# Safety Effects of Road Weather Information Systems (RWIS) – A Large-Scale Empirical Investigation

by

Davesh Sharma

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Department of Civil and Environmental Engineering

University of Alberta

# ABSTRACT

In countries like Canada and the United States, where most of the population lives in snowy regions, winter road maintenance (WRM) has become a significant challenge. Hundreds of people are killed, and thousands are injured every year due to inclement winter weather conditions. To combat this, transportation agencies spend a significant amount of their budget on conducting and maintaining WRM activities. Considering their limited budget and resources, it is indispensable to strategize their investments in equipment, labour, and material without jeopardizing commuter safety.

One of the most advanced techniques used for efficient mobilization of WRM services is Road Weather Information Systems (RWIS) - a critical highway intelligent transportation system (ITS) infrastructure. These systems have long been favoured by many North American and European highway authorities as they provide real-time and near-future road condition information collected using roadside sensors during the winter months. Information disseminated by individual RWIS stations is collectively used not only to proficiently organize WRM operations but also to promote safe travel and provide traveller information during adverse weather events. However, the high installation and operational costs of RWIS have necessitated the need to quantify their cost-effectiveness, particularly in improving traffic safety. Limited past efforts have been made to quantify the sole benefits of RWIS, but most analyses were either qualitative in nature or used a naïve safety evaluation technique that resulted in generating less conclusive findings.

Acknowledging the importance of determining their benefits as well as a large gap that exists in current methodologies, this thesis aims to develop a unique methodological framework that can be readily used to evaluate and quantify the sole safety effects of RWIS. In particular, this thesis attempts to tackle and answer two research questions: first, whether implementing RWIS stations reduces winter weather collisions and how much reduction can be expected; second, whether RWIS stations are a cost-effective countermeasure with explicit monetary benefits. These questions were answered by conducting a safety evaluation of RWIS stations and an economic analysis. Safety evaluation of RWIS stations was conducted by using one of the most established and statistically defendable methods used in traffic safety studies, namely, the before-and-after Empirical Bayes (EB) approach was used to perform safety evaluation of RWIS stations. A methodology was developed, and a state-wide investigation of RWIS stations in the state of Iowa was conducted. Geographic Information Science (GIS) based techniques were used for the preparation of intensive geospatial datasets required for calibration and validation of safety performance function (SPF). Furthermore, Yearly Calibration Factors (YCFs) were also locally calibrated using large-scale spatial data, where network-based service area analysis using GIS played a crucial role in selecting treatment and reference sites. The results of safety evaluation were used to conduct a detailed economic analysis and Benefit-to-Cost ratios (BCRs) were estimated as a parameter to assess the economic viability of RWIS stations. One-time installation cost, operations cost, and up-gradation cost for each RWIS station were compared with the monetary value safety benefits.

Utilizing the developed methodology in this thesis, the sole effectiveness of implementing RWIS was quantified to establish RWIS as a safety countermeasure. The findings from the case study showed safety effectiveness of RWIS that ranged from 31.53% to 88.23%, whereby implying that a significant portion of winter weather collisions was reduced after RWIS implementation. The BCRs of the stations ranged from 7.51 to 34.16, indicating a significant amount of safety benefits compared to the cost of RWIS. The research findings suggest that RWIS stations are an economically viable safety countermeasure, and that transportation professionals and highway authorities can now make more informed decisions on furthering RWIS implementations to improve the safety and mobility of the winter traveling public.

The main contributions of this thesis are three-fold. First, the safety effectiveness of RWIS stations was quantified for the first time in the literature using the state-of-the-art EB method with large-scale and multi-year datasets. Second, SPF was locally developed during the process, which is transferable and can be readily used for safety investigations at regions with similar geographical and weather characteristics. Finally, the economic viability of RWIS was quantified using a formal economic analysis at high granularity, which has been absent from the RWIS literature.

# PREFACE

The work presented in this thesis is either presented or under review for publication.

**Conference Proceedings**

1. **Sharma, Davesh,** Wu, Mingjian, Kwon, Tae J. (2020). Safety Effects of Road Weather Information System (RWIS) - A Cost-Benefit Analysis. *Presented at and Proceedings of the* $100^{th}$ *Transportation Research Board*, Washington, D.C., January 2021.

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1. **Sharma, Davesh,** Wu, Mingjian, Kwon, Tae J., El-Basyouny, Karim. (2021). Quantifying Safety Effectiveness of Road Weather Information System (RWIS) Using Geospatial Approaches. *Geo-spatial Information Science*, November 2021.

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| | |
|---|---|
| GDP | Gross Domestic Product |
| RSC | Road Surface Condition |
| DOT | Department of Transportation |
| WRM | Winter Road Maintenance |
| ITS | Intelligent Transport System |
| RWIS | Road Weather Information Systems |
| ESS | Environmental Sensor Stations |
| EB | Empirical Bayes |
| VMS | Variable Message Sign |
| SPF | Safety Performance Functions |
| YCF | Yearly Calibration Factors |
| BCR | Benefit-Cost Ratio |
| RSI | Road Surface Index |
| BC MOTI | British Columbia Ministry of Transportation and Infrastructure |
| NPV | Net Present Value |
| MDSS | Maintenance Decision Support Systems |
| RTM | Regression-to-the-Mean |
| NB | Negative Binomial |

| | |
|---|---|
| GIS | Geographic Information Science |
| SAS | Statistical Analysis System |
| CPI | Consumer Price Index |
| AV | Annual Value |
| PV | Present Value |
| AWOS | Automated Weather Observation System |
| IEM | Iowa Environment Mesonet |
| AADT | Annual Average Daily Traffic |

# Chapter 1. INTRODUCTION

## 1.1 Background

Road traffic injuries have a drastic impact on the safety of people worldwide. Collisions lead to the death of approximately 1.3 million people annually, and 20 to 50 million people are affected by non-fatal injuries. Apart from causing a significant amount of emotional and physical trauma, collisions are also a source of substantial financial loss to not only the individuals involved but also a country's economy. Collisions are estimated to cost around 3% of most countries' gross domestic product (GDP) (World Health Organization, 2021). As per Canada's Road Safety Annual Report, the societal cost of traffic collisions was 1.9% of GDP (Road Safety Annual Report 2016, 2016). In the United States (U.S.), the societal loss in terms of quality-of-life valuation was around 6% of total GDP (OECD, 2019).

People living in snowy regions face huge risks due to the unsafe driving conditions caused by inclement winter weather events. They frequently experience deteriorating road surface conditions (RSCs), which make driving dangerous. In Canada, snowy and icy roads were a reason for 30% of the collisions in 2010. In the same year, inclement weather conditions were a reason for over 1400 collisions (Canadian Collision Statistics in the Winter, 2021). The U.S. faces on average 21% vehicle collisions due to poor weather conditions, causing over 5000 fatalities and 418,000 injuries (U.S. Department of Transportation- Federal Highway Administration, 2020). Additionally, snowy, slushy, or icy pavements lead to 1300 fatalities and 116,800 injuries every year. (U.S. Department of Transportation- Federal Highway Administration, 2020).

Adverse winter weather conditions reduce mobility and impede the safety of commuters, which has drastic impacts on transportation systems around the world. Therefore, to ensure the safety of road users, maintaining roads during and after winter weather events is critical. The risk of increased litigation for transportation departments is also present, as departments may be held accountable for poor design and/or inadequate maintenance practices (McKeever, et al., 1998). The U.S. State Department of Transportation (DOT) allocates around 20% of its maintenance budget for winter road maintenance (WRM). Annually, more than 2.3 billion dollars is spent on snow and ice control activities by state and local agencies (U.S. Department of Transportation-

Federal Highway Administration, 2020). Minimizing these expenses and maximizing the returns have been a major goal of many transportation agencies. One way of maximizing returns is by improving the operational decision-making process for WRM, which is done by deploying one of the most advanced highway intelligent transportation system (ITS) facilities, namely, Road Weather Information Systems (RWIS). For their proven effectiveness, RWIS is being used widely across North America and many other countries around the world (Kwon, et al., 2015). There are two types of RWIS, mobile and stationary. A mobile RWIS continuously moves around the road network providing real-time weather information (Government of Alberta, 2020). A stationary RWIS station has a fixed position along the highway, providing weather information specific to that location (Manfredi, et al., 2005). This study focuses on quantifying the effects of stationary RWIS stations as they are dominantly used by highway agencies around the world. Figure 1-1 shows an illustrative image of the station.

**Figure 1-1 A typical stationary Road Weather Information Systems (RWIS) station**

An RWIS station is a unit of various Environmental Sensor Stations (ESS) and is deployed at set locations along the highway, where they collect and transfer field observations to a monitoring/recording center (Manfredi, et al., 2005; Government of Alberta, 2020). Further, it creates nowcasts and forecasts of weather variables, such as atmosphere, pavement, and water level conditions in a way that is understandable to the users (U.S. Department of Transportation-Federal Highway Administration, 2020). This information allows road maintenance personnel to take proactive measures for efficient maintenance of roads, providing safer driving conditions to road users. Based on the received information from RWIS, automated warning systems can be triggered to provide advanced warnings to supporting managers at road maintenance facilities, traffic management centers, and emergency operation centers. These warnings regarding upcoming weather events can then to disseminated to the public, allowing commuters to plan their trips accordingly (Manfredi, et al., 2005).

Efficient utilization of the information shared by RWIS has direct, indirect, and social benefits. Regarding direct benefits, RWIS provides prior knowledge about environmental conditions, allowing jurisdictions to reduce dispatch frequency for data collection purposes, thereby reducing labor and equipment costs. Indirect benefits include the reduced risk of lawsuits against transportation agencies as roads are safer due to more efficient maintenance activities. For social benefits, the reduced costs incurred by the public from improved travel time and safer roads lead to reduced pollution and collision costs (McKeever, et al., 1998).

Although RWIS has many benefits, they are costly to install, operate, and maintain. Therefore, it becomes crucial for agencies to understand whether there are more monetary benefits than the money spent in deploying RWIS stations. Such understanding allows them to allot more funds for RWIS implementation. The cost of RWIS installation, operations, and direct benefits are readily available in several documents as RWIS is one of the most widely used tools for WRM operations. The cost-benefit analysis of RWIS has also been conducted before (although they entailed qualitative assessments), including benefits such as improved level of service, reduced winter maintenance costs, and safer road conditions (Fay, et al., 2010). Notably, these studies either did not include the safety aspect or used naïve safety evaluation techniques for analysis. One of the studies evaluated its safety effectiveness using the before-after Empirical Bayes (EB) approach (El Esawey, et al., 2019). However, it considered a combined effect of RWIS and Variable Message

Signs (VMSs) and did not evaluate the sole effectiveness of RWIS stations. Therefore, whether the implementation of RWIS truly leads to safer road conditions and whether or not they are cost-effective is still inconclusive.

## 1.2 Problem Statement and Motivation

Implementation of RWIS provides timely weather information to maintenance professionals and allows them to conduct efficient road maintenance activities. As per literature, maintenance professionals experience that RWIS installation leads to well-maintained roads and safer driving conditions, which leads to a reduction in collisions. However, these are just anecdotal experiences. Very limited research has been conducted to confirm these experiences by quantitatively assessing whether the installation of RWIS leads to improved safety and whether RWIS is a cost-effective highway safety countermeasure.

This study acknowledges the current gaps in knowledge and methodological deficiencies concerning the safety assessment of RWIS. Therefore, there is a need to answer if RWIS implementation reduces winter collisions and by what degree are the collision reduced, assuming that transportation agencies timely perform WRM activities using the information shared by them. The answer to this question will affirm the anecdotal experiences of maintenance professionals, that efficient winter road maintenance due to the information shared by RWIS leads to a reduction in inclement winter weather collisions. This will further establish RWIS as a safety countermeasure and WRM authorities can make evidence-based decisions to further incorporate its safety effects while strategizing the implementation of stations.

Equally important, whether the reduction in collisions results in more monetary benefits than the costs of RWIS station implementation is another important question that warrants further investigations. This problem can be tackled by conducting an economic appraisal of RWIS and evaluating its safety benefits and costs. This assessment will allow transportation agencies to allocate more funds confidently for expanding their existing RWIS network.

## 1.3 Research Objectives

As discussed in the previous section, the primary objective of this thesis is to develop a methodological framework using the state-of-the-art before-after EB for quantifying the sole safety effects of one of the most sophisticated and critical highway infrastructures – *Road Weather Information Systems (*RWIS). This thesis has two specific objectives and associated tasks as summarized below.

Objective 1: Safety Evaluation of RWIS stations. This part of the thesis will:

- Conduct a comprehensive literature review on factors affecting winter road safety, including RWIS stations, the impact of RWIS, and studies used to conduct safety evaluation;
- Apply a statistically rigorous safety evaluation technique, the before-and-after EB approach, a method that is widely adopted to quantify the safety effectiveness of countermeasures or safety devices;
- Integrate large scale datasets, select sites for safety evaluation and model calibration using GIS tools;
- Calibrate local safety performance functions (SPFs) and yearly calibration factors (YCFs) to capture the variation of collision frequencies with site-specific attributes and consider additional confounding factors affecting the collision frequencies; and
- Conduct a real-world case study to demonstrate the applicability of the developed methodology.

Objective 2: Economic Analysis of RWIS stations. This part of the thesis will:

- Conduct a comprehensive literature review on studies conducted to quantify the benefit-cost ratio of RWIS including its safety benefits;
- Evaluate the number of collisions reduced from the results obtained during safety evaluation and quantify its associated monetary savings; and
- Estimate the benefit-to-cost ratio (BCR) of RWIS.

The outcomes of these two objectives will provide empirical evidence to transportation agencies about the safety effectiveness RWISs' implementations, which will affirm the experiences of WRM operators that the information used by RWIS improves safety. And by doing so, establish RWIS as a safety countermeasure. The comparison of monetary benefits to its costs will allow transportation departments to be more confident in allotting budgets for its strategic implementation. Furthermore, the developed methodological framework can be used to quantify the safety impacts of similar devices with no direct link to improving traffic safety.

## 1.4 Thesis Structure

The thesis contains five chapters, an overview of the remaining chapters is provided below:

Chapter 2 provides a literature review on the impact of winter weather on transportation and RWIS benefits. It further provides an overview of studies that conducted Cost-Benefit studies of RWIS. Furthermore, an overview and limitations of studies that conducted Cost-Benefit studies considering the safety benefits of RWIS stations are also discussed. Various techniques used for safety evaluation are discussed in this section.

Chapter 3 discusses the overall methodology used to answer the questions raised in this research. Furthermore, steps and equations required to conduct before-after EB analysis are provided here. Similarly, how the safety evaluation results are used to conduct an economic analysis are also discussed in this section.

Chapter 4 involves selecting a study area to demonstrate the developed methodology. The dataset used for the analysis is described thoroughly in this section. Additionally, the integration process of the data set is also discussed in detail. In the safety evaluation portion, results of the EB analysis and the models calibrated during the process are also included. Furthermore, steps taken to conduct the economic analysis of each station are elaborated in detail. The results of the safety evaluation and economic analysis of RWIS stations are summarized in this section.

Chapter 5 summarizes the key findings of the study. This chapter also includes information regarding research contributions, study limitations, and future research directions.

# Chapter 2. LITERATURE REVIEW

This chapter provides an overview of different factors affecting winter road safety, how weather hampers traffic safety, and how different maintenance activities are used to improve traffic safety. The following section describes the various steps involved in the safety management process and their application in winter road safety. The third section provides information on RWIS stations and discusses the importance of quantifying the safety effectiveness of the system. Additionally, this chapter further reviews studies that conducted an economic analysis of RWIS stations with and without considering their safety benefits. The results of these studies, methodologies used, and their limitations are also discussed. The fifth section provides a detailed discussion on different types of safety evaluation techniques and their limitations. The technique used to evaluate the effectiveness of RWIS stations is also discussed. Finally, a chapter summary is presented at the end to discuss the key findings and re-narrate the need for conducting the proposed research.

## 2.1 Factors Affecting Traffic Safety in the Winter

Inclement winter weather events reduce road friction levels and visibility, thereby increasing collision frequencies due to poor driving conditions. Although traffic volume decreases during these events, traffic delays increase. WRM operations seek to counteract these adverse effects by proactively maintaining RSCs and informing commuters about upcoming events. These operations, therefore, improve the safety of commuters during winters (Fu & Usman, 2018). Various studies have summarized the interactions between the environment and subsequent activities conducted by humans to improve the safety of commuters.

### 2.1.1 Effects of Weather on Traffic Safety

Fu and Usman (2018) addressed that minimal research had been conducted to evaluate the effects of WRM on winter traffic safety. They also pointed out that previous studies used aggregated data that were unable to account for the effect of site-specific features of the road network, variations in traffic volume, and weather. To quantify safety benefits of WRM related activities, the authors developed a systematic methodological framework and demonstrated how using disaggregated data could provide rigorous results (Fu & Usman, 2018).

Andreescu and Frost (1998) are one of the earlier studies that used regression analysis to understand the influence of temperature, rainfall, and snowfall on daily collisions. The study concluded that with higher intensity of the two weather events (rainfall and snowfall) the collision frequencies increased. Three years of weather and collision data of Montreal, Quebec was used for the study (Andreescu & Frost, 1998)

Another study by Knapp et al. (2000) used Poisson regression to assess the impacts of exposure, snowstorm duration, maximum wind gust speed, and snowfall intensity on collision frequencies. The results concluded that collision frequencies had a positive correlation with all these parameters. Weather data of fifty-four storms over a span of four years was collected for a stretch of forty-eight km long highway in Iowa (Knapp, et al., 2000).

Andrey et al. (2003) compared collision data during different times of the day in inclement weather and normal weather conditions and concluded both collisions severity and frequency increased by 45% and 75% respectively due to precipitation. Additionally, the study found that snowfall had a more pronounced effect on safety as compared to rainfall. Three years of collision and precipitation data of six Canadian cities were used for the study (Andrey, et al., 2003).

State-level Negative Binomial collision models were also developed using 25 years of collision, traffic, and weather data. The model found more association between non-fatal collisions and snow precipitation than fatalities and snow precipitation (Eisenberg, 2004; Fu & Usman, 2018). Eisenberg & Warner, (2005) used the same data and found that injuries and property damage collisions increased during snowstorms while fatalities decreased (Eisenberg & Warner, 2005). Knapp, et al., (2000) also conducted a similar study where the authors explained that the reduction in speed during such events might have reduced fatalities.

Hermans et al. (2006) analyzed the effects of different weather factors on winter road safety using four types of regression models: Poisson, zero-inflated Poisson, Negative Binomial, and zero-inflated negative binomial. Hourly weather data collected by 41 RWIS stations in the Netherlands was used for model development. Out of the four models, the Negative Binomial model provided the most conclusive results. The study concluded that precipitation duration influenced safety more than the precipitation amount (Hermans, et al., 2006).

Some recent studies used generalized linear models to assess the impacts of inclement winter weather on safety. Six winter seasons of Ontario were used to collect hourly weather data of snowstorms for model calibration. The results concluded that collision frequencies increased with an increase in wind speed and precipitation intensity (Usman, et al., 2010; Usman, et al., 2011; Usman, et al., 2012).

