Development and Evaluation of Models and Algorithms for Locating RWIS Stations

by

Tae-Jung Kwon

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Accurate and timely information on road weather and surface conditions in winter seasons is a necessity for road authorities to optimize their winter maintenance operations and improve the safety and mobility of the traveling public. One of the primary tools for acquiring this information is road weather information systems (RWIS). While effective in providing real-time and near-future information on road weather and surface conditions, RWIS stations are costly to install and operate, and therefore can only be installed at a limited number of locations. To tackle this challenging task, this thesis develops various different approaches in an attempt to determine the optimal location and density over a regional highway network. The main research findings are summarized as follows.

First, a heuristic surrogate measure based method (SM) has been developed. Two types of location ranking criteria are proposed to formalize various processes utilized in the current practice, including weather and traffic related factors. Consideration of these two types of factors captures the needs to allocate RWIS stations to the areas with the most severe weather conditions and having the highest number of traveling public. A total of three location selection alternatives are generated and used to evaluate the current Ontario RWIS network. The findings indicate that the current RWIS network is able to provide a reasonably good coverage on all location criteria considered.

Second, a cost-benefit based method (CB) has been proposed to give an explicit account of the potential benefits of an RWIS network in its location and density planning. The approach has been constructed on a basis of a sensible assumption that a highway section covered by an RWIS station is more likely to receive better winter road maintenance (WRM) operations. A case study based on the current RWIS network in Northern Minnesota show that the highest projected 25-year net benefits are approximately $6.5 million with cost-benefit ratio of 3.5, given the network of 45 RWIS stations.

Third, a more comprehensive and innovative framework has been developed by using the weighted sum of average kriging variance of winter road weather conditions. Methodologically, the formulation of the RWIS location optimization problem is foundational with several unique features, including explicit consideration of spatial correlation of winter road weather conditions and high travel demand coverage. The optimization problem is then formulated by taking into account the dual criteria representing the value of RWIS information for spatial inferences and travel demand distribution. The spatial simulated annealing (SSA) algorithm was employed to solve the combinatorial optimization

problem ensuring convergence. A case study based on four study regions covering one Canadian province (Ontario), and three US states (Utah, Minnesota, and Iowa) exemplified two distinct scenarios –redesign and expansion of the existing RWIS network. The findings indicate that the method developed is very effective in evaluating the existing network and delineating new site locations.

Additional analyses have been conducted to determine the spatial continuity of road weather conditions and its relation to the desirable RWIS density based on the case study results of the four study areas. Road surface temperature (RST) was used as a variable of interest, and its spatial structure for each region was quantified and modelled via semivariogram. The findings suggest that there is a strong dependency between the RWIS density and the autocorrelation range - the regions with less varied topography tend to have a longer spatial correlation range than the region with more varied topography.

The approaches proposed and developed in this thesis provide alternative ways of incorporating key road weather, traffic, and maintenance factors into the planning of an RWIS network in a region. Decision on which alternative to use depends on availability of data and resources. Nevertheless, all approaches can be conveniently implemented for real-world applications.

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Lastly, I would like to devote this thesis to my beautiful wife, YongBin Lee, for her greatest love and sacrifice in making this thesis possible, and my two adorable children, Chelsea Chae-Yeon and Brandon Hun-Yule, for making my life enjoyable and delightful.

Dedication

오늘의 이 작은 결실을 맺기까지 자식을 위하여 모든 것을 희생하여 주신 존경하는 부모님, 하늘에서 누구보다 기뻐하실 장인장모님, 끝으로 항상 사랑과 희생으로 옆에서 내조하여 준 아내에게 이 논문을 바칩니다.

To My Parents, JoongDal Kwon and ChulJae Jung,

To My Wife, YongBin Lee,

To My Children, Chelsea and Brandon

&

In Memory of My Parents-In-Law, WanJin Jang and MyungRae Lee

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List of Acronyms

AADT	Annual Average Daily Traffic
ASE	Average Standard Error
BLUE	Best Liner Unbiased Estimator
BPRT	Bare-Pavement Regain Time
CB	Cost-benefit
CPU	Central Processing Unit
DDS	Dynamically Dimensioned Search
DEM	Digital Elevation Model
DFLP	Discrete Facility Location Problems
DMS	Dynamic Message Sign
DOT	Department of Transportation
ESS	Environmental Sensor Stations
FFS	Free Flow Speed
FHWA	Federal Highway Administration
GA	Genetic Algorithm
GIS	Geographic Information System
HC	Highway Class
HRSC	Hazardous Road Surface Conditions
HT	Highway Type
KED	Kriging with External Drift
LHRS	Linear Highway Referencing System
MSE	Mean Standardized Errors
MST	Mean Surface Temperature
MTO	Ministry of Transportation Ontario
MVKT	Million Vehicle Kilometers Travelled
NIP	Non-linear Integer Programming
NPV	Net Present Value
NWS	National Weather Service
OATD	One At a Time Design
OK	Ordinary Kriging

POM	Percent Of Matching
RDR	RWIS Deficient Region
RK	Regression Kriging
RMSE	Root Mean Square Error
RSC	Road Surface Condition
RST	Road Surface Temperature
RPU	Remote Processing Unit
RWIS	Road Weather Information System
SSA	Spatial Simulated Annealing
SA	Simulated Annealing
SI	Spatial Inference
SK	Simple Kriging
SM	Surrogate Measure
SWE	Snow Water Equivalent
TM	Thermal Mapping
TS	Tabu Search
UK	Universal Kriging
VST	Variability of Surface Temperature
WADT	Winter Average Daily Traffic
WAR	Winter Accident Rate
WRM	Winter Road Maintenance

Chapter 1
INTRODUCTION

1.1 Background

During winter months, many regions in the US and Canada often experience a high frequency of inclement weather events, which can have a detrimental impact on the safety and mobility of motorists. Generally, road collision rates increase dramatically during inclement weather conditions due to degradation of visibility and traction on the roadway. A study by Goodwin (2002) indicated that in the United States, more than 22% of total collisions occurred during winter weather conditions, while a study by Qiu and Nixon (2008 a) revealed that snow storms would increase the collision rate by 84%. Ontario Road Safety Annual Reports (MTO, 2001-2010) show that vehicle collisions occurring during wet, slushy, snowy, and icy conditions accounted for up to 27.5% of total collisions. Wallman (2004) found that the average collision rate during a winter season would be 16 times higher in black ice conditions than in dry road conditions.

There is also extensive evidence showing that inclement winter events can significantly affect traffic mobility. A study by Liang et al. (1998) found that snow events would reduce the average operating speed by 18.13 km/hr, while Kyte et al. (2001) showed that snow could cause up to 50% reduction in speed. A comprehensive analysis by Agarwal et al. (2005) indicated that snow events at various severity levels caused 4.29-22.43% and 4.17-13.46% reductions in capacity and average operating speed, respectively. More recently, [1]Kwon and Fu (2011) and [2]Kwon et al. (2013) confirmed that winter weather events could negatively affect the mobility of road users; they established an empirical relationship between road conditions, and capacity and free-flow-speed (FFS) of urban highways. Their findings indicate that slippery roads can reduce the capacity and FFS by 44.24% and 17.01%, respectively. In general, snow storms that typically result in poor road conditions are strongly related to high collision rates, reduced roadway capacity, and reduced vehicle speed (Wallman and Åström, 2001; Datla and Sharma, 2008).

[1] Kwon, T.J., and Fu, L. (2011). Effect of Inclement Weather Conditions on Macroscopic Traffic Behavior. Paper presented at the 9th International Transportation Specialty Conference, *Canadian Society for Civil Engineering*, Edmonton, AB., 2011.

[2] Kwon, T.J., Fu, L., and Jiang, C. (2013). Effect of Winter Weather and Road Surface Conditions on Macroscopic Traffic Parameters. accepted for publication in *Transportation Research Record*: Journal of the Transportation Research Board, National Research Council. Washington D.C.

To minimize these safety and mobility impacts caused by winter weather events, an effective snow and ice control program is required to deliver various winter road maintenance services such as snow plowing, sanding, and salting. Not only can efficient and effective winter road maintenance programs reduce the risk of vehicle collisions but they can also vitalize and promote traffic movement. Fu et al. (2005) and Usman et al. (2012) showed with strong statistical evidence that lower rates of collisions on roads are associated with better road surface conditions that could result from improved winter maintenance operations such as anti-icing, pre-wetting, and sanding. Qiu and Nixon (2008) explored direct and indirect causal effects of adverse weather and winter maintenance actions on mobility in the context of traffic speed and volume. Their findings confirmed that plowing and salting operations have significant positive effects on increasing the speed at which it is safe to drive.

While winter road maintenance is indispensable, it entails substantial financial costs and environmental damage. North American transportation authorities, for instance, expend more than $3-billion annually on winter road maintenance activities such as doing snow removal and applying salt and other chemicals for ice control (Ye et al., 2009; Highway Statistics Publications, 2005). Use of these chemicals has become an increasing environmental concern because they could contaminate the ground and surface water, damage roadside vegetation, and corrode infrastructures and vehicles. To reduce the costs of winter road maintenance and the use of salts, many transportation agencies are seeking ways to optimize their winter maintenance operations and improve the safety and mobility of the traveling public.

One approach to improving the decision-making process for road maintenance is to make use of real-time information (i.e., for monitoring the current road conditions) and forecasts (i.e., for predicting the near-future road conditions) through utilization of innovative technologies such as road weather information systems (RWIS). This thesis is particularly concerned with a problem of locating RWIS stations in such a way that the benefits to maintenance personnel and road users can be maximized.

1.2 Road Weather Information Systems (RWIS)

RWIS can be defined as a combination of advanced technologies that collect, transmit, process, and disseminate road weather and condition information to help winter road maintenance (WRM) personnel make timely and proactive winter maintenance decisions. The system collects data using environmental sensor stations (ESS), and nowcast and forecast roadway-related weather and surface conditions.

Implementation of this information not only enables the use of cost-effective WRM but also helps motorists make more informed decisions for their travel.

There are two types of RWIS ESS (hereafter referred to as RWIS station as they are being used interchangeably), namely, stationary and mobile. A stationary RWIS station is installed in situ within or along a roadway and collects data at a fixed location, while a mobile RWIS station is installed on a patrol vehicle and collects data as it travels along the road network. Due to their different data collection mechanisms, the stationary system provides high temporal but low spatial coverage, while the mobile provides low temporal but high spatial coverage. Therefore, the information collected on road conditions between RWIS stations must be interpolated and/or generated using other sources (Ye et al., 2009). An RWIS station discussed in this thesis connotes a stationary station, which typically consists of atmospheric, pavement, and/or water-level monitoring sensors that constantly (every 10-15 min) collect road weather and surface conditions measurements. Furthermore, each RWIS station reports road surface condition status based on current observations: areas that experience hazardous road surface conditions (HRSC), which include snow/ice warning, ice warning, wet below freezing, and frost, are flagged for a prompt remedial winter maintenance action, as summarized in Table 1-1.

An RWIS generally consists of pavement and atmospheric sensors, remote processing units (RPU), central processing units (CPU), and communication hardware (e.g., wired and wireless) as depicted in Figure 1-1. The most visible components of stationary RWIS are roadside towers equipped with an RPU, to which pavement and atmospheric sensors are connected. Measurements from a typical RWIS station include but are not limited to air and pavement temperatures; wind speed and direction; (sub)surface temperature and moisture; precipitation type, intensity and accumulation; visibility; dew point; relative humidity; and atmospheric pressure (Manfredi et al., 2008). While not commonly included as part of an RWIS station, water level sensors are deployed in flood-prone areas to monitor site-specific characteristics and conditions. Some stations are also equipped with live webcams to provide information on conditions at the sensor location. These measurements from RPU can be made available directly via a dynamic message sign (DMS) to alert road users of any hazardous road conditions, and/or transmitted to a server where all data from remote locations are processed, compiled, and sent to the end users. Forecasting services from external sources may be combined with the RWIS data to generate short-term road surface temperature and condition forecasts. RWIS data can also be accessed directly by maintenance personnel via, for instance, web interface for monitoring and analyzing real-time site-specific road conditions and trends, and acquiring the latest forecasts.

Table 1-1: RWIS Surface Condition Status Definition (adopted from Mn/DOT SCAN Web, 2015)

Surface Condition Status	Description
Snow/Ice Warning	Continuous film of ice and water mixture at or below freezing (32ºF / 0ºC) with insufficient chemical to keep the mixture from freezing
Ice Warning	Continuous film of ice and water mixture at or below freezing (32ºF / 0ºC) with insufficient chemical to keep the mixture from freezing
Wet Below Freezing	Moisture on pavement sensor with a surface temperature below freezing (32ºF / 0ºC)
Frost	Moisture on pavement at or below freezing (32ºF / 0ºC) with a pavement temperature at or below the dew point temperature
Ice Watch	Thin or spotty film of moisture at or below freezing (32ºF / 0ºC)
Snow/Ice Watch	Thin or spotty film of moisture at or below freezing (32ºF / 0ºC)
Chemical Wet	Continuous film of water and ice mixture at or below freezing (32ºF / 0ºC) with enough chemical to keep the mixture from freezing
Wet	Continuous film of moisture on the pavement sensor with a surface temperature above freezing (32ºF / 0ºC)
Damp	Thin or spotty film of moisture above freezing (32ºF / 0ºC).
Trace Moisture	Thin or spotty film of moisture above freezing (32ºF / 0ºC). Surface moisture occurred without precipitation being detected.
Absorption at Dew Point	Currently not detected
Dry	Absence of moisture on the surface sensor
Other	Conditions not explicitly included in this table
No Report	The surface sensor is not operating properly and requires maintenance
Error	The surface sensor is not operating properly and requires maintenance

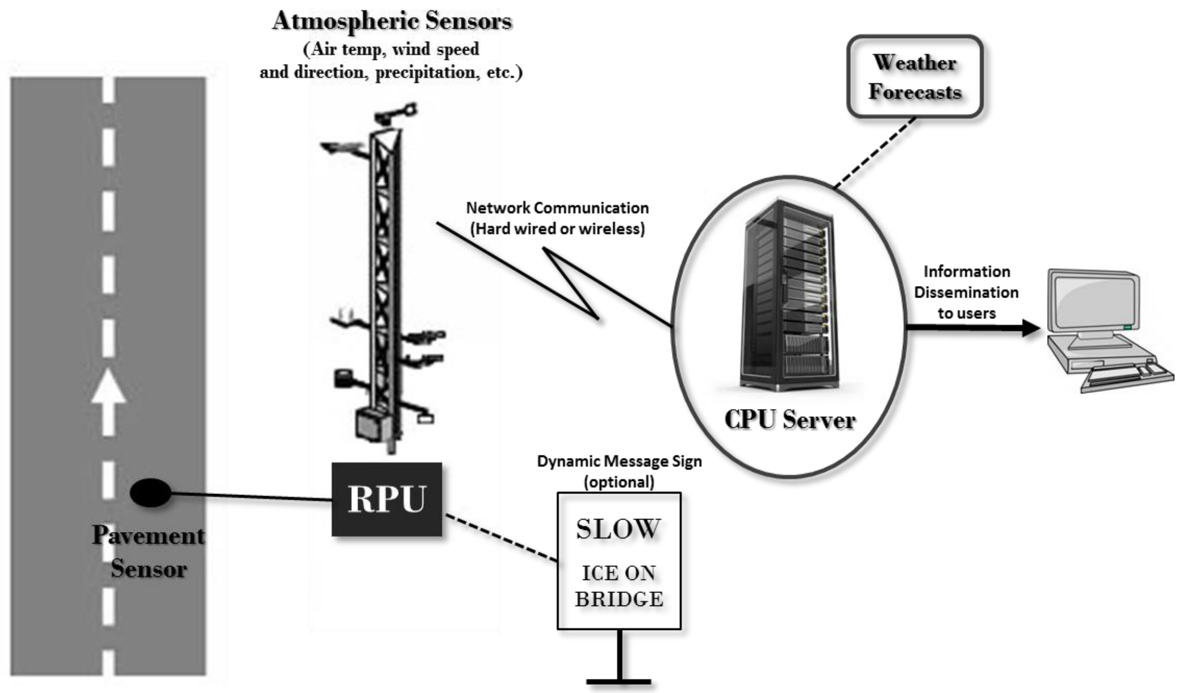


Figure 1-1: Major components of an RWIS station

Since the advent of sensor based-RWIS technologies in European counties between late 1970s and early 1980s, the system has gradually earned recognition for being a primary tool to aid and improve WRM operation decisions. Subsequently, the system was extensively adopted and used across Europe and North America as a means to enhance road weather and condition monitoring and prediction capabilities.

1.3 Current Practices on RWIS Network Planning

Transportation agencies that are interested in installing RWIS stations often face two relevant questions: how many RWIS stations should be installed to cover the road network and where should the new RWIS stations be placed. Answering the first question is equivalent to determining the optimal density and spacing of RWIS stations, i.e., determining the number of stations that are required to provide an adequate coverage of a region of interest. Despite of the importance of this problem, there are few tools and guidelines currently available guiding the decision process. A single reference most widely being adopted is the RWIS sitting guideline developed by FHWA in 2008, which recommends an average spacing of 30-50km along a roadway (Manfredi et al, 2008). However, this recommendation appears to be originated from the existing practice and experience with little scientific justification. Intuitively, the number of RWIS stations required for a region depends on the spatiotemporal variability of the region. Regions with winter weather conditions of high spatial variability would require a higher number of RWIS stations than those with uniform weather conditions. Currently, authorities responsible for RWIS planning have no reference available to assist them deciding the optimal density for their regions. Their decisions are primarily dictated by available budget with no information on the adequacy of their RWIS network thus the cost effectiveness of their investment.

In comparison, the problem of selecting suitable locations for a given number of RWIS stations has received relatively more attention recently because of its critical role in governing the overall effectiveness of the sensor suite and the representativeness of its observations on various road weather and conditions. As part of a Federal Highway Administration (FHWA) study, Manfredi et al. (2005) proposed a heuristic process for choosing the location of RWIS stations. First, weather zone maps that show regions exhibiting similar weather characteristics or patterns (i.e., regional representativeness) are examined with the support of meteorologists. Regional representativeness in this context refers to an area that experiences uniform and stable road weather and surface conditions such that it minimizes the possibility of adverse local weather effects and influences from other non-weather factors including heat, moisture, and wind barriers. Once the regions are determined in accordance with regional site guidelines, local maintenance personnel are consulted to identify the unique characteristics of each region and provide a general assessment of potential candidate locations. In this stage, planners ensure that the station would be located to satisfy road weather information requirements. Examples of these requirements include:

1. Areas with poor road surface conditions (RSC) such as historically cold spots that are likely to create slippery conditions, or spots likely to experience significant drifting snow,

2. Low-lying road segments where surface flooding may occur,

3. Areas with low visibility due to, for instance, a large local moisture source, and

4. High-wind areas with frequent occurrences of hurricanes along a confined valley or ridge top.

Other than those mentioned above, there are other local sitting considerations such as power, communication, aesthetics, safety, and security.

Thermal mapping (TM) is a technique that has been applied to determine the location of RWIS stations at some of the hot-spots described above (Gustavsson, 1999). TM is a process of identifying the variation pattern of pavement surface temperature along roadways by creating road surface temperature (RST) profiles. TM makes it possible to precisely identify cold trouble spots (i.e., potential location of RWIS stations) that may require more frequent monitoring and additional maintenance treatments (Zwahlen et al., 2003). Nevertheless, it requires substantial amount of time and effort, particularly for cities that are in need of a large-scaled implementation, posing a significant limitation of its applicability at the regional level.

Fu and Kwon (2012) conducted a survey (see Appendix C) to review and examine the current best practices for locating RWIS stations. In this survey, most of the North American survey participants stated that they would consider requirements similar to those mentioned above (i.e., hot spots such as ice and frost) when there was a need to install an RWIS station. The survey also revealed that participants would consider other non-weather-related requirements, including highway class, collision rate, traffic volume, and frequency of winter maintenance operations including salting and plowing. These results indicate that in locating RWIS stations transportation agencies would consider not only the meteorological representativeness but also the potential number of users - travelers who would be served. The survey further showed that making a decision on where to locate a station generally entails a series of discussions and interviews with many individuals including meteorologists, traffic engineers, regional/local maintenance personnel, and other industry experts. Despite such efforts, there are always tradeoffs in choosing one location over another because a location which satisfies one site condition may not be optimal for another site condition. For example, an area with high winds may not have significant snow accumulation. Another important factor to consider when installing an RWIS station is the proximity of power and communication utilities to ensure that the data could be obtained and processed in real time. Furthermore, RWIS station deployments are always constrained by tight budgets (Buchanan and Gwartz, 2005).

1.4 Factors Affecting Road Surface Conditions

Information on spatial variation of road surface conditions (RSC) along a roadway is deemed essential, particularly for highway authorities and road users to know when and where hazardous conditions are likely to occur during adverse winter weather events. Likewise, this information is critical when determining candidate RWIS locations as it helps delineate hot-spots as emphasized earlier (e.g., cold and icy).

The variation of RSC over a road network is affected by many factors, ranging from atmospheric and climatic, to geographical and topological. For example, the likelihood of having black ice or frost is determined by the energy receipt and loss at the road surface (Shao et al., 1997). This energy flow is affected by a number of factors, namely, atmospheric conditions (e.g., cloud cover, wind speed, and precipitation type and rate), climate patterns in both micro and macro levels, geographical features (e.g., vegetation cover and presence of buildings/obstructions), topographical settings (e.g. mountainous, flat, or rolling), and traffic. In addition, locational attributes such as latitude, longitude, elevation, distance to coast, and relative topography have been shown to affect RSC by a significant amount (Eriksson and Norrman, 2001). Vehicular traffic is another important contributing factor: an increased volume of slowly moving vehicles can produce temperature differences of up to 2 ^{o}C (White et al., 2006). These factors collated together can cause a considerable amount of variation in RSC from one location to another; for instance, winter RST during night-time can fluctuate as much as 10 ^{o}C along a regional roadway (Shao et al., 1996).

As mentioned earlier, a thermal mapping technique can be utilized to quantify the spatial variations of nocturnal RST on any given stretch of roads. This technique has long been in favor of local RWIS planners who could amicably examine thermal fingerprints and install RWIS stations at common trouble spots. However, thermal mapping can be very laborious and costly due to its nature requiring in-situ data collection, it remains a challenge to adopt and apply this technique for mapping spatial variation over large regional road networks, which is required for RWIS network planning. Therefore, it is essential to develop an effective methodology for representing and mapping spatial variation of RSC as an input to the RWIS location optimization process.

1.5 Problem Statement

While effective in providing valuable information, RWIS stations are expensive to install and operate and, therefore, can only be deployed at a limited number of locations. Considering the vast road network that often needs to be monitored and the varied road conditions that could develop during winter, RWIS stations must be placed strategically to ensure they are collectively most informative in providing the inputs required for accurate estimation of the road weather and surface conditions of the whole highway network. Currently, however, there are significant gaps in knowledge and methodology for effective planning of RWIS stations over a regional road network. The following paragraphs summarize the limitations of the current methods and the needs for new approaches to the problem of locating RWIS stations:

- The current RWIS deployment schemes are mostly heuristic, dependent heavily on subjective opinions of maintenance personnel with the lack of rationales and consistencies for choosing one location over another when determining RWIS sensor sites. Thus it is critical to formalize those heuristic approaches being adopted in practice such that the process of locating RWIS can be more systematic.

- While the heuristic approaches for choosing sensor locations are intuitive and reflection of field experts, an ultimate approach would be to take a full account of the costs and benefits of an RWIS. There are a few RWIS cost-benefit studies conducted in the past; however they do not provide systematic evidence of prospective monetary savings from RWIS installations. As such, it is necessary to develop an RWIS cost-benefit model by establishing a clear relationship between the various criteria being used in practice and their associated benefits to RWIS stations, and use such models to delineate new potential RWIS stations locations so as to maximize the benefits to all RWIS users.

- As discussed earlier, RWIS information makes possible to perform proactive winter maintenance operations such as anti-icing, which reduces the amount of time required to restore the roads to clear and dry state at lower costs. Since the largest portion of RWIS benefits lies in the use of RWIS information, it is sensible to locate the stations in such a way that would produce the most accurate prediction on the RSC of the entire network. This is similar to the problem of maximizing the monitoring capabilities of a sensor network, which requires addressing the challenge of developing correlation patterns of RSC based on the spatial RWIS measurements.

1.6 Objectives

As described, road authorities currently follow a laborious and time-consuming, yet subjective and ad-hoc process when deciding RWIS station locations. Furthermore, decisions on suitable RWIS locations can often become challenging, given that multiple factors must be considered. The primary goal of this thesis, therefore, is to develop and evaluate alternative approaches for determining the optimal RWIS station locations over a regional highway network. This thesis has the following specific objectives:

1. Formalize various heuristic approaches for determining the candidate RWIS station locations by incorporating criteria being considered in practice, and evaluate the implications of alternative location selection criteria.

2. Construct a cost-benefit based approach to the problem of finding the optimal location of RWIS stations by taking an explicit account of the benefits of RWIS information such as reduced maintenance costs and collisions.

3. Develop a spatial inference based approach such that the resulting RWIS network provides the optimal sampling pattern by considering the spatial variability of key RSC variables (i.e., hazardous road surface conditions) and interactions between candidate RWIS station locations.

4. Evaluate the existing RWIS network, make recommendation of new potential RWIS station locations using the proposed methodology, and demonstrate the effectiveness and applicability of the proposed methods through case studies.

5. Develop guidelines for determining the optimal RWIS network size (density or spacing) based on the spatial variability of road weather conditions of a region.

1.7 Organization of Thesis

This thesis consists of five chapters. The remaining thesis is organized as follows:

In Chapter 2, a literature review is presented covering current RWIS station location selection practices, RWIS benefits and costs, geostatistical analysis for spatial inference, and facility location models.

Chapter 3 describes the proposed methodology which consists of three distinctive methods including surrogate measures (SM) based approach, cost-benefit (CB) based approach, and spatial inference (SI) based approach.

Chapter 4 first presents a sensitivity analysis of the optimization parameters, and describes the real-world case studies, which encompass study areas, data descriptions and processing, and application of the three methods developed herein.

Chapter 5 highlights the main contributions of this research and potential extensions for future research.

Chapter 2
LITERATURE REVIEW

In past decades, several RWIS station location selection strategies have been explored and developed. Some have used heuristic measures while others have considered the variability of weather conditions for locating RWIS stations. However, there still exist some research gaps and challenges that are associated with designing an optimal RWIS network at a regional level. This Chapter provides the literature review on the past efforts on locating and/or optimizing RWIS stations using different location criteria.

This chapter is divided into four parts. In the first section, previous studies on RWIS station location selection strategies are presented. In the second part, past studies demonstrating the RWIS benefits and costs are described. The third section explains a kriging method for making spatial inference, which forms a foundation for developing an approach that maximizes the monitoring capabilities of an RWIS network. Finally, the fourth section discusses the discrete facility location problems and several solution algorithms.

2.1 RWIS Station Location Selection Strategies

As previously discussed, the existing guidelines and current best practices that most transportation agencies have adopted for deciding where to locate RWIS stations may not be optimal and can often be challenged. Despite these challenges, very few studies have been conducted to address RWIS location problems.

Eriksson and Norrman (2001) undertook a study on optimally locating RWIS stations in Sweden where they identified conditions hazardous to road transport as a criterion for locating RWIS stations at the regional level. In their study, they identified 10 different slipperiness types using one winter season of RWIS data, and linearly regressed each type with location attributes including latitude, longitude, elevation, distance to coast, etc. With the resulting regression model, they mapped out the occurrences of each slipperiness type over the entire study area. Candidate RWIS sites were recommended based on the estimated slipperiness counts and four different landuse groups. Although their proposed method seems to provide a good reference for analysis of station locations with respect to various locational attributes and landuse types, it is a heuristic approach considering only one location criterion—road weather condition. In addition, those authors did not provide much explanation/justification as to how their four landuse groups such as forest/water, open/water, forest, and open areas were determined. Such a categorization scheme is deemed subjective and thus scientifically less persuasive.

Another study by World Weather Watch (2009) conducted climatological study on determining RWIS station locations. Focusing on the general guidelines adopted by many transportation agencies, this study reviewed micrometeorological variations by investigating local physiography, topography, temperature, and snow precipitation amount in a small study area. The study also took into account hotspots that require regular monitoring as identified by the maintenance personnel. By combining all those factors, a list of high-risk sites were identified as the recommended locations for new RWIS stations in the region.

Alberta Department of Transportation conducted a similar but more inclusive study, in which a new approach was proposed to determine the location of RWIS stations by identifying and analyzing the RWIS-deficient regions (RDR) and by following general budget guidelines, respectively (Mackinnon and Lo, 2009). Similar to what the general guidelines suggest, their approach consisted of two parts: macro or regional assessments, and micro or local assessments. In the macro assessment phase, they took into account several factors when determining the RDR, factors such as traffic loads, accident rates, climatic zones, availability of meteorological information, and discussions with regional road maintenance personnel and key stakeholders. In the micro assessment phase, among the selected subsets of new potential RWIS locations, a final site was selected by conducting detailed field visits to ensure site suitability and project feasibility, for example, by ensuring appropriate sensor selection and configuration, conformance with budget, and access to power.

These two studies, while logical in methodology, lack scientific and systematic formulation of justification on how all those factors/criteria are put together to determine the potential high-risk sites. More importantly, both studies did not provide a clear linkage between the considered criteria and the purposes of RWIS stations. For instance, the latter study included accident rates as one of their potential location selection criteria, but did not establish a solid rationale as to why such a criterion should be given a priority when choosing a new location. Without a valid justification/explanation on why each location selection criterion is considered and utilized, incorporation of such selection criteria in the studies cannot be legitimized.

