilon \quad (10)$$

where  $X$  = vector of variables determining the discrete ordering,  $\beta$  = vector of estimable parameters, and  $\varepsilon$  = random disturbance term.

With the use of this equation, observed injury outcome data,  $y$ , for each crash is defined as:

- $y = 1$  if  $z \leq \mu_0$
- $y = 2$  if  $\mu_0 < z \leq \mu_1$
- $y = 3$  if  $\mu_1 < z \leq \mu_2$
- $y = \dots$
- $y = I$  if  $z \geq \mu_{I-1}$

where the estimable threshold parameters,  $\mu$ , define  $y$ , which corresponds to integer ordering, and  $I$  is the highest integer ordered response. The  $\mu$  represents parameters that are jointly estimated with the model parameters  $\beta$ . If the error term is assumed to be distributed as standard normal across observations, an ordered probit model results. Setting the lower threshold  $\mu_0$  equal to zero results in the outcome probabilities, as follows:

$$P(y = i) = \Phi(\mu_i - \beta X) - \Phi(\mu_{i+1} - \beta X) \quad (11)$$

where  $\mu_i$  and  $\mu_{i+1}$  represent the upper and lower thresholds for response category  $i$ , and estimation is done by standard maximum likelihood methods.

One concern that arises within the ordered probit is that each variable is assumed to have consistent effects across all severity levels (i.e., the proportional odds assumption). To mitigate this concern, the researchers employed a partial proportional odds model specification. This more flexible framework allows the effects of certain variables to vary across injury severity levels. This model specification is appropriate when some of the variables do not satisfy the proportional odds assumption.

### Horizontal Curve Investigation Results and Discussion

The results of the crash prediction models for horizontal curves are presented in Table 12.

**Table 12. Results of horizontal curve negative binomial model for freeways versus non-freeways**

Variable	Freeway		Non-Freeway	
	Estimate (Std Error)	p-value	Estimate (Std Error)	p-value
Intercept	-9.075 (1.48)	<0.001	-6.798 (1.972)	0.001
Ln(Directional AADT)	0.998 (0.097)	<0.001	0.601 (0.168)	<0.001
Median width	-0.004 (0.002)	0.027	-0.008 (0.003)	0.025
Paved outside shoulder	-0.552 (0.266)	0.038	N/S	N/S
Paved inside shoulder	N/S	N/S	0.273 (0.133)	0.040
Ln(Curve Radius)	-0.685 (0.169)	<0.001	-0.564 (0.18)	0.002
Independent curves	N/S	N/S	-0.227696	0.138
Overdispersion parameter	0.160	-	0.127	-
<b>Goodness of Fit</b>				
Intercept-Only AIC	994.83		699.58	
Fully-Specified AIC	907.16		695.81	