Agencies perform various winter maintenance activities such as plowing of snow, application of anti-icing and deicing agents, to reduce the associated risk of collisions. The effects of these activities are reviewed in the next section.

### 2.1.2 Effects of Maintenance on Traffic Safety

To overcome problems associated with winter weather, transportation agencies need to provide timely and effective maintenance of RSCs to improve driving conditions during inclement weather events. The intensity of the event and the RSC dictate the type of techniques used for maintenance. These techniques include but not are limited to sanding, salting, application of anti-icing agents, and plowing are used separately and often in combination for maintenance purposes. Such maintenance activities lead to safer driving conditions, and in turn, reduce collisions. To gain a quantitative understanding of the effects WRM has on traffic safety, various studies have been conducted in the past.

Hanbali (1992) was one of the first studies that compared the collision frequencies before and after salting on two-lane undivided highways and divided freeways. The results concluded that there was a significant reduction in collision frequencies after post salting. Data was collected for a randomly selected road network of 907 km in New York, Minnesota, and Wisconsin (Hanbali R. , 1992).

Norrman et al. (2000) estimated the distribution of collision frequencies over different types of RSCs. The study further defined a comparing parameter to assess the effect of WRM activity on collisions occurring at different road surface types. The results concluded that when maintenance activity increased, collisions reduced. Six years of collision and winter weather data were collected within a 25 km radius of two RWIS stations in Halland, Sweden (Norrman, et al., 2000).

Another study by Fu et al. (2006) analyzed the relationship between collision and different winter weather and maintenance parameters. The maintenance factors involved the amount and type of maintenance activity performed, including sanding, pre-wet salting with plowing, and anti-icing. The results concluded that these activities had a direct correlation with a reduction in collision frequencies. The study considered two sections of highway 401 for their analysis (Fu, et al., 2006).

There are few other studies that investigated the impact of maintenance activities on road surface index (RSI), assuming that RSI is a surrogate measure of traffic safety. The results concluded that for every 2% of collisions reduced, RSI improved by 1% (Usman, et al., 2010; Usman, et al., 2011; Usman, et al., 2012).

As discussed above, previous studies consistently show that winter road safety is hampered due to the type and intensity of weather events and that road maintenance is needed to improve RSC and road safety. Therefore, RWIS stations are used by maintenance authorities to receive advanced information of upcoming weather events and thereby improve the safety of commuters. The next section discusses different steps of the safety management process and further specify the steps used to conduct this study.

## 2.2 Winter Road Safety Management Process

This portion of the literature review discusses various steps involved in the safety management process and its use for improving road safety during inclement winter weather conditions. The entire process involves six steps as shown in Figure 2-1 (Highway Safety Manual, 2010).

The network screening step involves the selection of sites where countermeasures can be deployed. The importance of this step lies in the general understanding that transportation agencies have limited budgets, and therefore not all locations can be treated. A screening process must be done to identify locations with higher collision risks or "hotspots". Since collisions are random events, statistically rigorous methods are used for hotspot identification. Transportation agencies strategize WRM activities based on road class type. Roads higher in the hierarchy have more stringent requirements for the level of service and therefore require prioritized maintenance. These road types are further categorized based on collision risk using a suitable statistical method, then ranked for maintenance activity prioritization.

In the diagnosis step, the identified hotspots are further analyzed to understand the reason behind the observed collision frequencies, injury severities, and crash type. Conducting site investigations, documentation review, and collisions data assessment are a few of the methods used during this process. In winter safety studies, the diagnosis step is used to assess whether collisions occurred due to poor RSC or winter weather.

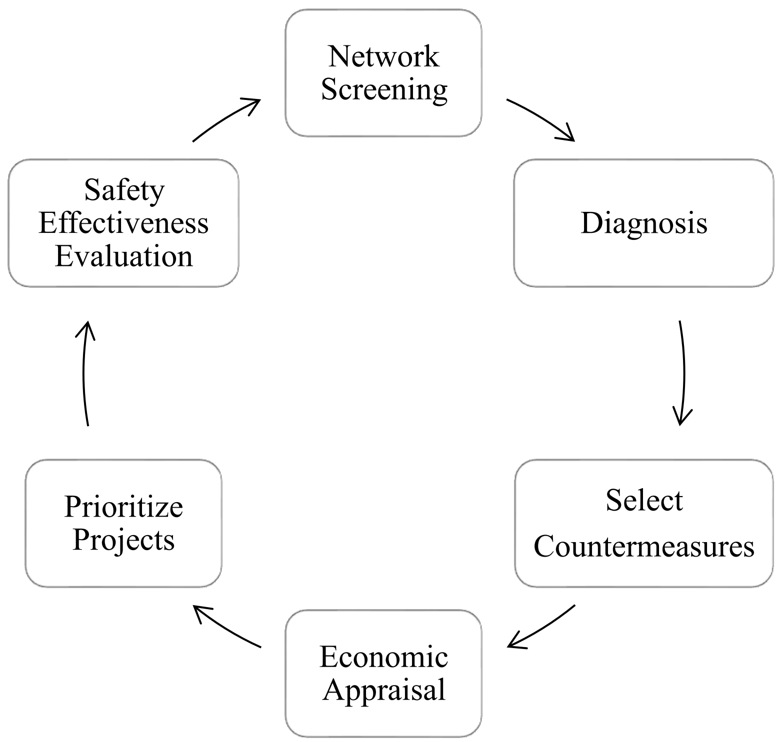


**Figure 2-1 Safety Management Process (adapted from the Highway Safety Manual, 2010))**

Once the reasons for collisions are identified, suitable countermeasures are selected in the next stage. A countermeasure is a safety device or treatment provided to reduce a specific type of collision. For instance, if poor RSC were identified as a leading cause of collisions, a suitable WRM activity would be implemented as a countermeasure to the identified region. Snow plowing, snow fencing, salting, applying anti-icing agents, and sands are some of the techniques used to improve RSC after a snowfall (Fu & Usman, 2018). To take proactive measures, WRM operators require prior information of upcoming weather events. Therefore, various tools are used to generate nowcasts and forecasts of weather conditions.

The economic appraisal stage compares the economic viability of implementing a countermeasure. The costs of implementing proposed countermeasures from the previous step are obtained. A countermeasure's ability to reduce collisions is evaluated, along with its costs and benefits. Efficient WRM involves complex decision-making, such as prioritizing roads with high level of service requirement, locating depots, fleet size, equipment, and material requirements. These factors lead to higher complexity in conducting cost-benefit analyses. Where evaluating the costs of these measures is simple and straightforward, quantifying the associated benefits is a complex process (Fu & Usman, 2018).

The project prioritization is the next step that uses the results obtained from the economic appraisal step. Benefits received and budget constraints are the deciding factors in prioritizing countermeasures. As discussed in the network screening step, higher class types require maintenance of a higher level of service, and therefore WRM activities are prioritized for these roads.

Once the prioritized countermeasure has been implemented, its safety effectiveness is evaluated to assess whether collisions are reduced post-implementation. The effectiveness of applying different WRM activities is also evaluated and if the countermeasure led to an overall reduction in collisions, reduction in a specific type of collision, or a drop in crash severity is reviewed in this step. In general, the safety effectiveness evaluation step plays a critical role in improving traffic safety as it reveals how practical the countermeasure is. It also provides support on whether the treatment should be expanded to other sites or whether more budget should be allotted for that specific treatment.

Since, RWIS stations are already implemented, this study focuses on evaluating its safety effectiveness and then use the results to conduct its economic appraisal. The next section provides detailed information on RWIS stations, its benefits, and the need to quantify these benefits.

## 2.3 Road Weather Information Systems (RWIS)

Road weather information systems (RWIS) stations are a combination of hardware, software, and communication interfaces initially deployed to serve transportation maintenance departments by gathering and transmitting site-specific information on winter weather conditions. Lately, RWISs are also being used to support operations and maintenance departments in supervising other road weather conditions (Manfredi, et al., 2005).

There are two types of RWIS presently used for WRM purposes, mobile and stationary. As the name suggests, a mobile RWIS unit is a downward-facing sensor installed on specific road maintenance vehicles. It focuses on providing enhanced awareness of the situation by collecting real-time measurements of pavement conditions such as temperature, friction, and chemical presence. In addition, it provides cost-effective and geographic-specific information at locations where stationary RWIS stations are not present (Government of Alberta, 2020). Stationary RWIS units combine various Environmental Sensor Stations (ESS) deployed along the highway with a communication system that collects, transfers, processes, and disperses several meteorological and pavement conditions that guide the maintenance agencies in making efficient operation decisions.

The information collected by these sensors includes pavement condition, chemical concentration, temperature, freezing point temperature, soil and air temperature, wind speed and direction, precipitation, visibility, atmospheric temperature, humidity, etc. Hazardous road conditions such as the presence of ice can also be detected using the pavement/sub pavement and atmospheric sensors (Manfredi, et al., 2005). The information shared by RWIS is used to develop nowcasts and forecasts reports for winter road maintenance managers. Among the variety of information shared by RWIS, its ability to provide precise conditions of road surface allows transportation professionals to make event-based decisions. Based on the information received, they can help increase or decrease deployment and use appropriate strategies based on the intensity of the snowstorm. Instead of randomly sending out maintenance staff and material, they can optimize material and staff usage. Additionally, the information is also used to trigger automated warning systems for reducing speed limits, modify traffic signal timings for efficient traffic flow, and optimize traffic operations by closing hazardous roads and bridges. Continuous monitoring of the information received also allows the managers to decide whether additional resources or measures are required (Manfredi, et al., 2005).

Jurisdictions also provide access to the collected information to commuters via interactive telephone systems, mobile apps, interactive maps, and websites, allowing them to make appropriate travel choices (Government of Alberta, 2020; U.S. Department of Transportation-Federal Highway Administration, 2020). For instance, in Alberta, Canada, RWIS is utilized by road maintenance operators to prepare for inclement winter weather events and plan maintenance strategies. A website named “511 Alberta” was created for public access to real-time weather information and road images. Additionally, dynamic messaging signs and other ITS technologies were also integrated with RWIS (Government of Alberta, 2020). The British Columbia Ministry of Transportation and Infrastructure (BC MOTI) uses a combination of RWIS and VMSs. As a result of high collision rates, BC deployed two VMSs alongside one RWIS station at six different locations; one VMS was deployed for each direction of travel. Real-time information collected by RWIS was used to activate the display of warning/advisory messages for the commuters (El Esawey, et al., 2019).

With such impressive applications for winter road maintenance, implementation of RWIS leads to various benefits or cost savings. McKeever et al. (1998) described these savings by dividing them into three different categories, namely, Direct, Indirect, and Social Cost Savings. The first category incorporates immediate benefits (direct savings) to the transportation agencies due to the information shared by RWIS, which involves reduction in costs due to efficient WRM. As discussed previously, effective utilization of nowcasts and forecasts of road conditions allows transportation managers to optimize labor, equipment, and materials for WRM activities. Notably, statewide RWIS in Wisconsin allowed their DOT to save more than 600 person-hours within one winter season. They also saved $75,000 worth of salt during one snowstorm by efficiently using deicing and anti-icing materials (McKeever, et al., 1998; Morris, 1994).

The second category of benefits is indirect savings, which can only be assessed qualitatively. Indirect savings comes from the reduced risk of lawsuits on transportation agencies. An optimized WRM operation minimizes the likelihood of being held liable for unsafe roads. For instance, if a commuter claims that improper deicing led to a collision, maintenance operators can use RWIS to investigate the pavement conditions at the time of the event. If ample chemical content is present in the data, then the road was treated correctly.

The third category involves social costs savings which come from reduced pollution, travel costs, and collisions. Pollution cost comes from reduced vehicle emissions, and travel cost comes from reduced travel times. Both are reduced as commuters would not have to wait in traffic or take different routes to avoid road closures. Another portion of pollution cost comes from the reduced amount of harmful chemicals used for deicing activities. Previous studies have shown that travel and pollution costs can be considered qualitative factors since their values are negligible (McKeever, et al., 1998; Hanbali R. , 1994; Pili-Sihvola, et al., 1993). The most crucial aspect of social cost savings comes from reduced collisions. Since a significant number of collisions occur during inclement winter weather events, implementation of RWIS leads to safer driving conditions and possibly a reduction in collision costs. These costs are different for each collision severity and are estimated based on factors like damage to property, injury or death of people directly involved in the event, indirect loss to family members, and societal loss due to reduced productivity (McKeever, et al., 1998). Ultimately, quantifying this reduction would create a direct link between RWIS implementation and its effect on road safety. The next section provides details of the studies conducted to quantify benefits of RWIS, with and without considering its safety effect.

## 2.4 Cost- Benefit Studies of RWIS

As discussed in the previous section, the implementation of RWIS leads to direct, indirect, and social benefits. Cost-Benefit studies conducted in the past have successfully quantified direct benefits, but only a few studies have attempted to evaluate the social benefits due to reduced collisions (McKeever, et al., 1998). This section provides a brief review of such studies.

One of the first studies that quantified a benefit-to-cost ratio (BCR) of 5:1 was conducted within Washington state assuming that improved weather information would lead to a reduction in routine patrols by maintenance personnel (Boselly III, et al., 1993; Boon & Cluett, 2002). The reduction in snow and ice control expenditures and the implementation costs of alternative RWIS options were considered as the sources of cost reduction in the models. The study compared these cost reductions between RWIS and pavement temperature models with detailed forecasts of weather and pavement conditions and concluded that the former led to significantly lower winter maintenance cost reductions. The safety benefits of RWIS were not considered in this study.

An artificial neural network approach was used by Strong and Shi (2008) to compute the BCR of 11:1 for the RWIS program in Utah (Fay, et al., 2010; Strong & Shi, 2008). Notably, this study also considered only labor and material cost savings. The safety benefits were not included in the analysis. A similar approach was used by Ye et al. (2009) to estimate the BCR of 1.8:1 for Iowa and 3.2:1 for Nevada. They considered benefits such as reduced staffing costs and reduced material and equipment usage. However, safety benefits were not considered in this study.

It was noted that some studies did consider the safety benefits of RWIS. The Net Present Value (NPV) of implementing RWIS was estimated using direct and social cost savings (McKeever, et al., 1998; Boon & Cluett, 2002). The researchers used a single RWIS station in Abilene, Texas, for the analysis and computed an NPV of $923,000. The study incorporated all the elements of direct benefits while considering only reduced collision rates as social benefits. The study pointed out that only reduced collision rates were considered, as benefits due to reduced time travel and pollution were comparatively negligible. A difference between the expected number of collisions with and without RWIS was used to estimate the expected reduction in collisions due to its implementation. Quantification of expected collisions was done by using the exposure parameter (vehicle-kilometers travelled) with winter weather collisions.

Veneziano et al. (2014) provided working details of a web-based cost-benefit analysis toolkit developed for the use of maintenance operators. Cost-benefit analysis of RWIS and Maintenance Decision Support Systems (MDSS) was conducted to demonstrate the effectiveness of the toolkit. A case study of Iowa was conducted to estimate BCR of 45.4:1 for 68 RWIS stations. Additionally, a BCR of MDSS was estimated as 3:1 for a case study of the state of Indiana. The study further pointed out that the safety benefits of RWIS were not quantified in previous studies. Therefore, assumed 10% collision reduction due to RWIS based on literature used to estimate collision reductions due to improvement in winter maintenance (Veneziano, et al., 2014).

Koeberlein, et al., (2015) used simple before and after crash data to evaluate the safety effects of RWIS implementation in Idaho, U.S. The data was assessed for 33 RWIS stations implemented between 2011 to 2013. The road segment where RWIS was implemented was associated with that station and winter collisions on that segment were collected. The study estimated a BCR of 22:1 considering only safety benefits of RWIS. The study used direct values of collision frequencies for analysis and considered only one-year collision data in the before period. Additionally, the statistical significance of the evaluated results was not determined.

The cost-benefit analysis approach to determine the deployment strategy for RWIS stations was utilized by Kwon, et al., (2015) as well. Benefits due to reduced road maintenance and collisions were considered in their study. The study pointed out that inclement winter weather collisions might occur for reasons apart from poor maintenance of roads in regions where RWIS was not implemented. The researchers, however, assumed that if RWIS information was provided to maintenance departments, proactive measures could be taken, and winter weather collisions could be reduced to some extent. In addition, the assumption was only applicable within the region where the RWIS station was installed because roads closer to an RWIS were more likely to receive efficient maintenance. Influenced and uninfluenced regions of RWIS were then derived and compared to compute the sole effectiveness of implementing RWIS stations. Linear regression models were developed to formulate a relationship between collisions and exposure parameter (vehicle-km travelled). The researchers estimated a BCR of 3.5:1 for the RWIS network in Minnesota.

The safety aspect was also considered by several other studies as a part of developing the RWIS location-allocation framework. A two-stage sequential model was developed by Zhao, et al., (2016) to optimize and prioritize the locations of RWIS in New York. The first stage involved optimization of RWIS numbers and locations by maximizing their spatial coverage with minimal overlap. The researchers acknowledged that transportation agencies might not have enough funds to implement RWIS stations at all the suggested locations. Therefore, they prioritized the already recommended locations from stage one using budget constraints and a cost-benefit analysis in stage two. In the cost-benefit analysis, they considered direct and social benefits of RWIS. Social benefits or benefits due to reduced collisions were quantified by estimating the expected collision reduction rate using both with and without RWIS information. The collision rates were estimated using exposure to wetness and ice. The study estimated a BCR range of 10.8 to 15.52 for the sites recommended in stage one. The study further estimated BCRs for different deployment strategies, that is, for deploying 10 stations, the BCR was 30:1, while deploying 15 and 20 stations resulted in BCRs of 23:1 and 19:1 respectively.

Another study categorized three sections of roads based on RWIS coverage, considering that sites within good coverage of RWIS are more dependent on its information than on continuous patrolling (Ewan & Al-Kaisy, 2017). The first category involved roads within 30 km of RWIS stations, these were assigned as good coverage sections. Roads within 30-65 km were assigned as fair coverage sections. And third category involved roads beyond 65 km of RWIS sites, these roads were assigned as poor coverage sections. A BCR of 33.3:1 was estimated for the network of stations in Montana. Reduced labor, collisions, and delay were considered as the benefits during cost-benefit analysis. The study directly used reduction values estimated by McKeever, et al. (1998), where crash rates were used for evaluation.

Esawey et al. (2019) also conducted a safety assessment for a combination of RWIS and two variable message signs (VMSs) using a before and after EB approach (El Esawey, et al., 2019). The information collected by RWIS stations was displayed on the two VMS for both directions of traffic. The results showed that serious winter collisions reduced from 8.0% to 59.2%, with an overall reduction of 32.7% for six of such sites on rural undivided highways in British Columbia. In addition, the BCR ranged from 1.1:1 to 38:1 with an overall BCR of 4.8:1. The net present value of this combination was reported to be more than 12 million Canadian dollars. Interestingly, this study also uses an influence region of 10 km for the combination, but it was assumed only for VMSs and not for RWIS stations. Likewise, the study considered only serious winter collisions (fatal and injury) and used limited data from rural undivided highways. Although the study calibrated local SPFs, YCFs were not included in their analysis, thereby not accounting for other possible confounding factors affecting the analysis. Most importantly, the study considered a combined effect of RWIS and VMS; the sole effect of RWIS stations was not evaluated.