Two recent studies by Jin et al. (2014) and Zhao et al (2015) attempted to address the RWIS location problem using a mathematical programming approach. Jin et al. (2014) used weather-related crash data and converted to a Safety Concern Index, using which the locations providing a good spatial coverage were identified as optimal locations. Zhao et al. (2015) applied the concept of influencing area to capture the effects on weather severity and traffic volume, and delineated a list of potential RWIS stations locations with the distance to existing RWIS stations considered explicitly. While the spatial variability is partially accounted in these two studies, the effect of distance and spatial patterns associated with a particular region are not fully utilized, and furthermore, the models presented do not account for the ultimate use of RWIS information for spatial inference.

Currently, the majority of provincial and municipal transportation agencies rely heavily on the experience of regional/local maintenance personnel for determining the potential RWIS station locations. All of the information (e.g., historically icy spots) is put together through a series of face-to-face meetings with key stakeholders and field experts to narrow down various candidate locations to a manageable size and decide based on the budget availability. Finding a solution through this process is laborious and time-consuming. Hence, a method, which formalizes all these heuristics for the purpose of locating candidate RWIS stations, is of high priority.

2.2 RWIS Benefits and Costs

As stated briefly earlier, information available from RWIS, for instance, detailed and tailored weather forecasts, can provide substantial benefits to users. Before RWIS technology was introduced, highway maintenance agencies reacted to current road conditions or forecasts obtained from only the publically available weather sources. Road patrollers were typically sent out to check road weather conditions, and when roads became icy or snow-covered, maintenance personnel were notified. This type of reactive response was inefficient and expensive in both time and materials (Boselly, 1992). On the other hand, RWIS provides information that offers proactive ways of doing business, and therefore, more efficient and cost-effective WRM operations can be realized to promote faster and safer road conditions. Table 2-1 identifies and summarizes the benefits of using RWIS-enabled winter maintenance practices.

Table 2-1: RWIS-Enabled Winter Maintenance Practices and Associated Benefits (adopted from Boon and Cluett, 2002)

RWIS-Enabled practices	**Associated Benefits**
Anti-icing	• Lower material costs
	• Lower labor costs
	• Higher level of service (improved road conditions), travel time savings, and improved mobility
	• Improved safety (fewer crashes, injuries, fatalities, property damage)
	• Reduced equipment use hours and cost
	• Reduced sand cleanup required
	• Less environmental impact (e.g., reduced sand/salt runoff, improved air quality)
	• Road surfaces returned to bare and wet more quickly
	• Safe and reliable access, improved mobility
Reduced Use of Routine Patrols	• Reduced equipment use hours and cost
	• Improved labor productivity
Cost-Effective Allocation of Resources	• Reduced labor pay hours
	• Reduced weekend and night shift work
	• Improved employee satisfaction
	• Reduced maintenance backlog
	• More timely road maintenance
	• Increased labor productivity
	• Overall higher level of service
	• More effective labor assignments
Provide Travelers Better Information	• Better prepared drivers
	• Safer travel behavior
	• Reduced travel during poor conditions
	• Fewer crashes, injuries, fatalities and property damage
	• Increased customer satisfaction
	• Improved mobility / reduced fuel consumption
	• Safer, more reliable access
Additional Benefits	• Share weather data for improved weather forecasts • Support the development of road weather forecast models • Insurance companies by determining risks of potential weather impacts • Use for long-term records and climatological analyses

When tailored road weather forecast information is available from RWIS, it becomes possible to predict near-future road weather conditions. With such information, anti-icing chemicals can be applied before a snow-storm hits, to prevent or minimize the formation of the bonded snow and ice layers (C-SHRP, 2000). When snow and ice are prevented from bonding to the road surface, the surface becomes less slippery, thus increasing traffic safety and mobility. Since the treatment is done proactively, a smaller amount of chemical is required to prevent the bonding than when applied to existing snow and ice layers, and thus reducing the environmental impact. According to more than 100 case studies, anti-icing in conjunction with RWIS can result in substantial cost savings, particularly from reduced material/labor/equipment usage (Epps and Ardila-Coulson, 1997).

Another potential benefit of implementing RWIS technology is reduction in the need for routine patrols for monitoring road conditions (Boselly, 1993). With the availability of RWIS information, the number of routine patrols can be reduced significantly by directly observing the site conditions without visiting the site in person; the camera sensor becomes the eyes of road maintenance supervisors, who can now monitor the current situation of the site in a remote area without exhausting the use of road patrols. Having a smaller number of patrols results in reduced equipment usage and improved labor productivity (Boon and Cluett, 2002).

Cost-effective allocation of WRM resources is also possible by using site-specific road weather and condition information available from individual RWIS stations. Road maintenance supervisors can better mobilize the available crew and equipment in terms of time and location. This efficiency can lead to more effective labor assignments, thus increasing labor productivity and improving employee satisfaction (Ye et al., 2009).

RWIS makes it possible to disseminate information on current and near-future road conditions via websites and dynamic message signs so that travellers can make better decisions on when, where, and how to travel. A recent study on RWIS and vehicle collision rates showed that a well maintained RWIS network significantly reduces collision rates (Greening et al., 2012).

Implementing RWIS technology can also improve weather forecasts by the sharing of weather data available from RWIS. Use of additional weather information from individual RWIS stations can enhance future weather prediction capability by generating more accurate forecasts. Insurance companies can also benefit from using RWIS data to help determine risks of potential impacts from foreseeable weather events. Furthermore, state climatologists and other organizations such as government and university can use RWIS data for long-term climatological analyses and for the development of road weather forecast models (Manfredi et al., 2005).

Some of the abovementioned benefits, particularly the foreseeable savings from anti-icing techniques, have been evaluated quantitatively through cost-benefit analyses in a limited number of past studies. The Strategic Highway Research Program of the National Research Council initiated a research project in 1991 to evaluate the cost-benefit effectiveness of RWIS (Epps and Ardila-Coulson, 1997). The authors investigated the potential for reducing collisions and minimizing material, equipment, and labor costs when anti-icing operations were done before an anticipated adverse weather event. Their study concluded that under certain conditions, the implementation of RWIS and anti-icing strategies could result in cost savings to highway agencies and reduce collisions by up to 15 percent. Their study also claimed that areas not under RWIS coverage would have ice- and snow-covered pavements for approximately 50 percent of the time, compared with about 40 percent of time for areas under RWIS coverage.

Another study performed in Milwaukee, Wisconsin evaluated the effectiveness of WRM operations and the associated economic implications for motorists (Hanbali, 1994). The study found that traffic collision costs and traffic severity during inclement weather conditions could be reduced by as much as 88 percent and 10 percent, respectively. In addition, the benefit-to-cost ratio of winter maintenance operations was 6.5 to 1.

A more recent study by McKeever et al. (1998) introduced a systematic method for highway agencies to evaluate the costs and benefits of implementing RWIS technology based on a synthesis of the preceding results. The authors developed a life cycle cost-benefit model to account for direct costs (e.g., RWIS installation, operating, and maintenance costs), direct savings (e.g., patrol, labor, equipment and material savings), and social cost savings (e.g., collision cost savings). The findings suggested that the incremental net present worth of installing a single RWIS station would be $923,000 over a 50-year life cycle. These foreseeable benefits were calculated based on some site specific conditions (i.e., weather, traffic, and maintenance) with the assumed uniform reduction rate, hence would not be applicable to other sites (McKeever et al., 1998).

As pointed out earlier, one of the main RWIS benefits is its ability to allow an agency to transition with confidence to an anti-icing strategy. From late 1980s to early 1990s, many US transportation agencies documented the benefits of RWIS driven anti-icing operations. Although the approaches undertaken to quantitatively assess and/or estimate the benefits are largely vague, they provide a good indication of RWIS benefits associated with anti-icing operations. Table 2-2 summarizes the findings reported by individual agencies.

While the aforementioned studies provide some quantitative evidence that implementing RWIS is cost-effective relative to having no RWIS, especially by the use of RWIS enabled anti-icing operations, the methods used in these studies are limited in several ways with the inability to quantify the sole benefits of RWIS being the primary one. This is a challenging task because in practice, in addition to the RWIS information, many other sources of information are often used in the maintenance decision making process. Thus, there is a need to develop an approach for determining the benefits associated exclusively with RWIS that can be incorporated into a cost-benefit based model for finding the most beneficial RWIS location.

Table 2-2: Cost Saving Resulting from Anti-Icing (adopted from Boselly, 2001)

Agency	Reported Cost Savings
Colorado DOT	• Sand use decreased by 55%. All costs considered, winter operations now cost $2,500 per lane mile versus $5,200 previously.
Kansas DOT	• Saved $12,700 in labour and materials at one location in the first eight responses using an anti- icing strategy.
Oregon DOT	• Reduced costs for snow and ice control from $96 per lane mile to $24 per lane mile in freezing rain events.
Washington DOT	• Saved $7,000 in labour and chemicals for three test locations.
ICBC (Insurance Corporation of British Columbia)	• Accident claims reduced 8% on snow days in Kamloops, BC: estimated savings to ICBC $350,000-$750,000 in Kamloops • Potential annual savings of up to $6 million with reduced windshield damage.

2.3 Kriging for Spatial Inference

In designing an environmental or meteorological monitoring network, development of efficient planning procedures is deemed a fundamental task for accurately understanding the spatial variations of, for instance, hazardous road surface conditions (HRSCs), which can be readily estimated using RWIS information (refer to Table 1-1). The problem can then be formulated as an optimal monitoring network design where the primary concern is to locate a given set of RWIS stations such that the best possible estimation results are guaranteed. Such problem formulation can be justified under a reasonable assumption that the more accurate the RWIS estimation measurements are, the more benefits are likely to be obtained by utilizing various efficient winter maintenance operations (e.g., anti-icing).

Kriging is a geostatistical technique widely used in optimizing a monitoring network. The technique is able to provide a best linear unbiased estimator (BLUE) for variables that have tendency to vary over space (Yeh et al., 2006). The main idea behind kriging is that the predicted outputs are weighted averages of sample data, and the weights are determined in such a way that they are unique to each predicted point and a function of the separation distance (lag) between the observed location, and the location to be predicted. In addition, kriging provides estimates and estimation errors at unknown locations based on a set of available observations by characterizing and quantifying spatial variability over the area of interest (Goovaerts, 1997).

Previous studies in a variety of different fields revealed the applicability and usefulness of geostatistics as a tool for an optimal selection of sites for monitoring environmental (e.g., groundwater) and meteorological (e.g., average air temperature) variables. For example, a number of authors used the geostatistics technique to optimize the groundwater observation wells by delineating the locations having maximum kriging error variance (Prakash and Singh, 1998; Cameron and Hunter, 2002; Nunes et al., 2004; Nunes et al., 2007; Yeh et al., 2006; Brus and Heuvelink, 2007). Another study conducted by van Groenigen et al. (1999) employed a heuristic optimization approach namely simulated annealing (SA) to determine the optimal soil sampling schemes for obtaining the minimal kriging variance. Another study by Amorim et al. (2012) addressed the problem of planning a network of weather monitoring stations observing average air temperature. The authors used the geostatistical uncertainty of estimation and indicator formalism to consider in the location process a variable demand surface, depending on the spatial arrangement of the stations, where the optimal set of locations were determined by incorporating two heuristic methods such as simulated annealing and generic algorithms.

The following sections introduce the kriging paradigm and three of its most important variants: simple kriging, ordinary kriging, and universal kriging.

2.3.1 The Idea of Kriging

Kriging is a generic term coined by geostatisticians for a family of generalized least-squares regression algorithms in recognition of the pioneering work of a mining engineer, Danie Krige (1951). Kriging provides estimates at unknown locations based on a set of available observations by characterizing and quantifying spatial variability of the area of interest. Let x and x_k be location vectors for estimation point and a set of observations at known locations, respectively, with $k = 1, \ldots, m$, and Z be a variable of interest. Based on m number of observations, we are interested in estimating a condition at any given location, denoted by $\hat{Z}(x)$. The expression of a general kriging model is as follows (Goovaerts, 1997):

$$\hat{Z}(x) = m(x) + \sum_{k=1}^{m} \lambda_k [Z(x_k) - m(x_k)] \qquad \text{2-1}$$

where $m(x)$ and $m(x_k)$ are expected values (means) of the random variables $Z(x)$ and $Z(x_k)$, and λ_k is a kriging weight assigned to datum $Z(x_k)$ for estimation location x.

The kriging estimator varies depending on the model adopted for the random function Z(x) itself. All kriging variants share the same goal of finding weights λ_k that minimize the variance of the estimator:

$$\sigma_E^2(x) = Var\{\hat{Z}(x) - Z(x)\} \text{ under the constraint, } E\{\hat{Z}(x) - Z(x)\} = 0 \qquad \text{2-2}$$

The random field, $Z(x)$ can be decomposed into two components namely residual component $R(x)$, and a trend component $m(x)$, and expressed as $Z(x) = R(x) + m(x)$ with $R(x)$ interpreted as a RF having a stationary zero mean and covariance $C_R(h)$:

$$E\{R(x)\} = 0, \;\; Cov\{R(x), R(x+h)\} = E\{R(x) \cdot R(x+h)\} = C_R(h) \qquad \text{2-3}$$

where h is a lag or separation distance between the observed points, and $C_R(h)$ is the residual covariance function, which is typically obtained from a semivariogram model, $\gamma(h)$. Under a second order stationarity assumption (i.e., constant mean, and covariance is dependent solely on distance vector *h* between any pairs of points), the following expression is satisfied (Goovaerts, 1997):

$$C_R(h) = C_R(0) - \gamma(h) = Sill - \gamma(h) \qquad \text{2-4}$$

where *Sill* denotes the semivariance value for large lag distances where spatial autocorrelation between the data appears to be very small thus negligible. Therefore, the semivariogram that is used in the kriging system represents the residual component of the variable of interest. Each of three main variants of kriging can be distinguished according to the model considered for the trend component, $m(x)$.

2.3.1.1 Simple Kriging (SK)

Simple kriging (SK) assumes the mean, $m(x)$, to be known and constant over the entire study area as depicted in Figure 2-1. Black dots appeared in this figure can be measured values of, for instance, any environmental or meteorological variable. The centerline represents the mean of the measurements that are constant over the global domain (i.e., 0 to 40) whereas the vertical dashed lines delineate arbitrary local segments or boundaries.

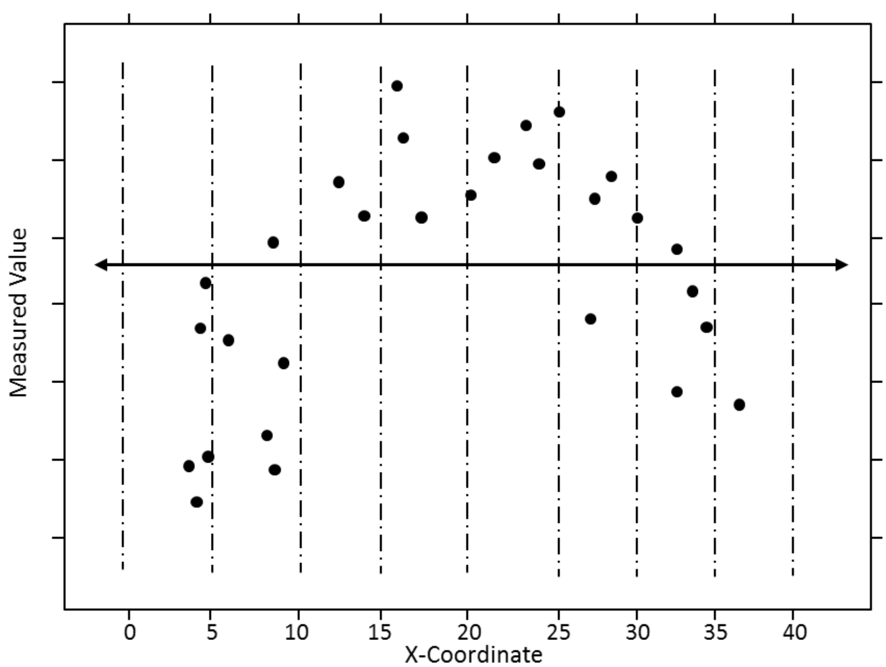


Figure 2-1: An example of Simple Kriging (SK)

With such assumptions, Equation 2-1 can be rewritten as:

$$\hat{Z}_{SK}(x) = m + \sum_{k=1}^{m} \lambda_k^{SK}(x)[Z(x_k) - m] \qquad \text{2-5}$$

where $\hat{Z}_{SK}(x)$ and $\lambda_k^{SK}(x)$ are SK estimate at and vector of SK weights for the estimation point, *x*. This estimate is then unbiased since $\mathrm{E}[Z(x_i) - m] = 0$, such that $\mathrm{E}\big[\hat{Z}_{SK}(x)\big] = \mathrm{E}[Z(x)] = m$.

The estimation error, $\hat{Z}_{SK}(x) - Z(x)$, can be regarded as a linear combination of random variables representing residuals, *R*(*x*) at the estimation point and $R(x_k)$ at the data point:

$$\begin{aligned} \hat{Z}_{SK}(x) - Z(x) &= [\hat{Z}_{SK}(x) - m] - [Z(x) - m] \\ &= \sum_{k=1}^{m} \lambda_k^{SK}(x) R(x_k) - R(x) = \widehat{R}_{SK}(x) - R(x) \end{aligned} \qquad \text{2-6}$$

where $R(x_k) = Z(x_k) - m$ and $R(x) = Z(x) - m$. Using the variance rules, the estimation error variance $\sigma_E^2(x)$ at site *x* is shown in Equation 2-7 (Olea, 1999):

$$\sigma_E^2(x) = C_R(x,x) - 2\sum_{k=1}^{m} \lambda_k(x)\, C_R(x_k, x) + \sum_{k=1}^{m}\sum_{j=1}^{m} \lambda_k(x)\, \lambda_j(x)\, C_R(x_k, x_j) \qquad \text{2-7}$$

The optimal SK weights, which minimize the estimation error variance, are subsequently obtained by taking the derivative of Equation 2-7 with respect to each of the SK weights and setting each derivative to zero. This leads to the following system of equations (Goovaerts, 1997):

$$\sum_{j=1}^{n} \lambda_j^{SK}(x)\, C_R(x_k, x_j) = C_R(x_k, x), \qquad k = 1, \ldots m \qquad \text{2-8}$$

Since SK assumes the constant mean, the covariance function for *Z*(*x*) can be explained in the same way that for the residual component, *R*(*x*), i.e., $C(\mathrm{h}) = C_R(\mathrm{h})$, the SK system can be written directly in terms of *C*(h):

$$\sum_{j=1}^{n} \lambda_j^{SK}(x)\, C(x_k, x_j) = C(x_k, x), \qquad k = 1, \ldots m \qquad \text{2-9}$$

The SK error variance is then given by:

$$\sigma_{SK}^2(x) = C(0) - \sum_{k=1}^{m} \lambda_k^{SK}(x)\, C(x_k, x) \qquad 2\text{-}10$$

For a more compact display of the results, Equation 2-9 can be conveniently expressed in a matrix form as

$$\lambda_{SK}(x) = G_{SK}^{-1} g_{SK} \qquad 2\text{-}11$$

where

$\lambda_{SK}(x) = [\lambda_1 \quad \lambda_2 \quad \ldots \quad \lambda_m]^T$ is the vector of the optimal SK weights for the estimator in Equation 2-5,

$G_{SK} = \begin{bmatrix} C(x_1, x_1) & \cdots & C(x_1, x_m) \\ \vdots & \ddots & \vdots \\ C(x_m, x_1) & \cdots & C(x_m, x_m) \end{bmatrix}$ is the matrix of covariances between data points, and

$g_{SK} = \left[C(x_1, x) \ \cdots \ C(x_m, x)\right]^T$ is the vector of covariances between the data and estimation points.

Once the SK weights are determined via Equation 2-11, the kriging estimates can be determined using Equation 2-1 and the SK error variance can be computed as:

$$\sigma_{SK}^2(x) = C(0) - \lambda_{SK}^T(x)\, g_{SK} = C(0) - g_{SK}^T G_{SK}^{-1} g_{SK} \qquad 2\text{-}12$$

2.3.1.2 Ordinary Kriging (OK)

It has been shown that SK entails a strong assumption of known and constant mean over the entire domain for solving the problem of finding weights that minimize the variance of the estimation error. On the contrary, Ordinary kriging (OK) assumes the mean to be unknown but constant over each local neighboring area as depicted in Figure 2-2.

This indicates that OK accounts for local fluctuations of the mean by limiting the domain of stationarity of the mean to the local neighbourhood (Olea, 1999). This is a valid assumption particularly when dealing with environmental or meteorological variables that typically show numerical fluctuations over space (Goovaerts, 1997; Ahmed et al., 2008).

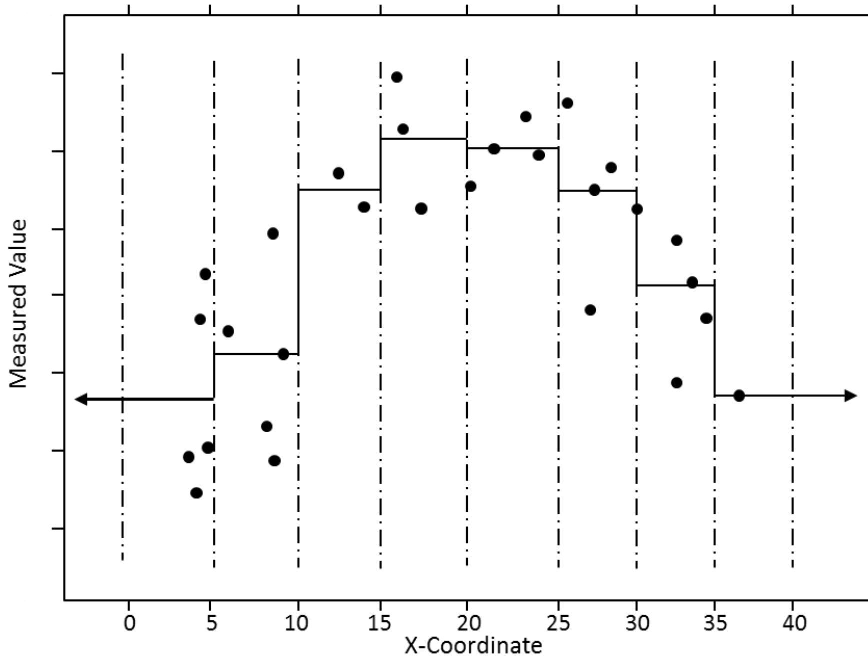


Figure 2-2: An example of Ordinary Kriging (OK)

Hence, the kriging estimator can be expressed as (Olea, 1999):

$$\hat{Z}(x) = \sum_{k=1}^{m} \lambda_k(x)\, Z(x_k) + \left[1 - \sum_{k=1}^{m} \lambda_k(x)\right] m(x) \qquad \text{2-13}$$

The unknown local mean is filtered from the linear estimator by forcing the OK weights to sum to 1. The OK estimator can then be written as:

$$\hat{Z}_{OK}(x) = \sum_{k=1}^{m} \lambda_k^{OK}(x)\, Z(x_k) \qquad \text{2-14}$$

$$\textit{subject to} \quad \sum_{k=1}^{m} \lambda_k^{OK}(x) = 1$$

Again, the weights are determined such that the estimated variance is minimized under non-bias condition, $E\{\widehat{Z}(x) - Z(x)\} = 0.$ The above constrained minimization problem can be transformed into an unconstrained problem using Lagrangian transformation as follows (Olea, 1999):

$$L(\lambda_1, \lambda_2, \cdots \lambda_m; \mu) = C(x,x) + \sum_{k=1}^{m}\sum_{j=1}^{m} \lambda_k \lambda_j C(x_k, x_j) - 2\sum_{k=1}^{m} \lambda_k C(x_k, x) + 2\mu\left(\sum_{k=1}^{m} \lambda_k - 1\right) \tag{2-15}$$

where C(x,x) is the variance of z(x), C(x_k, x_j) is the covariance between z(x_k) and z(x_j),and μ is the Lagrange multiplier. Then the weights that produce the minimum estimation variance are the solution to

$$\begin{cases} \sum_{k=1}^{m} \lambda_k \; C(x_k, x_1) + \mu = C(x_1, x) \\ \sum_{k=1}^{m} \lambda_k \; C(x_k, x_2) + \mu = C(x_2, x) \\ \cdots\cdots\cdots\cdots \\ \sum_{k=1}^{m} \lambda_k \; C(x_k, x_m) + \mu = C(x_m, x) \\ \sum_{k=1}^{m} \lambda_k = 1 \end{cases} \tag{2-16}$$

Unlike in SK where C(h) = C_R(h) is satisfied so that the SK system can be expressed directly in terms of C(h), the unit-sum constraint on the weights permits OK to be expressed in a form of semivariogram $\gamma(h)$, instead of $C_R(h)$. Once the OK weights and Lagrange parameter are determined by solving the system of equations illustrated in Equation 2-15, the OK error variance can be defined by Equation 2-17 (Olea, 1999):

$$\sigma_{OK}^2(x) = C(0) - \sum_{k=1}^{m} \lambda_k^{OK}(x)\, C(x_k, x) - \mu \tag{2-17}$$

Again, for a more compact display of the results, the following equation expressed in a matrix form can be used to determine the kriging weights:

$$\lambda_{OK}(x) = V_{OK}^{-1} v_{OK} \tag{2-18}$$

where

$$\lambda_{OK}(x) = \begin{bmatrix} \lambda_1 \\ \vdots \\ \lambda_m \\ \mu \end{bmatrix}, \quad V_{OK} = \begin{bmatrix} C(x_1, x_1) & \cdots & C(x_1, x_m) & 1 \\ \vdots & \ddots & \cdots & \vdots \\ C(x_m, x_1) & \cdots & C(x_m, x_m) & 1 \\ 1 & \cdots & 1 & 0 \end{bmatrix}, \quad v_{OK} = \begin{bmatrix} C(x_1, x) \\ \vdots \\ C(x_m, x) \\ 1 \end{bmatrix}$$

Upon determination of OK weights, the OK error variance can be calculated as:

$$\sigma_{OK}^2(x) = C(0) - v_{OK}^T V_{OK}^{-1} v_{OK} \qquad \text{2-19}$$

2.3.1.3 Universal Kriging (UK)

In the last decade, there has been an increasing interest in hybrid interpolation techniques, which gained much attention among geostatisticians. Hybrid techniques are referred to as methods which combine two conceptually different approaches to modeling and mapping spatial variability. One of these hybrid methods is called universal kriging (UK) which is based on point observations and regression of the target variable on spatially exhaustive auxiliary information (Hengl et al., 2007). It is mathematically equivalent to the methods known as kriging with external drift (KED) and regression kriging (RK), where auxiliary predictors are used to solve the kriging weights (Hengl et al., 2007). Recall that the local estimation of the mean in SK and OK allows one to account for any global trend (i.e., constant mean) in the data over the entire study area. This implies that these algorithms implicitly consider a non-stationary random function model where spatial autocorrelation is limited within each search boundary (Goovaerts, 1997). In some situations, such assumption may not hold true since the local mean of, for instance, air temperature, could also coherently vary over space with respect to some auxiliary variables such as elevation, geographical and topographical settings (Amorim et al., 2012). Furthermore, prior research indicated that in many cases, UK has been proved to be superior to the plain geostatistical techniques yielding more detailed results and higher accuracy of prediction by incorporating various covariates in modeling the trend component (Bourennane el al., 2000; Hengl et al., 2004).

Having understood the underlying mechanism of UK, its concept is very similar to OK, except that instead of fitting just a local mean of the estimation point of the search boundary, a linear or higher-order trend in the *x*, *y* coordinates are used to model the local trend as depicted in Figure 2-3.

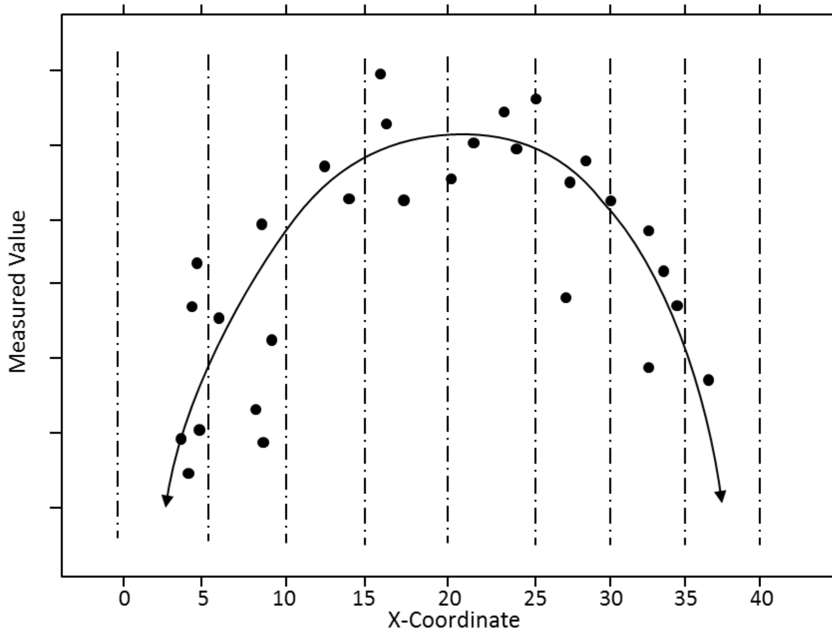


Figure 2-3: An example of Universal Kriging (UK) with a fitted second-order polynomial trend

Since the trend is typically associated with a smoothly varying component of the *z*-variability, a linear combination of coordinates is commonly employed to model the trend component, $m(x)$, which is given by (Goovaerts, 1997):

$$m(x) = m(x, y) = a_0 + a_1 x + a_2 y \qquad \text{2-20}$$

where (x, y) are the coordinates of the location x. Including such a model in Equation 2-1 involves the same kind of extension used for OK which, in fundamental, uses a zeroth-order trend model instead of a linear trend model with demand on a prior determination of trend functions and the covariance of the residual component, $C_R(h)$ (Bohling, 2005).

