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# Development of an Automated Methodological Procedure to Improve the Identification of Curve-Related Crashes in the Crash Records Information System (CRIS)

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## THE UNIVERSITY OF TEXAS AT AUSTIN CENTER FOR TRANSPORTATION RESEARCH

## Development of An Automated Methodological Procedure to Improve the Identification of Curve-Related Crashes in the Crash Records Information System (CRIS)

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Research Supervisor: Zhanmin Zhang, Ph.D.

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## Products

The product developed by this project is an automated methodological procedure for identifying curve-related crashes in CRIS documented in 0-7050-P1.

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## **Chapter 1. Introduction**

#### 1.1 Background

According to available data from the Texas Motor Vehicle Crash Statistics provided by the Texas Department of Transportation (TxDOT), there has not been a single deathless day on Texas roadways since Nov. 7th, 2000. In 2020, the fatality rate on Texas roadways increased by 18.94% compared to 2019 (TxDOT, 2021a). The total estimated economic loss resulting from 2020 Texas motor vehicle crashes is \$43,400,000,000 (TxDOT, 2021b). One of TxDOT's fundamental roles is to promote safety and protect the lives of the traveling public. In 2019, the Texas Transportation Commission established "the Road to Zero" goal, which aims to reduce the number of deaths on Texas roadways by half by 2035 and to zero by 2050 (TxDOT, 2021c). To accomplish this goal, TxDOT is in urgent need of effective crash prevention plans that can improve roadway safety across the state.

Recent statistics show that approximately 35,000 fatal crashes occur every year in the U.S., around 25 percent of which are closely related to horizontal curves. According to the Federal Highway Administration (FHWA), the average crash rate for horizontal curves is about three times that of other highway segment types. Curves also play a significant role in crashes in Texas. From 2010 to 2017, about 9 percent of all crashes and 22 percent of fatal crashes were related to curves. However, a recent analysis revealed that TxDOT's Crash Records Information System (CRIS) may substantially misclassify curve-related crashes. The CRIS variables missed about one-third of curve-related motorcycle crashes. Consequently, the role of curves in crashes and their safety impact are underestimated.

Identifying curve-related crashes is important to the understanding and characterization of curves' impact on crash risk and severity and, in turn, the reduction of such crashes. Better identifying such crashes will significantly facilitate the achieving of TxDOT's "Road to Zero" safety goals. Therefore, there is a need for improved methods to identify curve-related crashes, additional insights to better understand curve characteristics, and enhanced knowledge to assess curves' impact on crashes.

### **1.2 Research Objectives**

To fill the gap, the research team conducted a systematic study on improving the identification of curve-related crashes in the Crash Records Information System (CRIS). The UT/CTR research team began with a thorough review of the characteristics of horizontal curves and their impacts on traffic crashes. UT/CTR conducted a comprehensive study of available data sources that contain reliable roadway geometry and inventory information. Then, a data analysis was performed to identify the patterns and characteristics of curve-related crash misclassification in the CRIS database. Next, UT/CTR developed a methodological procedure for improving the identification of curve-related crashes. Leveraging Python programming language and ArcGIS Python libraries,

UT/CTR accomplished the automation of two major tasks in the procedure: 1) visualization of the customized CRIS data in ArcGIS Pro and 2) verification of curve-related crash classification using the Highway Curves Geographic Information System (GIS) layer as a reference. The outcome of a thorough performance evaluation proves that the automated methodological procedure can help identify curve-related crashes both effectively and efficiently. Finally, using the Texas Peace Officer's Crash Report (CR-3), UT/CTR performed a systematic investigation into potential causes of curve-related crash misclassifications in CRIS.

In summary, the specific objectives of this research are listed below:

- Identify patterns and characteristics of curve-related crash misclassifications in CRIS.
- Review the literature on:
  - o characteristics of horizontal curves;
  - o impacts of horizontal curves on crash risk, frequency, and severity;
  - o factors affecting crashes on horizontal curves; and
  - $\circ$  curve-related crash misclassification and potential contributors to misclassification.
- Develop an effective methodological procedure for improved identification of curverelated crashes and curve characteristics.
- Evaluate the performance of the developed methodological procedure.
- Analyze misclassified curve-related crashes to diagnose potential causes of misclassifications.

### 1.3 Work Plan

Figure 1-1 illustrates the work plan of the project, which is comprised of a total of eight tasks. Task 1 aims to ensure the project delivers timely and cost-effective results for the Receiving Agency. The rest of the tasks (Tasks 2–8) are grouped into four stages: Stage 1 is literature synthesis and information gathering (Task 2). Stage 2 is the identification and preparation of an integrated small dataset from existing TxDOT databases (Task 3, Task 4, and Task 5). Stage 3 is developing a methodological procedure for improved identification of curve-related crashes and curve characteristics (Task 6). Stage 4 is to evaluate the performance of the developed methodological procedure and diagnose the reasons for misclassification (Task 7 and Task 8). The details of each task are presented in the following sections.

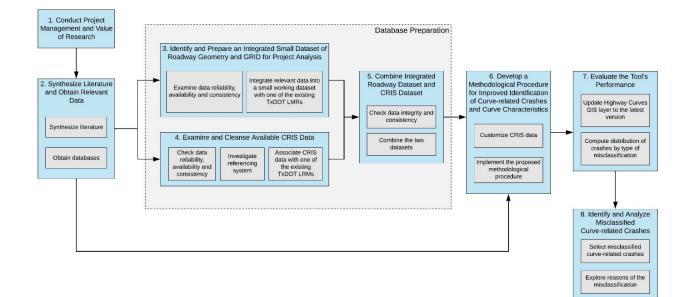


Figure 1-1. Structure of the Project Work Plan and Tasks

## **Chapter 2.** Literature Review

#### **2.1 Introduction**

This chapter investigates the characteristics and impacts of horizontal curves as well as patterns of curve-related crash misclassification. The study team conducted a comprehensive review of existing literature to collect information on geometric characteristics of horizontal highway curves; impacts of horizontal curves on crash risk, frequency, and severity; and safety factors affecting crashes that occurred on curved roadway segments.

#### 2.2 Literature Review

#### 2.2.1 Characteristics of Horizontal Curves

Horizontal alignment is a term used in roadway design to represent the route of a roadway. It is typically composed of straight-line sections (known as tangents) and various horizontal curves. Horizontal curves are sections at which a roadway alignment changes direction. Curves play a vital role in providing a safe and comfortable ride experience for passengers by preventing a sharp turn from one direction to another. Horizontal curves are integral parts of highways since their inclusion can help accommodate particular land usage expectations, which include but are not limited to topography needs, special restrictions, access to certain localities, and existing right-of-way while minimizing the scale of construction and costs.

#### **Components of Horizontal Curves**

This section presents the geometric background of horizontal curves. It introduces common terminologies used to describe the geometric components of horizontal curves, the fundamental properties of curves, different types of highway curves, and curve-related attributes and corresponding values in the CRIS database.

An illustration of the standard components of a simple horizontal curve is shown in Figure 2-1. As shown in the illustration,  $\Delta$  represents the central angle, R represents the radius of the curve, PC represents the start point of curvature, PT represents the end point of the curvature, and PI represents the point of intersection at which the two tangents intersect each other. The tangent distance T is the straight-line (Euclidean) distance from PC to PI (or PT to PI). The length of the curve L can be readily computed based on the central angle  $\Delta$  the radius R of the curve. The long chord LC is the straight-line segment connecting the PC and PT. The external distance E is the straight-line distance from the PI to the midpoint of the curve. The middle ordinate M is the straight-line distance from the midpoint of the long chord LC to the midpoint of the curve (WYDOT 2014). Table 2-1 lists the terminologies commonly used for describing horizontal curve components.

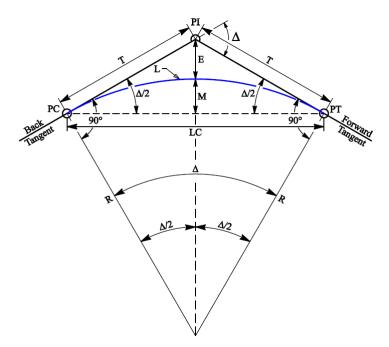


Figure 2-1. Horizontal Curve Components [source: WYDOT, 2014]

Symbol	Name	Description	Units	Equations
PC	Point of Curvature	point at which the curve begins	N/A	
PT	Point of Tangency	point at which the curve ends	N/A	
PI	Point of Tangent Intersection	point at which the two tangents intersect	N/A	
R	Radius of Curve	distance from PC or PT to the center of the circle	feet	
Δ	Central Angle, Delta Angle, or Deflection Angle	change in direction of two tangents	degrees	
D	Degree of Curvature	central angle D subtended by a chord of 100 feet	degrees per 100 feet of centerline	$D = \frac{36,000}{2\pi R} = \frac{5729.6}{R}$
L	Length of Curve	distance from PC to PT measured along the curve	feet	$L = \frac{\Delta \pi R}{180^{\circ}} = \frac{100\Delta}{D}$
Т	Tangent Length	distance from PC to PI or PI to PT	feet	$T = R \tan \frac{1}{2}\Delta$
LC	Length of Long Chord	straight line between PC and PT	feet	$LC = 2R\sin\frac{1}{2}\Delta$
М	Middle Ordinate	distance from the midpoint of LC to the midpoint of the curve	feet	$M = R(1 - \cos\frac{1}{2}\Delta)$
E	External Distance	distance from PI to the midpoint of the curve	feet	$E = R\left(\frac{1}{\cos\frac{1}{2}\Delta} - 1\right)$

Table 2-1. Terms for Horizontal Curve Components [source: Fricker and Whitford, 2004]

Note: N/A = Not applicable.

#### Types of Horizontal Curves and Relevant Attributes

This section presents an overview of horizontal curves, focusing on curve types based on geometric characteristics, curve classification based on the degree of curvature, and the attributes of curving highway alignment set forth in the *Texas Reference Marker System User's Manual* (TxDOT, 2005).

#### **Curve Type**

In the *Texas Reference Marker System User's Manual* (TxDOT, 2005), horizontal curves are systematically categorized into three types: point of intersection (PI) curve, normal curve, and spiral curve.

#### **PI Curve**

A PI curve is an alignment where the change of direction in horizontal alignment happens in a single point. The Texas Reference Marker (TRM) system defines a PI curve as "the point of intersection of two straight route segments and the delta angle of change in compass bearing that occurs at the location" (TxDOT, 2005). In the CRIS database, numeric value "2" is assigned to PI curves in the Curve Type ID field.

#### Normal Curve

Normal curves are horizontal curves with a constant rate. The TRM system defines a normal curve as "the location and all the elements necessary to define a route segment that curves at a constant rate" (TxDOT, 2005). In the CRIS database, numeric value "1" is assigned to normal curves in the Curve Type ID field.

#### **Spiral Curve**

Typically, as shown in Figure 2-2, a spiral curve comprises four points and three curved segments between these points. These four points, as listed in Table 2-2, are the beginning point of the first varying rate segment (TS), the ending point of the first varying rate segment (SC, which is also the beginning of the normal curve segment), the beginning point of the second varying rate segment (CS, which is also the endpoint of the normal curve), and the ending point of the second varying rate segment (ST). The three segments are the first varying rate segment, the normal curve segment, and the second varying rate segment. However, some spiral curves have only one varying rate segment at one end of the normal curve. The TRM system defines a spiral curve as "the location and all the elements necessary to define a route segment that curves at both a varying rate and a constant rate" (TxDOT, 2005). In the CRIS database, numeric value "3" is assigned to spiral curves in the Curve Type ID field.

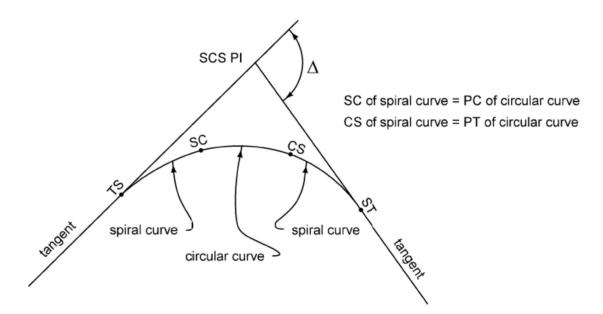


Figure 2-2. An Illustration of a Typical Spiral Curve [source: Iowa DOT, 2010]

Notation	Terminology	Description	
TS	Tangent to Spiral point	beginning point of the first varying rate segment	
SC	Spiral to Curve point	ending point of the first varying rate segment and beginning of the normal curve segment	
CS	Curve to Spiral point	beginning point of the second varying rate segment and ending of the normal curve	
ST	Spiral to Tangent point	ending point of the second varying rate segment	

Table 2-2. Points of a Spiral Curve

#### **Curve Classification**

In addition to the aforementioned curve types, horizontal curves can be classified into six classes based on the degree of curvature. The value ranges for each class, defined in the *Highway Performance Monitoring System Field Manual* (FHWA 2016), are listed in Table 2-3.

<b>Curve Classification</b>	Degrees	
А	Under 3.5 degrees (i.e., 0.061 radians)	
В	3.5 – 5.4 degrees (i.e., 0.061 – 0.094 radians)	
С	5.5 - 8.4 degrees (i.e., 0.096 - 0.147 radians)	
D	8.5 - 13.9 degrees (i.e., 0.148 - 0.243 radians)	
Е	14.0 – 27.9 degrees (i.e., 0.244 – 0.487 radians)	
F	28 degrees (i.e., 0.489 radians) or more	

Table 2-3. Curve Classification [source: FHWA, 2016]

#### **Curve Attributes**

Geometric attributes of horizontal curves established in the *Texas Reference Marker System User's Manual* (TxDOT, 2005) are listed in Table 2-4.

Terms	Definitions	Note
Curve Length	Total length of a curving highway alignment including spiral and normal curves, measured in miles to three decimal places.	PI curves have no length; they occur at a single point.
Curve Type Values	Indicates the configuration or kind of curve based on the number of points required to define it.	values: P/N/S
Curvature Degrees	Whole degree measurement of the rate of curvature, the angle change per one hundred feet, for a given normal curve.	value ranges from 00 to 89
Curvature Minutes	Whole minute measurement of the rate of curvature, the angle change per one hundred feet, for a given normal curve.	value ranges from 00 to 59
Curvature Seconds	Seconds measurement, to one decimal place, of the rate of curvature of a given normal curve.	value ranges from 00.0 to 59.9
Delta Degrees	Whole degree measurement of the change in direction at the point of tangency (PT) created by a curve.	value ranges from 000 to 179
Delta Minutes	Whole minute measurement of the change in direction at the PT created by a curve.	value ranges from 00 to 59
Delta Seconds	Seconds measurement to one decimal place of the change in direction at the PT created by a curve.	value ranges from 00.0 to 59.9
Tangent Length	The measurement from point of curvature (PC) to point of intersection and from point of intersection to point of tangent of a curve.	must be a positive numeric value
TS1 Tangent Length	<ul> <li>For a <i>normal curve</i>, the tangent length or distance in miles from the PC or PT to the projection point or intersection of the curve.</li> <li>For a <i>spiral curve</i>, the first spiral tangent length or distance in miles from the TS to the projected point of intersection of the spiral curve.</li> </ul>	<ul> <li>applies to Normal curve and Spiral curve</li> <li>in miles to three decimals, value ranges from 00.000 to 99.999</li> </ul>
TS2 Tangent Length	The second spiral tangent length or distance in miles from the ST back to the projected point of intersection of the spiral curve.	<ul> <li>applies to Spiral curve only</li> <li>in miles to three decimals, value ranges from 00.000 to 99.999</li> </ul>

#### 2.2.2 Impacts of Horizontal Curves on Crash Risk, Frequency, and Severity

According to the FHWA Office of Safety, approximately one out of four fatal crashes occurs on a curved road segment. The average crash rate for horizontal curves is about three times that of other highway segments. There are typically more horizontal curves within freeway segments than in non-freeway segments (Strathman et al., 2001). Over the past decades, several efforts have been made to explore the relationship between horizontal curves and crashes.

In an early study, Glennon et al. (1985) found that highway curves were more likely to experience severe, wet-icy, and single-vehicle run-off-road (ROR) crashes when compared with tangent segments. Based on the results of this study, the authors concluded that the average crash rate of highway curves was about three times greater than that of tangent segments on the same road; similarly, the average single-vehicle ROR crash rate of highway curves was approximately four times higher than that of highway straight segments. Moreover, the severity of roadway departure crashes on curved segments was significantly higher when compared to the same data collected from tangent segments.

Zegeer et al. (1991) proposed a statistical method to study the effects of horizontal curve characteristics on traffic safety and operations by analyzing data from 10,900 horizontal curves in Washington State. The results revealed that attributes of horizontal curves such as degree of curve, length of curve, presence of a spiral, superelevation, average daily traffic, width of roadway, and roadside condition could significantly impact the risk of crashes.

Shankar et al. (1995) examined the effects of roadway geometrics and climatic factors on the frequency of highway accidents. The geometric characteristics investigated in the study included the number of horizontal curves, the number of horizontal curves with different designed speeds, the maximum and minimum curve radii, etc. Some of the key findings from the study are listed below:

- The number of horizontal curves with a designed speed less than 96.5 kph (60 mph) had a positive effect on the frequency of sideswipe and rear-end crashes but had a negative effect on the frequency of fixed-object crashes.
- The number of horizontal curves per section had a positive effect on the frequency of fixedobject crashes.
- The average spacing of horizontal curves (adjacent curves) per section had a positive effect on the frequency of overturn crashes.
- The lowest horizontal curve radius in a section had a positive effect on the frequency of sideswipe crashes but had a negative effect on the frequency of overturn crashes.

Strathman et al. (2001) conducted a study to identify the statistical relationship between roadway design attributes and crash activities. The study report indicated that the maximum curve length had a positive effect on crash frequencies for rural non-freeway roads; in contrast, for urban freeway segments, the number of curves had a positive effect on crash frequencies.

In NCHRP Report 500, Volume 7 (Torbic et al., 2004), preventive strategies and countermeasures were developed to reduce crashes on horizontal curves, with particular focuses on preventing vehicles from leaving the traffic lane and on mitigating the consequences of leaving the roadway at curves. This study conducted a statistical analysis using U.S. highway records obtained from

the Fatality Analysis Reporting System. The result illustrated that 42,815 people died in fatal vehicle crashes in 2002. About one-fourth of deaths were located at horizontal curves. Also, 76 percent of fatal crashes that occurred on horizontal curves were single-vehicle crashes (e.g., ROR, struck a fixed object, or overturned). ROR and head-on crashes together accounted for more than 85 percent of the curve-related fatal crashes, as shown in Figure 2-3.

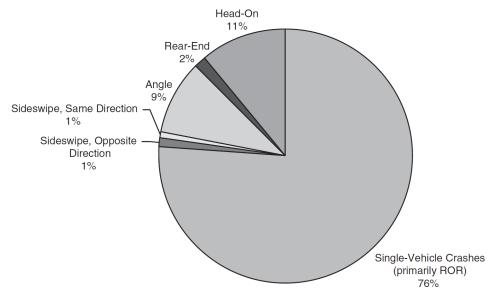


Figure 2-3. Curve-Related Fatal Crashes by Collision Type [source: Torbic et al., 2004]

Hummer et al. (2010) investigated the characteristics of crashes that occurred on horizontal curves based on North Carolina crash data from 2003 to 2005. The results of the analysis indicated that horizontal curves in rural areas tended to increase risk of crashes as compared to all other roads statewide. In terms of crash severity, the study found that crashes on two-lane curve segments had both higher fatality and severe injury rates than crashes on other road segments.

Souleyrette (2011) utilized statistical models to study the relationship between roadway geometric characteristics and crash rates. In this study, the models were first used to identify high crash locations for five crash types (i.e., curve-related crashes, fixed-object crashes, rural four-lane expressway intersection crashes, head-on crashes, and urban four-lane undivided corridor crashes). For crashes on horizontal curves, the study found that the degree of curvature and the length of curve had significant impacts on crash rates. Specifically, the report indicated that shorter curves tended to experience more crashes compared to longer curves.

Bauer and Harwood (2013) studied the interactions between horizontal and vertical alignments and their impacts on crash frequency using data retrieved from the Highway Safety Information System and crash records in Washington State. The results revealed that crash frequency increased with decreasing horizontal curve length and with decreasing horizontal curve radius. In addition, the models found that short, sharp horizontal curves; short horizontal curves at sharp crest vertical curves; and short horizontal curves at sharp sag vertical curves tended to experience higher crash frequencies than other road sections.

According to the *Low-Cost Treatments for Horizontal Curve Safety 2016* report (Albin et al., 2016) from the FHWA, there were approximately 33,000 fatalities caused by vehicle crashes reported in the United States in 2013. More than half of these fatalities were caused by roadway departure crashes. The report pointed out that horizontal curves typically had higher risks of roadway departure crashes than tangent road segments.

#### 2.2.3 Factors Affecting Crashes on Horizontal Curves

Empirical evidence shows that there is an overrepresentation of crashes on horizontal curves compared to tangent sections. Although there are multiple factors that cause this increase in crashes, the general principle is that changes in alignments increase the workload demand on the driver, the vehicle, and the pavement. For example, while driving a curve, the driver focuses his/her attention on keeping control of the vehicle, which decreases the attention paid to other routine driving actions (such as scanning for hazards) (Campbell et al., 2012). Therefore, in a curve, drivers have diminished capability to manage hazards on the road, respond to sudden changes from defective construction, or correct mistakes, among other actions.

However, this workload increase in a curve is not constant. Figure 2-4 shows a segmentation of a road section with a curve based on the driving workload demand (Campbell et al., 2012). Table 2-5 presents the main driving subtasks associated with each segment of Figure 2-4. As Table 2-5 indicates, the workload demand is low at the "Approach" segment and the beginning of the "Curve Discovery" segment. Then the workload increases from low to high at the beginning of the "Entry and Negotiation" segment and remains high until the "Exit" segment. After the driver exits the curve, the workload demand becomes low again.

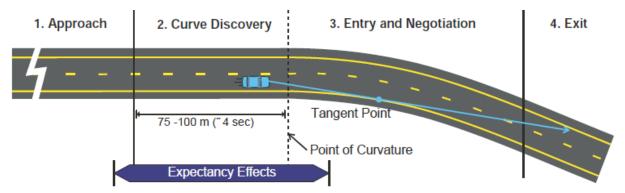


Figure 2-4. Segmentation of a Road Section with a Curve Based on the Workload of the Driving Task [source: Campbell et al., 2012]

Category	Approach	Curve Discovery	Entry and Negotiation	Exit
Workload Demand	Low	From low to high	High	Low
Subtasks	<ul> <li>Locate bend by recognizing visual cues indicating departure from straight path</li> <li>Get available speed information from signage</li> <li>Make initial speed adjustments</li> </ul>	<ul> <li>Estimate curve angle based on visual image and experience</li> <li>Determine conditions requiring (additional) speed reductions</li> <li>Read speedometer and or judge safe speed based on cues and experience</li> <li>Adjust vehicle path for curve entry</li> </ul>	<ul> <li>Adjust speed based on curvature/lateral acceleration</li> <li>Maintain proper trajectory</li> <li>Maintain safe lane position</li> </ul>	<ul> <li>Accelerate to appropriate speed</li> <li>Adjust lane position</li> </ul>

Table 2-5. Workload Demand and Driving Subtasks Involved while Driving a Curve

As Figure 2-4 and Table 2-5 illustrate, driving a curve is a complex task that involves multiple actions. Moreover, these driving actions are affected by factors that are internal and external to the driver. These key factors are summarized in the rest of this section. The factors can be classified into the following four groups (Campbell et al., 2012; Momeni et al., 2015; FHWA, 2020):

- Factors associated with horizontal curves
- Factors associated with drivers
- Factors that can facilitate recovery after lane departure
- Factors that can minimize crash severities

#### Factors Associated with Horizontal Curves

Crashes occurring on horizontal curves are one of the main causes of traffic fatalities in the United States (FHWA, 2020). For this reason, research historically has focused on the factors associated with curves and countermeasures to reduce crashes. Table 2-6 presents the main factors associated with curve safety and some of the common countermeasures used to prevent curve-related crashes (Campbell et al., 2012; Momeni et al., 2015; FHWA, 2020).

Factor	Description	Countermeasure(s)
Curve Radius	Visual demands from the driver seem to be related linearly and inversely to curve radius. Therefore, decreasing the radius of the curve increases the crash risk.	Geometric changes to road alignment
Deflection Angle	There is no strict threshold for deflection angles, but it has been observed that curves sharper than 9 degrees increase the workload demand of the driver compared to shallower curves. Different DOTs use different deflection angle thresholds to classify the curves in their network.	Geometric changes to road alignment
Design Consistency	Curves that are not consistent within themselves (e.g., irregular design) or curves that are not consistent with other curves of the same road section (e.g., a curve that is considerably sharper than other curves in the same road section) increase crash risk due to a conflict between the expectation of the driver and the actual curve.	Geometric changes to road alignment
Pavement Friction	Curves increase the friction demand of vehicles. Thus, low pavement friction increases crash rates, especially on wet pavements.	Increase pavement friction
Nighttime Visibility	One of the main tasks of the driver is to scan for the tangent point of the curve to assess the curve difficulty. Poor nighttime visibility impairs the driver's ability to accurately assess the curve and thus increases crash risk.	<ul> <li>Provide centerline and edge line</li> <li>Provide signs that can help to visualize the curve (curve delineators, chevrons, LED markers, etc.)</li> <li>Increase night lighting</li> </ul>
Turning Direction	Empirical evidence has not found a significant link between the turning direction (right or left) and crash risk.	None

Table 2-6. Factors	s Associated with	Horizontal Curves
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#### Factors Associated with Drivers

After the curve itself, the driver is the second most important variable in safely navigating curves. Although many driver decisions and behaviors are outside the control of public agencies, some factors can be mitigated to increase safety on horizontal curves. Table 2-7 presents the main risks associated with drivers' actions and some of the common countermeasures used (Campbell et al., 2012; Momeni et al., 2015; FHWA, 2020).

Factor	Description	Countermeasure(s)
Speed Selection	Speed selection is one of the most important factors in road safety. Two factors play a role when the driver is selecting the speed: 1) expectations about the curve, and 2) information about the curve. However, research shows that usually drivers give more weight to perception than signage information. This perception is based on the immediate observation of the curve and previous experience. Drivers may later try to correct speed based on the lateral forces during the "Entry and Negotiation" part of the curve.	<ul> <li>Most of the countermeasures focus on providing information to the driver that could reset his/her perception and overconfidence stemming from previous experience:</li> <li>Road signage</li> <li>Speed advisory signs</li> <li>Speedometers</li> <li>Beacon lights announcing a sharp curve</li> </ul>
Visual Demands of the Curve and Distracted Driving	The presence of visual stimuli such as signage/advertisements or irregular foliage can distract the driver and increase crash risk. Moreover, the driver can be distracted by activities such as changing the radio station or using a cellphone, which limit the driver's ability to identify the curve and reduce speed if needed.	<ul> <li>Avoid posting advertisements on curves</li> <li>Limit the presentation of complex information that requires reading and/or interpretation to the approach section</li> <li>Avoid irregular foliage in the curve</li> <li>Provide centerline and edge line</li> <li>Provide signs that can help driver to visualize the curve (curve delineators, chevrons, LED markers, etc.)</li> </ul>
Perception	Depending on the curve configuration, some horizontal curves have an apparent horizontal radius that is different from the real radius. This effect is higher on curves that include a vertical sag within the curve (Figure 2-5 provides an example).	<ul> <li>Increase horizontal curve radius</li> <li>Increase radius of sag vertical curve</li> <li>Provide centerline and edge line</li> <li>Provide signs that can help driver to visualize the curve (curve delineators, chevrons, LED markers, etc.)</li> </ul>
Psychomotor Factors	Some of the tasks drivers perform include eye movements for scanning the curve, necessary foot movements to adjust speed, and hand movements for steering control. Any psychomotor problems that can limit the driver's ability to perform these tasks increase the crash risk.	None

#### Table 2-7. Factors Associated with Drivers

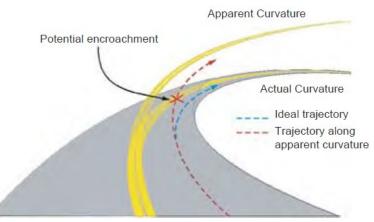


Figure 2-5. Driver's Perception of an Apparent Curve Radius Versus the Actual Curve Radius [source: Campbell et al., 2012]

#### Factors that Can Facilitate Recovery after Lane Departure

Lane departure occurs when the vehicle crosses the edge line, the center lane, or the traveled lane. Once a lane departure occurs, the risk of a crash increases due to possible conflicts with other vehicles or fixed objects. Therefore, one of the goals of DOTs is to provide room for recovery from lane departure before a crash occurs (FHWA, 2020). Table 2-8 presents the main factors that could help a vehicle to recover quickly from a lane departure (Campbell et al., 2012; Momeni et al., 2015; FHWA, 2020).