Table 2-1 summarizes the limitations of each of the studies discussed above. It can be concluded that studies conducted in the past have quantified direct benefits of RWIS, however, none of them used a statistically rigorous technique to quantify its sole safety effectiveness and subsequent benefits. The next section discusses various safety evaluation techniques and later summarizes which technique provides statistically significant results.

**Table 2-1 Summary of Cost-Benefit Studies of RWIS and their limitations**

| Study | Study Area | Considered Benefits | Results | Limitations |
|---|---|---|---|---|
| Boselly III, et al., 1993 | Washington | Maintenance | BCR- 5:1 | Safety benefit not considered |
| Strong & Shi, 2008 | Utah | Maintenance | BCR 11:1 | Safety benefit not considered |
| Ye et al. 2009 | Iowa and Nevada | Maintenance | BCR 1.8 and 3.2 | Safety benefit not considered |
| McKeever et al. 1998 | Texas | Maintenance and Safety | NPV- $923, 000 | did not capture- randomness in collisions, overdispersion of collisions, linear relation of collisions and exposure, Regression-to-the-mean (RTM) artefact, and effect of external factors. |
| Veneziano, et al., 2014 | Iowa | Maintenance and Safety | BCR 45.4:1 | Safety benefit assumed |
| Koeberlein, et al., 2015 | Idaho | Safety | BCR 22:1 | Statistical significance not verified; did not capture- randomness in collisions, overdispersion of collisions, linear relation of collisions and exposure, RTM artefact, and effect of external factors. |
| Kwon, et al. 2015 | Minnesota | Maintenance and Safety | BCR 3.5:1 | did not capture- randomness in collisions, overdispersion of collisions, linear relation of collisions and exposure, RTM artefact, and effect of external factors. |
| Zhao, et al., 2016 | New York | Maintenance and Safety | BCR 10.8-15.52 | did not capture- randomness in collisions, overdispersion of collisions, linear relation of collisions and exposure, RTM artefact, and effect of external factors. |
| Ewan & Al-Kaisy, 2017 | Montana | Maintenance, Safety, and Delay | BCR 33.3:1 | Safety benefit assumed from other literature |
| El Esawey, et al., 2019 | British Columbia | Safety | BCR 1.1-38 | Sole effectiveness not quantified; effect of confounding factors not considered |

## 2.5 Safety Evaluations

Safety evaluations are an efficient technique used to quantify the safety impacts of a treatment. The evaluation methodology is classified into two categories based on the type of data structure: longitudinal and cross-sectional evaluation. The change in collisions before and after implementation is evaluated under longitudinal evaluations. In cross-sectional evaluation, collision difference between treated and non-treated sites is compared using collision data collected after treatment implementation.

There are several reasons why safety evaluations prefer the before-and-after evaluation method. Firstly, treatments are not randomly assigned to a site. They are selected based on severe collision history or other safety concerns. Hence, making cross-sectional analysis difficult as collision patterns of treated and untreated sites can vary significantly. Secondly, cross-sectional evaluation requires both treated and untreated sites to be as similar as possible. Hence, maintaining similarity while collecting a larger sample size becomes a challenge. Following are the three main kinds of before-and-after evaluation techniques:

- Naïve before-and-after evaluation
- Before-and-after with comparison group
- Before-and-after with Empirical Bayes method

These methods follow a general format of breaking the time into two sets, namely, before period and after period. Where the former represents the time before the implementation of the countermeasure and the latter represents the post-implementation period. Collisions that would have happened if the countermeasure had not been put in place are predicted for the after-period; it is then compared to collisions that happened in the before period. The main difference between these methods is the measuring technique of predicting collisions in the period after a treatment is implemented (Hauer, 1997; Contini L. , 2015). The following sections provide more details of these evaluation techniques.

### 2.5.1 Naïve Before-and-After Safety Evaluation

As the name suggests, it simply predicts the collision frequency of the after period using the collision frequency of the before period had the countermeasure not been implemented (Hauer, 1997). Equation **(2-1)** shows the formula of the naïve evaluation technique.

$$\text{collision reduction} = \frac{\mathrm{N}_b - \mathrm{N}_a}{\mathrm{N}_a} \quad \textbf{(2-1)}$$

Where,

$\mathrm{N}_b$ = Number of collisions in the before period

$\mathrm{N}_a$ = Number of collisions in the after period

The assumption that collision frequency would remain constant without countermeasure ignores several factors such as regression-to-the-mean effects, confounding factors, maturation, and collision migration, which are described in more detail below.

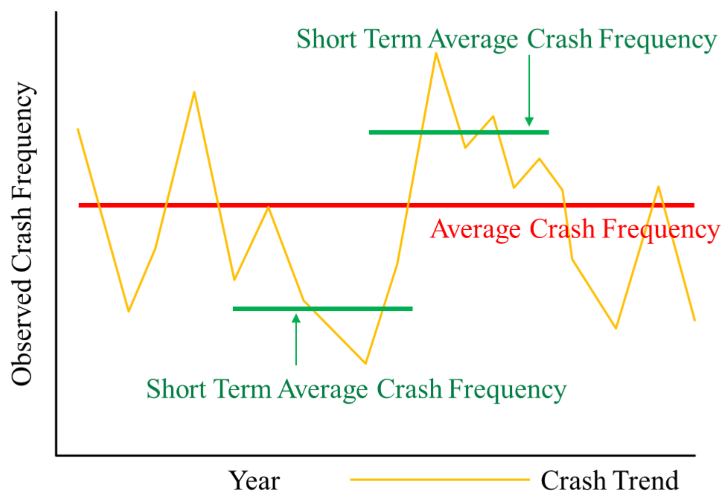


**Figure 2-2 Regression-to-the-mean artefact**

Regression-to-the-mean (RTM) effect is caused by natural fluctuation of collisions at a location. Higher collision frequency in the before-period tends to be followed by lower collision frequency in the after-period without any treatments or changes. **Figure 2-2** provides visual representation of the phenomenon. Ignoring such a statistical phenomenon would result in a questionable countermeasure evaluation. As shown in the figure above, considering a higher value short-term average overestimates the data, and considering a lower short-term average underestimates the data. This develops the need of estimating the true mean of collision frequency.

Another issue is not accounting for external factors; factors such as presence of other countermeasures, varying weather conditions, improvement in roadway, general traffic safety trends, or changes in collision reporting thresholds all impact collision frequencies.

Maturation is another issue. Similar to external factors, collision frequency is also influenced by changes in traffic volumes, infrastructure, etc. An increase in traffic volume increases the exposure of vehicles and may lead to an increment in collision frequency. Likewise, collisions can also decrease due to infrastructure improvements. These factors are not captured in the naïve before-and-after evaluation technique, which leads to misleading results on treatment effectiveness.

The last notable issue for naïve before-and-after is collision migration. As the name suggests, migration refers to the transfer of collisions from one site to another. For instance, reducing the speed limit at one location may lead to drivers choosing alternative routes. A reduced traffic volume at the treatment site means decreased exposure. Thus, it might reduce collision frequency while increasing collisions at surrounding sites due to the transfer of traffic volume. Likewise, improved road conditions at one location might decrease driver cautiousness, which leads to collisions at other locations where no improvements were made. Another interesting example of collision migration is an increase in a specific type of collision due to a countermeasure. For instance, head-on collisions may decrease by constructing medians, which might lead to an increase in fixed-objects collisions.

Though the naïve before-and-after evaluation technique is the simplest to apply, it fails to account for the above-discussed factors that critically impact the conclusiveness of safety evaluation results (Contini L. , 2015).

### 2.5.2 Before-and-After Evaluation with Comparison Group

The comparison group method makes improvement on the naïve before and after by accounting for maturation and confounding factors. A comparison group represents a group of sites very similar to the treatment sites and is used to estimate the collisions that would occur in the after-period. This technique assumes that the before and after ratio of collisions at comparison sites is equivalent to what would have occurred without treatment. The odds ratio shown in the following equation is used to express reduction in collisions.

$$\text{Odds ratio} = \frac{\frac{\text{Comparison}_{before}}{\text{Comparison}_{after}}}{\frac{\text{Treatment}_{before}}{\text{Treatment}_{after}}} \tag{2-2}$$

If this odds ratio is less than one, it indicates that collisions have reduced after countermeasure implementation.

Hauer identified two main assumptions associated with this method (Hauer, 1997). First, comparison and treatment groups must have similar trends in collision frequencies. The comparison group represents what would have happened to the treatment group if the treatment had not been implemented. Therefore, these two groups must have similar factors like collision frequency, road geometry, traffic volume, and geographic locations. Secondly, to ensure that the evaluation accounts for maturation and external factors, the comparison and treatment group should have a similar response to these effects. In order to use comparison groups to predict after-period collisions, it is essential to select comparison groups that are not influenced by the implementation of treatments. This is difficult to achieve as it was observed that drivers changed their travel behavior after treatment implementation, which can lead to an increase in collisions in the surrounding area (Contini L. , 2015). For the most accurate results, the following four requirements were suggested by Hauer (1997):

- Both groups should have comparable collision history in the before-period.
- Collisions at comparison group should be larger as compared to the treatment group.
- The length of before-and-after periods should be identical for both groups.

- Both groups should have similar changes in external factors.

### 2.5.3 Before-and-After Evaluation with Empirical Bayes

Selecting treatment sites based on high collisions frequency in the before period leads to RTM artifact. This bias is not accounted for in either the naïve method or comparison group method. However, using an expected value of collisions in the before period the EB method accounts for this effect. This method uses two separate pieces of information to predict the expected collision frequency had the treatment not been implemented. The first piece is estimated by the expected number of collisions in the before period. The second piece is predicted by the change in the expected number of collisions due to variations in traffic volume and external factors.

Hauer (1997) describes that the EB method uses two clues, collisions that have already occurred at the treatment site and a group of reference sites (Hauer, 1997). These reference sites are similar to treatment sites and represent what would have happened had the treatment not been implemented. Collision history in the before period is denoted by $K$, where $E\{\theta\}$ and $Var\ \{\theta\}$ are the mean and variance of collisions for the reference group. Therefore, $E\{\theta/K\}$ and $Var\ \{\theta/K\}$ are represented as the expected number of collisions and its variance at the treatment sites, respectively. The Bayes's probability distribution uses two assumptions to link the two clues. As per the first assumption, $K$, the collision frequency at treatment sites follows the Poisson distribution. This is because the rare, random, non-negative, and discrete nature of collisions can be successfully captured by this distribution. The second assumption states that Gamma probability distribution is followed by $\theta$. Therefore, $p\ (\theta/K)$, the posterior distribution follows Gamma distribution as shown in the equations below.

$$p\ (\theta/K) = \frac{p\ (K/\theta) \cdot p\ (\theta)}{p\ (K)} \quad \textbf{(2-3)}$$

where, $p\ (K)$ is the marginal distribution, and

$$E\left\{\frac{\theta}{K}\right\} = w \cdot E\{\theta\} + (1 - w) \cdot K \quad \textbf{(2-4)}$$

$$w = \frac{1}{1 + \frac{Var\,\{\theta\}}{E\{\theta\}}} \quad \textbf{(2-5)}$$

Where $0 \leq w \leq 1$

Equations **(2-4)** and **(2-5)** show that the expected number of collisions at the treatment site is the weighted sum of expected collisions at reference sites and the observed collisions at the treatment sites.

Hauer (1997) further recommends that the mean and variance of collisions can be calculated using method of sample moments; or by developing safety performance functions (SPFs) calibrated using negative binomial (NB) analysis.

Persaud & Lyon, (2007) used 1994 to 1999 data of stop-controlled intersections in California to compare the results of EB evaluation technique to similar before-and-after techniques. Researchers observed that the collisions with higher collision frequencies in the before-period (1994-96) had lower collision frequencies in the after-period (1997-99). Similarly, locations with lower collision frequencies in the before-period had higher collision frequencies in the after-period. The effect of RTM artifact was clearly visible in this study as this intersection experienced no change in the analysis period. Assessment of comparison group method and EB method provided further evidence that the predictions of the former evaluation technique were dependent on the value of collision frequencies in the before period. For instance, the results were over-predicted when the collision frequencies were higher in the before period and under-predicted when the collision frequencies were lower in the before period (Contini L. , 2015).

### 2.5.4 Summary of Assessment Methods

The before and after safety evaluation is affected by four issues.

- Regression-to-the-mean
- External Factors
- Maturation
- Collision Migration

Due to its ability to account for all four issues shown above, the EB method becomes the most preferred and statistically rigorous safety assessment technique. Therefore, it is adopted for safety evaluation in this thesis (Hauer, 1997; Persaud & C., 2007; Contini L. , 2015).

## 2.6 Summary

The initial section of this chapter summarized various literature conducted to evaluate the effect of winter on road safety. Although the results of the studies conducted show that WRM activities positively influence driver safety, it was noted that collision frequencies were directly used for assessment. The following section discussed various steps of the safety management process, and the role played by each step for improving WRM activities. The importance of conducting safety effectiveness evaluation was highlighted in this section as well. Furthermore, RWIS, an important device used for planning WRM activities was discussed in detail. Various benefits associated with its implementation and the need to quantify its benefits were also elaborated. The remaining sections provided a review of previous studies indicating that the implementation of RWIS led to a reduction in winter weather collisions. The literature review revealed most prior studies did not include the safety benefits in their cost-benefit studies. Moreover, the studies that included safety benefits used naïve safety evaluation techniques to quantify the reduction in collisions. These studies did not account for overdispersion and randomness of collisions, thereby making their assessments less conclusive. More importantly, none of the studies ever addressed the RTM bias within their modelling frameworks, and instead considered a relatively simple linear relationship between exposure and collisions (Highway Safety Manual, 2010). Additionally, these studies used limited analysis periods, which led to limited data sets and therefore, inconclusive results. Interestingly, one of the studies used before-and-after EB method for safety evaluation. However, the results they provided were for the combined effect of RWIS and VMS. The sole effect of RWIS on winter weather collisions was not covered in their approach. In addition, the results only applied to rural undivided highways.

As discussed, safety effectiveness evaluation is one of the most important steps in the roadway safety management process; it involves the assessment of the change in the number of collisions after the implementation of a countermeasure. Additionally, the economic analysis step helps comprehend whether the allocation of funds for safety improvement was cost-effective. The decision-making activities of transportation agencies, such as policy amendments and fund allocation, are positively influenced by the safety evaluation analysis (Highway Safety Manual, 2010). A literature review on the available safety evaluation techniques clearly pointed out the statistically rigorous technique mostly used for evaluation. Therefore, this study focuses on using the state-of-the-art before-and-after EB approach to determine the sole safety effects of RWIS, followed by an economic appraisal of RWIS by estimating the BCR in terms of safety benefits.

# Chapter 3. SAFETY ASSESSMENT OF RWIS

This chapter discusses the overall process used to attain the research objectives of this study. The first section provides an overview of the proposed methodological framework. This is followed by a discussion on the use of GIS for data integration and data processing. The third section then provides details on the methods used for model calibration and steps of the before-and-after EB method. Finally, the last section gives an overview of the steps required to conduct an economic appraisal of RWIS stations.

## 3.1 Proposed Methodological Framework

This study was divided into three stages: The first was the database development, which involved extraction of inclement winter weather collisions. The collision data was assessed, and a filtering process was conducted to extract collisions that efficient WRM activities could prevent. As already discussed, it was assumed that transportation agencies timely conducted these activities using the nowcasts and forecasts of weather data received from RWIS. This stage's road network development portion involved processing road network files through ArcGIS software and preparing them for analysis. Road class information was used to select major road networks because state DOTs prioritize them for WRM activities (Fu & Usman, 2018). Therefore, RWIS would have a direct impact on these networks as compared to minor roads. Generation of site-specific attributes of road networks such as road length, traffic volume, and number of lanes was also conducted. Lastly, the selection of RWIS stations used for analysis was critical in the database development stage. To avoid inconclusive results, each RWIS station was thoroughly reviewed based on its data availability of before and after periods, changes in geometry at the location where RWIS was implemented, and its operation data to ensure no data gaps during its operation period.

The second stage involved site selection and model calibration. The data were first integrated and processed to select reference and treatment sites. Treatment sites referred to the sites within the influence region of RWIS understudy, and reference sites referred to those not within the influence region on any RWIS station. Second, reference sites were used to locally calibrate SPFs and YCFs, a critical step to conduct safety evaluation using the before-after EB approach.

The last stage was the analysis stage, where safety evaluation was conducted to quantify the sole safety effectiveness of RWIS stations. The safety evaluation results were then combined with collision costs to conduct Economic Analysis and quantify the benefit-cost ratio of RWIS stations. Figure 3-1 provides a layout of the proposed methodological framework for the completion of this study.

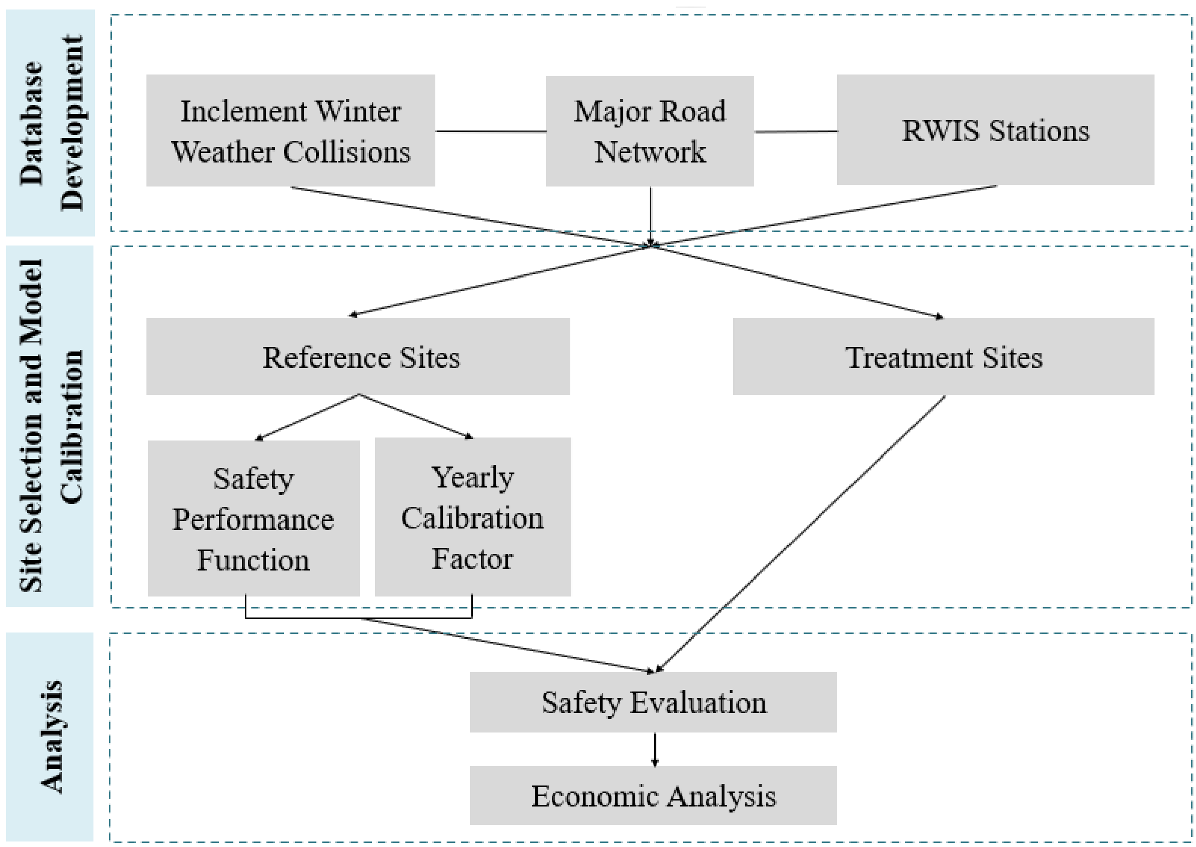


**Figure 3-1 Methodological Flowchart**

## 3.2 Data Processing and Integration using GIS

Geographic Information Science (GIS) has been extensively used for data integration, processing, and visualization (Loidl, et al., 2016; Silalahi, et al., 2020). For this reason, ArcGIS software was used to meet the intensive data requirements of the analysis in the initial stage of the research for database development since the proposed method requires a significant amount of geospatial data sets that need to be assimilated and processed for model development. The model calibration portion requires information on road segments and their associated parameters that might affect collision frequencies, such as road length, traffic volume, number of lanes, presence of medians, pavement type, etc. The collision records themselves are also needed. The service area route solver of the *Network Analyst* extension of ArcGIS was used while selecting reference and treatment sites, identified via influence region of RWIS stations. This extension uses various impedances to estimate the area accessible from a location on a network (Silalahi, et al., 2020; ArcGIS Desktop, 2021; Cullinan, et al., 2008). Assuming 30 km influence region an RWIS station, distance impedance of 30 km was used to provide an accessible network around the station (Kwon, et al., 2015; Manfredi, et al., 2005).