2.3.2 Semivariogram

In order to use kriging, one must identify and quantify the underlying spatial structure of the regionalized random variable to be monitored. In geostatistics, this problem is addressed by assuming that the correlation or covariance between any two locations is a function of separation and orientation delineated by the two locations. The underlying functional relationship is called semivariagram and can be calibrated in advance using available data. The development of such semivariagram is essential in most geostatistical analyses (Olea, 2006). Assuming an isotropic spatial process (equal in all directions), spatial autocorrelation can be expressed as a function of distance between two locations (i.e., isotropic intrinsic stationary). If the process is second order stationary (and thus intrinsic stationary), the covariance between any two random errors depends only on the distance and direction that separates them, not their exact locations (Webster and Oliver, 1992).

The semivariogram model used for capturing the spatial autocorrelation is expressed as follows:

$$\hat{\gamma}(h) = \frac{1}{2m(h)} \sum_{k=1}^{m(h)} \left[z(x_k + h) - z(x_k) \right]^2 \quad \text{2-21}$$

Where $\hat{\gamma}(h)$ is the sample semivariogram, $z(x_k)$ is a measurement taken at location k, and $m(h)$ is the number of pairs of observations separated by the lag distance, h. The number of pairs included in semivariogram estimation should, at least, be equal to 30 as set by Journel and Huijbrets (1978). Likewise, the lag distance of the sample semivariogram should be constrained to half the diameter in the sampling domain for all directions of analyses (Journel and Huijbrets, 1978). An important assumption of the above estimator is the absence of any systematic variations; hence if there exists any spatial patterns, then they must be removed first to be trend-free. An example of the sample variogram is illustrated in Figure 2-4.

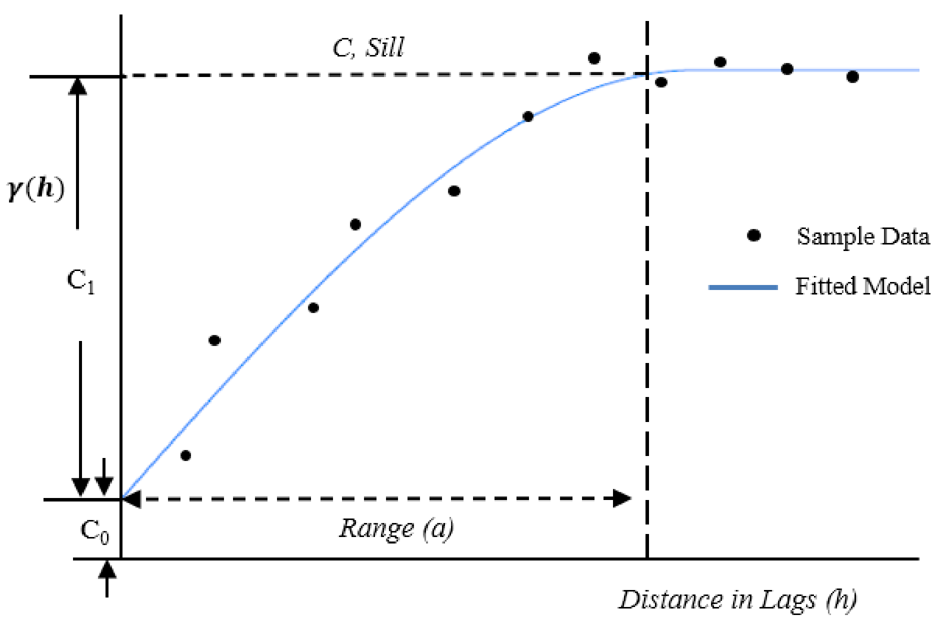


Figure 2-4: An example of a typical semivariogram (adapted/revised from Flatman et al., 1987)

where *sill*, *a*, C_1, C_0, and *h* represent the level of the plateau (if it exists), the lag distance where the semivariogram reaches the *sill* (i.e., degree of spatial correlation), the partial sill, the nugget effect which accounts micro scale variation and measurement errors (or any spatial variability that exists at a distance smaller than the shortest distance of two measurements), and the lag distance. Note that identical results can also be attained using covariogram or covariance function, which can be easily derived from semivariograms. Typically, a mathematical model is utilized to describe the sample semivariances owing to the fact that true spatial structure of a region is never known (Oliver and Webster, 1990). There are a larger number of mathematical formulas/equations that can be fitted to describe the semivariances of the sample data, but the most commonly employed models are described in Table 2-3 (Olea, 2006).

Table 2-3: Most commonly used semivariogram models (adopted from Olea, 2006)

Exponential	$Ex(h) = C\left(1 - e^{-\frac{3h}{a}}\right)$
Gaussian	$G(h) = C\left(1 - e^{-3\left(\frac{h}{a}\right)^2}\right)$
Spherical	$Sp(h) = \begin{cases} C\left(\frac{3h}{2a} - \frac{1}{2}\cdot\left(\frac{h}{a}\right)^3\right), & 0 \le \lvert h\rvert < \lvert a\rvert \\ C, & \lvert a\rvert \le \lvert h\rvert \end{cases}$
Pentaspherical	$Pe(h) = \begin{cases} C\left(\frac{15h}{8a} - \frac{5}{4}\cdot\left(\frac{h}{a}\right)^3 + \frac{3}{8}\cdot\left(\frac{h}{a}\right)^3\right), & 0 \le \lvert h\rvert < \lvert a\rvert \\ C, & \lvert a\rvert \le \lvert h\rvert \end{cases}$
Cubic	$Cu(h) = \begin{cases} C\left(7\cdot\left(\frac{h}{a}\right)^2 - \frac{35}{4}\cdot\left(\frac{h}{a}\right)^3 + \frac{7}{2}\cdot\left(\frac{h}{a}\right)^5 - \frac{3}{4}\cdot\left(\frac{h}{a}\right)^7\right), & 0 \le \lvert h\rvert < \lvert a\rvert \\ C, & \lvert a\rvert \le \lvert h\rvert \end{cases}$

Since it is critical to select the model that best replicates the shape of the spatial variability over the region of interest, one needs to assess the goodness of fit for each model. One possible approach would be to pick the best model by simple visual inspection. However it can be, at times, difficult to judge due to the subjectiveness, and hence, another approach involving a quantitative assessment via crossvalidation is desired. Crossvalidation is a verification process in which each observation is removed with replacement to produce an estimate at the same site of the removal (Olea 1999). The error incurred in this process is measured by taking the difference between the “actual value” and the “estimated value”. This process continues until all observations are tested. Once done, the analyst can obtain useful information about the semivariogram model parameters, and judge based on some statistical measures including root-mean-square-error (RMSE), which indicates how closely the fitted model predicts the measured values (i.e., smaller the better), and average standard error (ASE) and mean standardized errors (MSE) which represent the average of the prediction standard errors, and the mean of the standardized errors (i.e., closer to zero the better), respectively. A selection of the model, however, must be carried out cautiously because errors are not independent and there could be some other confounding factors that contribute to the error values (Olea, 2006).

2.4 Facility Location Problems and Solution Methods

Facility location problems have been well studied by operations researchers and engineers. Many innovative modeling techniques and solution algorithms have been developed, varying widely in terms of fundamental assumptions, mathematical complexity and computational performance (Klose and Drexl, 2005). In a broad perspective, there are two main different types of facility location models: discrete and continuous. Discrete facility models utilize discrete sets of demands and candidate locations. Continuous models, in contrast, assume that facilities can be located anywhere in the service area, whereas demands arise only at discrete locations (Daskin, 2008). In this research, discrete facility location problems (DFLP) are of particular interest, hence concisely reviewed in the following section along with a brief description on common solution algorithms.

2.4.1 Discrete Facility Location Problems (DFLP)

As mentioned, discrete facility location problems assume that there are a discrete set of demands to be serviced by facilities and a discrete set of sites where the facilities could be located. The location problems are typically formulated as integer or mixed integer programming problems (Revelle et al., 2008). Figure 2-5 summarizes the three broad types of discrete location problems including covering- and median-based problems, and others such as dispersion problems.

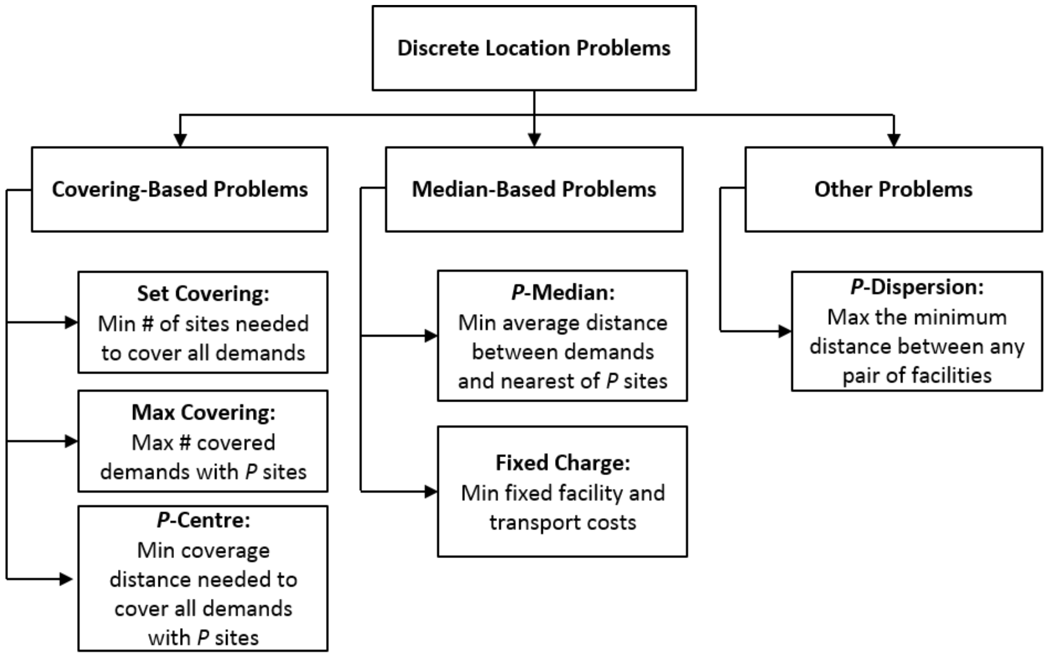


Figure 2-5: Breakdown of discrete location problems (adopted from Daskin, 2008)

Covering-based problems are constructed under the assumption that there is some critical coverage distance within which demands must be served if they are to be marked as "covered" or "served adequately" (Daskin, 2008). Such problems are typically implemented in designing systems for emergency services as there exists practical and legislative guidelines for coverage. The location set covering model aims to minimize the number of facilities needed to cover all demands (i.e., provide services to all customers) with constraints stipulating that each demand node should be covered (Toregas et al., 1971). However, in solving the set covering problem, the number of facilities required to cover all demand nodes often surpasses the available budget. Likewise, the model does not distinguish between the different sizes of demand nodes (i.e., large vs. small).

Acknowledging these limitations, Church and Revelle (1974) formulated the maximum covering problem in an attempt to locate a pre-specified number of facilities (i.e., *p* facilities) such that the number of covered demands would be maximized. The model differentiates between the big and small demands and allows some nodes to be left uncovered under a situation where the number of sites required to cover all nodes exceeds *p*. If the number of facilities required to cover all demand nodes exceeds the available resources, relaxing this constraint for total coverage could be one option (i.e., max covering). but alternatively one can choose to relax the service standard until a standard, which allows for total coverage with available resources, is found, an approach known as the *p*-center model (Hakimi, 1965). The *p*-center model minimizes the maximum distance between a demand node and the nearest sited facility (i.e., find the smallest possible coverage distance with every node being covered).

While covering based problems treat the coverage of a node as binary depending on whether a node is covered or not covered, the *p*-median model locates *p* number of facilities such that the demand-weighted total or average distance between demands and the nearest facility is minimized (Hakimi, 1964). The model constraints stipulate that each node is assigned while limiting the assignments only to open or selected sites (Daskin, 2008). The drawback of this model is that it implicitly assumes that the cost of siting a facility at any given candidate location is equal to that for all locations. Recognizing such limitation, an extension to this model (known as the uncapacitated fixed charge or the plant location model) has been formulated originally by Balinski (1965). In this model, the sum of the facility location costs and the transportation costs are minimized under constraints identical to those enforced in the *p*-median problem, except that the constraint on the number of facilities to locate is removed as the model automatically penalizes a larger number of facilities (Revelle et al., 2008).

Lastly, there are other problems that do not belong to either of those two categories mentioned earlier. *P*-dispersion model is one of those problems and its objective is to maximize the minimum distance between any pair of facilities. This model can be applied when locating, for instance, franchise outlets in such a way that the cannibalization of one's own market by another franchisee can be minimized by controlling the minimum distance between the two (Daskin, 2008).

2.4.2 Solution Algorithms

Prior research has proved that most discrete facility location problems are NP-hard (i.e., non-deterministic polynomial-time hard), for which only heuristic approaches are viable to solve large-sized problems (Revelle et al., 2008). Heuristic approaches combine the search of good or fair quality solutions with the limited computation time for solving complex and large-scale problems by removing the constraint of achieving a globally optimum solution (Amorim et al., 2012). Many different heuristic methods for solving NP-hard problems have been introduced, among which four most commonly adopted methods for solving location problems are briefly described below.

Simulated Annealing (SA) algorithm follows the principles presented by Metropolis et al., (1953) on statistical thermodynamics, and was first introduced by Kirkpatrick et al. (1983) as an algorithm to solve well-known combinatorial optimization problems. In the searching process, the SA not only accepts better but also worse solutions based on a certain probability in such a way that the risk of falling prematurely into local minima is reduced (Qin et al., 2012). Therefore, the algorithm is able to find high quality solutions that are not dependent on the selection of the initial solution compared to other local search algorithms. Another advantage of the SA is the ease of its implementation, but the need for relatively longer processing time remains as its drawback.

Spatial Simulated Annealing (SSA) is a spatial counterpart to simulated annealing, and has gained popularity over the last decade among operations researchers for its improved performance over its non-spatial counterparts (van Groeningen, 1997; van Groenigen and Stein, 1998). In searching for the optimality, this algorithm utilizes a vector *h* to control the direction and the length, with which random perturbations are made iteratively until some user-defined stopping conditions are met. It is this unique generation mechanism that has made the algorithm more attractive when dealing with optimizing a sensor network in two-dimensional geographic space (Brus and Heuvelink, 2007; Zhu et al., 2010; Mohammadi et al., 2012; Amorim et al. 2012; Pereira et al., 2013). More in-depth discussions on this method will be provided in Section 3.2.3 of this thesis.

Genetic Algorithm (GA) is another heuristic search technique which is formulated based on the analogy of natural evolution into search algorithm (Arifin, 2010). Similar to SA, it is also capable of computing the (near) global optimal solutions by avoiding to become trapped at a local optimum. GA starts with a bottom up approach by creating the initial population of randomly generated solutions called individuals or chromosomes (the process known as generation) and measures the fitness value of each individual of population through an objective function. It then performs recombination and mutation to generate a new population, from which the fitness value is checked and the individual with higher fitness values is evolved to form a new generation. The iterative process continues until stopping criteria are met, at which the individual with best fitness value is selected as an optimal solution. Like any other heuristic search algorithms, there is no absolute assurance that GA will find a global optimum and it has more parameter to adjust than SA thereby making the implementation more difficult (Arifin, 2010).

Tabu Search (TS), in principle, uses adaptive memory and responsive exploration to determine the optimal solutions (Glover and Laguna, 1997). The adaptive memory part of tabu search enforces a set of rules and disqualified solutions (i.e., tabu list) to filter which solutions will be admitted to the neighborhood to be explored in local search. Responsive exploration integrates the basic concept of intelligent search where good solution features are exploited while searching for new promising regions. The process iterates until some user specified conditions are met (e.g., a time limit or a threshold on the fitness score), at which, the best solution observed so far during the iterative process is returned. Given the underlying mechanism of the method being heuristic, it may miss some promising areas of the search space; hence the solution found is not guaranteed to be the global optimum (Glover, 1989).

Chapter 3
PROPOSED METHODOLOGY

Recognizing the complexity of the RWIS location planning problem and the variation and limitations in data availability, three distinct approaches are proposed and the detailed descriptions of each of the proposed method are provided in this chapter. This is followed by a description of the solution algorithm considered in this thesis, and a comparison of the three alternatives. Lastly, a method for evaluating RWIS location solutions is presented.

3.1 An Overview of RWIS Station Site Selection Framework

To address the complexity of the RWIS location problems, three distinct approaches are proposed differing in system settings, optimization criteria, and data needs. The first method is a *surrogate measures (SM) based approach* intended to formalize the current best practices of locating RWIS stations using various heuristic rules capturing not only weather-related factors (e.g., snowy roads) but also traffic-related factors (e.g., traffic volume). The second method is a *cost-benefit (CB) based approach* based on the assumption that historical maintenance costs and collision data are available that allow development of cost-benefit models at a patrol route level. The third approach, also the most sophisticated, is a *spatial inference (SI) based approach* introduced to incorporate the spatial interactions between RWIS stations such that an optimal sampling pattern can be achieved given a predefined objective function.

Figure 3-1 shows the overview of the proposed location selection methods discussed herein. As can be seen in this figure, there are many different types of data required to tackle the objectives, and those are weather (e.g., RWIS), geographic, highway network, traffic volume, vehicle collision, and winter maintenance data.

Since large amounts of datasets are to be assimilated, a geographical Information Systems (GIS) based platform will be used for an effective data handling. GIS has long been recognized as a powerful yet efficient tool, particularly for spatial data management since it can bring about more rapid handling and processing of any data with locational attributes (e.g., data with latitude and longitude). For this reason, GIS is widely adopted by transportation and climate research communities where GIS is elected as a main platform to better facilitate model accessibility, database maintenance and updating, and cartographic display of model results (Alterkawi, 2001; Caeiro et al., 2002; Goodchild, 2000; Arampatzisa et al., 2004).

In order to reduce the mathematical complexity of the proposed approaches, the region under investigation will be discretized and divided into a grid of equal-sized zones or cells. According to FHWA's sitting guidelines (Manfredi et al., 2008), the spacing of RWIS sites is suggested to be in the range between 30 and 50 kilometers. Alternatively, area per station (i.e., average coverage per one station) can be used as a proper spacing. Using the appropriate size, the grid covering the entire study area will be created, and then major road segments are superimposed onto the grid in such a way that only the cells containing the road segments can be selected for further analysis.

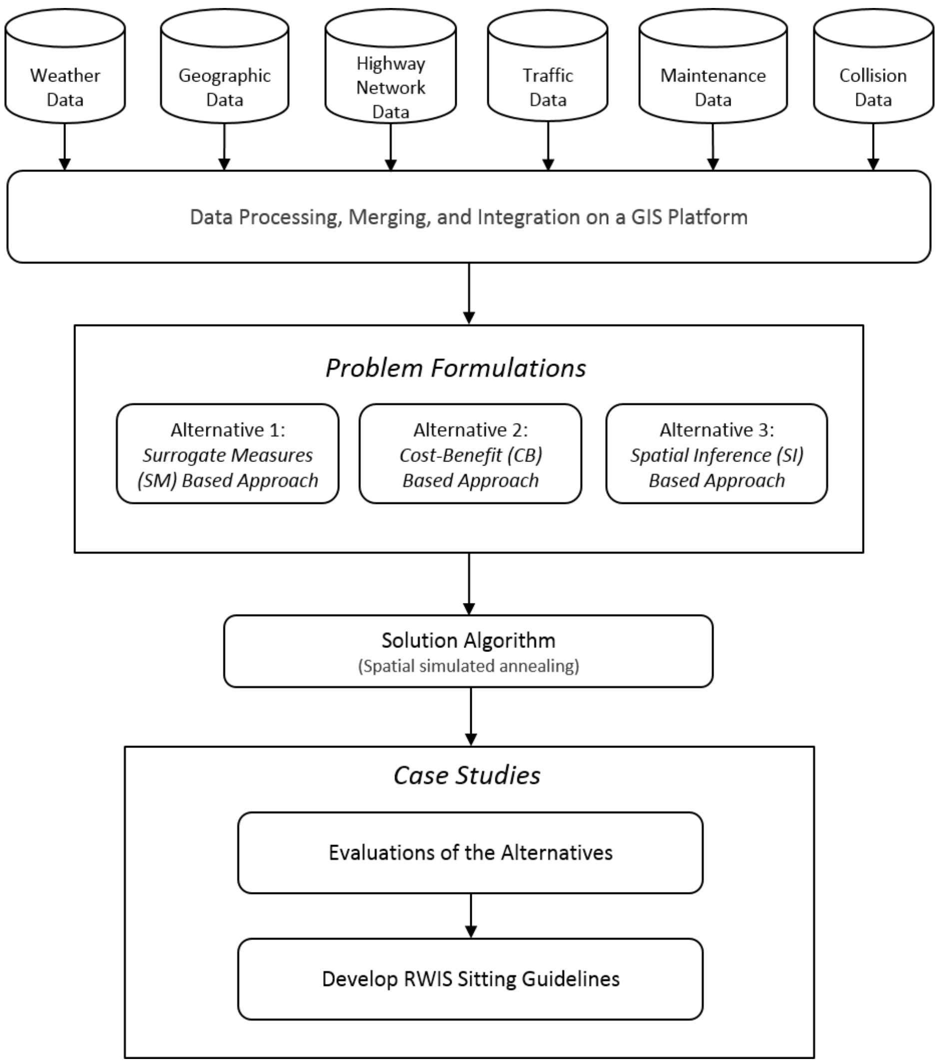


Figure 3-1: An overview of the proposed methodology

There are three primary reasons for adopting this representation. First, provision of a point location of an RWIS station may not be suitable for a real world application as there are often several other factors such as line of sights, right-of-way, etc. which must also be considered prior to deciding the exact location. Second, averaging the observations (i.e., collision frequencies) at the cell level is expected to provide a better estimate of expected collision frequencies. Lastly, structuring the problem discretely helps increase the computational efficiency.

The following descriptions of notations will commonly be used when formulating a problem for each proposed approach. Let i denotes a demand point (e.g., the needs of RWIS information for more effective and efficient WRM operations leading to an increase in safety and mobility of travelling public) with $i \in 1, \ldots, N$, where N is a total number of demand points. Let k be an RWIS station index with $k \in 1, \ldots, M$, where M is a total number of RWIS stations to be deployed. It is also assumed that the demand points are the potential sites where RWIS stations can be located. Let X be the solution set, where $X \in (x_1, \ldots, x_M)$, and $x_k = i$ if i is assigned with an RWIS station. Figure 3.2 shows an example of a discretized network with the notations defined herein.

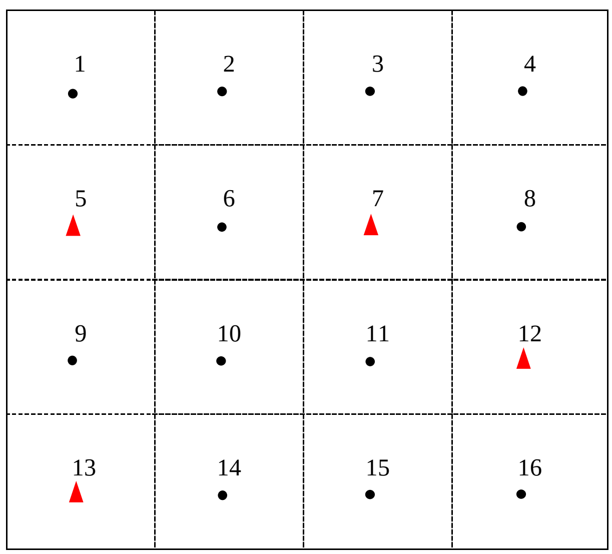


Figure 3-2: An example with i = { 1, . . . , 16}, k = {1, 2, 3, 4}, and $X = \{x_1, x_2, x_3, x_4\}=\{5,7,12,13\}$

In this example, there are a total of 16 potential locations (i.e., circles), 4 of which are allocated with RWIS stations (i.e., triangles). For example, the RWIS station located at the bottom left corner can be explained by its notations; it is indexed as the 4th RWIS station, located at the 13th cell (i.e., $x_4 = 13$).

Case studies will be conducted to evaluate the three alternative approaches and their solution sets, which will then be evaluated to describe the unique features of individual solution sets accordingly. For each solution set, the existing RWIS network (if available) will be used to evaluate the model outputs and recommend new location settings. A summary of the assessments will be made available for use as general guidelines to improve decision support on RWIS installation and siting. A comprehensive description on each component of the proposed method is provided in the following sections.

3.2 Proposed Approaches – The Idea

In this section, the three proposed alternative approaches, which are based on "*surrogate measures*", "*cost-benefit*", and "*spatial inference*", are described in details.

3.2.1 Alternative 1: Surrogate Measures (SM) Based Approach

As emphasized earlier, the current RWIS deployment schemes are inconsistent, and dependent heavily on subjective opinions of maintenance personnel with a lack of quantitative rationales for choosing a location. Thus, it is of high interest to investigate the feasibility of formalizing various heuristic approaches being adopted in practice such that the process of locating RWIS becomes more transparent, consistent and justifiable. Figure 3-3 shows the flowchart of the surrogate measures (SM) based approach for choosing provisional RWIS station locations. Three different groups of criteria, which include weather, traffic, and maintenance factors, are processed and normalized to calculate the total average score in each cell of the grid. Subsequently, a set of solutions for each individual criterion and combined criterion will be generated for further evaluation.

3.2.1.1 Regional Location Selection Criteria

As discussed previously, RWIS stations are installed to collect road weather and surface condition data and their value is reflected in the use of these RWIS data, including improved mobility and safety (i.e., benefit for motorists), and reduced winter road maintenance (WRM) costs and salt usage (i.e., benefit for agency and environment). Therefore, it is critical to clearly define the criteria that can be used to measure the "goodness" of a location for installing an RWIS station. The following is a list of surrogate location selection measures representing the main criteria considered by maintenance personnel in planning RWIS installation:

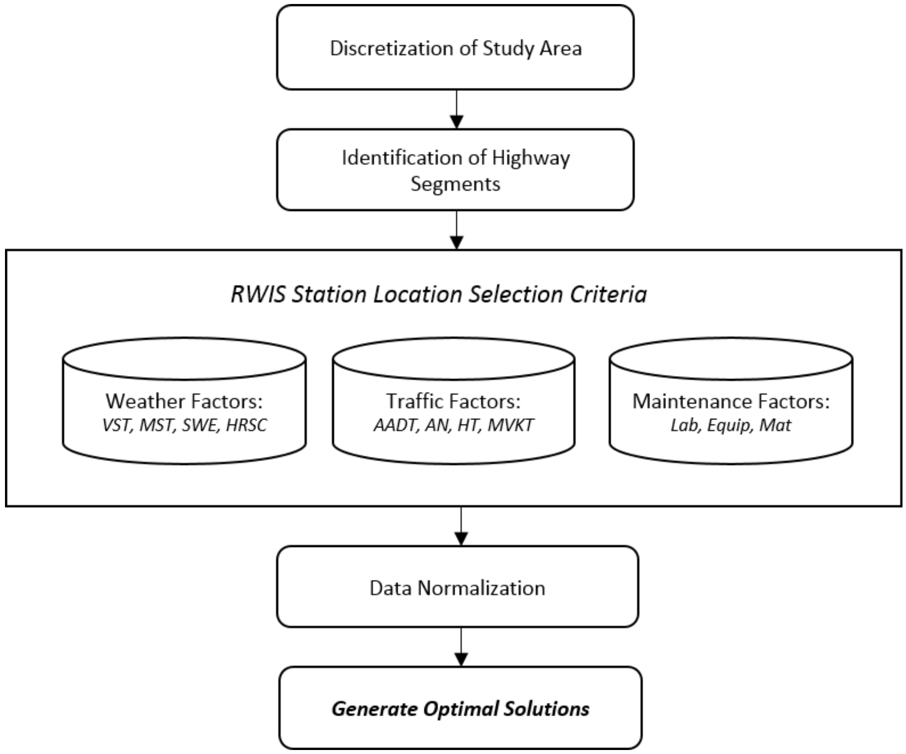


Figure 3-3: Flowchart of Surrogate-Measures Based Approach

Weather-related Factors:

Intuitively, RWIS stations should be placed in locations that experience severe yet less predictable weather patterns and thus are in need of real-time monitoring. Therefore, it is important to analyze the spatial distribution patterns of some critical weather variables such as temperature and precipitation. For example, the variability of surface temperature (VST), and mean surface temperature (MST) are important factors to be considered as they can provide a definite measure of how much the surface temperature would vary over time and space. Late November to early December is the time of year with the highest probabilities of having black ice or frost. The higher elevation and greater distance away from large water bodies can both contribute to generating colder surface temperatures. This gradually leads to longer winter months with higher likelihood of having frost on road surface, and thus exposes a great danger to motorists. Note that VST is standard deviation calculated using all available surface temperature observations. Snowfall water equivalent (SWE), which describes the amount of water contained in snow pack (kg/m^2), and can be an important factor as it makes logical sense that an RWIS station needs to be situated in areas where snowfalls occur the most. This is particularly true when having a better monitoring capability can intuitively increase mobility and safety by performing a prompter WRM operation (Ye et al., 2009). It is worthwhile noting that use of SWE as a weather surrogate measure can be, at times, misleading because it may not provide sufficient information on the actual amount of snowfall that is accumulated on the road surface. However, use of discrete grid covering a large area should minimize this bias and provide a good indication of adverse weather conditions. Other factors such as hazardous road surface conditions (HRSC) such as frost and ice can also be considered as they provide important information about locations with high probability of such conditions. Hence, the abovementioned weather factors are proposed to be included in the analysis for selecting a candidate location of an RWIS station.

