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A Comprehensive Optimization Methodology for Strategic Environmental Sensor Station Locations

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A Comprehensive Optimization Methodology for Strategic Environmental Sensor Station Locations

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A Comprehensive Optimization Methodology for Strategic Environmental Sensor Station Locations

by

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Adverse weather poses a significant threat to transportation safety. Road weather information systems (RWIS) aim to mitigate the impact of adverse weather by detecting spatiotemporal variations of weather and/or road pavement conditions in real time. Due to the lack of a detailed, unified guideline and diverse weather conditions across the United States, state and city transportation agencies follow different practices for choosing locations for environmental sensor stations (ESS) (the components that collect RWIS weather data). To fill this gap, this study proposes a comprehensive cell-based methodology that is data-driven, using crash records, weather data, and road network information. The contribution of the proposed methodology is that the model optimizes overall benefits derived from RWIS based on weather-sensitive crashes. Both normal and adverse weather crash data are used to derive cell-vulnerability rates in adverse weather. First, a sequential procedure is devised to identify the required number of stations for the region. Then, optimal weather station locations are identified using a genetic algorithm. The proposed approach is especially suited for optimizing region-wide ESS locations involving complex road networks or a large number of road segments. A case study was conducted using data from the Crash Records Information System (CRIS) between 2010 and 2013 in the Austin District, an area especially vulnerable to rain. It was found in the case study that ten ESSs would be a good choice to implement in the region. Their proposed global optimal locations layout would cover 94% of total crashes occurring in the region

based on 20 miles of coverage for each station. The RWIS would have spatial coverage of 48% and 92% reliability should one ESS fail.

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Chapter 1. Introduction

A wide range of factors and their interactions contribute to the occurrence of crashes, including road geometric characteristics, traffic volume, pavement surface conditions, lighting conditions, driver drowsiness, and weather conditions *(1-4).* Among these factors, adverse weather is significant and one that is perhaps the most uncertain and uncontrollable. The Federal Highway Administration (FHWA) defines weather-related crashes as "those crashes that occur in adverse weather (i.e., rain, sleet, snow, fog, severe crosswinds, or blowing snow/sand/debris) or on slick pavement (i.e., wet pavement, snowy/slushy pavement, or icy pavement)" (*5*). Rain, sleet, snow, and fog can undermine the driver's capability, vehicle control, road friction, and infrastructure traffic operations, making safe driving more challenging and increasing crash risk. During adverse weather conditions (e.g., rain or snowfall), a wet/icy pavement surface presents much lower skid resistance, which has been identified as a significant contributing factor in crashes. Approximately 5,870,000 vehicle crashes happen each year in the United States. It is estimated that, on average, 23% of all crashes are weather-related, leading to nearly 6,250 fatalities and 480,000 injuries each year nationwide (*5*). According to the 2013 crash report from the Texas Department of Transportation (TxDOT), 227 fatalities and 39,536 injuries occurred in Texas during adverse weather conditions (*6*).

Road weather information systems (RWISs) are emerging as a primary road weather response management tool that aims to reduce the impact of adverse weather on crashes and to aid maintenance management decisions. Through strategically placing environmental sensor stations (ESSs) to supply RWISs with data, region-wide weather and pavement conditions can be monitored in real time, which is the basis for providing traveler information and alerts. This information can be incorporated with existing intelligent transportation system (ITS) infrastructure to make strategic decisions. RWISs have become a critical component of many agencies' maintenance efforts. RWISs can include pre-existing data stations that are run by national agencies such as the National Weather Service (NWS), the Federal Aviation Administration, the US Geological Survey, the Department

of Agriculture, and the Environmental Protection Agency. Transportation agencies are considering ways to integrate RWIS with other ITS applications so weather information can support a broader range of ITS services. Studies show that an effectively deployed RWIS has a significant impact on reducing the number of crashes in a region *(24)*. Many DOTs have experienced a significant benefit in terms of better safety, maintenance, and traffic operation during adverse weather conditions when using a well-placed RWIS *(27)*.

The ESS location plays a crucial role in determining the performance of the system. Data acquired from ESS are useful for maintenance, operations, and traveler information purposes. The analytical problem of determining the optimal ESS locations has gained increased research interest in recent years. The FHWA has provided recommended ESS siting guidelines (*17*), but there are no specific standards for agencies to follow. In the absence of any established methodology, DOTs and other transportation agencies use different methods to determine ESS locations.

This study introduces a comprehensive ESS location modeling framework that can be modified based on the needs of different transportation agencies. Apart from the difference in specific performance criteria, the prevailing thought behind previous approaches is that ESSs should be deployed in the regions with more weather-related crashes. The key difference between this study and other studies lies in this study's assertion that not all crashes occurring during adverse weather are necessarily due to changes in weather conditions. Deploying ESS to minimize weather-related crash rates may not be effective. The proposed model combines regional crash data with road, traffic, and weather information to define a location's vulnerability to crashes when weather conditions change from good to adverse. The model incorporates two major planning elements: 1) spatial coverage and 2) reliability of the system under failure of one ESS, as constraints to the optimization problem. First, a sequential procedure is devised to identify the required number of stations for the region. Optimal weather station location layouts are identified using an iterative genetic algorithm procedure.

Organization of this thesis is as follows. This report consists of five major sections including this chapter. In Chapter 2, a detailed background of the ESS and its functions is

provided to convey its importance in RWIS, followed by a detailed literature review to understand industry and government considerations for deploying ESS. In Chapter 3, a strategic ESS methodology is proposed with framework details, optimization problem formulation, and solution approach. In Chapter 4, proposed methodology is applied to find the optimal ESS location layout for TxDOT's Austin District. An analysis of crash and weather data for the region between 2010 and 2013 is performed. The final layout for ESS location is discussed with analysis of the coverage and reliability of the resulting RWIS. Next, the effects of changing various input parameters in the proposed methodology are discussed. Finally, a conclusion is made in Chapter 5 with discussion of the limitations of this study along with suggestions for future work in this area.

Chapter 2. Literature Review

2.1 Road Weather Information System

The term *road weather information system* (RWIS) refers to the actual hardware, software, and communication interfaces necessary to collect, transmit, and receive field observations at the user end. Historically, an RWIS has been used mainly for winter maintenance purposes. However, recent developments have enabled RWISs to detect and monitor variations of road weather conditions that can impact roadway maintenance and operations year round. The component of an RWIS that collects weather and pavement data is the *environmental sensor station* (ESS).

ESSs are located at a fixed roadway location and measure atmospheric, roadway, and bridge surface and/or hydrological conditions. These stations are typically installed within 30 to 50 feet (9 to 15 meters) from the edge of the paved surface to shield the sensors from the effects of traffic (e.g., heat, wind, and splash) and thus preserve their accuracy, as shown in Figure 1 *(18)*. Various sensors and their typical heights installed on an ESS are shown in Figure 2 *(18)*. A sensor's height may need to be elevated in heavy snow or flooding areas. Stations typically operate on the local electric power line supply system with battery backup devices.

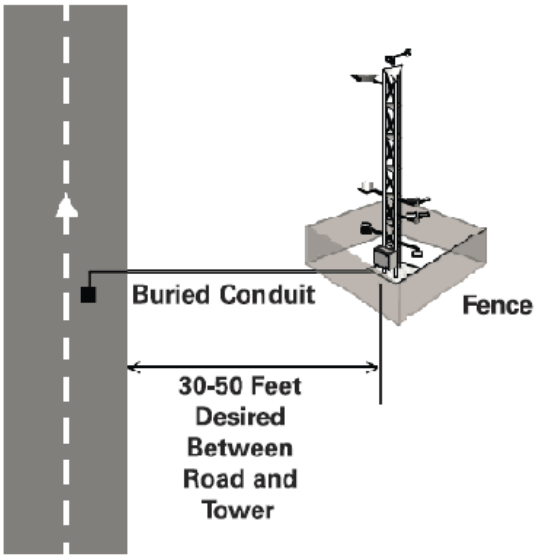


Figure 1. Desired Tower Location Relative to Roadway *(18)*

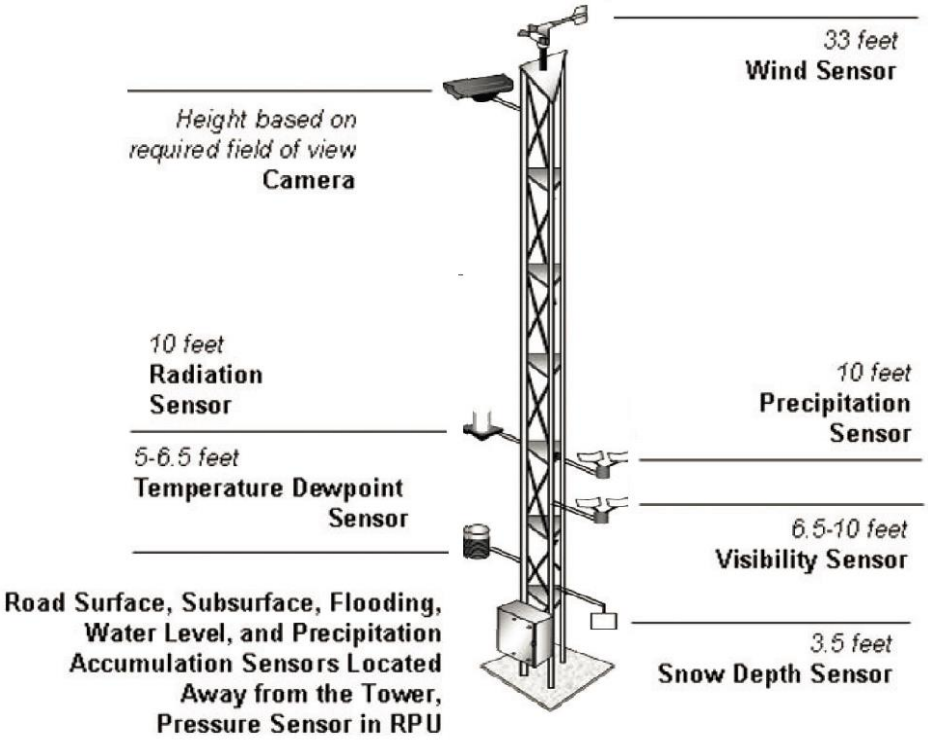


Figure 2. Typical ESS *(18)*

Remote processing units (RPUs) placed along the roadway may contain some or all of the road and weather sensors. In certain cases, pavement sensors are located apart from

the RPU, with several pavement sensors capable of being linked to one RPU. However, these RPUs have limited local intelligence for processing, so data is transmitted to a central server, which could be generically termed a central processing unit (CPU). This central server is typically located in a highway maintenance facility and provides communication, collection, archiving, and distribution of the data. The raw data are used directly or in coordination with a service provider to prepare now casts and/or forecasts. Forecasts can be used to predict site-specific weather and pavement conditions. A conceptual flow diagram of data flow and usage is depicted by Figure 3 *(16)*.

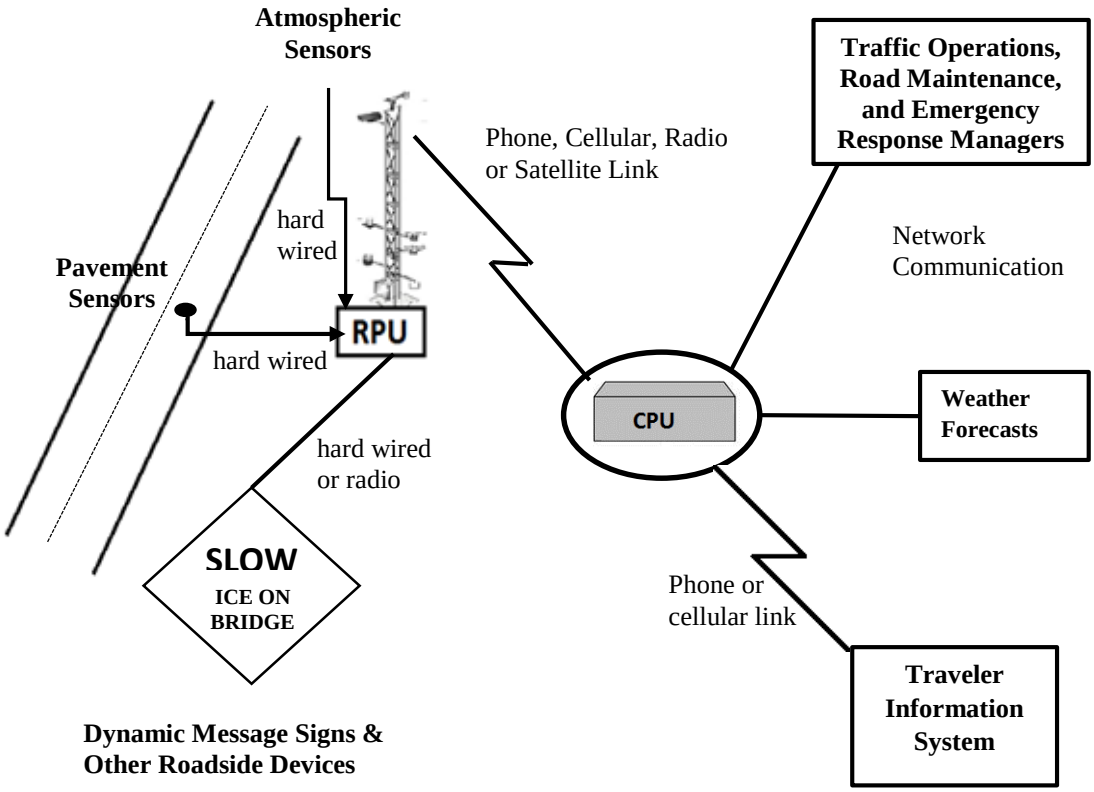


Figure 3. Conceptual Diagram for RWIS *(16)*

Data collected from environmental sensors in the field are stored onsite in an RPU located in a cabinet. This data is sent to the CPU and is then processed and used by automated warning systems and/or managers in traffic management centers, road maintenance facilities, and emergency operation centers for further decision-making.

The expected life of an ESS is typically 25 to 50 years, after which the entire system will need to be replaced *(28)*. Two types of cost are involved: capital, and operations and maintenance (O&M). Capital costs are those incurred during the design and deployment of an RWIS. The installation cost of the water detection system is almost half of the expense for the ice detection system *(16)*. O&M costs include those required for operation (e.g., electricity, data processing) and regular maintenance of sensors and other ESS components. Additionally, RPU and CPU systems need to be upgraded every 5 years. Details of unit costs for capital and O&M have been provided by the USDOT's ITS Joint Program Office (*31*). Table 1 shows details of some ESS installations in Abilene (Texas) and Florida *(30, 31)*.

Table 1. Capital and maintenance costs of ESSs deployed in Abilene and Florida

	Abilene, Tx	**Florida**
	[in 1997$]	[in 2009$]
Expected Life	50	25
Type	Icing Detection	Icing Detection
Capital Cost	$42,000	$25,000–40,000
O&M	$5,460 per unit per year	$1,600–3,000 per unit per year

ESS installation can be categorized as "regional" or "local" *(18)*. A single ESS can satisfy both regional and local needs. Regional ESSs are designed to provide road weather information that can be representative of conditions over a larger area or a road segment. A local ESS is used to gather information for a specific adverse weather occurrence at a specific location, such as icy pavement, flooding (such as at a short roadway segment with poor drainage), a low water crossing, cross drainage channel, or a certain bridge structure. Regional ESS site selection is mainly based on maximizing total coverage through the network of sensors. Local ESS siting focuses on a specific sensor's requirement; these are usually installed near bridges or intersections or in high crash locations. In general, regional ESSs have more types of sensors and are situated at locations with unobstructed field of view. A spacing of 20 to 30 miles along a road is recommended between regional ESSs. A

regional ESS should be located along a uniform roadway segment so that the local weather impacts on sensors can be minimized. Other conditions that affect the location of ESSs include available power, such as whether the unit can be directly wired to the system or might require a solar power system or generator with a backup battery supply (such as an ESS in a remote location).