Factor	Description	Common Countermeasure
Shoulder	Shoulders extend the cross-section of the pavement outside the travel lanes. Roadways with shoulders have been associated with lower crash risk.	Shoulders of 1ft or 3 ft
Rumble Strips	Rumble strips are designed to produce noise and/or vibrations in the vehicle to alert the driver when the vehicle leaves the lane.	<ul><li>Edge line rumble strips</li><li>Centerline rumble strips</li></ul>
Safety Edges	Safety edges provide an angle on the edge of the pavement to facilitate the recovery of vehicles that left the roadway.	Provide safety edges on the road section
Shoulder Widening	Shoulder widening extends the shoulders in the vicinity of curves that present a high risk of crashes.	Provide a wider shoulder on curves

Table 2-8. Facto	rs that Can Facilit	ate Recovery after	Lane Departure

#### Factors that Minimize Crash Severities and Measurements that Reduce Curve-Related Crashes

If a lane departure occurs and the driver is not able to recover into the correct travel lane, the chances of a crash are very high. Crashes can occur because of a conflict with a vehicle traveling in the same direction (when the road has multiple lanes running in the same direction), a vehicle

traveling from the opposite direction (head-on crashes), or an object outside the road (fixed-object crashes). One of the goals of DOTs is to minimize the severity of such crashes (FHWA, 2020) by reducing head-on crashes and fixed-object crashes. Table 2-9 presents the main factors that can minimize the severity of crashes caused by lane departures (Campbell et al., 2012; Momeni et al., 2015; FHWA, 2020).

Factor	Description	Common Countermeasure
Clear Zones	One of the most commonly hit fixed objects are trees. Proper maintenance that keeps zones around the curves free of fixed objects, whenever possible, can reduce crash severities.	Maintain or extend clear zones around curves
Protective Devices	Protective devices such as guardrails or concrete barriers can prevent head-on and fixed-object crashes.	Install protective devices

Table 2-9. Factors that Can Minimize Crash Severities Once a Lane Departure Occurs

#### **Other Factors**

Srinivasan et al. (2018) evaluated the effectiveness of the Development of Crash Modification Factors program, which conducted safety evaluations of horizontal curve realignment on rural, two-lane roads. The researchers determined the crash modification factors (CMFs) associated with curve realignment using the before/after empirical Bayes method and compared the results from cross-sectional studies on CMFs. They conducted a case study using data from rural, two-lane roads in California, North Carolina, and Ohio. The evaluation revealed a 68-percent reduction in total crashes, a 74-percent reduction in injury and fatal crashes, a 78-percent reduction in ROR and fixed object crashes, a 42-percent reduction in dark crashes, and an 80-percent reduction in wet crashes, all of which were statistically significant at the 95-percent confidence level.

The study found that the most important characteristic is the range of the before and after degree of the curve. The average degrees of curve in the before and after periods were 18.1 and 6.9, respectively. Other important characteristics include the average central angle of the curves, the average annual daily traffic, and the average length of the realigned segments. They compared the total crash CMFs with the results from two previous cross-sectional studies and found that the CMFs from this before/after evaluation were lower. The economic analysis revealed a benefit–cost ratio of 3.17:1 with a range of 1.75:1 to 4.38:1.

In another study, Donnell et al. (2019) identified and assessed several safety countermeasures and strategies. They conducted three statistical assessments to evaluate effectiveness, including an observational before/after study of "curve ahead warning" pavement markings, a cross-sectional study of delineators on guiderails along horizontal curves, and a cross-sectional study of the safety effects of geometric design consistency. The findings from these evaluations indicate that the expected number of roadway departure crashes is associated with the horizontal curve radius, radii of adjacent horizontal curves, and the tangent lengths between curves. In addition, the expected

number of roadway departure crashes is associated with side friction demand on horizontal curves. Guiderails with delineators are expected to reduce total, fatal-plus-injury, ROR, and nighttime crashes along horizontal curves that are four degrees or sharper. Horizontal-curve-warning pavement markings are associated with fewer expected total, fatal-plus-injury, ROR, nighttime, nighttime ROR, and nighttime fatal-plus-injury crashes on two-lane, rural highways.

#### 2.2.4 Curve-Related Crash Misclassifications and Their Potential Causes

Although considerable research has been devoted to analyzing curve-related crashes and the factors affecting them, less attention has been paid to analyzing misclassification issues pertaining to records of curve-related crashes and the potential causes of misclassification.

In a report that was published by the Texas A&M Transportation Institute (Shipp et al., 2018), researchers utilized the Texas Roadway Inventory with CRIS crash data to develop a curve analysis methodology. Researchers took the following steps:

- mapped the latitude and longitude points from the roadway inventory data
- created roadway segments from the mapped latitude and longitude points
- developed an online GIS-based tool to identify curves

The tool uses several tests to determine if a segment is a curve, including minimum deflection angle, minimum ratio of a segment's deflection angle to its length, and minimum contiguous curve segments required. To determine if a crash is curve-related, the tool allows a user to define the maximum crash-to-nearby-curve distance in feet.

Two curve-related misclassification situations were identified:

- Type A: Crashes not identified as being on a curve by the GIS Curve Identification Tool but identified as such by the officer (CRIS)
- Type B: The GIS Curve Identification Tool identifies crashes as being on a curve but the CRIS data indicates otherwise

The researchers tested the tool and conducted a case study using roadways RM 335, RM 336, and RM 337. A total of 293 crashes were identified as occurring on these roadways from 2010 to 2017. A total of 370 motorcycle riders were involved in these crashes as follows: RM335 (61 riders), RM336 (100 riders), and RM337 (209 riders). The GIS Curve Identification Tool results were compared to two variables in the CRIS data: the roadway inventory data appended to the crash record and the police officer's assessment coded under "road alignment" in his or her attempt to capture the geometric characteristics of the roadway. The results showed that 24 (6.5 percent of total crashes) were Type A misclassifications and 84 (22.7 percent of total crashes) were Type B misclassifications.

#### 2.3 Summary

This chapter identifies key findings from a comprehensive review of relevant literature on geometric characteristics of horizontal highway curves, effects of horizontal curves on the risk of vehicle crashes, safety factors affecting crashes that occurred on horizontal curves, and curve-related crash misclassification, as well as potential causes of misclassification in CRIS. Furthermore, a preliminary database review of crash records from 2017 to 2019 in CRIS identifies existing patterns of curve-related crash misclassification.

The geometric background of horizontal curves is reviewed in Section 2.2.1, including an introduction to common concepts and terminologies used to describe them (such as point of curvature, point of tangency, delta angle, degree of curvature, etc.). The relationships between different curve components are illustrated with corresponding equations. Based on geometric characteristics, horizontal curves can be categorized into three types: PI curve (P), normal curve (N), and spiral curve (S). In addition to these different types, horizontal curves are ranked from Class A to Class F based on the degree of curvature. The definitions and value ranges for curve-related attributes in the Texas Reference Marker System User's Manual (TxDOT, 2005) are listed in Table 2-4.

The safety impacts of horizontal curves on crashes are presented in Section 2.2.2. Previous studies have found that the average crash rate of horizontal curves is three times higher than that of other highway sections. Moreover, the severity of ROR crashes on curved segments is significantly higher than on tangent segments. Curve attributes such as degree of curve, length of curve, and presence of a spiral can significantly impact the risk of crashes. Other variables, such as the number of horizontal curves, the number of horizontal curves with different designed speeds, the maximum and minimum curve radii, and the maximum curve length also have a significant impact on the frequency of vehicle crashes.

The factors affecting crashes on horizontal curves are discussed in Section 2.2.3. Key factors that can affect driving actions while passing through a horizontal curve are grouped into four classes: factors associated with horizontal curves, factors associated with drivers, factors that can facilitate recovery after lane departure, and factors that can minimize the severity of crashes. Based on the literature review, factors associated with horizontal curves include curve radius, deflection angle, design consistency, pavement friction, and nighttime visibility.

The key preliminary findings regarding curve-related crash misclassification and its potential causes are documented in Section 2.2.4.

## Chapter 3. Identify and Prepare an Integrated Small Dataset of Roadway Geometry for Project Analysis

## **3.1 Introduction**

In Task 3, CTR conducted a thorough investigation to identify available data sources that contain reliable roadway geometry and inventory information maintained by TxDOT. In addition to the obtained data sources, useful variables that can support the analysis of subsequent curve-related crash misclassification were identified. Furthermore, CTR examined the completeness, reliability, and consistency of the available data. To explore proper referencing methods for integrating roadway geometry attributes from multiple data sources, CTR reviewed TxDOT's linear referencing methods (LRM). Ultimately, a small, integrated working dataset that encompasses roadway geometry and inventory parameters was presented.

### 3.2 Data Sources Investigation

In this task (Task 3), CTR conducted a comprehensive study of available data sources that contain reliable roadway geometry and inventory information. Also examined were curve-related parameters that can provide information for the identification of curve-related crashes in the CRIS database. This section presents an overview of the data sources explored in this task, including:

- Geometrics (Geo-HINI) database
- Geospatial Roadway Inventory Database (GRID)
- Highway Curves GIS layer

#### 3.2.1 The Geometrics (Geo-HINI) Database

The Geometrics (Geo-HINI) database used to be a component of the Texas Reference Marker (TRM) system. It restores geometric information for all horizontal curves along the centerline of highways maintained by TxDOT. As documented in a previous study (Tsyganov et al., 2005), the Geo-HINI database contains information on curve type (i.e., point curve, normal curve, and spiral curve), curve length, delta degree, and degree of curvature. Each curve has a unique identifier number, and the beginning and ending points of the curve are located through a given reference marker and displacement from that marker.

However, during the project kick-off meeting, CTR was informed by TxDOT that the Geo-HINI database is no longer in use. All the geometry and roadway inventory data originally stored in the Geo-HINI database have been merged into the Geospatial Roadway Inventory Database (GRID). Therefore, CTR removed it from the list of data source candidates.

## **3.2.2 The Geospatial Roadway Inventory Database (GRID)**

GRID is a GIS-based web platform developed by TxDOT to maintain roadway asset inventory data across the state (TxDOT, 2018). GRID contains parameters for all highway and roadway networks maintained by TxDOT, which include but are not limited to (TxDOT, 2020b):

- mileage for highway network segments
- secondary designations of each roadway segment
- district responsibilities for each roadway segment
- highway segments that are part of the National Highway System
- highway segments that are part of the Texas Turnpike System
- attributes associated with each highway and roadbed, including number of lanes, surface width, and traffic data, etc.

TxDOT updates and publishes roadway inventory datasets regularly on its Open Data Portal, which is publicly available at <u>https://gis-txdot.opendata.arcgis.com/</u>.

TxDOT's Roadway Inventory is a statewide dataset that is directly exported from the GRID system. It contains various data related to GIS linework and roadway inventory attributes for main lanes and frontage roads. In general, these attributes can be grouped into the following categories (TxDOT, 2020):

- Identification/referencing attributes, e.g., beginning/ending reference marker, beginning/ending reference marker displacement.
- **Geographic attributes**, e.g., district ID, county number, city number, rural/urban code, maintenance section, among others.
- Administrative attributes, e.g., roadway maintenance agency, functional classification, freight network, if the route belongs to national highway system, among others.
- **Operational attributes**, e.g., highway status, date opened to traffic, closure reason, speed limit, toll name, school zone, among others.
- **Physical/cross-section attributes**, e.g., median type and width, number of lanes, minimum row width, surface width, shoulder type and width, among others.
- **Traffic attributes**, e.g., annual average daily traffic (AADT), truck AADT percentage, peak factor, historical ADT, AADT for design year, among others.

- Highway Performance Monitoring System (HPMS) sample section attributes, e.g., HPMS current ID, HPMS volume group, physical roadbed, peak lane, lane width, curve classification, among others.
- **Common statistics**, e.g., length of section, lane miles, daily vehicle-miles traveled (VMT), and daily truck VMT.

CTR downloaded TxDOT's Roadway Inventory Dataset from the Open Data Portal (accessed at: <u>https://gis-txdot.opendata.arcgis.com/</u>) and carefully reviewed curve-related information. Based on the data examination, six attributes related to horizontal curves were identified:

- CURV-CLASS-A
- CURV-CLASS-B
- CURV-CLASS-C
- CURV-CLASS-D
- CURV-CLASS-E
- CURV-CLASS-F

These attributes indicate different types of horizontal curves based on the degree of curvature, as shown in Table 3-1.

Curve Classification	Degrees
CURV-CLASS-A	Under 3.5 degrees (i.e., 0.061 radians)
CURV-CLASS-B	3.5 - 5.4 degrees (i.e., 0.061 - 0.094 radians)
CURV-CLASS-C	5.5 – 8.4 degrees (i.e., 0.096 – 0.147 radians)
CURV-CLASS-D	8.5 – 13.9 degrees (i.e., 0.148 – 0.243 radians)
CURV-CLASS-E	14.0 – 27.9 degrees (i.e., 0.244 – 0.487 radians)
CURV-CLASS-F	28 degrees (i.e., 0.489 radians) or more

#### 3.2.3 Texas Highway Curves Geographic Information System (GIS) Layer

The Highway Curves GIS layer (available at <u>http://arcg.is/1SPG8i</u>) was provided by TxDOT. It visualizes horizontal curves on highways across the state and contains curve-related information.

As shown in Figure 3-1, the Highway Curves GIS layer has five attributes that describe basic characteristics of identified curve segments on Texas highways:

- roadway name (RTE\_NM),
- estimated curve degree (EST\_CURVE\_DEGREE),
- curve class (HPMS\_CURVE\_CLASS),
- beginning distance from origin (FROM\_DFO), and
- ending distance from origin (TO\_DFO).

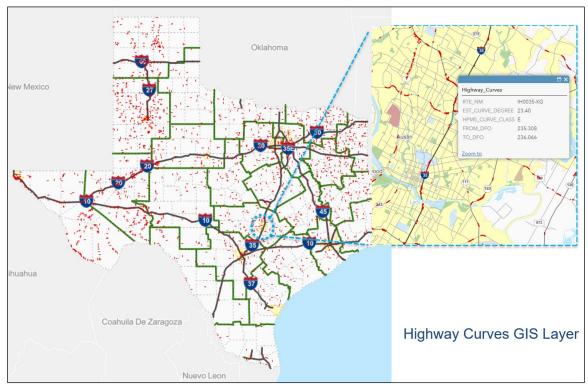


Figure 3-1. Screenshot of Texas Highway Curves GIS Layer

Users can zoom in and obtain the curve characteristics by clicking on the specific curve. CTR uses this layer as the referencing layer in identifying highway curves.

## 3.3 Linear Referencing Methods (LRMs)

In order to integrate and visualize attributes from different data sources on the same GIS map, CTR conducted research on LRMs. This section presents a brief introduction to LRMs as well as an overview of specific LRMs used by TxDOT.

#### 3.3.1 Overview of Linear Referencing Methods

An LRM is an approach to identifying spatial locations based on a known point along linear geographic features (AASHTO, 2021). With a reference point and a measurement of the point of interest, the location of any point along a route can be identified (ArcMap, 2020). LRMs are common tools utilized by transportation agencies. Features and events (e.g., crashes in the scope of this study) along a route can be located by using a unique identifier for the route and a linear measurement from a specified reference point to the feature of interest (Vandervalk et al., 2016).

As documented in the *State of The Practice on Data Access, Sharing, and Integration* report (Vandervalk et al., 2016), the most popular LRMs in use by State DOTs are Route Milepoint and Reference Point Offset. Route Milepoint refers to all linear measurements from the origin of the route, while Reference Point Offset refers to linear measurements from nearby reference markers along the route.

According to All Road Network of Linear Referenced Data from FHWA (Hausman et al., 2014), LRMs can be grouped into three categories:

- absolute methods
  - o Measurements from the origin of the route (or segment) to the event (e.g., crashes in the scope of this study), as illustrated in Figure 3-2.

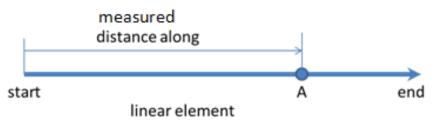


Figure 3-2. Absolute LRMs [source: Hausman et al., 2014]

- relative methods
  - o Measurements from a known reference location to the event of interest, as illustrated in Figure 3-3.

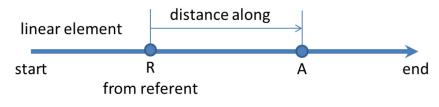


Figure 3-3. Relative LRMs [source: Hausman et al., 2014]

#### • interpolative methods

o Measurements as a fraction of the entire section distance, as illustrated in Figure 3-4.

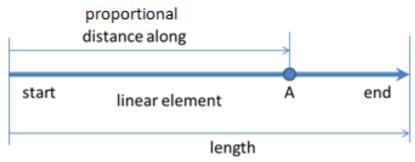


Figure 3-4. Interpolative LRMs [source: Hausman et al., 2014]

LRMs provide an efficient approach for State DOTs to integrate information from multiple data sources into a comprehensive database. By implementing LRMs, state agencies can associate various events that occurred on the route (e.g., traffic crash, pavement condition, construction project, among others) with a measurement from a known location. Information originally from different sources can be presented on the same map. The overall data integration within the entire organization can be improved. LRMs not only make it possible to access multiple data simultaneously, but also minimize potential data redundancy in databases. Consequently, the overall accuracy of the database can be improved (AASHTO, 2021).

#### 3.3.2 Linear Referencing Methods in GRID

Like many other DOTs, TxDOT takes advantage of well-developed LRMs to manage roadway networks and roadway inventory across the state. As shown in Figure 3-5, the LRMs used in GRID to locate features along state-maintained roadways include (TxDOT, 2018):

- distance from origin (DFO),
- Texas reference marker (TRM) + offset,
- control section milepoints (CSM), and
- route coordinates (latitude and longitude).

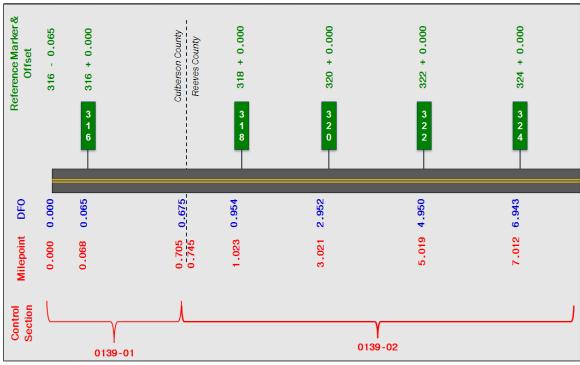


Figure 3-5. LRMs in GRID [source: TxDOT, 2018]

## Distance from Origin (DFO)

DFO is a type of Route Milepoint locating method. The DFO value of a point along a given route is defined as the distance from that point to the beginning point of that route. When the reference marker information is updated by users, DFO values are generated automatically from the TRM system, which is maintained by the Transportation Planning and Programming Division (TPP) (TxDOT, 2006; TxDOT, 2005). TxDOT mainly utilizes DFO as an effective tool for maintaining GIS roadway linework and off-system asset management (Chamberlain, 2016).

## Texas Reference Marker (TRM)

TRMs are physically located reference placards with a three-digit number that provides a consecutive numbering scheme from the beginning to the end of the route. These reference markers are installed at intervals along all state-maintained routes throughout Texas. They provide general reference points for improving on-system asset management (Chamberlain, 2016) and identifying locations of traffic crashes or roadway events (TxDOT, 2005; Tsyganov et al., 2005).

To manage a large number of reference markers across the state, TxDOT developed a systematic numbering system, Reference Marker Grid, as shown in Figure 3-6. The axes of the grid are set on extreme western and northern points. The numbering starts from ten and aggregates in subsequent markers (TxDOT, 2005; TxDOT, 2015). The directions in which the marker numbers increase depend on the type of the route, as indicated in Table 3-2.

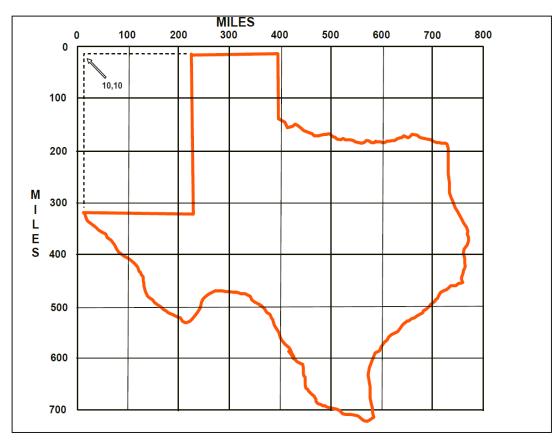


Figure 3-6. Reference Marker Grid [source: TxDOT, 2015]

Reference Marker Number Increasing Direction				
West to East South to North				
West to East				
North to South				
Clockwise				

 Table 3-2. Route Directions in TRM System [source: TxDOT, 2015]

#### Control Section Milepoints (CSM)

Control section is another reliable LRM in use by TxDOT for locating features along roadways across the state. A control section is a unique identifier assigned for a segment of a route. Although the name and number of a route may change over time, control sections tend to be stable and constant. Currently, both on-system highways and off-system routes have control section numbers that facilitate construction management projects within TxDOT (TxDOT, 2021e; TxDOT, 2021f; Chamberlain, 2016).

#### **Route Coordinates**

Route coordinates are latitude and longitude coordinates obtained from the Global Positioning System (GPS). Route coordinates are also referred to as GPS coordinates. As documented in the *Texas Reference Marker System User's Manual*, the definition of latitude is the "angular distance north from the earth's equator to a given point on the earth, measured in degrees, minutes, and seconds." Similarly, longitude is defined as the "angular distance west from the Greenwich Meridian to a point on the earth; measured in degrees, minutes, and seconds," (TxDOT, 2005). GPS technology has been used by TxDOT to locate spatial features and events along roadways for approximately 40 years (TxDOT, 2021d).

## **3.4 Data Examination**

To ensure data quality for this project, CTR examined the completeness, reliability, and consistency of the obtained data. This section provides key findings from the data examination.

## 3.4.1 GRID

CTR obtained the Roadway Inventory Dataset from TxDOT's Open Data Portal (<u>https://gis-txdot.opendata.arcgis.com</u>). However, CTR found that all the Curve Class fields (e.g., CURV\_CLASS\_A, CURV\_CLASS\_B, etc.) were blank, as illustrated in Figure 3-7. CTR reported this issue to TxDOT. According to TxDOT, curve attributes have not been migrated from the previous system to the Roadway Inventory Dataset. Therefore, the Roadway Inventory Dataset does not provide valuable curve-related data for use in analyzing curve-related crash misclassification in CRIS.

FZ	GA	GB	GC	GD	GE
CURV_CLASS_A 🔽	CURV_CLASS_B	CURV_CLASS_C 💌	CURV_CLASS_D 🔽	CURV_CLASS_E 🔽	CURV_CLASS_F
	₽↓	<u>S</u> ort A to Z			
	ZJ	, S <u>o</u> rt Z to A			
		Sor <u>t</u> by Color	>		
		Sheet <u>V</u> iew	>		
		<u>C</u> lear Filter From "CU	RV_CLASS_D"		
		F <u>i</u> lter by Color	>		
		Text <u>F</u> ilters	>		
		Search	Q		
		(Select All)	,		
		(Blanks)			

Figure 3-7. Curve Class (all blank) in Texas Roadway Inventory Dataset

#### 3.4.2 Texas Highway Curves GIS Layer

The Texas Highway Curves GIS Layer, provided by CTR, contains useful information on horizontal curves for both on-system routes (i.e., roadway designated on the state highway system and maintained by TxDOT) and off-system routes (i.e., roadway not designated on the state highway system and not maintained by TxDOT) across the state. After conducting a detailed examination, CTR noticed that a certain level of data was missing in the Highway Curves GIS layer. More precisely, in some roadway sections, the change of the road alignment can be observed on the GIS map but such curvatures are not reflected on the Highway Curves GIS layer. CTR categorized the issue into two types: missing curves and incomplete curves.

#### **Missing Curves**

Missing curves refer to those horizontal curves that are visible on the GIS map but not reflected on the Highway Curves GIS Layer. Some examples of missing curves are presented in Figure 3-8, Figure 3-9, and Figure 3-10.



Figure 3-8. Missing Curves in Highway Curves GIS Layer

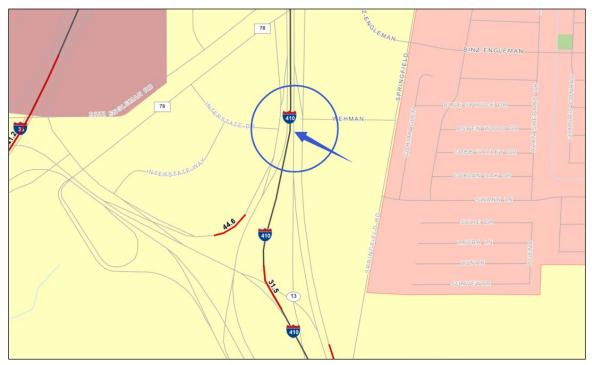


Figure 3-9. Missing Curves in Highway Curves GIS Layer

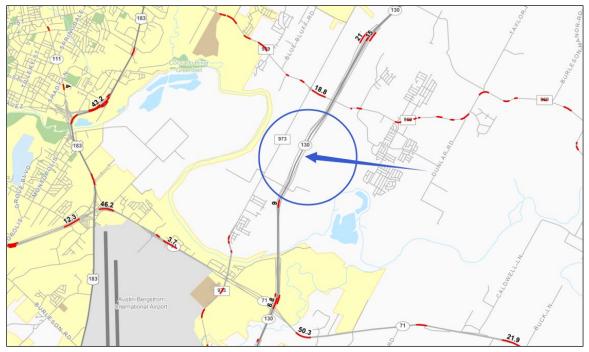


Figure 3-10. Missing Curves in Highway Curves GIS Layer

## **Incomplete** Curves

Incomplete curves refer to those horizontal curves that are partially but incompletely captured by the Highway Curves GIS layer. Figure 3-11 to Figure 3-14 demonstrate some examples of the incomplete curves obtained from the Highway Curves GIS layer.



Figure 3-11. Incomplete Curves in Highway Curves GIS Layer



Figure 3-12. Incomplete Curves in Highway Curves GIS Layer



Figure 3-13. Incomplete Curves in Highway Curves GIS Layer



Figure 3-14. Incomplete Curves in Highway Curves GIS Layer

Considering the magnitude of the roadway network across the state, the number of missing and incomplete curves account for a relatively small percentage of the entire system. The vast majority of horizontal curves along on-system routes appear on the Highway Curves GIS layer.

In addition, the Highway Curves GIS layer contains both roadway referencing attributes (e.g., beginning and ending DFOs) and curve-related information (e.g., curve degree and curve class). Information is presented in a well-developed GIS layer, which largely facilitates subsequent data analysis for curve-related crash misclassification in CRIS.

Therefore, the Highway Curves GIS layer is capable of serving as a reliable roadway geometry source for checking curve-related crash misclassification in CRIS. Hence, any inconsistency between the CRIS database and the Highway Curves GIS layer is treated as a misclassification in the CRIS database unless the curve information cannot be verified in the Highway Curves GIS layer.

## 3.5 Summary

This chapter documents key findings from the investigation of available data sources and useful roadway geometry attributes that can support the development of a small, integrated, working dataset of roadway geometry.

The data sources explored in this study include the Geo-HINI database (not considered in subsequent analyses as directed by TxDOT), GRID, and the Highway Curves GIS layer. Moreover, roadway geometry and curve-related parameters obtained from these databases are listed in this

section. These parameters can provide useful information for the identification of curve-related crash misclassification in CRIS. A brief introduction to LRMs, as well as an overview of the LRMs commonly used by TxDOT, are documented in Section 3.3. Results from the examination of the completeness, reliability, and consistency of the obtained data are organized in Section 3.4.

Based on the investigation of available data sources and the results from data examination, the Highway Curves GIS layer was found to be a reliable data source that encompasses both roadway geometric data and horizontal curve information. Therefore, CTR will use the Highway Curves GIS layer as a reliable reference in subsequent analysis for improving the identification of curve-related crash misclassification in CRIS.

# Chapter 4. Examine and Clean Available CRIS Data

## 4.1 Introduction

This chapter documents the general procedure for and key findings from examining and cleaning the publicly available crash data from the CRIS database.

In Task 4, CTR first obtained the publicly accessible statewide crash data through an online platform, CRIS Share (<u>https://cris.dot.state.tx.us/secure/Share/</u>). To improve the efficiency of data processing, the obtained annual data were split into several bimonthly datasets. A thorough data inspection was conducted to select useful variables that could support the identification of curve-related crash misclassification. After comparing different referencing methods used in CRIS, the GPS coordinates (latitude and longitude) method was selected to visualize crash data in ArcGIS, due to its accuracy and ability to accommodate complex data. Invalid crash records (e.g., missing location information, not on on-system roads) were also removed from the obtained dataset. After inspecting and cleaning the data, CTR categorized them into four subsets based on curve-related attributes. Finally, a comprehensive data examination was conducted to check the data consistency within the available CRIS data.

## 4.2 Data Acquisition

CRIS is an automated database that collects and tracks statewide traffic crash records; it contains all the data received from the Texas Peace Officer's Crash Report (form CR-3). In 2015, TxDOT started expanding the retention period for crash data from five to ten years (TxDOT, 2021g). The available crash data is from January 1, 2010, to early 2020 (up to the initiation of this project).