Traffic-related Factors:

Intuitively greater benefits can be obtained from RWIS when they are placed in locations of a greater number of travelling public. A recent study conducted by Greening et al. (2012) showed that a well maintained RWIS network would in fact reduce the accident rates by a significant amount, which in turn would bring huge savings. Notwithstanding the fact that other factors such as vehicle technology and weather severity could cofound the effect of real-time information from RWIS, their work clearly demonstrated that the use of RWIS information could potentially prevent accidents. Furthermore, the survey dedicated to providing the current practices of deploying an RWIS system showed that more than 60% of participated DOTs would also consider highway class along with collision rate and traffic volume. Their intension for taking highway class into account is similar to considering traffic volume in the context of providing benefits to a higher number of road users. As such, the traffic-related factors such as collision frequency or rate, traffic volume and highway class are included as location selection criteria.

Maintenance-related Factors:

As discussed, one of the primary reasons for installing an RWIS station is to reduce the maintenance costs. The benefits of utilizing additional information received from RWIS can intuitively increase by situating them in locations where the demand for maintenance operations and thus costs are high. Implementation of anti-icing operations, for instance, has been found to reduce the total maintenance costs through many case studies (Ketcham et al., 1996; Parker, 1997). Three dominant groups of maintenance operation costs can be broken down to labour (*lab*), equipment (*equip*), and material (*mat*) costs. Therefore, the costs from these three sources could be included in the analysis as a goodness measure for locating RWIS stations.

3.2.1.2 Problem Formulation - SM Based Approach

In order to consider all three types of surrogate location selection factors in a systematic framework, a weighting scheme is proposed to combine them into a single measure. As a result, the RWIS station location problem can be formulated to maximize the weighted total score of the three location selection factors, subject to a budget constraint. This problem fundamentally shares a similar trait with covering-based problems in DFLP. More specifically, the problem can be mapped into a max-covering problem, where facilities provide services (i.e., RWIS information) to each demand point such that the number of covered demands would be maximized. As mentioned in Chapter 2, the max-covering model is able to distinguish between big and small demands and allow some locations to be left uncovered when the number of locations required to cover all sites exceeds predefined *p* facilities.

Consider the problem that a total of *M* RWIS stations are to be located over a region. Let sw_{x_k}, st_{x_k}, and sm_{x_k} denote the scores of weather, traffic, and maintenance, respectively, of station *k*; the associated weights are represented by $\omega_w, \omega_t,$ and ω_m. Therefore, the problem for the surrogate measure based approach is formulated as:

$$Maximize\ \ S = \sum_{k=1}^{M} \left(\omega_w sw_{x_k} + \omega_t st_{x_k} + \omega_m sm_{x_k} \right) \qquad 3\text{-}1$$

where *S* is the total score function defined as the weighted sum of the scores of all selected sites, and and x_k is the location of an RWIS station *k*. The weights associated with the location criteria may vary by regions, which may be decided based on the series of interviews with regional maintenance personnel. The total available budget limits the number of RWIS stations to be located. During installation, the stations may be equipped with different sensors based on various requirements. Furthermore, the annual maintenance costs for individual sites may also vary depending on the proximity to maintenance facilities. As such, the budget constraint can be formulated as:

$$\sum_{k=1}^{M} C_{x_k} \leq B \qquad 3\text{-}2$$

where C_{x_k} and *B* represent individual installation cost at location x_k and total available budget, respectively. The solution algorithm for solving the above optimization problem will be discussed later in this chapter.

It is worthwhile mentioning that a discrete network representation is considered in all proposed methods as structuring the problem discretely helps increase the computational efficiency. Equally important, provision of a point location of an RWIS station may not be suitable for a real world application as there are often several other factors such as line of sights, right-of-way, etc., which must also be considered prior to deciding the exact location.

3.2.1.3 Estimating the Surrogate Measures

In order to solve the proposed location problem (i.e., determining hot-spots) based on the total score function defined in Equation 3-1, the three aforementioned surrogate measures, namely weather, traffic, and maintenance, need to be known at all demand points (i.e., potential RWIS stations locations) such that the score for individual components at every site can be calculated. However, it is almost inevitable that some factors must be estimated due to the nature of data being unavailable at all locations. For instance, weather factors are obtained from existing RWIS stations and/or local weather stations that their values must be estimated at unobserved locations. A number of past studies show that weather variables (e.g., temperature) tend to have a linear relationship with environmental and locational variables (Hurrell, 1996; Eriksson and Norrman, 2000; Stull, 2010; Wang et al., 2011). As such, a multiple linear regression (MLR) analysis will be employed to model the variables of interest. A MLR has a following functional form (Geladi and Kowalsk, 1986):

$$E(Y \mid X) = \alpha + \beta_1 X_1 + \cdots + \beta_p X_p \qquad \text{3-3}$$

where Y, X, α, β, and p are response and explanatory variables, intercept, coefficients, and the number of variables being considered, respectively. According to the findings of the literature (Eriksson and Norrman, 2001), variables such as latitude (*lat*), longitude (*long*), distance to water (d_w), relative topography at different search radius in kilometers ($RT_{1,5,10,20}$) will be used as explanatory variables.

3.2.2 Alternative 2: Cost-Benefit (CB) Based Approach

While the heuristic approaches for choosing sensor locations are based primarily on intuition and experiences by field experts, an RWIS cost-benefit model will be able to provide a more defendable way for prioritizing the candidate sensor locations. As stated earlier, there are several RWIS cost-benefit studies conducted in the past; however they do not provide evidence of sufficient granularity that can be directly used for location optimization. As such, it is necessary to develop an RWIS cost-benefit model by establishing a clear relationship between the various criteria being used in practice and their associated benefits to RWIS stations. In addition, using the cost-benefit model as a basis, an RWIS location optimization model should be developed to help RWIS planners evaluate and assess their existing RWIS network, and further delineate new potential locations so as to maximize the benefits to all RWIS users.

One possible approach to estimating the expected benefits to RWIS installations is comparing the maintenance costs, and safety and mobility outcomes between highways with and without RWIS stations nearby. This approach requires information from an existing RWIS network, which can then be used for developing cost-benefit models to estimate benefits and costs in all demand points (i.e., potential sites). Figure 3-4 shows a flowchart of the proposed CB approach for determining the optimal RWIS station location and density at a regional level. As shown, the method consists of three steps: data preparation and integration, RWIS benefit and cost modeling, and analysis of RWIS station location and density (i.e., generate optimal solutions).

3.2.2.1 RWIS Cost-Benefit Quantification

As shown in Step 1 in Figure 3-4, three sources of data are needed for the intended cost-benefit analysis and location optimization of an RWIS network. Collision data are filtered in such a way that only the wintery collisions derived from RWIS information are retained, which include those that occur during adverse weather and surface conditions such as icy and slushy. Although collisions could occur for reasons other than inadequate maintenance operations in areas with no RWIS station, it is assumed that collisions that occur during hazardous conditions could be considered as preventable, to some extent, if information from RWIS is available to maintenance personnel to enable them perform proactive and/or responsive maintenance actions. Maintenance data include labor, material (salt, sand and brine), and equipment (plower and salter). Traffic count data are represented by annual average daily traffic (AADT), which can be converted to winter average daily traffic (WADT), million vehicles kilometer travelled (MVKT), and bare-pavement target regain time (BTRT). All three types of data are integrated into one data set and expressed in terms of predefined base routes using a GIS for further analysis (to be discussed more in later sections).

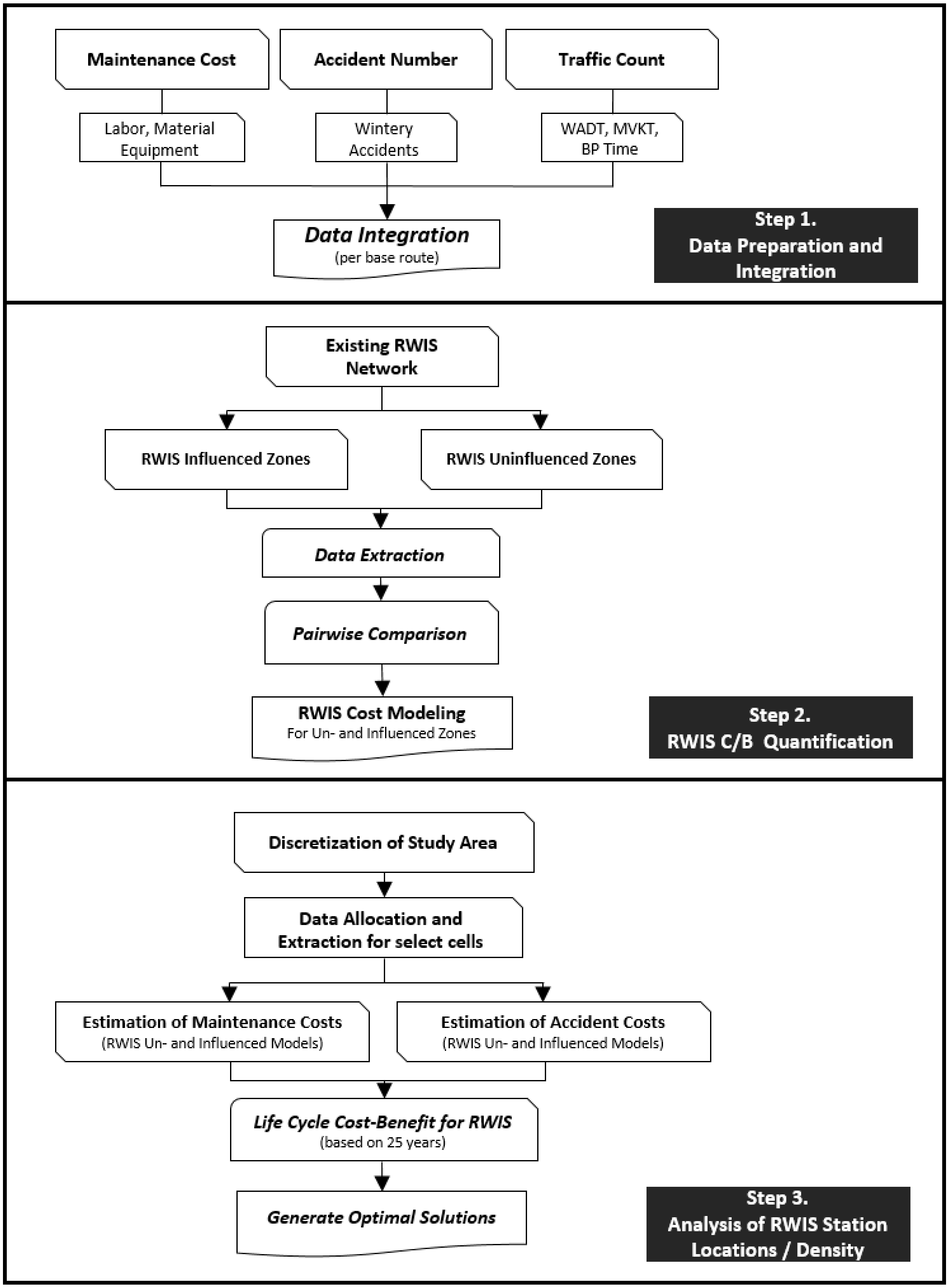


Figure 3-4: Flowchart of Cost-Benefit Based Approach

In Step 2, models will be developed to estimate the total benefit that could be derived from installation of an RWIS station at a given highway section as compared to the scenario of no RWIS station, such as reductions in maintenance costs, collisions and traffic delay. As mentioned previously, some RWIS benefits (e.g., environment) are difficult to quantify, hence only the first two benefit items, which are also the two largest benefit sources, are considered, and can be defined by

$$B_i^{Maintenance} = MC_i^{RWIS} - MC_i^{No\ RWIS} \qquad 3\text{-}4$$

$$B_i^{Safety} = AC_i^{RWIS} - AC_i^{No\ RWIS} \qquad 3\text{-}5$$

where $B_i^{Maintenance}$ = expected maintenance benefit, or, reduced annual maintenance costs due to installation of an RWIS station at area *i* (i.e., demand point);

B_i^{Safety} = expected safety benefit, or, reduced annual collision costs due to installation of an RWIS station at area *i*;

MC_i^{RWIS} = expected total annual maintenance cost for the given area *i* if there is an RWIS station nearby;

$MC_i^{NO\ RWIS}$ = expected total annual maintenance cost for the given area *i* without an RWIS station nearby;

AC_i^{RWIS} = expected total annual collision cost for the given area *i* if there is an RWIS station nearby;

$AC_i^{NO\ RWIS}$ = expected total annual collision cost for the given area *i* without an RWIS station nearby.

As shown in Equations 3-4 and 3-5, the two dependent variables of interest are the expected maintenance cost and expected collision cost for two distinct scenarios: one with RWIS and the other without RWIS. The rationale for adopting this method is that a highway section covered by a nearby RWIS station is more likely to receive more efficient and cost-effective WRMs than those far from RWIS stations. This rationale can be justified in that information coming from RWIS enables maintenance staff to predict near-future road weather conditions and apply anti-icing chemicals before a snow storm hits, thus preventing or minimizing the formation of bonded snow and ice layers (C-SHRP, 2000). Furthermore, since the treatment is done proactively, a smaller amount of chemical is needed to prevent bonding than when snow and ice already exist (Epps, 1997). Note that the proposed method assumes that all winter maintenance personnel use RWIS information in their WRM decision-making process such that maintenance costs and collision frequency can be reduced. This assumption is well supported by our interviews of maintenance personnel, which has revealed that RWIS information is always utilized in making more informed decisions whenever such information is available.

To quantify the sole benefits of RWIS, all existing station locations are buffered, and the roads that fall into these buffered areas are labeled as RWIS influenced roads and the rest labeled as RWIS uninfluenced roads. Since the size of diameter describes the maximum distance a single RWIS station could cover, it is critical to determine the representative size. A simple approach would be to use 30 km – 50 km as suggested by FHWA's RWIS sitting guidelines (Manfredi et al., 2008) or use the existing density. Using the appropriate size of buffer, the corresponding data at these two zones will be extracted for further analysis.

Once the data are classified and matched accordingly, a multiple linear regression technique will be employed to model the maintenance and accident costs. Since accident costs are not directly available, comprehensive costs of motor vehicle crashes by severity information (i.e., K-A-B-C scales, FHWA, 1994) will be used to convert each type of accidents to monetary figure. The average costs for each severity type also include many other costs incurred as a consequence of the collisions, and the most notable components include traffic delays (i.e., extra time, fuel, and pollution) and out-of-pocket expenses. This indicates that the safety benefit component incorporated in the proposed model would also capture (at least partially) the mobility benefits of RWIS.

The third step is to divide the region of interest into a grid of equally sized cells, or zones, which are assumed to be the minimum spatial unit for allocating a candidate set of RWIS stations. Once the grid covering the entire region is constructed, the base route is superimposed onto the grid, with only the cells containing the base route selected for further analysis. This process automatically eliminates the unnecessary cells and reduces the degree of complexity by removing the non-candidate cells.

3.2.2.2 Problem Formulation - CB Based Approach

Based on the cost-benefit location criteria defined, the RWIS station location problem can be formulated as to maximize the total net benefit, subject to a budget constraint. Using the cost-benefit models developed, the maintenance and collision costs for each cell with and without RWIS are readily estimated, which can then be used to estimate the benefit of RWIS station at each demand point for any given year.

The RWIS costs considered herein are summarized below (McKeever et al., 1998):

- Capital Costs (Total system) : $42,010 (every 25 years),
- Capital Costs (Total system): $10,446 (every 5 years),
- Total Operation and Maintenance Costs: $5,460 (per year),

The following equation is used for calculating the net present value (NPV):

$$NPV = \sum_{t=0}^{n} \frac{(C)_t}{(1+r)^t} \tag{3-6}$$

where r, t, and n represent discount rate, year, and the expected life of RWIS stations (i.e., 25 years), respectively. C indicates a cash flow, which can be calculated by taking the difference between the RWIS benefits and costs.

Once the benefits and costs are assigned to each cell for all candidate cells (i.e. demand points), the objective function can be formulated in a similar way to the one used for Alternative 1, and is to maximize the total net benefits calculated from the two benefits and annualized costs:

$$Maximize\ \ B = \sum_{k=1}^{M} \left(B_{x_k}^{Maintenance} + B_{x_k}^{Safety} - C_{x_k} \right) \tag{3-7}$$

where B is the objective total benefit function defined as the sum of the benefits of all selected sites minus the annualized costs. $B_{x_k}^{Maintanace}$and $B_{x_k}^{Safety}$ are expected benefits from reduction in annual maintenance and collision costs due to installation of an RWIS station, respectively, as defined in

Equations 3-4 and 3-5. C_{x_k} denotes the annualized costs associated with installing, operating, and maintaining a single RWIS station. Again, the budget constraint used in the SM approach (i.e., alternative 1) can also be utilized for this formulation (refer to section 3.2.1.2). Similar to Alternative 1, this problem is comparable to a max-covering problem in DFLP.

Lastly, the recommended density is used as a threshold to decide how many stations are to be deployed at a region. It should be noted that the further analysis is required to pinpoint the exact location of individual RWIS stations by considering other local siting requirements including power, communications, obstructions, ease in access for maintenance, and etc., as discussed previously. Furthermore, it is important to recognize that there exist other factors such as human behavior and vehicle conditions that may contribute to the occurrence of accidents regardless of the availability/presence of RWIS information during winter seasons. However, it is believed that the impact of these factors will likely be minimized by taking the difference of total annual collision costs between those in RWIS influenced areas and in RWIS uninfluenced areas as the outcomes will represent the benefits that are expected solely by the presence of RWIS stations.

3.2.3 Alternative 3: Spatial Inference (SI) Based Approach

While the first two proposed approaches are intuitive and easy to comprehend, they have some limitations. For example, SM is a surrogate-based approach that does not explicitly model the benefits of RWIS, which can only partially captured by the traffic, weather, and maintenance parameters. For CB, the RWIS benefit models are constructed based on the empirical data (from exiting RWIS stations) such that the findings may not be applicable to other areas. Likewise, it is challenging to determine all the underlying benefits (e.g., societal and environmental benefits) associated with RWIS. More importantly, both approaches do not take into consideration that data from RWIS stations can be collectively used to make inference about the conditions over a whole region – not just those that are covered by RWIS. It is this monitoring capability of RWIS network that is the foundation of the third method proposed to determine the optimal configuration (or spatial arrangement) of RWIS stations.

As previously discussed, RWIS information makes it possible to perform proactive winter maintenance operations such as anti-icing (i.e., applying salt, mostly in liquid form, in advance of an event), which reduces the amount of time required to restore the roads to a clear and dry state at lower costs. When the RWIS data are used to infer the conditions of the whole region, the benefits of anti-icing can be equally extended over the whole region and should be considered in location optimization. This argument remains valid under the assumption that an increase in estimation or monitoring capability of hazardous road surface conditions (HRSCs) will contribute to improving the overall quality of winter road maintenance operations.

In order to model the monitoring capability of an RWIS network, it is proposed to apply a popular geostatistical approach called kriging as described earlier. The monitoring capability of a given RWIS network is captured by determining the kriging error variances (i.e., the expected estimation errors). A nice property of the kriging errors is that they can be determined as part of the estimation process on the basis of the spatial correlation structure over the domain, which can be obtained as a function of distance (and perhaps direction) as a prior (van Groenigen and Stein, 1998). In other words, its error estimate depends entirely on the data configuration and the covariance functions, not on the actual observations themselves. This indicates that kriging errors can be used as a criterion to optimize and evaluate an RWIS location solution. In addition, another optimization criterion, namely vehicular collision frequency, is introduced to reflect the needs of installing an RWIS station for reducing / preventing collisions in its vicinity.

Selection of these criteria has been decided based primarily on the findings from a survey dedicated to reviewing and examining the current best practices for locating an RWIS station in North America (See Appendix C). In this survey, participants responded that they would consider weather related hot-spots, such as those commonly encountered when roads are icy, snowy, or frosty, as posing the greatest potential danger to motorists. Equally important, they would also consider high traffic and accident-prone areas that serve a large number of travelers as key factors to consider in RWIS station placement.

Therefore, the third method is proposed on the basis of the idea of minimizing the total spatial inference (i.e., estimation) errors for determining the optimal configuration (or spatial arrangement) of an RWIS network in a geographic space. The third approach is the most refined and sophisticated method, but requires much less data than the first two approaches, and can be conveniently generalized and applied to other regions. Figure 3-5 shows the flowchart of the proposed spatial inference based approach. The following section provides a detailed description of the kriging method as well as the location optimization criteria.

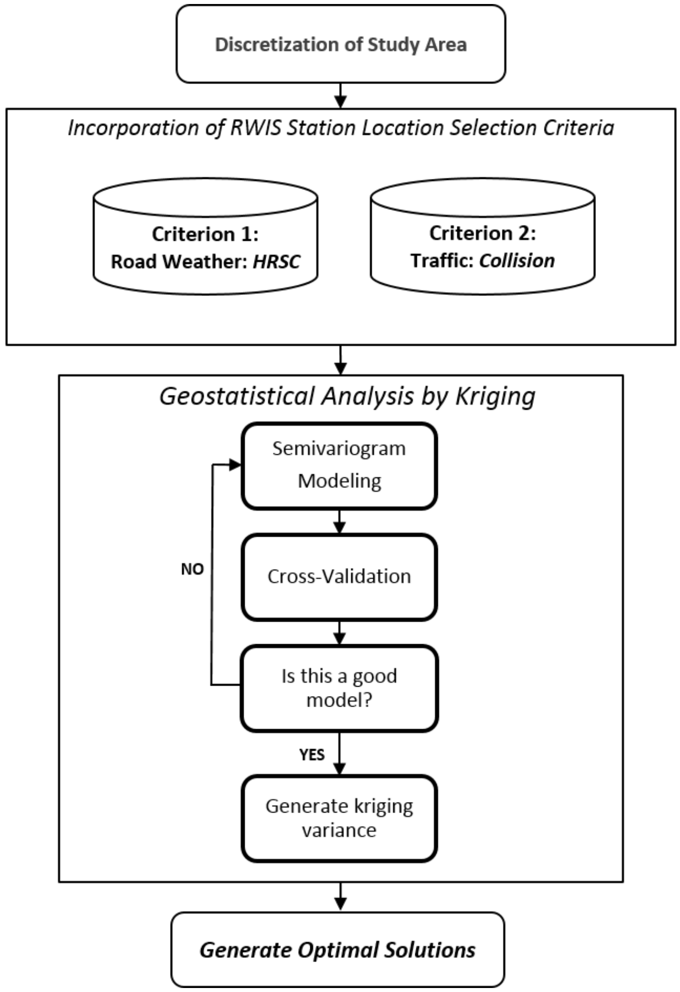


Figure 3-5: Flowchart of Spatial Inference Based Approach

3.2.3.1 Kriging for Spatial Inference

The core idea of kriging is that the estimated outputs are weighted average of observation data, and the optimal weights are determined based on their underlying spatial structure, and assigned to the observed location, and the location to be predicted.

Again, i is a demand point where $i \in 1, \ldots, N$, with N being a total number of demand points, k is an RWIS station index, where $k \in 1, \ldots, M$, with M being a total number of RWIS stations to be installed, and their locations are known and denoted by a vector X, where $X = [x_1, \ldots, x_M]$ and x_k represents the location (cell label) of RWIS station k. As discussed in Chapter 2, kriging is concerned with the estimation of $z(i)$ at any demand point, and this could be any "meaningful" variable of interest to be estimated from a set of known locations, X. z is a variable of interest, which is observable at the M locations., based on which we are interested in estimating the condition at any given location i, denoted by $\hat{z}(i|X)$, which is an estimate of the true value z(i) given observations at X. Figure 3.6 illustrates an example of discretized network and how the condition at any given location i can be estimated.

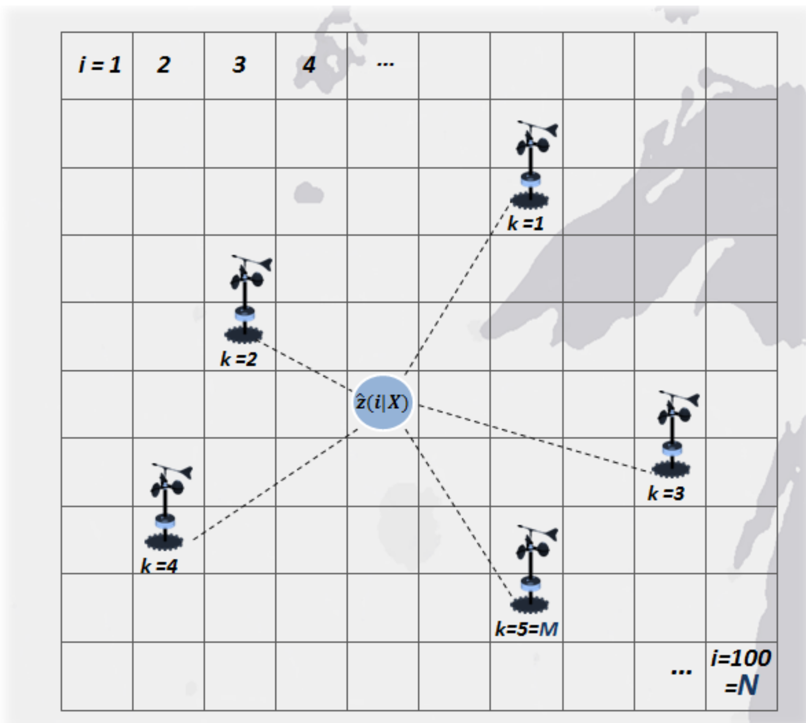


Figure 3-6: A discretized sample network – an estimation of any given point *i*.

The goal of using a geostatistical kriging technique is to estimate a value and its associated error of $z(i)$ at an unobserved location using a set of known observations. Recall from Chapter 2 that the kriging error variance (for ordinary kriging) at locations i is given by (Goovaerts, 1997),

$$\sigma^2\left[\hat{z}(i \mid X)\right] = C(i,i) - \sum_{k=1}^{m} \lambda_k \, C(x_k, i) - \Lambda \tag{3-8}$$

The kriging weights λ_k , can then be determined by Equation 3-9, which is conveniently expressed in a matrix form (refer to Section 2.3.1)

$$\lambda = V^{-1} v \tag{3-9}$$

where

$\lambda = [\lambda_1,\ \lambda_2,\ \ldots\ \lambda_m, \Lambda]^T$ is the vector of the optimal kriging weights

$V = \begin{bmatrix} C(x_1,x_1) & \cdots & C(x_1,x_m) & 1 \\ \vdots & \ddots & \cdots & \vdots \\ C(x_m,x_1) & \cdots & C(x_m,x_m) & 1 \\ 1 & \cdots & 1 & 0 \end{bmatrix}$, is the matrix of covariances between known data points

$v = \left[C(x_1,i), C(x_2,i), \cdots\ C(x_m,i),\ 1\right]^T$ is the vector of covariances between the data and estimation points.

As discussed in Chapter 2, semivariogram modeling approach will be conducted to determine the underlying covariances, followed by the cross-validation to ensure that the modeled semivariogram is accurate and representative. Once the kriging weights are determined via Equation 3-9, the kriging error variance can be computed as:

$$\sigma^2[\hat{z}(i \mid X)] = C(i,i) - v^T V^{-1} v \qquad 3\text{-}10$$

It is worthwhile to note that the method described above is used to solve the kriging system of equations in terms of covariances, instead of semivariances. This is primarily for convenience in handling the square matrices, despite the slight loss in generality (Olea, 1999). Under a second order stationarity assumption, both the covariance and semivariogram functions are related and their outputs are equivalent.

3.2.3.2 Road Collision Frequency

As discussed previously, RWIS stations are installed to collect weather and road surface condition data and their value is reflected in the use of these RWIS data to make more informed decisions including improved mobility and safety (i.e., benefit for motorists), and reduced winter road maintenance costs and salt usage (i.e., benefit for agency and environment). A number of prior studies have suggested that an RWIS station should be located at high-traffic-demand areas (Garrett et al, 2008; Buchanan and Gwartz, 2005; Mackinnon and Lo, 2009). Such a hypothesis is constructed based on a rational assumption and intuition that installation at such areas would increase the benefits for road users. For this reason, the majority of the North American transportation agencies (and other regions) are inclined to incorporate macro level traffic criteria such as collisions, traffic volume, and highway type / class.

Furthermore, a study conducted by Greening et al. (2012) showed that a well maintained RWIS network would likely reduce accident rates by a significant amount, which in turn would bring huge savings. Another recent study by [3]Kwon et. al (2014) provided numerical evidence of significant monetary benefits for installing an RWIS station in terms of reduction in maintenance costs and collision frequency. Likewise, a group of RWIS network planners from Minnesota (i.e., study site) provided a priority list of factors that should be considered, wherein collision frequency was ranked first. Hence, in addition to the first criterion representing HRSC frequencies, minimizing collision frequency is added as another criterion in designing a well-balanced RWIS network. It is worthwhile noting that when collision frequency data are unavailable, a comparable measure to collision frequency namely road class will be used instead.