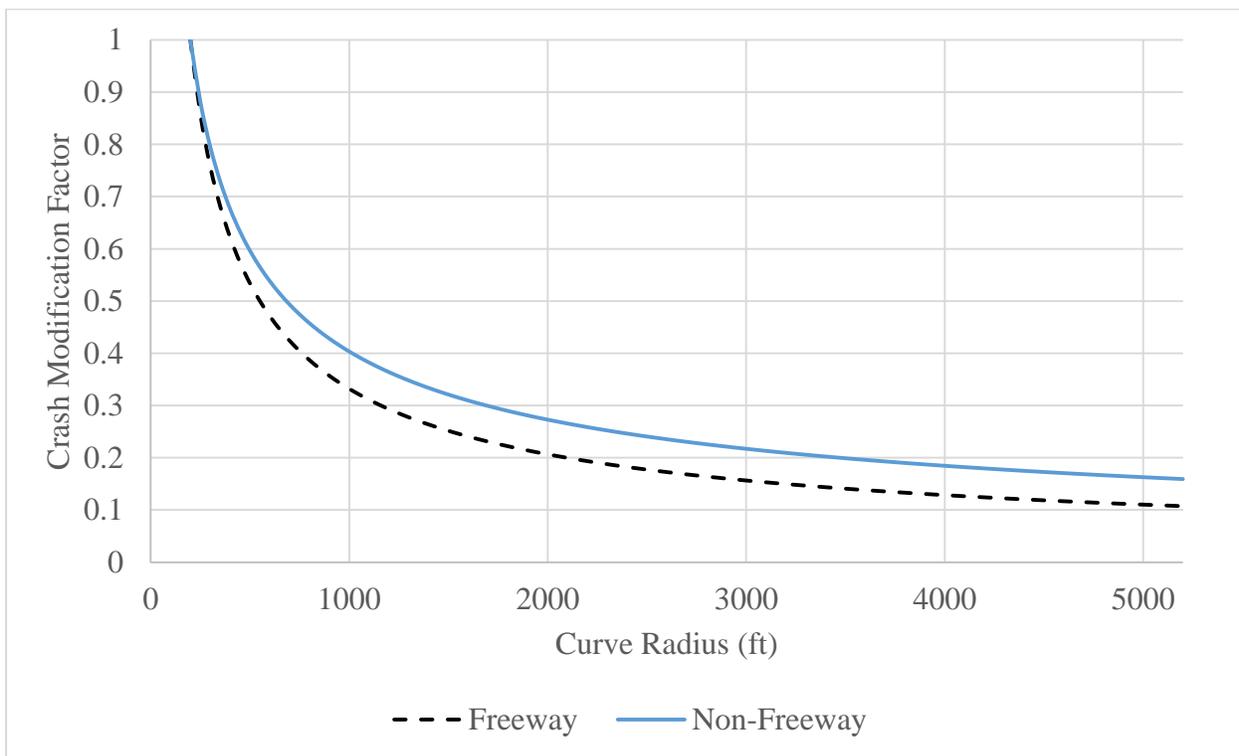
N/S = not statistically significant

Separate model results are included for non-freeways and freeways in the table. For each model, parameter estimates are provided, along with the associated standard errors and p-values. In each case, the negative binomial model was shown to provide significantly better fit than the Poisson models, a reflection of over dispersion among the segment-specific crash data. The researchers treated curve length as an offset variable. Consequently, these regression models can be used to estimate the number of crashes per unit length.

Examining specific variables of interest, crashes increased consistently with traffic volume in the two models. The effects were inelastic as a 1 percent increase in volume was associated with increases of 1.0 percent and 0.6 percent for freeway and non-freeway facilities, respectively.

Paved outside shoulders were associated with fewer crashes on freeways, while paved inside shoulders were associated with increased crashes on non-freeways. Intuitively, paved shoulders on either side of the roadway might be expected to be associated with lower crashes, as drivers have additional space to maneuver and avoid other vehicles; however, it is possible that the paved shoulders are simply located in areas that experience higher crash frequencies and are therefore provided to allow drivers a refuge to safely remove a damaged vehicle from the flow of traffic.

One of the primary concerns with horizontal curves is the effect of curve radius on crash frequency. The results of this study show crashes decreased as curve radius increased for both freeways and non-freeways. The effect was slightly more pronounced on freeways, which likely reflects more stringent design criteria on freeways relative to non-freeways when everything else is equal. Figure 26 provides the series of CMFs by curve radius, which are based on the results shown in Table 12.



**Figure 27. CMFs by curve radius for freeways versus non-freeways**

As the curve radius increases from 200 feet, a marked decrease is observed in crash frequency. The majority of the curves in the analysis dataset fell within the range of 1,000 to 5,000 feet in radius. Considering this range, crashes were found to roughly double. Non-freeway independent curves were also shown to be significantly safer compared to reverse curves and compound curves.

In addition to the crash frequency model, Table 13 presents the results of the partial proportional odds crash severity model.