## 3.3 Quantifying the Safety Benefits of RWIS

This section discusses the model calibration process and the overall procedure to conduct safety evaluation.

### 3.3.1 Safety Performance Functions

The Empirical Bayes (EB) method uses the safety performance functions (SPFs) to predict the collision frequencies as prior information for the estimation of the expected average collision frequencies (Highway Safety Manual, 2010). SPFs are mathematical models that are statistically developed to relate collision frequencies with explanatory variables such as traffic volume, segment length, number of lanes, and other site-specific attributes. In the EB method, they are calibrated using a group of reference sites comparable to the treated sites but are not influenced by any RWIS station. Suitable reference sites were selected based on road type and traffic volume. The Negative binomial error structure captures the over-dispersion in collision data and is used to express the collision distribution (Contini & El-Basyouny, 2016)**.** The functional form for the SPF adopted in this study is shown in Equation **(3-1)**

$$\mu = exp(\beta_0)\,.\,L^{\beta_1}(V)^{\beta_2} \tag{3-1}$$

Where:

$\mu$ is the predicted collision frequency per year,

$L$ is the road segment length in meters,

$V$ is the Annual Average Daily Traffic,

$\beta_0$, $\beta_1$, and $\beta_2$ are the regression parameters.

Several other explanatory variables were also considered during model development, but only statistically significant variables were retained using the backward stepwise elimination process. Parameters of the explanatory variables were estimated using Statistical Analysis System (SAS) GENMOD, which uses maximum log-likelihood for estimation (SAS). The goodness-of-fit of the model was assessed using Pearson Chi-square and Scaled Deviance generated during model calibration.

### 3.3.2 Yearly Calibration Factors

As described previously, the variation of collision frequency with respect to traffic volume and other site-specific attributes is determined using the SPFs. However, there are confounding factors that cannot be captured by SPFs, such as changes in weather conditions, improvements in the roadway, and general traffic safety trends that are likely to cause annual fluctuations in collision frequencies. Therefore, the yearly calibration factors (YCFs) are used to address this issue. The YCFs are calculated as ratios between the sum of the observed collision frequencies and the sum of the average collision frequencies predicted via SPFs in the same year. It was assumed that the impact of confounding factors is the same for both reference and treatment groups (Contini & El-Basyouny, 2016; Wu, et al., 2020). To obtain a more accurate prediction, the collision frequency predicted by SPFs was adjusted by multiplying the corresponding YCFs. The expression for YCF is shown in Equation **(3-2)**.

$$YCF_j = \frac{\sum_{Reference\ Sites} N_{Observed,j}}{\sum_{Reference\ Sites} N_{Predicted,j}} \quad \textbf{(3-2)}$$

Where:

$YCF$ is Yearly Calibration Factor,

$N_{Observed}$ is observed number of collisions for reference sites,

$N_{Predicted}$ is predicted number of collisions for reference sites,

$j$ is the year.

The safety effects of other countermeasures were also integrated in the YCFs, which allows this study to focus solely on the effect of stationary RWIS stations on winter collisions.

### 3.3.3 Before-and-After Evaluation with Empirical Bayes Method

The before-and-after safety evaluation with Empirical Bayes (EB) method is used to account for the RTM artifact or selection bias (Highway Safety Manual, 2010). The EB analysis accounts for this bias by incorporating two separate pieces of information to calculate the expected collision frequencies for the treatment sites, the collision history of treatment sites, and their predicted collision frequencies obtained from the SPFs. The ratio between the observed number of collisions and the expected number of collisions post-implementation is the safety effectiveness of the countermeasure (Hauer, 1997).

The first part of the EB method is estimating the Expected collision frequency in the before-period. This involves estimating the predicted collision frequency for each site in the before-period using the SPF model calibrated. The expected collisions for each site in the before-period are calculated in the next step using Equation **(3-3)** and Equation **(3-4)**.

$$N_{Expected,B} = w \times N_{Predicted,B} + (1 - w) \times N_{Observed,B} \quad \textbf{(3-3)}$$

$$w = \frac{k}{(k + N_{Predicted,B})} \quad \textbf{(3-4)}$$

Where:

$N_{Expected,B}$ is the expected collision frequency in the before-period,

$w$ is the weighted adjustment factor between 0 to 1,

$N_{Predicted,B}$ is the predicted collision frequency in the before-period,

$N_{Observed,B}$ is the observed collision frequency in the before-period,

$k$ is the negative binomial overdispersion parameter estimated from SPF.

The second part is the estimation of expected collision frequency in the after period in the absence of treatment. The SPF equation is again used to estimate the predicted collision frequency in the after period for each site. An adjustment factor for each site is estimated using Equation **(3-5)** that incorporates the variation in the duration of before and after period and traffic volume.

$$Adj = \frac{\left(\sum_{After\ Years} N_{predicted,A}\right)}{\left(\sum_{Before\ Years} N_{predicted,B}\right)} \quad \textbf{(3-5)}$$

Where:

$Adj$ is the adjustment factor, and $N_{Predicted,A}$ is the predicted collision frequency in the after-period,

In the next step, the adjustment factor is multiplied by the expected crash frequency of each site in the before period to find the expected collisions frequency of each site in the after-period. This process is shown in Equation **(3-6)**.

$$N_{Expected,A} = N_{Expected,B} \times Adj \quad \textbf{(3-6)}$$

Where: $N_{Expected,A}$ is the expected collision frequency in the after period.

The third part is estimating the effectiveness of the countermeasure. The first step of this component estimates the overall effectiveness of the countermeasure for all treated sites (shown in Equation **(3-7)**).

$$Odds\ Ratio' = \frac{\sum_{All\ Sites} N_{Observed,A}}{\sum_{All\ Sites} N_{Expected,A}} \quad \textbf{(3-7)}$$

Where:

$Odds\ Ratio'$ is the biased odds ratio, and $N_{Observed,A}$ is the observed collision frequency in the after-period.

There is a potential bias associated with this effectiveness, therefore, an adjustment factor is incorporated in its estimation such that unbiased effectiveness of the countermeasure is obtained, termed as $Odds\ Ratio$. Equation **(3-8)** shows the incorporation of the adjustment factor.

$$Odds\ Ratio = \frac{Odds\ Ratio'}{1 + \frac{Var(\sum_{All\ Sites} N_{expected,A})}{(\sum_{All\ Sites} N_{Expected,A})^2}} \quad \textbf{(3-8)}$$

Where:

$$Var\left(\sum_{All\ Sites} N_{expected,A}\right) = \sum_{All\ Sites} \left[(Adj)^2 \times N_{Expected,B} \times (1 - w)\right] \quad \textbf{(3-9)}$$

Furthermore, the percentage change in collision frequency is used to estimate the overall unbiased safety effectiveness using Equation **(3-10)**.

$$Safety\ Effectiveness = 100 \times (1 - Odds\ Ratio) \quad \textbf{(3-10)}$$

A positive value of safety effectiveness indicates a reduction in collisions.

The last part of the EB method is to estimate whether the results are statistically significant. The precision of the estimated odds ratio is calculated using Equation **(3-11)**.

$$SE(Odds\ Ratio) = \sqrt{\frac{(Odds\ Ratio')^2 \times \left[\frac{1}{\sum_{All\ Sites} N_{Observed,A}} + \frac{Var\left(\sum_{All\ Sites} N_{Expected,A}\right)}{\left(\sum_{All\ Sites} N_{Expected,A}\right)^2}\right]}{1 + \frac{Var\left(\sum_{All\ Sites} N_{Expected,A}\right)}{\left(\sum_{All\ Sites} N_{Expected,A}\right)^2}}} \quad \textbf{(3-11)}$$

Where:

$SE(Odds\ Ratio)$ is the standard error associated with $Odds\ Ratio$.

The statistical significance of the results is then estimated using the following equation.

$$t_{ratio} = \frac{(1 - Odds\ Ratio)}{SE(Odds\ Ratio)} \quad \textbf{(3-12)}$$

If the value of the $t_{ratio}$ is greater than 1.96, the results are significant with a confidence of 95%. Similarly, for results to be significant with 99% confidence, $t_{ratio}$ should be greater than 2.576.

## 3.4 Economic Analysis

The safety benefits obtained from the implemented countermeasure were compared to its cost by performing an economic analysis. The Benefit-Cost Ratio (BCR) was used to evaluate the financial feasibility of the countermeasure (Highway Safety Manual, 2010).

The costs of collisions and RWIS stations were not the same every year due to inflation and general changes in economies. Therefore, it was necessary to consider inflation and convert those costs into present values for each year. The inflation factor was used to estimate the value of the desired entity for the year of interest and was the ratio between the Consumer Price Index (CPI) for the year of interest to the CPI of the year for which the cost was available (Miller, et al., 1991) as shown in the following equation:

$$Inflation\ Factor_j = \frac{CPI_j}{CPI_i} \quad \textbf{(3-13)}$$

Where:

$CPI$ is Consumer Price Index, $j$ is the year of analysis and $i$ is the year for which that cost is available.

Each collision has a direct and indirect cost associated with it, where the direct costs include property damage, injury, or fatality. In contrast, indirect costs mainly represent the cost borne by the person's family involved in a collision. The safety effectiveness is used to estimate the reduction in collisions, which are multiplied by the relevant collision costs to calculate the benefits obtained per year. These are termed as annual project benefits calculated using Equation **(3-14)**. Benefits are then converted to Present Value (PV) using Equation **(3-15)**. Likewise, the annual operation and maintenance costs associated with RWIS installation were also converted to present value using Equation **(3-15)**. In addition, RWIS will require an up-gradation in the future, and its present value of that cost is estimated using Equation **(3-16)** (Zhao, et al., 2016). The total present value (cost) of RWIS was computed by adding its one-time implementation cost with the present value of operations cost and up-gradation cost.

$$Annual\ Value\ (AV)\ Benefits = Reduced\ Collisions \times Collision\ Cost \quad \textbf{(3-14)}$$

$$PV = AV \times \left[\frac{(1+r)^{n_s} - 1}{r \times\ (1+r)^{n_s}}\right] \quad \textbf{(3-15)}$$

$$PV\ (Upgrade) = Upgrade\ Cost \times \left[\frac{1}{(1+r)^{n_v}}\right] \quad \textbf{(3-16)}$$

Where:

$r$ is the rate of return, $n_s$ is the service life of RWIS, and $n_v$ is the upgrade years in a lifetime of a site.

Finally, the BCR was calculated using the following equation:

$$BCR = \frac{PV_{Benefits}}{PV_{Costs}} \quad \textbf{(3-17)}$$

If the value of the BCR is greater than 1, the countermeasure had more benefits than its costs.

# Chapter 4. CASE STUDY

This chapter demonstrates the methodology developed to attain the objectives of this research. A brief background of the study area is provided in the first section. The second section presents the database development stage where data description and processing of collision data, road network data, and RWIS data, along with the process of selecting RWIS sites. The next section details the second stage of the proposed methodology, where reference and treatment sites are discussed in detail, which includes the results of the calibrated models. The fourth section of this chapter discusses the results of safety effectiveness evaluation and economic analysis of RWIS stations.

## 4.1 Study Area

A case study of the state of Iowa in the U.S. was used in this research to demonstrate the developed methodology. Iowa lies in the center of the U.S., with the Mississippi River and the Missouri River on the eastern and western borders, respectively. The state constitutes a total of 99 counties spread over a land area of 144,669.30 sq km and a population of 3,155,070 (U.S. Censue Bureau , 2020). The largest city Des Moines is also the capital of the state. Interstate Highways 80 and 35 running across the east-west and north-south of Iowa respectively, intersect at the state capital crossroads (Iowa International Center, 2020). All the four seasons, spring, summer, fall, and winter are equally distributed throughout the year. With snow and wind, December to February is the coldest time of the year in Iowa (Iowa International Center, 2020).

Iowa has been focused on enhancing the efficiency of the transportation system during winter weather conditions. They have been deploying RWIS stations and using mesonets to expand the observation density for the WRM authorities. To provide public access to weather information, a website, WeatherView, was also developed in 1999. RWIS sensors, Automated Weather Observation Systems (AWOS), and regional and bridge frost forecasts were the information sources used for the website (Ye, et al., 2009). The state has a network of 86 RWIS stations and a website providing public access to their data (Iowa State University- Iowa Environmental Mesonet, 2021).

Incorporation and use of these technologies to reduce the adverse effects of inclement weather conditions, made it evident that the state has been taking extensive steps for efficient WRM operations. Indicating that the transportation agencies productively utilized the weather information shared by RWIS to execute maintenance activities. One of the reasons for selecting Iowa as the study area was the availability of the extensive datasets required for model development and evaluation. The Iowa DOT efficiently maintains and provides public access to these data sets. More importantly, before and after safety studies require the implementation date of countermeasures, such that the collisions in the before period and after period can be clearly defined. This critical information was shared on request by the Iowa DOT professionals. Therefore, Iowa was selected as the study area for this research. The following figure shows the major road networks and locations of all the RWIS stations in Iowa.

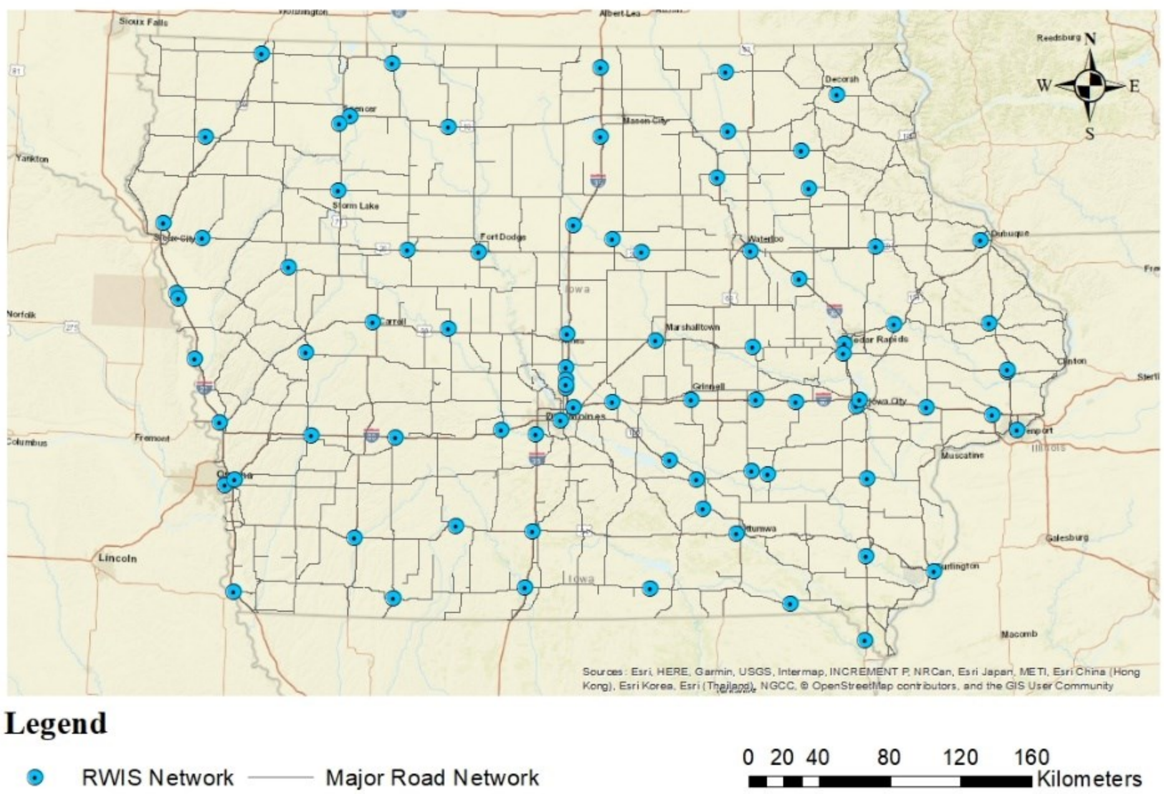


**Figure 4-1 Map of RWIS Network and Major Roads in the State of Iowa**

## 4.2 Database Development

This section provides a detailed discussion on the different types of data and their integration process.

### 4.2.1 Inclement Winter Weather Collisions

The collision data was collected from the Iowa DOT open data website (Iowa DOT Open Data, 2020). This data spanned from 2008 to 2019. Therefore, this duration was considered as the study period for the analysis. The collision data was downloaded in an Excel file format with rows representing individual collisions and columns providing details of each collision. A total of 639,470 collisions occurred during the entire study period. This study focused on collisions that occurred during winter weather conditions and that could be cured with efficient winter road maintenance activities since the major application of RWIS is for these conditions. Therefore, a filtering process was conducted to extract these collisions from the overall data set. Table 4-1 provides details of the data filtering process. The list under “Filtering criteria” were the columns of the collision data set, and “Selected attributes” were the options selected to filter out required collisions. As discussed earlier, December to February is the coldest time of the year in Iowa (Iowa International Center, 2020). However, a buffer period of one month was considered; thus, collisions from November to March were used for the study. Likewise, only collisions with a reported RSC of ice/frost, slush and snow, or mud/dirt, or having wet and icy road surface as a contributing factor were extracted for the study. This study considered road segment as the unit of analysis; therefore, collisions occurring only on road segments were involved. In total, the applied filter criteria selected 28,224 winter weather collisions.