The publicly available crash data can be accessed through the online CRIS Query tool (https://cris.dot.state.tx.us/public/Query/app/welcome) or the automated crash data extract files from CRIS Share (https://cris.dot.state.tx.us/secure/Share/). The online CRIS Query tool provides users a platform to build their queries based on certain criteria (e.g., year, location, crash severity, etc.). However, the platform only allows users to preview and download a maximum of 50,000 data entries at a time, and it does not support large amounts of data processing. As the average number of annual crash records is more than 600,000 across the state, an automated data extraction method was used to improve the efficiency of data acquisition. Two types of data files are available through the automated crash data extraction method: the standard extract and the public extract (TxDOT, 2021h). The former is available only to certain governmental agencies since it contains sensitive, personally identifiable information. Thus, the public extract CRIS data were used for this research.

## 4.3 Data Preparation

After a comprehensive investigation of data needs, CTR obtained statewide CRIS data from 2017 to 2019 (*note: due to the impact of COVID-19, the CRIS 2020 data was excluded from this study*).

Multiple data files were included in the information obtained from the public extract CRIS data. The crash-specific data files were used to help identify potential curve-related crash misclassification in CRIS; Figure 4-1 provides an example of the file listing.

Name
🔊 extract_2018_20200623085812_charges_20190101-20191231Texas.csv
Extract_2018_20200623085812_crash_20190101-20191231Texas.csv
extract_2018_20200623085812_damages_20190101-20191231Texas.csv
🛯 extract_2018_20200623085812_endorsements_20190101-20191231Texas.csv
💁 extract_2018_20200623085812_lookup_20190101-20191231Texas.csv
💁 extract_2018_20200623085812_person_20190101-20191231Texas.csv
💁 extract_2018_20200623085812_primaryperson_20190101-20191231Texas.csv
💁 extract_2018_20200623085812_restrictions_20190101-20191231Texas.csv
💁 extract_2018_20200623085812_unit_20190101-20191231Texas.csv
extract_2018_20200623085812168_68188_20190101-20191231Texas_manifest.xm

Figure 4-1. Screenshot of the Public Extract Crash Data (2019 data) from CRIS Share

To perform Task 4 in an effective manner, CTR conducted a series of data preparation activities, which includes the following:

- split large data files into a manageable size
- study data attributes in the CRIS dataset
- identify useful attributes that are relevant to curve-related crash misclassification
- remove invalid crash records
- select a proper referencing method to locate crash data in ArcGIS
- categorize crash data into subsets based on curve-related attributes

Sections 4.3.1 through 4.3.6 present detailed information for each of the above-listed activities.

## 4.3.1 Split Large Data Files into a Manageable Size

The data files extracted from the CRIS Share platform are massive, since these files contain all crashes that occurred in a specific year (e.g., 2019) across the state. It is challenging and very time-consuming to directly process this magnitude of data. To improve data processing efficiency, the original annual crash data were partitioned into several smaller, bimonthly datasets, as illustrated in Figure 4-2.

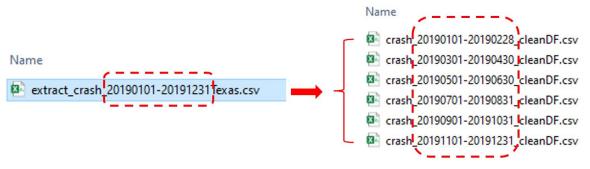


Figure 4-2. Large Annual Crash Data File Split into Bimonthly Datasets

#### 4.3.2 Review and Study Data Attributes

The publicly available CRIS dataset contains more than 170 attributes covering roadway identification, geographic information, and crash-related parameters. These attributes can be categorized into the following groups (TxDOT, 2021h):

- **CR-3 Reported Data Fields**, e.g., crash ID, fatal crash identifier, school bus crash identifier, railroad crash identifier, crash date, crash time, county name, city name, roadway alignment, and surface condition, among others.
- Interpreted Fields, e.g., if bridge related, if intersection related, if object struck, if manner of collision, and if first injury or damage–producing event, among others.
- System-Generated Fields, e.g., county ID, city ID, latitude, longitude, highway number, street name, DFO, control section, on-system flag, and rural flag, among others.
- Appended Roadway Attributes, e.g., highway design lane ID, median width, base type, number of lanes, width of the right-of-way, roadbed width, surface width and type, curb type, shoulder type and width, curve type, curve length, curve degree, delta left or right identifier, and delta degree, among others.
- **Count Fields**, e.g., suspected serious injury count, non-incapacitating injury count, possible injury count, total injury count, and death count, among others.

#### 4.3.3 Identify Useful Attributes

After carefully reviewing all data attributes in the available CRIS data, CTR identified 17 attributes that can assist the identification of curve-related crash misclassification. These attributes include unique identifiers of crashes, locations in the format of different referencing methods, and horizontal curve information. Table 4-1 provides more details on these 17 attributes.

No.	Attribute Name	Column Name in CRIS	1	
1	Crash ID	Crash_ID	System-generated unique identifying number for a crash	CR-3 Reported
2	Located Flag	Located_Fl	Indicates whether the CRIS locator application was able to locate the crash	System Generated
3	Latitude	Latitude	Latitude map coordinate of the crash	System Generated
4	Longitude	Longitude	Longitude map coordinate of the crash	System Generated
5	Street Name	Street_Name	Name of the road crash occurred on, as determined by the Locator application	System Generated
6	DFO	Dfo	The distance from the origin of the highway to the spot where the crash occurred	System Generated
7	On System Flag	Onsys_Fl	Indicates whether the primary road of the crash was on the TxDOT highway system	System Generated
8	Ref. Marker Nbr	Ref_Mark_Nbr	Reference marker number on the primary highway nearest the crash location	System Generated
9	Ref. Marker Displ.	Ref_Mark_Displ	The distance from the reference marker to the crash location	System Generated
10	Roadway Alignment	Road_Algn_ID	The geometric characteristics of the roadway at the crash site	CR-3 Reported
11	Curve Type ID	Curve_Type_ID	Type of curve, for crashes located on the state highway system	Appended Roadway Attributes
12	Length of Curve	Curve_Lngth	Length of curve, for crashes located on the state highway system	Appended Roadway Attributes
13	Curve degrees	Cd_Degr	Curve degrees (N & S type only), for crashes located on the state highway system	Appended Roadway Attributes
14	Curve delta degrees	Dd_Degr	Curve delta degrees (for crashes located on the state highway system)	Appended Roadway Attributes
15	Delta Left/Right ID	Delta_Left_Right_ID	Identifies whether the curve is right or left (for crashes located on the state highway system)	Appended Roadway Attributes
16	At Intersection	At_Intrsct_Fl	Indicates whether the crash occurred at an intersection	CR-3 Reported
17	IF- Intersection Related	Intrsct_Relat_ID	Specifies whether a crash occurred at an intersection, not at an intersection, or if the presence of an intersection contributed to the crash	Interpreted

Table 4-1. Attributes Relevant to Curve-Related Crash Misclassification

#### 4.3.4 Remove Invalid Crash Records

As mentioned in the previous section, the "Located Flag" field in CRIS is an indicator that reveals whether the location of a given crash can be identified by the system. When the "Located Flag" attribute equals "N," it means the crash cannot be located by the CRIS locator application. In this project, crash records with no location information are treated as invalid records and removed from the datasets, as they are not able to provide any useful information for identifying curve-related crash misclassification. In addition, crashes that are not on an on-system road were also removed from the datasets. These roadways are not designated on the state highway system and are not maintained by TxDOT; thus, the data are beyond the scope of this research.

#### 4.3.5 Select a Proper Method to Locate Crash Data in ArcGIS

Three referencing methods are used in the CRIS database: the Route Coordinates (i.e., latitude and longitude), the DFOs, and TRMs. After a thorough comparison among these referencing methods in CRIS, CTR found that Route Coordinates data are more complete than DFOs and TRMs. In CRIS, the "Located Flag" attribute is used to indicate if the CRIS locator application can locate a crash. Based on the result of a comprehensive data inspection, CTR noted that the Route Coordinates are highly consistent with the "Located Flag" field; in other words, if a crash can be located by the CRIS locator application, valid values are available in corresponding "Latitude" and "Longitude" fields, and vice versa. Therefore, the Route Coordinates were selected to locate CRIS data in ArcGIS Pro because Route Coordinates are accurate and capable of accommodating complex data.

#### 4.3.6 Categorize Crash Data into Subsets

In CRIS, the information indicating whether a crash occurred on a horizontal curve segment can be derived from two attributes: "CURVE\_TYPE\_ID" and "ROAD\_ALGN\_ID." To examine the data consistency in CRIS, CTR categorized the crash data into four subsets based on the values of these two attributes.

	ColumnName	ID ,	Description
ſ	CURVE_TYPE_ID	1	Ν
	CURVE_TYPE_ID	2	Р
L	CURVE_TYPE_ID	3	S
	ROAD_ALGN_ID	1	STRAIGHT, LEVEL
	ROAD_ALGN_ID	2	STRAIGHT, GRADE
	ROAD_ALGN_ID	3	STRAIGHT, HILLCREST
	ROAD_ALGN_ID	4	CURVE, LEVEL
1	ROAD_ALGN_ID	5	CURVE, GRADE
Į.	ROAD_ALGN_ID	6	CURVE,HILLCREST
	ROAD_ALGN_ID	7	OTHER (EXPLAIN IN NARRATIVE)
	ROAD_ALGN_ID	8	UNKNOWN
	ROAD_ALGN_ID	9	NOT REPORTED
	ROAD_ALGN_ID	94	REPORTED INVALID

Figure 4-3. Descriptions for Curve-Related Attributes in CRIS Database Lookup Table

#### Curve Type ID

The Curve Type ID (labeled as "CURVE\_TYPE\_ID" in CRIS) is a numeric variable used in CRIS to help identify the geometric characteristics of the road segment where the crash occurred. According to the CRIS lookup table, the values of Curve Type ID can be 1, 2, or 3. As Figure 4-3 shows, 1 represents Normal Curve, 2 represents PI Curve, and 3 represents Spiral Curve. Approximately 80 percent of crash data entries pertaining to curves are blank. A blank field can be interpreted to mean that either the crash did not occur on a curve or that information is missing, and it is impossible to distinguish between the two. In general, missing data is a common issue in most data sources. An investigation of all the potential reasons that CRIS may be missing data can be developed as a separate research project, but such a comprehensive investigation is out of the scope of this project. Therefore, if the Curve Type ID is blank, it is simply interpreted to mean that the crash did not occur on a horizontal curve.

#### Road Align ID

Road Align ID (labeled as "ROAD\_ALGN\_ID" in CRIS) is another curve-related attribute that originally comes from the police report on the crash. Road Align ID reflects the judgment of the police officer on the horizontal alignment of the road segment where a crash occurred. According to the descriptions in the CRIS lookup table, Road Align ID can take numeric values ranging from 1 to 9 as well as 94, as shown in Figure 4-3. In CRIS data from 2017 to 2019, CTR found that the actual values used for Road Align ID are {1, 2, 3, 4, 5, 6, 7, 8}. For this project, a value of 4, 5, or 6 means that the crash occurred on a curved segment, and other values indicate the crash is not curve related.

## CRIS Subsets Based on Curve Type ID and Road Align ID

To improve the efficiency and effectiveness of the project, the data in Curve Type ID and Road Align ID fields were regrouped into two categories: on-curve/curve-related or not-curve/not curve-related. For example, if the information retrieved from Curve Type ID was a numeric value (e.g., 1, 2, or 3), then the crash was grouped as curve-related; if the Curve Type ID field was blank, then the crash was grouped as not curve-related. Similarly, when the value of Road Align ID was 4, 5, or 6, the crash was grouped as curve-related; otherwise, the crash was grouped as not curve-related. The crosstab for the regrouped two variables is listed in Table 4-2.

Curve-related Attributes in		Road Align ID		
	CRIS	Curve-related Not Curve-rel		
Type	Numeric (Curve-related)	RAlignCurve_NUM	RAlignNotCurve_NUM	
Curve ID	Blank (Not curve-related)	RAlignCurve_BLANK	RAlignNotCurve_BLANK	

Table 4-2. Subsets of CRIS Based on Curve Type ID and Road Align ID

Based on the regrouped categories of Curve Type ID and Road Align ID shown in Table 4-2, crashes in CRIS are categorized into four subsets:

- Curve-related crash (RAlignCurve\_NUM): Both Curve Type ID and Road Align ID indicate the crash occurred on a curve segment.
- **Type A data conflict (RAlignNotCurve\_NUM)**: Curve Type ID indicates the crash occurred on a horizontal curve, but Road Align ID indicates the crash did not occur on a curve segment.
- **Type B data conflict (RAlignCurve\_BLANK)**: Curve Type ID indicates the crash did not occur on a horizontal curve but Road Align ID indicates the crash occurred on a curve.
- Non-curve crash (RAlignNotCurve\_BLANK): Both Curve Type ID and Road Align ID show the crash did not occur on a curve segment.

Any given crash in CRIS belongs to only one of the four subsets. Figure 4-4 shows the decision tree employed to develop these four subsets.

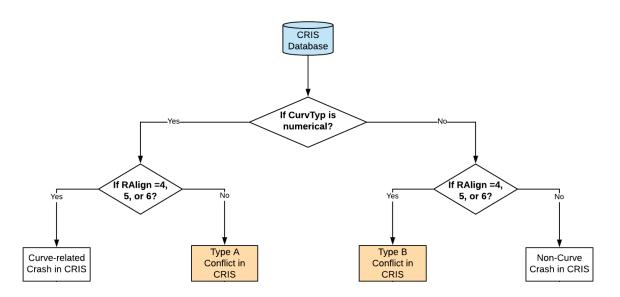


Figure 4-4. CRIS Data Subsets Based on Regrouped Curve Type and Road Alignment

## 4.4 Data Examination

In addition to inspecting and cleaning the available CRIS data, CTR performed a thorough examination concerning data consistency of curve-related attributes (i.e., Curve Type ID and Road Align ID). The key findings from the data examination are presented in this section.

#### 4.4.1 Curve Type ID

After processing the latest three years of CRIS data (i.e., 2017, 2018, and 2019), the CTR research team found that approximately 80 percent of crash data entries indicate they are not curve-related crashes. About 19 percent of total crashes occurred on normal curve segments, and less than 1 percent of the total on-system crashes occurred on PI or spiral curves. The percentages of crashes made up by each Curve Type ID from 2017 to 2019 are provided in Figure 4-5, Figure 4-6, and Figure 4-7.

#### 2019 PERCENTAGE OF CRASHES BY CURVE TYPE

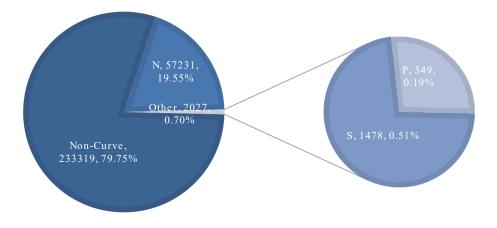


Figure 4-5. Crashes Occurring on On-System Roadways by Curve Type in 2019

#### 2018 PERCENTAGE OF CRASHES BY CURVE TYPE

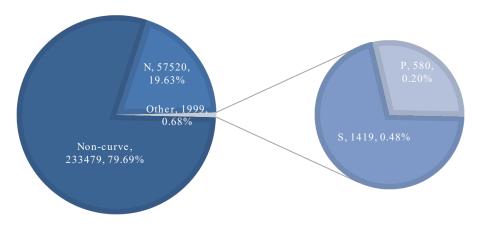


Figure 4-6. Crashes Occurring on On-System Roadways by Curve Type in 2018

#### 2017 PERCENTAGE OF CRASHES BY CURVE TYPE

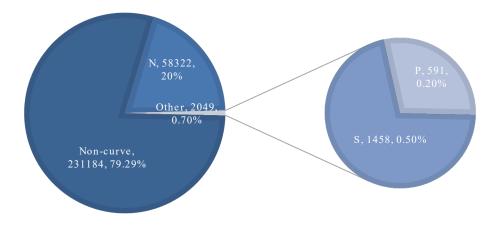


Figure 4-7. Crashes Occurring on On-System Roadways by Curve Type in 2017

#### 4.4.2 Road Align ID

Based on Road Align ID information from 2017 to 2019, CTR identified that more than 90 percent of crashes were reported as occurring on straight (non-curve) segments. Less than 9 percent of total crashes that occurred across on-system roads were recognized as curve-related crashes. Figure 4-8, Figure 4-9, and Figure 4-10 present the percentage of crashes each Road Align ID category made up from 2017 to 2019.

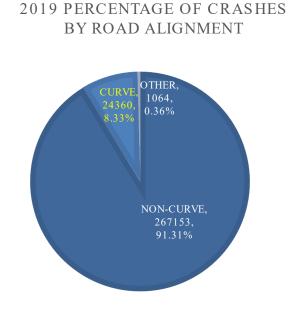


Figure 4-8. Crashes Occurring on On-System Roadways by Road Alignment in 2019

#### 2018 PERCENTAGE OF CRASHES BY ROAD ALIGNMENT

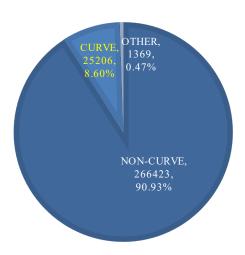


Figure 4-9. Crashes Occurring on On-System Roadways by Road Alignment in 2018

2017 PERCENTAGE OF CRASHES

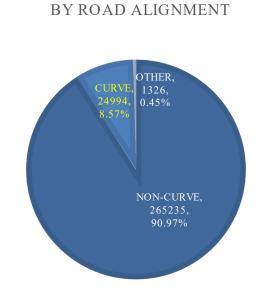


Figure 4-10. Crashes Occurring on On-System Roadways by Road Alignment in 2017

#### 4.4.3 Data Consistency between Curve Type ID and Road Align ID

In addition to separately investigating the distribution of crashes in the CRIS database using Curve Type ID and Road Align ID, CTR examined data consistency between information provided by Curve Type ID and by Road Align ID. This step helped explore potential data conflicts in curve-related crash classification in CRIS. Detailed information on the evaluation of data consistency in CRIS (from 2017 to 2019) is presented in this section.

Comparing the values in Curve Type ID with the information in Road Align ID using 2017–2019 CRIS data, CTR found that approximately 77 percent of crashes have consistent records while in 23 percent of crash records have conflicts between Curve Type ID and Road Align ID.

Specifically, both attributes agree that about 74 percent of crashes did not occur on a curve segment while around 3 percent of crashes occurred on a curve segment. However, in 17 percent of crashes, the Curve Type ID attribute indicates that they occurred on a curve segment, but the Road Align ID, from the police reports, indicates they are not curve related.

In contrast, about 5 percent of crashes did not occur on a curved segment based on the Curve Type ID, but the Road Align ID shows these crashes occurred on curved sections. Figure 4-11, Figure 4-12, and Figure 4-13 illustrate the data consistency between Curve Type ID and Road Align ID from 2017 to 2019.

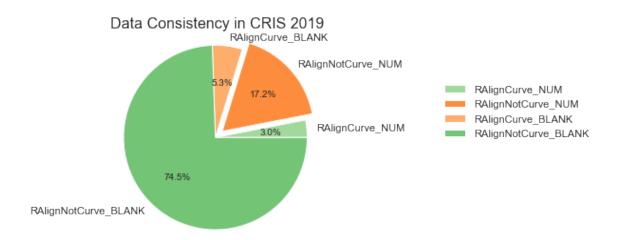


Figure 4-11. Data Consistency between Curve Type and Road Alignment in CRIS 2019

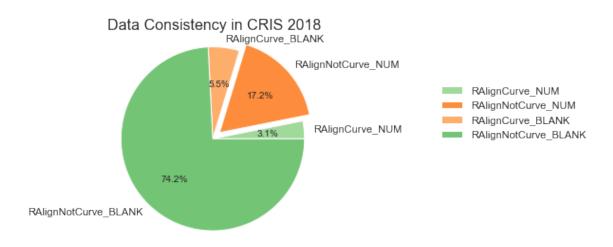


Figure 4-12. Data Consistency between Curve Type and Road Alignment in CRIS 2018

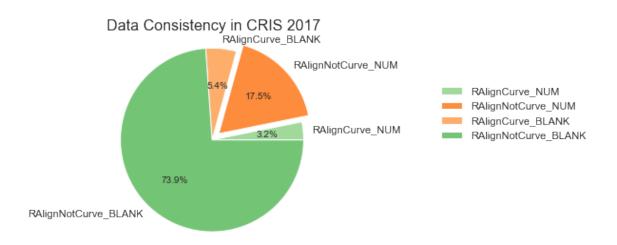


Figure 4-13. Data Consistency between Curve Type and Road Alignment in CRIS 2017

## 4.5 Summary

This chapter documents the procedure and key findings from examining and cleaning CRIS data (2017–2019) obtained from the publicly accessible CRIS Share system. Section 4.2 provides an introduction to the CRIS database and an overview of how data was acquired in Task 4. Section 4.3 presents the data preparation procedure, which includes splitting the massive amounts of annual data into smaller bimonthly files, studying attributes in CRIS, identifying useful attributes, selecting a proper referencing method, removing invalid data from the datasets, and categorizing crash data into subsets. Section 4.4 documents key findings from a comprehensive examination and consistency check of 2017 to 2019 CRIS data.

# **Chapter 5.** Combine Integrated Roadway Dataset and CRIS Dataset

# **5.1 Introduction**

This chapter documents the general procedure for and key findings from combining the integrated roadway geometry dataset (i.e., the Highway Curves GIS layer) and the CRIS dataset customized for this study.

In Task 5, the research team integrated two datasets prepared in Task 3 and Task 4 to perform a systematic data analysis for curve-related crash misclassification. Specifically, the customized CRIS dataset was integrated with the Highway Curves GIS layer via a desktop GIS application, ArcGIS Pro. The Route Coordinates (latitude and longitude) method was utilized to visualize CRIS data because of its accuracy and ability to accommodate complex data. Based on these latitude and longitude coordinates, all crash records from the customized CRIS dataset were mapped and visualized on the Highway Curves GIS layer. After integrating the datasets, the research team verified the curve-related crash information in CRIS using the Highway Curves GIS layer as the reference line. Based on the verification, the research team categorized curve-related crash misclassifications into six types. Finally, a comprehensive data analysis was performed to investigate the patterns and characteristics of curve-related crash misclassification in the CRIS database.

## **5.2 Data Preparation**

In Task 5, the data integration inputs are the outcomes from Task 3 (integrated roadway geometry dataset) and Task 4 (customized CRIS dataset). This section provides a brief review of the identification of the integrated roadway geometry dataset and the development of the customized CRIS dataset.

## 5.2.1 Integrated Roadway Geometry Dataset

In Task 3, the research team performed a comprehensive investigation of available data sources that contain reliable roadway geometry and inventory information maintained by TxDOT. The data sources include the Geometrics (Geo-HINI) database, GRID, and the Highway Curves GIS layer (available at <a href="http://arcg.is/1SPG8i">http://arcg.is/1SPG8i</a>). In addition to exploring the reliability and accuracy of these data sources, the research team also examined curve-related indicators that can provide information on the identification of curve-related crashes in the CRIS database. Based on a thorough examination, the research team found that the Highway Curves GIS layer can serve as a reliable data source that encompasses both roadway geometric data and horizontal curve information. Therefore, the Highway Curves GIS layer is used as the integrated roadway geometry dataset for verifying curve-related information in Task 5.

#### 5.2.2 Customized CRIS Dataset

In Task 4, the research team examined and cleaned the original CRIS data obtained from CRIS Share (available at <u>https://cris.dot.state.tx.us/secure/Share/</u>). The statewide CRIS data from 2017 to 2019 were retrieved (*note: due to the impact of COVID-19, the CRIS 2020 data was excluded from this study*). After a thorough data inspection, a total of 17 (out of over 170) attributes were found to be useful to the identification of curve-related crash misclassification (see Section 4.3.3). Invalid crash records (e.g., with no location information or on off-system roads) were removed from the obtained dataset. To improve the efficiency of data integration, each of the annual datasets was split into six bimonthly datasets. Then, based upon Curve Type ID and Road Align ID, each of the bimonthly datasets was split into four subsets. Accordingly, for each annual dataset, there were 24 subsets that formed the customized CRIS dataset.

## **5.3 Data Integration**

The Highway Curves GIS layer and the customized CRIS dataset were integrated into a single file using ArcGIS Pro. The research team compared different referencing methods in Task 4, and the Route Coordinates (latitude and longitude) method was selected to locate crash data because of its accuracy and ability to accommodate complex data.

## 5.3.1 Buffer Setting for Dataset Integration

Prior to integrating the Highway Curves GIS layer and the customized CRIS dataset, the research team conducted another round of data examination as a preparation for the integration. The research team noticed that the curve segments on the Highway Curves GIS layer have a small offset from roadways on the base map, as shown in Figure 5-1. Therefore, only a very small portion of the crashes that occurred on a curve can be detected successfully when the search distance around a curve is set to be zero. To solve this issue, a buffer zone was created around each curve in the integrated ArcGIS file, which provides an extension of the curve so that crashes overlapping with the zone can be detected automatically.

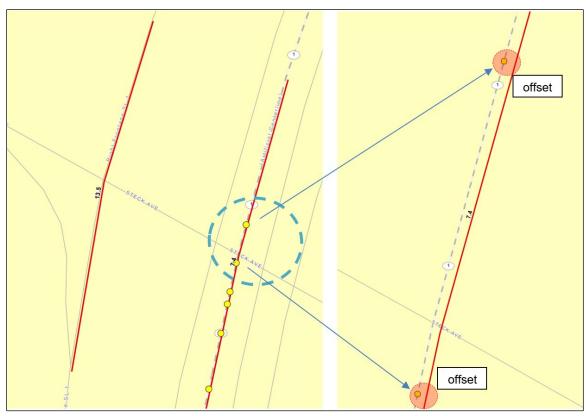


Figure 5-1. An Example of the Curve Offset between the Highway Curves GIS Layer and Base Map

To determine the optimal search distance, the research team tested distances from 1 foot to 500 feet with intermediate values (e.g., 1, 12, 25, 50, 75, 100, 200, 300, 400, and 500 feet). The consistency rate was used to quantify how many crashes have consistent curve-related information between the Highway Curves GIS layer and the CRIS dataset. The consistency rates were calculated under each of the tested search distances, which are shown in Table 5-1 and Figure 5-2.

Distances						
Search Distance (ft)	2019	2018	2017			
1	73.3%	73.0%	72.9%			
12	68.5%	68.3%	67.8%			
25	68.1%	67.9%	67.5%			
50	67.6%	67.4%	66.9%			
75	67.1%	66.9%	66.5%			
100	66.7%	66.4%	66.0%			
200	63.4%	63.1%	62.7%			
300	60.7%	60.4%	60.0%			
400	58.3%	58.1%	57.3%			
500	56.0%	55.8%	55.7%			

Table 5-1. Consistency Rates between the Highway Curves GIS Layer and CRIS Data Using Different Search Distances



Figure 5-2. Consistency Rates between the Highway Curves GIS Layer and CRIS Data Using Different Search Distances

As illustrated in Table 5-1 and Figure 5-2, the consistency rate between the Highway Curves GIS layer and the CRIS dataset (from 2017 to 2019) decreases as the search distances increase. When the search distance increases from 1 foot to 12 feet, the consistency rate decreases by around 5 percent. For example, for 2019 data the consistency rate decreases from 73.3 percent (search distance is 1 foot) to 68.5 percent (search distance is 12 feet). As the search distance increases, the

consistency rate shows a steady downward trend. Furthermore, the changes in consistency rate for all three-year CRIS datasets demonstrate the same trend.

In addition to the consistency rate, the research team also calculated the on-curve rate for crashes that occurred from 2017 to 2019 under different search distances. The on-curve rate of crashes refers to how many crashes occurred in curved road segments each year. As presented in Table 5-2 and Figure 5-3, when the search distance increases from 1 foot to 12 feet, the on-curve rate increases dramatically, by approximately 15 percent. Again using 2019 data as an example, the on-curve rate increases from 3.8 percent (search distance is 1 foot) to 18.7 percent (search distance is 12 feet). As the search distance increases, the on-curve rate shows a steady upward trend. Similar to the consistency rate, it can be observed from Figure 5-3 that the changes in the on-curve rate for each year's CRIS dataset demonstrate the same trend.