**Table 13. Horizontal curve partial proportional odds crash severity model results**

Variables	Freeway		Non-Freeway	
	Estimate (Std Error)	p-value	Estimate (Std Error)	p-value
No Protection	0.778 (0.335)	0.020	1.064 (0.471)	0.024
Not Ejected	-2.394 (0.376)	0.000	-1.391 (0.486)	0.004
Head-On	1.374 (0.388)	0.000	2.425 (0.746)	0.001
Broadside	0.887 (0.433)	0.041	-	-
Side Swipe-Opposite	1.006 (0.439)	0.022	2.232 (0.676)	0.001
Single Vehicle-Fixed Object	-	-	0.506 (0.193)	0.009
Single Vehicle-No Fixed Object	-	-	0.567 (0.188)	0.002
Alcohol, Drug, Medication	-	-	1.067 (0.395)	0.007
Male Driver	-0.467 (0.119)	0.000	-	-
Driver younger than 20 years old	-0.323 (0.208)	0.120	-	-
Concrete Barrier	-1.698 (0.675)	0.012	-	-
Left Curve	-0.176 (0.113)	0.119	-	-
Paved Inside Shoulder	-0.276 (0.172)	0.108	-	-
Dusk And Dawn	-0.488 (0.276)	0.077	-	-
<b>Thresholds</b>				
$\mu_1$	-2.029 (0.417)	-	-0.352 (0.51)	-
$\mu_2$	-1.469 (0.417)	-	0.49 (0.506)	-
$\mu_3$	-0.627 (0.423)	-	1.223 (0.512)	-
Airbag Deployed- $\mu_1$	-0.761 (0.179)	-	-1.166 (0.227)	-
Airbag Deployed- $\mu_2$	-0.326 (0.225)	-	-1.208 (0.237)	-
Airbag Deployed- $\mu_3$	-0.5 (0.338)	-	0.209 (0.489)	-
Single Vehicle-No Fixed Object- $\mu_1$	-0.486 (0.134)	-	-	-
Single Vehicle-No Fixed Object- $\mu_2$	-0.682 (0.154)	-	-	-
Single Vehicle-No Fixed Object- $\mu_3$	0.029 (0.333)	-	-	-
<b>Goodness of Fit</b>				
Intercept-Only AIC	998.37		568.13	
Fully-Specified AIC	876.74		474.29	

AIC=Akaike's Information Criterion

The results of this analysis showed a variety of roadway, vehicle, and driver characteristics influenced the degree of injury severity. When examining the parameter estimates in Table 13, a positive coefficient is reflective of a factor that tends to increase the probability of the most severe injury (i.e., fatal), while a negative coefficient indicates a specific variable is associated with a lower degree of injury when a crash occurs.

On both freeways and non-freeways, lack of use of protective equipment (e.g., seatbelts, helmets) was shown to be significantly associated with increased crash severity, a result that is not surprising. Similarly, when drivers were not ejected from the vehicle, crash outcomes were typically less severe.

The effect of airbag deployment was shown to vary across crash severity levels for the freeway and non-freeway models. For the freeway model, the threshold value decreased across all severities, indicating that airbag deployment is associated with increased severity; however, the effect was greatest when considering the threshold between property damage only and possible injury crashes. For non-freeway crashes, the deployment of the airbag was actually shown to increase the threshold between the fatal/incapacitating injury and the non-incapacitating injury, indicating that airbags are most effective at reducing the severity of what would have otherwise been an even more severe crash outcome.

The manner of collision was shown to be highly associated with crash outcome. For the freeway model, head-on, broadside, and sideswipe opposite crashes were consistently shown to be associated with increased severity, while single vehicle crashes where no fixed object was struck were generally associated with increased severity, with the exception of being associated with lower instances of the highest severity crashes. For non-freeways, head-on, sideswipe-opposite, and single vehicle crashes were all associated with increased crash severities.

Consistent with expectation, drivers on non-freeways who were under the influence of drugs, alcohol, or medications were shown to have more severe crash outcomes. The freeway model revealed some surprising findings, as male drivers and young drivers (younger than 20) were typically associated with lower severity crash outcomes. These drivers are typically considered to be more risk-prone; therefore, it is likely that the results of this analysis indicate that these drivers are simply more resistant to injury when involved in a crash.

Additionally, the freeway model revealed that, from a roadway geometry standpoint, crashes tended to be less severe on left curves and where concrete barriers are present, and where paved inside shoulders are present. These conditions are likely associated with a decreased likelihood of a vehicle crossing the median of a divided highway and being involved with a vehicle traveling in the opposite direction.

Finally, crashes occurring at dusk or dawn were shown to be associated with decreased crash severity. This may potentially be due to drivers using extra caution at these times of day or may be reflective of different driving conditions during these periods.

## CONCLUSIONS

Intersections and horizontal curves present two high-priority areas for engineering countermeasures to improve safety by reducing both the frequency and severity of crashes. The implementation of countermeasure programs is generally focused on high-risk locations, which are identified based on extensive historical traffic safety data (i.e., crash history).

Unfortunately, the identification of candidate locations for engineering countermeasures is often challenging due to the random and rare nature of traffic crashes, as well as related analytical issues such as regression-to-the-mean (RTM). These challenges are particularly pronounced on rural highways, where many potentially high-risk locations may be difficult to identify given lower traffic volumes.