3.2.3.3 Problem Formulation – SI Based Approach

Considering the nature of the proposed problem using the spatial inference or estimation errors, the RWIS station location problem can be classified as a p-median facility location problem, where the demand is defined based on the demand-weighted distance to all other available RWIS sites (i.e., one location is interrelated with all other locations).

As discussed, average kriging variance is calculated to reflect the needs for installing RWIS stations for improved winter road maintenance operations (i.e., locations with higher errors require more attention than others with lower errors), and sum of average kriging variance should therefore be minimized. The traffic criterion pertaining to a vehicular collision frequency, on the other hand, should be maximized since an RWIS station should be located at high-risk areas. Therefore, in order to combine these two criteria, collision frequency measurements must be inverted such that the problem can be solved as a minimization problem.

[3] Kwon, T. J., Fu, L. & Jiang, C. (2014). RWIS Stations – Where and How Many to Install: A Cost Benefit Analysis Approach, Canadian Journal of Civil Engineering (CJCE), DOI: 10.1139/cjce-2013-0569

To formulate the problem as an integer programming problem, a decision variable y_{ki} is introduced where $i \in 1, \ldots, N$, and $k \in 1, \ldots, M$ with $y_{ki} = 1$ if an RWIS station k is assigned to cell i, 0 otherwise. Following the previous notation, $y_{k,i}$ is related to x_k in X as follows:

$$x_k = \sum_i \left(y_{k,i} \cdot i\right), \ \forall i \in N, \forall k \in M \tag{3-11}$$

The fitness function (objective function) combining the two location criteria is expressed in the following discrete formula:

$$\underset{X \subset \Omega}{Min} \quad \phi(X) = \left[\frac{1}{N} \cdot \sum_i \left(\sqrt{\sigma^2 \left[\hat{z}(i) \mid X \right]} \right) \cdot \omega_1 + \frac{1}{M} \cdot \sum_i \left(\mu_i^{-1} \cdot \sum_k y_{k,i} \right) \cdot \omega_2 \right], \quad \forall i \in N, \ \forall k \in M \tag{3-12}$$

Subject to:

$$\sum_i \sum_k c_{k,i} \cdot y_{k,i} \le B, \ \forall i \in N, k \in M \tag{3-13}$$

$$\sum_i \sum_k y_{k,i} = M, \ \forall i \in N, k \in M \tag{3-14}$$

$$y_{k,i} \in \{0,1\} \ \ \forall i \in N, k \in M \tag{3-15}$$

where,

Ω	an index set that defines all of the candidate RWIS station locations in the study area,
X	a subset of Ω and a solution set, X = [x_1, …, x_m],
N	a total number of all highway grid cells,
M	a total number of RWIS stations to be deployed,

$c_{k,i}$ a total cost of an RWIS station k at site i,

B a total available budget,

$\sqrt{\sigma^2\left[\hat{z}(i) \mid X\right]}$ the square root of the kriging error variance at i given X

μ_i^{-1} the inverse of mean collision frequency at i, and

ω_1, ω_2 the weights for criteria 1 and 2

In Equation 3-12, the objective function represents the sum of average kriging variance of estimating the HRSC frequency and average collision frequency, given X. The kriging variance term is root-squared, as appeared in the first part of the objective function so that estimation errors can be expressed in the same unit as the observations themselves. The weighting factors can be viewed as a way to combine the two measures into a common unit. The second term of the objective function represents the sum of average collision frequency. The binary decision variable y_{ki} is there to take account for those measured only when an RWIS station location, k is allocated to site i. Average collision frequency is calculated using the minimum gridded cell, within each of which, all collision events are aggregated. It is important to point out that the candidate cells are pre-determined by filtering out those cells that do not contain any segment of the highway network under investigation. This reduces the solution space of the optimization model significantly and thus the computational time. The constraint provided in Equation 3-13 represents the cost limit of installing RWIS stations in the study region. During installation, the stations may be equipped with different sensors based on various requirements. Furthermore, the annual maintenance costs for individual sites may also vary depending on the proximity to maintenance facilities. Hence, c_{ki} is added to take account for all supplementary costs in addition to the cost of installing a single RWIS station k at site i. Another constraint that appears in Equation 3-14 ensures that a fixed number of RWIS stations are deployed. The weighting terms, ω_1, ω_2 are added so that an RWIS planning department can adjust and/or apply different weights according to their importance. For simplicity and convenience herein, a fixed number (and a uniform cost) of RWIS stations are deployed.

It is worthwhile noting that some sites may not have access to power and/or communication utilities; another important factor that must be considered to ensure that the data can be obtained and processed in real time (Manfredi et al., 2008). The optimization framework introduced therein, however, can be easily extended to take additional factors into account by introducing another binary decision variable (i.e., 1 if a potential RWIS site has power/communication network in its vicinity, and 0 otherwise). Alternatively, the cells that do not satisfy the local requirements can be filtered out first such that only candidate locations are considered.

3.2.3.4 Optimization with Spatial Simulated Annealing (SSA)

The problem formulated previously is a non-linear integer programming (NIP) problem which is computationally intractable; heuristic techniques are often required to solve these types of problems of realistic sizes. In this research, a variant of one of the most successful techniques called spatial simulated annealing is used (SSA,van Groeningen and Stein, 1998).

SSA is an iterative combinatorial optimization algorithm in which a sequence of combinations is produced by deriving a new combination from slightly and randomly modifying the previous combination (van Groenigen et al., 1999). SSA is a spatial counterpart to simulated annealing (SA, Kirkpatrick et al. 1983), specifically designed to optimize sampling designs of environmental variables using kriging. SA is a stochastic metaheuristic search algorithm first proposed by Metropolis et al. (1953) and mimics the annealing of metal. SA is fundamentally same as Monte Carlo annealing, probabilistic hill climbing, statistical cooling, and stochastic relaxation (Aarts and Korst, 1989). The term “annealing” is related to the metallurgical process of metal alloy heating and relaxed cooling to increase toughness and reduce brittleness (Goovaerts, 1997). The method has a unique generation mechanism for transforming a randomly chosen sampling point over a vector h - the direction chosen at random, and the length also drawn randomly in the interval [0 and h_{max}], thus giving the sampling scheme the chance to “freeze” in its optimal sampling design by terminating with very small perturbations (van Groeningen, 1997). This method is proven to produce dramatic improvements compared to its non-spatial counterparts (van Groeningen, 1997; van Groenigen and Stein, 1998).

In principle, by discretizing the region of interest, kriging variance for all possible combinations of the station locations could be evaluated and the combination that produces the smallest value would be selected as the optimal solution. However, this is impractical as the number of combinations would be formidable, meaning that an exhaustive search over all possible outcomes is computationally infeasible. In the search process, SSA not only accepts improving solutions, but also worsening solutions, based on a certain probability that is defined to minimize the risk of falling prematurely into local minima (van Groeningen and Stein, 1998). Therefore, the algorithm is able to find high quality solutions that are not dependent on the selection of the initial solution compared to other local search algorithms.

SSA has gained its popularity due to its robustness and easy implementation, particularly for optimizing sampling schemes in situations where observations are spatially correlated in geographic space (Sacks and Schiller, 1998; van Groenigen et al., 1999; Heuvelink, 2006; Brus and Heuvelink, 2007; Zhu et al., 2010; Heuvelink et al., 2010; Melles et al., 2011; Mohammadi et al., 2012; Amorim et al. 2012; Pereira et al., 2013). The workflow of the SSA algorithm is depicted in Figure 3-7.

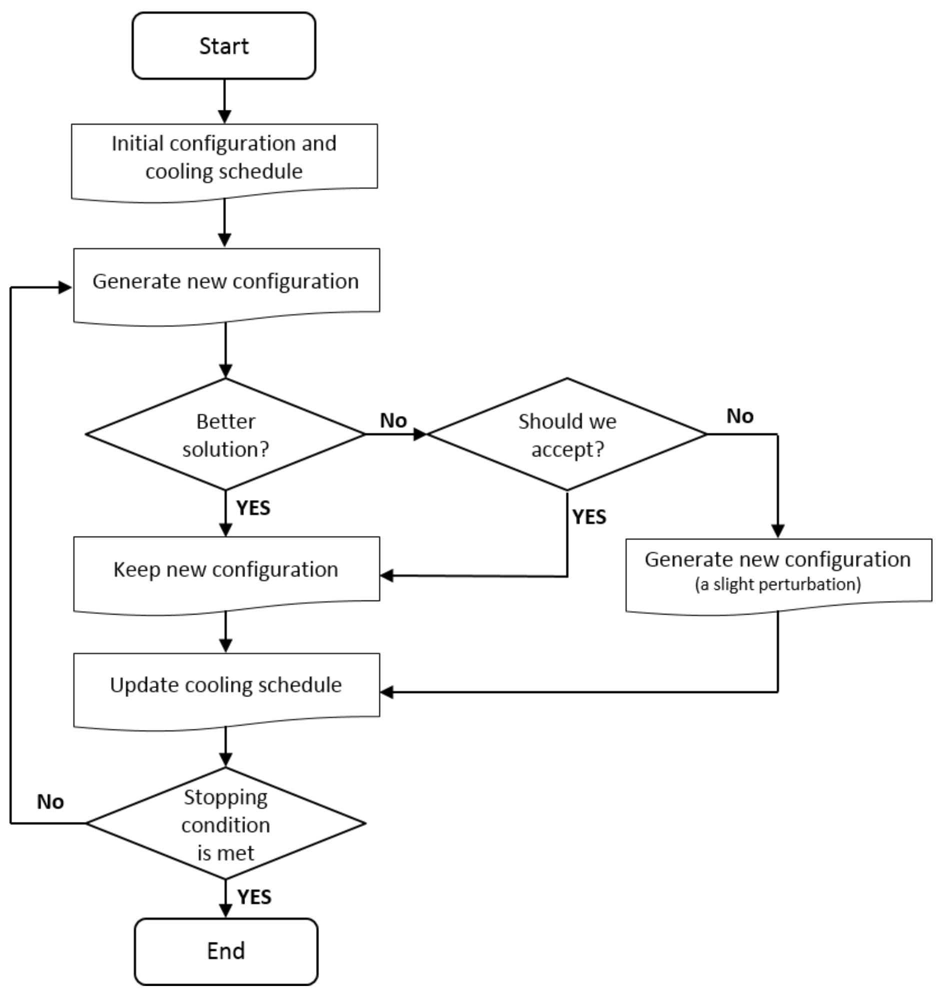


Figure 3-7: Workflow of Spatial Simulated Annealing Algorithm

First of all, there are a few parameters that must be specified prior to running the algorithm, including initial probability of accepting an inferior solution *p*, absolute temperature T_a, and cooling factor or cooling temperature *c*. The probability *p* is set to avoid selection of local minima. Absolute temperature T_a is used as a stopping criterion; but one may simply use the number of iterations or alternatively decide if there is lack of progress in improving the quality measure (i.e., combination of kriging variance and vehicular frequency). Cooling factor *c* controls the rate at which *p* decreases to zero. Thus, smaller cooling factors would converge slowly while higher numbers would provide slow cooling. Once initial parameters are set, optimization begins with a random solution $\mathrm{X}_0 \in \mathrm{X}^{\mathrm{m}}$ where *X* denotes the collection of possible solutions with *m* being the number of observations. The iterations then move forward with a sequence of random perturbations X_{n+1} of X_0 with a probability $P(X_n \rightarrow X_{n+1})$ of being accepted. Thus, even if a new solution does not improve the quality measure (i.e. objective function), the algorithm could still accept it to avoid being trapped in a local optimum, as described above. This transition probability follows the principles presented by and defined as Metropolis criterion (Metropolis et al., 1953):

$$
\begin{aligned}
P_T(X_n \rightarrow X_{n+1}) &= 1, & \quad if\ \phi(X_{n+1}) \le \phi(X_n) \\
P_T(X_n \rightarrow X_{n+1}) &= \exp\left(\frac{\phi(X_n) - \phi(X_{n+1})}{c}\right), & \quad if\ \phi(X_{n+1}) > \phi(X_n)
\end{aligned}
\qquad \text{3-16}
$$

Where ϕ is a so-called objective function with $\phi(\cdot): X^n \rightarrow \Re^+$ to be optimized (i.e., minimized in our case), and *c* is a positive control parameter (i.e., cooling temperature). Thus, if X_{n+1} is accepted, iterations proceed and the new cooling schedule is used for the next randomly perturbed configuration X_{n+2}; iterations continue until the stopping condition is met; and the best solution is presented as an optimal configuration (Aarts and Korst, 1989; van Groenigen et al., 1999). The *c* value of the Metropolis criterion (Eq. 3-15) gradually decreases during the optimization using an Equation suggested by Aarts and Korst (1989):

$$
c_{k+1} = \alpha \cdot c_k,\ \ k = 1,2,\ldots, \qquad \text{3-17}
$$

where α denotes a constant parameter, generally chosen to be close to 1 (e.g., 0.999), and *k* denotes the number of the performed optimization iterations. The simplest and most commonly adopted cooling schedule of SSA is to configure in such a way that *p* could exponentially decrease as a function of number of iterations and the initial cooling factor to ensure convergence (Heuvelink et al., 2006; Brus and Heuvelink, 2007; Melles et al., 2011).

When the SSA algorithm is used to solve the optimization problem formulated earlier, it is critical to investigate the effect of the parameters setting on the solution as well as the running times. Despite its importance, there is very limited information available to decide what ranges of SSA parameters should be chosen when running the optimization. Thus, a simple yet informative sensitivity analysis method, namely, one-at-a-time designs (OATD, Yang et al. 2009), will be carried out to determine the sensitivity of individual SSA parameters on the optimization outcomes.

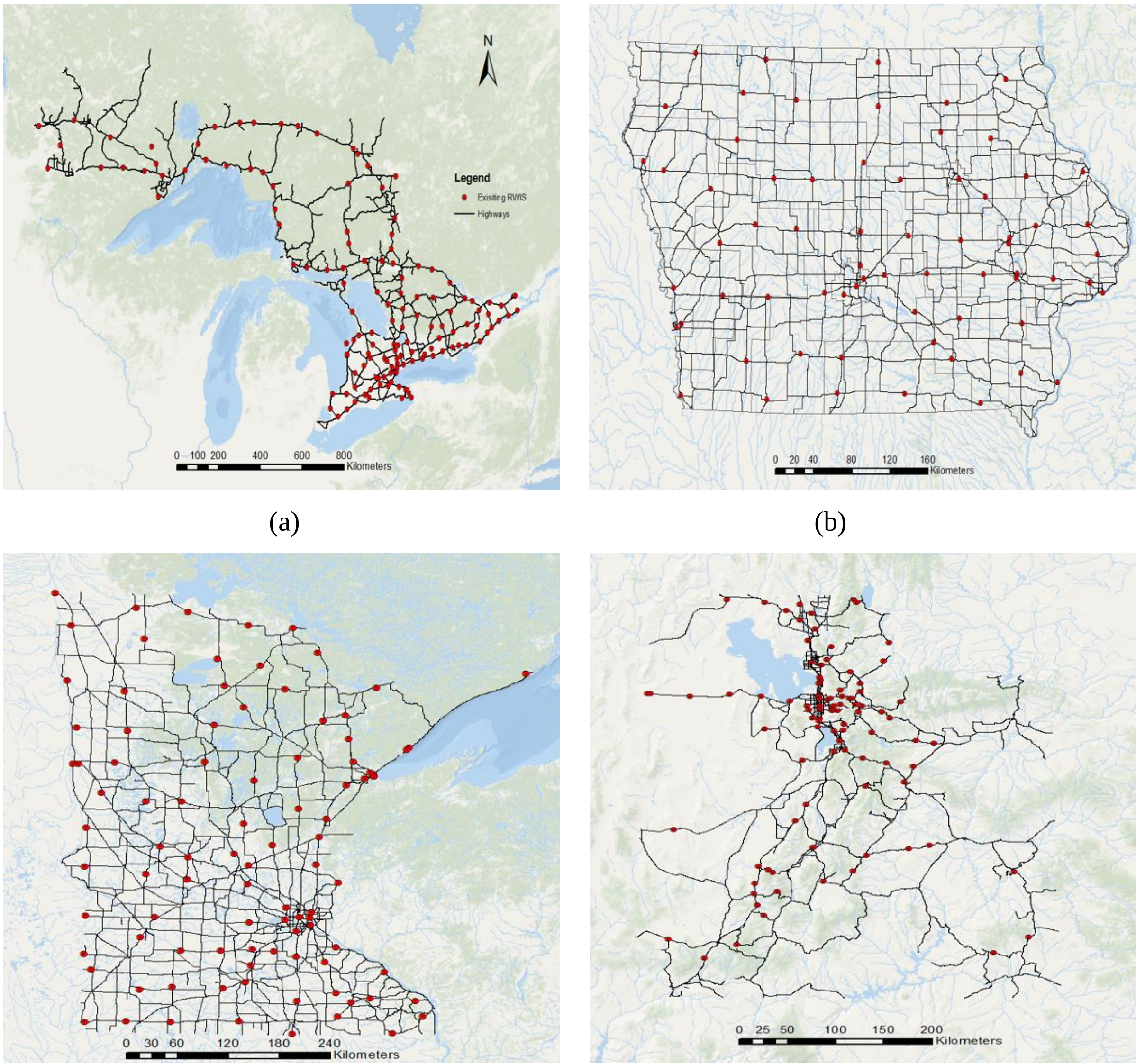
Chapter 4
CASE STUDIES

4.1 Study Areas

The proposed approaches are examined via four case studies covering one Canadian province (Ontario), and three US states (Utah, Minnesota, and Iowa) using various dataset provided by each region under investigation. These four regions are a good candidate as they already have a well distributed and dense RWIS network with distinctive and unique meteorological (lake effect) and topographical (mountainous) characteristics, from which more reliable assessments can be realized. The findings from each region should provide sensible guidelines and measures as to how the optimal location and density would vary from one region to another.

Ontario is the second largest Canadian province, situated in east-central Canada, and has a continental climate like most other provinces of Canada. Northern Ontario has long, very cold winters and short summers whereas the southern part enjoys the tempering effect of the Great Lakes. Southwestern Ontario is typically flat with many rolling hills. To its north contains mainly flat and wet surface. Utah is situated in the Mountain States (also called the Mountain West) from one of the nine geographic divisions of the United States. Because of its geographic location, Utah has extremely varied topography with a large portion of the State being mountainous. The lowest area is in the southwestern part with altitude of 750m, while the highest points lies in the northeastern part with altitude higher than 4000m. Utah is also known for very diverse climates – for instance, there are definite variations in temperature with altitude and with latitude. Average temperature differences between the southern and northern counties at around similar altitudes typically range between 6 and 8 degrees with the northern counties having lower temperatures. The topographies of Iowa and Minnesota, on the other hand, consist mainly of rolling plain and flat prairie. The differences of their lowest and highest altitudes are also small, ranging from the lowest points of 183m and 146m to the highest points of 702m and 509m for Minnesota and Iowa, respectively. Iowa and Minnesota's climates, because of their latitude and interior continental location, are characterized by marked seasonal variations.

Ontario, Iowa, Minnesota, and Utah currently have 140, 67, 97, and 96 RWIS stations in place, respectively, and their RWIS network expansion initiatives are underway to deploy an additional number of stations over the next 5 to 10 years in all regions.



(a) (b)

(c) (d)

Figure 4-1: Study areas under investigation and the existing RWIS networks: (a) Ontario, (b) Iowa, (c) Minnesota, and (d) Utah

4.2 Data Descriptions

This section provides a description of various different data sources, which are used in the analyses described in the later sections.

Weather Data

The weather data from several different sources, namely, road weather information system (RWIS), National Weather Service (NWS), and Daymet are incorporated. Daymet provides weather data including surface weather and climatological summaries available in different temporal resolutions. The data comes in a raster format, which can be conveniently integrated on a GIS platform for extracting various weather records (*Thornton et al, 2012*). RWIS data, in particular, are a primary source in classifying the various types of hazardous road conditions due to its unique measurements focusing on road surface conditions. The four transportation agencies provided their regional RWIS data which were collected at 10-15-min intervals over three consecutive winters (i.e., October to March) between 2010 and 2013 (2006 – 2008 for Ontario). The data came stratified by individual stations each containing nearly one million rows of measurements including the variable of interest - surface condition status. There are a total of 15 surface status codes describing current representative surface conditions expressed in a descriptive format (see Section 1.2). These status descriptions are listed in order of severity and further classified into four different categories with the most critical category listed first. In this study, the top category representing so-called hazardous road surface conditions (HRSC) were considered, and they were snow/ice warning, frost, wet below freezing, and snow/ice watch.

Geographic Data

Geographical parameters including latitude, longitude, and altitude provide a good measure of weather-related characteristics of data with locational attributes. For instance, altitude can play a significant role in triggering the temperature variations of a road surface since temperatures at high altitude can be noticeably different from those at lower altitude. When altitude information is not available, Digital Elevation Model (DEM) can be used instead to extract the said information as well as other road geometric and topographic features such as slope, and relative topography, which is a measure of surface roughness.

Maintenance Data

Maintenance data contains winter maintenance cost records. Each maintenance record is expressed using a unique project identification number along with information on labor, equipment, sand, salt, and brine costs.

Traffic Volume Data

Annual average daily traffic (AADT) data includes location description, highway type/class, geocoding information, and section length. This data are used, where necessary, to determine bare-pavement target regain time (BPRT) as well as million vehicle kilometers travelled (MVKT) as additional parameters in this study.

Collision Data

Historical collision data sets contain individual crash records with detailed information. Each record lists time, day, month, year, data reliability, location, severity (i.e., fatality, injury, and property damage), number of vehicles involved, type of collision, surrounding weather, and surface condition information. Another form of collision data is also available which provides an annual accident number along with geocoding information for mapping onto a GIS platform.

Highway Network Data

The highway network consists of geocoded line features onto which traffic and collision data can be mapped. This is also known as linear highway-referencing system (LHRS) defined as a location-referencing method that is used to identify a specific location with respect to a known point (Baker and Blessing, 1974).

4.3 Data Processing

As indicated above, there are six main categories of different data sources that need to be processed and merged onto a corresponding road segment/grid. This road segment of equal length are used as the minimum spatial unit for determining the provisional RWIS station locations. For this, a GIS based platform is implemented due to the large amount of data sets to be processed in an efficient manner. A schematic diagram of the steps involved in data integration and aggregation on a GIS platform is depicted in Figure 4-2.

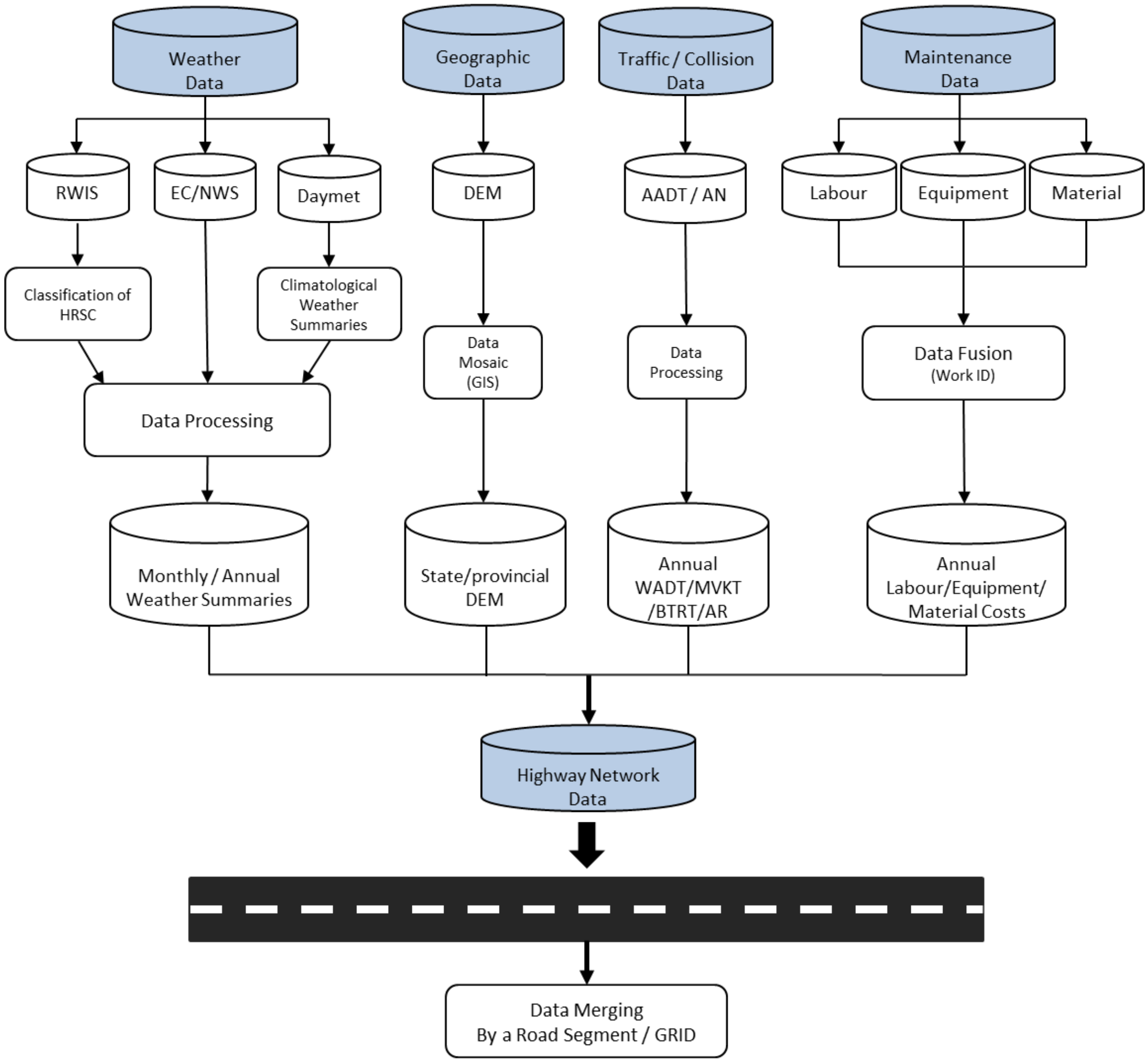


Figure 4-2: A Schematic Diagram for Data Processing and Merging

Weather Data Processing

As mentioned, the weather data are utilized in this study. Different weather variables such as precipitation amount and surface temperature collected from RWIS, and Daymet are used as surrogate measures to delineate the candidate RWIS station locations. Some select weather variables will also be used as predictors in the modeling phases to improve the explanatory power of target variables. Furthermore, the data are also used to appreciate and capture the spatial variability (i.e., weather trends) in the region of interest. RWIS data in particular are a primary source in classifying the various types of hazardous road conditions due to its unique measurement characteristics that are focused primarily on road weather surface and conditions. RWIS data that were provided by the four transportation agencies consisted of nearly 60 million rows of data, thus a script program was written to efficiently process all the data, returning a yearly (seasonal) average of HRSC frequency for each corresponding RWIS station for all regions. All available weather data are then merged onto an equal-sized grid on a GIS database platform.

Geographic Data Processing

Digital elevation model (DEM) are distributed and packaged in small tiles. To keep files sizes and processing times manageable, a title with 1-km spatial resolution (appropriate for large-scale study) are used in this study. Since the data are stored as ASCII files, GIS software are utilized to convert them to raster files for display on a GIS platform. A set of converted tiles are mosaicked to a single raster tile to increase the computational efficiency.

Traffic and Collision Data Processing

Traffic data are received in a form of annual average daily traffic (AADT). A few derivatives of AADT such as WADT, MVKT, and BTRT are calculated for analysis in this study. Since the focus of the analysis is winter (i.e., periods when RWIS information is being utilized), winter average daily traffic (WADT) are used to provide a more representative value, and calculated on a basis of the number of winter days assumed in the analysis. Million vehicle kilometers travelled (MVKT) will also be used as a measure of traffic flow or exposure. Another measure is bare-pavement target regain time (BTRT). During winter storms, a winter maintenance schedule requiring staggered work hours may be used to provide the level of service recommended. Each maintenance area, district, and division develops a schedule of effort needed to achieve BTRT, thus it can be an essential surrogate measure for representing the type of highway and the target level of service.

Collision data consists of additional information describing the type of individual collisions along with weather conditions at the time of collision. These collision data are filtered in such a way that only the preventable collisions derived from RWIS information can be retained, which include those that occur during adverse weather and surface conditions such as icy and slushy. Although collisions could occur for reasons other than inadequate maintenance operations in areas with no RWIS station, it is assumed that collisions that occur during hazardous conditions could be considered as preventable if information from RWIS was available to maintenance personnel to help them perform proactive and/or responsive maintenance actions.

Maintenance Data Processing

Maintenance data are expressed in terms of annual winter maintenance costs in three different categories: labor (hours), equipment, and material (sand, salt, brine). Each maintenance record is described using a unique project identification number. Using a project ID number as a reference, the three data components are fused to calculate the total annual maintenance costs.

Data Merging

Once all the required data are processed as explained previously, highway network data are used as a base route onto which the pre-processed data are integrated and merged. The primary purpose of this step is to allocate all the data with different spatial resolutions to an equal-sized road segment or grid such that each road segment or grid can be considered as a candidate RWIS station location. This step will require a significant effort in geo-processing the individual sets of data on a GIS platform to obtain the representative values for each parameter being considered.

4.4 Application of the Proposed Methods

4.4.1 [4]Application of the SM Method

This section discusses the application of our first RWIS location optimization approach – SM for analysing the Ontario RWIS network planning problem. Two types of surrogate measures, namely, weather- and traffic-related factors, are considered.

