MOUNTAIN-PLAINS CONSORTIUM

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SAFETY SUPPORT SYSTEM FOR HIGHWAY RAIL GRADE CROSSINGS

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16. Abstract

As a result of the considerable differences in mass between vehicles and trains, crashes at highway-rail grade crossings (HRGCs) often result in severe injuries and fatalities. Therefore, HRGC safety is considered a crucial transportation safety issue. Transportation decision makers and agencies need an efficient safety decision-making framework that is able to predict crash occurrence and severity likelihoods in the same prediction model, identify and quantify contributors and their marginal effects, quantify geometric and countermeasures' safety improvement effectiveness, and rank the priorities for the crossings in terms of their safety improvement needs. This study proposed a statistical approach for HRGC crash analysis. The proposed method is competing risk model and the approach is Cox proportional hazard regression. This predictive method was well established in the bioscience area but never utilized in the transportation area. Competing risk model (CRM) is a special type of survival analysis to accommodate the competing nature of multiple outcomes from the same event of interest; in transportation safety analysis, the competing multiple outcomes are accident severity levels while the event of interest is accident occurrence.

Transportation decision makers need a prioritization system to categorize crossings' risk level based on their expected crash frequency and crash severity simultaneously. Therefore, with a hazard-ranking approach, which considers a crossing's crash severity and frequency output, transportation decision makers are able to ensure that federal and state funds for grade crossing improvement projects are spent at crossings that are considered the most in need of improvement. Moreover, significant contributors, including geometric contributors and countermeasures, are identified, and their marginal effectiveness is also summarized. In this study, the hazard ranking model based on crash likelihoods resulted by the proposed CRM method is used to classify grade crossings and crossing locations based on their crash frequency and severity likelihood simultaneously. The risk analysis is conducted by using the risk matrix and spatial risk analysis. Finally, an interactive app that incorporates all the findings of the research is developed for agencies to use as a simulation tool.

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Safety Support System for Highway Rail Grade Crossings

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EXECUTIVE SUMMARY

Highway-rail grade crossings (HRGCs) are a specific spatial location where two transportation modes of rail and road intersect with each other at grade level. HRGC accidents are mostly associated with potential points of conflict between roadway traffic and train traffic. Because of the substantial mass difference between automobiles and trains, crashes usually have relatively severe results. In addition, traffic delays of both the railway and the roadway can considerably extend the economic loss of crashes at HRGCs, and the expenditures from disruptions to both the roadway and railway networks can also be significant.

The research proposed an innovative statistical method, competing risk modeling (CRM), to identify the contributors, quantify marginal effects of geometric factors and control devices, and predict crash occurrence and severity simultaneously. Traffic exposure variables such as annual average daily traffic, day through train, night through train, train speed, and percentage of trucks are all significant contributors. The type of train services, commercial power availability, and train detection technologies are also identified as significant contributors. Moreover, the research also further quantified the four geometric contributors' effects and conducted detailed marginal effectiveness analysis for traffic control devices considering the pre-control conditions. The four geometric factors are distance between a crossing and its nearest intersection, crossing angle as a continuous variable, number of lanes, and number of tracks. These geometric factors are spatially calculated with GIS software if they are not readily available.

The research also proposed an approach investigating the potential use of the effectiveness and prediction results from the CRM to rank and prioritize crossings in North Dakota based on the predicted cumulative crash likelihood assuming equal weight on property damage only (PDO), injury crashes, and fatal crashes. Inverse distance weighted (IDW) interpolation is utilized to map the crossings' crash likelihood ($\boldsymbol{CIF_c}$) resulted from CRM in North Dakota. This assigned value is a geographically weighted average of crash likelihoods, estimated by considering the distance between interpolated spots and the known crossings nearby. IDW assumption is that the calculated crash likelihoods have a local effect, and this effect decreases as the distance increases. Moreover, an interactive app is developed to illustrate the findings of the study.

The applied approach suggests that the method is easy to use and interpret in practical applications, and the following conclusions are drawn from the study:

1) Hazard index should include both crash severity and crash occurrence likelihoods.
2) Prediction model should be able to predict both crash severity and crash occurrence simultaneously to account for unmeasurable variances with the same set of predictors.
3) Some contributors can be found significant to certain crash levels but not significant to others.
4) One contributor can positively impact certain crash levels but negatively impact others.
5) The dependency between competing risks exists, so the prediction model should consider such dependency. The independent censoring assumption could result in under-estimated contributor effects.
6) Marginal countermeasure effectiveness should be dependent on the pre-existing conditions. In other words, adding a same device to crossings with different existing control devices will present different effectiveness.
7) Adding a traffic control device to a crossing does not always result in improved safety performance.
8) Adding a traffic control device to a crossing may result in a positive improvement effect on certain crash levels but a negative improvement effect on others.

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1. INTRODUCTION

Highway-rail grade crossings (HRGCs) are a specific spatial location where two transportation modes of rail and road intersect with each other at grade level. HRGCs crashes are mostly associated with potential points of conflict between roadway traffic and train traffic. Because of the substantial mass difference between automobiles and trains, crashes usually have relatively severe results. In addition, traffic delays of both the railway and the roadway can considerably extend the economic loss of crashes at HRGCs, and the expenditures from disruptions to both the roadway and railway networks can also be significant.

Safety concerns at HRGCs in the United States have been social concerns for decades because crashes at those locations are often catastrophic and result in greater economic loss for both highway and railway users. There are about 205,000 at-grade crossing in the United States. The number of HRGC accidents declined substantially over time because more safety research promotions and more transportation safety infrastructure improvements have been conducted. However, from Figure 1.1, one can tell that incidents/million train miles traveled show an upward U-shaped curve trending. It is important for transportation agencies, decision makers, and stakeholders to be more innovative and rethink the realm of possibilities to enhance safety (Andersen, 2013).

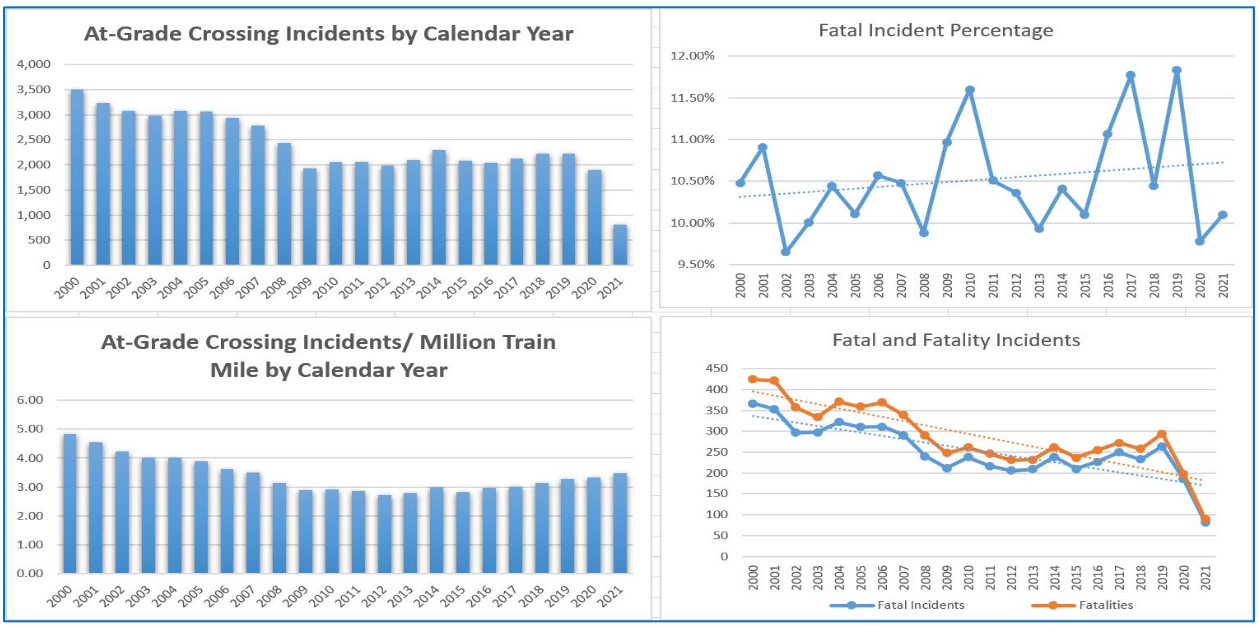

Figure 1.1 U.S.A. HRGC Incident Trends Overview, 2000-2021

About 11% of HRGC crashes resulted in 11,269 fatalities, while only 0.5% of all roadside crashes led to deaths nationwide (Zheng et al., 2018). Compared with national data, as seen in Figure 1.2, North Dakota (ND) is one of the safest states in terms of at-grade crossing crash frequency. However, crashes in the state tend to be more severe than the national average. Based on the past 22 years of data, on average, there are about 3.4 incidents per million train-miles at the national level, but the ND at-grade crossing crash rate is nearly 0 per million train miles traveled; however, 10.5% of all national-level HRGC crashes are fatal and the ND value is 15%, compared with a 0.5% roadside fatal ratio.

In ND, the need to improve HRGC safety has been a major social concern for decades. Transportation agencies and other stakeholders must identify the factors that contribute to the likelihood of various levels of HRGC crashes to better predict crash and severity probability and understand the marginal effectiveness of the countermeasure treatments to provide direction for RGC designs and improvement strategies that will reduce crash numbers. This research intends to improve agencies' understanding of HRGC safety performance and safety improvement treatment selections.