Search Distance (ft)	2019	2018	2017
1	3.8%	3.8%	3.8%
12	18.7%	19.0%	19.2%
25	19.6%	19.8%	19.9%
50	20.7%	20.8%	21.1%
75	21.6%	21.7%	22.1%
100	22.5%	22.7%	23.0%
200	27.8%	28.0%	28.3%
300	31.8%	32.1%	32.5%
400	35.3%	35.6%	36.3%
500	38.4%	38.6%	38.7%

Table 5-2. Crash On-Curve Rate Using Different Search Distances

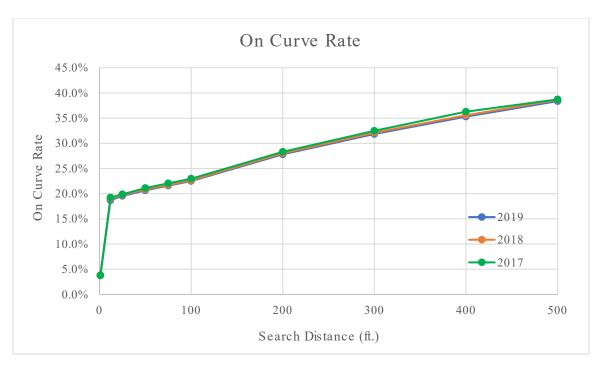


Figure 5-3. Crash On-Curve Rate Using Different Search Distances

Based on the results, the search distance (buffer zone) between the Highway Curves GIS layer and the customized CRIS dataset was set at 1 foot, as this distance resulted in the highest data consistency rates between the two datasets.

#### 5.3.2 Types of Curve-Related Crash Misclassification in CRIS

As discussed in Chapter 3, the research team used the Highway Curves GIS layer provided by TxDOT as a reliable data source for identifying curve-related crash misclassification in CRIS. The curve-related attributes (i.e., Curve Type ID and Road Align ID) in CRIS are verified using the highway curve information provided by the Highway Curves GIS layer. If an inconsistency in curve-related information is detected in the integrated ArcGIS file, it will be treated as a curve-related crash misclassification in CRIS unless the curve information cannot be verified in the Highway Curves GIS layer (e.g., missing data). The curve-related crash misclassifications in CRIS identified by this analysis can be categorized into the following six types:

- **Type 1 Misclassification:** Both Curve Type ID and Road Align ID indicate that the crash occurred on a curve, *but* the Highway Curves GIS layer shows the crash was on a straight segment.
- **Type 2 Misclassification:** Curve Type ID indicates the crash occurred on a curve, *but* Road Align ID indicates the crash did *not* occur on a curve; the Highway Curves GIS layer shows the crash was on a highway curve.

- **Type 3 Misclassification:** Curve Type ID indicates the crash occurred on a curve, *but* Road Align ID indicates the crash did *not* occur on a curve; the Highway Curves GIS layer shows the crash was on a straight segment.
- **Type 4 Misclassification:** Curve Type ID indicates the crash did *not* occur on a curve, *but* Road Align ID indicates the crash occurred on a curve; the Highway Curves GIS layer shows the crash was on a highway curve.
- **Type 5 Misclassification:** Curve Type ID indicates the crash did *not* occur on a curve, *but* Road Align ID states the crash occurred on a curve; the Highway Curves GIS layer shows the crash was on a straight segment.
- **Type 6 Misclassification:** Both Curve Type ID and Road Align ID indicate the crash did *not* occur on a curve, *but* the Highway Curves GIS layer shows the crash was on a highway curve.

The six types of curve-related misclassifications are also summarized in Table 5-3.

Type of	Cu	rve-Related A	Highway Curves GIS Layer			
Misclassifications	Curve	Curve Type ID Road Align ID				
	On Curve	Not Curve	On Curve	Not Curve	On Curve	Not Curve
Type 1	✓		~			✓
Type 2	✓			✓	✓	
Type 3	✓			~		✓
Type 4		✓	~		✓	
Type 5		~	~			✓
Туре б		~		✓	✓	

 Table 5-3. Six Types of Curve-related Crash Misclassification in CRIS

As illustrated in Table 5-3, the identification of curve-related crash misclassification is primarily based on the comparison among information presented by Curve Type ID, Road Align ID, and the Highway Curves GIS layer. Any inconsistency among these data sources would result in a certain type of curve-related crash misclassification in CRIS.

A decision tree was developed by the research team to illustrate the procedure for identifying curve-related crash misclassification, as shown in Figure 5-4.

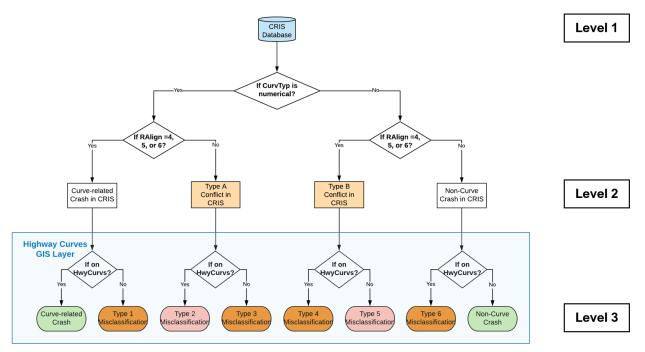


Figure 5-4. Tree Chart for Six Types of Curve-Related Crash Misclassification in CRIS

The two green boxes at Level 3 represent crash data with consistent curve-related information between the Highway Curves GIS layer and the CRIS dataset. The burnt orange boxes represent four types (i.e., Type 1, Type 3, Type 4, and Type 6) of curve-related crash misclassifications. Type 1 and Type 6 are caused by inconsistency between the Highway Curves GIS layer and the CRIS dataset, but Curve Type ID and Road Align ID are consistent. Type 3 and Type 4 are caused by inconsistency between the Highway Curves GIS layer and the CRIS dataset. These four types of misclassifications are highlighted using the same color because they all reflect a conflict between the Highway Curves GIS layer and the *Curve Type ID* attribute, which is identified as the primary curve indicator of the CRIS dataset in this project. The two pink boxes present two types (i.e., Type 2 and Type 5) of curve-related crash misclassifications caused by inconsistency between the Highway Curves GIS layer and the *Road Align ID* attribute in the CRIS dataset.

# 5.4 Data Analysis

With the six misclassification types well defined, the distribution of crashes in CRIS (from 2017 to 2019) are presented in Table 5-4 and Figure 5-5 to Figure 5-8.

Crash Type	2019	2018	2017	Average
Curve-related	0.4%	0.4%	0.4%	0.4%
Non-curve	72.9%	72.6%	72.4%	72.6%
Type 1 Misclassification	2.6%	2.7%	2.7%	2.7%
Type 2 Misclassification	1.4%	1.4%	1.5%	1.5%
Type 3 Misclassification	15.8%	15.8%	16.0%	15.9%
Type 4 Misclassification	0.3%	0.4%	0.4%	0.4%
Type 5 Misclassification	4.9%	5.1%	5.0%	5.0%
Type 6 Misclassification	1.6%	1.6%	1.5%	1.5%

Table 5-4. Percentage of Crashes by Type

2019 PERCENTAGE OF CRASHES BY TYPE

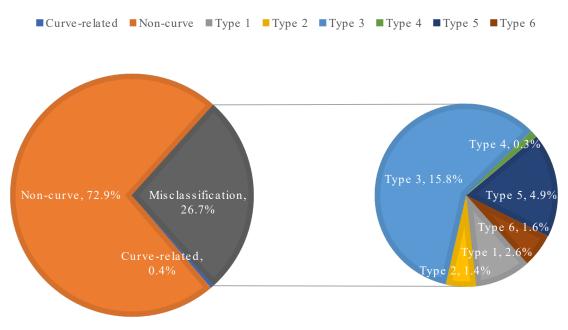


Figure 5-5. Crashes by Curve Relationship and Crash Misclassifications by Type in CRIS 2019

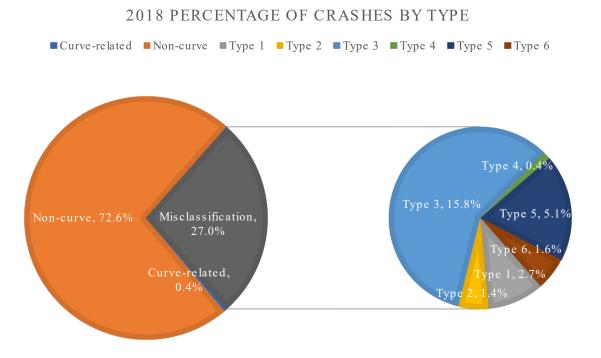


Figure 5-6. Crashes by Curve Relationship and Crash Misclassifications by Type in CRIS 2018

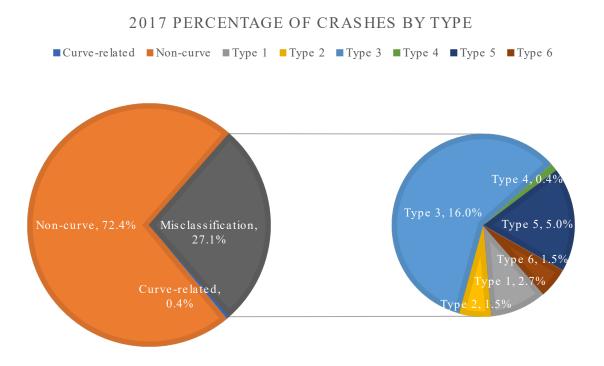
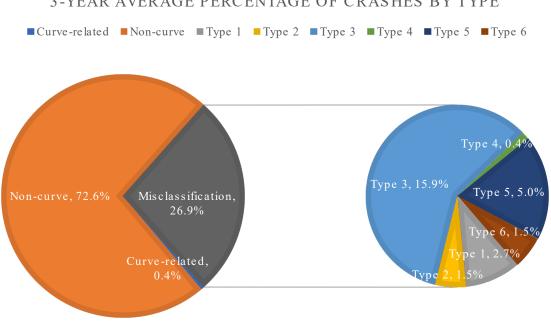


Figure 5-7. Crashes by Curve Relationship and Crash Misclassifications by Type in CRIS 2017



**3-YEAR AVERAGE PERCENTAGE OF CRASHES BY TYPE** 

Figure 5-8. Average of Crashes by Curve Relationship and Crash Misclassifications by Type from 2017 to 2019

Comparing the Highway Curves GIS layer with the curve-related information in the CRIS dataset (i.e., Curve Type ID and Road Align ID), the research team found that approximately 73 percent of crashes in the customized CRIS dataset had consistent curve-related information with the Highway Curves GIS layer. Specifically, curve identifiers from both datasets indicate that about 72.6 percent of crashes are non-curve crashes while around 0.4 percent occur on a curved segment. In contrast, about 27 percent of crash records have inconsistent curve information between the CRIS data and the Highway Curves GIS layer. These 27 percent of crash records are defined as curve-related crash misclassifications and categorized into six types. As Figure 5-5 to Figure 5-8 demonstrate, Type 3 Misclassification is the primary component of the curve-related crash misclassification, accounting for around 15.9 percent of all the crash records. The next-mostcommon misclassification is Type 5, which shows up in approximately 5 percent of all crashes, followed by Type 1 (about 2.7 percent), Type 6 (about 1.5 percent), and Type 2 (about 1.5 percent). Type 4 Misclassification occurs least frequently, in only about 0.4 percent of crashes.

### 5.5 Summary

This chapter documents the procedure used for and key findings from analyzing the integrated roadway geometry dataset (i.e., the Highway Curves GIS layer) and the customized CRIS dataset. Section 5.2 provides a brief review of the identification of the integrated roadway geometry dataset and the development of the customized CRIS dataset. Section 5.3 presents the procedure used for data integration, which starts with investigating a proper search distance for creating buffer zones around highway curves in the Highway Curves GIS layer. The research team tested different search distances from 1 foot to 500 feet to determine the optimal search distance, based on the consistency rate between the Highway Curves GIS layer and the customized CRIS dataset and the crash oncurve rate. The optimal search distance was determined to be 1 foot, as it resulted in the highest data consistency rate between the two data sources. The research team then compared the curve information in the customized CRIS dataset with the Highway Curves GIS layer, and discrepancies were categorized into six types of curve-related crash misclassifications. Section 5.4 provides a data analysis of the distributions of curve-related crash misclassifications. The research team found that approximately 27 percent of crashes were misclassified in terms of whether they were curve related. Statistics from 2017 to 2019 show that Type 3 is the most common curve-related crash misclassification in CRIS, occurring in about 15.9 percent of all crashes, followed by Type 5 (about 5 percent), Type 1 (about 2.7 percent), Type 6 (about 1.5 percent), Type 2 (about 1.5 percent), and Type 4 (about 0.4 percent).

# **Chapter 6. Develop a Methodological Procedure for Improved Identification of Curve-related Crashes and Curve Characteristics**

# 6.1 Introduction

This chapter documents the development of the automated methodological procedure for improved identification of curve-related crashes and curve characteristics in CRIS.

In Task 6, the CTR research team developed a methodological procedure based on ArcGIS API for Python to automatically identify curve-related crash misclassifications. Particularly, the Python programming language was utilized in CRIS data cleaning and preparation, which included splitting large CRIS data files into a manageable size, removing invalid crash records with missing location information or that did not occur on on-system roads, removing attributes that are irrelevant to curve-related crash misclassification, and categorizing crash data into subsets based on curve-related attributes in CRIS. After the data preprocessing, the CTR research team employed ArcGIS API for Python to automatically create crash layers in ArcGIS Pro using the customized CRIS datasets. Based on the curve information in the Highway Curves GIS layer, the automated procedure can calculate the number of crashes that belong to each type of curve-related misclassification. Later, CRIS 2019 data was used to test the performance of the proposed automated methodological procedure. The outcomes derived from the automated procedure are identical to the results of the manual process performed in Task 5. Finally, the automated procedure was applied to CRIS 2020 data to examine the impact of the COVID-19 pandemic on the patterns and characteristics of curve-related crash misclassifications.

# 6.2 Background and Methodology

Previously, in Task 5, the CTR research team performed a comprehensive data analysis to investigate the patterns and characteristics of curve-related crash misclassifications in the CRIS database. The data integration in Task 5 was completed manually using ArcGIS Pro. For a large-scale project with a significant amount of data to be analyzed, however, it would be a time-consuming process. To improve the efficiency of the proposed method, Task 6 aimed to develop a user-friendly tool that can automatically implement the procedure for identifying curve-related crash misclassifications. This section presents an overview of the background and methodology for the automated procedure for improved identification of curve-related crashes and curve characteristics.

# 6.2.1 Python

Python is one of the most popular programming languages and is widely used in data science, machine learning, artificial intelligence, software applications, and image processing, among other uses. As one of the fastest-growing languages, it provides users with powerful tools (e.g., libraries and packages) that can help developers focus on problems of interest. Also, Python is an open-

source programming language that is free to use and distribute. Broadly speaking, the benefits of programming in Python include but are not limited to (GeeksforGeeks, 2021):

- presence of third-party modules
- extensive support libraries
- open source and community development
- easy to read, learn, and write
- user-friendly data structures
- object-oriented language
- portability

Due to its versatility and extensibility, Python has served as the primary language for automation in ArcGIS Pro (ESRI, 2022a). The existence of many preexisting packages in Python significantly facilitates the efficiency of programming in the ArcGIS community.

## 6.2.2 ArcGIS API for Python

API, the acronym for application programming interface, refers to a software intermediary allowing communications between two applications. ArcGIS API for Python is a Python library developed for performing GIS visualization and analysis, spatial data management, and GIS system administration tasks (ESRI, 2022b, 2022c). It provides an easy-to-use method for users and developers to automate their workflows and minimize repetitive tasks.

The ArcGIS API for Python is distributed as a Python package, named "*arcgis*." The package encompasses a considerable number of useful functions that are systematically categorized into various modules, as illustrated in Figure 6-1, based on their specialized aspects (ESRI, 2022d).

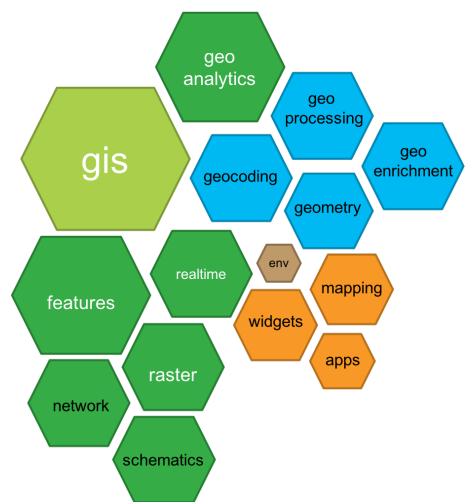


Figure 6-1. Various Modules Present in the ArcGIS API for Python [Source: ESRI, 2022d]

## 6.2.3 ArcPy

In addition to ArcGIS API for Python, the other ArcGIS Python library is ArcPy. ArcPy is a Python site package that provides productive tools (e.g., modules, functions, and classes) to manage geographic data, perform spatial analytics, build spatial machine learning models, and automate maps with Python (ESRI, 2022e, 2022f, 2022g, 2022h). ArcPy makes it easier for users to develop customized programs that make full use of geographic data. With ArcPy and other Python tools, users can access a great number of ready-to-use Python modules developed by GIS professionals and programmers from multiple fields (ESRI, 2022e).

### 6.2.4 Notebooks in ArcGIS Pro

ArcGIS Notebooks are built-in Python notebooks that provide users with a convenient real-time environment to manage (e.g., create, edit, and save) their Python codes. ArcGIS Notebooks are derived from and supported by the Jupyter Notebook, which is an open-source, web-based interactive computational environment for creating Python notebooks (Jupyter, 2022). These documents are comprised of explanatory text, mathematics, computations, and output in a variety of formats (Jupyter, 2022).

By integrating ArcGIS Notebooks, ArcGIS Pro allows users to access GIS map content, conduct real-time data analysis, and obtain instant results that can be visualized in a geographic context (ESRI, 2022i). ArcGIS Notebooks provide an efficient approach that can significantly relieve users of the burden of repetitive operations by automatically executing the workflow. In addition, ArcGIS Notebooks can be saved and shared within a project team, thus boosting the efficiency of collaborations and communications (Gimmler and Kalisky, 2020). Other usages of ArcGIS Notebooks include data cleaning, numerical simulation, statistical modeling, and machine learning, among others (ESRI, 2022i).

# 6.3 Implementation

In order to automatically implement the procedure for curve-related crash identification, the CTR research team first performed data cleaning and generated customized CRIS datasets using Python programming language via Jupyter Notebook. After the data preparation, the customized CRIS datasets were automatically imported into ArcGIS Pro for further visualization and analysis using Python libraries including ArcGIS API for Python and ArcPy. To evaluate the accuracy of the automated methodological procedure, its results were compared to the results of the manual process performed in Task 5 using CRIS 2019 data. The CTR research team observed that the two sets of results were identical. This section provides detailed information on the implementation of the automated methodological procedure for identifying curve-related crashes. Figure 6-2 presents the framework of the automated methodological procedure.

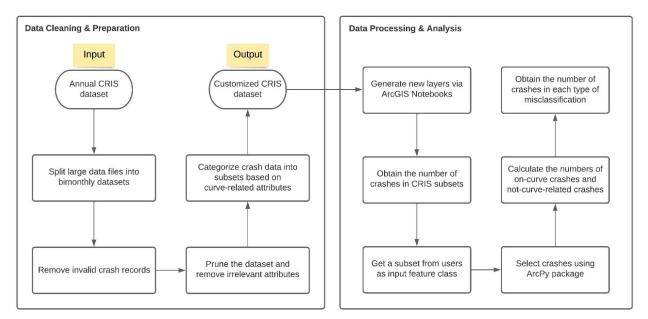


Figure 6-2. Implementation of the Automated Methodological Procedure for Identifying Curve-Related Crashes

### 6.3.1 Data Cleaning and Preparation

Data cleaning and preparation were completed via Jupyter Notebook, an open-source web application used to manage Python code. The activities included in data cleaning and preparation in this phase are listed below:

- Split large data files into a manageable size (i.e., bimonthly datasets).
- Remove invalid crash records (e.g., crashes missing location information or that are not on on-system roads).
- Prune the dataset and retrieve attributes that are relevant to curve-related crash misclassifications.
- Categorize crash data into subsets based on curve-related attributes.

To improve the efficiency of data processing, each of the annual datasets was first split into 6 bimonthly datasets, as shown in Figure 6-3.

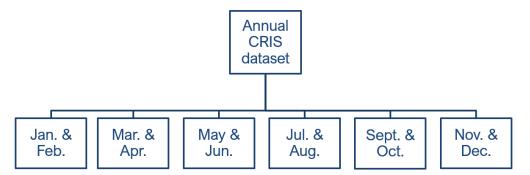


Figure 6-3. Large Annual Crash Data File Split into Bimonthly Datasets

After splitting the data into smaller datasets, each of the bimonthly datasets was disassembled into four subsets based on curve information provided by Curve Type ID and Road Align ID, as shown in Figure 6-4.

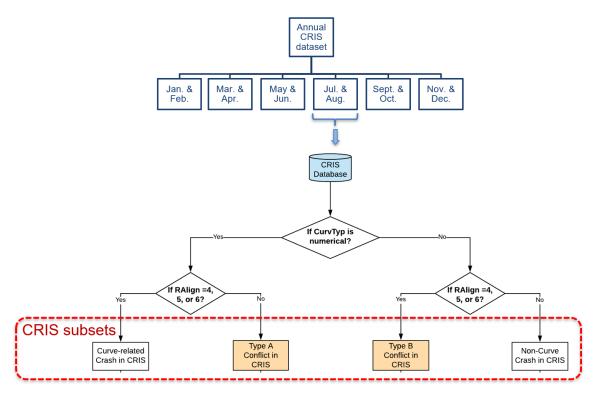


Figure 6-4. CRIS Data Subsets Based on Curve Type and Road Alignment

All the aforementioned data processing activities were completed in Jupyter Notebook. The final outputs from this phase of the analysis were automatically saved as plain text files in the format of comma separated values (CSV). For each annual dataset, as shown in Figure 6-5, there were 24 (six bimonthly datasets \* four CRIS subsets) bimonthly subsets that formed the customized CRIS dataset. The customized CRIS dataset was then used as input for the data analysis in ArcGIS Pro.

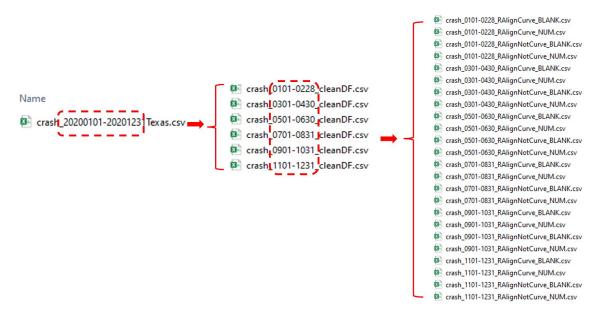


Figure 6-5. Large Annual Crash Data File Split into 24 Bimonthly Subsets

### 6.3.2 Data Processing and Analysis

After preparing the data, the CTR research team performed a comprehensive data processing and analysis in ArcGIS Pro using the customized CRIS data as inputs. In this phase, leveraging Python programming language and ArcGIS Python libraries, the CTR research team accomplished the automation of two major tasks—visualization of the customized CRIS data in ArcGIS Pro and verification of curve-related crash classification using the Highway Curves GIS layer as a reference. A step-by-step workflow of the automated procedure is summarized as follows:

- Step 1 Generate new layers via ArcGIS Notebooks using the customized bimonthly CRIS datasets. In this activity, the Python code first loads a bimonthly dataset (e.g., 11/01–12/31 from CRIS 2019) into ArcGIS Pro. For each bimonthly dataset, the imported data includes four subsets that are classified based on curve-related attributes (i.e., Curve Type ID and Road Align ID). For each of these subsets, the code will automatically create a new layer to visualize the crashes on the Highway Curves GIS map.
- Step 2 Compute the number of crashes in each of the four CRIS subsets.
- Step 3 Obtain one CRIS subset as the input feature class for the next step.
- Step 4 Select crashes using the Layers and Table Views toolset provided by the ArcPy package. Parameters defined in this step include input features, selecting features, relationship between selected features, search distance (set at 1 foot in this task), selection type, etc.
- Step 5 Calculate the number of on-curve crashes based on the predefined relationship between the selected crash layer and the Highway Curves GIS layer.
- Step 6 Compute the number of crashes that are not curve-related using the outputs from Step 2 and Step 5.
- Step 7 Check if all four CRIS subsets have been completed. If yes, go to Step 8; otherwise, go back to Step 3.
- Step 8 Obtain the number of crashes in each classification category, as illustrated in Figure 6-6.

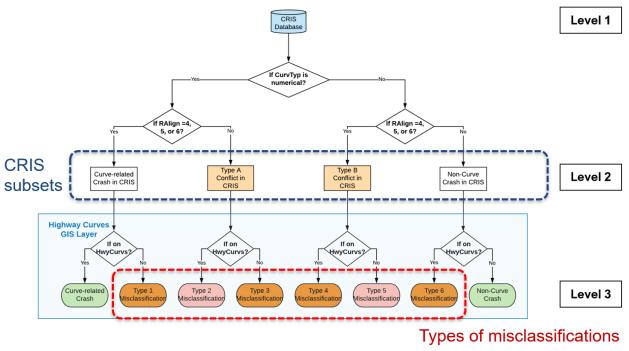


Figure 6-6. Tree Chart for Six Types of Curve-Related Crash Misclassification in CRIS

Finally, CRIS 2019 data was used to test the performance of the proposed automated methodological procedure. The outcomes derived from the automated procedure are identical to the results of the manual process performed in Task 5. This confirmed the effectiveness of the automated methodological procedure.

## 6.4 Data Analysis

The automated procedure was applied to CRIS 2020 data to investigate the patterns and characteristics of curve-related crash misclassification during the COVID-19 pandemic. With the six misclassification types well defined, the distribution of crashes in CRIS from 2017 to 2020 is presented in Table 6-1. In addition to the table, Figure 6-7 and Figure 6-8 present the crash distribution pie charts for 2020 and the average of 2017–2019, respectively.

Crash Type	2017	2018	2019	3-yr average (2017– 2019)	2020	Difference between 2020 and 3- yr average	Percentage of the difference
Curve Related	0.42%	0.40%	0.41%	0.41%	0.48%	0.07%	17.19%
Non-curve	72.43%	72.63%	72.87%	72.64%	72.16%	-0.48%	-0.66%
Type 1 Misclassification	2.73%	2.72%	2.64%	2.70%	2.93%	0.23%	8.66%
Type 2 Misclassification	1.52%	1.43%	1.44%	1.46%	1.50%	0.04%	2.55%
Type 3 Misclassification	16.04%	15.76%	15.77%	15.86%	15.56%	-0.30%	-1.87%
Type 4 Misclassification	0.37%	0.36%	0.34%	0.36%	0.37%	0.01%	2.30%
Type 5 Misclassification	5.02%	5.12%	4.94%	5.03%	5.37%	0.34%	6.76%
Type 6 Misclassification	1.46%	1.58%	1.60%	1.55%	1.63%	0.09%	5.76%

Table 6-1. Percentage of Crashes by Type

#### 2020 PERCENTAGE OF CRASHES BY TYPE

■Curve-related ■Non-curve ■Type 1 ■Type 2 ■Type 3 ■Type 4 ■Type 5 ■Type 6

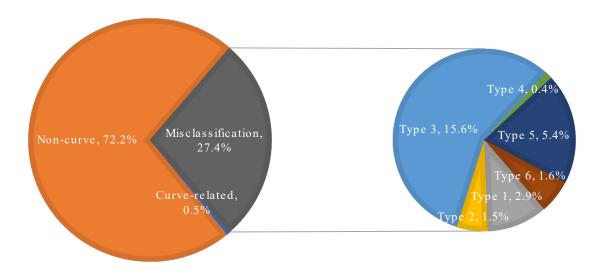


Figure 6-7. Crashes by Curve Relationship and Crash Misclassifications by Type in CRIS 2020

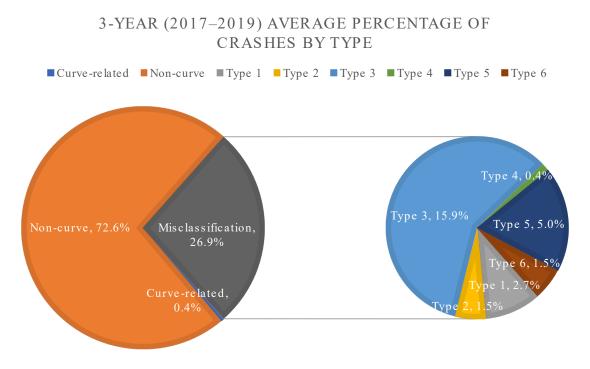


Figure 6-8. Average of Crashes by Curve Relationship and Crash Misclassifications by Type from 2017 to 2019

Comparing the Highway Curves GIS layer with the curve-related information in the CRIS 2020 dataset, the CTR research team observed that approximately 72.7 percent of crashes in the customized 2020 CRIS dataset had curve-related information consistent with the Highway Curves GIS layer. This number is slightly less than the three-year average obtained from CRIS 2017–2019 (i.e., around 73 percent). Within the consistent data, about 72.2 percent of crashes are non-curve crashes while around 0.5 percent occurred on a curved segment.