[4] This section is based on a published paper: Kwon, T. J., & Fu, L. (2013). Evaluation of alternative criteria for determining the optimal location of RWIS stations. Journal of Modern Transportation, vol. 21., pp 17-27. DOI: 10.1007/s40534-013-0008-9

4.4.1.1 Surrogate Measures

It was mentioned earlier that RWIS stations should be located at areas that exhibit severe yet less predictable weather events such that the benefits of RWIS (i.e., enhanced monitoring capability) can be maximized.

Mean Surface Temperature (MST) and Variability of Surface Temperature (VST): The two commonly used indicators for measuring winter weather severity are the mean surface temperature (MST) and the variability of surface temperature (VST) as defined by the standard deviation of surface temperature. For the areas (or grid cells) that are covered by nearby observation stations (e.g., regular weather station or RWIS), both measures can be directly estimated using observations. For the areas that are not covered, it is necessary to apply a technique to estimate these variables. In this research, regression models are developed for the relationship between the two temperature measures to several known variables including latitude (lat), longitude (long), elevation (elev), distance from water (d_w), and relative topography (RT). The justification for choosing such variables is that latitude is expected to affect the spatial variation of surface temperature, whereas longitude may capture the influence of winds. Elevation in meters above mean sea level could be linked to the variability of surface temperature (e.g., higher the elevation, lower the temperature), and distance from large water bodies, the Euclidean distance in kilometers, represents the degree of continentality (Eriksson and Norrman, 2001). Lastly, relative topography is included to describe the exposure, and is calculated by taking the difference in elevation between each station location and an average of pixels within the respective radius range (e.g., 1km, 3km, and 5km).

Since the monthly variation of surface temperature can vary significantly from one month to another, the two dependent variables, VST and MST, are modeled on a monthly basis. For the Ontario case study, 3-year surface temperature data collected in 2006 to 2008 from a total of 45 Ontario RWIS stations for the month of January are used for modeling. ArcGIS 10.1 is used as a base platform for this study, where digital elevation model (DEM) with 1-km spatial resolution as well as water layers including lakes and sea are utilized to obtain the aforementioned auxiliary information. Once all the required information has been obtained, SPSS is used to perform the multiple linear regression (MLR) analysis with all variables being tested at the 5% significance level. The resulting equations for the two dependent variables are as follows:

$$VST = 0.403(lat) + 0.076(long) + 0.161(dis_w) - 0.011(RT_5) - 5.974,\ R^2 = 72.2\% \qquad 4\text{-}1$$

$$MST = -2.398(lat) - 0.518(long) - 0.016(elev) + 0.296(dis_w) - 0.049(RT_3) + 61.937,\ R^2 = 88.3\% \qquad 4\text{-}2$$

The above calibrated equations are used to calculate both VST and MST values for each cell for all cells. Figure 4-3 shows the resulting VST and MST maps.

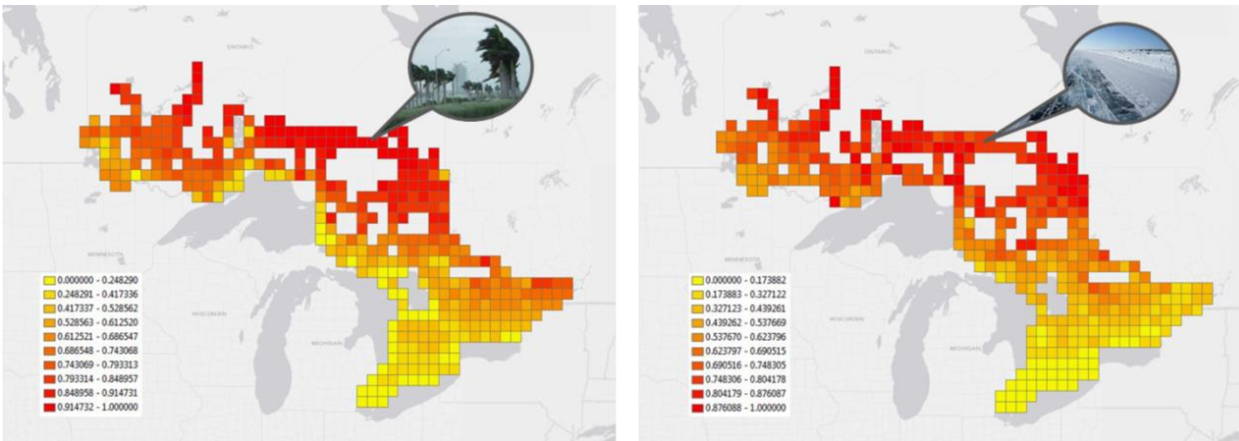


Figure 4-3: Processed VST (left) and MST (right) Maps

From Equations 4-1 and 4-2, it can be clearly seen that all regression coefficients make intuitive sense. For instance, latitude, longitude, and distance to water have a positive correlation with VST implying that as values of each parameter increase, so does the VST. It is true particularly during colder months that surface temperature would likely vary at a greater range at high latitude regions. Furthermore, VST is likely higher as it moves into deeper continents which are typically more mountainous causing a larger temperature variation. These phenomena are explained graphically in Figure 4-3 (left) that VST cells in southern regions and/or nearby lakes tend to exhibit less variation compared to other cells. As for the MST, all the regression coefficients except for distance to water are found to be negative. This is observed since the minimum surface temperature would drop as it moves to the northern regions with higher elevations. Notice that MST can vary by a significant amount (~20ºC) between the northernmost and southernmost cells in Figure 4-3 (right).

Precipitation (Snowfall): Distribution of precipitation amounts, particularly of snowfall amounts must thoroughly be investigated to determine the regions where heavy snowfalls are likely to occur so that recommendations for RWIS stations can be made accordingly. This can be done by analyzing the long-term historical snowfall observations. Daymet is an online weather data archive where daily surface weather and climatological summaries are available for public use (Thornton et al., 2012). Snow-water-equivalent (SWE) describes the amount of water contained within the snowpack expressed in kg/m^2. The average annual summary maps for SWE are obtained for periods from 2001 and 2005 covering the entire North America. Since these files came in a raster format, 5-year average map is generated by taking an average of all available SWE layers using ArcGIS 10.1. Once all the maps have been combined and averaged, each cell is assigned with the corresponding SWE value (i.e., sum of all SWE data within each cell) for the entire grid. Note that because the SWE data is available at the level of individual grid cell (1km^2), there is no need to develop models to infer this variable over the entire region as in the case of MST and VST. Figure 4-4 (a) shows the processed SWE map, where central regions seem to have the most snowfalls, and the amounts are being gradually diminished as it moves to outer regions. Far-most southern regions are appeared to have the least amount of snow.

Traffic Volume (WADT), Accident Rate (WAR), & Highway Type (HT): It was emphasized earlier that an RWIS station should be located in places where traffic volumes and accident rates are high such that the benefits to road users can be maximized. This reasoning can also be applied to highway type where higher classes of highways should be given a higher priority when installing an RWIS station. For this reason, winter average daily traffic (WADT), winter accident rate (WAR), and highway type (HT) are considered as the new surrogate measures for locating RWIS stations. Traffic information management center at the MTO provided data for the 2000 to 2010 provincial highways winter traffic volumes and accident numbers along with highway class, all of which are geocoded with linear highway referencing system (LHRS). MTO currently has a total of 2588 geocoded locations across the province. With these geocoded locations, WADT data have been mapped onto the grid where the data are averaged and assigned to the corresponding cells. WAR used in the analysis is defined as the number of reportable accidents occurring during winter months on a particular highway section for every million vehicle kilometers (MVK) travelled on that section during the same periods. Representative section lengths for all geocoded points are used when calculating WAR. As for HT, four different types that are currently being used by MTO are defined. Following the similar approach of other traffic dataset, HT data have been first geocoded using the LHRS and then the averaged values are assigned to each cell.

Figure 4-4 (b), (c), and (d) depicts the processed WADT, WAR, and HT, respectively. As can be seen in the figure, WAR and WADT data are appeared to share some common traits that there are many number of "high-risk" cells in the southern region for having relatively heavier traffic loads and higher accident rates. This makes a logical sense that increase in exposure would likely increase the number of accidents. On the other hand, northern regions consist of many low-valued cells indicating that they are less important when considering traffic as a location criterion. Similar conclusions can be drawn by analyzing the HT figure that a great number of high-class highways are situated in the southern region suggesting the needs of RWIS stations.

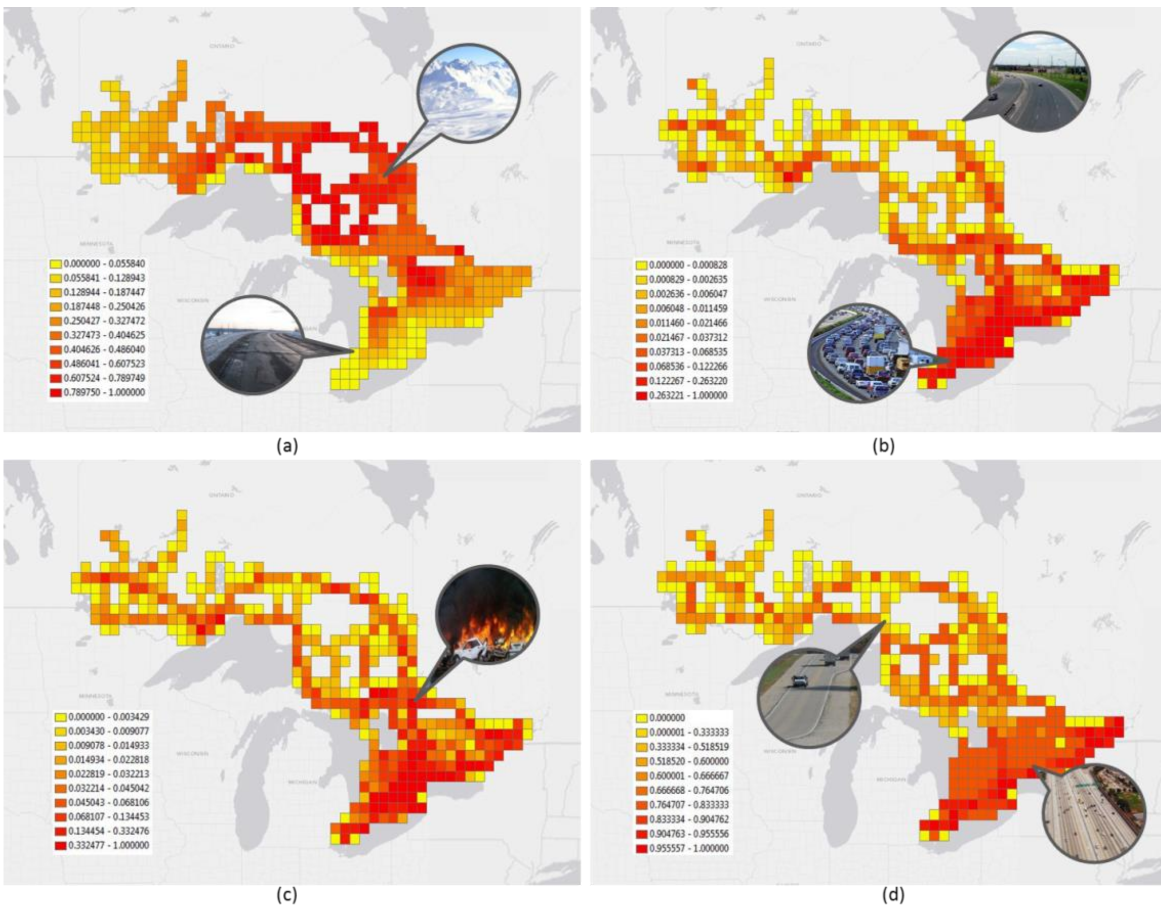


Figure 4-4: (a) SWE, (b) WADT, (c) WAR, and (d) HT

4.4.1.2 Evaluation of Alternatives

In this section, different alternatives are evaluated by applying them to relocate Ontario's existing RWIS stations and comparing the results to their current locations. For each alternative, the objective function formulated earlier is used to determine the candidate locations based on their values of the given selection criterion. For the analysis, different weighting schemes are considered for weather and traffic factors, and the maximum number of stations allowed to be installed was set to 140.

Alternative 1: Weather Factors Only

The weather factors are used to evaluate the current RWIS network in the province of Ontario. VST values in each cell have been added to the corresponding cell of SWE. Note that both factors are normalized with a range between 0 and 1 to enforce a fair comparison. Figure 4-5 describes the result of the combined location selection criteria. It also shows the current Ontario RWIS stations that have been superimposed on the map. Highlighted cells represent the optimized 140 cells that are recommended as potential RWIS station locations.

As can be seen in the figure, a map generated by combining two weather factors suggests potential RWIS sites to be in the middle to upper part of the region, where VST and SWE are also found to be significant in those regions. A percent of matching (POM), which describes an evaluation metric for benchmarking the current location setting, is found to be 30% by having 42 cells matched with the existing RWIS station locations. Notice that there are many cells (i.e., highlighted) in the central regions where no RWIS stations are there to monitor the highly varying weather conditions with historically heavy snowfall events. From this analysis, it can be stated that the current RWIS location setting is less susceptible to capturing the variability of weather conditions.

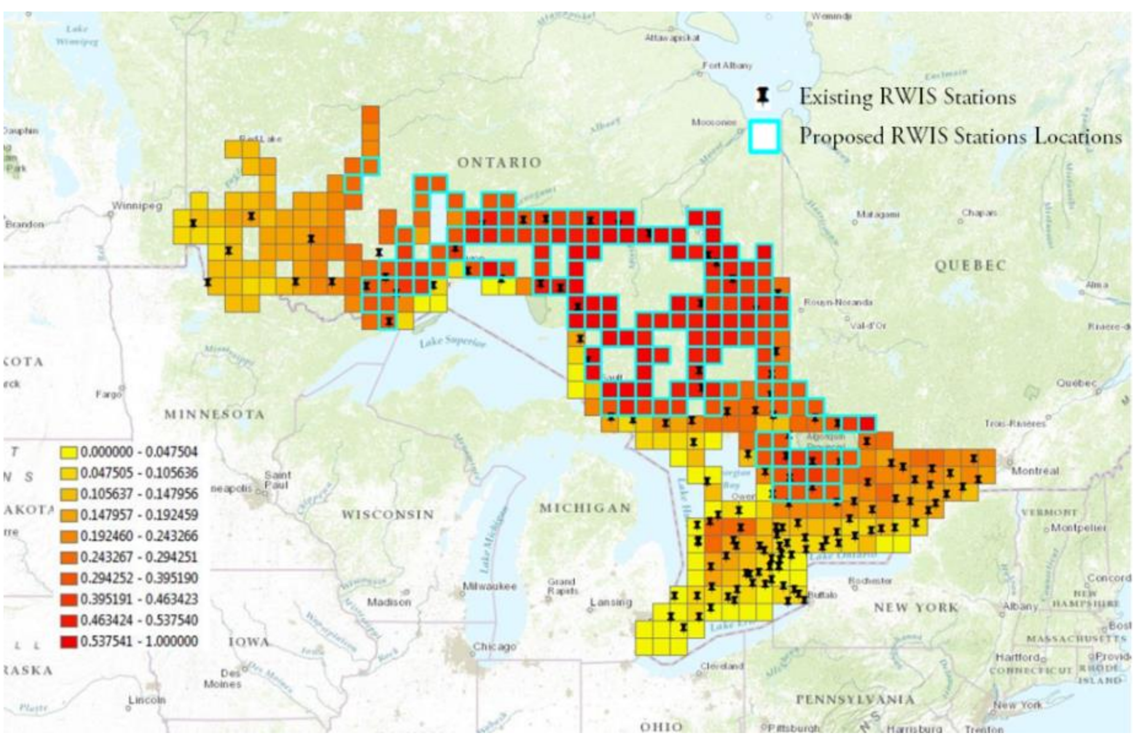


Figure 4-5: Alternative 1 with the weather factors combined

Alternative 2: Traffic Factors Only

A second alternative considers the two traffic-related factors, namely, WAR and HT (without weather factors). The intent of this analysis is to determine the potential RWIS stations locations considering traffic factors only, and evaluate the current RWIS network setting on the coverage of traffic demands.

Figure 4-6 illustrates the proposed 140 locations of RWIS stations when considering the traffic factors only. Notice that the map now focuses more on the areas where high accident rates/highway class exist. This alternative suggests that almost all southern parts of the province should have RWIS stations installed while many parts in the northern region are left uncovered. 110 of the 140 existing RWIS stations (79%) would be located at the same sites based on this alternative. Such a high matching rate should not be viewed as an indication that this location criterion is better than Alternative 1; instead, it should rather be considered as an indication that these factors are heavily weighted in Ontario's current RWIS location planning practice.

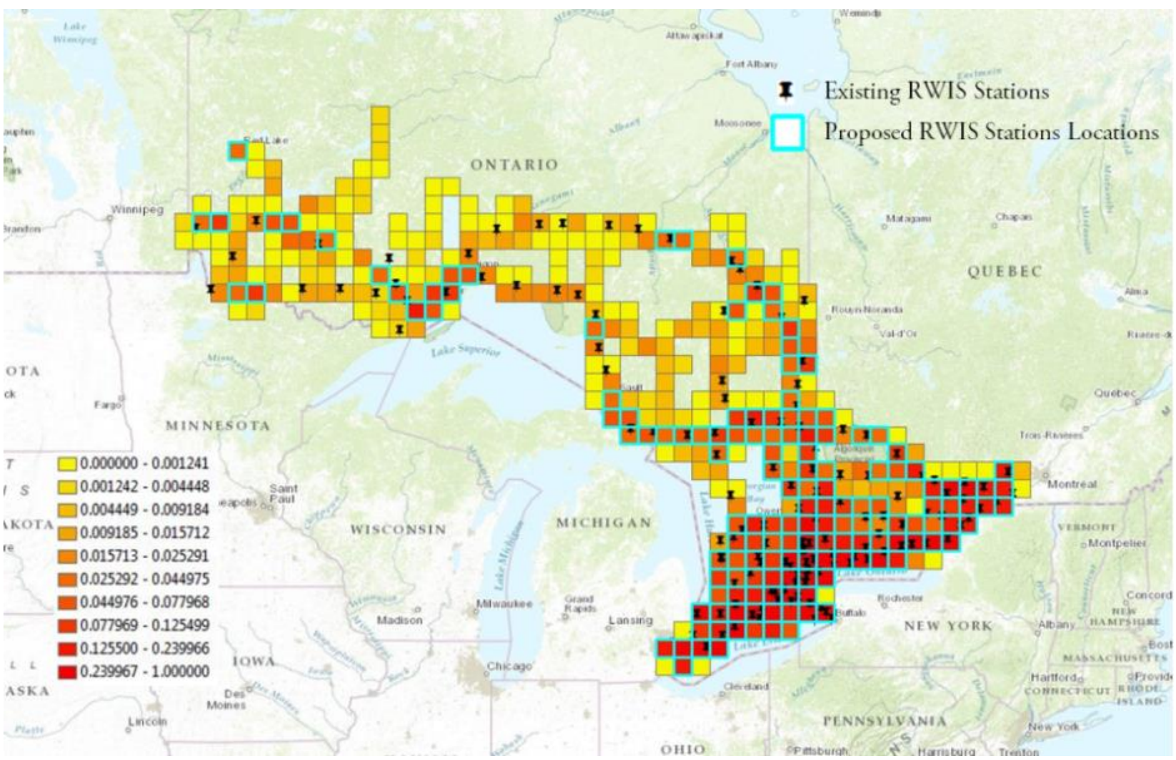


Figure 4-6: Alternative 2 with the traffic factors combined

Alternative 3: Weather & Traffic Factors Combined

A third alternative is proposed by combining both weather and traffic factors to balance out the deficiencies and limitations of alternatives 1 and 2. Figure 4-7 shows the proposed 140 locations where RWIS stations are recommended to be sited when considering the combined factors. The POM for alternative 3 is found to be the highest (i.e., 85%) and the visual inspection also shows that the identified cells are better distributed over the entire province than that of alternatives 1 and 2. It is also worthwhile to emphasize that the percent of matching is based on the evaluation with respect to the current locations of Ontario RWIS stations, and thus does not provide an absolute measure of the performance.

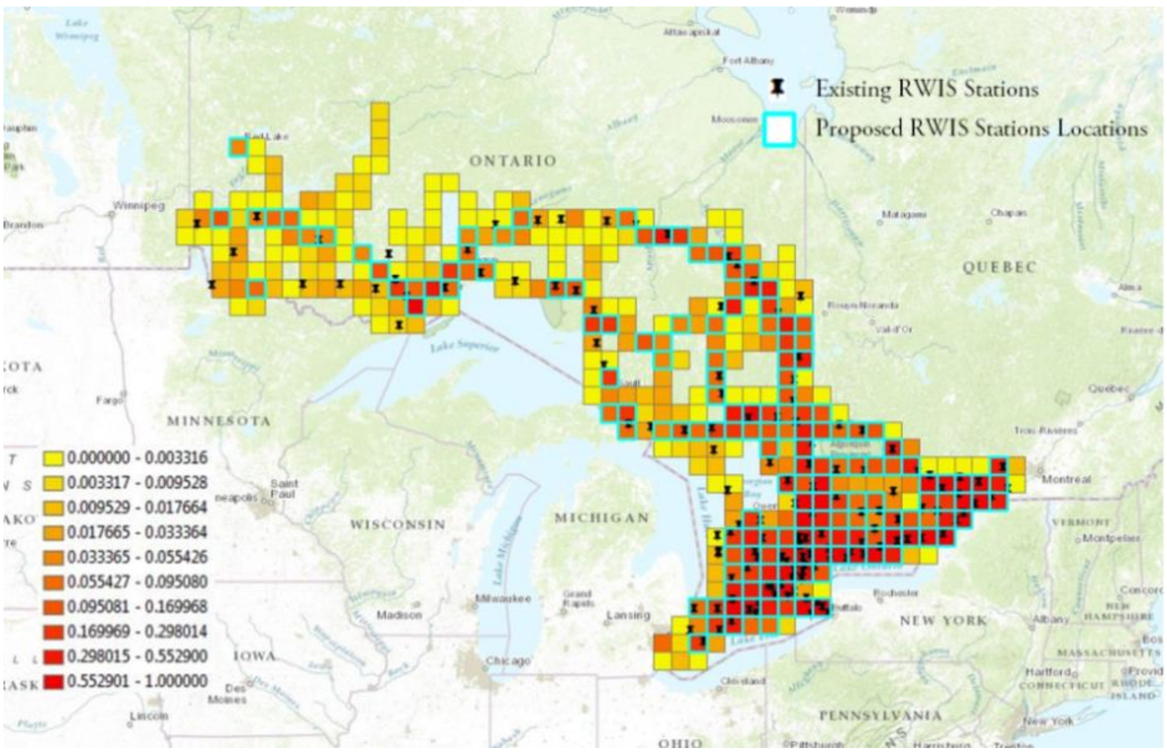


Figure 4-7: Alternative 3 with all factors combined

4.4.1.3 Summary

In this section, the surrogate measure based approach (SM) for choosing the potential locations of RWIS stations at a regional level has been investigated through a case study. Two types of surrogate measures are considered, including three weather related factors (variability of surface temperature (VST), mean surface temperature (MST), and snow water equivalent (SWE)) and three traffic related factors (winter average daily traffic (WADT), winter accident rate (WAR), and highway type (HT)). The weather criteria are to follow the logic that RWIS should be placed to areas where the weather is most severe and varied while the traffic criteria meet the rationale that serving a higher number of travelling publics would provide more benefits. A total of three location selection methods have been formulated. Alternative 1 takes account for the weather factors only while alternative 2 includes traffic factors only. Alternative 3 is a combination of alternatives 1 and 2. These alternatives are used to evaluate the current Ontario RWIS network. The findings have revealed that Alternative 1 is more focused on the northern region comprising of highly varying weather conditions, while Alternative 2 is more focused on the southern region with heavy traffic loads. The high POM rate of Alternative 2 indicates that the current RWIS network has been set up in such a way that it predominantly considers the need of covering the road network. Likewise, the large difference between the traffic and weather related criteria suggests that the RWIS stations may not have been located optimally. Alternative 3 seems to balance the limitations of the first two alternatives by showing the potential candidate RWIS locations across the whole province. It is unknown how much of weight needs to be put on each of the criteria discussed here, but it is clear that the proposed framework is easy to apply when planning an RWIS network expansion by introducing different weights to individual criteria based on their importance.

4.4.2 [5]Application of the CB Method

This section shows the application of the cost-benefit based approach (CB) for analyzing the Minnesota RWIS network. Considering the amount of data that need to be prepared, integrated, and processed, only the northern part of Minnesota is evaluated, which currently has a total 46 RWIS stations covering a road network of approximately 11,500km, as depicted in Figure 4-8.

The individual RWIS stations and the Minnesota highway network are shown by red circles and yellow lines, respectively. Figure 4-8 also shows a grid of cells, each having an area of 30 x 30 km^2. This spatial resolution was determined based on the survey, which revealed that most states would keep a distance of 20 to 50 km between two RWIS stations. Also, Mn/DOT set 30 km as a desired spacing for locating RWIS stations, although this criterion is not a requirement and can be adjusted according to

[5] This section is based on a published paper: Kwon, T. J., Fu, L. & Jiang, C. (2014). RWIS Stations – Where and How Many to Install: A Cost Benefit Analysis Approach, Canadian Journal of Civil Engineering (CJCE), DOI: 10.1139/cjce-2013-0569

different standards and needs (Rockvam et al, 1998). As mentioned previously, the state highway network is used to extract only the cells that intersect with the lines, because others are not considered as potential RWIS candidate sites – cells placed on top of the lake area cannot have RWIS stations. It should be noted that the methodology discussed in the following section can equally applied to any grid size.

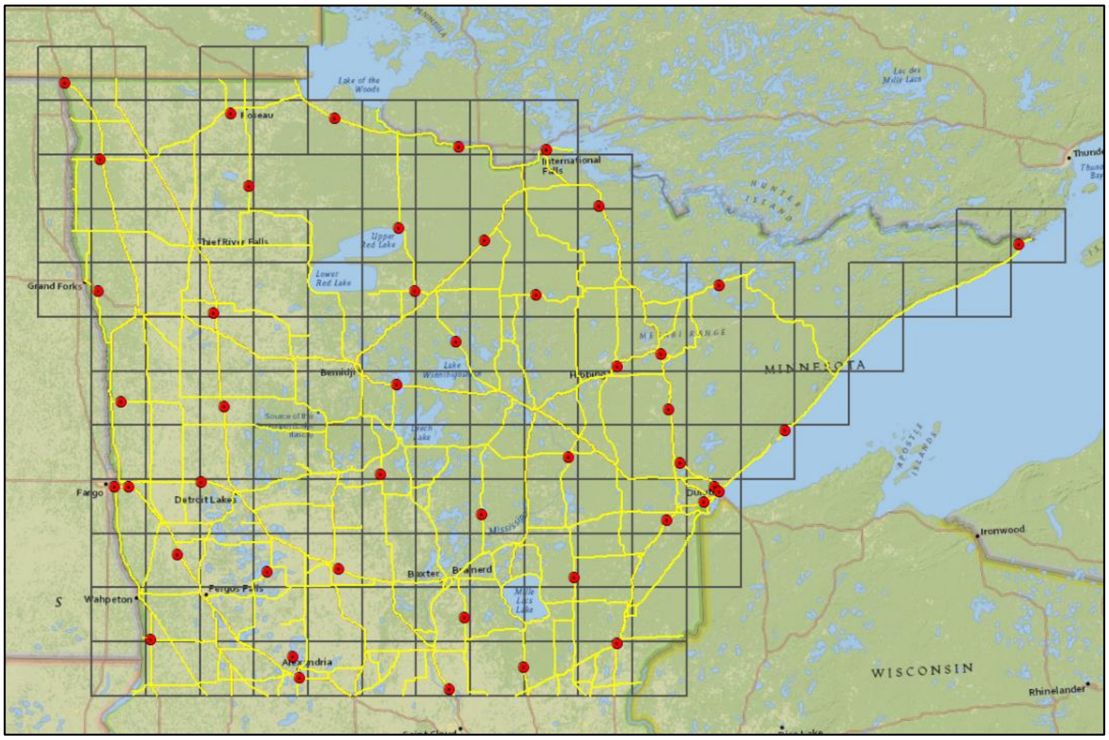


Figure 4-8: Case-study area with RWIS stations (red circles) and highway network (yellow lines)

4.4.2.1 Data Processing and Integration

Three sets of data – maintenance, collision, and traffic data – were provided by Mn/DOT. The data were processed and then integrated into one data set for use in later steps. Software used was ArcGIS 10.1 and QGIS 1.8, primarily for processing and compiling geocoded data and analyzing mapped information.

Maintenance data were received in an Excel file containing all 1,836 winter maintenance event records collected over a total of 16 winter months from 2011 to 2013. Each maintenance record was expressed using a unique project identification number along with information on labor, equipment, sand, salt, and brine costs. Using a project ID number as a reference, the results of all available maintenance event records were added and averaged to obtain the annual average cost for each maintenance route. Data on geocoded base route created for the purpose of mapping the maintenance data were provided by Mn/DOT. Using the base route data, the processed maintenance data were joined by matching the project ID numbers, and thus became geocoded to be presented on the map.

Collision data collected over a 5-year period (i.e., 2008 to 2013) contained individual crash records with detailed information. Each record listed day, month, year, data reliability, location, and severity, number of vehicles involved, type of collision, weather, and surface condition information. As noted earlier, it is important to consider only the collisions that can potentially be avoided by the proactive and responsive WRM operations using information from (at least partially) nearby RWIS. As such, 18,360 records were extracted for collisions that occurred during inclement weather conditions such as freezing rain and blowing snow, and hazardous RSCs such as wet snow, slush, and ice. Using locational attributes (e.g., latitude and longitude), individual collision records were superimposed onto the base map, and the sum of all available collisions was calculated for each base route, for a total of 369 available routes.