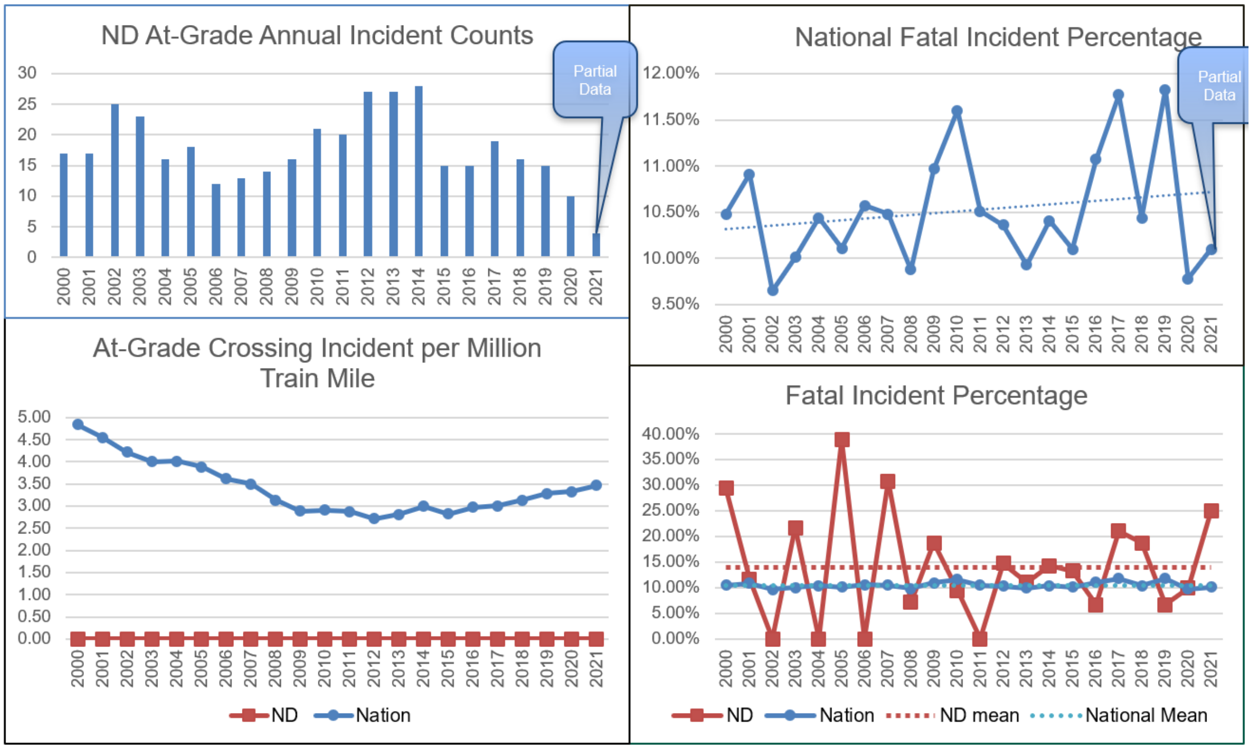

Figure 1.2 ND HRGC Incident Trends Overview, 2000-2021

The following research report is organized with chapter two focusing on the literature review on the HRGC safety research. Chapter three introduces the crash prediction models. Chapter four focuses on improvable contributor effects analysis. Chapter five summarizes countermeasure effect analysis to improve HRGC safety performance. Chapter six explains the interactive display app developed by the team. Chapter seven illustrates ND HRGC hazard ranking, and the last chapter focuses on summary and future research directions.

2. LITERATURE REVIEW

2.1 Literature on HRGC Crash Frequency and Severity

A large volume of literature has been found to analyze and predict transportation incidents. Most of the previous research studies have focused on roadway intersection or roadway crashes (Cai et al., 2017; Geurts et al., 2005; Hao et al., 2019; Huang et al., 2017; Islam and Brown, 2017; Kumar et al., 2017; Lee et al., 2017; Li et al., 2017; Paul, 2019; Qin et al., 2004; Ulak et al., 2019; Veeramisti et al., 2019; Wang and Abdel-Aty, 2006; Zheng et al., 2018). Relatively little research effort has focused on HRGC crashes compared with roadway crashes (Cho and Rilett, 2006; Ghomi et al., 2016; Haleem, 2016; Khattak et al., 2012a; Lu and Tolliver, 2016; Tung and Khattak, 2015; Yue and Jones, 2010; Zhao and Khattak, 2017; Zheng et al., 2019; Zheng et al., 2016). Moreover, among all the previous HRGC crash analyses, the majority of them focus only on either crash frequency, often based on crossing inventory databases (Lu and Tolliver, 2016; Austin and Carson, 2002; Guadamuz-Flores and Aguero-Valverde, 2017; Heydari et al., 2018; Heydari and Fu, 2015; Hu et al., 2012; Hu and Lin, 2012; Khattak et al., 2012b; Khattak and Luo, 2011; Lee et al., 2004; Medina and Benekohal, 2015; Millegan et al., 2009; Oh et al., 2006; Saccomanno et al., 2007; Saccomanno and Lai, 2005; Yan et al., 2010), or on crash severity analysis, often based on historical crash police report databases (Ghomi et al., 2016; Eluru et al., 2012; Fan et al., 2015; Haleem and Gan, 2015; Hao and Daniel, 2016; Hao and Daniel, 2014; Hao and Daniel, 2013; Hu et al., 2010; Kang and Khattak, 2017; Liu and Khattak, 2017; Ma et al., 2018; Savolainen et al., 2011; Zhao et al., 2019; Zhao and Khattak, 2015). To understand and predict crash frequency and severity simultaneously and consistently is important for agencies seeking to improve safety so they can account for the common factors affecting both crash frequency and severity. Separate forecasting models help to determine what factors affect the likelihoods of a crash occurrence or crash severity levels; however, there are several application obstacles: (1) Identified contributors are not consistent. Policy-reported surface conditions are often used in severity models but are not available for crash occurrence models. (2) Estimated crash severity likelihoods are conditional probabilities given crash occurrences based on a unique set of identified contributors and not transferable for agencies to calculate absolute probability for a specific crash level. For example, separate forecasting models could provide 20% crash likelihoods with one set of contributors, say A to E, and 25% level-one crash severity, 30% level-two crash severity, and 45% level-three severity with another set of contributors, say D to H. Because of F, G, and H contributors, the probabilities are not transferable among different models; however, safety improvement agencies need consistent and commonly available information to assist in safety improvement decision-making based on both crash occurrence and crash severity. The same forecasting model to account for both crash frequency and severities with commonly available contributors is needed so that unmeasurable variance can be accounted for in the same error term and the estimated likelihoods can be directly used by agencies.

2.2 Literature on Contributor Effects of HRGC Safety Performance

There is extensive literature on identifying safety performance contributors. Contributing factors can be geometric factors of crossings like crossing angles and distance to a nearby intersection or traffic exposure factors, such as daytime train traffic, roadway traffic, and train speed. Table 2.1 demonstrates the contributors that 39 state DOTs consider in their grade crossing safety improvement projects based on the reports provided by Sperry et al. (2017a, 2017b) and FHWA (2014). Table 2.1 indicates that the three most common contributors that state DOTs considered are annual average daily traffic (AADT), train volume, and crossing control types, which are all used by more than 90% of state DOTs. Other key contributors are crash history (crash frequency), train speed, and the number of main tracks.

Table 2.1 Contributing Factors Adopted by States (Sperry et. al., 2017a)

Contributors	**Number of States**
Annual Average Daily Traffic (AADT)	39
Train Volume	39
Crossing Control Types	36
Crash History	29
Train Speed	29
Number of Main Tracks	28
Number of Traffic Lanes	24
Roadway Paved Condition	23
Highway Speed Limit	5
Distance to the Nearest Intersections	3
Type of Train Service	3
Crash Severity	1
Crossing Angle	1
Pavement Markings	0
Train Detection System	0
Commercial Power	0
Percent of Trucks	0

The most researched contributors are either traffic exposure variables such as AADT and travel speed or traffic control devices such as gates. In general, the traffic exposure contributors are believed to have positive impacts on crash frequency and severity (Chadwick et al., 2014; Djordjević et al., 2018; Liu et al., 2015; Lu and Tolliver, 2016; Ma et al., 2018; Saccomanno et al., 2007; Witte and Donohue, 2000; Wu et al., 2014; Zhang et al., 2018; Zhao and Khattak, 2015); in other words, the higher the traffic exposures the more likely the crash occurs.

A complete understanding of how HRGC geometric factors affect HRGC crash severity and frequency is also critically important. Motor vehicle drivers have more flexibility in terms of their route and speed of traveling choices; in contrast, trains are restricted to a fixed guided path and strict traveling speed (Ogden and Cooper, 2019). Moreover, with reduced friction between the steel wheel and the steel rail, trains take much longer distance to stop compared with trucks on the road. Consequently, to avoid HRGC collisions, trains have the right of way. Because of this, highway and railroad engineers who design, operate, and improve the safety performance of HRGCs not only need to identify contributing factors such as geometric variables but also need to understand their effects on safety performance (Ogden and Cooper, 2019).

Distance between a crossing and its nearest highway intersection indicates the potential number of vehicles to be queued up by the intersection traffic control. Moreover, it also impacts the highway users' sight distance. A short distance indicates less storage capacity, which will potentially increase the chances of secondary crashes for the vehicles trapped between crossings and intersections; however, a short distance provides better vision, which will help alert drivers to the existence of the crossing and the rail traffic. Crossing angles, number of tracks, and number of highway lanes could also impact the vehicle struck position such as T-bone crashes or side-swipe collisions. T-bone crashes, which will more likely happen when the crossing angle is close to 90°, can be one of the most serious types of crashes. While side-swipe collisions are more likely to happen with acute angles and with more highway traffic lanes. On the other hand, acute crossing angles and multiple main tracks will increase track clearance distance (Transport Canada, 2019). Increased track clearance distance will certainly increase the chances that highway users become trapped on crossings, which will in turn have an impact on severity.

It is commonly agreed that geometric features can affect collision frequency because these features can impact travel operations and sight distances at HRGCs. However, their overall quantitative effects on crash frequency and crash severity likelihood are unclear. Moreover, the long-term effects of geometric features also need to be explored to fully understand their effects on safety performance over time.