In contrast, about 27.4 percent of crash records are inconsistent with the information in the Highway Curves GIS layer, which is also slightly higher than the three-year average of CRIS 2017–2019. Due to the inconsistency, these 27.4 percent of crash records are defined as curve-related crash misclassifications and categorized into six types. For these curve-related crash misclassifications, it can be observed from Figure 6-7 and Figure 6-8 that Type 3 Misclassification is the most common, accounting for around 15.6 percent of all crash records. The next misclassification type in frequency is Type 5, which was the case for approximately 5.4 percent of all crashes, followed by Type 1 (about 2.9 percent), Type 6 (about 1.6 percent), and Type 2 (about 1.5 percent). Type 4 Misclassification has the smallest percentage, accounting for only about 0.4 percent.

Compared to the previous years (2017–2019), the percentages of Type 1 and Type 5 misclassifications slightly increased in CRIS 2020. In contrast, Type 3 misclassifications decreased slightly. However, these slight differences in various percentage values should be

statistically insignificant. Therefore, the CTR research team concluded that the crash distribution in CRIS 2020 shows a similar trend to what has been observed from CRIS 2017–2019.

# 6.5 Summary

This chapter documents the procedure used for and key findings from developing the automated methodological procedure for improved identification of curve-related crashes and curve characteristics.

Section 6.2 provides a brief overview of the background and methodology for developing the automated procedure for improved identification of curve-related crashes and curve characteristics. The programming language and support tools used to accomplish the task are introduced here.

Section 6.3 presents the framework and implementation of the automated methodological procedure for identifying curve-related crashes. The implementation consisted of two phases, 1) data cleaning and preparation, and 2) data processing and analysis. A step-by-step workflow of the automated procedure is summarized in this section.

The automated procedure was then applied to CRIS 2020 data to investigate the patterns and characteristics of curve-related crash misclassification during the COVID-19 pandemic. Section 6.4 documents the data analysis of the distributions of curve-related crash misclassifications in CRIS 2020. Based on the comparison between crashes that occurred before and during the COVID-19 pandemic, the CTR research team concludes that crash and misclassification distributions in the CRIS 2020 data do not show any significant shift from the trends derived from the CRIS 2017–2019 data.

# Chapter 7. Evaluate the Performance of the Developed Methodological Procedure

# 7.1 Introduction

This chapter documents the general procedure for and key findings from evaluating the automated methodological procedure for improved identification of curve-related crashes and curve characteristics.

In Task 6, the CTR research team developed a methodological procedure based on ArcGIS API for Python to automatically identify curve-related crash misclassification. Task 7 aimed to evaluate the performance of the automated methodological procedure for identifying curve-related crash misclassifications. First, the Highway Curves GIS layer used in the data analysis was updated to the latest version published by TxDOT's Transportation Planning and Programming (TPP) Division. Based on this update, the CTR research team investigated the optimal buffer zone setting (i.e., search distance) to maximize the data consistency rates between the new Highway Curves GIS layer and CRIS database. Under the optimal buffer zone setting, the research team computed the number of crashes belonging to each type of the six curve-related crash misclassifications. The outcomes of the data analysis are summarized in this chapter.

# 7.2 Performance Evaluation

Previously, in Task 5, the CTR research team developed a methodological procedure that can improve the identification of curve-related crash misclassification in the CRIS database. Following the procedure, the team performed a comprehensive data analysis to investigate the patterns and characteristics of curve-related crash misclassification in the CRIS database. The data integration in Task 5 was completed manually using ArcGIS Pro. However, this can become a tedious process for a large-scale project with a large set of data to be analyzed. To address this problem, Task 6 employed ArcGIS Python libraries to develop a user-friendly tool that can automatically implement the procedure for identifying curve-related crash misclassification in the CRIS database, which significantly improves efficiency.

In order to evaluate the automated procedure's performance, the CTR research team undertook the following major activities in Task 7:

- Updated the Highway Curves GIS layer to the latest version.
- Explored the optimal buffer zone setting based on the new Highway Curves GIS layer.
- Computed distributions of crashes in CRIS 2017–2020 under the optimal search distance.

#### 7.2.1 Update the Highway Curves GIS Layer to the Latest Version

In Task 3, the CTR research team performed a comprehensive investigation of available data sources that contain reliable roadway geometry and inventory information maintained by TxDOT. The data sources include the Geometrics (Geo-HINI) database, GRID, and the Highway Curves GIS layer (available at <u>http://arcg.is/1SPG8i</u>). In addition to identifying the most reliable and accurate data source for roadway geometry and inventory, CTR also examined curve-related attributes that can provide information to assist with the identification of curve-related crashes in the CRIS database. Based on a thorough examination, the research team concluded that the Highway Curves GIS layer can serve as a reliable data source that encompasses both roadway geometric data and horizontal curve information. Therefore, the Highway Curves GIS layer, as shown in Figure 7-1, was used as the integrated roadway geometry dataset for verifying curve-related information in Task 5 and Task 6.

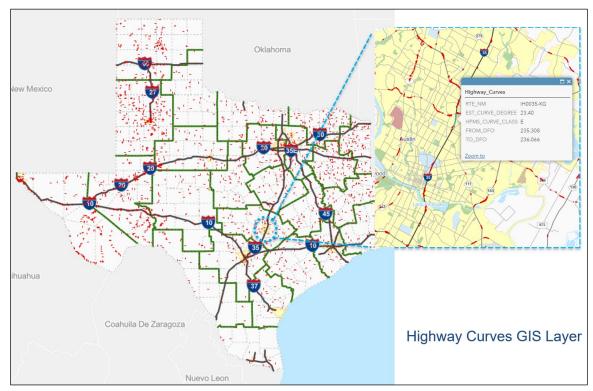


Figure 7-1. Screenshot of Texas Highway Curves GIS Layer

As illustrated in Figure 7-2, the TPP Division published a new version of the Highway Curves GIS layer on July 22, 2021. The CTR research team noticed this update shortly after it was released, while working on developing the automated methodological procedure (Task 6). In order to keep the project findings consistent with the latest Highway Curves GIS layer, the team decided to incorporate this update into Task 7.

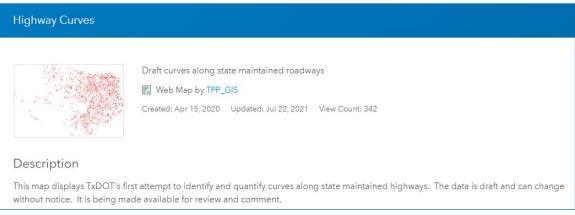


Figure 7-2. Screenshot of the Updated Version of Texas Highway Curves GIS Layer

# 7.2.2 Explore the Optimal Buffer Zone Setting Based on the New Highway Curves GIS Layer

Before implementing the automated methodological procedure for identifying curve-related crash misclassification, the CTR research team performed a data examination of the new Highway Curves GIS layer. Based on the results, the research team noticed that the curve segments on the Highway Curves GIS layer have a small offset from roadways on the base map, as shown in Figure 7-3. The displacement of such offsets varies from one segment to another. Likewise, a considerable number of crash points are not exactly located on roadway centerlines presented in the new Highway Curves GIS layer, as demonstrated in Figure 7-4. The CTR research team discussed this issue with the Project Management Team, who confirmed that the roadway centerlines change frequently due to daily maintenance. Thus, such offsets are inevitable.

Due to these offsets, however, only a very small portion of the crashes that occurred on a curve can be detected successfully when the search distance around a curve is set to be zero. To address this issue, a buffer zone was created around each curve in the integrated ArcGIS file, providing a transverse extension of the curve so that crashes falling within the buffer zone can be detected and regarded as crashes on the curve.

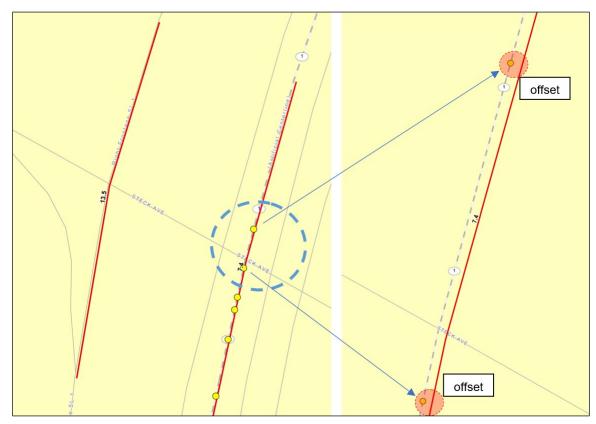


Figure 7-3. An Example of the Offset between Highway Curves and Roadway Centerlines in the Highway Curves GIS Layer

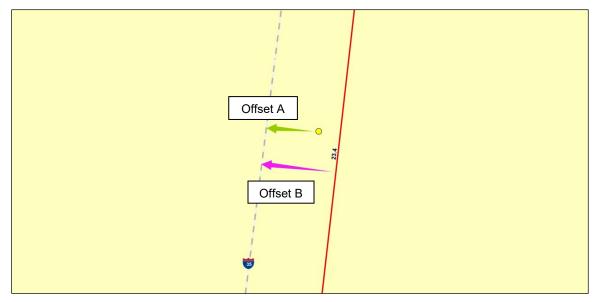


Figure 7-4. An Example of the Offset between CRIS Crash Points and Roadway Centerlines in the Highway Curves GIS Layer (Offset A: distance between the crash point and roadway centerline; Offset B: distance between the curve and roadway centerline)

Based on the analysis performed in Task 5, the optimal search distance identified between the Highway Curves GIS layer and the CRIS dataset was 1 foot, as this distance resulted in the highest data consistency rates between the two datasets (consistency rate is an indicator that presents how many crashes have consistent curve-related information between the Highway Curves GIS layer and the CRIS dataset). In this task, CRIS 2019 was selected to explore the new optimal search distance. In addition, CRIS 2020 data was used to verify the result from CRIS 2019.

To identify the optimal search distance for the new Highway Curves GIS layer, the CTR research team tested the search distance from 1 foot to 12 feet with intermediate values (i.e., 1, 2, 4, 8, and 12 feet). The consistency rates calculated under each of the tested search distances are presented in Figure 7-5.



Figure 7-5. Consistency Rates between Highway Curves GIS Layer and CRIS Data under Different Search Distances

The results presented in Figure 7-5 confirm that the optimal search distance between the new Highway Curves GIS layer and the CRIS dataset remains 1 foot, as this distance resulted in the highest data consistency rates between the two datasets. The consistency rate for both datasets (CRIS 2019 and 2020) decrease as the search distance increases.

# 7.2.3 Compute Distribution of Crashes in CRIS 2017–2020 Using the Optimal Search Distance

In Task 6, the CTR research team conducted a comparison study between crashes that occurred before and during the COVID-19 pandemic. Based on the results, they concluded that crash distribution in the CRIS 2020 data does not show any significant shift from the trend derived from the CRIS 2017–2019 data. Therefore, the CRIS 2020 data was included in the Task 7 analysis along with CRIS 2017–2019 data.

Using the optimal buffer zone setting identified in the previous section, the CTR research team calculated the percentage of crashes belonging to each type of curve-related crash misclassification. The results from the computation are presented in Table 7-1 and Figure 7-6 to Figure 7-10.

Crash Type	2017	2018	2019	2020	4-yr average
Total on-system crashes	291,555	292,998	292,577	259,421	284,138
Curve-related (correctly classified)	0.42%	0.40%	0.41%	0.48%	0.43%
Non-curve (correctly classified)	72.30%	72.63%	72.87%	72.16%	72.49%
Type 1 Misclassification	2.75%	2.72%	2.64%	2.93%	2.76%
Type 2 Misclassification	1.52%	1.43%	1.44%	1.50%	1.47%
Type 3 Misclassification	16.02%	15.76%	15.77%	15.56%	15.78%
Type 4 Misclassification	0.37%	0.36%	0.34%	0.37%	0.36%
Type 5 Misclassification	5.04%	5.12%	4.94%	5.37%	5.12%
Type 6 Misclassification	1.59%	1.58%	1.60%	1.63%	1.60%

 Table 7-1. Percentage of Crashes by Type

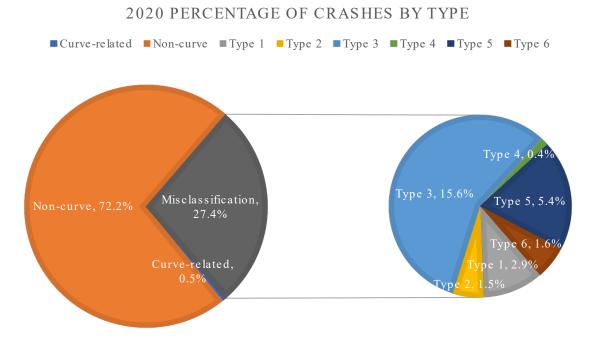


Figure 7-6. Crashes by Curve Relationship and Crash Misclassifications by Type in CRIS 2020

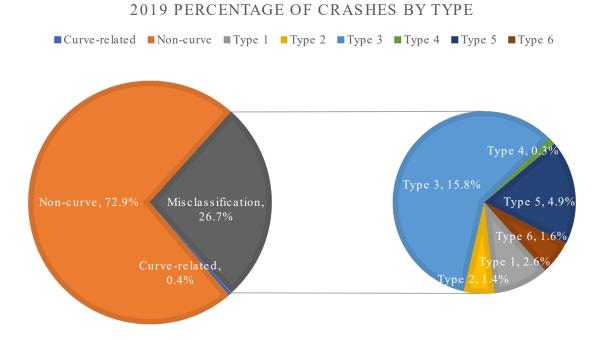


Figure 7-7. Crashes by Curve Relationship and Crash Misclassifications by Type in CRIS 2019

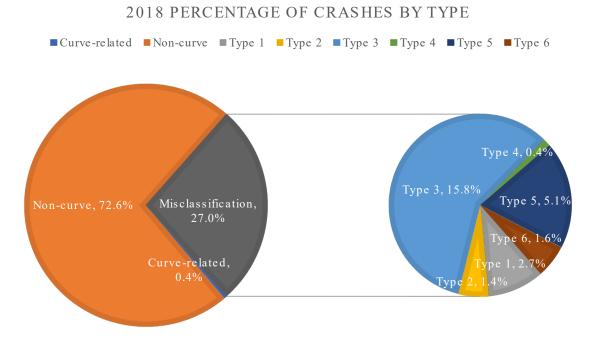


Figure 7-8. Crashes by Curve Relationship and Crash Misclassifications by Type in CRIS 2018

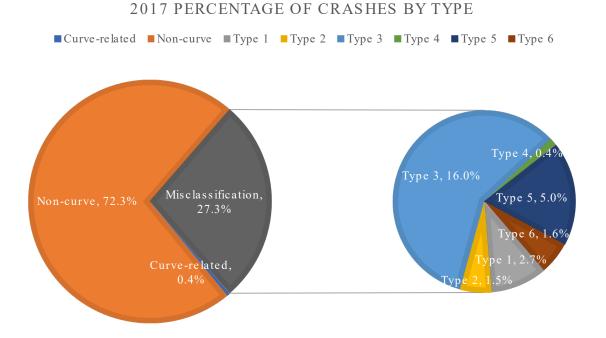


Figure 7-9. Crashes by Curve Relationship and Crash Misclassifications by Type in CRIS 2017

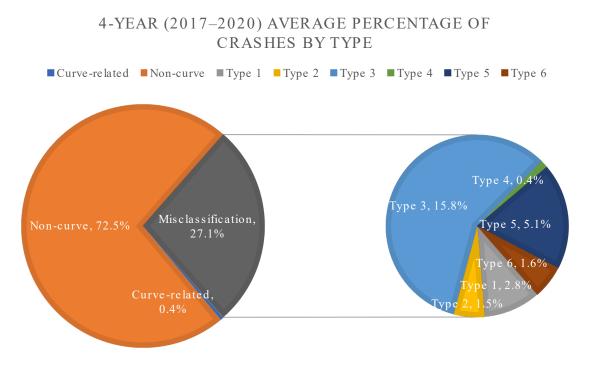


Figure 7-10. Average of Crashes by Curve Relationship and Crash Misclassifications by Type from 2017 to 2020

As demonstrated in Figure 7-6 to Figure 7-9, the percentages of crashes by misclassification type in all four years are quite consistent. The four-year average data is shown in Figure 7-10. According to the curve-related information from the new Highway Curves GIS layer, approximately 72.9 percent of crashes in the CRIS dataset had curve-related information consistent with the new Highway Curves GIS layer. Specifically, curve identifiers from both datasets indicate that about 72.5 percent of crashes are non-curve crashes while around 0.4 percent occur on a curved segment. In contrast, about 27.1 percent of crash records are inconsistent with the information in the Highway Curves GIS layer. These 27.1 percent of crash records are defined as curve-related crash misclassifications and categorized into six types. Of these, Type 3 Misclassification is the most common, accounting for around 15.8 percent of all the crash records. The next most common is Type 5, which includes approximately 5.1 percent of all crashes, followed by Type 1 (about 2.8 percent), Type 6 (about 1.6 percent), and Type 2 (about 1.5 percent). Type 4 Misclassification is the most infrequent, occurring for only about 0.4 percent of crashes.

## 7.3 Summary

This chapter documents the procedure used for and key findings from evaluating the performance of the automated methodological procedure for identifying curve-related crash misclassification. In Task 7, after updating the Highway Curves GIS layer to the latest version, the research team re-investigated the optimal buffer zone setting, using zones ranging from 1 foot to 12 feet. The optimal buffer zone setting remains 1 foot, as identified in Task 5. Under the optimal buffer zone setting, the research team computed the percentage of crashes belonging to each type of curve-

related crash misclassification for CRIS 2017–2020 data. The data analysis showed that the fouryear average percentage of curve-related crash misclassification was approximately 27.1 percent. Type 3 Misclassification is the dominant curve-related crash misclassification in CRIS, comprising around 15.8 percent of all crashes, followed by Type 5 (about 5.1 percent), Type 1 (about 2.8 percent), Type 6 (about 1.6 percent), Type 2 (about 1.5 percent), and Type 4 (about 0.4 percent).

# Chapter 8. Identify and Analyze Misclassified Curve-Related Crashes

## 8.1 Introduction

The primary goal of this project is to conduct a systematic study on improving the identification of curve-related crashes in CRIS. This chapter documents the major findings from analyzing CRIS curve-related crash data to diagnose possible reasons for misclassifications.

In previous tasks (Tasks 5–7), a methodological procedure that integrated crash data from CRIS with the Highway Curves GIS layer to improve the identification of curve-related crashes was developed and evaluated. Based on the results from the data analysis, curve-related crash misclassifications in CRIS were classified into six types.

In Task 8, to understand the reasons behind these curve-related crash misclassifications, the CTR research team analyzed data from Texas Peace Officer's Crash Reports (CR-3). The CR-3 report is a detailed crash investigation form that is completed by the law enforcement officer investigating a traffic crash when the damage exceeds \$1,000, or when the crash resulted in injury or death (TxDOT, 2022). These reports include field drawings and narrative notes from the police officers who conducted the on-site investigation into the crash. This information can provide meaningful insights into potential reasons why the crash was misclassified, but unfortunately, it is not captured in the CRIS database. Therefore, a careful review of these reports can offer additional valuable information about the circumstances leading up to the crash.

During this task, the misclassified crashes were systematically analyzed, and key findings from reviewing CR-3 crash reports were documented with graphs, tables, and detailed text descriptions. This chapter aims to provide a better understanding of curve-related crashes and of potential reasons for misclassifications in CRIS.

# 8.2 General Procedure

For its thorough investigation based on CR-3 crash reports, the CTR research team selected 60 cases across the state for detailed crash analysis (i.e., for each type of misclassification, 10 crashes were selected randomly). These crashes were selected through a manual searching approach; the research team first identified locations with particularly high crash rates (i.e., crash hotspots) and then randomly selected crashes that occurred in these locations. After that, CR-3 crash reports for the selected crashes were obtained and grouped by type of misclassification. As discussed in the previous section, CR-3 reports are detailed crash forms that contain a considerable number of data fields. Instead of reading every detail of each CR-3 report, the research team identified the most useful attributes for better understanding why crashes were misclassified in CRIS. Examples of such attributes are field diagrams (drawings that illustrate how the crash occurred) and the investigator's narrative opinion of what happened. Then, the CTR research team systematically examined the retrieved CR-3 reports to extract the information identified in the previous step.

Meanwhile, information derived from CR-3 crash reports was carefully compared with the curverelated attributes (i.e., Curve Type ID and Road Align ID) from the integrated GIS map developed in Task 7. Based on the results of the comparative study, the research team determined potential contributors to each curve-related crash misclassification. Finally, the team used the crash analyses to draw conclusions regarding causes for each type of misclassification.

## 8.3 Crash Analysis

This section presents the results and key findings from the crash analyses based on the CR-3 reports. As illustrated in Table 8-1 and Figure 8-1, ten crashes were analyzed for each type of misclassification, for a total of 60. Through the analysis, the CTR research team identified the following as the most useful information for providing insights into the nature of curve-related crash misclassification in CRIS: crash ID, location (i.e., latitude and longitude), type of misclassification, curve-related data (i.e., Curve Type ID, Road Align ID, and Highway Curves GIS), visualization on the integrated ArcGIS Map (i.e., the outcome from Task 7), field diagram, and investigator's narrative. This data has been collected for each selected crash and is presented here. The research team also presented the most likely contributor(s) to the misclassification for each selected case. In addition, other crash attributes that can provide useful information, such as the year, city, county, agency, crash severity, charges, contributing factors, and environmental and roadway conditions, were investigated and at times informed the suggested misclassification contributor(s). The most significant information gleaned from these analyses is presented in Appendix A. , which directly improves our understanding of why curve-related crashes may be misclassified in CRIS.

			5 51		
Type of Misclassifications			Crash IDs		
Type 1	17976521	18034581	18031933	17918194	17893599
	18037628	17135803	17267815	17083299	17086966
Type 2	17767876	17890088	17769219	17726770	17871870
	17710571	17463191	17450166	17168847	17188751
Type 3	17835845	17756585	17784399	17707386	17846929
	17766197	17186953	17184128	17422116	17850490
Type 4	17745564	17127370	17718659	17700930	17669897
	17043933	16870093	16866212	16911375	16844434
Type 5	17672411	17708260	17641420	17953850	17700680
	17686040	17417889	17410379	17410019	17118456
Type 6	17786334	17840508	17864020	17992011	17951640
	17048589	17011562	16930787	17184164	16948923

Table 8-1. List of Selected Crash IDs by Type of Misclassification

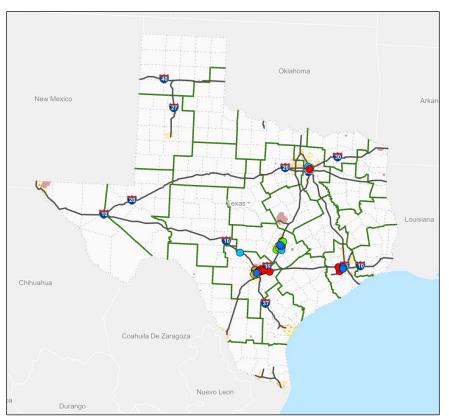


Figure 8-1. GIS Map of Selected Crashes

## 8.3.1 Analysis Results

After analyzing the 60 crash case studies, the CTR research team found that pinpointing the exact cause(s) behind each type of misclassification was almost impossible, but rational inferences could be made on the probable cause(s) based on available information. The summarized results and key findings for each type of curve-related crash misclassification are below.

### Type 1 misclassification

1. In eight out of ten cases, the field diagrams clearly show that the crash is on a curved segment, which is consistent with both CRIS Curve Type ID and Road Align ID. Many of them occurred on ramps or frontage roads, and the GIS layer may not be precise enough to accurately differentiate these from main lanes.

- 2. In the other two cases, the field diagrams do not contain any curves. However, both CRIS Curve Type ID and Road Align ID indicate the crash occurred on a curve. For these cases, the scale of the field diagram is too small to identify if the roadway segment is straight or curved.
- 3. Based on the ten cases, we conclude that Type 1 misclassification is mainly caused by inaccurate GPS coordinates that do not reflect the location where the crash actually occurred, as illustrated in Table 8-2.

Misclassification Contributor	Crash IDs
Inaccurate GPS coordinates	17976521, 18034581, 18031933, 17918194, 17893599, 18037628, 17135803, 17267815, 17083299, 17086966

Table 8-2. Summary	of Contributors to	Type 1 Misclassification
	01 00101040015 00	

### Type 2 misclassification

- 1. In nine out of ten cases, the field diagrams are consistent with Road Align IDs, supporting that the crash occurred on a non-curve road segment. In three of these cases, the field diagram shows the crash occurred at an intersection, when the vehicle was turning and traveling like on a curve segment.
- 2. In the other case, the field diagram conflicts with the Road Align ID. The police officer input the incorrect Road Align ID.
- 3. Six of the ten cases are derived from an incorrect Road Align ID, while four cases show that inaccurate GPS coordinates are another likely cause of Type 2 misclassifications.
- 4. Overall, Type 2 misclassifications are mainly caused by either an incorrect Road Align ID or inaccurate GPS coordinates that do not precisely reflect the location where the crash occurred, as presented in Table 8-3.

<b>Misclassification</b> Contributor	Crash IDs
Incorrect Road Align ID	17767876, 17890088, 17769219, 17726770, 17168847, 17188751
Inaccurate GPS coordinates	17871870, 17710571, 17463191, 17450166

 Table 8-3. Summary of Contributors to Type 2 Misclassification

### Type 3 misclassification

1. In eight out of ten cases, field diagrams do not contain any curves, which is consistent with Road Align IDs and the Highway Curves GIS layer, so the Curve Type IDs are very likely incorrect.

- 2. In the other two cases, the crash occurred at a location that is very close to a curved segment. However, the Highway Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the actual location where the crash occurred.
- 3. Overall, we conclude that Type 3 misclassifications are mainly caused by incorrect Curve Type IDs or inaccurate GPS coordinates that may not precisely reflect the location where the crash occurred, as shown in Table 8-4.

Misclassification Contributor	Crash IDs
Incorrect Curve Type ID	17835845, 17756585, 17784399, 17846929, 17186953, 17184128, 17422116, 17850490
Inaccurate GPS coordinates	17707386, 17766197

Table 8-4. Summary of Contributors to Type 3 Misclassification

### Type 4 misclassification

- In nine out of ten cases, field diagrams clearly show that the crash occurred on a curve segment, which is consistent with the Road Align ID and the Highway Curves GIS layer. For these cases, Curve Type IDs are very likely incorrect. One of these crashes occurred on a non-curve segment, but the location was very close to a curve segment. In this case, the misclassification was most likely caused by inaccurate GPS coordinates that do not precisely reflect the location where the crash occurred.
- 2. In the other case, the field diagram does not contain a curve, but its scale is too small to identify if the crash occurred on a curve. However, the Curve Type ID is likely incorrect.
- 3. Overall, Type 4 misclassifications are mainly caused by an incorrect Curve Type ID. Also, another possible contributor is inaccurate GPS coordinates that do not precisely reflect the location where the crash occurred. These causes are illustrated in Table 8-5.

Misclassification Contributor	Crash IDs
Incorrect Curve Type ID	17127370, 17718659, 17700930, 17669897, 17043933, 16870093, 16866212, 16911375, 16844434
Inaccurate GPS coordinates	17745564

Table 8-5. Summary of Contributors to Type 4 Misclassification

### Type 5 misclassification

1. In four out of ten cases, the field diagrams do not contain any curves. Hence, Road Align IDs might be incorrect. In two of these, the field diagrams show the crash occurred at an intersection when the vehicle was turning and changing directions, similar to traveling on

a curve segment. That might be the reason why the officer classified the Road Align IDs as on a curve.

- 2. In five out of ten cases, the field diagrams illustrate that the crash occurred on or near a ramp that contains a curved segment. However, the Highway Curves GIS layer only reflects centerlines. Hence, in these cases, GPS coordinates may not accurately reflect the location where the crash occurred.
- 3. In the tenth case, the field diagram supports the Road Align ID, which clearly shows the crash occurred on a curve. The location described in the narrative is consistent with the GPS coordinates. However, based on the GPS coordinates, no curve can be observed near this location on the GIS map. It is difficult to draw a conclusion based on available information.
- 4. Overall, Type 5 misclassifications are caused by either an incorrect Road Align ID or inaccurate GPS coordinates that do not precisely reflect the location where the crash occurred, as shown in Table 8-6.

Misclassification Contributor	Crash IDs
Incorrect Road Align ID	17708260, 17641420, 17686040, 17118456
Inaccurate GPS coordinates	17953850, 17700680, 17417889, 17410379, 17410019
Other (insufficient evidence)	17672411

Table 8-6. Summary of Contributors to Type 5 Misclassification

### Type 6 misclassification

- 1. In five out of ten cases, the field diagrams show that the crash did NOT occur on a horizontal curve. This is consistent with both the Curve Type ID and Road Align ID, which also indicates the crash occurred on a non-curve segment. However, the Highway Curves GIS layer clearly shows the crash location is on a curve. Based on the investigation, we conclude that in these cases GPS coordinates do not accurately reflect the location where the crash occurred.
- 2. In three out of ten cases, the field diagrams show that the crash occurred on a ramp. However, the Highway Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, in these cases, GPS coordinates may not accurately reflect the location where the crash occurred.
- 3. In one case, the field diagram clearly shows that the crash occurred on a curve. Thus, both Curve Type ID and Road Align ID are incorrect.