While considering the road weather information requirement, it is important to note that weather sensors for specific types of severe weather might not be available or have inherent limitations. For example, observations for weather conditions that develop quickly, such as a thunderstorm, are difficult to automate using sensors deployed as a part of an RWIS ESS. Currently, there are no automated sensors for sun glare, which can potentially blind a motorist depending on time of day and direction of travel. Sun glare has been cited as a contributing factor for crashes *(18)*. Sensors also have limitations in measuring cloud coverage (the sensor typically only scans directly overhead) as an individual standing on the ground sees it. Cloud sensors are not usually deployed as a part of ESSs as they require frequent maintenance compared to other ESS sensors.

2. 2 ESS Siting Methods

Substantial research efforts have been devoted to measuring the impacts of various adverse weather conditions on road safety, based on statistical modeling and experimental observations. This problem is intrinsically complicated, due to the interplay of multiple factors, such as weather and pavement, weather and driver adjustment, etc. As an example, *(1)* and *(3)* both attempted to quantify the contribution of adverse weather to crashes, along with other factors, including roadway design, traffic, daylight, and pure randomness. In *(7)*, a comprehensive review is presented on studies from 1970 to 2005 regarding adverse weather and crashes; a meta-analysis is applied to summarize the findings. Major findings included the conclusion that the crash rate usually increased during precipitation, while snow had a greater impact on crash occurrence than rain did. In *(8)*, crash rate ratios were developed to evaluate the relationship between crash risks and skid resistance, with the suggestion that higher skid scores were required for wet weather conditions to maintain the

same safety level. Other case studies, field observations, and descriptions of the state of the practice can be found in *(9)* through *(14).* A critical review is presented in *(15)*, which compared two schools of thought for analyzing the weather-safety relationship (i.e., explanatory modeling versus data-driven analysis) based on a summary of weather-safety studies from 1960s to 1990. In *(21)*, road slipperiness is estimated through regression and recommendations are made based on slipperiness and local and regional climate variations. In *(22)*, a cell-based approach is proposed in which a region is divided into equal-sized cells, and these cells are ranked based on criteria considering such factors as road surface temperature, precipitation, traffic, and collision pattern. In *(23)*, a safety concern index is proposed, and optimal RWIS locations are identified as the ones that produce minimal index scores for the road network under consideration.

Over 2,400 of the ESSs deployed by state agencies are primarily used for winter-maintenance activities. States have seen significant benefits from using RWIS. For example, Kansas saved $12,700 in labor and materials at one location the first eight times that the state DOT used information from the RWIS for decision-making on winter maintenance operations *(25)*. Massachusetts reported a savings of $53,000 in 1994–1995 by using RWIS information for winter maintenance. The Minnesota DOT used the information from their 17 RWIS stations to improve their winter maintenance efficiency, with an estimated return on their RWIS investment of 200 to 1,300%. The Oregon DOT expects to save $7 million over 25 years due to reduction in usage of chemicals (i.e., for deicing), more efficient scheduling of crews, and decreased damage to vegetation. Over two winters, an RWIS station saved Pennsylvania more than $57,000.

2.3 State of Practice

In 2003, the FHWA compiled a list of best practices for road weather response management *(20)*. However, due to the lack of a detailed unified guideline and the diversity of road weather issues throughout the country (e.g., snow is a concern in New Hampshire, Minnesota, Idaho, Montana; floods present problems in Dallas and South Carolina), state and city transportation agencies in the United States now follow different, localized

practices in choosing ESS locations. State DOTs may prioritize ESS location placement according to a variety of factors, which include logistics in winter maintenance and environmental footprint (New Hampshire DOT), regional coverage (North Dakota DOT), local and regional balance (Michigan DOT), and past experience and analysis of accident-prone spots (Caltrans, Alaska DOT). More details on the state of practice about RWIS ESS implementation are described below.

The Alaska Department of Transportation and Public Facilities (ADOT&PF) operates a network of ESSs strategically located along the highway system. The primary consideration in establishing new sites is feedback from the Department's maintenance and operations personnel in regard to making winter maintenance decisions, such as snow plowing and anti-icing applications *(32)*. Other considerations include the NWS use of the observations to improve local forecasting and weather warnings, and to help the public make informed travel decisions through the 511 traveler information system. Other significant factors are cost and the availability of power and communication. Sites that don't have direct power require a power generator, while sites that do not have nearby telephone or State of Alaska network service require a wireless communication solution. Other factors include topography, the natural environment around the site that can affect sensor readings, and the availability of right-of-way. Each active camera is polled one to four times per hour, capturing a single still image each time. The ADOT&PF temporarily archives these images for up to 2 days.

The Minnesota DOT deployed 76 ESSs by using siting procedures developed in conjunction with a meteorologist from the University of North Dakota. Locations for the sensors were determined by the sensor's function, i.e., whether for maintenance operations or forecasting *(33)*. Then, meteorologists were able to assess local weather conditions at each location and determine the siting method that would provide representative readings of weather data. In all, 94 stations were distributed throughout the state with color cameras at 74 sites. All the sites are networked and most are broadband to achieve higher reliability, greater flexibility, and the ability to share information with other data sources like traffic counts.

Since 2004 the Iowa DOT has used the USDOT's Clarus and the FHWA Road Weather Management Program to develop and demonstrate an integrated surface transportation weather observation data management system, to support their maintenance operations (34). The Iowa DOT maintains 62 observing stations located along major roads in the state. These stations provide about six observations per hour (35).

The Montana RWIS consists of 73 sites across the state, as shown in Figure 4 *(36)*. Weather information is mainly used by the maintenance division to schedule personnel and equipment, based on weather and pavement conditions. Real-time weather information improves response time, increases the efficiency of winter maintenance practices, and minimizes public exposure to hazardous conditions.

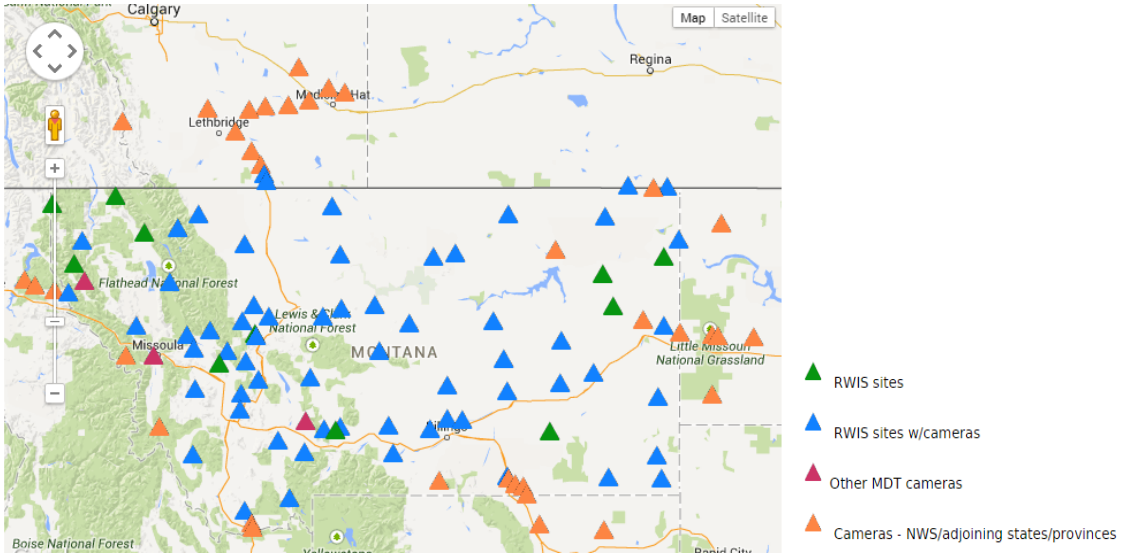


Figure 4. Montana RWIS Locations *(36)*

In Florida, the weather conditions most likely to impact traveler safety are low visibility from fog, smoke, and heavy rain, as well as hazards presented by strong winds, wet pavement, and freezing temperatures. As adverse weather hazards risks tended to arise only at specific locations (i.e., bridges) rather than being distributed along roads, the Florida DOT (FDOT) deployed RWIS stations at the specific locations where the risks existed *(37)*. As most of these conditions are local in nature, data on weather conditions at individual RWIS stations provided little guidance in assessing when and where such

conditions exist regionally on Florida roads. Thus, FDOT did not intend to use data from individual RWIS stations as a part of its decision-making process in responding to road weather conditions. Instead, the data from the RWIS stations was to be integrated with other data in the weather models used by meteorologists to generate weather condition and forecast data for individual road segments. Wind-speed monitors were placed on bridges (shown in Figure 5).

Figure 5. Florida RWIS Locations ***(37)***

Unlike other state DOTs, the Wisconsin DOT (WiSDOT) is not responsible for actual maintenance activities. WiSDOT contracts with each county to maintain the state and federal highways *(38)* within county borders. There are 56 ESS located throughout the state, as shown in Figure 6. The main purpose of the sensors is to provide toll-free and timely access to weather information to facilitate proactive anti-icing operations and advance warning systems. Wisconsin lacks the infrastructure through which to transmit to and share information with its 72 counties, which reduces the effectiveness of RWIS in the state.

Figure 6. Wisconsin RWIS Locations *(44)*

2.4 Literature Review Findings

The literature review revealed that RWIS can have significant impact on traffic and mobility during adverse weather conditions. In spite of the difference in practices among various DOTs for deciding ESS locations, two notable similarities are discernable. Most of the RWIS ESSs are situated along major highways and data are used mainly for road maintenance activities. Therefore, site selections are mainly focused on state-system roadway routes considering average annual daily traffic (AADT), geometrical conditions, local weather patterns, crash history, and distance from a maintenance center and/or ITS facilities. This approach is not effective for regional-level RWIS deployment.

Several studies have proposed discretizing a road network and analyzing the crash pattern along route segments. Road networks are complex in geometry and have irregular shapes. Solving such a problem is computationally demanding. Some recent studies have adopted a cell- or zone-based weather-related crash aggregation approach to locate ESSs at the regional level. Weather-related crash count is mostly used to justify the need for ESSs in an area. Moreover, the total number of stations to be deployed is usually assumed

to be known and optimization formulations are focused only on site selection. There are no studies that look into how RWIS effectiveness as a whole system changes with the addition of a new station. A cell-based approach is proposed in Chapter 4, which addresses these limitations and can be used to determine the optimal number of sensors as well as their locations for larger regions.

Chapter 3. Methodology

The location of an ESS depends on how the road weather information will be used. Different data usages will lead to different objective functions. If the information is used primarily for winter maintenance-related activities, our objective would be to minimize the sum of total distances from the existing ITS facilities to the nearest ESS while maximizing ESS data benefits. However, if information derived from ESS data is used for road temperature modeling for supporting a weather-responsive traffic management or travelers information system (e.g., 511 system), we may be interested in optimizing the total information demand covered under an RWIS. Selection of an appropriate site can be best accomplished by a team of local road and weather experts. Having information on local road, traffic, and meteorological conditions could increase the usefulness of an RWIS. The approach developed in this study provides a general framework that can incorporate various objectives and constraints. This can be helpful to analyze ESS locations from different points of view. Northern US states may be mainly interested in using an RWIS for winter maintenance activities. However, southern states, such as Texas, may prioritize weather-responsive traffic management or travelers information systems.

This study is intended to contribute to the methodology of establishing a uniform ESS siting guideline and to optimize the overall utility of RWIS by strategically choosing deployment locations. Finding the optimal allocation of a resource based on a certain scenario is classic—e.g., logistic systems, electric systems, etc. This problem is commonly known as the *Facility Location Problem*. For RWISs, information distribution is a resource. Such information can affect a driver's response and hence plays a key role. Based on the different objectives of RWIS deployment, the proposed framework can be formulated as different types of the Facility Location Problem, such as maximum coverage, P-centered, and P-median facility location problem. These formulations are computationally demanding to solve for finding a global optimum.

In reality, for the exact ESS site location selection, many other factors are taken into consideration, such as road segment topography, right-of-way, sources of sensor

hindrance, etc., so that collected information can be treated as representative of the nearby area. Adverse weather conditions usually prevail in a region rather than at a specific location on the road. The proposed approach considers weather conditions as uniform within a cell and information provided by a station in the cell is representative of weather conditions of every location in the cell. Road networks usually have a complex geometry, and defining candidate locations along the length of each road can create a large number of decision variables for a practical network. A cell-based approach is more practical to identify weather-sensitive crash areas within a larger area. It analyzes crash counts at an aggregate level so that crash count during different weather and traffic conditions can be compared in a simple and intuitive way.

3.1 Proposed Framework

The study area can be represented as $S(C, O)$ where C is the set of all cells and O is the geographical reference point. Location of each cell (m, n) is assumed to be at the center of the cell. Each cell is identical with length (l) and width (b). Theoretically, a cell size is decided such that traffic and weather conditions remain uniform throughout the cell. The study area is divided into small cells. Cell size should be chosen reasonably. If the cell size is too large, local crash risk factors are not captured, whereas if cell size is too small, it becomes computationally challenging to solve the facility location problem for optimum location. A simple approach to determine cell size is to start with a larger cell size and reduce cell size by half during every next iteration. The cell size that consistently yields optimal locations during consecutive iterations can be used as the cell size.

The following attributes of each cell have been used in the model:

- Cell size (unit: miles squared): $L * L$
- Cell index: (m, n)
- Study period (unit: days): T
- Duration of adverse weather in T (unit: days): N_A
- Crash count in good weather conditions: G_{mn}

- Crash count in adverse weather conditions: A_{mn}
- Cell-averaged AADT: $AADT_{mn}$
- Cell effeteness: E_{mn}
- Planning horizon: P
- Normalized crash rate in good weather condition in cell (m,n): G'_{mn}
- Normalized crash rate in adverse weather condition in cell (m,n): A'_{mn}

Where, the cell-averaged AADT is calculated as the weighted sum of freeway, arterial roads, and minor road AADT, and where the weights are calculated according to the total length of different types of roads. A day is defined as an adverse weather day if any weather-related event crosses a predefined threshold value on that day—for example, rainfall greater than 0.3 inches, visibility during fog lower than 0.6 miles, etc. The threshold value to define a day as either good or adverse is subjective and may vary from location to location. To account for different exposures to traffic at different road locations, crash counts have been converted into a crash rate. The normalized crash rate within a cell is defined as the number of crashes per 100,000 vehicles. For each year, crash counts have been normalized as follows:

$$G'_{mn} = \frac{G_{mn} * T}{(T - N_A) * AADT} \tag{1}$$

and

$$A'_{mn} = \frac{A_{mn} * T}{N_A * AADT} \tag{2}$$

Well-posedness requires $(T - N_A), N_A > 0$. The value of N_A depends on the temporal resolution of the data available. In this study, the smallest time duration of one day has been considered.

Cell vulnerability: Some crashes happen irrespective of weather conditions. A high crash count at a location could be due to several reasons, such as poor design or road condition, high traffic, low skid resistance on the pavement surface, drivers' behavior, etc., that are unrelated to adverse weather. Deploying a weather sensor at such a location does not

necessarily lead to an improvement in safety. Hence, it is important to separate crashes that occur under normal conditions from those crashes that can be potentially prevented using weather-related measures. The vulnerability of a cell is defined based on the change in crash intensity during adverse weather.

$$\textit{Vulnerability of a cell (m, n)}\ (V_{mn}) = A'_{mn} - G'_{mn} \tag{3}$$

Benefit/utility function: Several location attributes can limit the utility of an RWIS. For example, an RWIS station just near a hilly area may not be representative of weather conditions compared to an RWIS location in a flat area. These considerations can be easily incorporated as additional cell attributes that define their effectiveness for RWIS. For a given cell, the utility of RWIS stations is related to the vulnerability of cell, its effectiveness, and the distance of the cell from the nearest RWIS station.

Utility/benefit of ESS located in cell (*m', n'*) for a cell (*m,n*) (4)

$$B_{mn} = E_{m'n'} * V_{mn} * f(d)$$

Where, $f(d)$ is the ESS coverage function. In *(26)*, coverage function used is an exponentially decreasing effective coverage function based on Euclidean distance between a candidate location and the nearest RWIS station. There has been no established research that maps the effectiveness of a station to a location on the ground. For simplicity, a linearly decreasing coverage for ESS is assumed.

$$B_{mn} = E_{m'n'} * V_{mn} * (1 - \frac{D_{mn}}{Range}) \tag{5}$$

Where, D_{mn} is the distance between the center of a cell (m, n) to the center of the nearest station cell (m', n').