Most existing identification and analysis of various contributors to HRGC safety performance focus on the investigation of their association with injury severity levels (Eluru et al., 2012; Fan et al., 2015; Ghomi et al., 2016; Haleem and Gan, 2015; Hao and Daniel, 2016, 2014, 2013; Hu et al., 2010; Kang and Khattak, 2017; Liu and Khattak, 2017; Lu and Tolliver, 2016; Ma et al., 2018; Savolainen et al., 2011; Zhao et al., 2019; Zhao and Khattak, 2015; Zheng et al., 2016). Hao and Daniel (2013) applied an ordered probit model with 10 years of crash data to identify the significant variables impacting crash severity at HRGCs in the United States. Their study indicated that, compared with male and younger drivers, female and older drivers are more likely to be involved in severe injury crashes. Hao and Daniel (2014) continued their studies and found that peak hour, visibility, motor vehicle speed, train speed, driver's age, area type, and traffic volume have effects on driver injury severity at both active and passive highway-rail crossings. Eluru et al. (2012) used the latent ordered response model with 10 years of U.S. HRGC crash data and found that travel time, truck sequence, and aggressive driving maneuvers impact crash severity. Hu et al. (2010) investigated three years of crash data from Taiwan with a generalized logit model and found that volumes of train traffic and truck traffic have positive relationships with crash severity. Recently, Zhao et al. (2019) used binary logit models and a generalized linear mixed model and found that train speed, freight train service, absence of flashing lights, advance warnings, rural areas, and lower visibility significantly impact crash severity. Although extensive research has focused on identifying safety performance contributors, there have been relatively few attempts (Austin and Carson, 2002; Berg et al., 1982) at quantifying the effects of geometric factors on safety performance at HRGCs. This gap could result from the lack of detailed HRGC geometric measurements (Washington and Oh, 2006). The most commonly used database for grade crossing geometric information is the Federal Railroad Administration's (FRA) highway-rail grade crossing inventory data. Crossing angle and the distance between a crossing and its nearest roadway intersection are continuous numerical variables. However, the recorded values provided by FRA have been categorized into truncated groups. Thus, these two variables are shown as nominal variables with three crossing angle levels (0°–29°, 30°–59°, and 60°–90°) and two distance levels (no greater than 500 feet [152.4 m] and greater than 500 feet [152.4 m]). Ogden and Cooper (2019) indicated that these two variables could have an effect on collision frequency because of their potential impacts on sight distance and vehicle storage capacity. A few studies examined these two HRGC geometric factors' effects on crash severity levels. However, all the researchers used the geometric variables as nominal variables in their research. Zhao et al. (2019) considered the smallest crossing angle as one of the potential factors associated with pedestrian injury severity levels. They used the smallest crossing angle factor as a nominal variable with two levels (1: less than 60°; 0: otherwise). Haleem (2016) investigated the effects of distance to the nearest intersection with four levels (≤ 75 feet [23 m], 75–200 feet [23–61 m], 200–500 feet [61–152.4 m], and>500 feet [152.4 m]) and found that the variable is not significant in both models. Yan et al. (2010), Liu and Khattak (2017), and Oh et al. (2006) also considered both variables as nominal variables with different levels in their analysis and concluded they are not always significant contributors to HRGC crash frequency or crash severity.

A few researchers also tried to identify the effects of some other HRGC geometric factors in their crash severity/frequency analyses (Austin, 2000; Liu and Khattak, 2017; Oh et al., 2006; Yan et al., 2010). Yan et al. (2010) indicated that number of traffic lanes has a significant impact on crash frequency with the negative binomial (NB) model but not with a hierarchical tree-based regression (HTBR) model; but the number of tracks is significant in both models. Moreover, Liu and Khattak (2017) showed that the number of traffic lanes has a significant impact on injury severity while the number of tracks does not. However, the number of tracks was found to have a strong association with gate violations.

2.3 Literature on HRGC Hazard-Ranking

Transportation officials and decision makers need systematic approaches to evaluate and identify crossings that need safety improvements. Identifying these systematic methods is essential to ensure that federal and state funds for highway-rail grade crossing improvement projects are allocated to locations and crossings at a higher risk for crashes (Ogden and Cooper, 2019). The most prevalent prioritization approaches for ranking highway-rail grade crossings are hazard index and collision prediction formula techniques. While the hazard index is used to estimate a value that ranks crossings in relative terms (the higher the quantified index, the more hazardous the crossing), the collision prediction formula (prediction model) is utilized to quantify the predicted crash frequency or severity. A few research projects and state DOTs used hybrid models, which consist of both a crash frequency (as the output of the collision prediction formula) and a hazard index approach (Niu et al., 2014; Weissmann et al., 2013).

The most common hazard-ranking approaches used by state DOTs are 1) the U.S. DOT Accident Prediction Formula, 2) the New Hampshire Hazard Index Formula, 3) the NCHRP Report 50 Accident Prediction Formula, and 4) the Peabody–Dimmick Formula. Figure 2.1 indicates the distribution of HRGC hazard-ranking models and formulas utilized by state DOTs according to a review of the state Section 130 program reports (FHWA, 2014). Among all the states, 39 (78%) utilize one or more hazard-ranking formulas in grade crossing evaluation for project prioritization and selection (Sperry et al., 2017a). One of the earliest hazard-ranking approaches for grade crossings is the New Hampshire Hazard Index, which depends on the hazard index formula. Kansas, Louisiana, Massachusetts, Michigan, and Nevada utilize the New Hampshire Hazard Index as their primary approach for ranking highway-rail grade crossings and their crossings' safety improvements (Sperry et al., 2017a).

The crash prediction model is another approach to prioritize grade crossings by utilizing the mathematical formula to calculate the predicted crash frequency (or severity) at a crossing. Therefore, the predicted value is used as the ranking metric for HRGCs' prioritization targets. Figure 2.1 shows that, among states, 19 (38%) have utilized the U.S. DOT accident prediction model and 11 (22%) developed their own state-specific prediction model for hazard-ranking purpose. The advantage of the crash prediction model is that it considers several characteristics or factors that have significant effects on the crossings' crash risk. Moreover, prediction models' output can be integrated with economic data (e.g., crash costs) to produce a comprehensive economic analysis associated with grade crossing improvement projects (Ogden and Cooper, 2019).

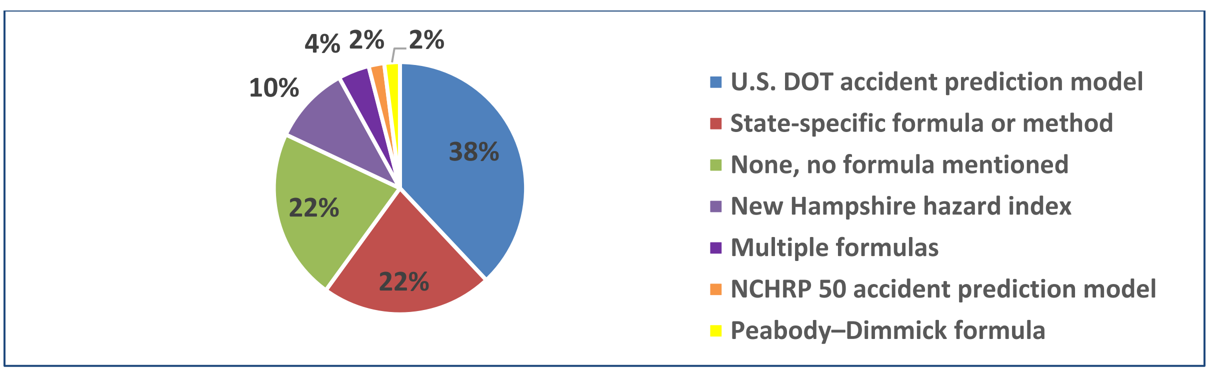

Figure 2.1 State DOTs' Grade Crossing Hazard-Ranking Models

Although the USDOT Accident Prediction Model, NCHRP 50 Accident Prediction Model, and Peabody-Dimmick formula are common hazard-ranking methods for state DOTs, some states (Niu et al., 2014; Sperry et al., 2017a; Weissmann et al., 2013) have developed state-specific hazard-ranking models in accordance with their accident trends and available crash records. However, most state DOTs' hazard-ranking models have focused on either crash prediction models (Farr, 1987b; Ogden, 2007; Schoppert and Hoyt, 1967) or calculation of hazard index (Abioye et al., 2020; Faghri & Demetsky, 1986; Qureshi et al., 2003; Tustin et al., 1986), and only a few studies have explored a hybrid model incorporating both the accident prediction model and hazard index (Niu et al., 2014; Weissmann et al., 2013).

Moreover, the vast majority of prioritization systems designed by state DOTs only consider the crash frequency at crossings. According to Sperry et al. (2017a), only one state considered crash severity as a factor in grade crossing hazard-ranking. Therefore, a comprehensive hybrid risk-method, which is able to consider both crash frequency and severity in identifying crossings that have higher priority in receiving improvement services, is needed.

2.4 Current Research Gap

Several research gaps are identified and will be the focus of this study based on the literatures summarized in the previous three sections:

1) To measure and predict crash frequency and severity simultaneously, which is critical for transportation decision makers seeking to improve safety at grade crossings so they can identify and investigate the common factors affecting both crash frequency and severity changes.
2) To better understand the effectiveness of grade crossings' geometric factors on crash occurrence and severity level changes.
3) To investigate countermeasures' effectiveness on both crash occurrence and severity levels.
4) To establish a prioritization or ranking system to classify crossings risk levels based on both crash frequency and crash severity.