Traffic data consisted of 1369 geocoded annual average daily traffic counts collected over a 10-year period starting in 2001. Since the interest in this study focuses on winter seasons, winter average daily traffic was calculated by utilizing a simple conversion factor. The conversion factor implemented in this study was determined based on the empirical evidence confirming that the magnitude of the difference of the average daily traffic between normal days and wintry days being stable and consistent. However, it is important to note that the application of the uniform conversion factor for an entire analysis region may not be appropriate nor representative as the traffic counts could vary depending on the location of analysis. Furthermore, million vehicle kilometers travelled (MVKT), to be used as a measure of traffic flow or exposure, was calculated using the following equation:

$$MVKT = \frac{AADT \times 212 \times SectionLength}{1{,}000{,}000} \tag{4-3}$$

where *Section Length* is expressed in kilometers and was determined using a geometry tool available in ArcGIS for all routes. Note that a numerical value of 212 (i.e., number of wintry days in one year) was used instead of 365 to correctly reflect the wintry traffic exposure.

Another important measure used in analysis is the target bare-pavement target regain time (BTRT) of a highway route. During winter storms, a winter maintenance schedule requiring staggered work hours may be used to provide the level of service recommended. Each maintenance area, district, and division develops a schedule of effort needed to achieve target BTRT, thus it can be an essential surrogate measure for representing the type of highway. This is particularly important for enforcing pair-wise comparisons for constructing RWIS benefit models. By following the bare lane indicator guidelines shown in Table 4-1, traffic count data were used to determine the BTRT (e.g., WADT of 1,000 is given BTRT of 9 hrs).

Once completed, traffic data together with three new measures – WADT, MVKT, and BTRT – were integrated and merged onto the base routes to form a new database, each measure being expressed in terms of base route. These three measures were included in the RWIS benefit-cost modeling phase to investigate their degree of implications to the savings from reduced maintenance costs and collision frequencies.

Table 4-1: Bare lane indicator guidelines

Classification	Traffic Volume	Bare-pavement Target Regain Time
Super Commuter	Over 30,000	1 - 3 hrs.
Urban Commuter	10,000 - 30,000	2 - 5 hrs.
Rural Commuter	2,000 - 10,000	4 - 9 hrs.
Primary	800 - 2,000	6- 12 hrs.
Secondary	Under 800	9 - 36 hrs.

4.4.2.2 Modeling the RWIS Benefits and Costs

As previously described, the two dependent variables of interest are maintenance cost and collision number expressed as their corresponding base routes for two distinct scenarios: one with RWIS and the other without RWIS. The rationale for adopting this method is that a highway section covered by a nearby RWIS station is more likely to receive more efficient and cost-effective WRMs than those far from RWIS stations. Although RWIS information alone may not provide sufficient information to maintenance personnel in their decision-making process, use of additional information (i.e., RWIS data) will certainly help provide better estimations, leading to better WRM servicing. This is particularly true when the pavement surface condition forecasts become available to maintenance staff to decide and apply anti-icing chemicals before a snow storm hits such that the formation of bonded snow and ice layers can be prevented or minimized (C-SHRP, 2000). Furthermore, since the treatment is done proactively, a smaller amount of chemical is needed to prevent bonding than when snow and ice already exist (Epps and Ardila-Coulson, 1997). Note that the proposed method relies on a reasonable assumption that winter maintenance personnel would use RWIS information in their WRM decision-making process to some extent, which would lead to reduction in maintenance costs and collision frequency. This assumption is well supported by several prior studies (Strong and Fay, 2007; Buchanan and Gwartz, 2005; Boselly, 2001), and survey results (see Appendix C).

Figure 4-9 shows the existing RWIS stations, buffered zones, and the roads that are covered or not covered by RWIS stations, illustrated by yellow and red circles, and blue and red lines, respectively.

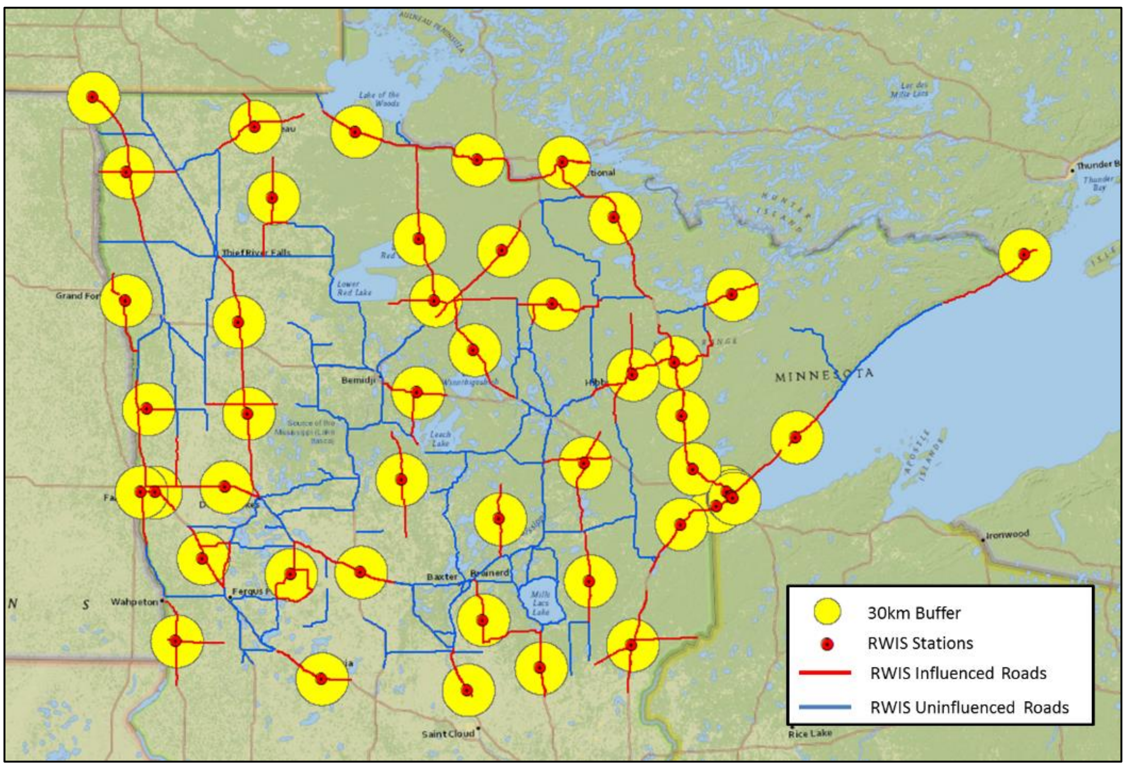


Figure 4-9. Implementation of the proposed method

As the figure shows, the routes that contain RWIS stations were selected and categorized as routes with RWIS, while the rest was assigned to routes without RWIS. Note that for this case study, a buffer zone with a 30-km diameter was chosen as in the current practice an average separation distance between 20 km and 50 km would typically be used as a guide for installing another regional RWIS station (Manfredi, et al., 2005). This assumption was made to best separate the two categories of routes such that the effect of RWIS could be properly presented and investigated. Such an assumption may not hold true at times, and the maximum range that RWIS could influence may vary by locations. However, the underlying methodology for quantifying the RWIS benefits can equally apply, regardless the grid size selected for analysis.

Once the two groups of routes were identified, the data – including length of route, maintenance cost, collision frequency, WADT, MVKT, and BTRT – were extracted from the integrated database constructed earlier, for further analysis. Two groups of data were then compared and matched according to their highway type and location by conducting a pair-wise comparison so as to enforce a fair assessment (e.g., the number of roads that are Class 1 in RWIS influenced areas should be equal to that in RWIS uninfluenced areas). Multiple linear regression analyses were conducted to develop models relating unit maintenance costs and collision frequency as a function of various variables. All variables were tested at the 5% significance level to determine the statistically significant factors that affect the variation of maintenance cost and collision frequency for the two groups. The resulting equations for the two dependent variables are as follows:

$$UMC_i^{RWIS} = 0.094 \times WADT - 52.593 \times BTRT + 1956.568, R^2 = 53.5\% \qquad 4\text{-}4$$

$$UMC_i^{No\ RWIS} = 0.128 \times WADT - 29.003 \times BTRT + 2196.544, R^2 = 45.7\% \qquad 4\text{-}5$$

$$CF_i^{RWIS} = 20.486 \times MVKT + 1.118, R^2 = 65.8\% \qquad 4\text{-}6$$

$$CF_i^{No\ RWIS} = 64.872 \times MVKT + 1.229, R^2 = 61.7\% \qquad 4\text{-}7$$

where *UMC* and *CF* are unit maintenance cost in \$/lane-km, and collision frequency, respectively. With the unit maintenance cost (i.e., UMC_i^{RWIS} and $UMC_i^{No\ RWIS}$), the annual maintenance cost of a given maintenance route (i.e., MC_i^{RWIS} and $MC_i^{No\ RWIS}$) can be expressed as the product of total route lane kilometers by the unit maintenance cost. Similarly, the annual collision cost of a given maintenance route (i.e., AC_i^{RWIS} and $AC_i^{No\ RWIS}$) can be determined by multiplying the collision frequency (i.e., CF_i^{RWIS} and $CF_i^{No\ RWIS}$) by unit collision cost. According to FHWA's collision costs (FHWA, 1994) and historical collision data, the unit collision cost was estimated to be $17,472, which was used in this analysis. Analyses of these equations and their coefficients show that the highway routes with RWIS have lower estimated maintenance costs and lower number of collisions than those of the routes without RWIS, clearly indicating the benefits of installing RWIS stations. Note that the resulting equations have moderate R-square values, which is expected as there are likely many other factors than the ones considered in this study to affect the observed variability in the collision frequency and maintenance costs. Collisions are rare events and are often caused by a combination of multiple factors related to the driver, the vehicle and the environment. It should be noted that the benefit and cost models could be further improved by considering other potential contributing factors such as savings due to reduced patrolling and travel time costs, realized by more effective and efficient winter maintenance operation activities.

4.4.2.3 Analysis of Optimal Number of RWIS Stations

With the explicit account of the potential benefits of a RWIS network, the CB method also provides an opportunity to investigate the optimal number of RWIS stations for a given region. This section shows how such an analysis can be performed using the same Minnesota network.

The costs associated with a RWIS system can be estimated on the basis of various nominal cost statistics reported in literature. Based on the literature, RWIS stations normally last for 25 years and the average cost is about $90,000, which includes the costs of utility installation, traffic control, training sessions, and contract administration (Buchanan and Gwartz, 2005). In addition, RPU and CPU need to be upgraded every 5 years at a projected cost of $10,446. Also, each RWIS station needs to be monitored regularly to ensure that the data being collected are correct and that the station is operating well, a task that would typically cost $5,460 per year (McKeever et al., 1998). Therefore, the annualized cost for installing, operating, and maintaining a typical RWIS station would be $11,149. It should be noted that the unit cost of an RWIS station could vary largely over different vendors, and are also dependent on many other factors including the type and number of sensors used. The cost items used in the case study was based on what is currently available in the literature, and new values can be easily implemented in the analysis to see how they would affect the results.

Figure 4-10 shows the NPV of 25-year life cycle RWIS benefits and costs, and net benefits expressed in terms of number of stations, respectively. As clearly depicted in the figure, the optimal number of

RWIS stations is 45 stations, given the total benefits from cost reductions in maintenance and collision. The number was found simply by taking the difference between the values of two lines, RWIS benefits and RWIS costs, at their corresponding number of station; the station having the greatest difference in two values was selected as the optimal number. Note that the optimal number found in this study is very similar to the current RWIS network, which includes a total 42 RWIS stations.

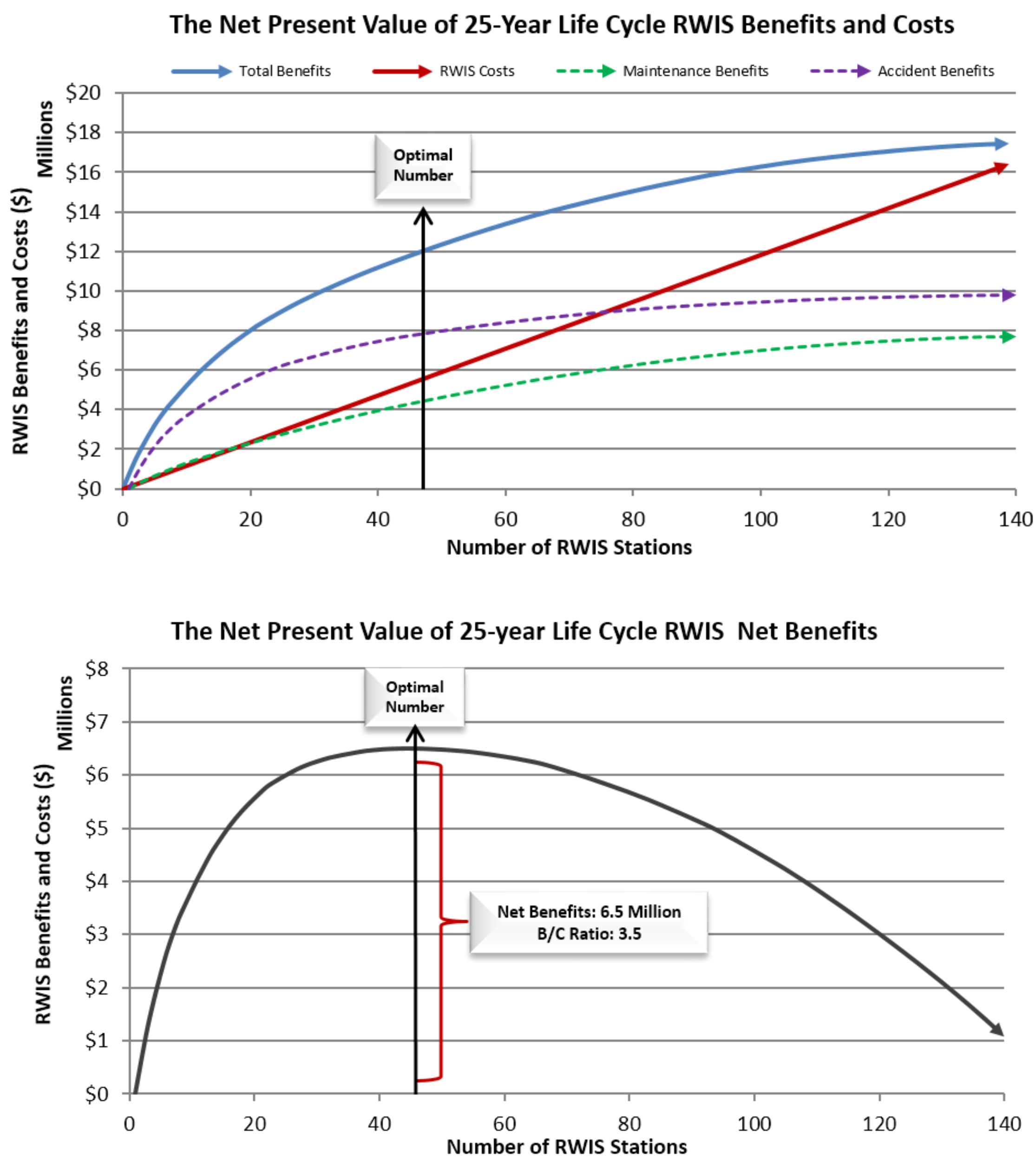


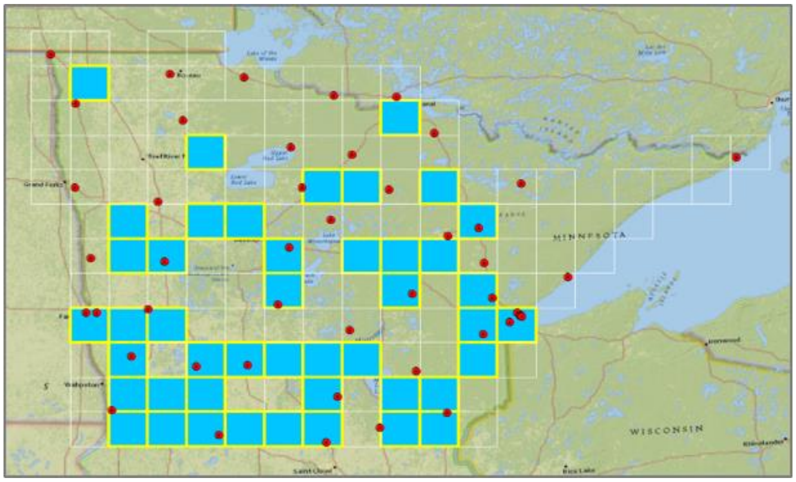
Figure 4-10: 25-year life cycle RWIS benefits & costs (top), and projected net benefits (bottom)

This finding suggests that the proposed method can be used to test the current RWIS setting, examine whether it needs a greater or a smaller number of RWIS stations, and recommend where to locate the next RWIS stations. As illustrated at the bottom figure, using the defined number, the total net benefit over the next 25 years is projected to be approximately $6.5 million. Additionally, using these benefits and costs, the cost-benefit ratio is found to be approximately 3.5. Note that the optimal number found in this study could have been different if there were changes in the inputs (i.e. cost or life expectancy of a single RWIS station as suggested in the referenced literature). However, it is worthwhile to emphasize that the method illustrated herein is dedicated to providing a systematic framework, which can easily be applied to regions in need of estimating the foreseeable monetary benefits to support their decision-making in how many RWIS stations should be deployed.

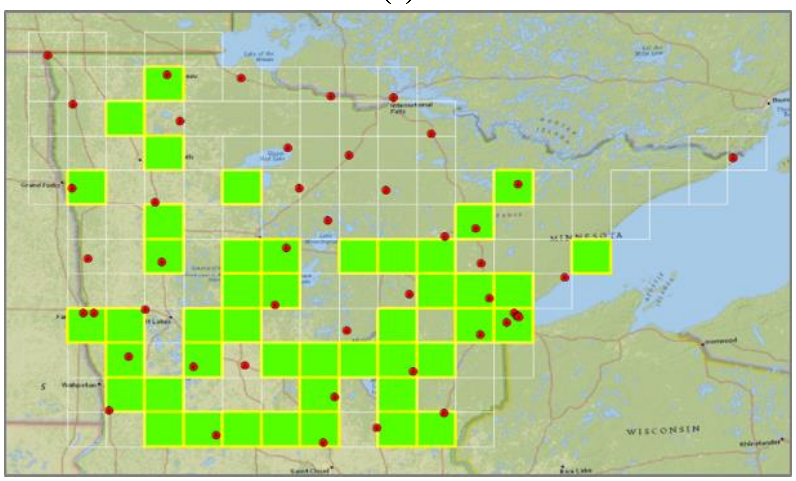
4.4.2.4 Analysis of Optimal RWIS Location

In the next step for determining the optimal RWIS station locations, the estimated benefits for both maintenance and collision were sorted in descending order such that cells with higher benefits can be given priority for consideration over cells with lower benefits. The optimal number of RWIS stations found in the previous step was used as a threshold to select the top 45 cells as the optimal RWIS station locations in the area being analyzed. Figure 4-11 shows the select top 45 cells (colored cells) recommended as the optimal locations, where the highest benefits can be obtained from maintenance, collision avoidance, and the combined savings.

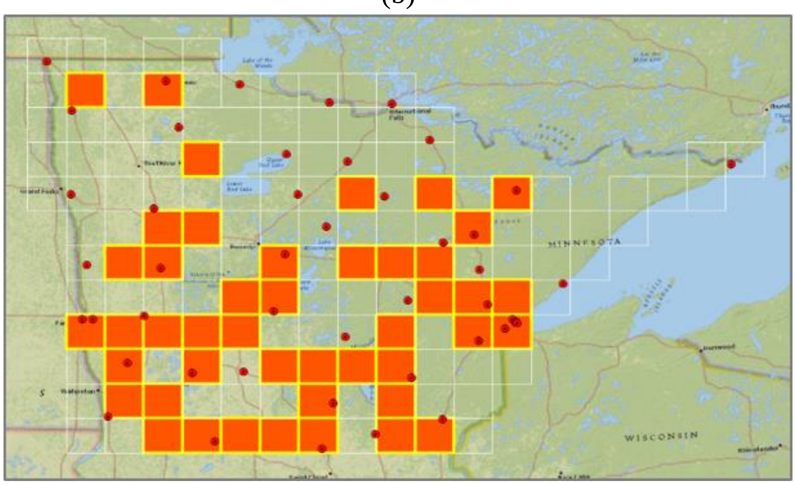
In all sub-figures, it can be seen that the recommended sites are generally well distributed over almost entire region except the north part of the state that is relatively less covered by RWIS. This can be attributed to the models that do not account for topographical and meteorological variations. Analysis of such variations is essential because inclusions of those factors in the models would likely increase the explanatory power such that the benefits associated with those variations can be better modeled. It is important to note that the foreseeable monetary benefits presented herein may not be perceived as absolute benefits that are expected to occur across all different regions with different traffic and weather conditions as they could conceivably vary when other evaluation criteria are used.



(a)



(b)



(c)

Figure 4-11. The optimal RWIS station locations using maintenance benefits (a), collision benefits (b), and the combined benefits (c) criteria

It is worthwhile to emphasize that the proposed method has provided a framework, with which the existing RWIS network can be evaluated quantitatively. The underlying work should be regarded as an incremental effort to the existing literature in lack of quantitative evidence for corroborating that an implementation of such is truly beneficial. Therefore, it is anticipated that the proposed method will provide provincial highway agencies with a useful tool they need to evaluate and optimize their RWIS network.

4.4.2.5 Summary

In this section, the cost-benefit based method (CB) described in the previous section was applied to analyze the location and density of the Minnesota RWIS network. The method is the first of its kind to attempt to formalize the ultimate benefits of a RWIS network. A case study based on the current RWIS network in Northern Minnesota was used to test the applicability of the proposed method. RWIS benefit models were developed for two groups of highway maintenance routes representing one covered by RWIS and the other not covered by RWIS, using three types of data including maintenance costs, collisions, and traffic counts. For data preparation, the study area was divided into 139 equal-size cells, and auxiliary information was extracted from individual cells to estimate the annual costs for both maintenance and collisions. The 25-year life cycle benefits and costs were then determined using the calibrated models and used in identifying the optimal station density and location. The highest projected 25-year net benefits were found to be approximately $6.5 million, corresponding to a network of 45 RWIS stations. The corresponding cost-benefit ratio was found to be approximately 3.5. The optimal station density was found to be similar to the current density of 42 in northern Minnesota. When determining the locations, the benefits based on each criterion have been sorted in a descending order to prioritize the cells with greater benefits. The optimal station density was used as a threshold to select only the top 45 cells for all three criteria – maintenance, collision and combined benefits – and the corresponding POMs were found to be 80%, 75.6%, and 77.8%, respectively. Similar yet high POMs indicate that the current RWIS setting is able to provide a reasonably good coverage on all three criteria. The findings in this study indicate that the proposed method is methodologically sound and, thus, is suitable for analyzing whether a RWIS network of any given region has reached or surpassed the optimal density and for recommending where to locate additional RWIS stations if needed. As mentioned previously, it needs to be cautioned that the data used and the models developed in this study are aggregated on an annual basis such that the factors that would influence the operational decisions (i.e., when to perform WRM) may be concealed. However, for the high-level planning purpose, the proposed method could serve as part of a decision support tool for optimizing the needs of RWIS stations in terms of their locations and density at a regional level.

4.4.3 [678]Application of the SI Method

The third alternative – Spatial Inference (SI) based approach is formulated on the basis of minimizing the spatial inference errors (i.e., kriging variance) of RWIS measurements while maximizing the coverage of accident-prone and/or high travel demand areas. This optimization framework takes explicit account of the value of information from an RWIS network, providing the potential to enhance the overall efficacy of winter maintenance operations and the safety of the travelers. The features of this method are demonstrated using four real world case studies from Ontario, Minnesota, Iowa and Utah. Note that all the analyses were performed on a Windows operating desktop computer equipped with a 3.39 GHz processor and 8.00 GB of RAM, and a series of functions coded in R (R Development Core Team, 2008) was used in this study.

4.4.3.1 Sensitivity analysis of the SSA algorithm

Prior to applying the SI method to the available study areas, it is essential to conduct a sensitivity analysis of the optimization parameters such that the values, with which reliable solutions can be achieved, can be identified. In this study, a simple one-at-a-time-designs (OATD) sensitivity analysis is implemented to quantify the effects of the three SSA parameters on the optimization outputs. The three parameters considered include cooling factor (*c*), absolute temperature (T_a), and probability of accepting inferior designs (*p*). The cooling factor dictates how fast the algorithm cools down and controls the rate at which the *p* decreases to zero. Thus, if the large cooling factor is used, the algorithm will cool down slowly whereby reducing the chance of being trapped in a local minima. Absolute temperature in this study indicates the stopping criterion, which is given by a number of iterations

This section is based on the following published and submitted papers:

[6] Kwon, T. J., Fu, L., Melles, S., and Perchanok, M. (2015). Optimizing the locations of road weather information system (RWIS) stations – a sampling design optimization approach. Proceedings of the XXVth World Road Congress, Seoul, Nov 2-6, 2015.

[7] Kwon, T.J., Fu, L., & Melles, S. (2015). Location optimization of road weather information system (RWIS) network considering the needs of winter road maintenance and the traveling public. (Submitted to Computer Aided Civil and Infrastructure Engineering on July 2015)

[8] Kwon, T.J., Fu, L., & Perchanok, M. (2015). Spatiotemporal variability of road weather conditions and optimal RWIS density – Case Studies. *Proceedings of the 95th Annual TRB conference*, Washington D.C., Jan 10-14

without improvement in search of a better design. The benchmarking parameters of SSA were initially set as c = 1000, T_a = 200, and p = 0.2 based on prior studies (Kirpatrick, 1984; Heuvelink et al., 2006; Brus and Heuvelink, 2007; Melles et al., 2011). In addition, a total of three different autocorrelation ranges including 150km (long), 100km (intermediate), and 50km (short) were utilized to see how they would affect the optimization outputs. To reduce the computational time, a synthetic example having a total area of 250 km^2 was used, and a total number of RWIS stations to be located was fixed to 5. Note that the objective function values reported in this section were normalized to enforce a fair comparison between the three different range groups.

First, fix the absolute temperature T_a and the probability of taking on worsening solutions p, and let the cooling factor c change in the range of $c \in [10, 1000]$. The optimal solutions and the implementation time are shown in Figure 4.12. It can be found from Figure 4.12 that the long range would require a cooling factor of 700 to obtain a reliable solution. In addition, the intermediate and short ranges would require around 100 to converge. This is probably due to the fact that given a longer spatial autocorrelation range, a larger number of calculations are required for the algorithm to obtain a reliable result. As anticipated, higher the cooling factors are, the more it would take for the solutions to converge. For the balance between the solution and the implementation time, the cooling factor can be chosen in the range of [700, 1000], which are comparable with the literature since the higher cooling factors would yield slow cooling whereby more improved solutions could be achieved (van Groenigen and Stein, 1998; Yang et al., 2009; Pereira et al., 2013).

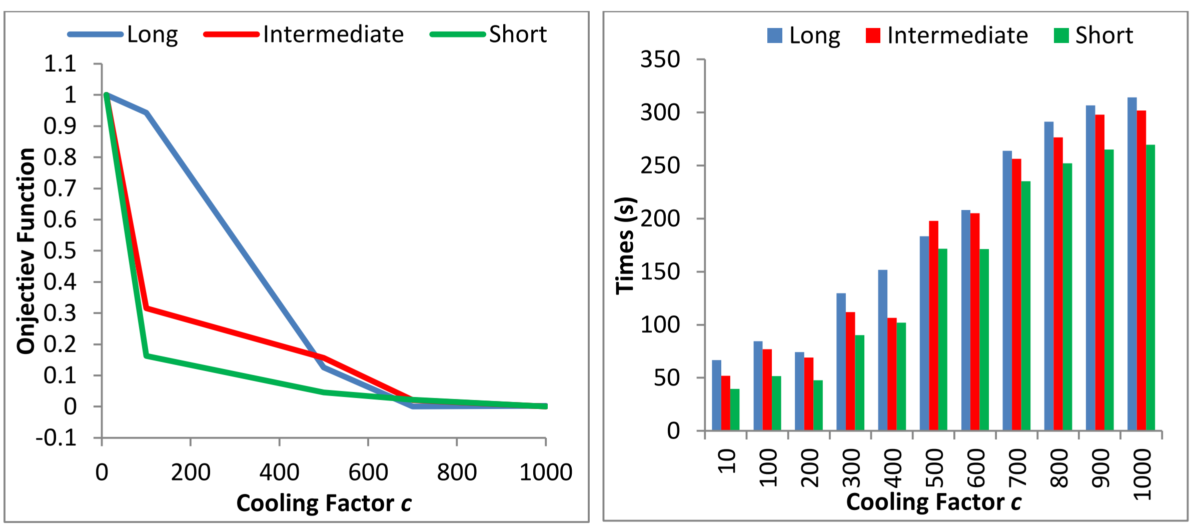


Figure 4-12: Results in different cooling factors

Second, fix the cooling factor c and the probability of taking on worsening solutions p, and let the absolute temperature T_a change in the range of $T_a \in [30, 500]$. The optimal solutions and the implementation time are shown in Figure 4.13. Similar results were found that a lower value of T_a would be required when a shorter range was used than when a longer range was used. The results indicate that it would require T_a of 100, 200, and 300 for short, intermediate and long ranges, respectively. Similarly, the optimizing running times increase with the values used for T_a, and are proportionally related to the length of autocorrelation ranges. This makes intuitive sense as the shorter ranges would need lesser amount of computations as opposed to the longer ones. When it is used for all-range, the absolute temperature should be chosen in the range of [300, 500]. Again, choosing higher T_a values makes intuitive sense since they would provide a higher chance of finding a "better" solution than the previously searched and stored solutions, as evidenced by the number of prior studies (Yang, 2009; Strimbu and Paun, 2012).