Total cost: Ideally, RWISs should be located as close to an existing ITS facility as possible for power supply and convenient maintenance. The total cost includes fixed initial cost of deployment and total maintenance cost over the planning horizon.

$$\text{Total Cost } (C) = (N * FC + \sum_i D_{ik} * MC * P)/P \quad (6)$$

Where,

FC is the fixed cost for deploying one RWIS station

MC is the operation and maintenance cost per year per unit mile

D_{ik} is the minimum distance from sensor station *(i)* to ITS facility *(k)*

N is the total number of new RWIS stations to be deployed

Coverage: Many state agencies may want their RWIS stations to be uniformly distributed in the region *(39)*, which can be achieved by imposing a certain minimum uniformity index. For example, most crashes typically occur in the downtown area. Thus, the optimal solution may suggest putting more than one RWIS station near the downtown area. However, an agency may want to deploy RWIS stations more uniformly over the state so that various regions can be covered by one station, although those regions have fewer crashes. To avoid bunching the stations and to create an even dispersal within the space under an optimal solution, a minimum coverage index that will ensure specified minimum coverage is introduced in the region.

Spatial coverage index: This index assumes each RWIS station has a decreasing spatial coverage function as the distance of a location from the nearest ESS increases.

$$C_{mn} = f(d_{mn}) \quad (7)$$

Where $d_{mn} = minimum\ distance\ from\ cell(m,n) to the\ nearest\ ESS\ station$

Coverage index is defined as the ratio of current coverage to maximum coverage by ESS for a given number of stations.

$$Spatial\ Coverage\ Index\ (CI) = \frac{Existing\ Coverage}{Maximum\ Coverage} = \frac{\sum_{mn}(1-\frac{d_{mn}}{range})}{Z} \quad (8)$$

Where *Z'* is the maximum coverage area provided by '*N*' sensors, given by:

$$Z' = max \sum_{m,n} C_{mn} \quad (9)$$

$$s.t \sum_{m,n} X_{mn} = N \tag{10}$$

$$X_{mn} = \begin{cases} 1 & if\ a\ sensor\ station\ is\ locted\ in\ cell(m,n) \\ 0 & otherwise \end{cases}$$

For a given number of sensor locations, the objective function has a unique value. A higher minimum coverage index results in a spread optimal location solution.

Robustness index: Although we assume two stations are typically similar in their functionality, their importance is not similar. An RWIS station located in a crash-vulnerable area, such as a downtown area, has much more importance than an RWIS station in a remote location. If a sensor station downtown fails, there is major risk to RWIS functionality. Thus, another constraint is introduced to ensure a minimum system reliability so that the failure of one ESS is not going to affect the functionality of the overall RWIS. Robustness index is defined as the ratio of an ESS system's total utility under the failure of one ESS to the combined utility of all stations.

$$Robustness\ Index\ (RI) = \frac{Utility\ of\ (n-1)\ station}{Total\ Utility} = \frac{\sum_i \sum_{m,n} B_{-i\ \ mn}}{N * \sum_{m,n} B_{mn}} \tag{11}$$

Where, $B_{-i\ \ mn}$ is the utility/benefit of a cell (*m*,*n*) assuming the *ith* ESS is not working The robustness index represents the reliability of the RWIS in case of the failure of one ESS. A higher robustness index requires RWIS stations to be closely spaced. The coverage and robustness index can be altered to achieve the desired optimal location configuration for a fixed number of RWIS stations.

Location constraint: There may be limitations for station locations due to geometry, existing infrastructure, or required right-of-way, etc. A cell is defined as a candidate cell if there is any road segment where DOTs have the available right-of-way and an ESS can be set up.

3.2 Problem Formulation

Our objective is to maximize overall benefits derived from an RWIS per unit cost over the planning horizon. Additionally, coverage index and robustness index are bounded by $[\alpha_1, \alpha_2]$ and $[\beta_1, \beta_2]$ respectively. The proposed optimization formulation can be written as:

$$Z = max \quad \frac{\sum_{m,n} B_{mn}}{C} \tag{12}$$

$$s.t \sum_{m,n} X_{mn} = N$$

$$B_{mn} = E_{m'n'} * \theta_{mn} * (1 - \frac{d_{mn}}{range})$$

$$C = (N * FC + \sum_{i} D_{ik} * MC * P)/P$$

$$\alpha_1 \leq \frac{\sum_{m,n}(1 - \frac{d_{mn}}{range}}{Z} \leq \alpha_2 \tag{13}$$

$$\beta_1 \leq \frac{\sum_{m,n} B_{-i\ mn}}{B_{mn}} \leq \beta_2 \quad \forall\, i \in all\ sensor'slocation \tag{14}$$

Where, $X_{mn} = \begin{cases} 1 & if\ a\ sensor\ station\ is\ located\ in\ cell(m,n) \\ 0 & otherwise \end{cases}$

d_{mn} is distance from cell(m, n) to the nearest ESS station

D_{ik} is the minimum distance from ESS station(i) to ITS facility(k)

α_1, α_2 are lower and upper limits for coverage index

β_1, β_2 are lower and upper limits for robustness index

Z' is the maximum spatial coverage provided by N ESS

$$Z' = max \sum_{m,n} C_{mn}$$

$$s.t \sum_{m,n} X_{mn} = N$$

$$C_{mn} = f(d_{mn})$$

3.3 Solution Procedure

As the number of stations increases, both benefit and cost increases. When there are large number of stations in the RWIS, their range will start to overlap. Thus, after a certain number of stations, the cost required to deploy an additional station will become more significant than the benefit derived from it. Identifying the point at which cost outweighs benefit will lead to an optimal number of stations. The solution approach consists of three major stages. The first stage is transforming crash data and weather data into the crash vulnerability rating of smaller cells of the region. The second stage is solving the optimization problem using a sequential algorithm to determine the desired number of stations to be deployed. The third stage is solving the complete optimization formulation to find the global optimal solution under coverage and reliability constraints. This section details the method used to achieve each of these three objectives. A flow chart for the complete methodology is shown in Figure 7.

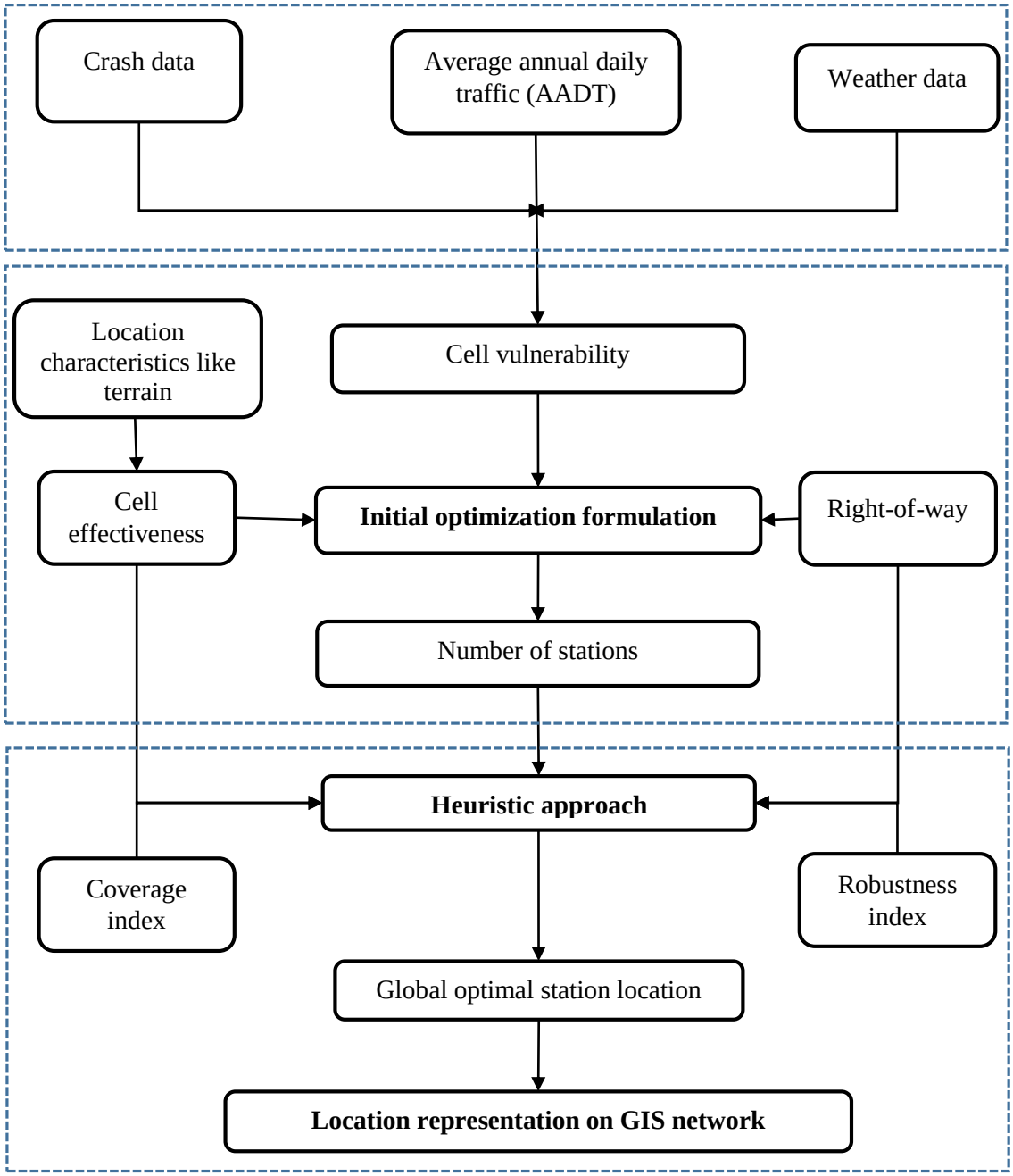


Figure 7. Flow Diagram of Conceptual Model to Find Optimal ESS Locations

During the first stage, input data are combined to calculate the equivalent crash rate of each cell. Based on good and adverse weather crash patterns, the median vulnerability of cells is calculated. Instructions for data processing procedure are provided below.

1) Statewide crash data for Texas is available through TxDOT's Crash Records Information System (CRIS) database. Use Excel Visual Basic for Applications (VBA) to extract data for required counties and/or cities within the region (Appendix A).
2) Weather data is available through the NWS Forecast Office in .txt format. Import .txt file into Excel for initial data cleanup.
3) Import crash data into MATLAB to separate good and adverse weather crashes. Import weather data into MATLAB to extract good and adverse weather days.
4) Divide study area into cells of equal length and width. Determine crash count of various cells using the coordinates of crash locations.
5) CRIS data also contains information on AADT at various crash locations. Other data sources such as TxDOT's Project Management Information System can provide AADT information. Impute for missing AADT data as described in Section 3.2. Calculate cell-averaged AADT as the weighted sum of freeway, arterial roads, and minor road AADT, where the weights are calculated according to total length of different types of roads.
6) Calculate equivalent crash rate for both good and adverse weather. Calculate vulnerability of each cell over the years.
7) Calculate median vulnerability of each cell in the study area.

During the second stage, the optimization formulation without any coverage, robustness, and number of stations constraints has been solved using a sequential algorithm to identify the desired number of stations. Cell vulnerability produces an irregular pattern over space and usually the objective function turns out to be non-convex. Several heuristic approaches—such as Genetic Algorithm, Simulated Annealing, Tabu search, etc.—have been developed in recent years to solve non-convex problems to obtain global optimal solutions. However, solving the ESS location problem formulation with heuristic approaches can be computationally challenging. A sequential algorithm gives approximate information on the number of stations that would be required to achieve a given level coverage and reliability. It is important to note that the solution of a sequential algorithm does not depend on the total number of stations to be deployed—i.e., whether we are looking to deploy 50 stations or 100 stations, the location of the first 10 stations would be

the same in both cases. Exploiting this fact, we can set the initial number of stations to be unrealistically high, say (N=500). The sequential algorithm can be summarized as:

Initialize: Set i = 1; find cells (a,b) to maximize objective function Z.

Step 1: Set $i = i + 1$, and set new station to first feasible cell. Recalculate value of objective function. Set Z = value of objective function.

Step 2: For each candidate cell (m,n) with no station, put *ith* station in cell (m,n).

Step 2.1: If any constraints are not satisfied, go to Step 2.3.

Step 2.2: Recalculate objective function. If value of objective function > Z, then assign ith station to current cell (m,n).

Step 2.3: Go to next cell.

Step 3: If $i < N$, go to Step 1.

A graph of the marginal benefit-cost ratio versus the number of stations is obtained. The desired number of stations can be decided by policymakers based on the additional benefits of a new station in an RWIS, budget constraints, and total RWIS system costs. After deciding the number of stations to be used, the optimization formulation is solved again using heuristic approaches for finding a global optimal solution. A genetic algorithm in MATLAB has been used to solve for the global optimal solution. Although the genetic algorithm has emerged as a powerful tool for finding the global optimal solution, its performance strongly depends on various factors like initial population, population size, mutation, crossover, tolerance level, and stopping criteria. The solution from a sequential algorithm can be a good guess for an initial feasible solution for faster convergence. To improve the optimality of the solution, an iterative procedure has been adopted to reach the final solution.

Step 1: Set the solution from the sequential algorithm as the initial population for initialization of the genetic algorithm. Set population size as ten times the number of decision variables.

Step 2: Set several separate and parallel cases with different mutation and crossover fraction values.

For each candidate cell (m, n) with no station, put ith station in cell (m, n).

Step 3: Set the initial population as the corresponding solution during the last run. Find the best solution in each run. Store the solution and its corresponding objective value.

Step 4: If the global optimal solution from various runs is repeated five or more times, then stop. Else, go to Step 1 for a maximum of 50 iterations.

Finding solutions via one run of the genetic algorithm can take several minutes. For a larger network and various input options, the complete optimization process can take several hours, depending on the problem's complexity. The high computational time for a better solution can be justified, as ESS deployment is not run often—perhaps every 10 years. Optimal sensor locations have been visualized using ArcGIS.

Chapter 4. Case Study: Austin District

4.1 Study Area

The TxDOT Austin District, shown in bold red outline in Figure 8, is spread over 9,437 miles consisting of 11 counties: Bastrop, Blanco, Burnet, Caldwell, Gillespie, Hays, Lee, Llano, Mason, Travis, and Williamson *(40, 41)*. The climate of the Austin District is humid subtropical with hot summers and relatively mild winters. Elevations within the region vary from 400 feet to just above 1,000 feet above sea level. Mild weather prevails during most of the winter, but temperatures fall below freezing on average 25 days a year. Strong mid-winter cold fronts blow through occasionally.