In this study, a novel competing risk algorithm and Cox proportional hazard regression is proposed to predict crash frequency and severity simultaneously through the application of ND at-grade crossing data. Mover, four critical crossings' geometric parameters are investigated and measured at 3,194 public grade crossings in North Dakota. These four geometric features of crossings are: 1) acute crossing angle, 2) number of tracks, 3) the roadway distance between each crossing and the nearby intersection, and 4) number of highway traffic lanes. Note that distance to the nearest intersections and grade crossing angles are spatial calculations drawn from geographic information systems (GIS). The proposed CRM approach is also used to estimate countermeasures' effects on crash occurrence and severity likelihood simultaneously by estimating their marginal effect and instantaneous risk. In addition, spatial risk analysis is performed based on ranking by crash frequency and severity.

3. CRASH PREDICTION MODELS

3.1 Research Efforts and Publications

As summarized in the previous sections, prediction models on grade safety performance have focused on either crash occurrence frequency or crash severity. Those studies shed light on the modeling and understanding of crash occurrence and severity separately; however, they do not provide applicable assistance for highway agencies to account for the common factors affecting both crash frequency and severity simultaneously to control unaccounted covariates affecting prediction variations. In this study, the competing risk method is developed and proposed for grade crossing accident safety analysis. The method is a well-developed algorithm that has been widely applied in the medical field but is still relatively new in transportation safety analysis. The detailed methodology explanations can be found in Keramati et al. (2020a) and Keramati et al. (2020b), which are the two journal papers published from this research effort and which summarized the key research efforts under this research goal.

The competing risk model as a novel prediction model was proposed to examine crash frequency and severity simultaneously for public highway-rail grade crossings in North Dakota from 1990 to 2018. The competing risk model has the capability to identify specific crossings' characteristics and to simultaneously model collision occurrence and crash severity probabilities. Easy-to-interoperate outputs are one of the advantages of the model. These outputs include the estimated coefficients, hazard ratios, and cumulative probabilities. Moreover, the model indicates its ability to consider the dependence of contributors' effects on crash severity levels.

3.2 Results Discussion

Table 3.1 summarizes the identified important contributors by their importance and estimated percent of hazard ratio change for all three severity levels and for crash frequency. The hazard ratio reveals critical risk information regarding the contributors' influence on instantaneous crash and severity likelihood. Results estimated from the short-term instantaneous hazard ratio can be underestimated because of independent censoring assumption. Hazard ratio is a direct isolated influential indicator to a specific failure event like crash occurrence in this study. The isolated influential effect is not able to consider the same contributor's impact on other competing events. Consequently, it causes the underestimating of the covariate's impact when HR estimations are applied for analyzing the marginal likelihood of cause-specific events considering the competing nature of multiple causes to the same event of interest.

To account for contributors' effects on hazard ratio and long-term effects, the cumulative-incidence-based effect analysis is also conducted. Wolbers et al. (2014) demonstrated that a covariate does not have a significant effect on the risk of a competing-event failure based on the results of cause-specific hazard function; however, it still might have a significant impact on the competing event based on cumulative incidence function (cumulative risk probability). Subsequently, a covariate, which has no direct effect on one specific type of failure event, might still significantly affect the cumulative injury probability (CIF) of that failure event. The marginal probability of a specific failure event can be estimated by its cause-specific probability and the overall cumulative survival probability. The detailed explanations of the methodology can be found in Keramati et al. (2020a) and Keramati et al. (2020b).

Figure 3.1 displayed the estimated cumulative probabilities of failure for a selected contributor, train service. One can see that the cumulative crash probabilities have an increasing trend over time at different rates with fluctuations. In general, grade crossings with intercity passenger train service are more likely to have all severity and crash occurrence risks, except for injury risk, in comparison with the crossings with freight train services. The figure also shows that the overall increase in cumulative PDO crash probability is faster than the injury and fatal crash probability for both types of train service.

Table 3.1 Contributors and Hazard Ranking Based on Hazard Ratio

Variable	PDO		Injury		Fatal		Crash	
	Rank	**%Impact**	**Rank**	**%Impact**	**Rank**	**%Impact**	**Rank**	**%Impact**
Type of Train Service:								
Intercity Passenger	1	82%	5	18%	2	101%	2	49%
Train Detection:								
CWT	5	22%	1	65%	1	172%	2	49%
DC	3	50%	3	45%	3	86%	1	50%
Is Commercial Power Available?								
No	8	10%	2	50%	6	35%	6	18%
Is Roadway/Pathway Paved?								
No	2	55%	4	33%	8	18%	3	45%
Total Daylight Through Trains	6	22%	7	11%	7	33%	5	22%
Total Night-time Through-Trains	7	18%	6	18%	4	65%	7	10%
Total Switching Trains	10	1%	11	3%	5	65%	9	3%
Maximum Train Speed	11	0.4%	10	5%	10	3%	10	2%
Annual Average Daily Traffic	14	0.01%	14	0.004%	14	0.01%	13	0.01%
Percent Trucks	9	8%	9	10%	9	4%	8	9%

In addition, Figure 3.1, part c reveals that the absolute magnitude of the increasing rate is also small between freight and intercity services, but over 30 years, the increased fatal probability proportion is almost doubled for HRGCs with intercity passenger train services in comparison with HRGCs with freight train services. With the short-term effect analysis, the grade crossings with intercity passenger service did not have a significant influence on instantaneous injury crash risk compared with crossings with freight train services regardless of competing risks. However, grade crossings with intercity passenger service were identified as significant to CIF compared with the ones with freight train services when considering competing risks. Similar findings are observed for other contributors such as CWT detection systems.

The full report of the results and discussions can be found in the two journal publications (Keramati et al., 2020a; and Keramati et al., 2020b). In general, this study found: 1) except night train traffic, all the analyzed contributors have direct positive cause-specific effects on certain crash severity levels but not on all the levels, 2) contributors can be identified as significant based on long-term cumulative probability analysis with competing risk dependency assumed but may not be significant based on short-term hazard ratio analysis, 3) contributors' effects on safety performance are different for different levels of severity and crash occurrence.

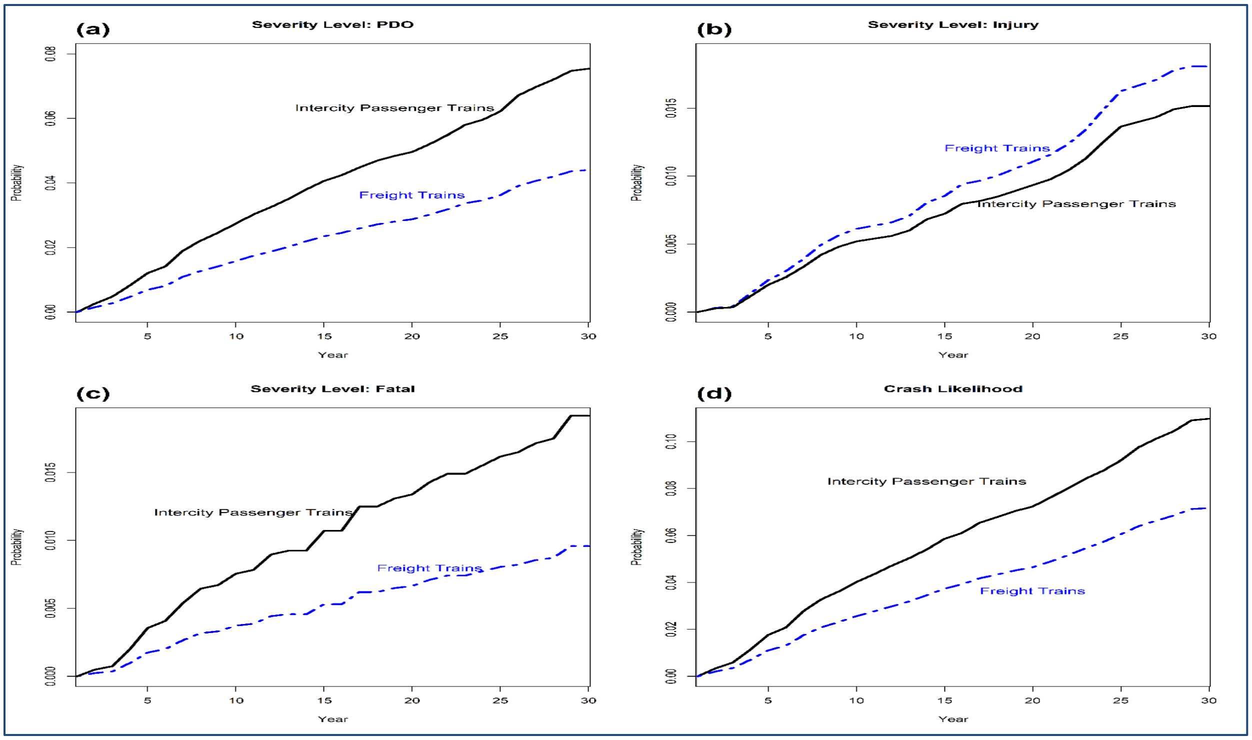

Figure 3.1 CIF of Crash and Severity for Train Services

4. GEOMETRIC CONTRIBUTORS' EFFECTS ANALYSIS

This section presents the research efforts, publications, and findings on geometric contributors' effects analysis. As indicated earlier, it is critical to truly understand safety improvement effects of the geometric contributors so that safety improvement agencies can utilize such information to make design, planning, and improvement decisions. Previous research has identified grade crossing geometric factors that significantly impact safety performance. In this chapter, the proposed competing risk model (CRM) is applied to identify contributing geometric factors and calculate their effects on grade crossing crash frequency and severity probabilities. Correspondingly, the aims of this chapter are to 1) investigate the crossing geometric factors' significance on safety performance considering both crash severity and crash occurrence in the same model (CRM), and 2) calculate geometric factors' instantaneous and long-term effects on grade crossing safety performance.

4.1 Research Publications and Findings

The complete research report can be found in Keramati et al. (2020b), which is the main journal publication from this section's research effort. Four main grade crossing geometric contributors shown below are researched in this study: 1) distance between crossings and their nearest roadway intersections, 2) highway-railway crossing angle, 3) number of traffic lanes, and 4) number of main tracks.