- 4. In the tenth case, the narrative indicates that the police officer was not able to mark the exact location where the crash occurred because both drivers involved made conflicting statements about the crash. Hence, it is difficult to draw a conclusion based on available information.
- 5. Overall, Type 6 misclassifications are mainly caused by inaccurate GPS coordinates that do not precisely reflect the location where the crash occurred. Other less common contributors could be that both Curve Type ID and Road Align ID are incorrect or that the original crash location information is unavailable. These causes are presented in Table 8-7.

Misclassification Contributor	Crash IDs
Inaccurate GPS coordinates	17786334, 17840508, 17864020, 17992011, 17011562, 16930787, 17184164, 16948923
Both Curve Type ID and Road Align ID are incorrect	17951640
Other (insufficient evidence)	17048589

Table 8-7. Summary of Contributors to Type 6 Misclassification

### 8.3.2 Discussion

Based on this analysis, Type 1 and Type 6 misclassifications are mainly caused by inaccurate GPS coordinates that do not precisely reflect the location where the crash occurred. Type 2 and Type 5 misclassifications are most likely caused by either incorrect Road Align IDs or inaccurate GPS coordinates. Type 3 and Type 4 misclassifications are mainly caused by incorrect Curve Type IDs or inaccurate GPS coordinates.

The data indicates that inaccurate GPS coordinates are the primary contributor to curve-related crash misclassifications in CRIS. Since the team used the GPS coordinates from the CRIS database to locate a crash on the Highway Curves GIS layer and determine the road alignment at that location, if the coordinates do not reflect the actual location where the crash occurred, it is impossible to verify whether the crash is curve-related on the Highway Curves GIS layer.

Meanwhile, one should be aware of the challenge and difficulty in practice to obtain accurate GPS coordinates of the original crash location. As some of the case studies indicate, due to traffic and safety considerations vehicles sometimes must be moved from the road and police officers cannot always identify the exact location of a crash when filling out the CR-3 report. This can lead to incorrect GPS coordinates and even misidentification of other features of the crash location.

In 47 out of 60 cases, the narrative and field diagram in a CR-3 report are consistent with the Road Align ID. Of the other 13 cases, two crashes clearly have an incorrect Road Align ID. However, for crashes that occurred on a ramp or at an intersection, it is difficult to determine if the location is on a curve since the Highway Curves GIS layer only reflects centerlines. In these cases, GPS coordinates may not accurately reflect the location where the crash occurred. Additionally, in some cases, the Road Align ID might be incorrect, but it is not able to obtain useful information from

the field diagram, as these are often drawn to only reflect a tiny segment of the roadway, making it difficult to identify the larger road alignment.

It is important to note that Road Align IDs are very subjective attributes that are input directly by law enforcement officers. Based on available information, it can be difficult to verify the reason why a specific code was selected. For example, some police officers classified crashes that occurred at intersections as on-curve crashes, possibly because an involved vehicle was turning and changing directions, similar to traveling on a curve. However, other cases show that some police officers classify crashes that occur at intersections as non-curve crashes if they do not recognize any obvious curves near the location of the crash.

Additionally, it is worth noting that some curves could be difficult for police officers to observe without professional measuring devices. As a result, crashes that occurred on a nonobvious curve could easily end up classified as non-curve crashes. An example of such a case is Crash #17168847 (case study 9 in the Type 2 misclassification category) in Table A-19. The crash happened west of the intersection between W. US 290 Highway eastbound and W. William Cannon Dr. The primary cause of the misclassification is an incorrect Road Align ID in the CR-3 report. Based on an aerial view of the location from Google Maps, as seen in Figure 8-2, the segment of Highway 290 west of the intersection is curved, but the segment east of the intersection appears to be straight. However, as shown in Figure 8-3 and Figure 8-4, it is hard to see this change in the road alignment from the street views on Google Maps. Therefore, it is understandable that the officer might have judged this section as straight.



Figure 8-2. An Aerial View of the Location of Crash #17168847 on Google Maps



Figure 8-3. Street View Facing West from the Intersection



Figure 8-4. Street View Facing East from the Intersection

# 8.4 Summary

This chapter documents the general procedure for and key findings from analyzing CRIS curverelated crash data using law enforcement officers' CR-3 reports. This analysis offers a better understanding of the identification of curve-related crashes in CRIS and diagnoses possible reasons for misclassifications.

In Task 8, the CTR research team conducted a thorough investigation of curve-related crashes that were misclassified in CRIS using the associated CR-3 crash reports. Sixty cases across the state were selected for detailed crash analysis, and their CR-3 crash reports were obtained and grouped by type of misclassification (10 crashes for each type). Then, the team reviewed the elements of the reports most useful for determining the cause of curve-related crash misclassification (e.g., field diagrams and investigator's narrative notes). The information from the crash reports was used to verify curve-related attributes (i.e., Curve Type ID and Road Align ID) obtained from the integrated GIS map developed in Task 7. Even though pinpointing the exact cause(s) behind each type of misclassification was almost impossible, rational inferences could be made on the probable cause(s) based on available information. Based on the results, the research team determined potential contributors leading to each type of curve-related crash misclassification. Finally, conclusions were drawn from the crash analysis for each type of misclassification: Type 1 and Type 6 misclassifications are mainly caused by inaccurate GPS coordinates that do not precisely reflect the location where the crash occurred. Type 2 and Type 5 misclassifications are most likely caused by either incorrect Road Align IDs or inaccurate GPS coordinates. Type 3 and Type 4 misclassifications are mainly caused by incorrect Curve Type IDs or inaccurate GPS coordinates.

# **Chapter 9. Conclusions**

The research team began this project with a thorough review of horizontal curves and their impacts on traffic crashes. This review encompassed the following topics: characteristics of horizontal curves; impacts of curves on crash risk, frequency, and severity; and factors affecting crashes on horizontal curves. A comprehensive study of available data sources that contain reliable roadway geometry and inventory information was then conducted. Curve-related parameters that can provide information on the identification of curve-related crashes in the CRIS database were also examined. Then, a systematic data analysis was performed to identify the patterns and characteristics of curve-related crash misclassification in the CRIS database. Next, a methodological procedure to improve the identification of curve-related crashes was developed, automated, and evaluated. Finally, using the Texas Peace Officer's Crash Reports (CR-3) of sixty randomly selected crashes, the research team comprehensively investigated potential causes of curve-related crash misclassification in CRIS.

Through an analysis of data consistency in the CRIS database, the research team found that approximately 77 percent of crash records have consistent curve-related information, whereas 23 percent of crash records contain internally inconsistent curve attributes, showing in one data field that the crash is curve-related but in in the other that the crash did not occur on a horizontal curve.

In addition to the investigation of data consistency within the CRIS database, the research team also verified the accuracy of curve information in CRIS using the Highway Curves GIS layer provided by TxDOT. Based on this examination, curve-related crash misclassifications in CRIS were categorized into six types. Under the optimal buffer zone setting, the research team computed the percentage of crashes that fell into each of the six misclassification categories using CRIS 2017–2020 data. The analysis showed that, on average, 27.1 percent of crashes during this period were misclassified in terms of whether they were curve-related.

To improve curve-related crash identification in CRIS, the research team first developed a methodological procedure for systematically identifying misclassifications of curve-related crashes. Leveraging Python programming language and ArcGIS Python libraries, the CTR research team accomplished the automation of the developed methodological procedure through two major tasks: 1) visualization of the customized CRIS data in ArcGIS Pro, and 2) verification of curve-related crash classification using the Highway Curves GIS layer as a reference. The performance evaluation proved that the automated methodological procedure could help identify curve-related crashes both effectively and efficiently.

Finally, the research team reviewed 60 randomly selected CR-3 reports and summarized the results and key findings. In fact, it is challenging to pinpoint the exact cause(s) behind each type of misclassification, but the research team made rational inferences on the probable cause(s) based on available information. The team inferred that Type 1 and Type 6 misclassifications are most likely caused by inaccurate GPS coordinates that fail to precisely reflect the location of the crash,

Type 2 and Type 5 misclassifications are most likely caused by either incorrect curve classification derived from CR-3–reported data fields or inaccurate GPS coordinates, and Type 3 and Type 4 misclassifications are mainly caused by incorrect curve information generated by the CRIS system or inaccurate GPS coordinates.

Identifying curve-related crashes is important to understanding and characterizing curves in terms of their impact on crash risk and severity and, in turn, the reduction of such crashes. The automated methodological procedure developed in this project provides TxDOT with an effective approach to identifying curve-related crashes in CRIS. This can significantly help improve the accuracy of the CRIS database and enhance the reliability of crash analysis based on CRIS data. Moreover, the improved identification of curve-related crashes in CRIS will allow TxDOT to enhance its identification of crash hotspots. It will, in turn, result in more reliable crash prediction models in support of TxDOT's safety goal of zero fatalities. In summary, the research outcomes from this research will enrich the knowledge about curve characteristics and their impact on traffic crashes, contributing to improving the safety of highway system operations and saving people's lives.

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# Appendix A. Crash Analyses Based on CR-3 Reports

Appendix A. presents the results and key findings from the crash analyses based on the CR-3 reports.

# Type 1 Misclassification

**Type 1 Misclassification**: Both Curve Type ID and Road Align ID indicate that the crash occurred on a curve, but the Highway Curves GIS layer shows the crash was on a straight segment.

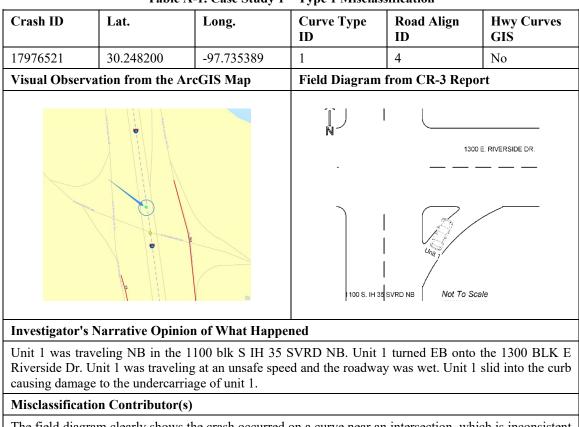
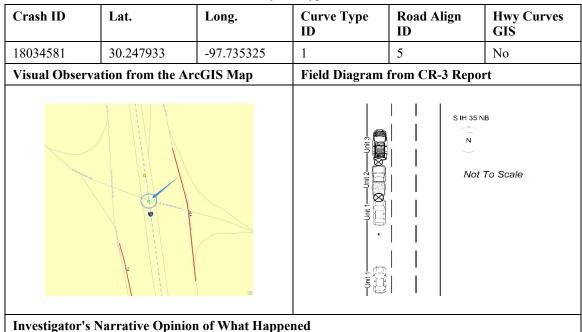


Table A-1. Case Study 1 – Type 1 Misclassification

The field diagram clearly shows the crash occurred on a curve near an intersection, which is inconsistent with the crash location on the GIS map. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

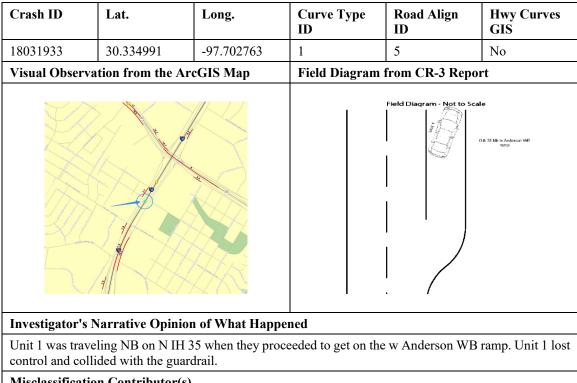


## Table A-2. Case Study 2 – Type 1 Misclassification

Units 3, 2, and 1 were traveling in that order, north on S IH 35 NB in the left lane. Traffic slowed and unit 1 struck the rear of unit 2. Unit 2 was already nearly stopped and was pushed by unit 1 into the back of unit 3. Unit 1 appears to take the most damage as it was towed. Minor damage was observed to the rear of unit 3. Minor damage was also observed to the front and back of unit 2.

### **Misclassification Contributor(s)**

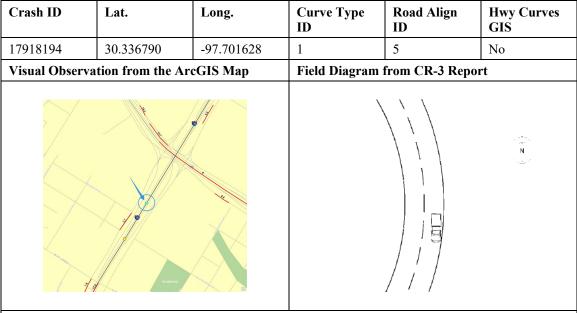
The field diagram does not contain any curves. The scale of the field diagram is too small to clearly indicate if the roadway segment is straight or curved. However, GPS coordinates may not accurately reflect the location where the crash occurred.



## Table A-3. Case Study 3 – Type 1 Misclassification

#### **Misclassification Contributor(s)**

The field diagram shows that the crash occurred near an exit ramp, which may contain a curve. However, the Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.



## Table A-4. Case Study 4 – Type 1 Misclassification

Investigator's Narrative Opinion of What Happened

Unit 1 was southbound on the fly over from E Anderson ln to southbound IH 35. When according to the driver the tie rod broke which caused Unit 1 to his retention wall. unit bounced off the wall and rolled over and came to a stop at the bottom of the ramp.

#### **Misclassification Contributor(s)**

The field diagram clearly shows the crash occurred on a curve, which is inconsistent with the crash location on the GIS map. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

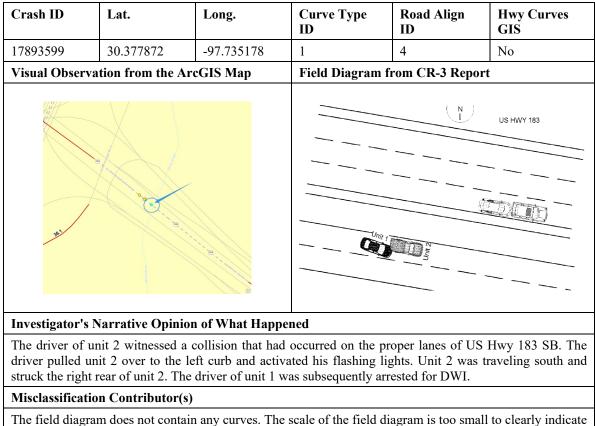
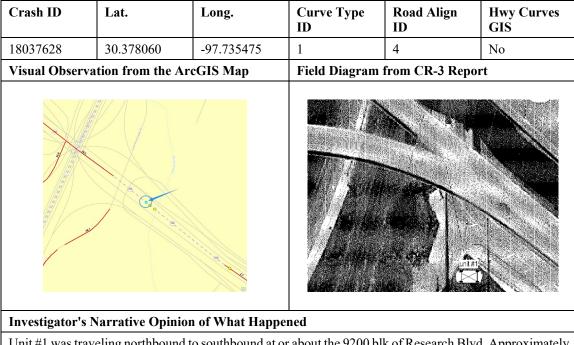


Table A-5. Case Study 5 – Type 1 Misclassification

The field diagram does not contain any curves. The scale of the field diagram is too small to clearly indicate if the roadway segment is straight or curved. However, GPS coordinates may not accurately reflect the location where the crash occurred.

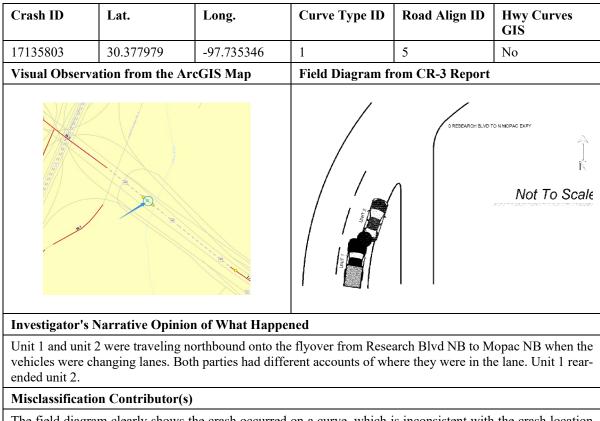


## Table A-6. Case Study 6 - Type 1 Misclassification

Unit #1 was traveling northbound to southbound at or about the 9200 blk of Research Blvd. Approximately one quarter mile NW of Shoal Creek Blvd. Unit #1 driver may have been having a medical issue that caused him to lose control of his vehicle and leave the roadway. The vehicle drove into a ditch causing the vehicle to roll over and strike a retention wire for a metal electrical or utility pole.

### **Misclassification Contributor(s)**

The field diagram clearly shows the crash occurred on a curve, which is inconsistent with the crash location on the GIS map. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.



## Table A-7. Case Study 7 – Type 1 Misclassification

The field diagram clearly shows the crash occurred on a curve, which is inconsistent with the crash location on the GIS map. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

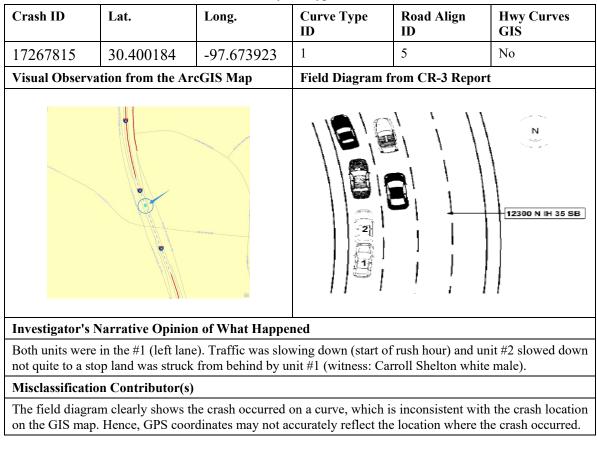
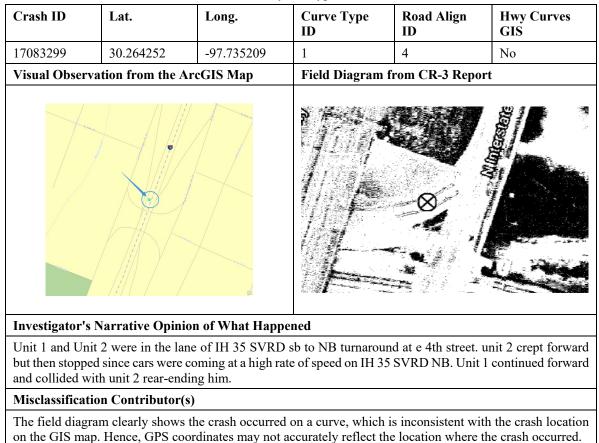


Table A-8. Case Study 8 – Type 1 Misclassification



## Table A-9. Case Study 9 – Type 1 Misclassification

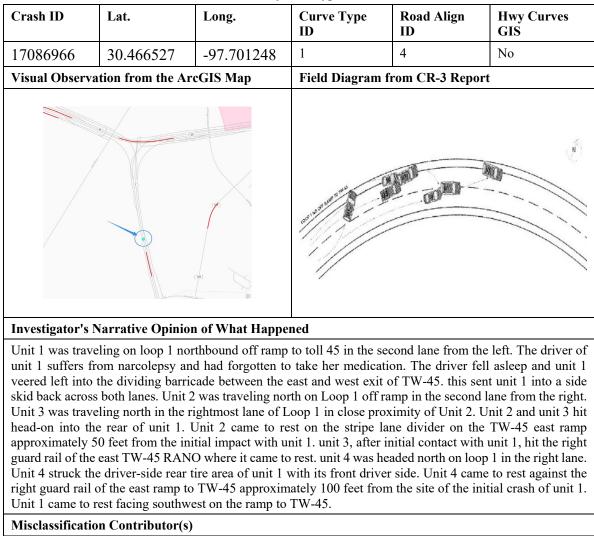


Table A-10. Case Study 10 – Type 1 Misclassification

The field diagram clearly shows the crash occurred on a curve, which is inconsistent with the crash location on the GIS map. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

# Type 2 Misclassification

**Type 2 Misclassification:** Curve Type ID indicates the crash occurred on a curve, but Road Align ID indicates the crash did not occur on a curve; the Highway Curves GIS layer shows the crash was on a highway curve.

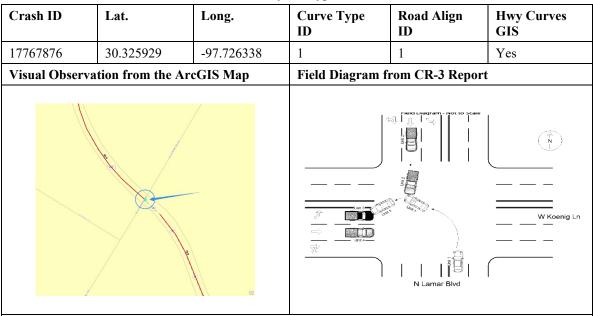


Table A-11. Case Study 1 – Type 2 Misclassification

# Investigator's Narrative Opinion of What Happened

Unit 1's driver was 14 years old and was driving with another 14-year-old as his passenger, with no adult in the car. He claimed to have a permit but I did not find one on file for him. Unit 1 was heading NB on N Lamar Blvd, turning WB onto w Koenig Ln. Unit 2 was coming southbound on N Lamar Blvd in the left lane. Units 1 and 2 both had green lights. Unit 1 had a "yield on green" he did not have a protected left arrow. Unit 1 turned left in front of unit 2 causing unit 2 to hit him. Units 3 and 4 were waiting at their red light heading EB on W Koenig in. When unit 1 collided with unit 2, unit 1 was pushed into unit 3 and unit 3 was pushed into unit 4. Unit 1 caused this collision.

# Misclassification Contributor(s)

The field diagram shows that the crash occurred at an intersection that does not contain any curve. Road Align ID might be incorrect. According to the narrative and field diagram, however, the crash occurred when the vehicle is turning and traveling like on a curve segment. From the GIS map, it can also be observed that the crash is located at the edge between a curve and a straight segment.

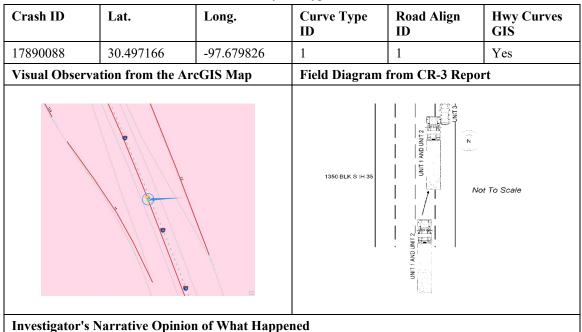


Table A-12. Case Study 2 – Type 2 Misclassification

Unit 1 (semi-truck) was in the middle lane driving northbound while unit 2 (Pontiac) was in the far right lane also traveling northbound. Unit 1 attempted to change lanes and did not see unit 2 until unit 1 rubbed wheels with the back left wheel well of unit 2. Damage was minimal.

## **Misclassification Contributor(s)**

The field diagram does not contain any curves. Hence, Road Align ID might be incorrect. However, the scale of the field diagram is too small to clearly indicate if the roadway segment is straight or curved. Also, it could be difficult for the police officer to recognize whether the crash location is on a curve without a special measuring device since the curve is not obvious.

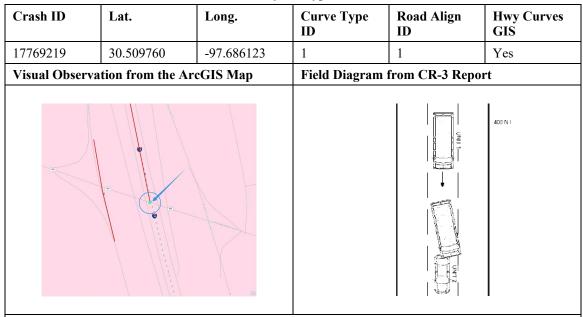


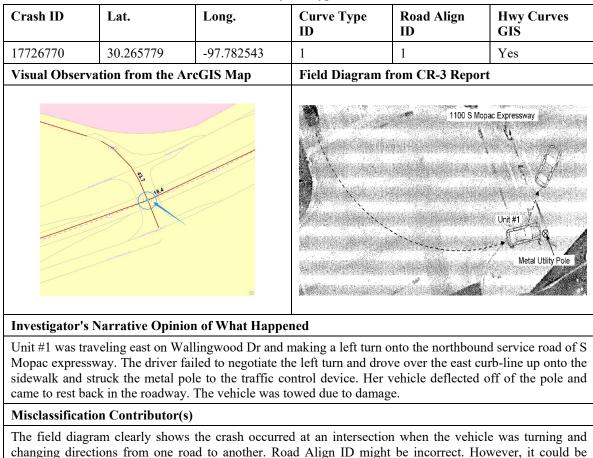
Table A-13. Case Study 3 – Type 2 Misclassification

Investigator's Narrative Opinion of What Happened

Unit 2 was slowing/ stopped for traffic in the 400 blk N IH 35 s/b. Unit 1 was behind unit 2. The driver of unit 1 stated he was distracted by a phone call, failed to control the speed with driver inattention and struck unit 2.

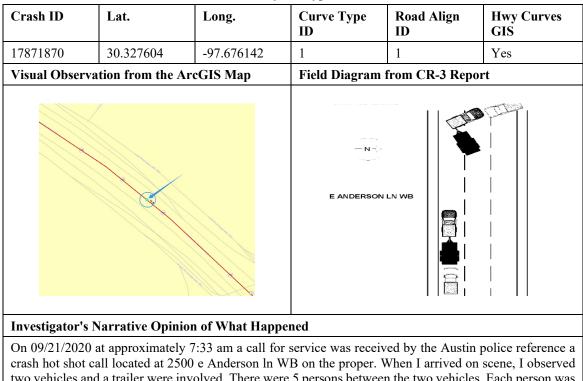
### **Misclassification Contributor(s)**

The field diagram does not contain any curves. Hence, Road Align ID might be incorrect. However, the scale of the field diagram is too small to investigate if the roadway segment is straight or curved. Moreover, it can be observed that the crash is located at the edge between a curve and a straight segment on the GIS map.



## Table A-14. Case Study 4 – Type 2 Misclassification

The field diagram clearly shows the crash occurred at an intersection when the vehicle was turning and changing directions from one road to another. Road Align ID might be incorrect. However, it could be difficult for the police officer to recognize the crash location is on a curve without a special measuring device, since the curve is not obvious.

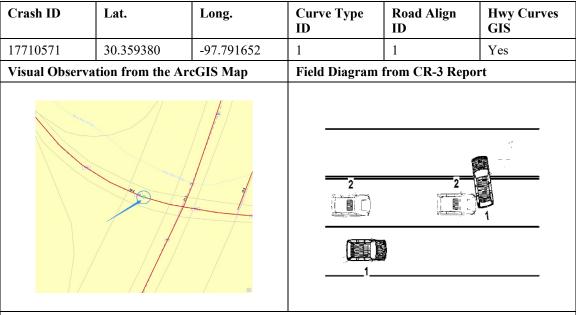


## Table A-15. Case Study 5 – Type 2 Misclassification

crash hot shot call located at 2500 e Anderson ln WB on the proper. When I arrived on scene, I observed two vehicles and a trailer were involved. There were 5 persons between the two vehicles. Each person was attended to be EMS and no one was transported. Traffic westbound on E Anderson ln was heavier than usual. Unit 2/3 was driving westbound in the left-hand lane. Unit 2 was stopped for traffic. Unit 2 said he was rear-ended by unit 1. Unit 1 said she was driving westbound on E Anderson ln in the left lane. Unit 1 said unit 2 came to a stop. She was not able to stop in time and rear-ended unit 2/3. There were approximately 60 ft of skid marks showing unit 1 was likely operating at a higher rate of speed unsafe for roadway conditions and showing unit 2 did not come to an immediate stop directly in front of unit 1.

## Misclassification Contributor(s)

The narrative and field diagram indicate that the crash occurred on E Anderson Ln. However, the GPS coordinates show that the crash is on US 183. Hence, GPS coordinates may not reflect the location where the crash occurred.



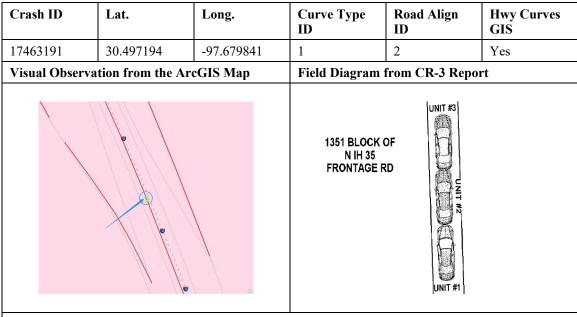
## Table A-16. Case Study 6 – Type 2 Misclassification

Investigator's Narrative Opinion of What Happened

Both units were EB in the 5700 blk of FM 2222. Unit 2 was in the inside, left turn lane, to turn NB onto N Capital of Texas Hwy. Unit 1 was in the #2 lane, a left turn lane. Unit 1 made an unsafe U-turn, to go back WB on FM 2222. Unit 1 turned in front of unit 2 and the front of unit 2 struck the left-back quarter of unit 1.