Figure 4-2 is a map of inclement weather collisions in Iowa that occurred from 2008 to 2019. The density of collisions in specific regions of the state is visible from the figure. These are the regions with high population density. The central region surrounding Des Moines has the largest cluster of collisions.

**Table 4-1 Criteria for selecting winter weather collisions**

| Filtering criteria | Selected attributes |
|---|---|
| Month of Crash | November to March |
| Contributing circumstances- Environment | Winter Conditions |
| Contributing circumstances- Roadway | Surface condition (e.g., wet, icy) |
| Surface condition | 1. Ice/Frost<br>2. Mud, Dirt<br>3. Slush<br>4. Snow |
| Type of Roadway Junction/Feature | All non-intersection collisions |

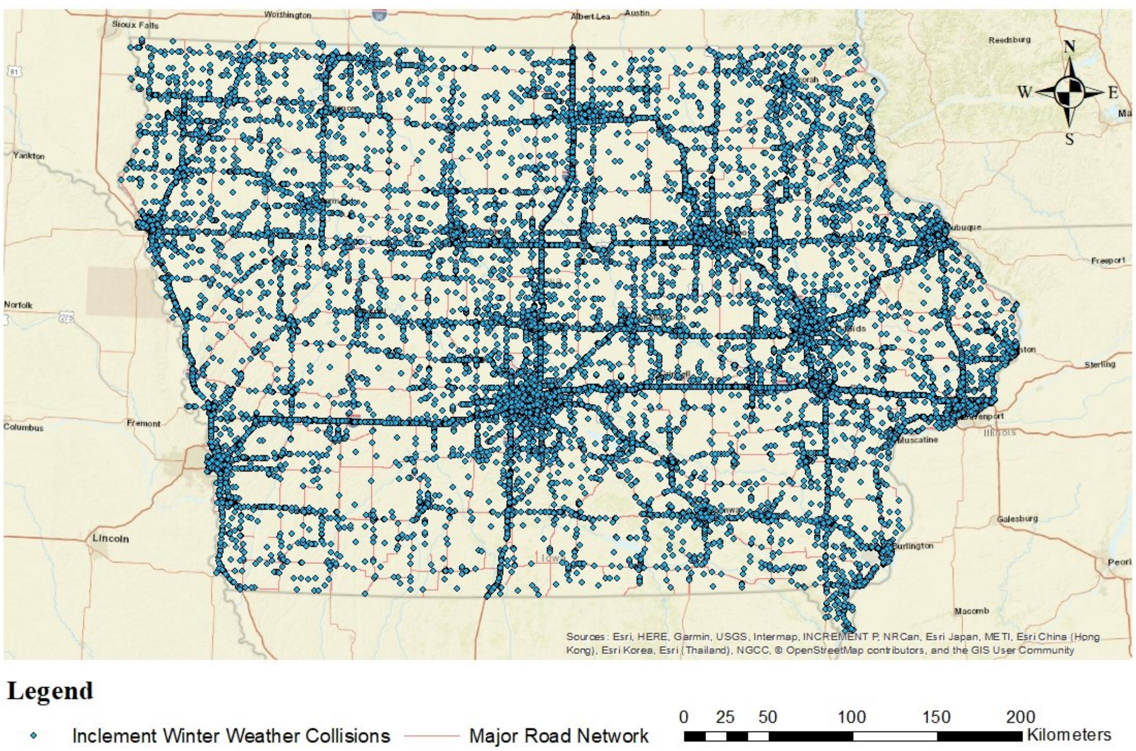


**Figure 4-2 A map of Inclement Winter Weather Collisions in Iowa**

### 4.2.2 Major Road Network

Major highways are prioritized for winter maintenance operations. Therefore, it was assumed that information shared by RWIS would have the most observable impact on these roads. The major road network data was collected from the Iowa DOT open data website in a shapefile format. Figure 4-3 shows the layout of this network in Iowa. Interstate Highways, State Highways, US Highways, Main Streets, and Co-Highways were part of this data set. Due to the nature of the data set, the road network shapefile was not present in a single plane and a road segment was divided into multiple segments. This led to erroneous road length information. Various ArcGIS tools were used to update the file into the required format. The file had other important attributes such as number of lanes and traffic volume. However, the traffic volume information ranged from 1974 to 2020, making the information less reliable. Therefore, a separate file containing appropriate traffic volume information was also downloaded and will be discussed in the next section.

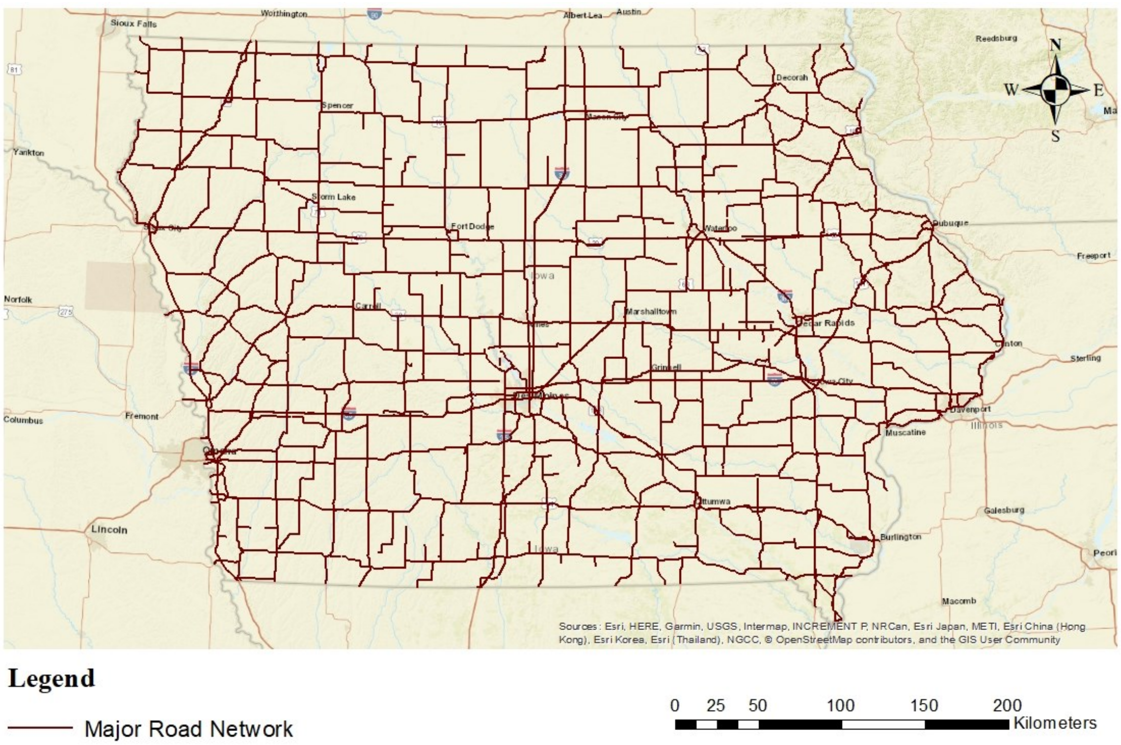


**Figure 4-3 Major Road Network in Iowa**

### 4.2.3 Traffic Volume

The EB analysis requires calibration of SPFs so that variation in collisions can be captured. Traffic volume is a critical factor influencing this variation and hence it was important to develop the traffic volume data of road segments for the entire study period. The downloaded file had road segments with traffic volume for the year 2020 only. Therefore, state-wide growth rates were collected from the annual and monthly reports developed by the Iowa DOT (Automatic Traffic Recorders 2009-2019, 2020; Automatic Traffic Recorder Monthly Report December- 2020, 2020). The following table summarizes the growth rates from 2008 to 2020, there was a growth rate of -11.5% from the year 2019 to 2020. These growth rates were further used to estimate the traffic volume of road segments throughout the study period.

**Table 4-2 Growth rate of traffic volume for Iowa during the study period**

| Year | ‘08 | ‘09 | ‘10 | ‘11 | ‘12 | ‘13 | ‘14 | ‘15 | ‘16 | ‘17 | ‘18 | ‘19 | ‘20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Growth Rate (%) | -2.50 | 1.20 | 1.40 | -1.00 | 0.60 | -1.20 | 0.50 | 2.60 | 2.20 | 1.50 | -0.70 | 0.40 | -11.50 |

### 4.2.4 Selection of RWIS Sites

The Iowa Environment Mesonet (IEM) archives RWIS information dating back to 1995, using a direct feed from the state DOT. Their website has open access to crucial data, including but not limited to air temperature, dew point temperature, wind speed, pavement temperature, and pavement condition collected by the network of 86 RWIS stations in Iowa (Iowa State University-Iowa Environmental Mesonet, 2021). For a before and after safety evaluation, it is necessary to have collision data before and after the implementation of a countermeasure. Therefore, operation information of each RWIS station in the state was collected as summarized in Appendix A. RWIS stations were further categorized based on this information. 56 RWIS stations were implemented before 2008, and out of these, 52 stations were operational throughout the study period (2008-19); the remaining 4 stations ended operations early (before 2008). For better discussions and understanding, these 56 stations were termed “Old” stations. With no collision data for the before period, these stations could not be considered for analysis. However, they were used to select reference sites where RWIS had no influence. Furthermore, 30 stations were implemented within the study period and were considered for further assessment. Ultimately, it was important to remove those RWIS stations that might have led to inconclusive results to provide a comprehensive analysis. Therefore, stations were filtered based on a review criterion shown in Figure 4-4.

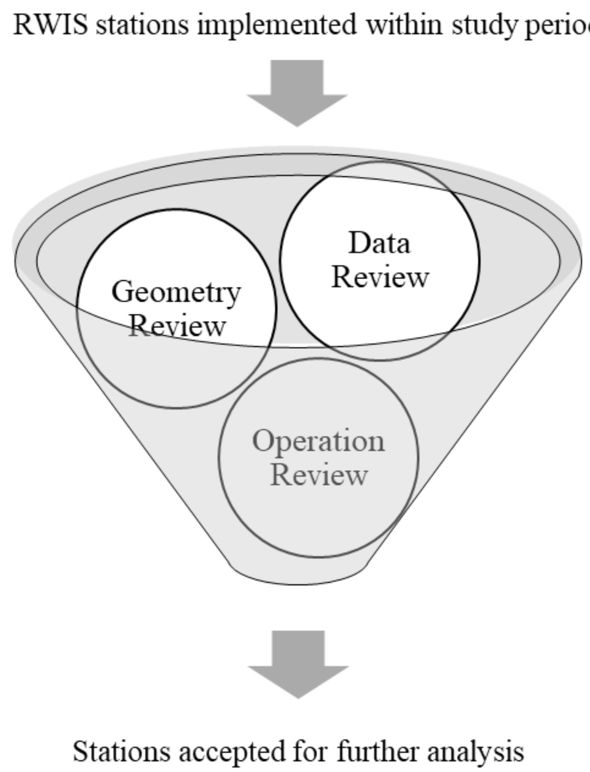


**Figure 4-4 Station selection criteria**

The overall review process is discussed below:

*4.2.4.1 Data Review*

It is recommended to use a minimum period of 3-4 years for both the before and after group for safety-effectiveness evaluation to provide a conclusive analysis (Highway Safety Manual, 2010). It is done so that the study has an ample amount of data set for conclusive analysis. Studies had also conducted their analysis using only one-year data sets (Wu, et al., 2020). However, this study only included winter weather collisions where one year included only five winter months. Therefore, to have ample observations, a minimum of 2 years of before and after periods were considered during the data review. The actual before and after period depended on the implementation year, which varied for each RWIS station. Applying this minimum criterion ensured the selection of stations with significant before and after periods. Stations that did not meet this requirement were removed from the analysis. For instance, stations implemented in 2009 had only one year of data in the before-period, and stations implemented in 2018 had only 1 year of data in the after-period. Additionally, there were stations with shorter operational period with insufficient amounts of data recorded.  Therefore, due to the above-mentioned concerns, stations with inadequate data sizes were removed from the analysis.

#### *4.2.4.2 Geometry Review*

Geometrical changes at sites during before or after periods have a major impact on traffic volume and collisions, making it difficult to quantify the sole effectiveness of RWIS stations. This is because variation in geometry often leads to an unexpected increase or decrease in collisions, resulting in misleading results on RWIS effectiveness. Therefore, satellite images of the network near RWIS stations were reviewed to understand whether there were any major construction activities during the analysis period. Any stations with major geometrical changes were removed from the analysis. For illustration purposes, two of such stations are discussed below.

RWIS station named Rockwell City with station ID- RRWI4 was implemented in January 2013 and was operational till the end of the study period. The before period for this station was 2008-2012. Figure 4-5 shows satellite images of the network around this station. The top left, top right, bottom left, and bottom right images were taken during 2008 October, 2009 September, 2010 September, and 2011 September, respectively. It was visible from the images that East-West bound highway was under construction during this entire period. Moreover, a satellite image from 2012 also showed signs of construction activity at this location. This added road segment would have led to a sudden increase in traffic volume, which might be a reason for potential increase in collisions in the after-period. Detailed analysis of collision data at this site also revealed that most of the collisions occurred on the east-west bound highway after 2013. Therefore, it was concluded that major construction activity at a site leads to fluctuation in collisions; hence, the effectiveness of RWIS could not be evaluated at this location. Even if the analysis was conducted for this site, the results would have been inconclusive as the collision data was heavily influenced by geometric changes.

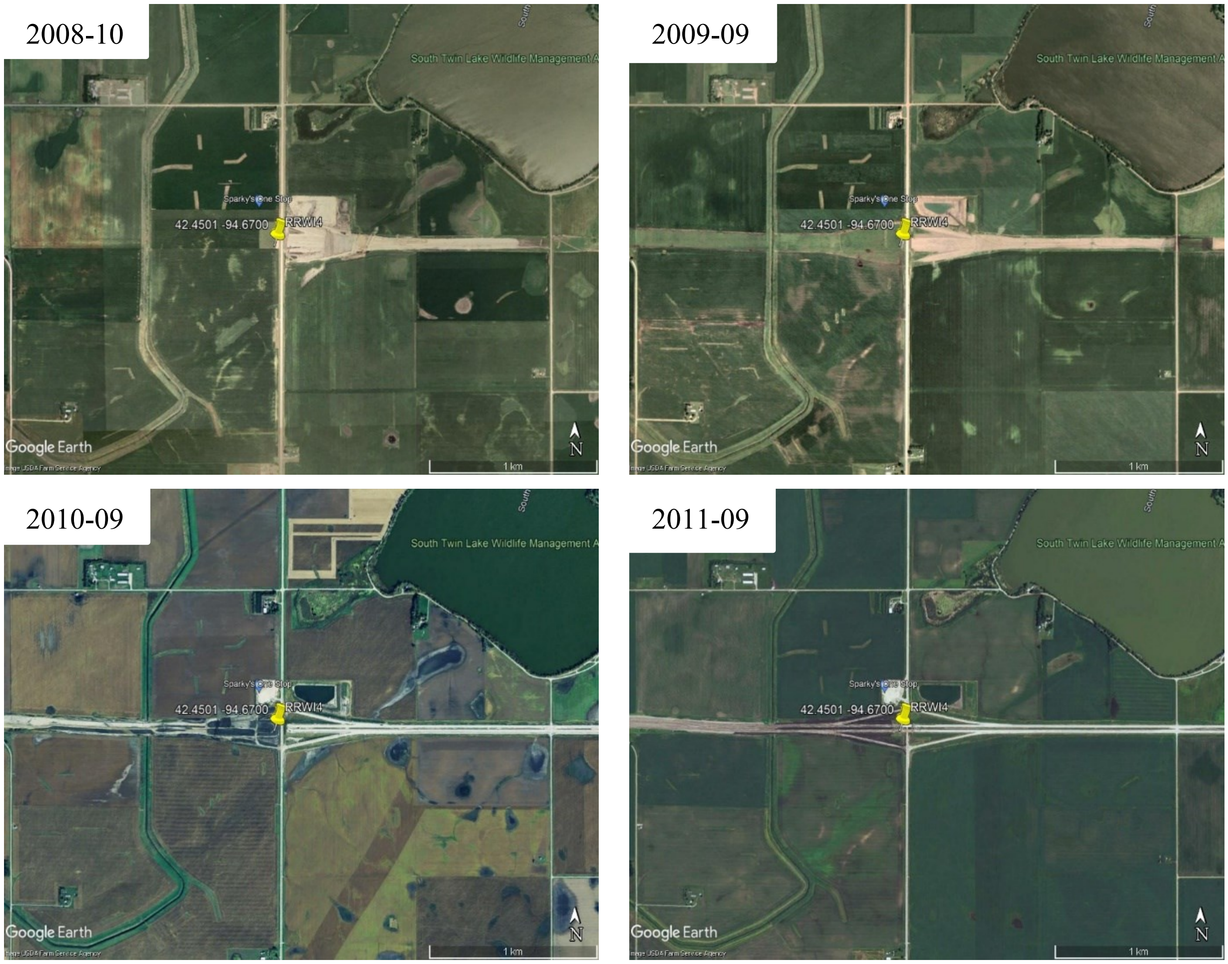


**Figure 4-5 Satellite images of road network near RRWI4 station**

Figure 4-6 shows satellite images of the road network around the RWIS station named Tipton with ID-RTPI4. The caption at the top left of each image represents the year and month they were captured. The station was operational from 2009 till the end of the study period. By comparing the top left and right images, it was clear that a bridge with greater width was being constructed. Moreover, images from 2008, 2009, and 2010 clearly show the merging of two roads right in front of the implemented RWIS station. As discussed in the previous illustration, such construction activities might have led to major fluctuations in traffic volume and possible issues in the accuracy of the data provided by RWIS. Additionally, this site had only one year of before-period data; it failed to meet both data size requirements and fixed geometric conditions. Therefore, this station was also removed from the analysis.