Table 4.1 summarizes the estimated coefficient and hazard ratio for short-term hazard analysis. As expected, all four geometric factors are identified as significant contributors to crash occurrence except the distance between crossing and its nearest intersection. Note that factors can be identified as significant contributors on the likelihood of certain crash severity levels, but not necessarily on others. For example, crossing angle is a significant contributor for injury, fatal, and crash occurrence but not for PDO. These results can be a consequence of under-estimation because of the independent censoring assumption in cause-specific function of the short-term hazard ratio analysis.

Table 4.1 Hazard Ratio and Estimated Coefficients

Geometric Factors	**PDO**		**Injury**		**Fatal**		**Crash Occurrence**	
	Coef	**Pr(>|z|)**	**Coef**	**Pr(>|z|)**	**Coef**	**Pr(>|z|)**	**Coef**	**Pr(>|z|)**
Crossing-Intersection Distance	-0.001	0.024 **	-0.00006	0.87	0.0005	0.32	-0.0005	0.13
Acute Crossing Angle	-0.003	0.48	-0.01	0.02 **	0.004	0.63	-0.005	0.01 *
Number of Road Lanes	0.38	0.054 *	0.20	0.37	-0.07	0.88	0.30	0.03 **
Number of Main Tracks	0.44	0.45	1.80	0.03 **	1.79	0.11	0.93	0.03 **

Additional findings from short-term hazard ratio are 1) distance between crossing to its nearest intersection is found to be positively significant on fatal crashes but not the others, 2) angle positively impacts fatal crash likelihood but not the others, 4) number of road lanes have negative impacts on fatal crashes but not the others, and 4) number of tracks has positive impacts on all four likelihoods.

Figure 4.1 summarizes the findings for geometric factors' impacts with long-term cumulative probability analysis and competing risk assumption with the calculated cumulative probability and its trends for each geometric factor. The range of values for each geometric feature is defined based on the actual data information used in this study. Distance range between a crossing and the nearest intersection is defined from 0 meters to 3,000 meters. Acute crossing angle ranges from 1° to 90°. The number of roadway lanes ranges from 1 to 4. And the number of main tracks ranges from 1 to 3.

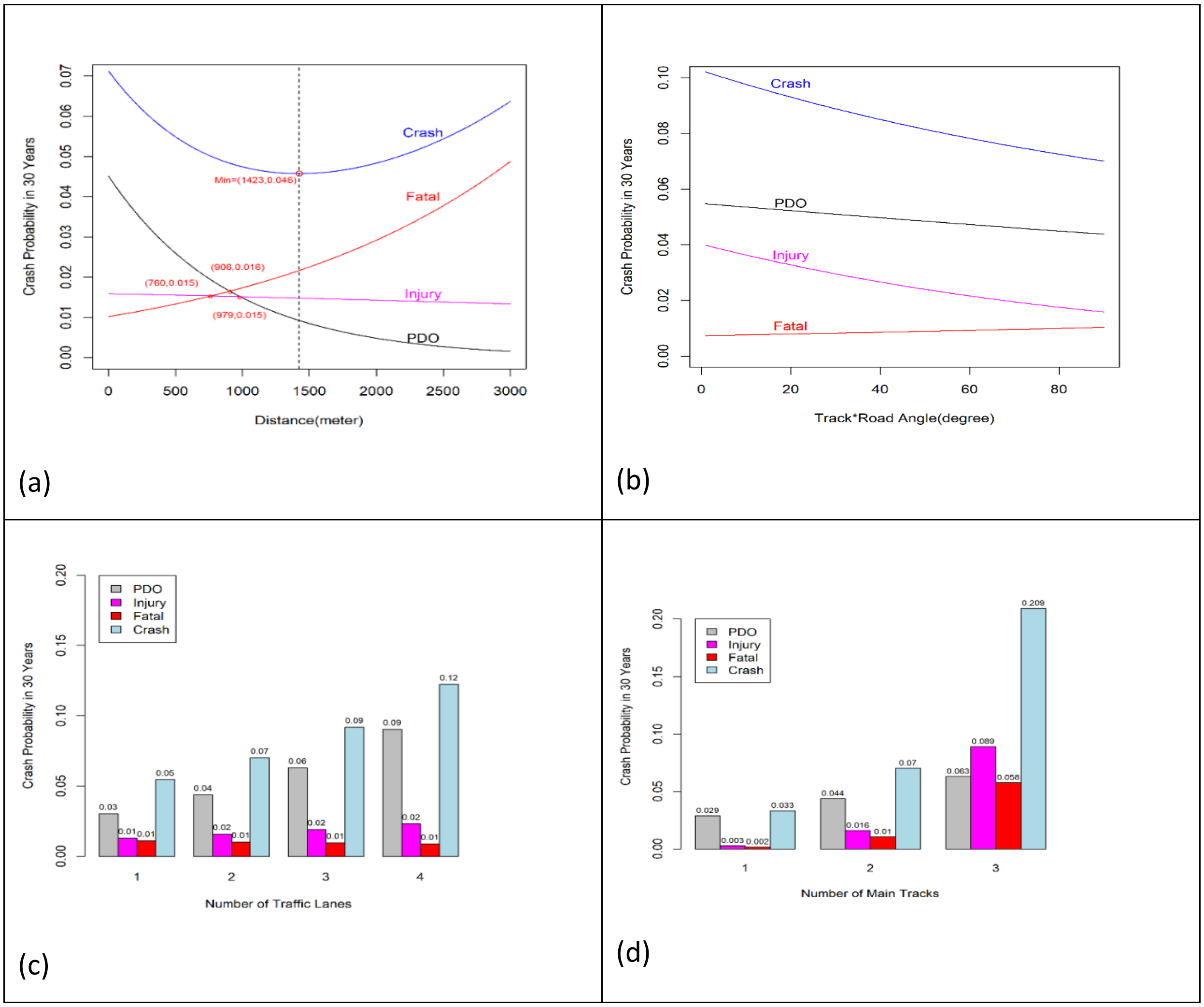

Figure 4.1 Cumulative Crash/Severity Probabilities for Geometric Factors

Figure 4.1 indicated that distance to intersection has a relatively smaller impact on injury than on PDO and fatal accident cumulative likelihood. The distance to nearest intersection positively impacts fatal accident probability but negatively impacts PDO probability. Around 1,423 meters, the lowest crash occurrence probability is about 4.6%. The distance between a crossing and the closest intersection can define vehicle storage capacity. The crash likelihood declined before reaching 1,423 meters, with the vehicle storage capacity increasing. On the other hand, when the distance to the intersection is more than 1,423 meters, the benefit of a larger capacity of vehicle storage will be hindered by more limited highway user's sight distance. The Railroad-Highway Grade Crossing Handbook (RHGCH) verified the minimum safe sight distance must be between 21 to 284 meters to guarantee safe stopping distances at various travel speeds (Ogden, 2007; Ogden and Cooper, 2019). This study results suggest a substantially longer distance, 1,423 meters, when considering traffic operational effects with the nearest roadway intersection. Figure 4.1 also shows that cumulative probabilities of crash, PDO, and injury crashes decrease while the acute crossing angle increases. One possible explanation for this result might be related to improved sightlines. According to Wigglesworth (2001), at acute-angled crossings, it may be difficult for highway users to detect a train while it is approaching from one of the rear quadrants. It increases the risk of an "over-the-shoulder" accident. On the other hand, with the increasing crossing angle, the fatal crash likelihood increases moderately, from about 0.8% to 1%. This increase might be because improved travel conditions may promote aggressive driving behavior, and perpendicular angle is associated with T-bone crashes, which often end with fatal crashes. According to Figure 4.1, when the number of traffic lanes increases from 1 to 4, crash likelihood increases from 5% to 12%; when the number of tracks increases from 1 to 3, crash likelihood increases from 3.3% to 21%. To clearly represent the four geometric factors' effects, the average marginal impact (change in likelihood for one unit change in a contributor) is calculated and presented in Table 4.2.

Table 4.2 Average Marginal Effects

Severity Level	Crossing Angle	Distance to Intersection	Number of Road Lanes	Number of Main Tracks
PDO	-0.01%	**-0 .0014%**	44%	48%
Injury	-0.03%	-0.00008%	21%	443%
Fatal	0.0033%	0.0013%	7%	440%
Crash	-0.036%	-0.00025%	31%	155%

5. COUNTERMEASURES' EFFECTS ANALYSIS

This section focuses on exploring the effects of traffic control devices, such as crossbuck signs, gates, and stop signs, as countermeasures with our developed models. As summarized in the literature, all existing research findings have shed light on understanding the effect of specific crossing warning devices on either crash rate or severity levels. However, these researches have not accounted for 1) the impact of modifying the crossing controls' combination on crash frequency and severity changes considering different pre-improvement control conditions (pre-improvement condition difference), or 2) the long-term time impact of HRGC warning device improvements on crash frequency and severity changes. In addition, grade crossing characteristics, including crossing traffic controls, might be changed over time, including before and after a collision occurrence (Liu & Khattak, 2017). Correspondingly, estimating crash rate and crash severity level changes need to consider the long-term time effect and recorded information changes for all crossing characteristics annually. The detailed study on quantifying countermeasures' effects on crash frequency and severity likelihood in our model is published as a journal paper, which can be found in Keramati et al. (2020b)

Figures 5.1 and 5.2 show the 29-year prediction of cumulative crash severity and occurrence likelihoods by comparing eight pairs of crossing control device options. The alternative options are compared by adding a specific device into a device or combination of devices as a base option, except for Figure 5.1(a). In Figure 5.1(a), the base case is crossbucks-only, and the alternative option is upgrading the control device to gate-only. Figure 5.1(a) reveals that upgrading from a passive control device to active control will likely decrease injury and fatal crash probability. However, this switching will increase both crash occurrence and PDO probabilities. These findings seem counterintuitive as it is normally expected to improve safety performance in crash occurrences and in all severities if a change is made from passive control to active control. However, the result reveals that changing the control device from crossbucks-only to gate will reduce the effects on more severe crashes (fatal and injury crashes) but will not decrease PDO crashes and crash occurrence in general. Figure 5.1(b) shows that adding gates to the crossings equipped with cantilevered flashing lights, standard flashing lights, and audible warning devices will decrease both crash occurrence and PDO probabilities but increase injury and fatal crash likelihood. In other words, upgrading crossings already equipped with flashing lights and audible devices will only decrease the likelihood of crash occurrence and PDO crashes but will not decrease the likelihood of more severe crashes. Figure 5.1(c) shows that adding stop signs to crossings with crossbucks will considerably increase the crash occurrence and severity likelihoods. These likelihoods are increased significantly by 284%, 235%, 333%, and 364%, respectively (annually). Figure 5.1(d) indicates that adding stop signs to actively controlled crossings will decrease crash occurrence, injury, and fatal crash probability. However, for PDO, a less severe crash likelihood, it is increased cumulatively by 47% in the 29-year study period. Note that this study finding reveals that adding stop signs to crossings with crossbucks-only will have negative effects on crash occurrence and all severity crashes, but adding a stop sign to an already actively controlled crossing will have additional positive effects on decreasing crash occurrence and more severe crashes. In addition, it has a negative effect of increasing the likelihood of less severe crashes such as PDO.