## **Misclassification Contributor(s)**

The field diagram does not contain any curves. The scale of the field diagram is too small to clearly indicate if the crash occurred on a curve. GPS coordinates may not accurately reflect the location where the crash occurred. Meanwhile, the curve might be not obvious and the police officer might not recognize the location as on a curve without a special measuring device.



## Table A-17. Case Study 7 – Type 2 Misclassification

Investigator's Narrative Opinion of What Happened

Unit #1 was traveling northbound in the 1351 block of N IH 35 frontage Rd, when she failed to control her speed and struck unit #2 from behind, sustaining damages to the front distributed portion of her vehicle and pushing unit #2 into unit #3. Unit #2 was traveling northbound in the 1351 block of N IH 35 Frontage Rd when it was struck from behind by unit #1 sustaining damages to the rear distributed portion of the vehicle. Unit #3 traveling northbound in the 1351 block of N IH 35 Frontage Rd when it was struck by unit #2 sustaining small damages to the rear portion of the vehicle.

# Misclassification Contributor(s)

The narrative and field diagram indicate that the crash occurred on N IH 35 Frontage Rd, which is inconsistent with the location on the GIS map (IH 35). The Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

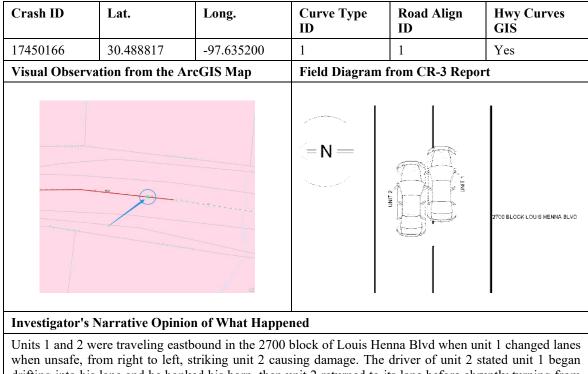
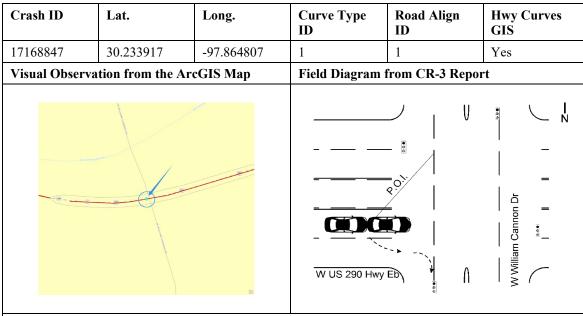


Table A-18. Case Study 8 – Type 2 Misclassification

Units 1 and 2 were traveling eastbound in the 2700 block of Louis Henna Blvd when unit 1 changed lanes when unsafe, from right to left, striking unit 2 causing damage. The driver of unit 2 stated unit 1 began drifting into his lane and he honked his horn, then unit 2 returned to its lane before abruptly turning from the right to left lane striking unit 1. The driver of unit 1 stated unit 2 was traveling slowly in the left lane so unit 1 began to pass unit 2 in the right lane. The driver of unit 2 stated as she was merging left to pass unit 2, it sped up and caused her to strike unit 2.

# Misclassification Contributor(s)

The narrative and field diagram indicate that the crash occurred on Louis Henna Blvd, which is inconsistent with the location on the GIS map (SH 45). Hence, GPS coordinates may not accurately reflect the location where the crash occurred.



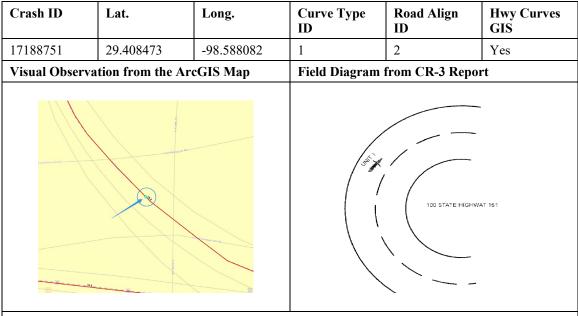
## Table A-19. Case Study 9 – Type 2 Misclassification

## Investigator's Narrative Opinion of What Happened

Unit #1 was traveling east on W US 290 Hwy EB approaching the intersection of W US 290 Hwy EB & W William Cannon Dr. unit #2 was stopped at a red light near the intersection of W US 290 Hwy EB & W William cannon dr. Unit #1 was traveling at a high rate of speed and collided with unit #2 in the rear. Unit #1 then left the scene by backing up and then turning to go southbound on W William Cannon Dr. Unit #1, person #1 was shortly caught by a police officer who witnessed the collision and the fleeing the scene. Unit #1, person #1, after an investigation was completed, was arrested for failure to stop and render aid. Unit #2, person #1 advised he received injuries to the back of his neck and lower back area. Unit #1, person #1 advised he did not need EMS to respond to the scene to treat his injuries.

## **Misclassification Contributor(s)**

The field diagram shows the crash occurred at an intersection, but its scale is too small to identify if the crash occurred on a curve. Road Align ID might be incorrect. However, the curve might not be obvious, making it difficult for the police officer to recognize that the location is on a curve without a special measuring device.



## Table A-20. Case Study 10 - Type 2 Misclassification

# Investigator's Narrative Opinion of What Happened

Unit 1 is a new motorcycle still trying to become experienced and does not have a motorcycle license. Unit 1 rider does not know what happened but the accident did happen on a curve and I believe he failed to control his speed and dropped his motorcycle which caused him to fall and break his left arm. Unit 1 rider left to university hospital for his injuries and insurance was not confirmed.

### **Misclassification Contributor(s)**

The narrative and field diagram clearly show that the crash did occur on a curve. However, the police officer input the incorrect Road Align ID by accident.

# **Type 3 Misclassification**

**Type 3 Misclassification**: Curve Type ID indicates the crash occurred on a curve, but Road Align ID indicates the crash did not occur on a curve; the Highway Curves GIS layer shows the crash was on a straight segment.

Crash ID	Lat.	Long.	Curve Type ID	Road Align ID	Hwy Curves GIS
17835845	29.589863	-98.607330	1	1	No
Visual Observation from the ArcGIS Map			Field Diagram from CR-3 Report		
				u2 Loc	DP 1604 E
Investigator'	s Narrative Opini	on of What Happ	ened		
him to crash i		of u3 stated that u	2 crashed into u1 fi		into him was caused id u2 & crashed into
Misclassifica	tion Contributor(	s)			
			ne scale of the field t Curve Type ID is		nall to identify if the

Table A-21. Case Study 1 – Type 3 Misclassification

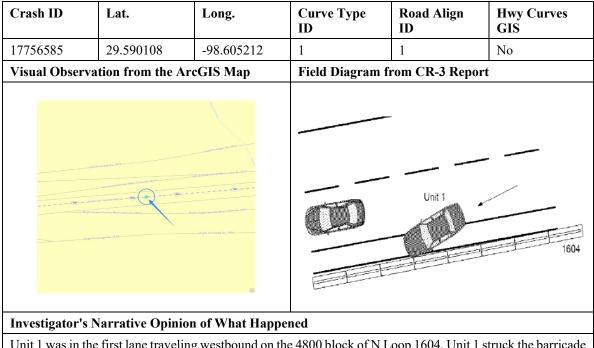


Table A-22. Case Study 2 – Type 3 Misclassification

Unit 1 was in the first lane traveling westbound on the 4800 block of N Loop 1604. Unit 1 struck the barricade due to a faulty evasive maneuver. Unit 1 driver stated that a vehicle cut him off, and to avoid a collision, he swerved toward the barricade. EMS checked unit 1 driver and was not transported. Unit 1 driver stated BWC and Coban available.

## **Misclassification Contributor(s)**

The field diagram does not contain any curves. The scale of the field diagram is too small to identify if the crash occurred on a curve. But it is most likely that Curve Type ID is incorrect.

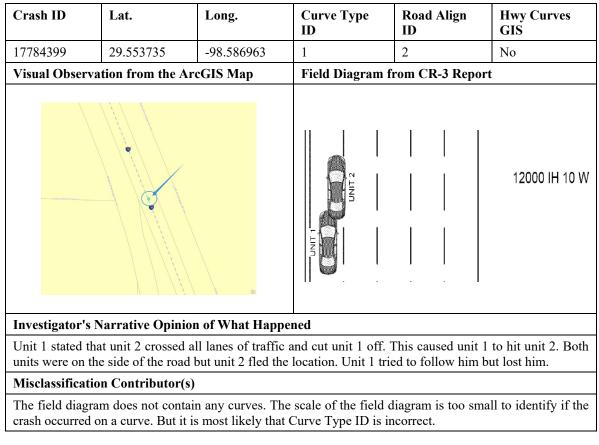


Table A-23. Case Study 3 – Type 3 Misclassification

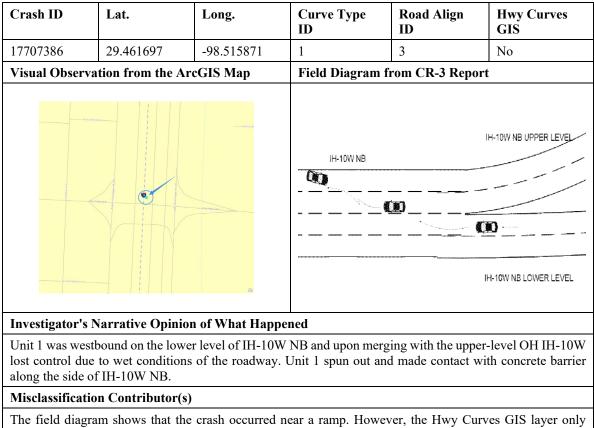
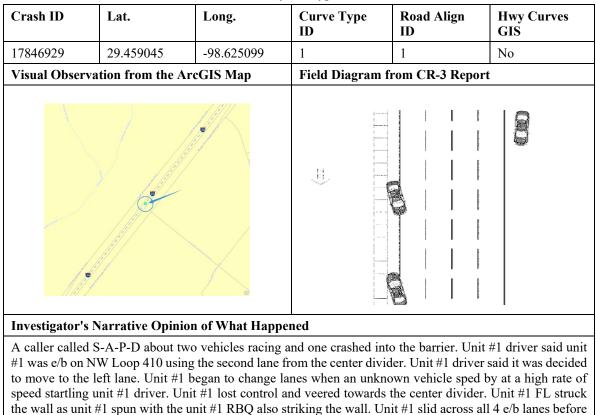


Table A-24. Case Study 4 – Type 3 Misclassification

The field diagram shows that the crash occurred near a ramp. However, the Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

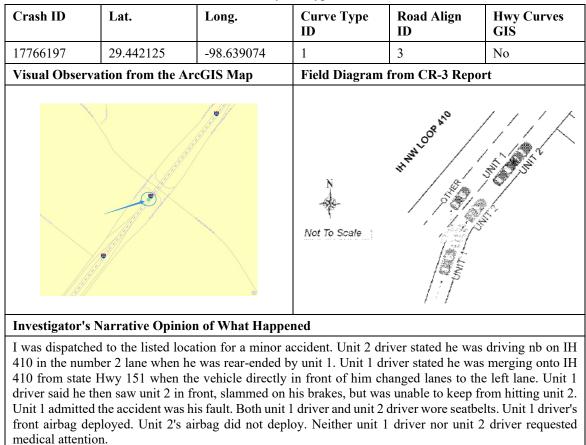


### Table A-25. Case Study 5 – Type 3 Misclassification

## **Misclassification Contributor(s)**

coming to a stop.

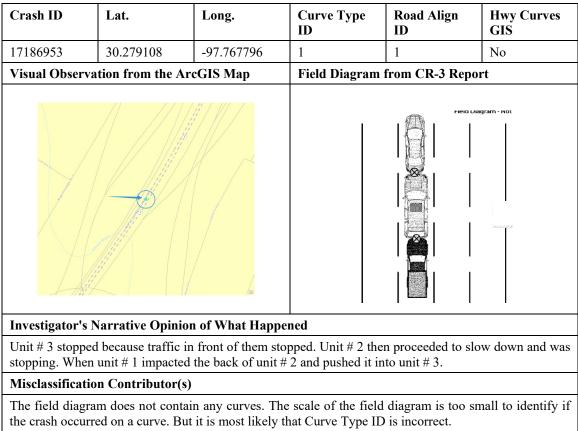
The field diagram does not contain any curves. The scale of the field diagram is too small to identify if the crash occurred on a curve. But it is most likely that Curve Type ID is incorrect.



### Table A-26. Case Study 6 – Type 3 Misclassification

### **Misclassification Contributor(s)**

The field diagram shows that the crash occurred near a ramp. However, the Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.



## Table A-27. Case Study 7 – Type 3 Misclassification

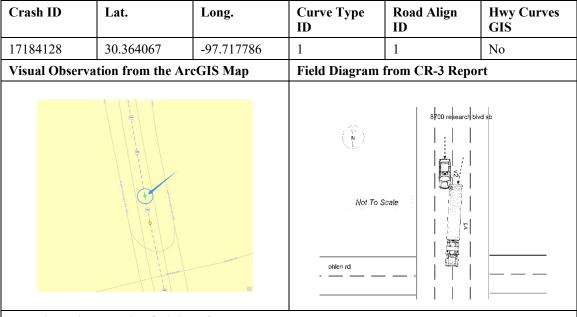


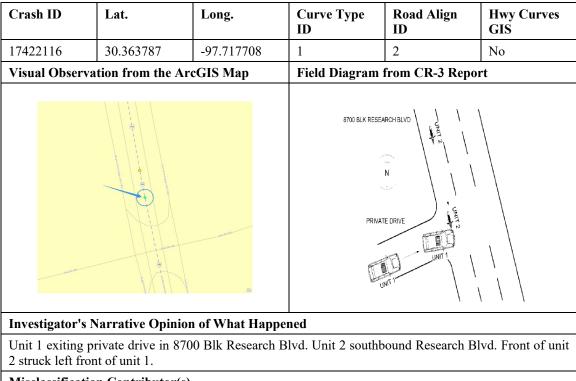
Table A-28. Case Study 8 – Type 3 Misclassification

Investigator's Narrative Opinion of What Happened

V2 was traveling sb in the 8700 blk of Research Blvd SVRD SB. V1 was to the left of v2, and changed lanes to the right, striking v2. V1 left the scene. The driver of v2 was only able to describe v1 as a semi-trailer.

### **Misclassification Contributor(s)**

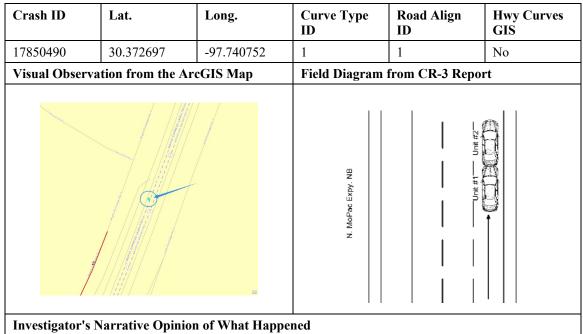
The field diagram does not contain any curves. The scale of the field diagram is too small to identify if the crash occurred on a curve. But it is most likely that Curve Type ID is incorrect.



## Table A-29. Case Study 9 - Type 3 Misclassification

#### **Misclassification Contributor(s)**

The field diagram does not contain any curves. The scale of the field diagram is too small to identify if the crash occurred on a curve. But it is most likely that Curve Type ID is incorrect.



## Table A-30. Case Study 10 - Type 3 Misclassification

Unit #2 was driving NB in the outside lane of N Mopac EXPY NB in the 8200 BLK, and stopped due to traffic unit #1 was also driving NB in the outside lane of N Mopac EXPY NB in the 8200 BLK, and was directly behind unit #2. When unit #2 stopped due to traffic, unit #1 struck unit #2 from behind. Unit #1 was following too closely behind unit #2 due to a collision having taken place.

## **Misclassification Contributor(s)**

The field diagram does not contain any curves. The scale of the field diagram is too small to identify if the crash occurred on a curve. But it is most likely that Curve Type ID is incorrect.

# Type 4 Misclassification

**Type 4 Misclassification:** Curve Type ID indicates the crash did not occur on a curve, but Road Align ID indicates the crash occurred on a curve; the Highway Curves GIS layer shows the crash was on a highway curve.

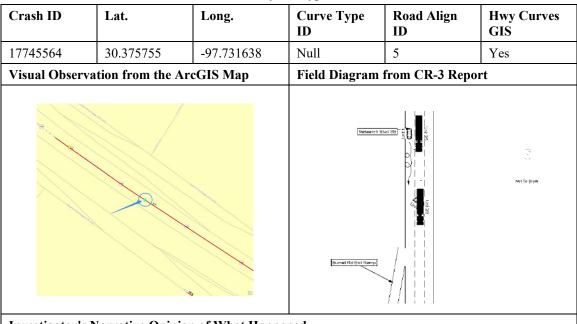


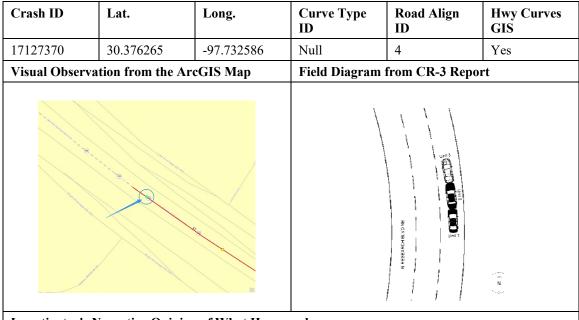
Table A-31. Case Study 1 – Type 4 Misclassification

# Investigator's Narrative Opinion of What Happened

Unit 2 was traveling south on Research Blvd in the center lane. Unit 1 was in the right-hand lane also traveling south on Research Blvd. Unit 1 hydroplaned due to heavy ongoing rain and struck the front right wheel of unit 2 with the front left wheel of unit 1. Unit 1 then spun around, continued to hydroplane and then struck unit 3, which was the trailer being towed by unit 2. Unit 1 became lodged under unit 3.

# Misclassification Contributor(s)

The field diagram shows that the crash occurred near a ramp. However, the Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.



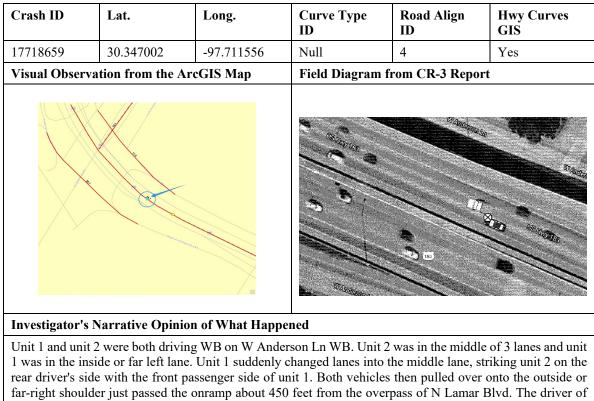
### Table A-32. Case Study 2 – Type 4 Misclassification

Investigator's Narrative Opinion of What Happened

Unit 1 was traveling NB on N US 183 in the right lane. Unit 1 was behind unit 2 and unit 3 was the lead vehicle. Unit 3 stopped for traffic possibly due to debris in the roadway. Unit 2 stopped in time but unit 1 failed to stop in time and struck unit 2 which caused unit 2 to hit unit 3. Unit 2 had a 30-day temporary tag but when it was run, came back to a 72-hour permit tag that belonged to a different vehicle. The owner of the vehicle was passenger in the car and said he had just bought the vehicle.

**Misclassification Contributor(s)** 

The field diagram clearly illustrates the crash occurred on a curve. Curve Type ID is most likely incorrect.



### Table A-33. Case Study 3 – Type 4 Misclassification

rear driver's side with the front passenger side of unit 1. Both vehicles then pulled over onto the outside or far-right shoulder just passed the onramp about 450 feet from the overpass of N Lamar Blvd. The driver of unit 1 immediately fled running WB on the shoulder of W Anderson Ln WB. The driver of unit 1 was found still running WB by other officers and was detained. after conducting SFST it was determined that the driver of unit 1 was intoxicated and he was placed under arrest for DWI with 1 prior conviction, a class A misdemeanor.

### **Misclassification Contributor(s)**

The field diagram shows that the crash occurred on a curve (not obvious but can be recognized through a thorough observation). Hence, Curve Type ID is incorrect.

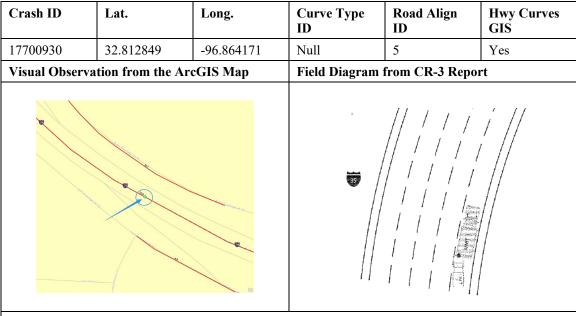


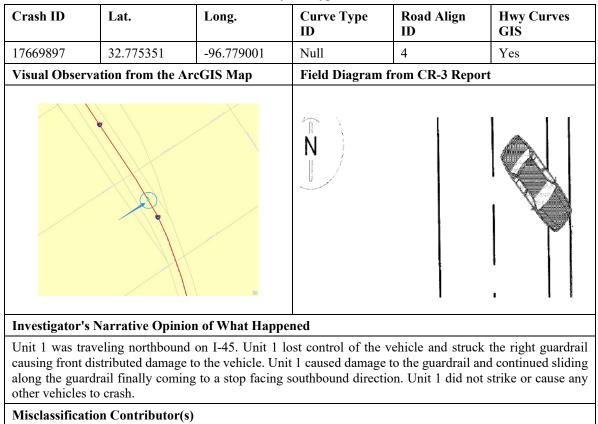
Table A-34. Case Study 4 – Type 4 Misclassification

Investigator's Narrative Opinion of What Happened

Units 1 and 2 were traveling northbound on Stermons freeway in the right lane. Unit 1 stated a vehicle made an unsafe lane change into his lane causing him to apply the brakes abruptly, while applying his brakes unit 2 struck unit 1 on the left rear quarter. Unit 2 stated unit 1 applied his brakes and did not have enough time to stop and struck unit 1 in the rear. Both units were able to safely pull onto the shoulder and no injuries were reported. Unit 2 was following too close to unit 1 and was a contributing factor in the collision.

### Misclassification Contributor(s)

Curve Type ID is incorrect because the field diagram clearly shows the crash occurred on a curve.



### Table A-35. Case Study 5 – Type 4 Misclassification

The field diagram does not contain any curves. However, the scale of the field diagram is too small to identify if the crash occurred on a curve. It is most likely that Curve Type ID is incorrect.

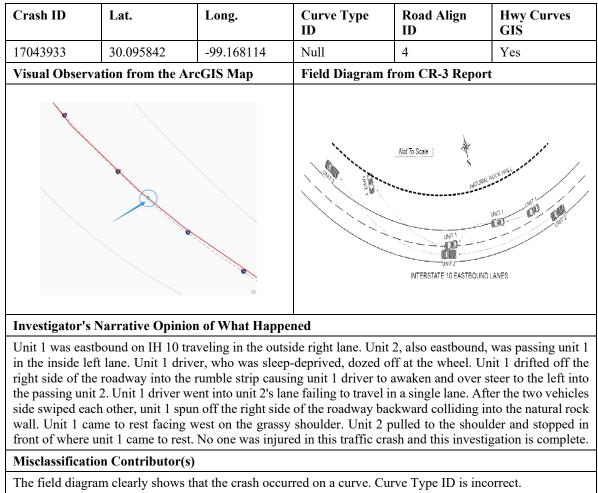
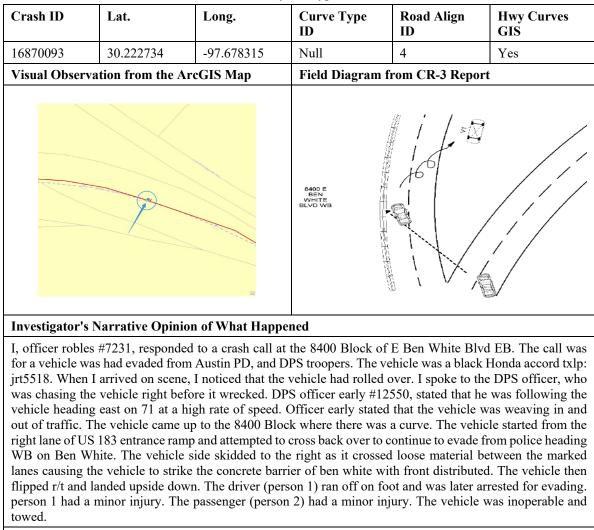


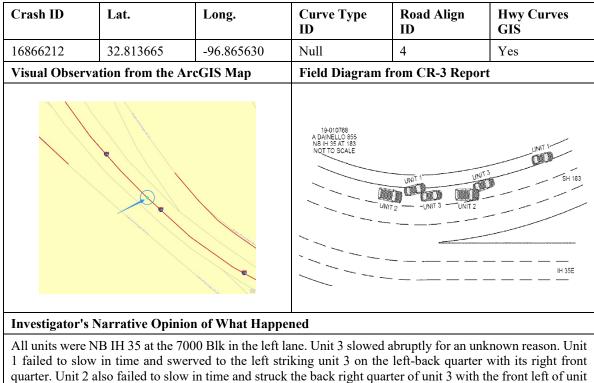
Table A-36. Case Study 6 – Type 4 Misclassification



### Table A-37. Case Study 7 – Type 4 Misclassification

#### **Misclassification Contributor(s)**

The narrative and field diagram indicates that the crash occurred on a curve. Curve Type ID is incorrect.

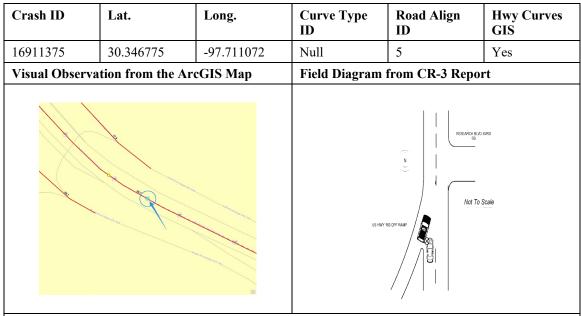


### Table A-38. Case Study 8 – Type 4 Misclassification

All units were NB IH 35 at the 7000 Blk in the left lane. Unit 3 slowed abruptly for an unknown reason. Unit 1 failed to slow in time and swerved to the left striking unit 3 on the left-back quarter with its right front quarter. Unit 2 also failed to slow in time and struck the back right quarter of unit 3 with the front left of unit 2. The driver of unit 3 stated that he slowed due to a vehicle in front of him and was hit from the back two times. The drivers of units 1 and 2 both stated that unit 3 came to a stop for no apparent reason, while in the left lane.

### Misclassification Contributor(s)

The field diagram clearly shows that the crash occurred on a curve. Curve Type ID is incorrect.



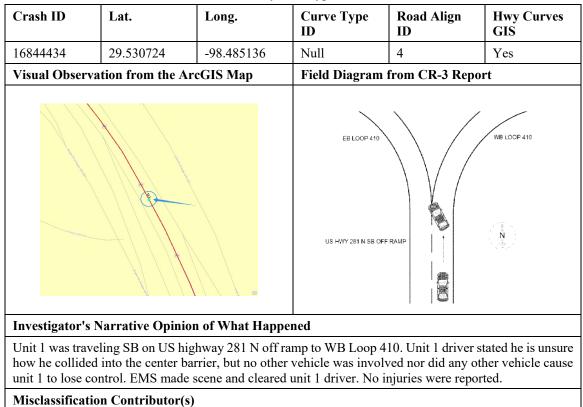
### Table A-39. Case Study 9 – Type 4 Misclassification

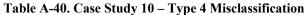
### Investigator's Narrative Opinion of What Happened

Unit 1 was exiting the proper of US Hwy 183 SB. Unit 2 was traveling south on the outside lane of Research Blvd SVRD SB. Unit 1 made an unsafe lane change from the off ramp, when the driver crossed two solid white lines in order to enter the inside lane of Research Blvd SVRD SB. The driver of unit 1 was attempting to make a right into the parking lot, when she continued the unsafe lane change, striking unit 2 both vehicles sustained moderate damage and had to be towed from the scene.

### **Misclassification Contributor(s)**

The field diagram clearly shows the crash occurred on an off-ramp that contains a curve. Curve Type ID might be incorrect. Meanwhile, GPS coordinates may not accurately reflect the location where the crash occurred.





The field diagram clearly shows that the crash occurred near a curved off-ramp. Curve Type ID might be incorrect. Meanwhile, GPS coordinates may not accurately reflect the location where the crash occurred.

# Type 5 Misclassification

**Type 5 Misclassification:** Curve Type ID indicates the crash did not occur on a curve, but Road Align ID indicates the crash occurred on a curve; the Highway Curves GIS layer shows the crash was on a straight segment.