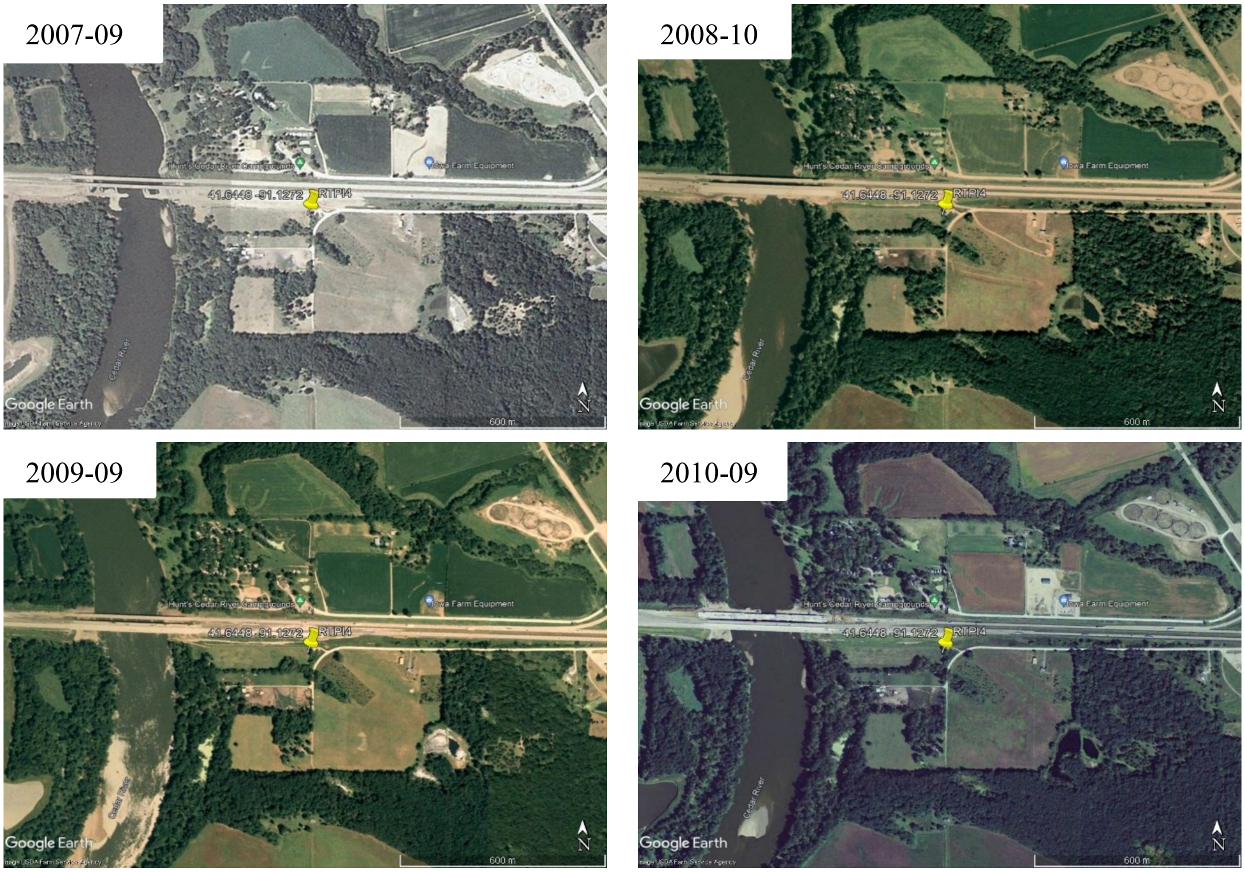


**Figure 4-6 Satellite images of road network near RTPI4 station**

### *4.2.4.3 Operation Review*

The operational efficiency of RWIS stations was analyzed based on the frequency of data they provided. The data collected by RWIS stations recorded readings every 10 minutes, which can be used to assess whether there were gaps in the data. Additionally, only winter months were considered as the summer period is not applicable to WRM. A station with a lower frequency of data collection would indicate operational issues. If a station collected no data or a significant data gap was present, then that RWIS was considered to have a negligible effect on WRM due to lack of information provided. Hence, it was be removed from the analysis.

After this rigorous review, 11 stations were eliminated and 19 stations were considered for further evaluation, they were termed as “Eliminated” and “Accepted” stations respectively. The following table provides an overview of the station selection process discussed in this section.

**Table 4-3 Overview of station selection process**

| Details of RWIS Stations | No. of Stations |
|---|---|
| Total RWIS Stations | 86 |
| Stations implemented before study period- “Old” | 56 |
| Stations implemented within the study period | 30 |
| • Stations eliminated during review – “Eliminated”<br>• Stations considered for further evaluation- “Accepted” | 11<br>19 |

The next step was selection of reference and treatment sites, critically important to conduct before-after EB studies.

## 4.3 Site Selection and Model Calibration

This section provides detailed discussions on the process of selecting reference and treatment sites. The calibrated SPFs and YCFs are also discussed here.

### 4.3.1 Selection of Reference and Treatment Sites

Treatment sites are referred to as sites that are under the influence of countermeasures. Hence, the safety evaluation of a countermeasure is conducted for these sites. Reference sites are very similar to treatment sites in terms of geometry, traffic flow conditions, and collision trends. However, they are not influenced by the implemented countermeasure. They are used in the analysis to provide a quantitative understanding of what would have happened if the countermeasure was not implemented. A 30 km radius was assumed to be the influence region of an RWIS station as suggested by prior studies (Kwon, et al., 2015; Manfredi, et al., 2005). It was determined through a survey and represents a region that can be considered representative of the weather conditions shared by a station. Therefore, the sites within this influence region were considered as treatment sites, and sites which were not within the influence region of any RWIS stations were considered as reference sites. Several techniques can be used to identify the influence region of a facility. One way is to use buffer analysis in ArcGIS, a simple technique which considers Euclidean distance. A more practical approach would be to use network distance to identify the influence region. Service area analysis, an extension of the *Network Analyst* tool in ArcGIS software, uses network distance to find the service area of a facility (ArcGIS Desktop, 2021). Service area is a region that incorporates all the accessible roads within a specified distance or time from the facility. Service area analysis provides the road network accessible within the 30 km network distance from RWIS station. This accessible road network is the influence region of the RWIS station. Therefore, road networks within the 30 km influence region of the "Accepted" stations were considered treatment sites. The influence regions of "Old and Eliminated" stations were also identified.

Figure 4-7 illustrates the placement of RWIS stations across Iowa. There are several regions where multiple stations were implemented close to each other, which led to overlapping influence regions of "Accepted" stations and "Old and Eliminated" stations. Therefore, to avoid selecting a site that could be influenced by "Old and Eliminated" stations, the influence region of these was considered at 35 km, as eventually this region was removed from the study. This way, the overlap due to the influence regions of two station groups, "Accepted" and "Old and Eliminated", did not bias the selection of treatment sites. Out of the 19 "Accepted Stations", the influence region of 12 RWIS stations was either completely overlapped or partially overlapped with "Old and Eliminated" stations, leaving no or insignificant data. Therefore, 7 stations with significant influence region and treatment sites were considered for this study.

Figure 4-7 provides a visual representation of the above discussed process. It shows the location of RWIS stations that were not considered for the study that include stations implemented before the study period- "Old" stations, stations removed during the review- "Eliminated" stations, and stations with no or insignificant data due to overlap of influence region. The location of 7 RWIS stations considered for safety evaluation, their influence region, and road network within this region is also shown in the figure. These road networks within the understudy service area are considered treatment sites. As discussed earlier, reference sites should not be under the influence of any RWIS stations; therefore, sites outside the influence area are classified as reference sites. In Figure 4-7, treatment sites are red and reference sites are blue. It can be observed that there is a high degree of overlap between the stations in the central region. This is a key example of why overlapped influenced regions were not considered in this study, it becomes difficult to determine if treatment effectiveness is due to one station or multiple stations working together.

Table 4-4 provides information on the 7 RWIS stations considered for this study. RWIS ID is the identification number provided to these stations, and Start Year and Month is when their operation started. The operation end date was capped at the end of the analysis period, which is December 2019. Furthermore, the number of treatment sites identified within the influence region of each RWIS station was also identified.

Figure 4-8 provides a detailed map for the 7 stations under evaluation. Their service area and treatment sites are visible on this map. The influence regions of RCCI4 and RSOI4 clearly represented the reduction in treatment sites due to the overlap in influence regions. This was due to the presence of other RWIS stations close to these stations.

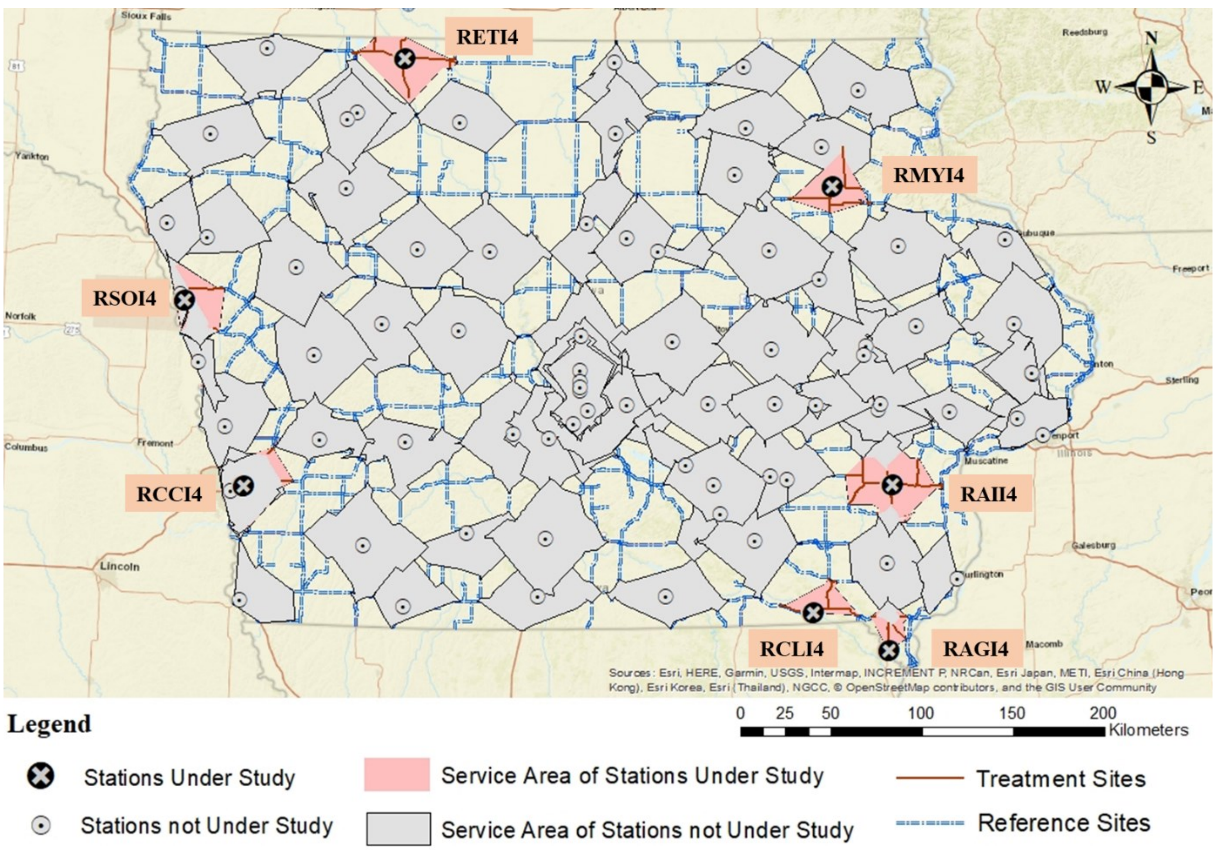


**Figure 4-7 Map showing location of RWIS stations, their influence region, treatment sites, and reference sites**

**Table 4-4 Information on RWIS stations used for study**

| Sr. No. | RWIS ID | Start Year | Month | End Year | Month | Number of Sites |
|---|---|---|---|---|---|---|
| 1 | RCCI4 | 2014 | February | 2019 | December | 7 |
| 2 | RCLI4 | 2012 | August | 2019 | December | 12 |
| 3 | RETI4 | 2013 | February | 2019 | December | 22 |
| 4 | RSOI4 | 2015 | March | 2019 | December | 4 |
| 5 | RAGI4 | 2010 | August | 2016 | January | 12 |
| 6 | RAII4 | 2010 | April | 2017 | March | 19 |
| 7 | RMYI4 | 2010 | April | 2015 | November | 20 |

Table 4-4 shows that RCCI4 had 7 sites; however, from Figure 4-8, it appears that there were only 2 sites under this station. This was because the major roads intersected with several minor roads. When performing road level analysis, even though there is one major road, it could technically be divided into multiple segments based on where it intersects with the minor roads. Additionally, since only major roads were considered in this study, minor road segments are not visible in the figure.

Table 4-5 contains descriptive statistics of the data used in the study. The "Details" column are the variables considered in this study. "Total Sites" represent the number of sites in the reference group and the treatment group. In addition, information on collisions, length, and Annual Average Daily Traffic (AADT) is also provided. The influence region of station RETI4 had the highest number of collisions and the largest number of treatment sites. Two other stations—RAII4 and RMYI4—had a comparable number of collisions and treatment sites to RETI4. This is also evident by looking at the service area of these three stations in Figure 4-8. Service areas like RCCI4 and RSOI4 were smaller, and consequently had fewer treatment sites and fewer collisions within their influence region. It's important to point out that not all treatment sites had collisions. Sites with zero collisions were also considered in both reference and treatment groups to obtain a wide variety of data sets. As a result, road segments with comparatively shorter road lengths were also considered in the study.

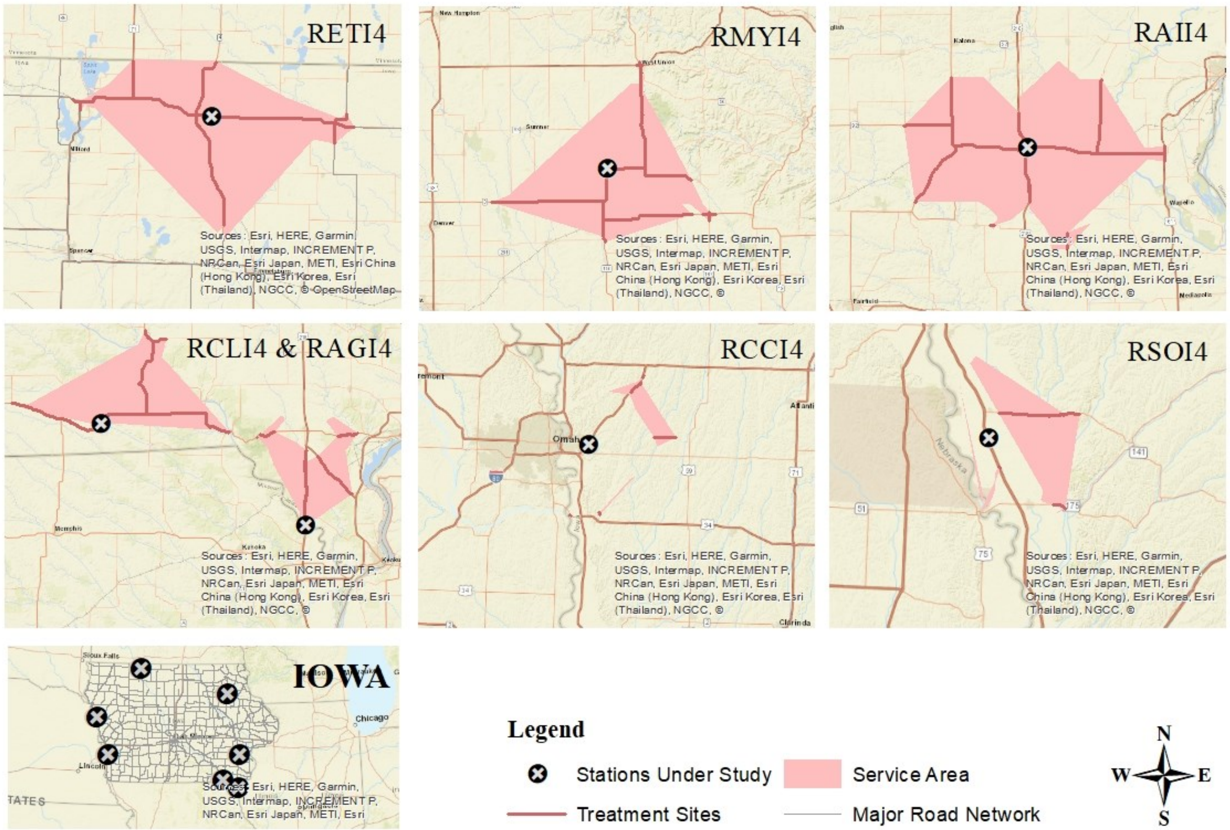


**Figure 4-8 Iowa map showing location of stations under study, their influence regions, and treatment sites**

**Table 4-5 Descriptive statistics of reference and treatment group data used for the study**

| Details | Reference Sites | Treatment Sites | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | RCCI4 | RCLI4 | RETI4 | RSOI4 | RAGI4 | RAII4 | RMYI4 |
| **Total Collisions** | 1843 | 19 | 5 | 109 | 12 | 9 | 55 | 30 |
| **Mean Collisions** | 3.051 | 2.714 | 0.417 | 4.955 | 3.000 | 0.750 | 2.895 | 1.500 |
| **SD Collisions** | 4.939 | 3.094 | 1.165 | 8.324 | 3.559 | 1.357 | 3.160 | 2.800 |
| **Total Sites** | 604 | 7 | 12 | 22 | 4 | 12 | 19 | 20 |
| **Min. Length (m)** | 7.361 | 217.879 | 11.991 | 17.682 | 164.477 | 13.235 | 26.707 | 143.521 |
| **Max. Length (m)** | 40584.551 | 7076.107 | 29975.389 | 28732.632 | 20038.125 | 11688.492 | 15367.287 | 22559.476 |
| **Mean Length (m)** | 7841.247 | 2663.241 | 6060.047 | 5447.408 | 6077.080 | 3955.869 | 7464.065 | 5274.316 |
| **SD Length (m)** | 8134.131 | 2718.548 | 10096.005 | 7971.050 | 9412.797 | 4462.677 | 5887.354 | 7747.807 |
| **Min. AADT** | 77 | 109 | 968 | 784 | 653 | 49 | 226 | 993 |
| **Max. AADT** | 22075 | 20988 | 2512 | 14680 | 15876 | 6226 | 15543 | 8437 |
| **Mean AADT** | 3475.553 | 4470.857 | 1850.000 | 6961.955 | 4993.500 | 4420.417 | 4102.158 | 3082.400 |
| **SD AADT** | 3167.979 | 7696.562 | 451.391 | 5146.992 | 7288.032 | 2695.754 | 4116.777 | 1960.251 |

### 4.3.2 Model Calibration

Developing SPFs is the first step in the safety evaluation process, and a set of reference sites were required for calibrating a meaningful SPF. As discussed earlier, reference sites should be similar to treatment sites as they represent what would have happened had the countermeasure not been implemented. As seen in Figure 4-7, desired reference sites were extracted with site-specific information such as road type and traffic volume similar to treatment sites. Initially, reference groups for all the 7 treatment groups were extracted to calibrate individual SPFs. However, this led to fewer sites in the reference group, and therefore calibrated SPFs were not statistically significant. Thus, a reference group representing all 7 treatment groups was extracted for calibration. Furthermore, while calibrating SPF for each collision severity, the reference group was segregated based on collision severity type. However, due to limited datasets, meaningful SPF could not be developed for each collision severity. Therefore, an overall SPF was developed for total collisions regardless of the severity type. Site-specific parameters such as road length, traffic volume (AADT), number of lanes, pavement type, etc., were used for calibration. Nevertheless, during the backward stepwise calibration process, only road length and AADT had statistically significant coefficients and provided meaningful SPF. The road length parameter was measured in meters. The results of the calibrated SPF are summarized in Table 4-6.