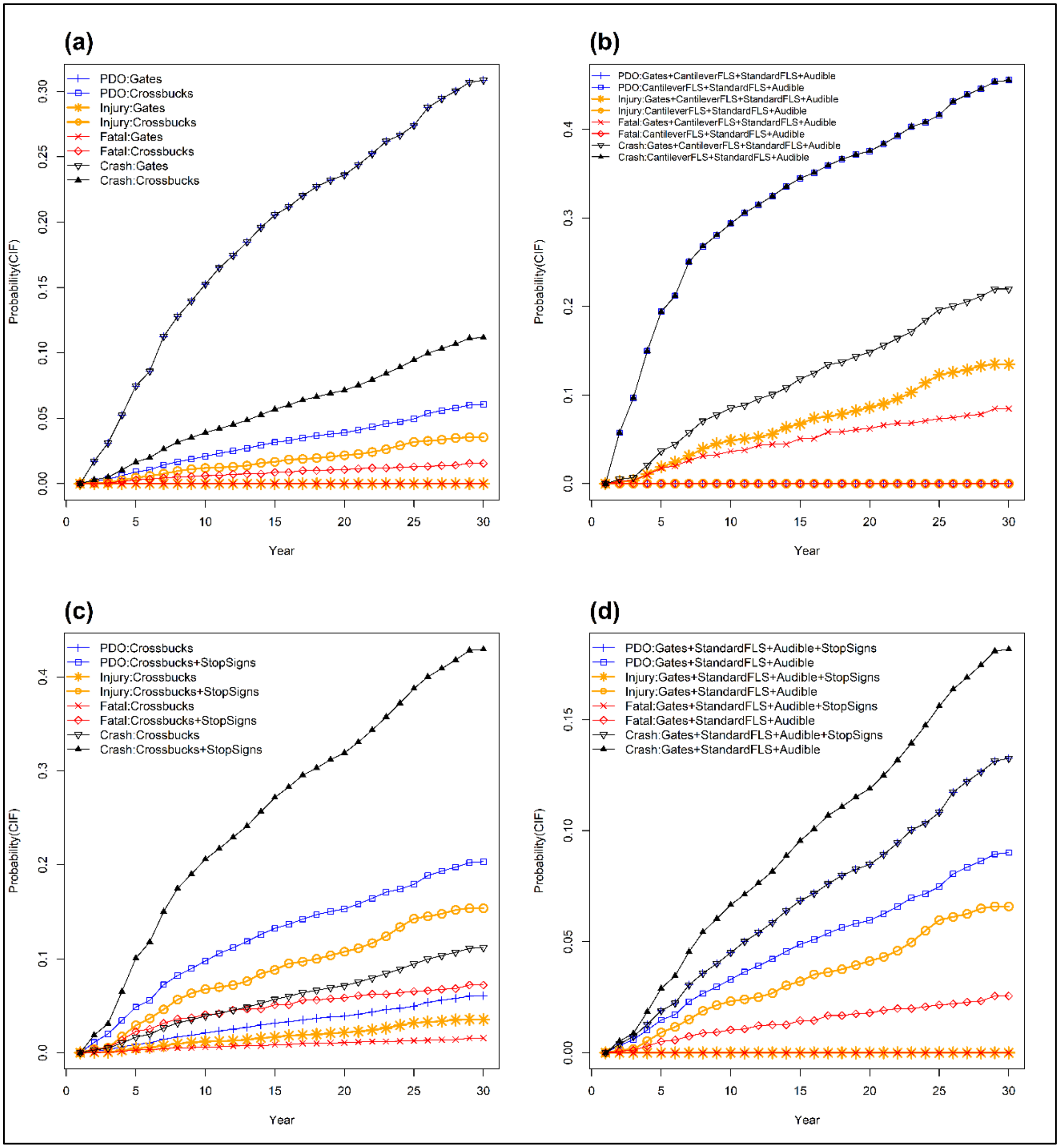

Figure 5.1 Crash Severity and Frequency Likelihoods for the First HRGC Control Pairs

As seen in Figure 5.2(a), adding audible devices to crossings with a combination of gates, cantilevered flashing lights, and standard flashing lights will decrease crash occurrences and PDO crashes by 16% and 100%, respectively, annually. Doing so will also result in a moderately decreased injury crash likelihood between years 4 and 25 and show no effect on injury crash probability for the rest of the study period. Figure 5.2(b) shows adding an audible device to crossings with gates will decrease PDO and fatal accidents to nearly zero. Moreover, such improvements will decrease crash occurrence by around 24% cumulatively during the 29-year study period. However, in this research, adding bells as an audio device at HRGCs equipped with gates and flashing lights will increase injury crash probability. Figure 5.2(c) reveals that adding standard flashing lights to crossings with gates, cantilevered flashing lights, and audible devices, will reduce PDO crashes and crash occurrences but will increase injury and fatal crashes. Adding standard flashing lights as supplemental flashing light signals or side lights at HRGCs with cantilevered flashing lights will increase the visibility of the crossing, thus making more highway users aware they are approaching a crossing or that a train is approaching. Correspondingly, it is expected that crossings with standard flashing lights installed as additional warning lights are more likely to have more severe crashes. Figure 5.2(d) shows that adding standard flashing lights to crossings with the combination of gates and audible devices will reduce crash occurrence and injury likelihoods but will increase PDO and fatal crash probabilities. Although adding flashing lights to crossings with a combination of gates and audible devices increases the crossings' fatal and PDO crash risk, the difference is small, both less than 0.1%.

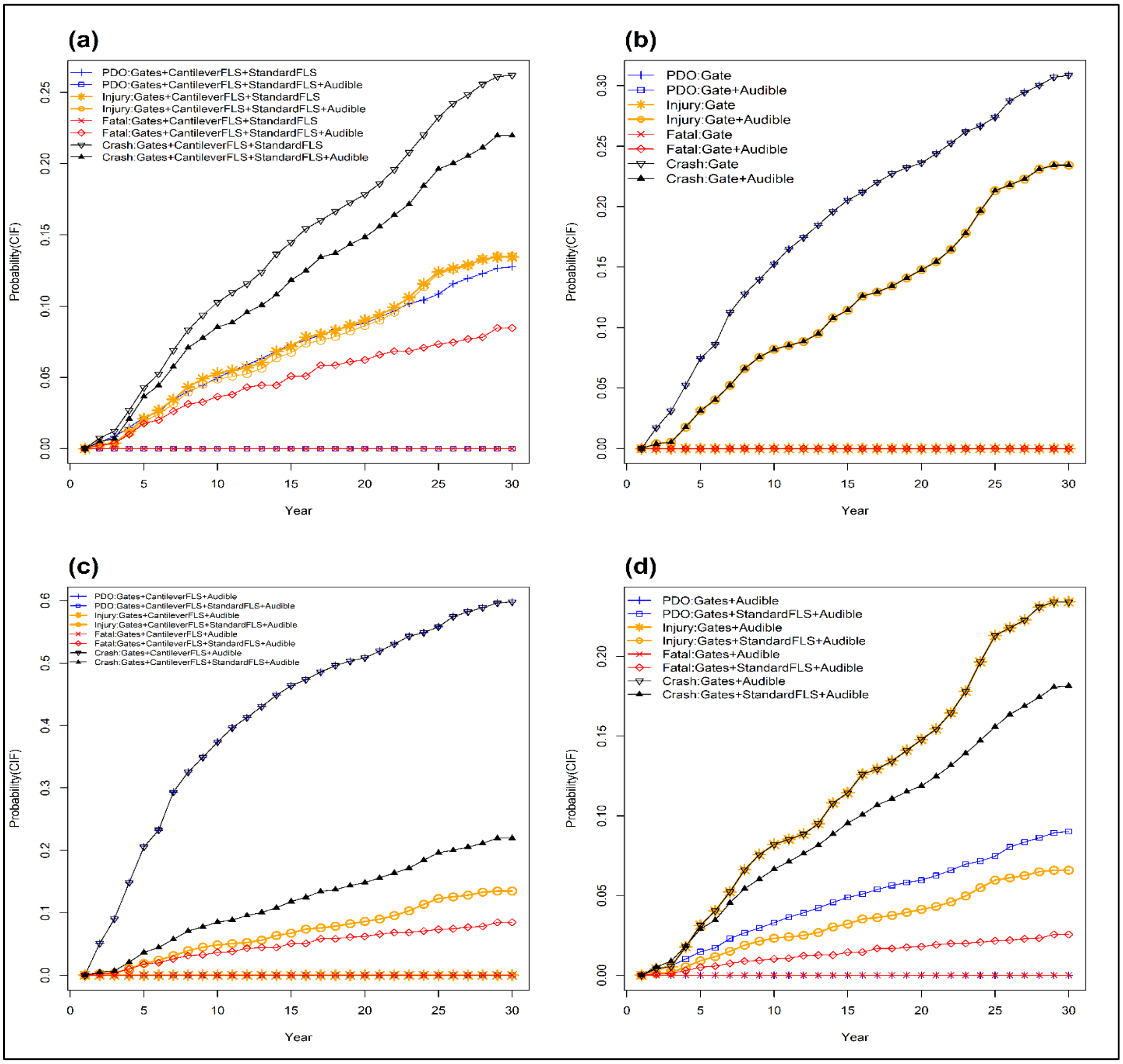

Figure 5.2 Crash Severity and Frequency Likelihoods for the Second HRGC Control Pairs