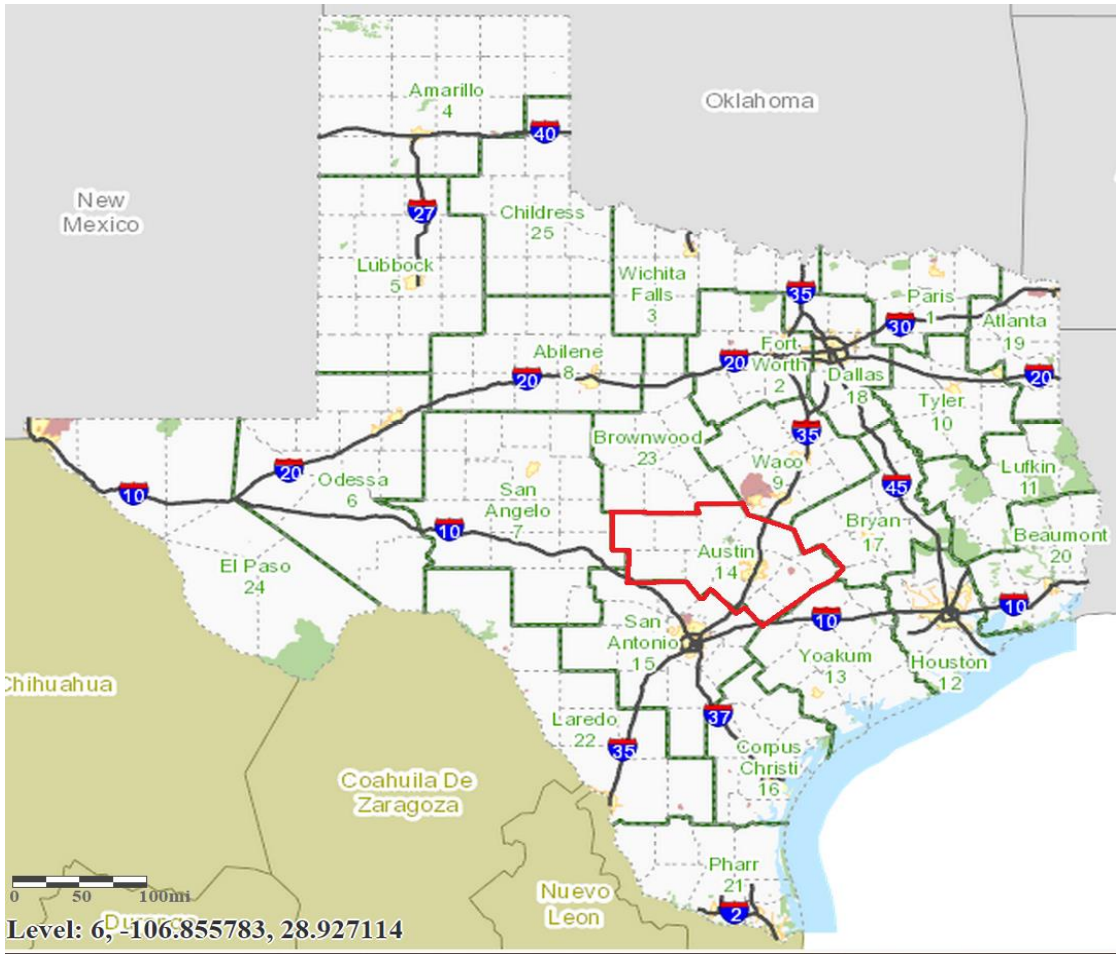


Figure 8. The Austin District's Location within Texas *(41)*

Austin, the Texas State capital, is the major city in the Austin District. It is located at the junction of the Colorado River and the Balcones Escarpment, separating the Texas Hill Country from the Backland Prairies to the east. I-35, US-290, SL-1, SH-29, and US-183 are major arterial road for commuting within and outside of the District. These roads carry heavy traffic during morning and evening peak hours. TxDOT is the state agency responsible for the day-to-day operations and maintenance of the system. Weather challenges for the transportation system in TxDOT's Austin District are different from those in most parts of the United States. Table 2 compares the various factors responsible for weather-related crashes within the Austin District to those of the rest of the nation (*29*). Weather-related crash statistics within the Austin District have been obtained by analyzing crash data obtained from TxDOT's CRIS. In most parts of the United States, ice on the roads is a major concern for state DOTs, whereas rain is the major concern for TxDOT. Snow is responsible for around 17% of total weather-related crashes nationwide whereas it accounts for only 1.7% in the Austin District. On an average, 74% of total weather-related crashes on US roads occurred due to rain whereas rain caused 89% of crashes on roads in the Austin District. Reduced visibility on roads due to fog is the second major concern in the region, accounting for the remaining 3.9% of crashes.

Table 2. Comparison between weather-related crashes (in percentage) in the Austin District and the nationwide average

	National 10 years average	**Austin District**				
	(2002–2012)	**2010**	**2011**	**2012**	**2013**	**Average**
Rain	74	87.55	86.56	87.35	90.43	88.57
Snow/Sleet	17	2.81	4.13	0.1	1.26	1.7
Fog	3	2.05	2.97	5.12	3.44	3.93
Overall weather-related crashes	23	12.25	7.39	9.3	11.5	10.8

Traditionally RWISs are used to support winter maintenance activities, as they enable faster and more effective maintenance and operation activities. For the rest of the

year, RWIS stations serve as source of weather updates for travelers. In Texas, wet pavement conditions are a major concern during adverse weather. Nearly 85% of all crashes during adverse weather in Texas occurred in rainy conditions (cloudy weather is not considered an adverse weather condition) *(42)*. RWIS information can be used by traffic operation managers to better control traffic on roads during adverse weather. Traffic managers may use road weather observations to modify signal timings, reduce speed limits, and close hazardous roads and bridges. The proposed methodology was applied to the Austin District area to achieve maximum reduction in crashes per unit cost of deploying RWIS stations.

4.2 Data and Assumptions

Crash data used in this study was obtained from TxDOT's CRIS database for crashes that occurred from 2010 to 2013. CRIS contains crash data submitted by law enforcement on form CR-3, Texas Peace Officer's Crash Report. The crash data includes temporal and geographical information to allow CRIS to properly place the crash in time and space. This data is submitted to TxDOT and then forwarded to a private contractor for processing and encryption. The contractor then returns the encrypted data file to TxDOT for uploading to CRIS. However, not all information on the crash report can be extracted for use in CRIS; this includes diagrams, written statements, and other information provided by the investigating officers that is not written or typed in the pre-defined data fields. CRIS also contains several quantitative facts about accidents—such as weather condition, pavement condition, crash severity, and vehicle information—that can be used to study various causes of accidents. For locations missing the AADT figure, the AADT values were imputed using cell averages of AADT for the particular road type, as described in Section 3.2. Weather data for years 2010 to 2013 was obtained from the NWS Forecast Office.

Table 3 shows the distribution of weather crashes by weather conditions and year. The majority of crashes (88%) in the area occurred under good weather conditions. Such crashes can occur due to various factors, such as reduced pavement friction, hydroplaning,

location and degree of horizontal curves, number of lanes, lane width, presence of a paved shoulder, road design, traffic conditions, vehicle speeds, and driver's judgement and behavior. Approximately 10% of overall crashes in the Austin District occurred during rain, although this figure fell to 6.7% in 2011, likely due to that year's drought conditions. Snow accounted for a high percentage of weather-related crashes in 2010 and 2011. In 2012, a disproportionally high percentage of crashes occurred, with 0.51% attributed to fog as compared to the typical average of 0.12%.

Table 3. Summary statistics for Austin weather-related crashes from 2010 to 2013 (values are in percentage for grey cells)

Year	Unknown	Clear/ cloudy	Rain	Sleet or hail or snow	Fog	Other	Weather-related crashes	Total crashes
2010	0.92	86.83	11.53	0.37	0.27	0.08	23,436	201,482
2011	0.36	92.26	6.70	0.32	0.23	0.13	15,939	157,525
2012	0.66	90.04	8.70	0.01	0.51	0.08	19,304	166,771
2013	0.41	88.08	10.77	0.15	0.41	0.17	25,598	213,206
Average	**0.53**	**88.80**	**9.92**	**0.19**	**0.44**	**0.12**	84,277	738,985

MATLAB code (Appendix B) was used to read and process all input data and the results are shown using the GIS network in ArcGIS. The raw crash pattern of the Austin District shows the majority of crashes occurred on major highways and downtown (Figure 9). This crash data is distributed over a 5-mile x 5-mile grid. Cell-based representation can also help us to visualize hot spots for crashes in the region and smooth network level details. This simplifies the crash pattern representation and solution approach to find optimal sensor locations.

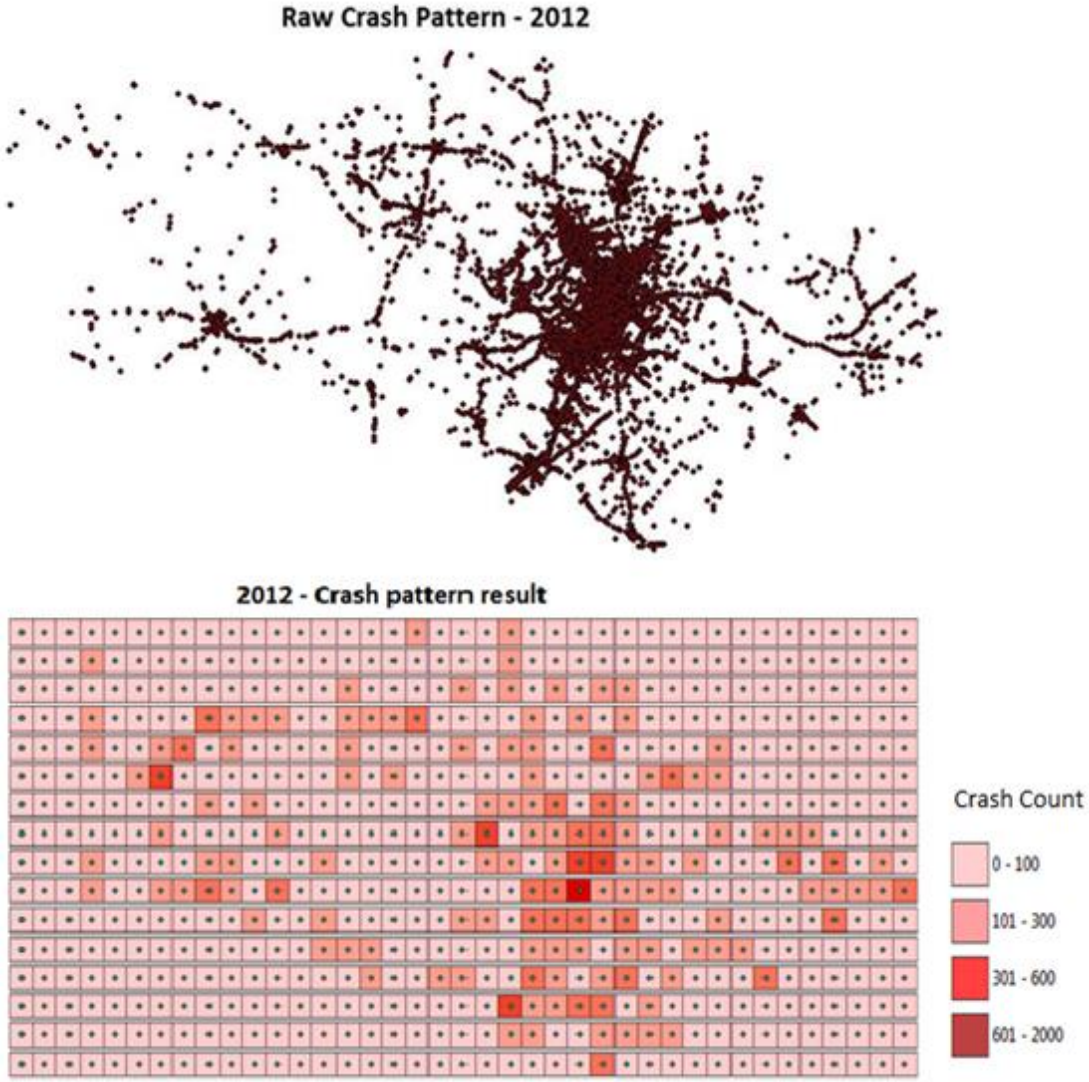


Figure 9. Spatial Distribution of All Crashes and the Cell-Based Representation in 2012 within the Austin District

Due to unavailability of detailed data, the following assumptions were made for this study within the context of the proposed methodology. Rainfall of 0.25 inch corresponds to either a light rain for 2–3 hours, a moderate rain for 30–60 minutes, or a heavy rain for 15 minutes, forming many puddles that do not disappear easily. Rainfall of 0.5 inch corresponds to either a moderate rain for 1–2 hours, or a heavy rain for 30–45

minutes, resulting in deep standing water for long periods of time. A day has been defined as an adverse weather day if there is any incident of sleet, snow, fog, or overall rainfall greater than 0.3 inch per day. There are two major weather stations located in the region: Austin-Bergstrom International Airport and Austin Camp Mabry. Austin-Bergstrom International Airport weather station data has been used to define good and adverse weather days. Daily weather condition data for 5 miles by 5 miles granularity over four years were not available. Good and adverse weather conditions were assumed to be same over the entire region for a single day.

Drivers make fewer trips during adverse weather than during good weather. Reduction in traffic count on roads during adverse weather depends on various factors, including weekday or weekend travel *(43)*. During adverse weather, vehicle count is assumed to be reduced by 12%. An ESS is assumed to have a range of 20 miles with linearly decreasing effectiveness *(18)*. The capital cost of deploying one station is $50,000 and annual maintenance cost is $500 per unit mile per year. Primary analysis has been done for a planning horizon of five years. For demonstration, six major ITS locations or ESS maintenance facilities are assumed to located across the study area, as shown in Figure 10. Due to limitations of data and time availability for this study, the effectiveness of all cells is assumed to be uniform (i.e., $E_{mn} = 1$ for every cell (m,n)).

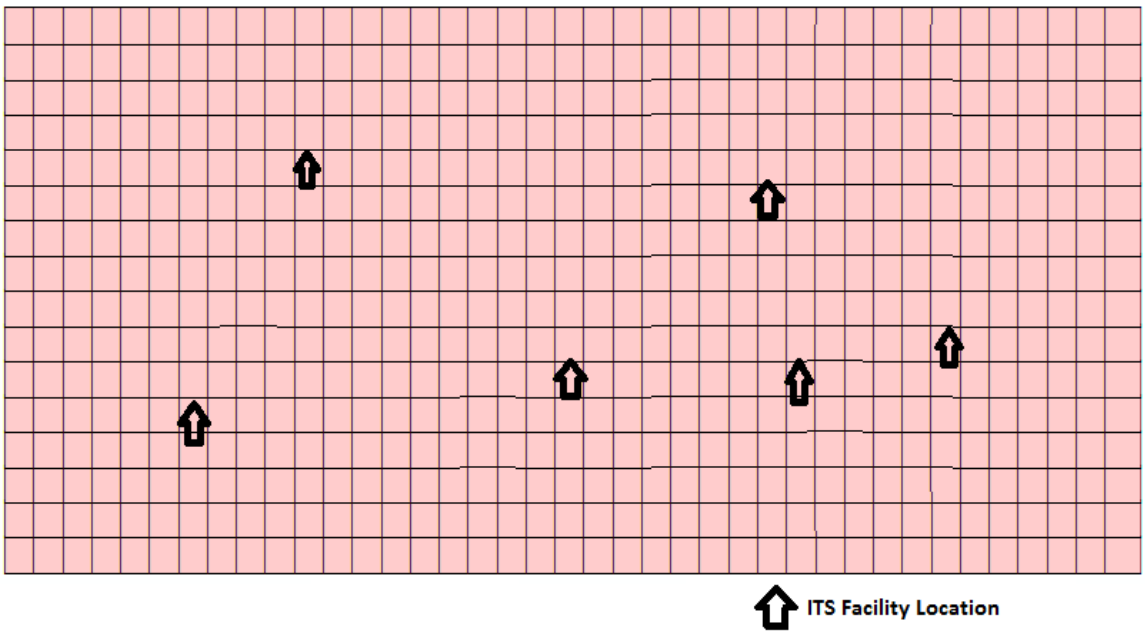
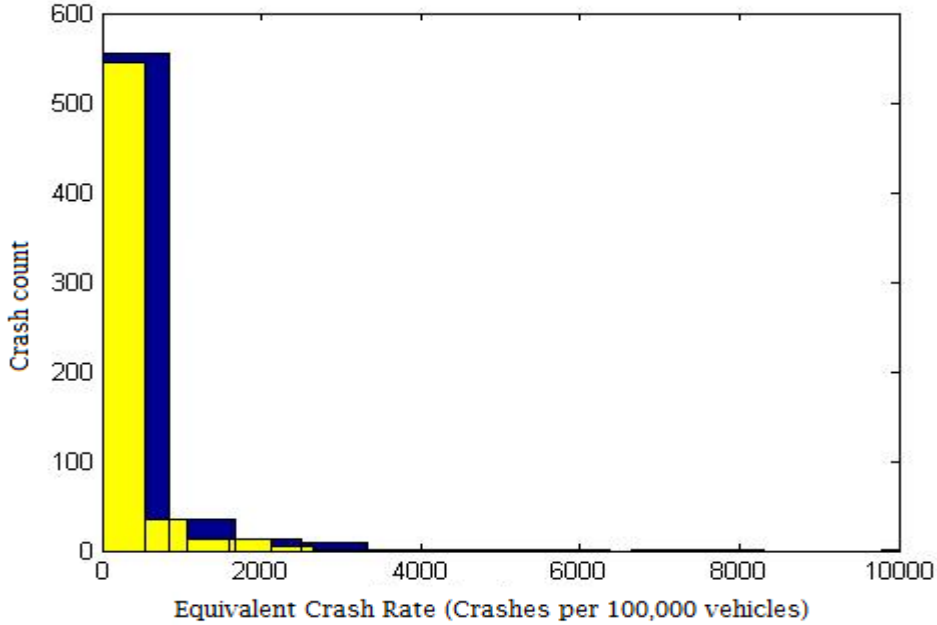