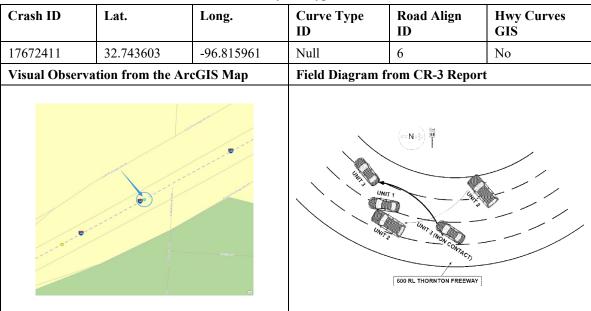


Table A-41. Case Study 1 – Type 5 Misclassification

### Investigator's Narrative Opinion of What Happened

Unit 1, 2, and 3 were traveling SB IH-35 just south of Marsalis Avenue. Unit 2 was traveling in an unknown lane, unit 2 lost control and spun into the right concrete barrier with its front end. Unit 2 came to a stop in the center-left lane. Unit 3 (non-contact) was traveling in the center-left lane. To avoid striking unit 2, unit 3 (non-contact) swerved into the center-right lane. Unit 1 was traveling in the center-right lane. Unit 1 swerved to the right lane to avoid impact with unit 3 (non-contact). Unit 1 merged back into the center-right lane but struck unit 2 on its right passenger side with unit 1's left passenger side. Unit 2 was left abandoned at the scene.

### **Misclassification Contributor(s)**

The field diagram clearly shows the crash occurred on a curve. The location described in the narrative is consistent with the GPS coordinates. However, no curve can be found near this location on the GIS map. It is difficult to draw a conclusion based on available information.

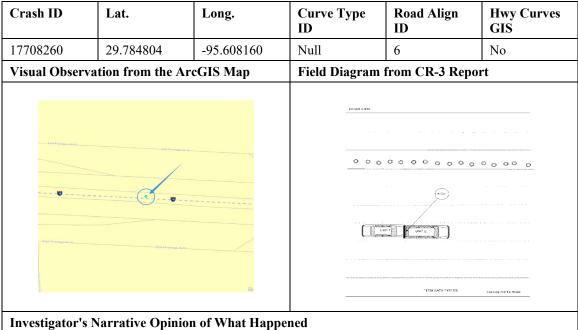


Table A-42. Case Study 2 - Type 5 Misclassification

Unit 1 and unit 2 ware traveling eacthound in the 11700 block of the Ke

Unit 1 and unit 2 were traveling eastbound in the 11700 block of the Katy Fwy. Unit 1 failed to control speed striking unit 2 from the rear.

### **Misclassification Contributor(s)**

The field diagram does not contain any curves. Road Align ID might be incorrect. However, the scale of the field diagram is too small to identify if the roadway segment is straight or curved.

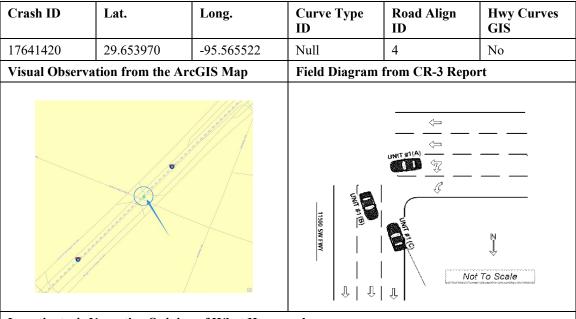


Table A-43. Case Study 3 – Type 5 Misclassification

### Investigator's Narrative Opinion of What Happened

Unit #1 was traveling north under 11500 southwest freeway turn lane when his vehicle fishtailed, and struck the curb. no other damage or vehicles were involved. The ground was wet, and the vehicle hydroplaned. {Investigator's assignment: South Gessner}

#### **Misclassification Contributor(s)**

The field diagram shows the crash occurred at an intersection that does not contain any curved segments. Road Align ID might be incorrect. However, the crash occurred when the vehicle was turning and changing directions, which the officer could have interpreted as traveling on a curve.

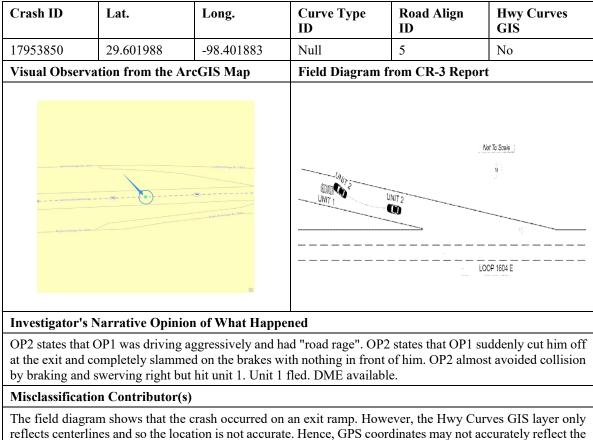


Table A-44. Case Study 4 - Type 5 Misclassification

location where the crash occurred.

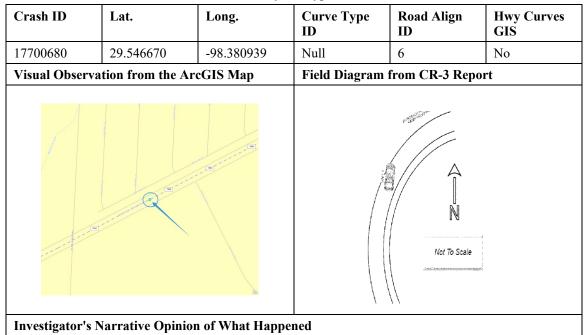
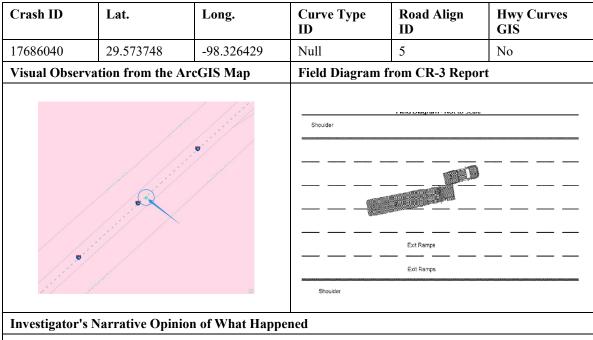


Table A-45. Case Study 5 – Type 5 Misclassification

I was dispatched to the listed location for a minor accident. Upon arrival, I located unit 1 parked along the entrance ramp from Wetmore Rd to Wurzbach Pkwy EB. Unit 1 was unoccupied. No one was located nearby, and no vehicles were located nearby. Unit 1 had damage to the front left portion of the vehicle. Unit 1's steering wheel airbag was deployed. Unit 1 was towed to Growdon. BWC/Coban is available.

### **Misclassification Contributor(s)**

The narrative and field diagram indicate the crash occurred on a curved ramp. However, the Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.



### Table A-46. Case Study 6 – Type 5 Misclassification

The driver of unit 1 explained that he was merging to the left due to an accident blocking the right lanes. unit 3 was changing lanes next to unit 1. Unit 3 would suddenly stop causing the left front of unit 1 to strike the right rear of unit 3. The driver of unit 3 explained that he was merging to the left due to the other accident. Traffic was heavy and moving slowly. Unit 1 would suddenly strike the right rear of unit 3. I was on scene of the other accident. That case number is 20-09538. I was working on putting out cones when I observed the vehicles involved in this accident blocking several lanes.

### Misclassification Contributor(s)

The field diagram shows that the crash occurred on a non-curved road segment. The narrative does not include any information about the location of the crash. But it is most likely that Road Align ID is incorrect.

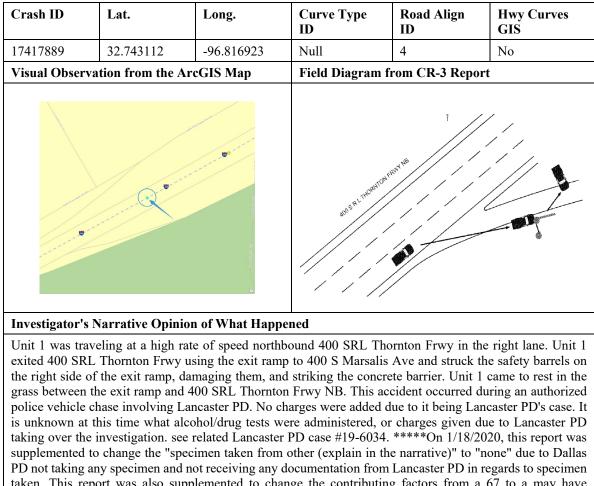


Table A-47. Case Study 7 – Type 5 Misclassification

taken. This report was also supplemented to change the contributing factors from a 67 to a may have contributed "had been drinking" factor. This report is now complete. \*\*\*\*\*

### **Misclassification Contributor(s)**

The field diagram shows that the crash occurred on an exit ramp that contains a curve. However, the Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

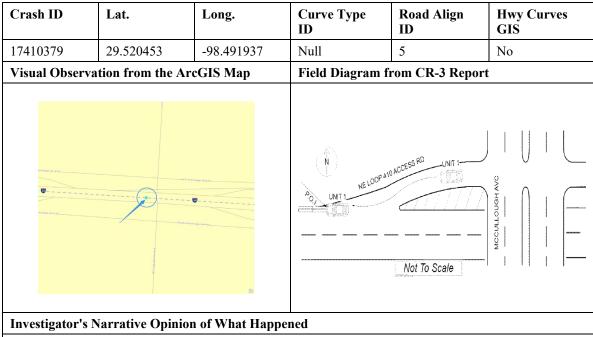


Table A-48. Case Study 8 – Type 5 Misclassification

I was dispatched to the location as the cover officer for an accident report. Upon arrival, I observed damage to unit 1. Witness (w1) advised officers on scene that he observed unit 1 traveling westbound on NE Loop 410 Access Rd, w1 states he then observed unit 1 crash into a barrier at the onramp leading to westbound NE Loop 410. W1 states that he observed the driver of unit 1 operating said vehicle and also said "he (driver) would have been hurt if he wasn't drunk". Handling officer Drew #147 had reason to believe the driver of unit 1 was intoxicated so the driver was arrested on scene. The driver of unit 1 was being belligerent and did not tell officers on scene his version of how the accident occurred. Coban and body-worn camera available.

### **Misclassification Contributor(s)**

The field diagram shows that the crash occurred on an on-ramp that contains a curve. However, the Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

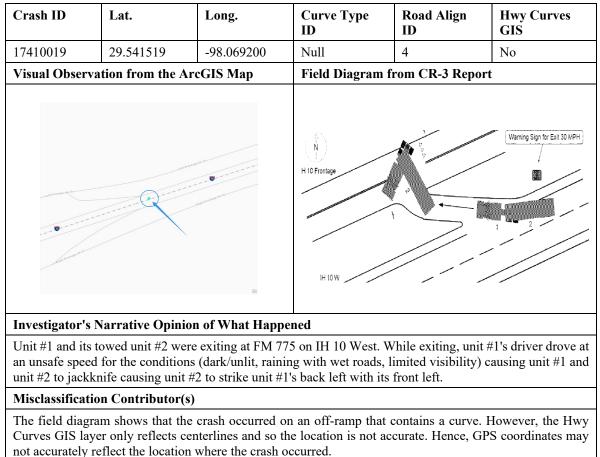


Table A-49. Case Study 9 – Type 5 Misclassification

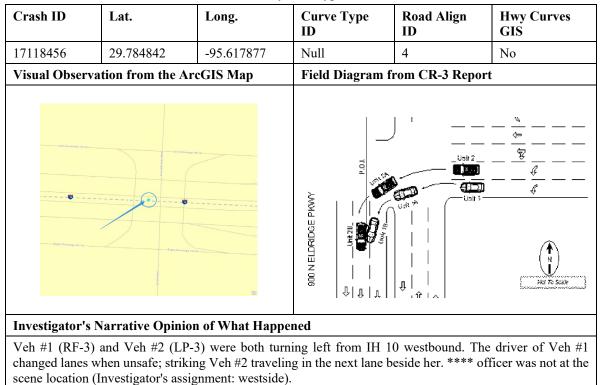


Table A-50. Case Study 10 - Type 5 Misclassification

### **Misclassification Contributor(s)**

The field diagram shows the crash occurred at an intersection that does not include any curved segments. Road Align ID might be incorrect. However, the crash occurred when the vehicles were turning and changing directions, which the officer could have interpreted as traveling on a curve.

# **Type 6 Misclassification**

**Type 6 Misclassification:** Both Curve Type ID and Road Align ID indicate the crash did not occur on a curve, but the Highway Curves GIS layer shows the crash was on a highway curve.

Crash ID	Lat.	Long.	Curve Type ID	Road Align ID	Hwy Curves GIS		
17786334	29.729999	-95.448929	Null	2	Yes		
Visual Observation from the ArcGIS Map			Field Diagram from CR-3 Report				
			4000 SOUTHWE	4000 SOUTHWEST FREEWAY			

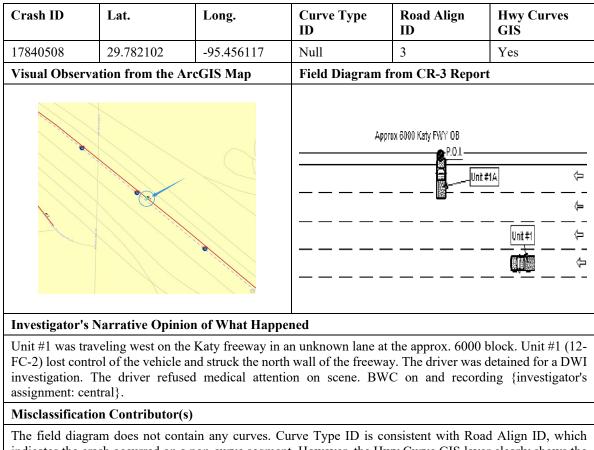
Table A-51. Case Study 1 – Type 6 Misclassification

### Investigator's Narrative Opinion of What Happened

Unit #2 was driving westbound in the 4000 block of the southwest freeway in lane five of seven. Unit #1 was driving westbound in the 4000 block of the southwest freeway in lane six of seven. Unit #1 changed from lane six into lane five striking unit #2. unit #1 changed lanes when unsafe. Unit #1 issued a citation for changing lanes when unsafe and for no insurance. Unit #1 sustained damage --7-LBO-1, unit #2 sustained damage --10-LFO-1. No vehicles towed no injuries {investigator's assignment: South Gessner}

### **Misclassification Contributor(s)**

The field diagram does not contain any curves. Curve Type ID is consistent with Road Align ID, which indicates the crash occurred on a non-curve segment. However, the Hwy Curve GIS layer clearly shows the crash location is on a curve. Based on the investigation, we conclude that the GPS coordinates may not accurately reflect the location where the crash occurred.



### Table A-52. Case Study 2 – Type 6 Misclassification

The field diagram does not contain any curves. Curve Type ID is consistent with Road Align ID, which indicates the crash occurred on a non-curve segment. However, the Hwy Curve GIS layer clearly shows the crash location is on a curve. Based on the investigation, we conclude that the GPS coordinates may not accurately reflect the location where the crash occurred.

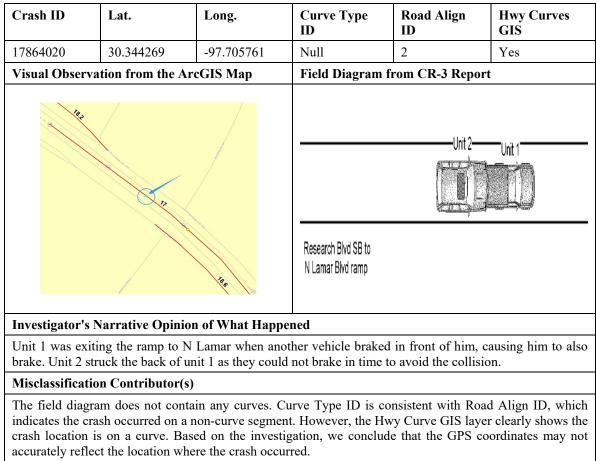


Table A-53. Case Study 3 – Type 6 Misclassification

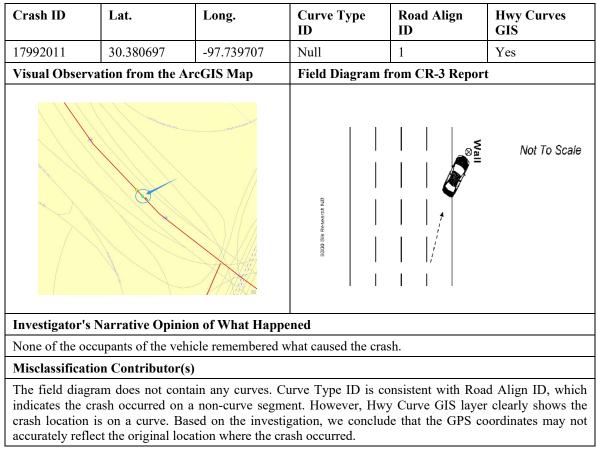
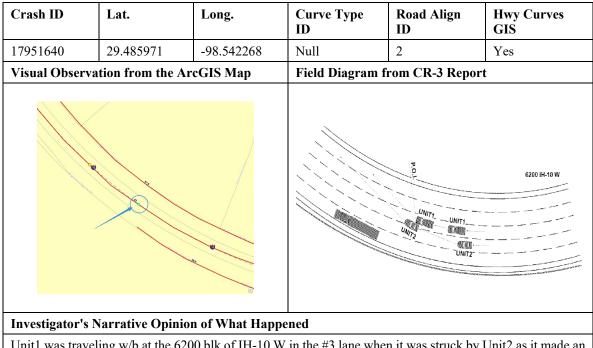


Table A-54. Case Study 4 – Type 6 Misclassification



Unit1 was traveling w/b at the 6200 blk of IH-10 W in the #3 lane when it was struck by Unit2 as it made an unsafe lane change from the #2 to #3 lanes. Unit1 was struck on the driver side front quarter/bumper area by Unit2. Unit1 had very minor damage/scratches. Unit1 driver attempted to get the TXLP for Unit2 but it fled too fast on NW Loop 410 w/b. Unit1 driver said there was a semi traveling w/b in the #1 lane as Unit2 approached from the rear and cut in front of his truck heading towards the NW Loop 410 exit ramp.

### **Misclassification Contributor(s)**

The field diagram clearly shows the crash occurred on a curve. Therefore, Curve Type ID is incorrect. Also, the police officer input the incorrect Road Align ID by accident.

Table A-55. Case Study 5 – Type 6 Misclassification

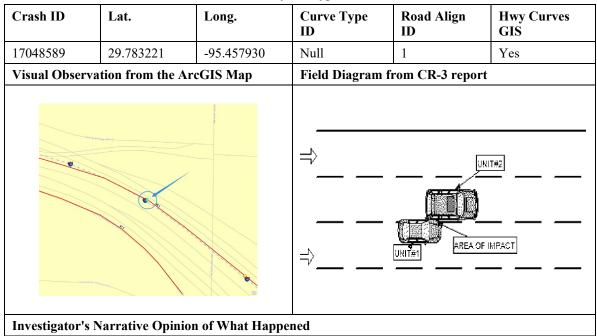


Table A-56. Case Study 6 – Type 6 Misclassification

Unit#1 and unit#2 traveling eastbound on Katy Fwy. Unit#1 changed lane unsafe and struck unit#2. unit#1 damage ID-1, unit#2 damage RBQ-1. No witness scene where the officer was called out. The officer did not make the original location/ scene where the crash occurred. Both drivers had conflicting statements on what happened at the time of the crash. {investigator's assignment: downtown}

### **Misclassification Contributor(s)**

The narrative indicates that the police officer did not mark the precise location where the crash occurred because such information was not available.

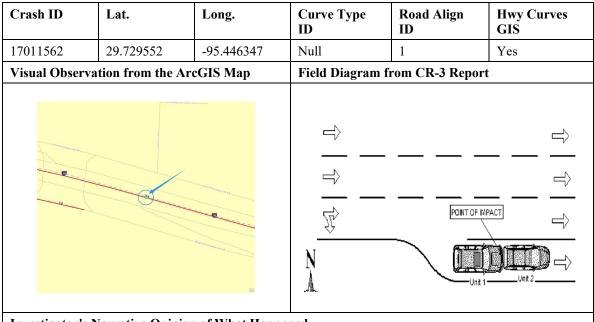


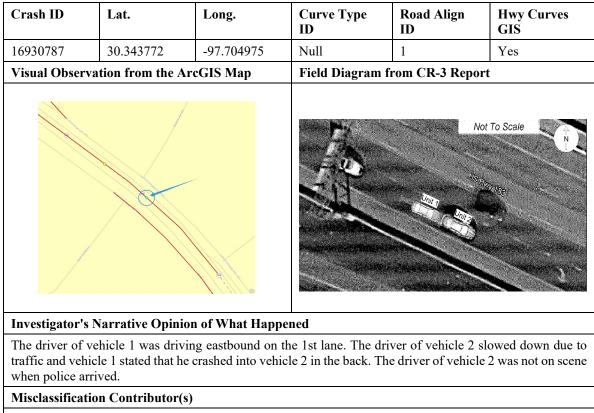
Table A-57. Case Study 7 – Type 6 Misclassification

Investigator's Narrative Opinion of What Happened

Unit #2 was traveling eastbound on the 3200 block of SW Fwy IB and took the Weslayan exit, in front of unit #1. Unit #1 was traveling eastbound on the 3200 block of SW Fwy IB and took the Weslayan exit, behind unit #2. Unit #1 was distracted in the vehicle and failed to control speed crashing into the back of unit #2. Unit #1 is at fault. BWC used 1A51D and 1A53D {investigator's assignment: central}.

### **Misclassification Contributor(s)**

The field diagram shows that the crash occurred on an exit ramp. However, the Hwy Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.



### Table A-58. Case Study 8 – Type 6 Misclassification

The field diagram does not contain any curves. Curve Type ID is consistent with Road Align ID, which indicates the crash occurred on a non-curve segment. However, the Hwy Curve GIS layer clearly shows the crash location is on a curve. Based on the investigation, we conclude that the GPS coordinates may not accurately reflect the location where the crash occurred.

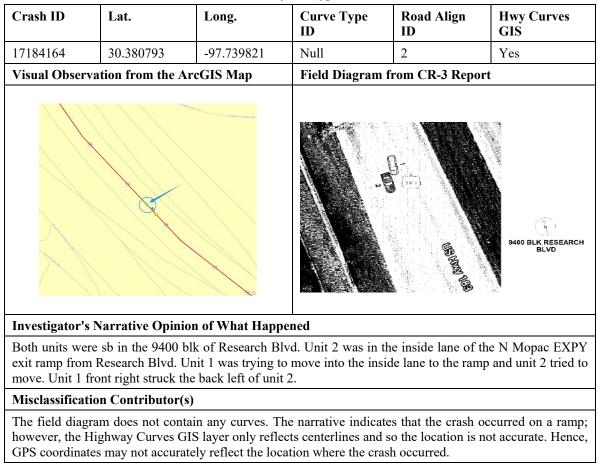
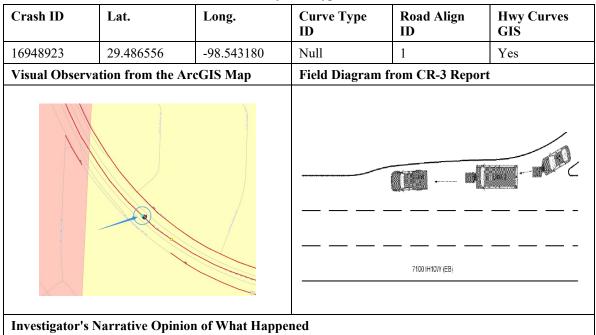


Table A-59. Case Study 9 – Type 6 Misclassification



### Table A-60. Case Study 10 - Type 6 Misclassification

Unit #1 was driving eastbound on 110W Access Road and entering 110E at the crossroads entrance ramp. Unit #1 had a couch which fell off the back of their vehicle and struck unit #2 and unit #3. No parties were injured during the accident.

### Misclassification Contributor(s)

The narrative and field diagram indicate the crash occurred on an entrance ramp. However, the Highway Curves GIS layer only reflects centerlines and so the location is not accurate. Hence, GPS coordinates may not accurately reflect the location where the crash occurred.

# Appendix B. Value of Research (VoR)

# Introduction

The scope of TxDOT project 0-7050 includes a statement on the value of the research (VoR) that the UT/CTR team conducted. For the establishment of VoR, a total of six functional areas were identified spanning the qualitative category. A summary of the selected functional areas is shown in Table B-1.

Benefit Area	Qualitative	Economic	Both	TxDOT	State	Both
Level of Knowledge	Х			Х		
Customer Satisfaction	X			Х		
Traffic and Congestion Reduction	Х				Х	
Reduced User Cost	Х				Х	
Engineering Design Improvement	Х					Х
Safety	X					Х

Table B-1. Functional Areas of Project 0-7050

# **Qualitative Benefits**

The project identified six functional areas that contributed to the qualitative benefits:

- Level of Knowledge
- Customer Satisfaction
- Traffic and Congestion Reduction
- Reduced User Cost
- Engineering Design Improvement
- Safety

# Level of Knowledge

Project 0-7050 increased the Level of Knowledge related to the identification of curve-related crashes in the Crash Records Information System (CRIS). The results from the literature review boosted the Level of Knowledge regarding the characteristics and impacts of horizontal curves on traffic crashes. The outcome of the assessment of curve-related attributes in the CRIS database helped users better understand data consistency in CRIS. In addition, the key findings from investigating the peace officer's crash reports provided meaningful information on probable causes for curve-related crash misclassification in CRIS. Overall, the outcomes from this research

advanced the understanding of curve-related crashes in CRIS together with potential reasons for curve-related crash misclassifications.

## **Customer Satisfaction**

Customer satisfaction is an essential consideration for TxDOT when designing segments of the Texas highway system. TxDOT manages both the largest and busiest highway network in the country; on-system roadways include around 198,000 lane miles and around 37,000 bridges. TxDOT is responsible for providing a safe and comfortable travel environment to road users. The methodological procedure developed in this project provides TxDOT with an effective approach to identifying curve-related crashes in CRIS. This can significantly improve the accuracy of the CRIS database and enhance the reliability of crash analysis based on CRIS data. This will help TxDOT to improve the safety performance of roadways across the state. Therefore, the results of this study will help keep traveling consumers satisfied with lower risks for traffic crashes, and for the delay and congestion they cause.

## **Traffic and Congestion Reduction**

As mentioned above, the methodological procedure developed in this project can improve the identification of curve-related crashes in CRIS. This will give TxDOT more insights into pinpointing locations where crashes are more likely to occur. By identifying these crash hotspots, TxDOT will be able to create more reliable crash prediction models as well as robust crash prevention plans. Accordingly, it will help reduce the likelihood of traffic and congestion caused by crashes.

## **Reduced User Cost**

The outcome of this project will help TxDOT better understand curve-related crash misclassification in CRIS. The improved understanding of crash data will increase the reliability and accuracy of the CRIS database. With this information, more effective policies can be implemented to reduce the frequency and severity of crashes. Thus, road users will have lower risks of delay, congestion, harm, and financial loss due to traffic crashes.

## **Engineering Design Improvement**

In this project, the research team carefully categorized, thoroughly analyzed, and systematically documented all the information obtained from the literature review on geometric characteristics of horizontal highway curves; impacts of horizontal curves on crash risk, frequency, and severity; and safety factors affecting crashes that occurred on curved roadway segments. The key findings from the review together with other outcomes from the research will help TxDOT highway engineers gain a better understanding of the characteristics and impacts of horizontal highway curves. This knowledge will directly lead to an improved highway design in the future.

## **Safety**

The research outcomes from this project will reduce the negative consequences due to the underestimation of the safety impact of horizontal curves caused by curve-related crash misclassification in CRIS. One of TxDOT's significant roles is to promote safety and protect the lives of the traveling public. The automated methodological procedure as well as other findings from this research will improve the accuracy of CRIS and thus enhance TxDOT's ability to make high-impact traffic safety improvements across the state. The identified contributors to curve-related crash misclassifications will help TxDOT take proper action to improve data accuracy in the CRIS database. In summary, the outcomes from this research will enhance the knowledge of curve characteristics and their impact on traffic crashes and will contribute to improving the safety of highway system operations and Texas roadway users.

# Declaration

The key findings and outcomes of this project can directly help improve the identification of curverelated crashes in CRIS. It may further help TxDOT improve the accuracy of the CRIS database and enhance the reliability of crash analysis based on CRIS data. However, mathematically, it is a considerable challenge to translate these findings into quantitative economic benefits. For instance, this project identified that 23 percent of crash records in CRIS contain inconsistent curve attributes internally, showing in one data field that the crash is curve-related but in another data field that the crash did not occur on a horizontal curve. Moreover, the analysis performed in this project showed that, on average (based on CRIS 2017–2020 data), 27.1 percent of crashes in CRIS are misclassified in terms of whether they were related to curves. Although these statistics indicate the benefit that resolving misclassifications will have on traffic safety, they cannot be easily expressed as economic benefits in dollar amounts.