6. HAZARD RANKING IN ND HRGCS

To rank all public grade crossings in North Dakota according to their crash frequency likelihood (equal weight is given to PDO, injury, and fatal crashes), long-term cumulative probability, CIF_c for 3,194 grade crossings, is estimated. Crossings are then ranked in relative terms, a higher CIF_c representing a higher hazardous crossing. For example, Table 6.1 lists the first 10 hazardous crossings based on their crash likelihood in part (a) and the 10 crossings with the lowest crash likelihood in part (b). Table 6.1 indicates that the likelihood of crash occurrence at crossings listed in part (a) over 29 years is almost 100%, while the same likelihood for crossings in part (b) is almost 0%.

To understand the risk level of each crossing based on its crash frequency likelihood, crossings are classified into four risk groups: very low risk, low risk, moderate risk, and high risk. Crossings are classified as very low risk if their estimated CIF_c is less than 10%. Crossings with CIF_c between 10% and 20% are classified as low risk, and crossings with CIF_c between 20% and 40% are classified as moderate risk. Finally, if crossings' CIF_c is higher than 40%, they are classified as high-risk crossings. This study dataset indicates that in North Dakota, 1) 65.3% of public grade crossings are at very low risk, 2) 23.5% of grade crossings are at low risk, 3) 10.2% of crossings are at moderate risk, and 4) only 1.01% of crossings are at high risk given the equal weights on PDO, injury, and fatal crashes.

Table 6.1 Crossings with Highest (a) and Lowest (b) Crash Frequency Likelihood

a)			b)		
Crossing ID	Crash Likelihood ($\boldsymbol{CIF_c}$)	Rank	Crossing ID	Crash Likelihood ($\boldsymbol{CIF_c}$)	Rank
082143X	100.00%	1	102792E	0.00003%	3194
062486A	100.00%	2	690558H	0.00005%	3193
071099G	99.99%	3	080673F	0.00006%	3192
071735C	99.97%	4	062575S	0.00007%	3191
086876F	99.83%	5	081107Y	0.00007%	3190
086787N	99.77%	6	103407C	0.00007%	3189
071003P	99.76%	7	082305X	0.00007%	3188
087695E	99.35%	8	691842D	0.00009%	3187
093368H	99.32%	9	102477N	0.00009%	3186
695902Y	98.91%	10	102865M	0.00010%	3185

Despite of identifying crossings that have the most need for safety improvements, transportation decision makers need a systematic method to ensure that federal and state funds for highway-rail grade crossing improvement projects are allocated to the locations that are considered the most in need of improvement (Ogden, 2007). Consequently, in this study, inverse distance weighted (IDW) interpolation is utilized to map the crossings' crash likelihood (CIF_c) resulting from CRM in North Dakota. The IDW interpolation structures a continuous crash likelihood surface covering the space for each crossing. The altitude of this surface varies according to the grade crossing's crash likelihood in a similar location. IDW assigns unknown locations a value associated with the crossings' crash likelihood in nearby areas. This assigned value is a geographically weighted average of crash likelihoods, estimated by considering the distance between interpolated locations and the known crossings nearby.

Figure 6.1 indicates the results of IDW interpolation according to the crossings' crash likelihood in North Dakota. Figure 6.1 illustrates locations at four risk levels. Three areas of A, B, and C are defined as high-risk areas, which contain crossings more likely to have a crash likelihood of more than 40%. Areas A, B, and C include 10, 4, and 10 high-risk crossings, respectively.

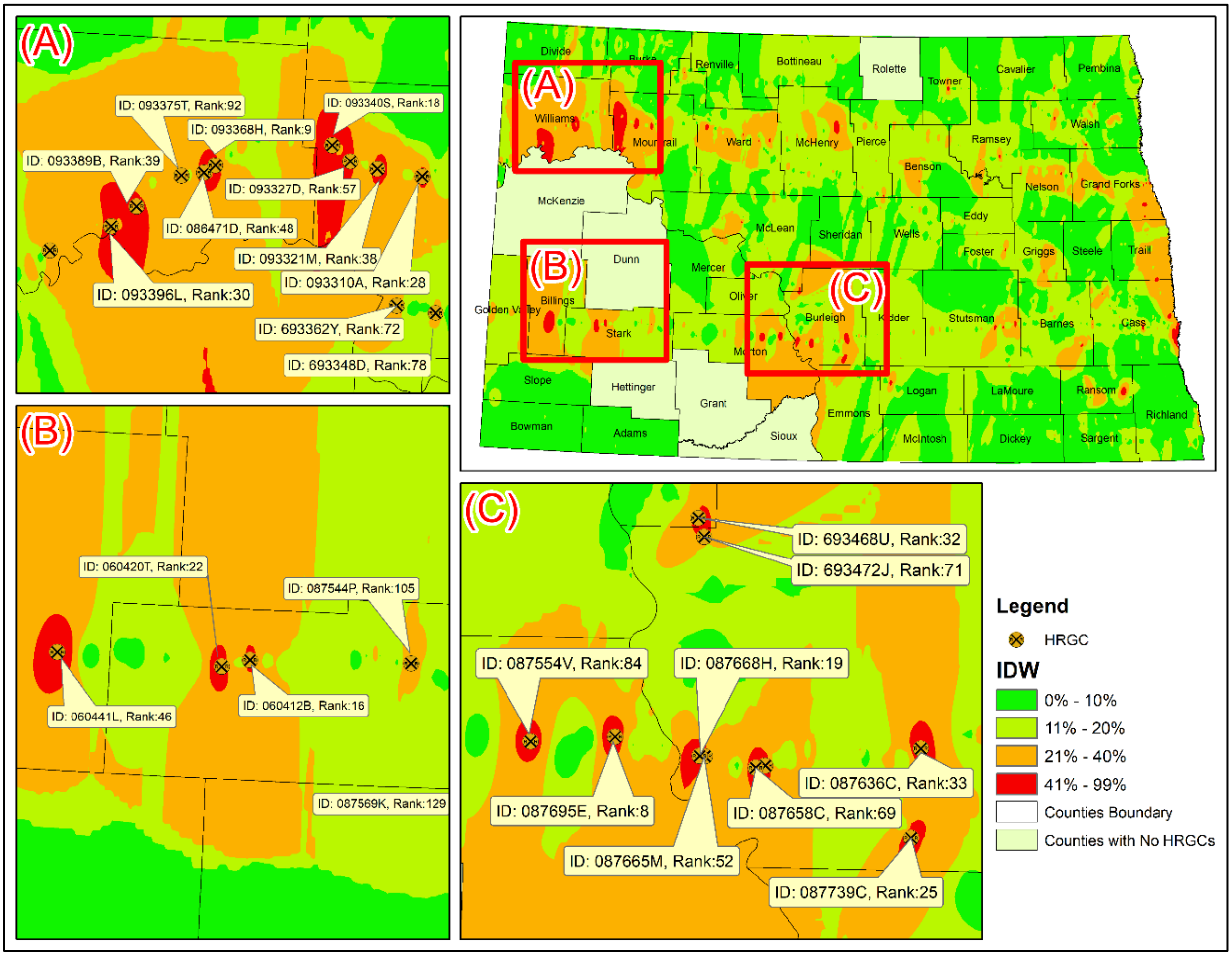

Figure 6.1 IDW Interpolation Based on Cumulative Likelihood for 29 Years with Equal Weights

7. HRGC-ND WEB APP

7.1 Introduction

The HRGC interactive web app (HRGC-IWA) is a platform designed to predict crash occurrence and severity likelihood changes over time (year). The prediction model is based on the competing risk model (CRM), which is one of the survival analysis approaches, and was developed by the authors. Previous chapters illustrated some of the CRM model results, and the development of this app is intended to visualize those results and provide an easy-to-use simulation tool for ND agencies to understand and interpret those results. Consequently, to make application of the CRM model easier and increase its potential for technology transfer, HRGC-IWA was developed to deliver the results of this novel approach's application in ND HRGCs. With this web app, users (transportation agencies) can modify crossing characteristics (e.g., traffic control devices and geometric factors) and the app will estimate and visualize the crash severity and likelihood of changes over time for those modifications.

7.2 Web Development

The R programming language is used to modify and apply the competing risk algorithm for crash analysis at highway-rail grade crossings. Consequently, Shiny, which is one of the R packages, is used to develop and construct the HRGC-IWA. Shiny makes it easy to build interactive web apps straight from R codes. For more information, please refer to the Shiny website (https://shiny.rstudio.com). The developed app can be accessed at: [https://kmtgis.shinyapps.io/ak_plot/.](https://kmtgis.shinyapps.io/ak_plot/)

7.3 App Framework and Illustration

Figure 7.1 indicates the general app platform. It shows the platform has two main sections: "Prediction Panel," and "Input Panel." Through the Input Panel, the user can define or change the characteristics of a crossing, and the effect of those characters on crash frequency and severity prediction will be visualized in the Prediction Panel. In the following, all elements of each panel are explained according to the assigned numbers in Figure 7.1.