The aim of this study was to provide assistance in the identification of risk factors for traffic crashes on two facility types in Iowa: intersections and horizontal curves. The researchers identified risk factors through the analysis of a robust database for Iowa roadways, which combined data from various sources that included traffic volumes, roadway geometry, and other characteristics, as well as Iowa crash data.

### **Intersection Risk Factors**

Overall, the five-year intersection crash study results for Iowa's primary roadways reinforce several important geometric design characteristics that affect traffic safety. Looking at a primary factor of interest for intersections, the researchers found crashes to increase with skew angle at both three-leg and four-leg intersections. The researchers found the effect of skew was generally similar to the CMFs provided in the HSM (AASHTO 2010).

For broadside and angle crashes, the effects of skew on four-leg intersections were even more pronounced. When comparing broadside and angle crashes to the total number of crashes at four-leg intersections, the through movement on the minor leg was impacted more by skew angle.

The presence of unpaved approach legs was associated with fewer crashes at high-speed, rural intersections, which is likely a reflection of less frequent turning movements from the major road and also crossing movements from the minor road (with the unpaved approach leg).

Crashes were also less frequent at three-leg intersections where lighting was present, as well as at locations with larger volumes of heavy vehicles. This may be due, in part, to the fact that those highways tend to be of a higher functional class, which would be correlated with other roadway features. These roadways generally have wider lanes and shoulders, larger clear zones, and other higher design standards that may lead to fewer crashes than similar lower functional class facilities.

## **Horizontal Curve Risk Factors**

Turning to horizontal curve risk factors, crashes were found to increase with traffic volumes on both freeways and non-freeways, as well as in the presence of paved left shoulders on non-freeway segments. Crashes were less frequent on freeway segments with paved outside shoulders and on independent curves on non-freeway segments. Crashes were more frequent on sharper curves (with smaller radii), as well as where curves in opposing directions were present in the immediate vicinity of one another.

The researchers also conducted a crash severity analysis for horizontal curves, with the results showing that injuries tended to be more severe when drivers were unrestrained or ejected from the vehicle, or when the airbags deployed. Crashes were also more severe when crashes involved a single-vehicle, broadside crash, or two vehicles traveling in opposite directions. Collectively, these findings reflect the greater impact forces that are exerted on motorists in these types of crashes.

Based on the analysis of the freeway segments, males were less likely to be injured than females, and younger drivers were also less likely to experience high-severity crash outcomes, which are findings that may relate to physiological or behavioral differences.

Crashes also tended to be less severe on horizontal curves during dawn and dusk conditions. Additionally, crashes on left curves where concrete barriers or paved inside shoulders were present were associated with decreased crash severity, which likely reflects a lower likelihood of vehicles crossing the median when these features are present.

## **Implementation Readiness and Benefits**

The intersection analysis provides important results that reinforce the extant research literature as to the relationship between intersection skew angle and crash frequency. The Iowa intersection database that was developed contains additional information and site types, which would allow for a detailed investigation into other questions of interest.

This study is one of the first to exploit Iowa's horizontal curve information using the Curve Finder tool. The results of the horizontal curve analyses provide some important preliminary insights into the relationship between traffic crashes and various curve characteristics, which may be used for effective network surveillance and the identification of high-risk horizontal curves. This may include the identification of curves where additional traffic warning signs (e.g., chevrons, advisory speed signs) may be installed.

Moving forward, the extensive databases developed as a part of this study may be supplemented with additional information. As intersections and horizontal curves continue to be emphasis areas for improving safety, the identification of risk factors will allow for the proactive and cost-effective implementation of various engineering countermeasures.

### **Future Intersection Safety Research**

There are several prospective avenues for further intersection safety research and more detailed investigation is warranted into several areas of importance identified in this study. For example, disaggregate-level turning movement counts would provide insights as to the findings related to auxiliary turn lanes and unpaved approach legs. As this study only considered total crashes and broadside/angle crashes, future research could explore various crash types in conjunction with major causes for crashes.

Over the course of a data quality review of the intersection database, concerns arose as to the accuracy of several factors, including offset, rumble strip presence, bicycle lane and crosswalk presence, and other factors. With the continued refinement of the intersection database, additional risk factors could also be investigated.

### **Future Horizontal Curve Safety Research**

As the quality assurance/quality control (QA/QC) process involving information from the Curve Finder tool progresses, the data may be used to conduct further investigations into factors affecting the frequency and severity of crashes along horizontal curves. This database will also provide an opportunity to further investigate curves on other facility types.



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