The estimated coefficient for road length was 0.8246, a positive sign of the parameter makes intuitive sense and is in line with the general understanding of collision trends. As the road length increases, commuters' exposure will increase, leading to more collisions. Additionally, 0.2291 was the estimated coefficient of traffic volume, with a positive sign. This coefficient also makes perfect sense since an increase in traffic volume leads to an increase in exposure and a subsequent rise in collisions. The coefficient value of road length was comparatively higher, indicating that road length had a larger impact on collisions in the given reference group. Furthermore, the p-value of both parameters clearly indicated that they were statistically significant with a 95% confidence interval. The degree of freedom was n-p (604-2), n representing the total number of sites, and p representing the number of site-specific parameters used for calibration. In addition, the Pearson Chi-square and scaled deviance were less than the tabulated chi-square value of 660.188 (602 degrees of freedom and 95% confidence interval), representing a good fit of the model (Soper, 2020). Dispersion value of 0.7092 was automatically estimated during calibration. It was then used to determine the k value (overdispersion parameter), which is the inverse of the estimated dispersion. Since the overdispersion parameter was not 0, overdispersion is therefore present in the data. SPF is also considered more reliable when overdispersion is close to 0 (Highway Safety Manual, 2010).

**Table 4-6 Details of calibrated SPF**

| **Parameter** | **Estimated Values** |
|---|---|
| Intercept | -10.4861 |
| Road Length | 0.8246** |
| Traffic Volume | 0.2291** |
| p-value (road length) | <0.0001 |
| p-value (traffic volume) | <0.0001 |
| Degree of Freedom | 602 |
| Pearson Chi-squared | 634.58** |
| Scaled Deviance | 608.60** |
| Tabulated Chi-Square | 660.188 |
| Dispersion | 0.7092 |
| $\boldsymbol{k}$ (Overdispersion parameter) | 1.41 |

Note: ** variable is significant with a 95% confidence interval.

The calibrated SPF equation is shown below:

$$\mu = e^{(-10.4861\ )} L^{0.8246} \, . \, V^{0.2291}$$

The impact of confounding factors was accounted for by the inclusion of YCFs in the analysis. Their values are shown in the following table.

**Table 4-7 Yearly Calibration Factors throughout the study period**

| **Year** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **YCFs** | 1.865 | 1.189 | 1.490 | 1.009 | 0.795 | 0.884 | 1.089 | 0.779 | 0.913 | 0.537 | 0.669 | 0.976 |

YCF is a ratio between the sum of observed collisions and the sum of predicted collisions for reference sites. It provides a clear explanation for the observed variation in YCF values. The calibrated SPF equation was used to predict collisions for reference sites, which had the traffic volume parameter with a positive coefficient, implying there is a positive correlation between volume and predicted collisions. Therefore, the increase in traffic volume over the years led to an increase in the value of predicted collisions. However, observed collisions represent raw data collected for reference sites. Therefore, YCF values were comparatively lower in recent years.

## 4.4 Results and Discussions

### 4.4.1 Quantifying Statewide Safety Effectiveness of RWIS

Once SPF and YCFs were calibrated, the safety effectiveness of RWIS was estimated using the procedures discussed in Chapter 3. Appendix B provides the complete estimated effectiveness results while the most important findings are discussed in detail in this section.

Figure 4-9 shows a chart representing expected and observed collisions after the implementation of each RWIS station. The expected collisions in the after-period are the unbiased or true mean of collision frequency. It can be observed that the value of expected collisions in the after-period was directly affected by the value of observed collisions. A substantial difference between the two values is clearly visible from this figure. Higher values of expected collisions and lower values of observed collisions provided a preliminary indication of potential safety improvements at these stations.

Figure 4-10 shows the estimated collision reduction for each station used in the study. Notably, the results were statistically significant with a 99% confidence interval. The reduction values vary from 31.53% to 88.23%, with an average reduction of 65.20%. This simply means that 31.53% of collisions that occurred due to inclement winter weather conditions were reduced after the implementation of the RETI4 RWIS station. The overall average of 65.20% was at a higher end as higher effectiveness values of few stations were also incorporated. It also seemed too good to be true. As already discussed, the higher effectiveness of few stations was because of limited observations. Therefore, an average effectiveness of stations with significant after period observed collisions was also estimated. Hence, average effectiveness of 47.20% of stations RETI4, RAII4, and RMYI4 was considered more reliable.

It was observed that there was a substantial reduction in collisions after the implementation of RWIS stations. Interestingly, reduction factors for three stations, namely, RCLI3, RSOI4, and RAGI4 were exceedingly high. This was likely because of the extremely low observed collision values in the after-period, as shown in Figure 4-9. Similarly, collision reduction from RETI4 was comparatively lower than other sites, which can be explained by the higher value of observed collisions in the after-period. It was concluded that such variation was because of the nature of the data sets and the difference between expected and observed collisions. Additionally, not all RWIS stations in Iowa were implemented at locations facing major safety concerns; the primary motive was to provide better winter weather information. Therefore, implemented location and consequently its influence region might have resulted in variation in safety effectiveness. Nonetheless, these results clearly indicated that information shared by RWIS stations had a considerable role in WRM operations, as the roads became safer for commuters.

Whether there were any monetary benefits due to the improved safety, was quantified by conducting economic analysis and estimating the benefit-to-cost ratio (BCR) for all the RWIS stations as presented in the following section.


**Figure 4-9 Expected and Observed After collisions at stations under study**

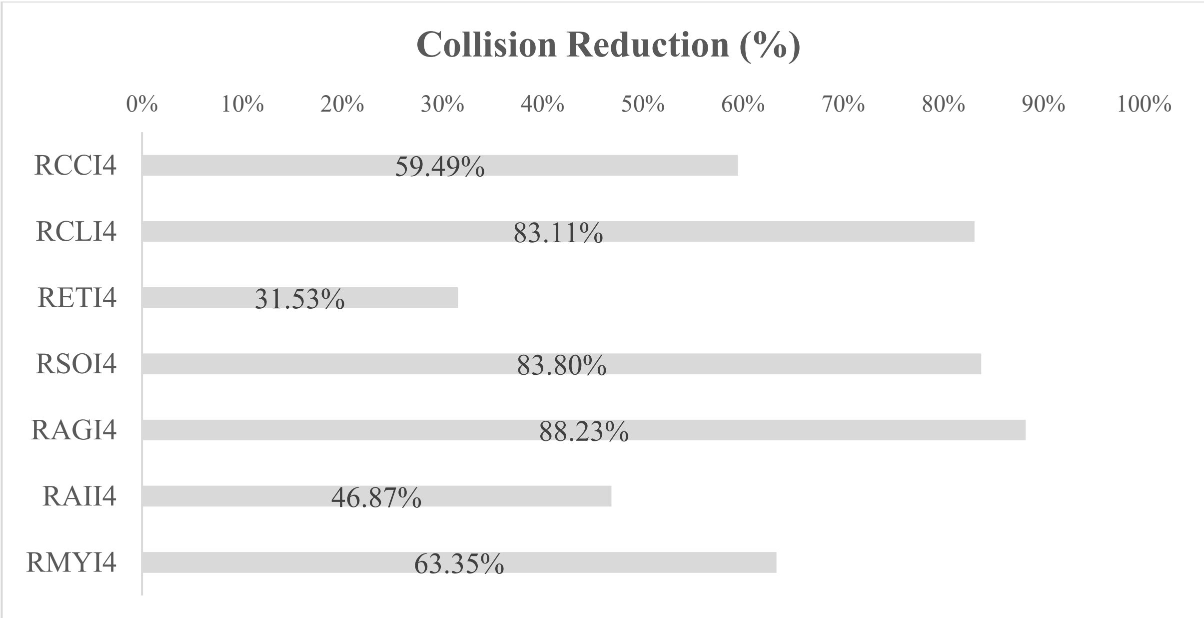


**Figure 4-10 Safety Effectiveness of each RWIS station under study**

### 4.4.2 Economic Analysis

The economic analysis for the RWIS stations was conducted by estimating separate capital, operation, and collision costs. As RWIS stations were not implemented in the same year, inflation will vary for each station. Similarly, the cost of collisions will also vary due to inflation. The capital investment included the cost of utility installation, administration of the contract, and traffic control during construction. Kwon et al. and Buchanan et al. had used a reported upfront cost for RWIS implementation, i.e., $90,000 (Kwon, et al., 2015; Buchanan & Gwartz, 2005). The assumed annual operation cost was $5,460 for regular monitoring and operations. $10,446 was also included as an up-gradation cost of the remote processing unit and central processing unit done every 5 years (McKeever, et al., 1998). All these costs were used for the analysis period of 2013. For this study, inflation factors were calculated to estimate these costs for each station's respective years (Crawford, et al., 2017). The inflation factors were calculated as a ratio of CPI value of the required year to the CPI value of the year for which costs were available. The required year was the implementation year, and the year for which costs were available was 2013. This factor was directly multiplied by the costs of 2013 to obtain the costs for the years of RWIS implementation.

As per literature, 25 years was assumed as the service life of an RWIS station (Kwon, et al., 2015; Buchanan & Gwartz, 2005). However, a few stations were operational only for a short period; hence, their operational period was considered as their service life. For instance, station RAGI4 was operational from 2010 to 2016; therefore, its service life was 7 years. In addition, 3% discount rate of return was used for analysis as recommended in literature (Nicholson, 2013; Pederson, 2014). The total present value of implementing RWIS stations was then calculated by adding the capital cost to the sum of operational costs. The analysis was conducted for overall collision regardless of severity type. Therefore, an average collision cost of $17,472 was used for the study, which was also converted using inflation factors of the collision's respective year (Kwon, et al., 2015; Miller, et al., 1991; Buchanan & Gwartz, 2005). Reduced collisions were calculated as a product of the expected number of collisions and estimated safety effectiveness of each station. These were the collisions reduced every year after RWIS was implemented. The reduced collisions were further multiplied with collision costs to estimate the amount of costs saved at each station. The costs saved were termed as the annual benefits and their monetary benefits were then converted to the present value of benefits. The ratio of the present value of benefits to costs is the BCR for each station. Table 4-8 illustrates the results of the overall analysis. The steps required in conducting the economic analysis of each RWIS station are provided in detail in Appendix C.

The analysis revealed that BCR values for the stations varied from a minimum of 7.51 to a maximum of 34.16. Such variation occurred due to variation in expected collisions estimated at each station. For instance, the value of the expected collision at station RSOI4 was comparatively lower (i.e., BCR of 7.51), which affected the number of collisions reduced and the annual benefits of this station. In contrast, the station RETI4 had the highest number of expected collisions, and even though the safety effectiveness was not high, the number of reduced collisions was high for this station. Consequently, RETI4 had greater benefits and a higher BCR ratio of 34.16. Additionally, the service life of each station also played a major role in the variation of BCR results. An overall average of BCR for each station was 16.89 and an average BCR of stations with significant after period observations was also estimated as 25.46. Overall, the results concluded that RWIS station is a highly cost-effective countermeasure in terms of safety.

**Table 4-8 Summary of Benefit-to-Cost Analysis**

| Details | RCCI4 | RCLI4 | RETI4 | RSOI4 | RAGI4 | RAII4 | RMYI4 |
|---|---|---|---|---|---|---|---|
| **Service Life (Years)** | 25 | 25 | 25 | 25 | 7 | 8 | 6 |
| **Inflation Factor** | 1.016 | 0.986 | 1 | 1.017 | 0.936 | 0.936 | 0.936 |
| **RWIS Cost** | | | | | | | |
| **Capital** | $91,460 | $88,701 | $90,000 | $91,569 | $84,243 | $84,243 | $84,243 |
| **Operation/year** | $5,549 | $5,381 | $5,460 | $5,555 | $5,111 | $5,111 | $5,111 |
| **Operation/5year** | $10,615 | $10,295 | $10,446 | $10,628 | $9,778 | $9,778 | $9,778 |
| **Present Value** | $197,510 | $191,551 | $194,357 | $197,744 | $125,578 | $129,612 | $121,422 |
| **RWIS Benefits** | | | | | | | |
| **Expected Collisions** | 9.40 | 10.81 | 69.22 | 5.73 | 16.01 | 60.61 | 36.93 |
| **Collision Reduction** | 59.49% | 83.11% | 31.53% | 83.80% | 88.22% | 46.87% | 63.35% |
| **Collision Cost** | $17,755 | $17,220 | $17,472 | $17,777 | $16,354 | $16,354 | $16,354 |
| **Annual Benefits** | $99,321 | $154,720 | $381,306 | $85,284 | $230,990 | $464,595 | $382,655 |
| **Present Value** | $1,729,493 | $2,694,163 | $6,639,729 | $1,485,057 | $1,439,133 | $3,261,311 | $2,072,918 |
| **BCR** | 8.76 | 14.06 | 34.16 | 7.51 | 11.46 | 25.16 | 17.07 |

### 4.4.3 Impact of safety effects of RWIS on Equity

Equity in transportation prioritizes the justice and fairness in distribution of benefits and costs of a facility. The policy and planning decisions made for a transportation facility should focus on equal distributions of benefits and costs based on the ability and need of population. In other words, favoritism of individuals or groups should be avoided. This is termed as horizontal equity. Another aspect of equity is to cater the differences in income and social class of individuals and groups while designing facilities. This is referred as vertical equity of income and social class. Furthermore, another interesting aspect of equity is vertical equity in terms of mobility needs and abilities of individuals or groups. This aspect is concerned about designing accessible design and catering the need of commuters with mobility impairments (Litman, 2021).

The direct, indirect, and social benefits of RWIS discussed in the Chapter 2.3.2, do not prioritize any individual or group, nor do they provide special considerations based on commuters' income, social class, mobility needs, and abilities. However, the level of benefits might differ based on the locations where RWIS are implemented. This is again because the regions where RWIS stations are not present, receive comparatively poor road maintenance because the information of road conditions and other weather conditions is not available to the maintenance operators. Therefore, the safety benefits quantified in this study has varying impact based on the regions under RWIS influence. As safety benefits of regions within RWIS influence are different, the people travelling or living within these regions would receive unequal benefits. This difference would magnify for commuters with older age, lesser driving experience, and disabilities as these commuters would hesitate to travel due to poor road surface conditions. Furthermore, active mode users in regions under RWIS influence would receive safer commuting conditions as compared to users in uninfluenced regions. This also impacts people with different class or income, as commuters with higher income might not hesitate in taking a day off if the driving conditions are unsafe. However, commuters with lower income would still have to travel regardless of the road conditions and hence increasing their exposure to collisions.

## 4.5 Summary

The developed methodology in Chapter 3 was applied to conduct a state-wide investigation of RWIS program. Iowa was selected as the study area as it provided public access to the datasets. Additionally, the implementation information of RWIS was shared on request by the Iowa DOT professionals, a critical information required to perform before and after safety evaluation. Further, the study period was defined based on collision data, winter weather collisions were extracted, road network data was updated, and a review of each RWIS station was conducted before considering them for analysis. Treatment and reference groups were identified using the influence region of RWIS stations, which was based on the assumption that sites closer to RWIS received better weather information, and therefore more efficient road maintenance. Safety Effectiveness evaluation was conducted for a total of 7 RWIS stations and the results showed a statistically significant reduction in winter weather collisions after the implementation of these stations. Furthermore, monetary values of the reduced collisions were estimated, and a cost-benefit analysis of RWIS was conducted. The results concluded that there were more safety benefits than the cost of implementing these stations. The effects of the quantified safety benefits on equity are also summarized at the end. Though the safety benefits of RWIS provide equal opportunities for commuters with different groups. It does not provide special benefits to commuters based on their income or social class, mobility needs, and abilities. However, as the safety benefits of RWIS are more dominant for commuters within their influence region, the impact of safety benefits is enhanced for the commuters living or travelling within such regions.

# Chapter 5. CONCLUSIONS AND FUTURE RESEARCH

This chapter provides an overview of the research undertaken in this thesis and summarizes the key findings of the conducted case study. Major contributions of this research, its limitations, and recommendations for future research are also discussed.

## 5.1 Overview of the Research

Inclement winter weather events lead to a significant amount of road traffic collisions and thereby have a considerable impact on the safety of commuters. Transportation agencies continuously seek to provide more efficient winter road maintenance (WRM) activities to provide safer driving conditions. Implementation of Road Weather Information System (RWIS) provides nowcasts and forecasts to the transportation agencies, allowing them to take proactive measures for timely road maintenance services. The weather information disseminated by individual RWIS stations is also provided to road users allowing them to better plan their trips before an inclement weather event. As per the experiences of maintenance operators, implementation of RWIS leads to efficient WRM, which in turn leads to a reduction in collisions. However, no study has been conducted that attests to this experience. Furthermore, high installation and operation costs associated with RWIS necessitate the need to conduct benefit-cost studies of the system such that more budgets can be allotted for installing stations in a sustainable way. For the first time in literature, this study used large spatiotemporal datasets covering the entire state of Iowa as well as a statistically rigorous before-and-after Empirical Bayes (EB) method to conduct a thorough safety evaluation of implementing RWIS stations. The study also estimated the benefit-to-cost ratio in relation to its safety benefits to examine if RWIS is a cost-effective safety countermeasure for the vast travelling public during winter months.

## 5.2 Key Research Findings

This study evaluated the safety effectiveness of RWIS and established RWIS as a safety countermeasure. It confirmed the anecdotal experiences of maintenance professionals that the implementation of RWIS leads to safer roads. Additionally, it also proved that RWIS is a cost-effective safety countermeasure. Overall, it successfully answered the two questions raised in the introduction section: whether implementation of RWIS led to a reduction in collisions occurring due to inclement winter weather events and how much did the collisions reduce by; and whether there were more safety benefits than costs when implementing RWIS. The results of the case study for the state of Iowa concluded that RWIS is an economically feasible countermeasure in terms of safety benefits, making it an effective countermeasure.

The first research question was answered by conducting a safety evaluation of RWIS using a before-and-after EB method, where the results clearly show the effectiveness of RWIS in reducing winter weather collisions. The collision data, road network data, traffic volume, and locations and operation information of RWIS stations were thoroughly assessed during the initial stages of the research. Later, Safety Performance Function (SPF) was locally calibrated to account for the variation of collisions with site-specific attributes such as traffic volume and road length. The calibration process involved the selection of treatment and reference groups, which was based on the assumption that sites closer to RWIS would be more likely to receive timely and effective maintenance services. As maintenance personnel would receive detailed road weather information for sites closer to RWIS. The treatment and reference groups were delineated by conducting a service area analysis of RWIS stations using ArcGIS. Yearly Calibration Factors (YCFs) were also calibrated and included in the analysis to account for the impact of confounding factors (e.g., WRM activity types, reaction time, etc.) on collision frequencies. The safety evaluation results, the estimated safety effectiveness of RWIS stations, and collisions reduced after RWIS implementation were used to answer the second research question. Lastly, a cost-benefit analysis was conducted to estimate the BCR of RWIS stations.

The two main findings of the study are summarized below:

- The analysis conducted for 7 RWIS stations showed a collision reduction of 31.53% to 88.23%, with an average reduction of 65.20% and 47.20%. This indicates that a significant amount of winter weather collisions was reduced after the implementation of RWIS.
- Economic analysis results showed that the BCRs for stations vary from 7.51 to 34.16 with an average BCR of 16.89 and 25.46 for a 3% discount rate, implying that there were more safety benefits than the cost of implementing RWIS. For instance, a BCR of 25.46 signifies that there were 25.46 monetary safety benefits for every dollar invested.