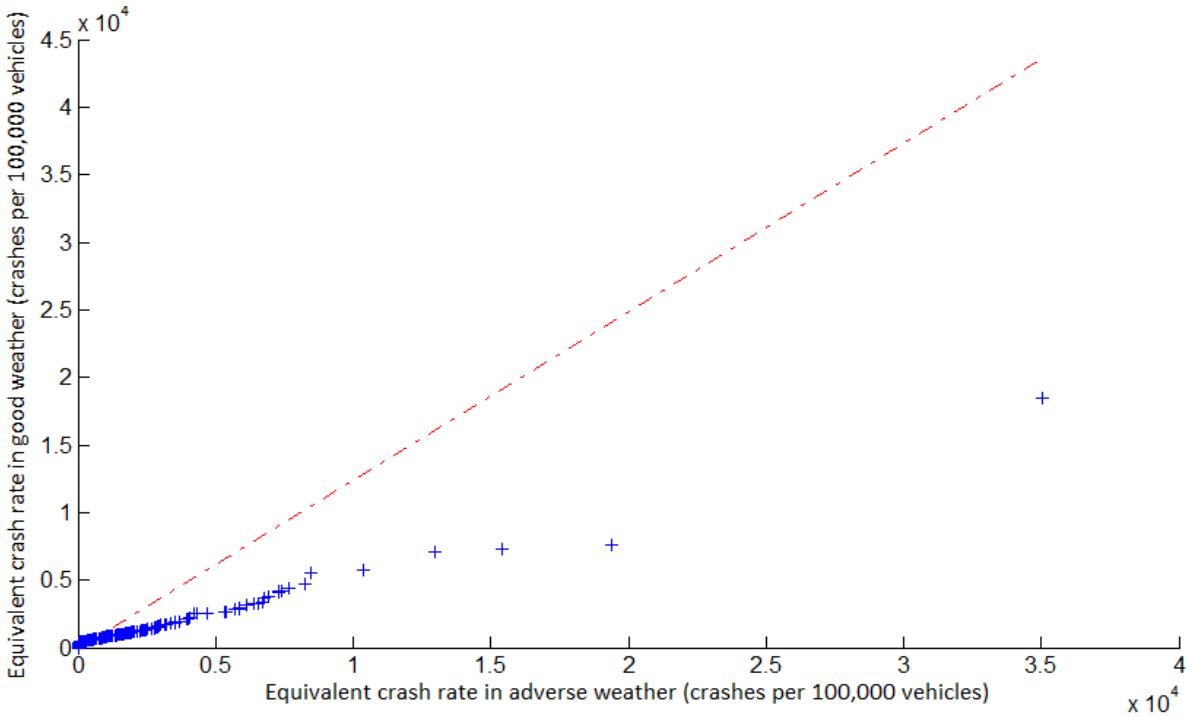
Figure 10. Assumed Cells with ITS Facilities

4.3 Weather-Sensitive Crash Pattern

As shown in Table 4, on an average day, more crashes occur during good weather conditions than in adverse weather conditions. However, traffic count on roads during adverse weather is less than the traffic count on an average day. A quantile-quantile (QQ) plot (Figure 11) between equivalent adverse weather crashes and the equivalent good weather crash rate for 2013 suggests that the adverse weather crash rate is slightly higher than the good weather crash rate. This shows that under similar traffic conditions on a good day and on an adverse day, there is a greater chance of accidents during adverse weather conditions. Some cells, especially cells on city arterial roads, are found to be highly vulnerable even with low weather-related crashes and some cells with high weather-related crashes are less vulnerable. Thus, weather-related crash count may or may not be a good indicator of crashes occurring due to change in weather conditions. The good weather crash pattern is distinguished from the adverse weather crash pattern by defining vulnerability for each cell, as described in Section 3.1.



(a) Comparison of histograms (blue: good weather; yellow: adverse weather)



(b) Quantile-Quantile plot

Figure 11. Comparison of Equivalent Crash Rates in Good and Adverse Weather based on 2013 Data

Figure 12 shows the crash pattern during good weather over time. For comparison, the range for the top 2% of crashes in adverse weather is used as the high crash rate range, followed by medium risk for the next 20% of crashes. Good weather equivalent crash rates are more consistent over the year and are concentrated along major highways and downtown areas. However, Figure 13 shows that adverse weather equivalent crash rates within a cell vary over the year. Thus, adverse weather crashes are more unpredictable in both time and space. Good weather crashes occur more predictably due to several factors, like traffic, road design, etc. In contrast, adverse weather crashes have a random pattern over the year and are less predictable in nature. Deploying an RWIS in the area can assist traffic operation managers and drivers to make informed decisions.

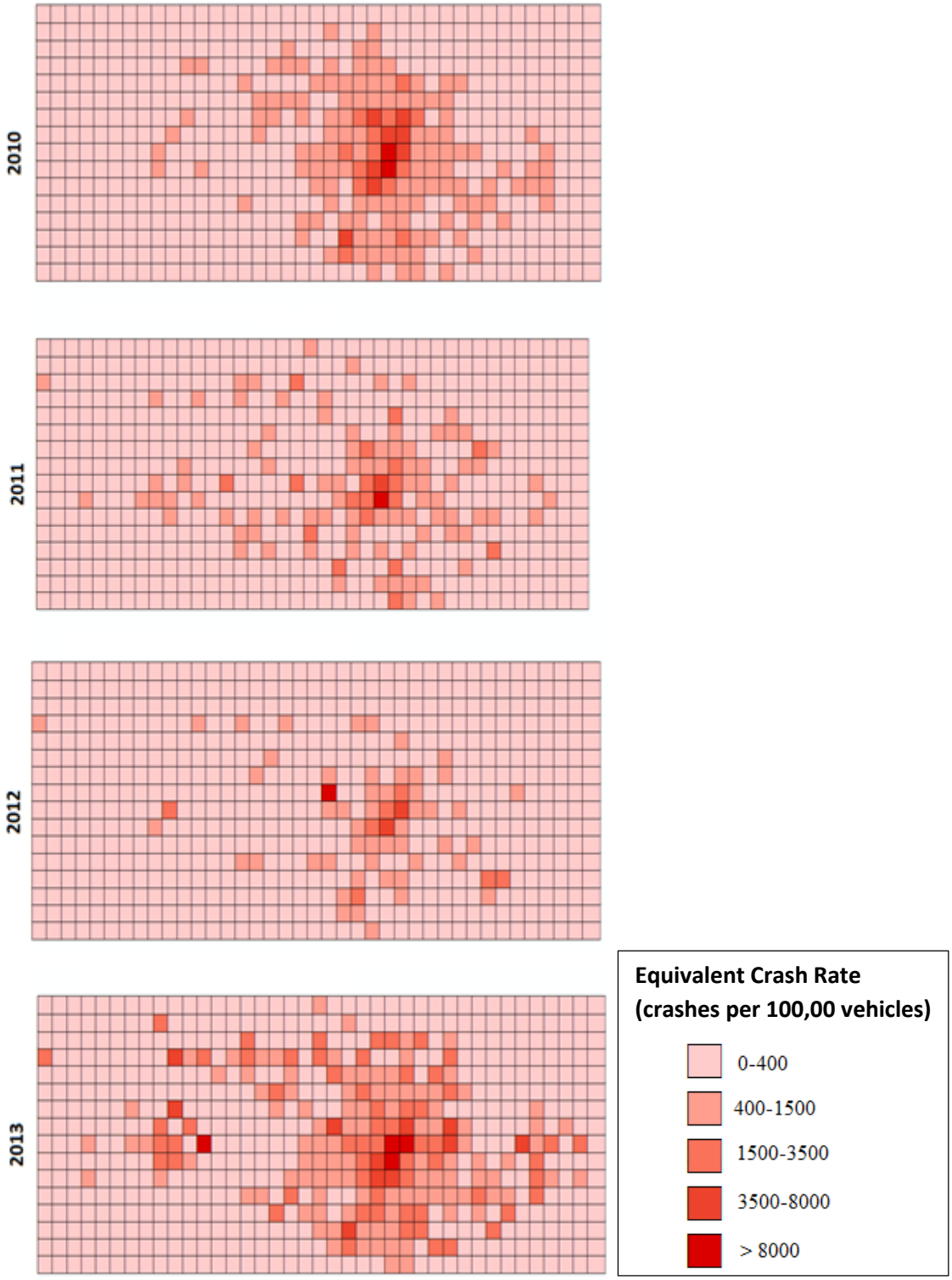


Figure 12. Austin District Equivalent Crash Rate in Good Weather from 2010 to 2013

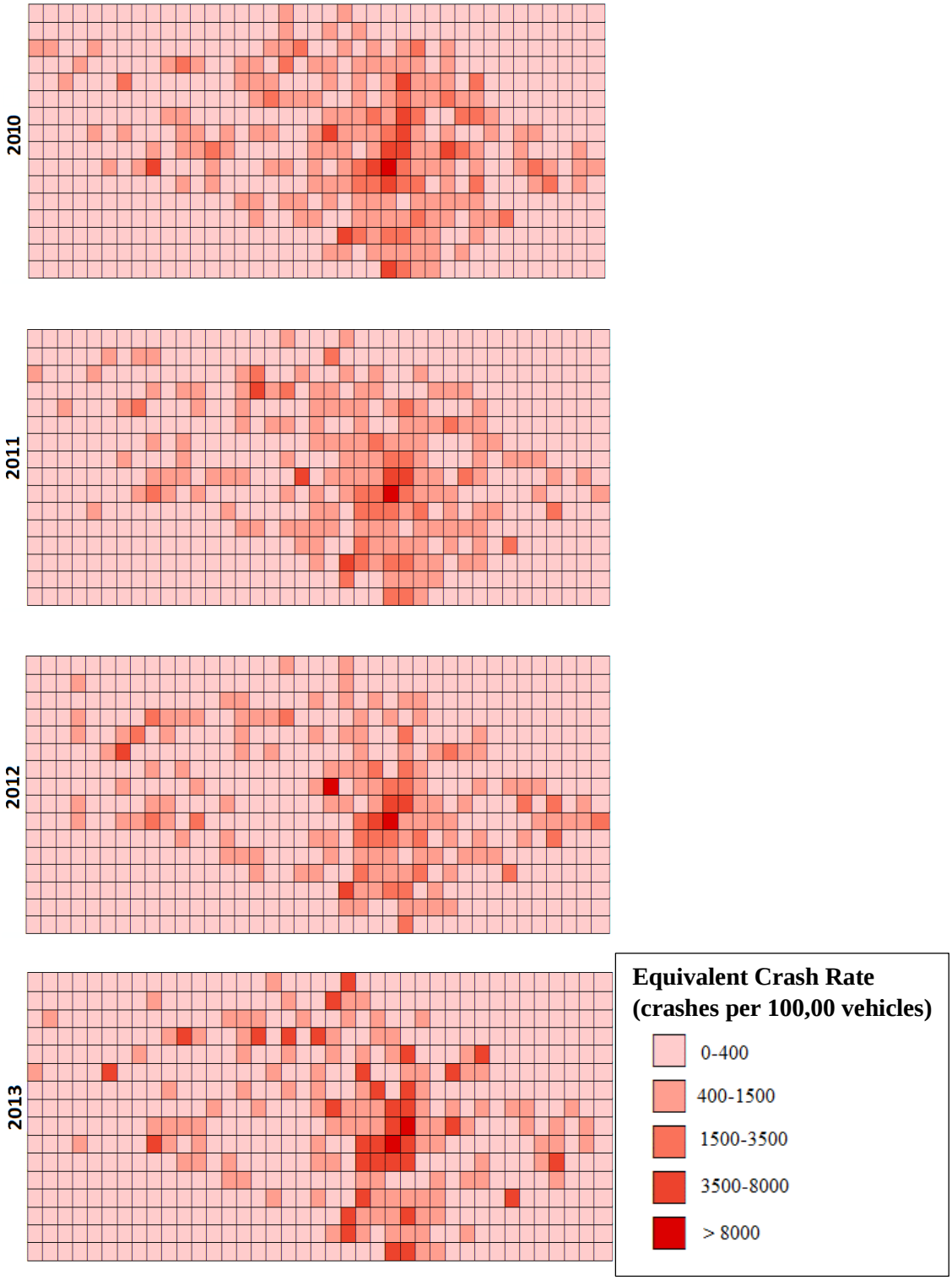


Figure 13. Austin District Equivalent Crash Rate in Adverse Weather from 2010 to 2013

The vulnerability of each cell was calculated according to Equation 3 using MATLAB code (Appendix C). To account for large variations in crash patterns over the year, median cell vulnerability over four years was obtained and is shown in Figure 14. Median vulnerability was input in the model for further analysis. The crash pattern varies significantly from 2010 to 2013. To account for outliers in data over four years, the median vulnerability for each cell was used. All cells were defined as candidate cells with a uniform effectiveness of one.

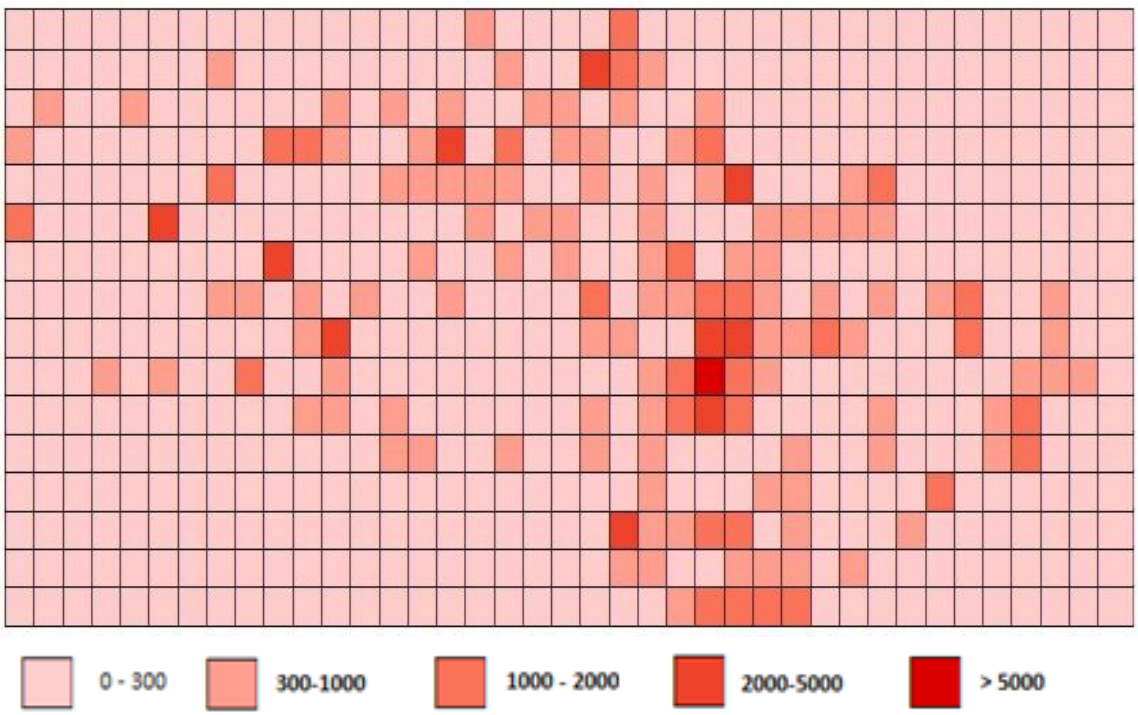


Figure 14. Median Vulnerability (in crashes per 100,000 vehicles) of Cells within the Austin District

4.4 Recommended ESS Location

First, a sequential algorithm was solved to optimize total utility of the RWIS (Equation 12) without any station, coverage, and reliability constraints (Appendix D). The value of objective function, coverage index, and reliability index has been calculated as described in Section 3.2. As Figure 15 illustrates, the graph of the benefit versus number

of stations is increasing. This is expected, as with more stations in the system, we can have more information about weather conditions. More stations can help provide detailed information throughout the region and can help improve safety and mobility on our road networks. However, as we add more and more stations, their range would start to overlap, resulting in less marginal benefit. However, the total cost of deploying more stations is also increasing, as both fixed initial cost and maintenance cost over the planning horizon are increasing (Figure 16). The value of our objective, which is benefit-cost ratio, is decreasing with the number of stations (Figure 17). Thus, the cost of deploying a new station in the system is increasing faster than the benefit received from it.