Figure 7.1 HRGC-IWA General View

1) **Crash Severity Box**: By clicking on this box, the user can define predictions associated with each crash severity level as visualized by the plot (#8) and bar chart (#9) in the prediction panel. By selecting any of these options shown in Figure 7.2(a), the title and notification of the plot and bar chart in the prediction panel, respectively, change. For example, in Figure 7.1, since "PDO" is selected as the crash severity level, the plot title is "Crash Severity: PDO" and the bar chart notification is "PDO Prob Diss = 3.68%".

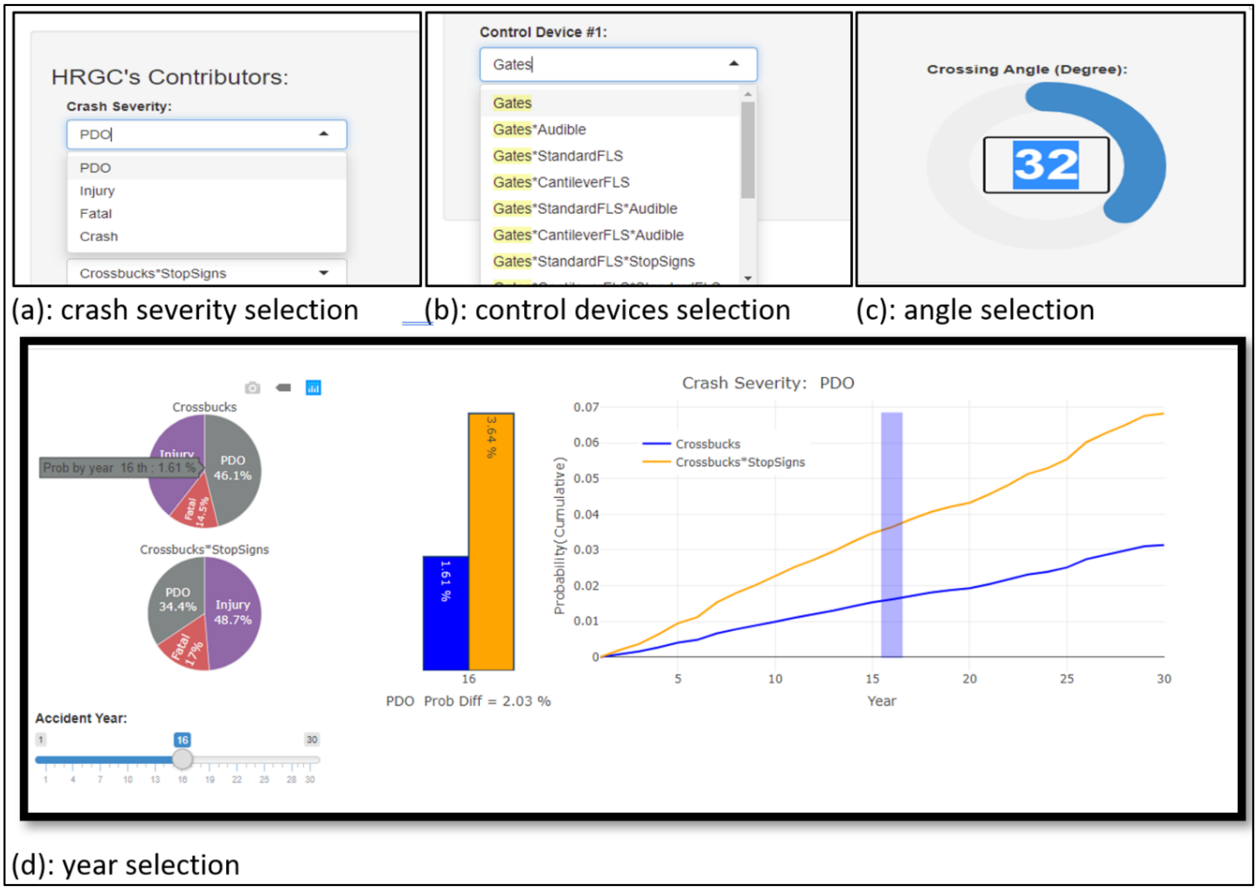

Figure 7.2 App Input Selection Options

2) **Control Device #1**: By clicking on this box or typing in the box, users can select one of the 28 control devices as the first selected control device that prediction can be based on and calculated. The prediction results associated with Device #1 are indicated by the orange line and column in the plot and bar chart, respectively, in the Prediction Panel. These sets of predictions can be served as reference options.

3) **Control Device #1**: Similar to Control Device #1, users can select another control device to compare the effect of two different control devices on the prediction results. Consequently, there are two lines in the plot (blue line is related to Control Device #2), two columns in the bar chart (blue column is related to Control Device #2), and two pie charts (#10), each indicating the safety results associated with one of the control devices. These sets of predictions can be served as an alternative option.

4) **Number of road lanes**: This is the number of roadway traffic lanes crossing the track. Users can select one of the traffic lane numbers from one to four to investigate the effect of this geometric factor on the prediction result in the Prediction Panel.

5) **Crossing to intersection distance (meter)**: Nearest intersecting roadway is determined by identifying roads parallel to the railroad that intersect with the road that is part of the HRGC. The Railroad-Highway Grade Crossing Handbook (Ogden, 2007) indicated that some collisions at HRGCs could result from the short storage distance for vehicles waiting to move through the crossing and the intersection. Users can change this geometric factor range from 1 meter to 2,500 meters by using the slider (#5).

6) **Crossing angle (degree)**: One of the main factors impacting the sight distance at a crossing is its highway-railway angle. Users can type or select the smallest angle between the roadway and the track by using the round slider (#6), or part (c) in Figure 7.2. The minimum and maximum angle are 1° and 90°, respectively.

7) **Accident year**: Users can use this slider to define a year, the results of which should be visualized by that time in bar and pie charts. Figure 7.2(d) indicates that by adjusting the slider on the 16th year, year 16 is highlighted in in the plot (#8), the x axis of bar chart (#9) indicates year-16, and the explanation of fractions on the pie chart (put cursor on the pie chart fractions to view) release information for the 16th year.

8) **Cumulative probability plot**: The plot (#8) indicates the cumulative probability of crash occurrence over 29 years (by year 30). Depending on the adjustment in section number #1, the plot is baled to indicate crash occurrence or crash severity likelihood over 29 years. For example, the plot in Figure 7.1 indicates that a crossing with defined characteristics in Input Panel will be more likely to have a PDO crash if it has both crossbucks and stop signs compared with the scenario of having only crossbucks over 29 years (by year 30).

9) **Bar chart**: Bar chart extracts the information from the plot associated with a specific year defined by the Accident Year slider. For example, the bar chart in Figure 7.2(d) indicates that a crossing with only crossbucks has a 1.61% likelihood of having a PDO crash, while a crossing with both crossbucks and stop sign might have a 3.64% likelihood of having a crash occurrence with PDO severity level by year 16. The bar chart caption indicates the difference in height between two columns. For instance, in Figure 7.2(d), the caption releases the PDO crash likelihood might increase by 2.03% by year 16 if adding a stop sign to a crossing currently equipped with crossbucks only.

10) **Pie charts**: Pie charts indicate the fraction of each crash severity level based on the control device and by the specific year. For example, the PDO fraction for a crossing by a specific year can be estimated as PDO Fraction = $\frac{prob(PDO)}{prob(PDO)+prob(injury)+prob(fatal)} \times 100$

    Consequently, in Figure 7.2(d), the PDO fraction of crossing with crossbucks-only by year 16 is estimated as $\frac{1.61}{1.61+1.38+0.51} \times 100 = 46.1\%$

    Note: the estimated fraction for each severity level does not indicate the likelihood of a crash in that severity level. It indicates the fraction of crash occurrence likelihood associated with the specific severity level by specific year. For example, the upper pie chart in Figure 7.2(d) indicates that PDO crash likelihood accounts for 46.1% of total crash occurrence likelihood ($0.61\% + 1.38\% + 0.51\% = 2.5\%$) for crossing with crossbucks-only by year 16. This fraction decreased to 34.4% after adding stop signs (another pie chart), but the PDO crash likelihood increased from 1.61% to 3.64% by the 16th year. The likelihood information can be seen by putting a cursor on each pie chart fraction.

8. CONCLUSION AND FUTURE WORK

At-grade crossing safety performance is of utmost importance, and safety improvement agencies need tools to help them understand safety performance, understand countermeasures' effectiveness, and rank the crossings based on their hazard levels to allocate resources to improve their safety performance. This research tried to demonstrate a data-driven-based algorithm to provide such tools for the state of North Dakota. A summary of findings based on the ND data analysis is listed below:

1) Hazard index should include both crash severity and crash occurrence likelihoods.
2) Prediction model should be able to predict both crash severity and crash occurrence simultaneously to account for unmeasurable variances with the same set of predictors.
3) Some contributors can be found significant to certain crash levels but not significant to others.
4) One contributor can positively impact certain crash levels but negatively impact others.
5) The dependency between competing risks exists so the prediction model should consider such dependency. The independent censoring assumption could result in underestimated contributors' effects.
6) Marginal countermeasure effectiveness should be dependent on the preexisting conditions. In other words, adding the same device to crossings with different existing control devices will present different effectiveness levels.
7) Adding a traffic control device to a crossing does not always result in improved safety performance.
8) Adding a traffic control device to a crossing may result in a positive improvement effect on certain crash levels but a negative improvement effect on others.

Of note are the research limitations and the potential future research directions. Those summaries are listed below:

1) To truly account for countermeasures' effectiveness, before-and-after analysis is needed to control other contributors' effects. Our study is a data-based empirical analysis, so some of the counterintuitive findings may be the results of other contributors' mixed effects.
2) The interaction effects of contributors are not considered and quantified in this study; however, they are under-researched and need to be investigated.
3) Safety effectiveness cannot be used solely to help the improvement investment decision. The life-cycle cost analysis including cost of construction, operational and maintenance costs, and other social and economic costs should also be included.

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