## 5.3 Research Contributions

This study estimated the safety effects of RWIS stations and evaluated their economic viability by conducting a state-wide investigation. During the process, this study provided significant research contributions, which are summarized below:

- This study was the first of its kind in quantifying the sole effect of implementing RWIS stations on inclement winter weather collisions. The state-of-the-art before and after EB method was used to establish RWIS as a safety countermeasure. The findings of this study will allow transportation professionals to implement RWIS with confidence like any other safety device, which can be done by analyzing hot spots of inclement winter weather collisions.
- SPF was locally calibrated during evaluation to account for the variation in collision frequencies. Literature suggests that SPFs are transferrable; hence, the calibrated SPF in this research can be applied to other similar studies for the state of Iowa. In addition, it can also be used to assess the variation of collisions in other states.
- For the first time, economic appraisal of RWIS stations was conducted using benefits obtained from collision reduction. It is anticipated that the winter road authorities and decision-makers can now use the research findings to develop a sustainable and cost-effective RWIS network in their respective regions.
- This study applied the concept of an influence region to identify treatment and reference sites. Service area analysis technique of the *Network Analyst* extension of ArcGIS was used for this purpose. Overall, this study developed a methodological framework and further conducted a state-wide investigation to prove its applicability. A similar approach can be used to quantify the effectiveness of other devices with no direct link to traffic safety.

## 5.4 Limitations and Future Research

The method presented herein also has several assumptions like any other study, and therefore warrant further discussion. First, the delineation of reference and treatment groups could have led to a bias as it assumed that the influence region of RWIS was 30 km. Although efforts were made to minimize this bias by implementing a buffer of 5 km while delineating these groups, a sensitivity analysis should be conducted to provide a more objective way to determine an RWISs' influence region. One possible approach would be to conduct a geostatistical semivariogram analysis and determine their respective spatial autocorrelation range of RWIS measurements. Secondly, due to limited data set, SPF could only be developed for overall collisions regardless of the severity type, which further led to using overall collision costs during economic analysis. Lastly, the costs of fatalities, injuries, and property damage varied significantly and hence considering just one cost for collisions would undermine the effect of collision severity on the analysis.

One possible extension to this research would be to develop location-allocation frameworks for the strategic implementation of RWIS stations and determine their optimal locations to maximize the safety benefits of RWIS. The estimated safety effectiveness and monetary benefits resulting from this study can be included as a deciding factor while selecting new locations for RWIS stations.

Another future research option would be to understand the impact of influenced and uninfluenced region of RWIS on equity. Regressions models of various factors of equity can be developed in these regions and their exposure to collisions can be assessed. The results of such a study can significantly impact the location-allocation strategies of RWIS stations. Transportation professionals can make decisions of selecting new RWIS locations based on the demographics covered under the influence of these stations.

Notwithstanding the fact that more case studies are necessary to further attest to the reasonableness and conclusiveness of the method presented herein, the findings of this study provide, for the first time in literature, a level of justification and empirical evidence to highway authorities and RWIS planners that RWIS is a cost-effective countermeasure with substantial safety benefits.

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# APPENDIX A- RWIS STATIONS IN IOWA

**Table A-1 Location and Operation Information of RWIS stations in Iowa**

| Sr. No. | RWIS ID | Name | Latitude | Longitude (-W) | Starting Year* | Month | Ending Year* | Month |
|---|---|---|---|---|---|---|---|---|
| 1 | HKYI4 | Hawkeye | 42.9652 | -91.9531 | 2018 | May | 2020 | December |
| 2 | RAGI4 | Argyle | 40.46477 | -91.568067 | 2010 | August | 2016 | January |
| 3 | RAII4 | Ainsworth | 41.2913 | -91.53315 | 2010 | April | 2017 | March |
| 4 | RAKI4 | Ankeny | 41.7608 | -93.5697 | 2006 | February | 2020 | December |
| 5 | RALI4 | Algona | 43.0830 | -94.3985 | 2006 | January | 2012 | May |
| 6 | RAMI4 | Ames | 42.0340 | -93.5702 | 2006 | January | 2020 | December |
| 7 | RASI4 | Ames 6S | 41.9498 | -93.5700 | 2013 | December | 2014 | December |
| 8 | RAVI4 | Avoca | 41.4982 | -95.2915 | 2006 | January | 2013 | February |
| 9 | RBFI4 | Bedford | 40.6773 | -94.7149 | 2007 | March | 2020 | December |
| 10 | RBUI4 | Burlington | 40.8130 | -91.0992 | 2006 | January | 2013 | October |
| 11 | RCAI4 | Carroll | 42.0785 | -94.8975 | 2006 | January | 2020 | December |
| 12 | RCBI4 | Council Bluffs | 41.2325 | 95.8662 | 2006 | January | 2020 | December |
| 13 | RCCI4 | Council Bluffs No2 | 41.2605 | -95.8031 | 2014 | February | 2020 | December |
| 14 | RCDI4 | Cedar Rapids | 41.9780 | -91.6745 | 2006 | January | 2020 | December |
| 15 | RCEI4 | Creston | 41.0498 | -94.3080 | 2006 | January | 2020 | December |
| 16 | RCFI4 | Colfax | 41.6890 | -93.2598 | 2007 | January | 2020 | December |

| Sr. No. | RWIS ID | Name | Latitude | Longitude (-W) | Starting Year* | Month | Ending Year* | Month |
|---|---|---|---|---|---|---|---|---|
| 17 | RCII4 | Cedar Rapids | 41.9300 | -91.6838 | 2006 | January | 2020 | December |
| 18 | RCLI4 | Cantril | 40.6578 | -92.062 | 2012 | August | 2020 | September |
| 19 | RCMI4 | Cambridge | 41.8632 | -93.5711 | 2015 | March | 2020 | December |
| 20 | RCNI4 | Centerville | 40.7397 | -93.0027 | 2006 | January | 2020 | December |
| 21 | RCRI4 | Anamosa | 42.0712 | -91.3357 | 2006 | January | 2020 | December |
| 22 | RDAI4 | Adair | 41.4963 | -94.7263 | 2006 | January | 2020 | October |
| 23 | RDBI4 | Dubuque | 42.4903 | -90.7310 | 2006 | January | 2020 | December |
| 24 | RDCI4 | Decorah | 43.2455 | -91.6997 | 2006 | January | 2020 | December |
| 25 | RDEI4 | De Soto | 41.5415 | -94.0112 | 2006 | January | 2020 | December |
| 26 | RDMI4 | Des Moines | 41.5957 | -93.6113 | 2007 | March | 2020 | December |
| 27 | RDNI4 | Denison | 41.9185 | -95.3439 | 2008 | August | 2020 | September |
| 28 | RDSI4 | Des Moines | 41.5275 | -93.7723 | 2006 | January | 2020 | December |
| 29 | RDTI4 | DeWitt | 41.8173 | -90.5706 | 2013 | December | 2016 | March |
| 30 | RDVI4 | Davenport | 41.6023 | -90.6777 | 2006 | January | 2020 | December |
| 31 | RDWI4 | DeWitt | 41.8262 | -90.5705 | 2006 | January | 2020 | December |
| 32 | RDYI4 | Eddyville | 41.1465 | -92.6436 | 2007 | April | 2020 | December |
| 33 | RETI4 | Estherville | 43.3993 | -94.7973 | 2013 | February | 2020 | December |
| 34 | RFDI4 | Fort Dodge | 42.4463 | -94.1835 | 2006 | January | 2020 | December |
| 35 | RGAI4 | Granger | 41.7396 | -93.7757 | 2018 | June | 2020 | December |
| 36 | RGRI4 | Grinnell | 41.6975 | -92.7257 | 2006 | January | 2020 | December |

| Sr. No. | RWIS ID | Name | Latitude | Longitude (-W) | Starting Year* | Month | Ending Year* | Month |
|---|---|---|---|---|---|---|---|---|
| 37 | RHAI4 | Hanlontown | 43.3922 | -93.3498 | 2006 | January | 2020 | December |
| 38 | RIAI4 | Iowa City | 41.6575 | -91.5988 | 2006 | January | 2020 | December |
| 39 | RIFI4 | Iowa Falls | 42.5178 | -93.2631 | 2013 | November | 2015 | March |
| 40 | RIGI4 | Ida Grove | 42.3515 | -95.4783 | 2006 | January | 2020 | September |
| 41 | RIOI4 | Iowa City | 41.6891 | -91.5812 | 2006 | January | 2020 | December |
| 42 | RJFI4 | Jefferson | 42.0518 | -94.3783 | 2006 | January | 2020 | December |
| 43 | RKNI4 | Elkhart No 2 | 41.8059 | -93.5708 | 2015 | March | 2020 | December |
| 44 | RKSI4 | Elkhart No 1 | 41.778 | -93.571 | 2015 | March | 2020 | December |
| 45 | RLEI4 | Leon | 40.7387 | -93.8417 | 2006 | January | 2020 | December |
| 46 | RLMI4 | Lime Springs | 43.4336 | -92.3046 | 2010 | April | 2010 | October |
| 47 | RMCI4 | Mason City | 43.0380 | -93.3418 | 2006 | January | 2020 | December |
| 48 | RMNI4 | Manchester | 42.4710 | -91.4473 | 2006 | January | 2020 | December |
| 49 | RMPI4 | Mount Pleasant | 40.8957 | -91.5555 | 2006 | January | 2020 | December |
| 50 | RMQI4 | Maquoketa | 42.0685 | -90.6835 | 2006 | January | 2020 | December |
| 51 | RMTI4 | Marshalltown | 42.0037 | -92.9617 | 2006 | January | 2020 | December |
| 52 | RMVI4 | Missouri Valley | 41.5495 | -95.9173 | 2006 | January | 2020 | December |
| 53 | RMYI4 | Maynard | 42.773943 | -91.902254 | 2010 | April | 2015 | November |
| 54 | RNHI4 | New Hampton | 43.0672 | -92.4592 | 2006 | January | 2020 | December |
| 55 | ROCI4 | Osceola | 41.0265 | -93.7938 | 2010 | April | 2010 | June |
| 56 | RONI4 | Onawa/Sloan (off-data) | 41.8653 | -96.1032 | 2006 | January | 2014 | June |

| Sr. No. | RWIS ID | Name | Latitude | Longitude (-W) | Starting Year* | Month | Ending Year* | Month |
|---|---|---|---|---|---|---|---|---|
| 57 | ROOI4 | Oskaloosa | 41.2937 | -92.6856 | 2013 | December | 2018 | May |
| 58 | ROSI4 | Osceola | 41.0267 | -93.7943 | 2006 | January | 2020 | December |
| 59 | ROTI4 | Ottumwa | 41.0168 | -92.4212 | 2006 | January | 2020 | December |
| 60 | RPFI4 | Plainfield | 42.8332 | -92.5371 | 2008 | March | 2020 | December |
| 61 | RPLI4 | Pella | 41.3902 | -92.8725 | 2006 | January | 2020 | December |
| 62 | RQCI4 | Quad Cities | 41.5171 | -90.5131 | 2009 | March | 2020 | December |
| 63 | RRCI4 | Sloan | 42.2000 | -96.2421 | 2010 | November | 2013 | October |
| 64 | RROI4 | Red Oak | 40.9800 | -94.9838 | 2006 | January | 2020 | December |
| 65 | RRWI4 | Rockwell City | 42.4501 | -94.6700 | 2013 | January | 2020 | December |
| 66 | RSBI4 | Steamboat Rock | 42.4534 | -93.0583 | 2006 | January | 2020 | December |
| 67 | RSCI4 | Moville | 42.4822 | -96.0787 | 2006 | January | 2020 | December |
| 68 | RSDI4 | Sidney | 40.6895 | -95.7834 | 2006 | January | 2020 | December |
| 69 | RSGI4 | Sigourney | 41.3363 | -92.3145 | 2006 | January | 2020 | December |
| 70 | RSLI4 | Storm Lake | 42.7475 | -95.1515 | 2006 | January | 2020 | December |
| 71 | RSMI4 | Sioux City | 42.5497 | -96.3479 | 2010 | June | 2018 | December |
| 72 | RSNI4 | Sigourney | 41.3175 | -92.2052 | 2013 | December | 2018 | May |
| 73 | RSOI4 | Sloan | 42.1713 | -96.2295 | 2015 | March | 2020 | December |
| 74 | RSPI4 | Spencer | 43.1268 | -95.0888 | 2006 | January | 2020 | December |
| 75 | RSWI4 | Spencer | 43.0879 | -95.1611 | 2010 | October | 2020 | October |
| 76 | RSYI4 | Sibley | 43.4335 | -95.7149 | 2007 | February | 2020 | December |

| Sr. No. | RWIS ID | Name | Latitude | Longitude (-W) | Starting Year* | Month | Ending Year* | Month |
|---|---|---|---|---|---|---|---|---|
| 77 | RTMI4 | Tama | 41.9649 | -92.2983 | 2007 | May | 2020 | August |
| 78 | RTNI4 | Alton | 42.9978 | -96.0843 | 2006 | January | 2020 | December |
| 79 | RTOI4 | Altoona | 41.6597 | -93.5222 | 2006 | January | 2020 | December |
| 80 | RTPI4 | Tipton | 41.6448 | -91.1272 | 2006 | January | 2020 | December |
| 81 | RURI4 | Urbana | 42.3125 | -91.9758 | 2006 | January | 2020 | December |
| 82 | RWBI4 | Williamsburg | 41.6877 | -92.0087 | 2006 | January | 2020 | December |
| 83 | RWII4 | Williams | 42.5875 | -93.5315 | 2006 | January | 2020 | December |
| 84 | RWLI4 | Waterloo | 42.4557 | -92.3090 | 2006 | January | 2020 | December |
| 85 | SRGI4 | Sartoga | 43.3706 | -92.4701 | 2018 | May | 2020 | December |
| 86 | VCTI4 | Victor | 41.6960 | -92.2800 | 2018 | May | 2019 | August |

*Note- The data files of each RWIS stations were large and were taking time to download. Since, the study period was 2008-2019, operation data was downloaded from 2006-2020. Therefore, 2006 is the start year and 2020 is the end year of many RWIS stations. They might be operational before this year.

# APPENDIX B- SAFETY EVALUATION RESULTS

**Table B-1 Estimated values of different steps involved in safety effectiveness evaluation.**

| RWIS ID | $OC_A$ | $EC_A$ | Var ($EC_A$) | $Odds\ Ratio'$ | $Odds\ Ratio$ | Var ($Odds\ Ratio$) | $S.E.$ | t-ratio | Safety Effectiveness |
|---|---|---|---|---|---|---|---|---|---|
| **RCCI4** | 4 | 9.403 | 4.4307 | 0.4254 | 0.4051 | 0.0492 | 0.2219 | 2.6810 | 59.49% |
| **RCLI4** | 2 | 10.811 | 11.1740 | 0.1850 | 0.1689 | 0.0170 | 0.1303 | 6.3782 | 83.11% |
| **RETI4** | 48 | 69.216 | 61.7243 | 0.6935 | 0.6847 | 0.0158 | 0.1257 | 2.5083 | 31.53% |
| **RSOI4** | 1 | 5.725 | 2.5713 | 0.1747 | 0.1620 | 0.0283 | 0.1682 | 4.9824 | 83.80% |
| **RAGI4** | 2 | 16.030 | 15.5038 | 0.1248 | 0.1177 | 0.0078 | 0.0881 | 10.0174 | 88.23% |
| **RAII4** | 33 | 60.610 | 90.9878 | 0.5445 | 0.5313 | 0.0155 | 0.1247 | 3.7591 | 46.87% |
| **RMYI4** | 14 | 36.934 | 46.5852 | 0.3790 | 0.3665 | 0.0142 | 0.1191 | 5.3190 | 63.35% |

Where:

$OC_A$ is the Observed Collisions in the after period, $EC_A$ is the expected collisions in the after period, $Odds\ Ratio'$ is the biased odds ratio, $Odds\ Ratio$ is the unbiased odds ratio, Var ($Odds\ Ratio$) is the variance in odds ratio, and S.E. is the standard error.

# APPENDIX C- COST-BENEFIT ANALYSIS PROCESS

**Table C-1 Overall steps involved in the estimation of BCRs of each station**

| RWIS ID | RCCI4 | RCLI4 | RETI4 | RSOI4 | RAGI4 | RAII4 | RMYI4 |
|---|---|---|---|---|---|---|---|
| Start Year | 2014 | 2012 | 2013 | 2015 | 2010 | 2010 | 2010 |
| Month | February | August | February | March | August | April | April |
| End-Year | 2019 | 2019 | 2019 | 2019 | 2016 | 2017 | 2015 |
| Month | December | December | December | December | January | March | November |
| Service Life | 25 | 25 | 25 | 25 | 7 | 8 | 6 |
| Number of Sites | 7 | 12 | 22 | 4 | 12 | 19 | 20 |
| Consumer Price Index | 236.74 | 229.59 | 232.96 | 237.02 | 218.06 | 218.06 | 218.06 |
| Inflation Factor | 1.02 | 0.99 | 1.00 | 1.02 | 0.94 | 0.94 | 0.94 |
| Present Value Factor | 17.41 | 17.41 | 17.41 | 17.41 | 6.23 | 7.02 | 5.42 |
| Upgrade Years | 4 | 4 | 4 | 4 | 1 | 1 | 1 |
| Present Value Upgrade Factor | 0.89 | 0.89 | 0.89 | 0.89 | 0.97 | 0.97 | 0.97 |

| RWIS ID | RCCI4 | RCLI4 | RETI4 | RSOI4 | RAGI4 | RAII4 | RMYI4 |
|---|---|---|---|---|---|---|---|
| **Safety Effectiveness** | 59.49% | 83.11% | 31.53% | 83.80% | 88.22% | 46.87% | 63.35% |
| **Expected Collisions** | 9.40 | 10.81 | 69.22 | 5.73 | 16.01 | 60.61 | 36.93 |
| **Reduced Collisions** | 5.59 | 8.99 | 21.82 | 4.80 | 14.12 | 28.41 | 23.40 |
| **Collision Cost** | 17755.43 | 17219.77 | 17472.00 | 17776.50 | 16354.41 | 16354.41 | 16354.41 |
| **Monetary Benefit** | 99321.11 | 154720.03 | 381305.52 | 85283.67 | 230990.06 | 464594.58 | 382655.41 |
| **Present Value Benefit** | 1729493.17 | 2694162.73 | 6639729.29 | 1485057.08 | 1439133.40 | 3261310.91 | 2072917.63 |
| **Capital Cost** | 91459.97 | 88700.75 | 90000.00 | 91568.53 | 84243.19 | 84243.19 | 84243.19 |
| **Operation/Year** | 5548.57 | 5381.18 | 5460.00 | 5555.16 | 5110.75 | 5110.75 | 5110.75 |
| **Operation/5 Year** | 10615.45 | 10295.20 | 10446.00 | 10628.05 | 9777.83 | 9777.83 | 9777.83 |
| **Present Value Cost** | 197509.76 | 191551.16 | 194356.92 | 197744.20 | 125577.66 | 129612.14 | 121422.15 |
| **Benefit-Cost Ratio** | 8.76 | 14.06 | 34.16 | 7.51 | 11.46 | 25.16 | 17.07 |