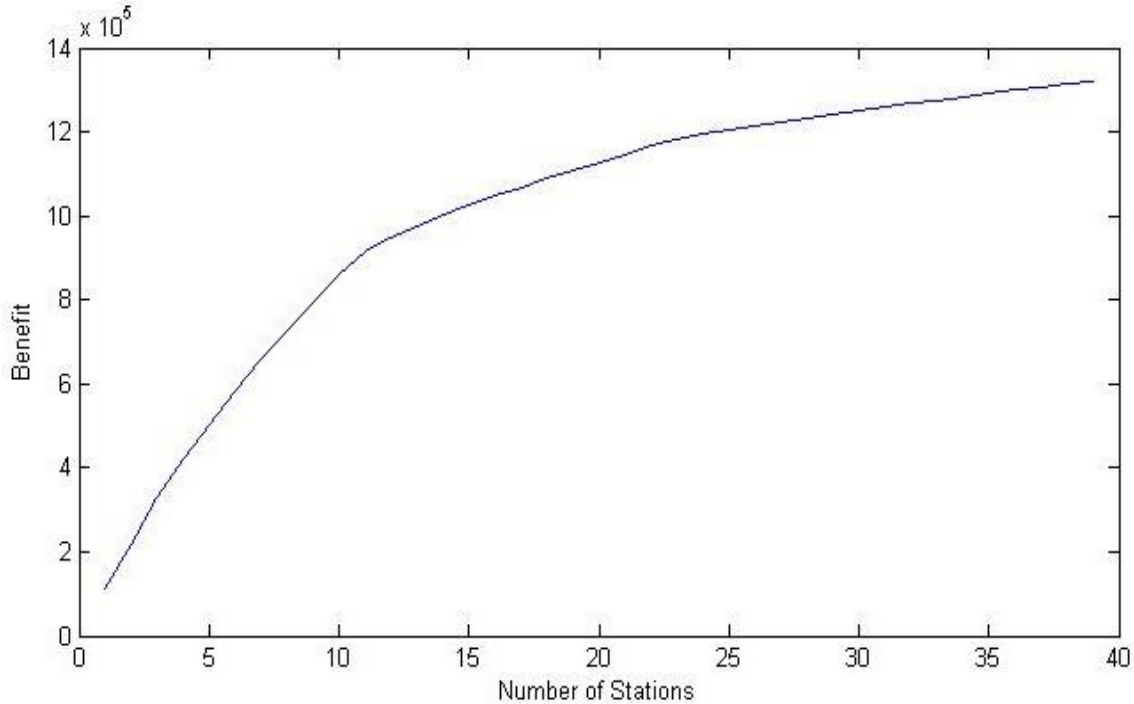


Figure 15. Variation of Benefit with Number of Stations

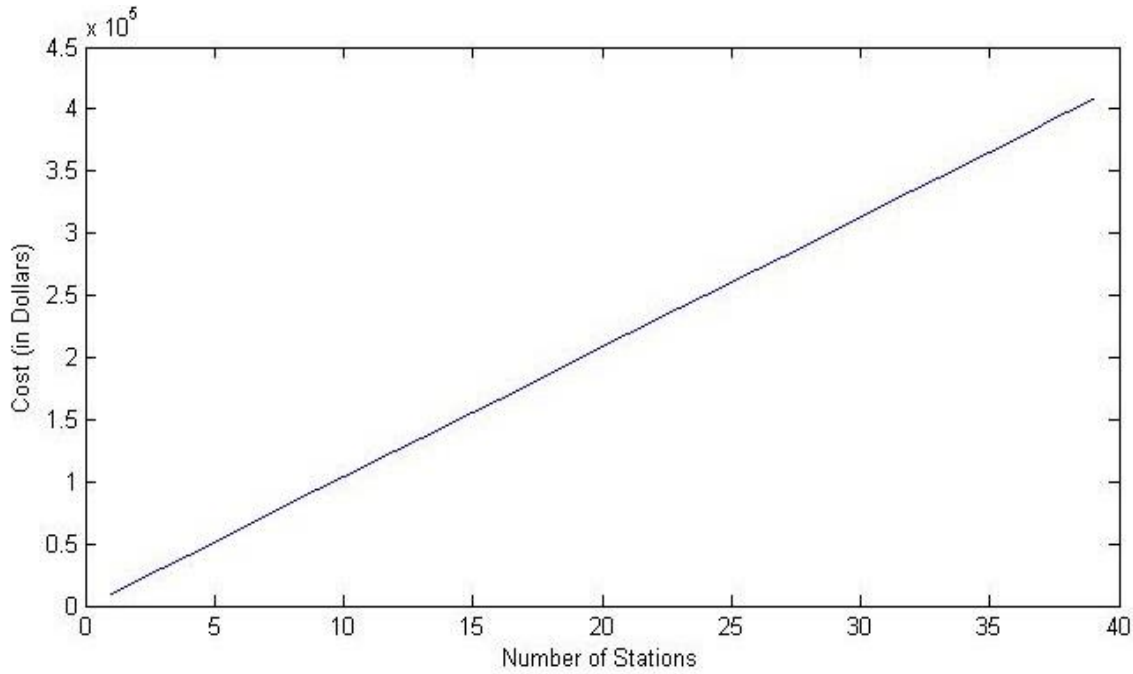


Figure 16. Variation of Cost with Number of Stations

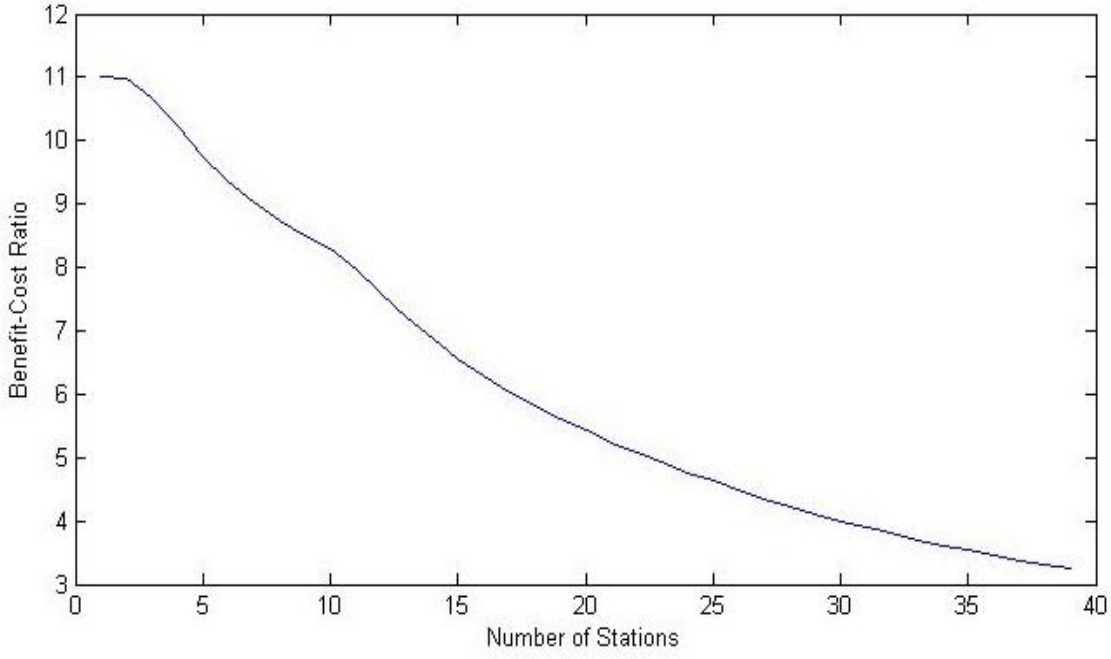


Figure 17. Benefit-Cost Ratio Variation with Number of Stations

Figure 18 shows a marginal change in the benefit-cost ratio for new stations. Policymakers can choose the number of stations based on their budget and the amount of

benefit per dollar they are looking to achieve. The plot of marginal benefit-cost ratio versus station number suggests either 4 or 10 stations would give a good overall utility for an RWIS based on money spent. Based on budget constraints, the final number of stations can be obtained. If budget is not a constraint, the number of stations corresponding to the last minimum point can be chosen as the number of stations to be deployed. In this case study, we assume that budget is not a concern; hence, 10 stations would be deployed in the region.

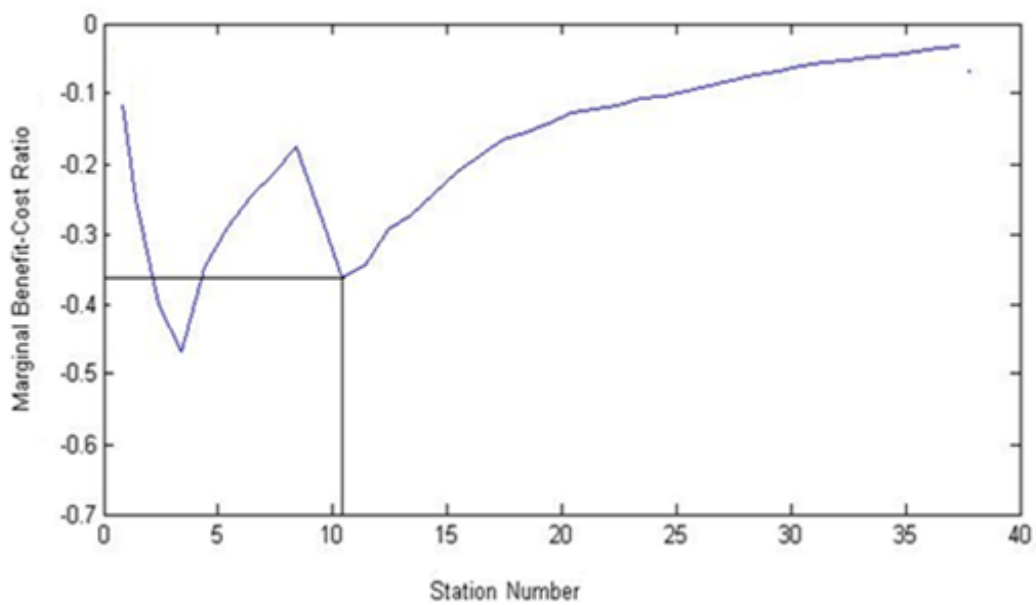


Figure 18. Marginal Benefit-Cost Ratio Variation with Station Number

Plots of the coverage index and robustness index are obtained using a sequential algorithm, as shown in Figure 19 and Figure 20 respectively. As the number of stations is increasing, their coverage and robustness is also increasing. However, marginal coverage and robustness index decreases for each new station. This graph can be used by decision-makers to define coverage and robustness level or to choose the appropriate number of stations to achieve the desired coverage and robustness. Based on the initial graph and number of stations, we can decide reasonable bounds on coverage index and robustness index. For further calculation, ($\alpha 1 = 0.3, \alpha 2 = 1;\ \beta 1 = 0.5, \beta 2 = 1$) has been used as the bound for the coverage index and robustness index.

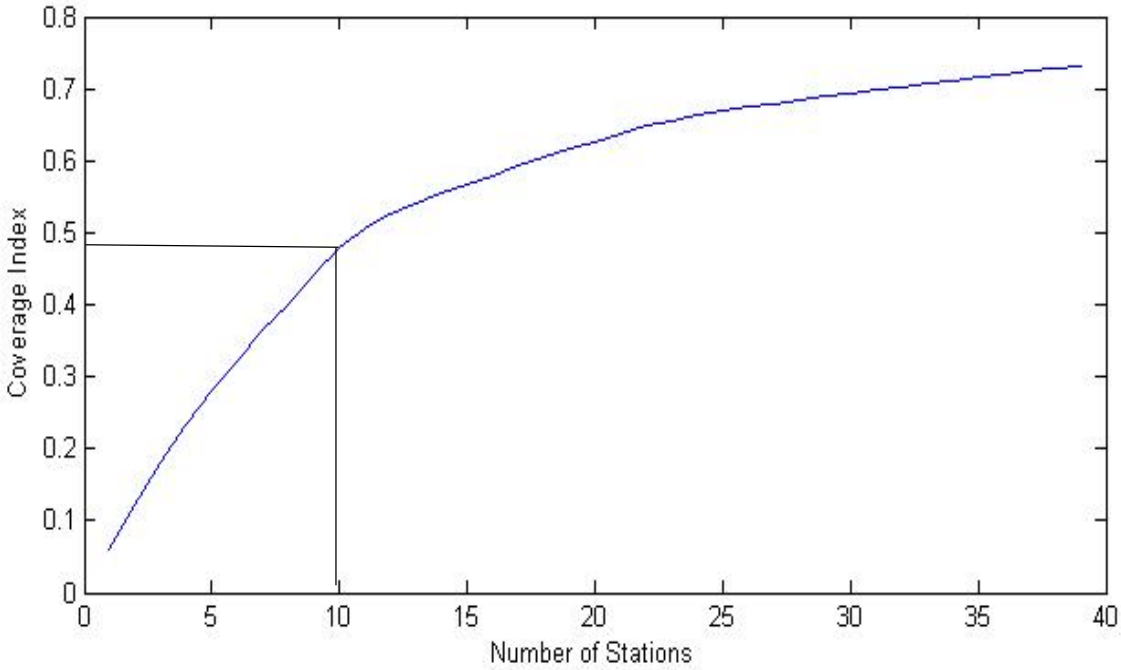


Figure 19. Variation of Coverage Index with Number of Stations

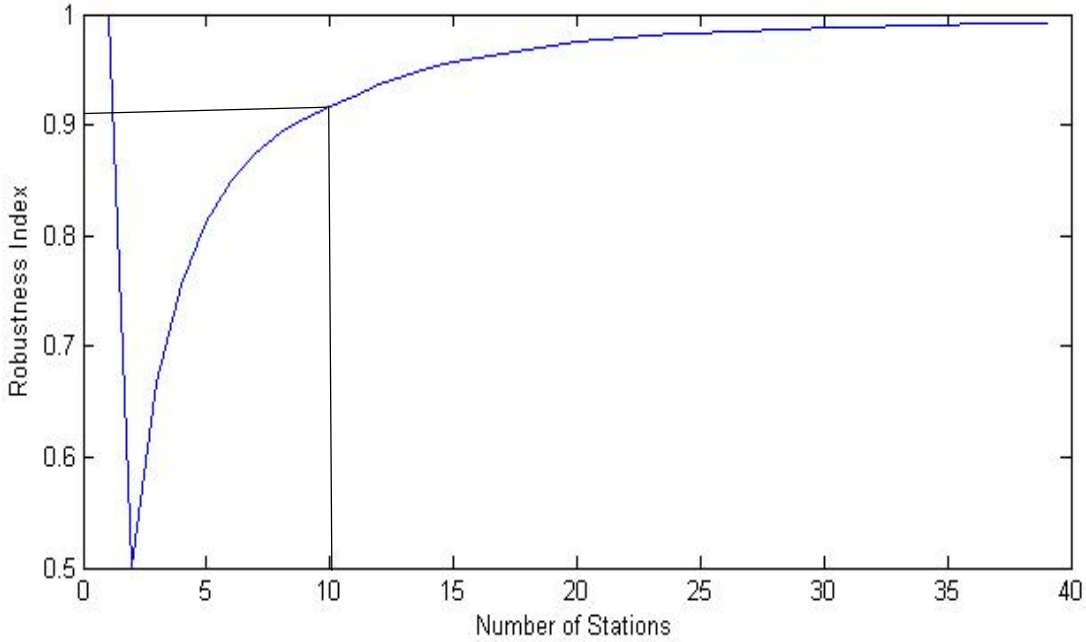


Figure 20. Variation of Robustness Index with Number of Stations

After defining vulnerability and deciding on the desired number of stations to be deployed, the complete optimization problem defined by Equation 12 with all constraints has been solved using a genetic algorithm in MATLAB, as described in Section 3.3 (Appendix E). Figure 21 shows the location of ten ESSs in the Austin District. An RWIS consisting of ten ESSs would cover 94% of total crashes occurring in the region. Recalculation for coverage index and robustness index for new locations suggests that an RWIS will have spatial coverage of 48% and on average remain 92% reliable should one ESS fail.

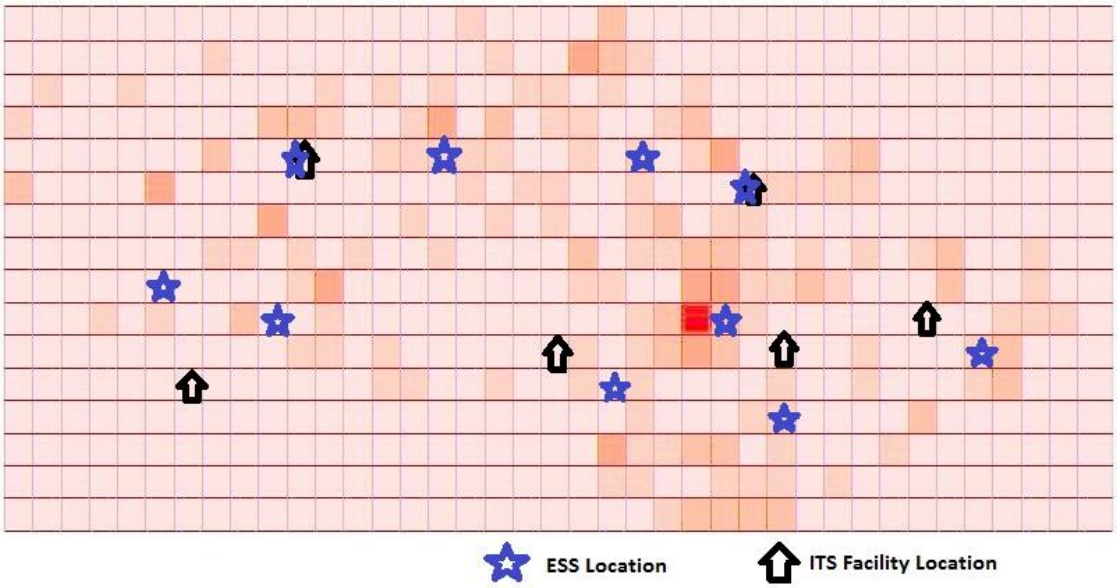


Figure 21. Optimal ESS Locations

4.5 Sensitivity Analysis

There were some assumptions made on the values of parameters during ESS location problem formulation and its implementation. Using the proposed methodology we can predict the effects of change in various parameters on the optimal solution of number of stations and their locations. The effects of change in some of the important parameters are described below:

1) An increase in capital cost or reduction in maintenance cost will increase the significance of the maintenance cost over capital cost for the planning horizon. This will result in optimal sensor locations shifting closer to the nearest ITS facility. Similarly, increasing the planning horizon, say from 5 years to 10 years, will shift optimal sensor locations closer to ITS facilities. For a hypothetical planning horizon of 50 years, six of the 10 sensor locations are located exactly at six ITS facilities (Figure 22). In this case, maintenance cost over 50 years is highly significant compared to the initial capital cost.

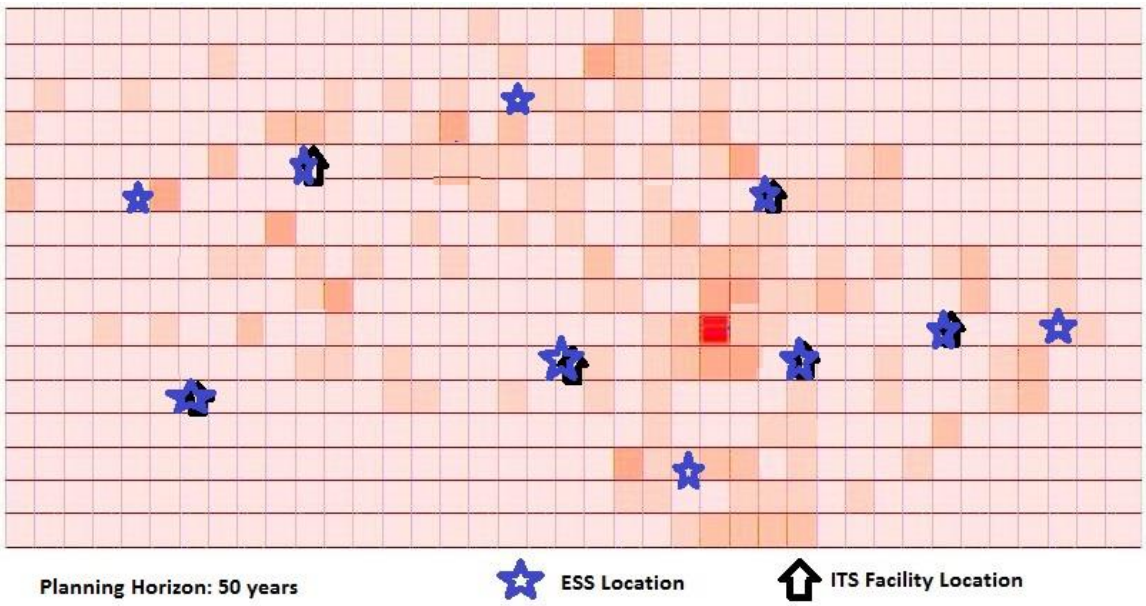


Figure 22. Optimal Station Location for Planning Horizon of 50 Years

2) The range of each ESS is assumed to be 20 miles (50% coverage for 10 miles). If the range of an ESS is decreased (say for a local ESS), more ESSs will be required for the same weather-sensitive crash and spatial coverage. The ESSs will be closer to high weather-sensitive crash areas like downtown.

3) **Virtual nodes formation under data sharing environment:** As the distance between two ESSs is large, it is reasonable to assume that information provided by two ESSs at a location are independent and the station closest to the location has more accurate road and weather information. However, information provided by two ESSs can be

combined to obtain approximate information on road and weather conditions at locations between them. In this scenario, Equation 4 has to be modified to incorporate the effects of more than one station. Stations in a data-sharing environment are expected to be located farther apart than stations considered under the current assumption. Fewer ESSs will be required in data-sharing enviornment for the same weather-sensitive crash and spatial coverage.

4.6 Discussion

Most of the crashes in the Austin District occurred either along the major highways or in the downtown area. Under the assumptions made in Section 4.2, an adverse weather day has been found to have a greater crash rate than a good weather day. Good weather crashes in the Austin District were more predictable over the year than adverse weather crashes. Good weather crashes are mostly those that happen in everyday life due to poor roadway design or other reasons. A crash occurring in adverse weather may or may not have happened due to the weather change. The QQ plot between equivalent good weather crashes and adverse weather crashes shows that the vulnerability of a location for a crash during adverse conditions is different than for normal weather-related crash counts. It is an important aspect for RWISs, as these are the crashes that occur due to changes in weather conditions—and that can actually be reduced using an RWIS.

The benefit-cost ratio decreases with an increase in the number of stations. So marginal change in the benefit-cost ratio with an additional station can be used to decide how much benefit an agency would get if they spent more money for an additional ESS. The results show that ten ESSs would be a good choice to implement in the region and their global optimal locations have been found via the proposed methodology. An RWIS consisting of ten ESSs would cover 94.25% of total crashes occurring in the region. Meanwhile, the RWIS would have spatial coverage of 48%. On average, the system would be 92% reliable should one ESS fail.

Chapter 5. Conclusion and Recommendation

An ESS is the core component of an RWIS in road weather response management. Siting and instrumenting ESSs requires consideration of safety, operations, logistics, maintenance, construction, and environmental factors. A comprehensive optimization methodology has been proposed that seeks the optimal ESS locations at the regional level, aiming to simplify the decision-making in RWIS planning. It consists of discretizing an urban region into cells, identifying the weather-sensitive crash pattern, and then maximizing the total utility of monitoring. The proposed approach is robust and portable for different criteria for different agencies. In addition, the proposed approach is suitable for tackling large-scale problems, e.g., those involving thousands of lane miles. For such problems, approaches based on detailed road-segment-level crash modeling and predictions are simply not practical due to the excessive modeling and calibration efforts needed. Lastly, since a number of DOTs (e.g., Alberta DOT) have already deployed hotspot analysis tools in ESS siting, our approach will be effectively integrated into existing road weather decision-support systems.

Our case study with the Austin District area yielded several insights. First, adverse weather is a significant factor influencing crash rate. Second, the weather-sensitive location identification results show that vulnerable locations are spatially distributed, rather than concentrated, and the vulnerable location distribution is different from the weather-related crash distribution. This finding implies support for the significance of the 'weather-sensitivity' notion. In the end, based on four-year median weather-sensitivity analysis, ESS locations were obtained that provide very good coverage of crash-prone areas as well as the study area as a whole, which demonstrates the usefulness of the proposed approach. It also ensures minimum reliability of RWIS in case of failure of any ESS.

This project laid the basic framework for further analysis that can be done to find better locations for ESSs to form an RWIS on a regional level. Further improvements in the proposed problem formulation and solution can be made to improve the usage of RWISs. This methodology has limitations for identifying ESS locations for local coverage,

such as a bridge ice detection system. Selection of such sites can be best accomplished by a team of local road and weather experts. Due to the lack of available data on spatial terrain, power availability, and ITS facilities, certain assumptions about weather conditions were made for the study, as Section 4.2 outlines.

Due to the lack of any established research, another important assumption made in this study was that an ESS would have a linearly decreasing impact on reducing the crash pattern in its neighborhood. More research on the impact of RWIS on crash patterns is needed to fully understand how ESSs help to improve safety and mobility. First, evaluating the value of ESS in the broader context of traveler information systems is a necessary step. This will require detailed considerations of driver perception and behavioral changes. Second, considering the operations cost, an agency partnership and information sharing will be essential. Finally, fusing data from alternative sources (e.g., NOAA weather record and Google traffic data) will help to compensate for the missing data issue encountered in this study.

Appendices

Appendix A. EXCEL VBA CODE FOR AUSTIN DISTRICT DATA PROCESSING

```
Sub SelectedCounties()
Dim myarray() As Variant, path As String, curdir As String
Dim rng As Range
myarray = Array("11", "16", "27", "28", "86", "105", "144", "150", "157", "227", "246")
curdir = ActiveWorkbook.path & "\"
Dim projest As Workbook
For i = 1 To 5
path = curdir & 2009 + i & "_allDistrict"
Set projest = Application.Workbooks.Open(path)
Range("a1:g1").Select
Selection.AutoFilter Field:=3, Criteria1:=myarray, Operator:=xlFilterValues
Set rng = Application.Intersect(ActiveSheet.UsedRange, Range("A1:G700000"))
rng.SpecialCells(xlCellTypeVisible).Select
Selection.Copy
Workbooks.Add
ActiveWorkbook.Worksheets(1).Paste
ActiveWorkbook.SaveAs curdir & 2007 + i & ".csv"
ActiveWorkbook.Close SaveChanges = True
projest.Close SaveChanges = False
Next i
End Sub
```

Appendix B. MATLAB CODE FOR COMPUTING CRASH RATE IN CELL

```
ncol = 7;
% temp declaring good and adverse crashes
goodcrash2010= zeros(1,ncol);goodcrash2011= zeros(1,ncol);goodcrash2012=
zeros(1,ncol);goodcrash2013= zeros(1,ncol);
badcrash2010= zeros(1,ncol);badcrash2011= zeros(1,ncol);badcrash2012=
zeros(1,ncol);badcrash2013= zeros(1,ncol);

crash2010 = xlsread('./Austin District crashes/2010.xlsx');
crash2011 = xlsread('./Austin District crashes/2011.xlsx');
crash2012 = xlsread('./Austin District crashes/2012.xlsx');
crash2013 = xlsread('./Austin District crashes/2013.xlsx');
total_years = 4;
% Rwis crash data processing
total_crash = {crash2010,crash2011,crash2012,crash2013};
good_crash = {goodcrash2010,goodcrash2011,goodcrash2012,goodcrash2013};
bad_crash = {badcrash2010,badcrash2011,badcrash2012,badcrash2013};

tname = ['2010'; '2011'; '2012';'2013';'2010'; '2011'; '2012';'2013'];
name = cellstr(tname);ndays = zeros(1,total_years);
bad = zeros(1,total_years);

for i= 1:total_years
   k = 1;kk=1;
   rows = size(total_crash{i});
   nrow = rows(1);
   curyear = total_crash{i};
   for j = 1:nrow
```

```
        if curyear(j,2) == 1 || curyear(j,2) == 11 || curyear(j,2) == 12
            good_crash{i}(k,:) = curyear(j,:);
            k = k+1;
        else
            bad_crash{i}(kk,:) = curyear(j,:);
            kk = kk+1;
        end
    end
end

% define Origin
% X = Long Y= Lat % long(.9-.64)= 15.531 miles  %lat (.5-.225) =
% 19.011 miles
% Per Long = 59.7346 miles && Per Lat = 69.1309 Miles
perlat = 69.1309; perlong = 59.7346;
origin_long = -99.5;
origin_lat = 29.70;
oppCorner_long = -96.7;
oppCorner_lat= 31;

%define width and height of grid in Miles
gridsize = 5;
width_long = gridsize/perlat;
width_lat = gridsize/perlong;
% number of cells along x-axis and y-axis
ncells_long = round((oppCorner_long - origin_long)/width_long);
ncells_lat = round((oppCorner_lat - origin_lat)/width_lat);
a= zeros(ncells_long,ncells_lat);
```

```
AADT_type ={a,a,a,a,a,a,a;a,a,a,a,a,a,a;a,a,a,a,a,a,a;a,a,a,a,a,a,a};
AADT_type_count ={a,a,a,a,a,a,a;a,a,a,a,a,a,a;a,a,a,a,a,a,a;a,a,a,a,a,a,a};
for n = 1:total_years
   current_crash = total_crash{n};
   temp1 = size(current_crash);
   nrow = temp1(1);
   current_crash = sortrows(current_crash,6);
   crash_count = zeros(ncells_long,ncells_lat);
   k = 1;
   active =0;

   for i=1:nrow

      if (origin_long + (k-1) * width_long <= current_crash(i,6) &&  current_crash(i,6) <
origin_long + k * width_long)
         active =1;

         for j = 1:ncells_lat
            if(origin_lat + (j-1) * width_lat <= current_crash(i,5) && current_crash(i,5) <
origin_lat + (j) * width_lat );
               if isnan(current_crash(i,7))
               else
                  AADT_type{n,current_crash(i,4)}(k,j)=
AADT_type{n,current_crash(i,4)}(k,j) + current_crash(i,7);
                  AADT_type_count{n,current_crash(i,4)}(k,j)=
AADT_type_count{n,current_crash(i,4)}(k,j) + 1;
               end

            end
```

```
            end
        else
            if active == 1 && k < ncells_long
                k = k+1;
            end
        end
    end

end
%}
AADT_avg ={a,a,a,a,a,a,a;a,a,a,a,a,a,a;a,a,a,a,a,a,a;a,a,a,a,a,a,a};
for i = 1:4
    for j = 1:7
        for k =1:ncells_long
            for l = 1:ncells_lat
                AADT_avg{i,j}(k,l) = AADT_type{i,j}(k,l)/AADT_type_count{i,j}(k,l);
            end
        end
    end
end
%%% for good weather crashes
for n = 1:total_years *2
    % current_crash = total_crash{n};
    if n <= total_years
        current_crash = good_crash{n};
        n1=n;
    else
        current_crash = bad_crash{n-total_years};
```

```
    n1= n- total_years;
end

temp1 = size(current_crash);
nrow = temp1(1);
%display(nrow)
% Sort based on longitude for a faster algorithm
current_crash = sortrows(current_crash,6);
crash_count = zeros(ncells_long,ncells_lat);
k = 1;
% active =0;
for i=1:nrow

    if (origin_long + (k-1) * width_long <= current_crash(i,6) &&  current_crash(i,6) <
origin_long + k * width_long)
        for j = 1:ncells_lat
            if(origin_lat + (j-1) * width_lat <= current_crash(i,5) && current_crash(i,5) <
origin_lat + (j) * width_lat );

                if current_crash(i,4) == 1
                    if ~isnan(AADT_avg{n1,1}(k,j))
                        crash_count(k,j) = crash_count(k,j) + 100000/ AADT_avg{n1,1}(k,j);
                    else
                        crash_count(k,j) = crash_count(k,j) + 100000/135000;
                    end
                elseif current_crash(i,4) ==2

                    if ~isnan(AADT_avg{n1,2}(k,j))
                        crash_count(k,j) = crash_count(k,j) + 100000/ AADT_avg{n1,2}(k,j);
```

```
                else
                    crash_count(k,j) = crash_count(k,j) + 100000/47000;
                end
            else
                if ~isnan(AADT_avg{n1,3}(k,j))
                    crash_count(k,j) = crash_count(k,j) + 100000/ AADT_avg{n1,3}(k,j);
                else
                    crash_count(k,j) = crash_count(k,j) + 100000/21500;
                end
            end
            break;
        end
    end

    else
        if k < ncells_long
            k = k+1;
        end
    end
end

if n ==1
    goodcrashcount2010 = crash_count;
elseif n==2
    goodcrashcount2011 = crash_count;
elseif n==3
    goodcrashcount2012 = crash_count;
elseif n==4
```

```
        goodcrashcount2013 = crash_count;
    % Bad crashcount
    elseif n==5
        badcrashcount2010 = crash_count;
    elseif n==6
        badcrashcount2011 = crash_count;
    elseif n==7
        badcrashcount2012 = crash_count;
    else
        badcrashcount2013 = crash_count;
    end
end
```

Appendix C. MATLAB CODE FOR CALCULATING VULNERABILITY

```
Ngoodcrashcount2010 = goodcrashcount2010 * 365 / good(1,1);
Ngoodcrashcount2011 = goodcrashcount2011 * 365 / good(1,2);
Ngoodcrashcount2012 = goodcrashcount2012 * 365 / good(1,3);
Ngoodcrashcount2013 = goodcrashcount2013 * 365 / good(1,4);

Nbadcrashcount2010 = badcrashcount2010 * 365 / bad(1,1);
Nbadcrashcount2011 = badcrashcount2011 * 365 / bad(1,2);
Nbadcrashcount2012 = badcrashcount2012 * 365 / bad(1,3);
Nbadcrashcount2013 = badcrashcount2013 * 365 / bad(1,4);

Ngood_crashcount =
{Ngoodcrashcount2010,Ngoodcrashcount2011,Ngoodcrashcount2013};
Nbad_crashcount =
{Nbadcrashcount2010,Nbadcrashcount2011,Nbadcrashcount2012,Nbadcrashcount2013};
Nyears = total_years;
for k = 1:Nyears
   diff_crash1{k} = (Nbad_crashcount{k}- Ngood_crashcount{k});
end
crash_mod = zeros(ncells_long,ncells_lat);
crash_median = zeros(ncells_long,ncells_lat);
for i = 1: ncells_long
   for j = 1:ncells_lat
      temp5=0;
      temp4 = zeros(Nyears,1);
      for k = 1: Nyears
         temp5 = temp5 + (diff_crash1{k}(i,j)*diff_crash1{k}(i,j));
         temp4(k) = diff_crash1{k}(i,j);
```

```
        end
        crash_mod(i,j) = sqrt(temp5);
        temp4 = sort(temp4);
        if rem((Nyears),2) == 0
            crash_median(i,j) = temp4((Nyears)/2)+ temp4((Nyears)/2+1);
        else
            crash_median(i,j)= temp4(round((Nyears)/2));
        end
    end
end
name = cellstr(tname);
cmin = min([min(min(Ngood_crashcount{1})) min(min(Ngood_crashcount{2}))
min(min(Ngood_crashcount{3})) min(min(Ngood_crashcount{4})) ]);
cmax = max([max(max(Ngood_crashcount{1})) max(max(Ngood_crashcount{2}))
max(max(Ngood_crashcount{3})) max(max(Ngood_crashcount{4})) ]);
cmin1 = min([min(min(Nbad_crashcount{1})) min(min(Nbad_crashcount{2}))
min(min(Nbad_crashcount{3})) min(min(Nbad_crashcount{4})) ]);
cmax1 = max([max(max(Nbad_crashcount{1})) max(max(Nbad_crashcount{2}))
max(max(Nbad_crashcount{3})) max(max(Nbad_crashcount{4})) ]);
for n = 1:Nyears *2
% figure();
    if n <= Nyears
        h = surf(Ngood_crashcount{n}); colorbar; caxis([cmin cmax]);axis tight; axis equal;
    else
         h = surf(Nbad_crashcount{n-Nyears}); colorbar;caxis ([cmin1 cmax1]);axis tight;
axis equal;
    end
view([-89 -90]);
title({name{n};''});
if n <= Nyears
```

```
saveas(h,sprintf('Ngoodcrash%d.jpg', n));
xlswrite('myFile.xlsx',Ngood_crashcount{n},sprintf('sheet%d', n));
else
   nn = n - Nyears;
   saveas(h,sprintf('NAdversecrash%d.jpg', nn));
   xlswrite('myFile.xlsx',Nbad_crashcount{n-Nyears},sprintf('sheet%d', n));
end
end
cmin = min([min(min(diff_crash1{2})) min(min(diff_crash1{3}))
min(min(diff_crash1{4})) min(min(diff_crash1{5}))]);
cmax = max([max(max(diff_crash1{1})) max(max(diff_crash1{2}))
max(max(diff_crash1{3})) max(max(diff_crash1{4})) max(max(diff_crash1{5}))]);

for n = 1:Nyears
% figure();
h = surf(diff_crash1{n}); colorbar;caxis([cmin cmax]);axis tight; axis equal;view([-89 -
90]); title({name{n};''});
saveas(h,sprintf('Vulnerability%d.jpg', n));
end

h = surf(crash_mod); colorbar; view([-89 -90]);axis tight; axis equal;
title({'Vulnerability point distance from origin';''});
saveas(h,sprintf('crash_mod.jpg'));
xlswrite('myFile.xlsx',crash_mod,sprintf('sheet%d', n+1));

h = surf(crash_median); colorbar; view([-89 -90]);axis tight; axis equal;
title({'Median Vulnerability over years ';''});
saveas(h,sprintf('crash_median.jpg'));
xlswrite('myFile.xlsx',crash_median,sprintf('sheet%d', n+2));
```

Appendix D. MATLAB CODE FOR FINDING OPTIMAL NUMBER OF STATIONS

```
% BENEFIT FUNCTION
% Assuming Linear Range Function
% Location_Rwis is a n * 2 vaectors where n is number of station deployed,
% location is in the terms of cell number
function B = Benefit_rwis(Location_Rwis)
% Range of RWIS
global crash_median ncells_long ncells_lat gridsize;
range1 = 20/gridsize;
nRwis = size(Location_Rwis,1);
B = 0;
Eff = ones(ncells_long,ncells_lat);
if nRwis ~= 0

dist = range1 * ones(ncells_long,ncells_lat);
for  i= 1 : ncells_long
   for j = 1:ncells_lat
      for k = 1 : nRwis
         temp1 = sqrt((Location_Rwis(k,1)-i)^2 + (Location_Rwis(k,2)-j)^2);
                  if temp1 < dist(i,j)
            dist(i,j) = temp1;
         end
      end

      if dist(i,j) < range1
         B = B + EFF(i,j) * crash_median(i,j) * (1 - dist(i,j)/range1);
```

```
        end
    end
end
end
end


% Cost function
function C = Cost_rwis(Location_Rwis)
% fixed cost on installing one Rwis
% Maintaince cost per unit miles during one planninf Horizon

global Location_ITS nITS ii gridsize;

fixedcost = 50000;
MC = 500*ii/gridsize;

%C = 0;
nRwis = size(Location_Rwis,1);
if nRwis ~= 0
C = nRwis * fixedcost;
dist = ones(nRwis,1)*10000000;

%display(nITS)
for i = 1:nRwis
    temp = 100000000000;
    for j= 1:nITS
```

```
        temp = sqrt((Location_Rwis(i,1)-Location_ITS(j,1))^2+(Location_Rwis(i,2)-
Location_ITS(j,2))^2);
        %display(temp);
        if temp < dist(i)
            dist(i) = temp;
        end
    end
    %display(dist(i));
    C = C + MC * dist(i);
    %display(C);
end

C = C / ii;
%display(nRwis);
end

end

% Coverage Index
function coverageindex = Coverage_rwis(Location_Rwis)
global ncells_long ncells_lat gridsize;
nRwis = size(Location_Rwis,1);
range2 = 30/gridsize; % expressed in terms of cells unit

Cover = 0;
if nRwis == 0
else
dist = range2 * ones(ncells_long,ncells_lat);
```

```
for  i= 1 : ncells_long
   for j = 1:ncells_lat
      temp1 = 0;
      for k = 1 : nRwis
         temp1 = sqrt((Location_Rwis(k,1)-i)^2 + (Location_Rwis(k,2)-j)^2);
         if temp1 < dist(i,j)
            dist(i,j) = temp1;
         end
      end
      if dist(i,j) < range2
         Cover = Cover +  (1 - dist(i,j)/range2);
      end
   end
end
coverageindex = Cover/(ncells_lat*ncells_long);
end
end

% Robustness Index
% Robustness of system
%global nRwis crash_median ncells_long ncells_lat

function RobustnessIndex = Robustness_total(Location_Rwis)

nRwis = size(Location_Rwis,1);
RobustnessIndex = 0;
if nRwis == 1
RobustnessIndex = 1; % in reality it should be zero
```

```
elseif nRwis ~= 0

RobustnessIndex = 0;
Original_Location = Location_Rwis;
for i = 1:nRwis
   Location_Rwis(i,:) = [];
   RobustnessIndex = RobustnessIndex +
Benefit_rwis(Location_Rwis)/Benefit_rwis(Original_Location);
   Location_Rwis = Original_Location;
end
end

RobustnessIndex = RobustnessIndex / nRwis;

end

% List of facilities here
global nITS Location_ITS
nITS = 6;

Location_ITS = [
   7 5;
   11 11;
   10 6;
   27 10;
   28 6;
   33 7;
   ];
```

```
% Sequential Algorithm for finding locations
% Sequqntial Algorithm
x = zeros(ncells_long, ncells_lat);
alpha1 = 0; alpha2 = 1; % lower and upper bound on coverage
beta1 = 0; beta2 = 1; % lower and upper bound on robustness


Location = [];
maxBenefit_rwis = ones(nRwis,1)*(-1000000);
Location_sol = [];
kk = 1;
for k = 1 : nRwis
%     if k > 5
%         alpha1 = 0.01; alpha2 = 1; % lower and upper bound on coverage
%         beta1 = 0.6; beta2 = 1; % lower and upper bound on robustness
%     end
      for i = 1:ncells_long
         for j = 1:ncells_lat
            temp = 0;
            proceed1 = false;
            Location(kk,:) = [i j];
            tempCoverage_rwisindex = Coverage_rwis(Location);

            if tempCoverage_rwisindex >= alpha1 && tempCoverage_rwisindex <=
alpha2
               temprobustindex = Robustness_rwis(Location);
```

```
            for p = 1:kk
                if temprobustindex(p)>= beta1 && temprobustindex(p) <= beta2
                    proceed1 = true;
                end
            end
        end

        if proceed1 == 1

            if Cost_rwis(Location) ~= 0
                temp = Benefit_rwis(Location)/Cost_rwis(Location);
            end
            if maxBenefit_rwis(kk) < temp
                maxBenefit_rwis(kk) = temp;
                Location_sol(kk,:) = [i j];
            end
        end
    end
end
if size(Location,1) ~= size(Location_sol,1)
    Location(kk,:) = [];
    %display(kk);        display('fail');
    break
else
    %display(size(Location,1));
    %display(size(Location_sol,1));
    Location(kk,:) = Location_sol(kk,:);
    kk = kk + 1;
```

```
        end
end

for k = 1:kk-1
    x(Location_sol(k,1),Location_sol(k,2)) = 1;
end
%end
```

Appendix E. MATLAB GENETIC ALGORITHM CODE FOR OPTIMAL STATION LOCATION

```
% Genetic Algorithm objective function in MATLAB is designed for minimization.
Negative of our Benefit-cost ratio has been defined as objective function here

function rwisvalue = rwis(x)

global crash_median lambda ncells_long ncells_lat;

dist1 = ones(ncells_long,ncells_lat)*1000000000000000000000000000000000000;

disttemp = ones(ncells_long,ncells_lat)*1000000000000000000000000000000000000;

rwisvalue = 0;

Eff =1;

for i = 1:ncells_long

   for j = 1:ncells_lat

      kk=1;

         for k = ncells_long * ncells_lat

           if x(k) ~=0

              lat1 = floor(k./ncells_long)+1;

              long1 = mod(k,ncells_long);     if long1 ==0 long1 = ncells_long; lat1 = lat1-
1; end

              disttemp(i,j) = sqrt((long1-i)*(long1-i) + (lat1-j)* (lat1-j));

               if kk == 1

                   dist1(i,j)= disttemp(i,j);

               else

                     if disttemp(i,j) < dist1(i,j)

                     dist1(i,j) = disttemp(i,j);

                     end

               end

               kk = kk+1;

           end
```

```
        end
    rwisvalue = rwisvalue - crash_median(i,j) * Eff * crash_median(i,j) * (1 -
dist(i,j)/range1);
end
end
end
%non linear constraints

function [c,ceq] = NonLinearCons_rwis(x)
global ncells_long ncells_lat

alpha1 = 0.3; alpha2 = 1;
beta1 = 0.5; beta2 = 1;
temp = zeros(1,2);
k =1;
for i = 1 : ncells_long
  for j = 1:ncells_lat
    if x(i+(j-1)*ncells_long) == 1
    temp(k,:) = [i j];
    k = k +1;
    end
  end
end
tempCoverage_rwisindex = Coverage_rwis(temp);
temprobustindex = Robustness_rwis(temp);

c = [alpha1 - tempCoverage_rwisindex; tempCoverage_rwisindex - alpha2; beta1 -
temprobustindex; temprobustindex - beta2];
ceq = [];
```

```
end
global crash_median lambda ncells_long ncells_lat;
nvar = ncells_long * ncells_lat;
lb= zeros(1,nvar);
ub = ones (1,nvar);
a= ones(1,nvar); b = 5;
aa =[1:1:nvar];
lambda = 0.08;

option = gaoptimset('InitialPopulation',x,CrossoverFraction, 0.8000,MutationFcn,
{[@mutationgaussian]  [1]  [1]});
optimal_location = ga(@rwis, nvar,a,b,[],[],lb,ub,[],aa,@ NonLinearCons_rwis);
optimal_location_temp = optimal_location;
for i = 1:50
option = gaoptimset('InitialPopulation',optimal_location,CrossoverFraction,
0.8000,MutationFcn, {[@mutationgaussian]  [1]  [1]});
optimal_location = ga(@rwis, nvar,a,b,[],[],lb,ub,[],aa, NonLinearCons_rwis);
if rwis(optimal_location) < rwis(optimal_location_temp)
   optimal_location_temp = optimal_location;
end
end
  % repeat above function for other inputs
   optimal_location= optimal_location_temp;

dd=1;
answe = zeros(ncells_long,ncells_lat);
for k = 1: ncells_long * ncells_lat
                lat1 = floor(k./ncells_long)+1;
```

```
            long1 = mod(k,ncells_long);     if long1 ==0 long1 = ncells_long; lat1 = lat1-
1; end
            answe(long1,lat1)= optimal_location(k);
            if optimal_location(k) > 0
               lo(dd)= long1;
               la(dd)= lat1;
               dd=dd+1;
            end
end
h = surf(answe); colorbar;  view([-89 -90]);
```

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