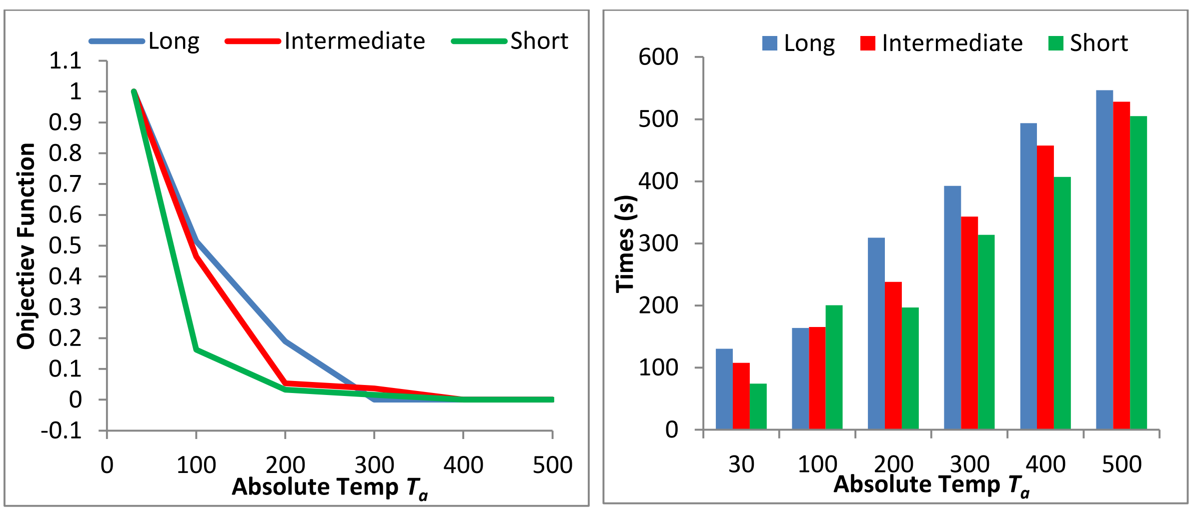


Figure 4-13: Results in different absolute temperatures

Lastly, fix the absolute temperature T_a and the cooling factor c, and let the probability p change in the range of $p \in [0.1, 0.5]$. The optimal solutions and the implementation time are shown in Figure 4.14. It can be found from Figure 4.14 that the probability of accepting an inferior design is not very sensitive to the different lengths of autocorrelation ranges, but should be chosen between 0.2 and 0.3. The implementation times were found to be mostly comparable, but took the longest times at p = 0.3. Considering the quality of solutions obtained and the times it would require to achieve convergence, p

of 0.2 would be recommended for all ranges, which agree with the literature (Kirpatrick, 1984; Heuvelink et al., 2006; Brus and Heuvelink, 2007).

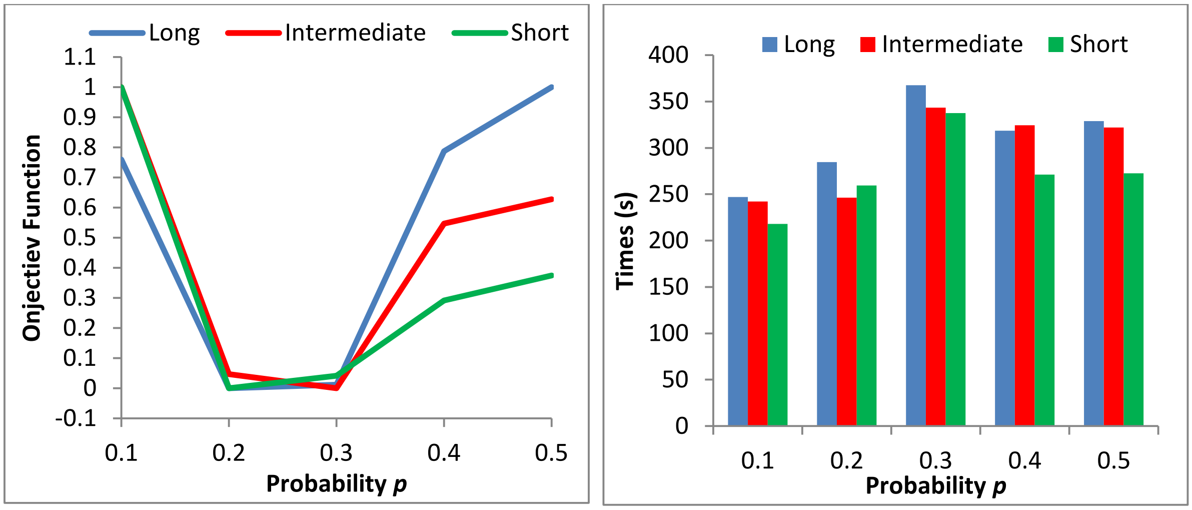


Figure 4-14: Results in different probabilities

Therefore, the three SSA parameters, namely, the absolute temperature T_a and the cooling factor *c*, and the probability of accepting worsening designs *p* are set based on the results obtained in this section when running the spatial inference (SI) based optimizations.

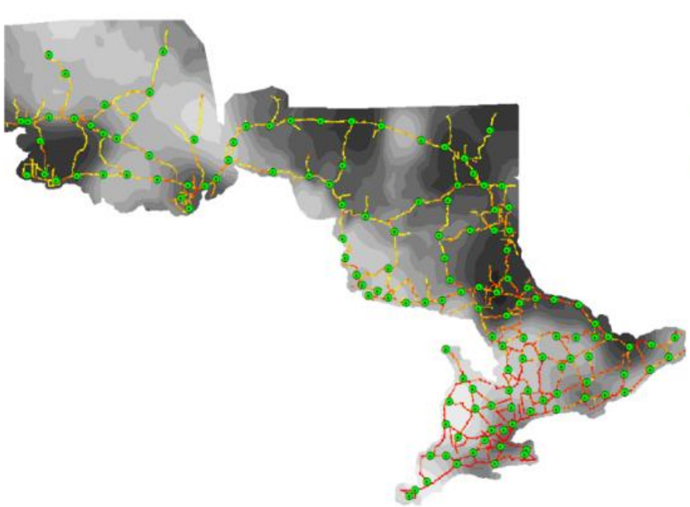
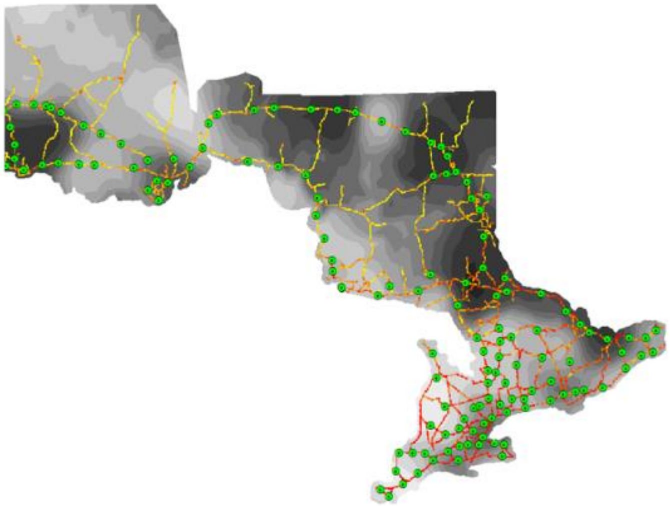
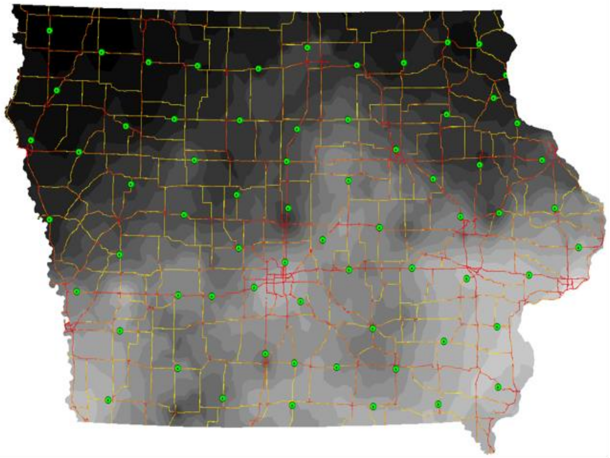
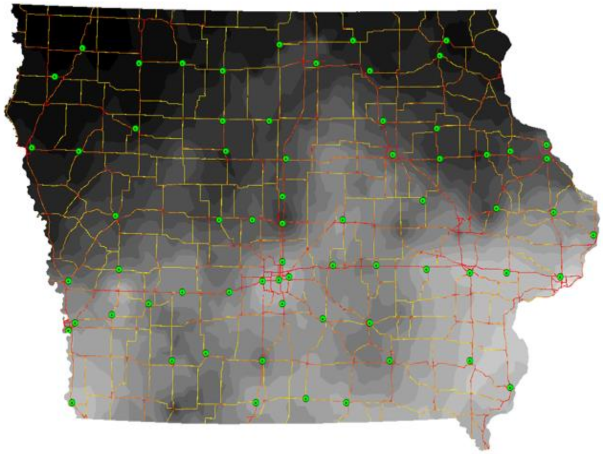
4.4.3.2 All-new optimal RWIS network

This section conducts an analysis of the hypothetical problem of relocating the entire set of existing RWIS stations for each of four regions. The objective of the exercise is to gain valuable information with the current location settings and simulate how optimal locations will change when assigning different weights to the two different criteria considered in this study. As discussed earlier, the greatest benefit of the proposed approach is its ability to simulate and optimize RWIS station locations under any given settings that users define. This ability is advantageous as the costs associated with establishing any monitoring stations are very high (Chang et al., 2007). Likewise, it provides decision makers with the freedom to choose different weights depending on the needs of the traveling public, winter road maintenance requirements, and their respective priority in locating RWIS stations.

The square root of kriging variance of HRSC frequencies as well as the collision frequencies discussed in Section 3.2.3 were implemented as the dual criteria in the objective function to maximize the monitoring capability of hazardous surface conditions, and the coverage of accident-prone areas. A uniform grid of 1km by 1km was used as the minimum spatial unit in all optimization performed in this section. The RWIS network optimized under two different scenarios (weather only, and weather and traffic combined) is presented in Figure 4-15. In this figure, the optimized RWIS stations are denoted by green circles. Due to unavailability of collision data across the entire region of Utah, another traffic criterion representing highway class has been used instead. The aggregated collision frequencies and kriged HRSC measurements are superimposed on the same map to help better appreciate and recognize how assignment of different criteria could contribute to deciding the optimal location for an individual RWIS station. It is worthwhile to note that for each scheme, the optimization was run three times and the outputs were visually compared to confirm that the optimization outputs were very similar and comparable to each other. The intent of multiple tryouts was to ensure that the SSA algorithm had reached a (near) optimal solution without being trapped in local minima; an inherent problem of the SSA algorithm and all other metaheuristic algorithms currently available today.

Figure 4-15 (Column Crit1) represent a case when kriging variance is solely used in the objective function to minimize the spatially averaged kriging variance. In all of these figures, it is evident that RWIS stations are concentrated at locations with high HRSC occurrences, particularly in the darker areas representing a high occurrence of hazardous road surface conditions, without offering much consideration to the travelling public. It is also clear that sites are well distributed over the entire study regions maximizing the coverage at a global scale. In the right-hand side of Figure 4-15, the traffic criterion (i.e., Crit 2), representing vehicular collision (or road class for Utah), has been added to the first criterion with equal weights. As can be seen clearly, incorporation of the traffic criterion was able to capture high travel demand areas, providing an improved balance. Such a difference in its pattern is well manifested; a higher number of RWIS stations have been allocated to areas exposed to higher traffic demand. Note that the locational attributes (i.e., lat/long) of the all-new RWIS sitting plans are provided in Appendix A of this thesis.

As for the iteration schedule of the performed optimizations, Figure 4-16 illustrates the decrease of the dual objective function as the number of iterations increases for three runs (i.e., Minnesota case). It is apparent after around 6,000 iterations, the objective function for all runs starts to level off and slowly reaches its minimum value as evidenced by the lower value obtained at the 10,000th iteration.

Region	Crit1	Crit1+2
Ontario		
Iowa		

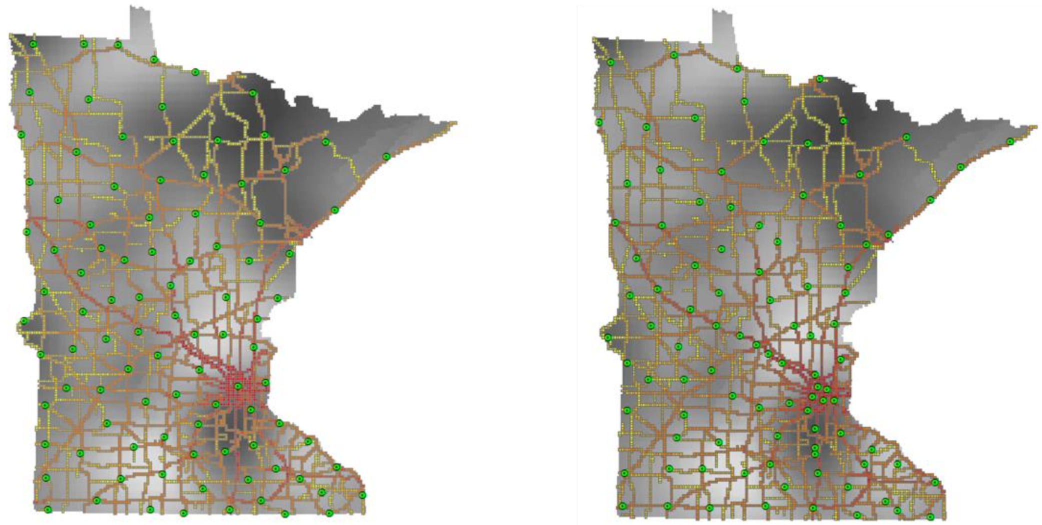
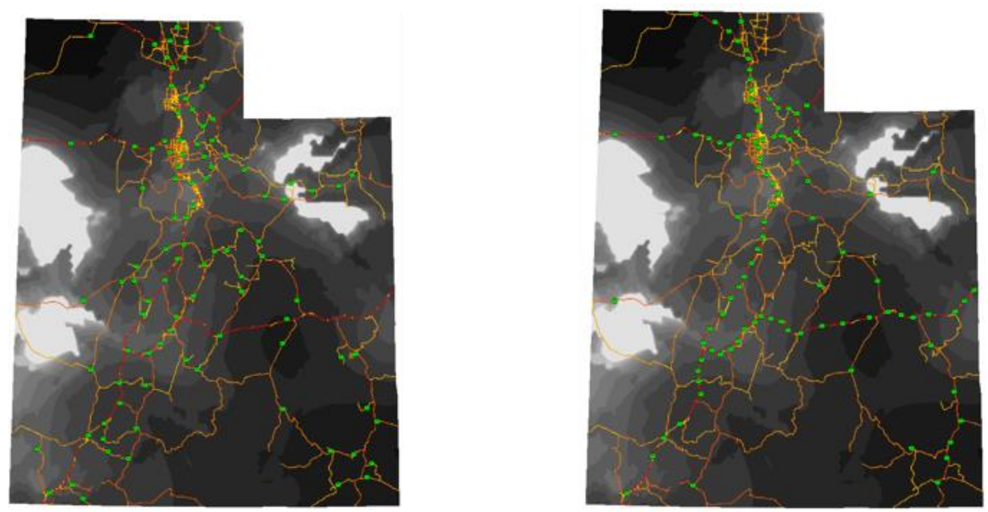
Minnesota	
Utah	

Figure 4-15: All new optimized RWIS station locations

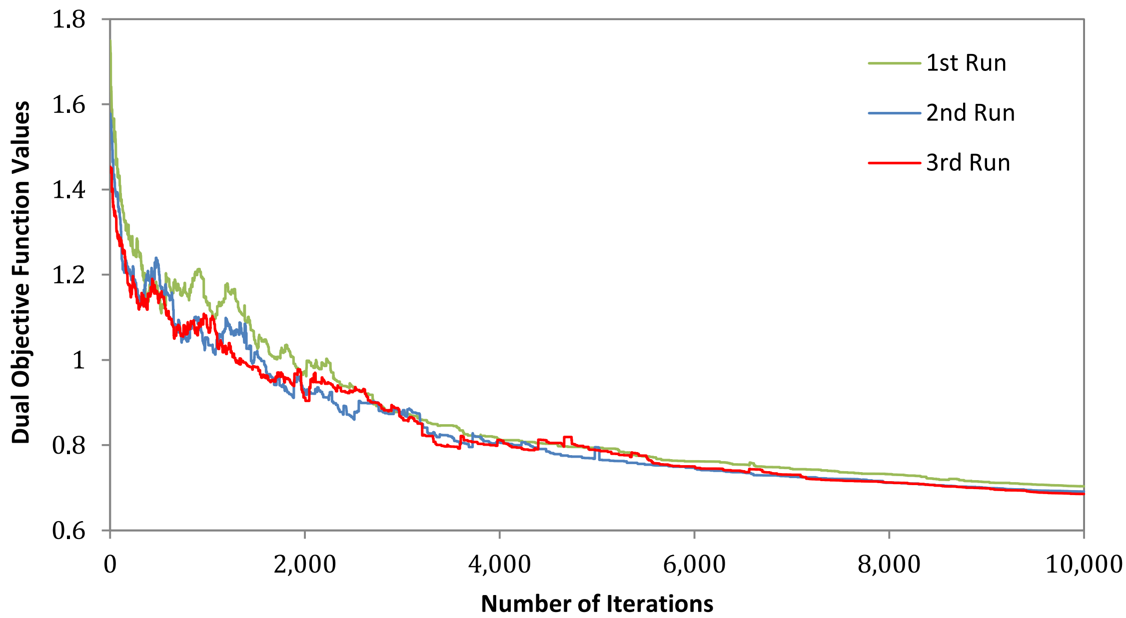


Figure 4-16: Decrease of the combined objective function as a function of iterations (Minnesota)

As explained previously, the SSA algorithm has a mechanism that reduces the risk of falling prematurely into local minima, provided that there is a certain probability and a decaying function controlling how fast the objective function converges. Such behavior is well presented by the continuous fluctuations and peaks observed until it stabilizes at around 6,000 iterations. In terms of computational efficiency, optimization took an average running time of approximately 9 hours for optimizing each given network.

To evaluate the overall efficacy of each optimized network (Fig. 4-15) with respect to the existing network (Fig. 4-1), the objective function was used to calculate its corresponding numerical value for all individual outputs as well as the current RWIS network. This evaluation metric is simply the lowest value obtained at the end of each optimization. For the existing network, a comparable yet equivalent approach is exercised by adding the averaged kriging variance and vehicular collision frequency given the current RWIS station locations. Table 4-2 below compares the lowest objective function value (three runs) associated with each optimal solution and the current network, along with percentage of improvement (i.e., percentage of differences between the base and the optimal scenarios). As expected, percentage of improvement, which can also be interpreted as perceived benefits, was found to vary between 11% and 16%, signifying that the optimized networks are "better" in terms of monitoring capabilities of various hazardous road surface conditions while considering the needs of serving the traveling publics, as defined in the objective function.

Table 4-2: Comparison of objective function values of the optimized and current networks.

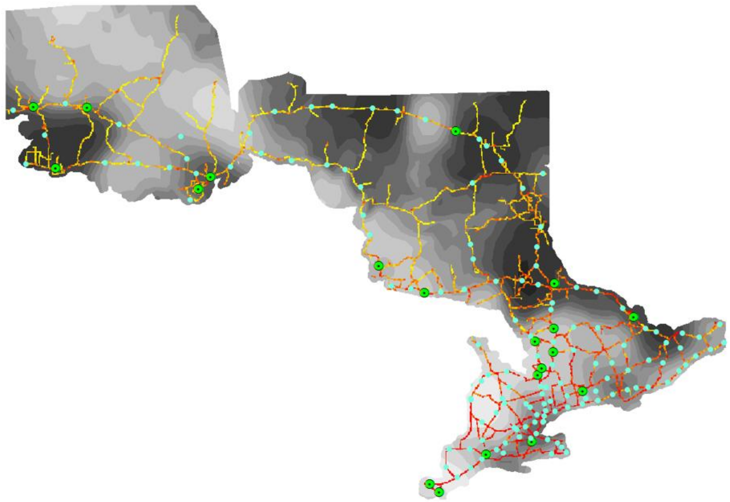
Scenarios	Obj. Function Optimized / Base Case	% Improvement
Ontario	0.4154 / 0.4771	**12.94%**
Iowa	0.7425 / 0.8748	**15.12%**
Minnesota	0.6854 / 0.8182	**16.23%**
Utah	0.7921 / 0.8942	**11.14%**

4.4.3.3 Expansion of current RWIS network

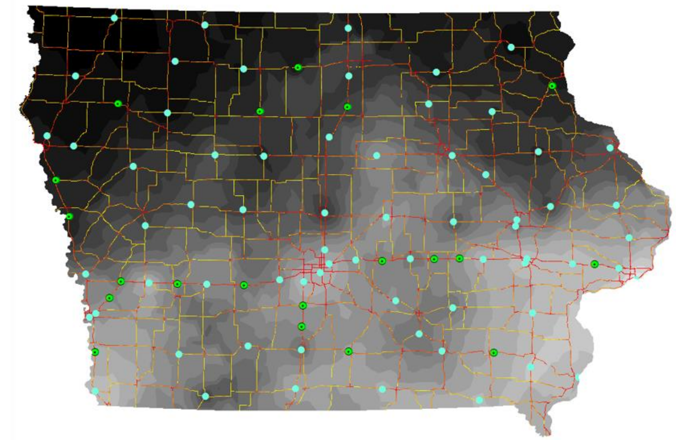
In the previous section, the proposed method was applied to delineate optimal locations for the entire existing set of RWIS stations. This section shows how to apply the proposed method to develop expansion plan for the four regions. The optimization problem was modified to reflect the changes in the base condition. The objective function is evaluated at each iteration considering that there are permanently fixed RWIS stations (existing) throughout the entire optimization process. Identical optimization parameters and weighting schemes (w1 = w2 =1) were used to locate 20, 40, 60 additional RWIS stations (green circles) for all four study areas, and the locations of 20 stations are depicted in Figure 4-17. Note that the optimization results for 40 and 60 additional RWIS stations locations are provided in Appendix B of this thesis.

As can be seen in this figure, if the location optimization objective is to minimize the total kriging variance, new stations would be located in the vicinity of existing stations (cyan circles). Likewise, incorporation of the traffic criterion was able to capture high travel demand areas (shown in red-colored areas), providing an improved balance. From a visual inspection, it can be asserted that new stations nicely fill gaps in the existing RWIS network. Furthermore, evaluation of objective function values show that the current network of Ontario, Iowa, Minnesota, and Utah was improved in terms of the defined objective function by 14.7%, 15.9%, 16.3%, 13.6% , respectively with the placement 20 additional stations.

It is worthwhile noting that the optimization formulation developed herein is able to leverage the existing RWIS network in neighboring states, for instance, to further improve the forecasting and monitoring capabilities of regional weather conditions.



(a)



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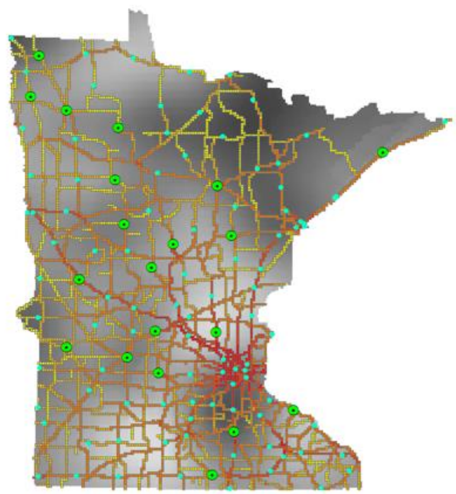
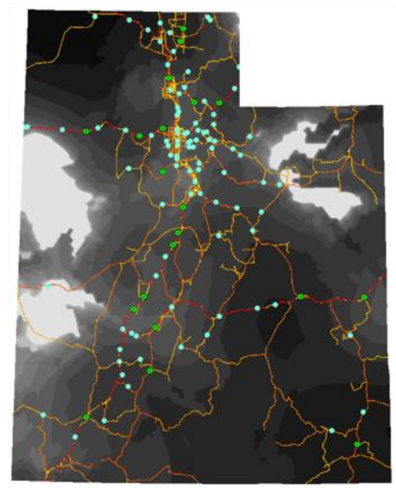


(c)



(b)

Figure 4-17: Placement of 20 Additional RWIS Stations for (a) Ontario, (b) Iowa, (c) Minnesota, and (d) Utah

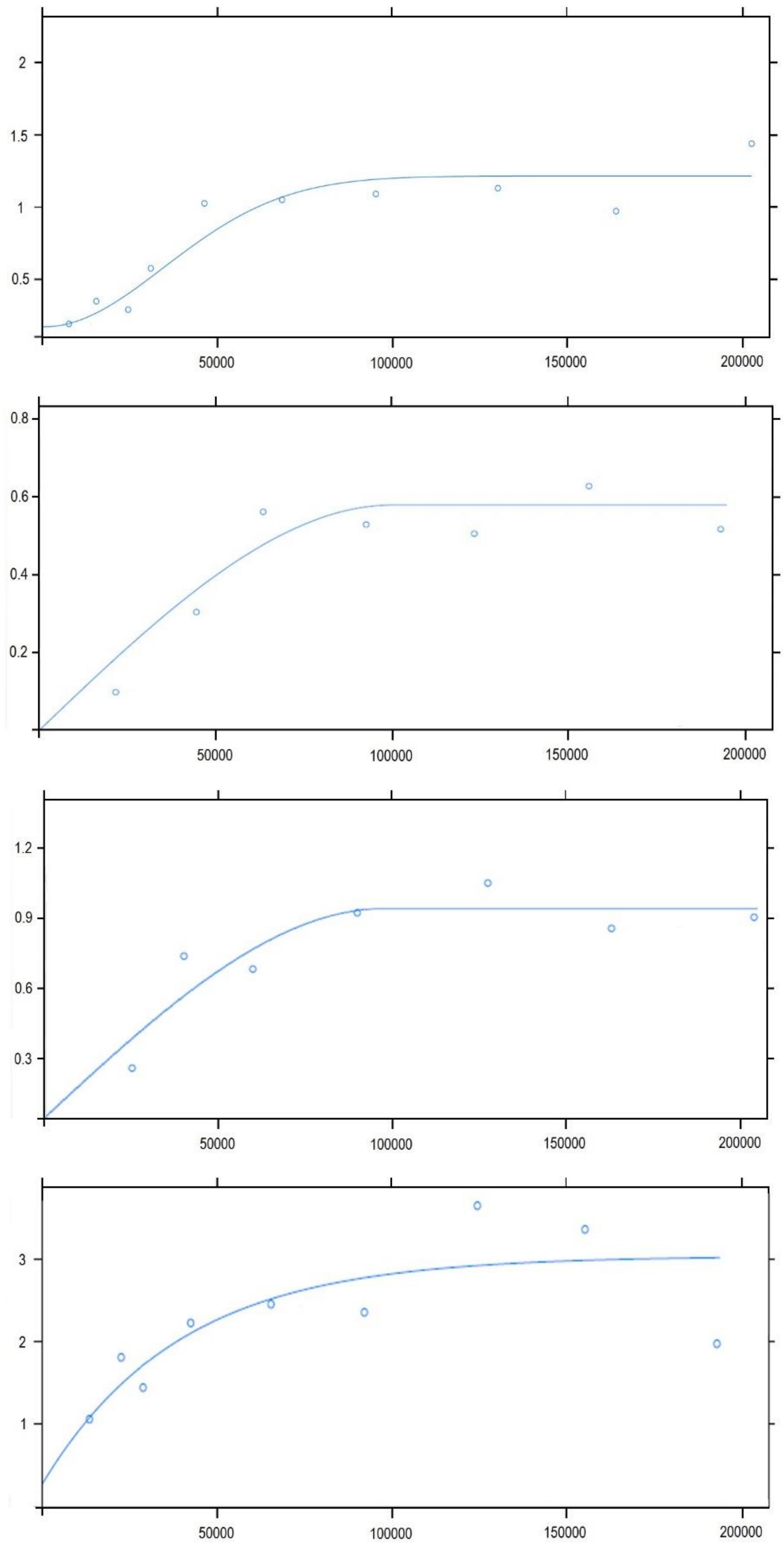
4.4.3.4 Optimal density and its relationship to spatial variability

The aim of this section is to investigate the hypothesis that the optimal RWIS density or spacing for a region is dependent of the spatial variability of the road weather conditions of the region. To examine this hypothesis, a geostatistical approach introduced earlier is implemented to characterize the spatial variability of a variable of interest over a given region, which is subsequently applied to determine the corresponding optimal RWIS density or spacing for the region. To fulfill this task, topological and climate patterns of the four study areas under analysis are first characterized and compared. Without loss of generality, road surface temperature (RST) is selected as the variable of interest to represent the overall road weather conditions. The data came stratified by individual stations each containing measurements including the variable of interest – road surface temperature (RST). To assure the validity of the data, a data quality check was performed and definite outliers (i.e., -9999 ºC) recorded as a result of sensor malfunctions were removed. The data from the four study areas together contained nearly 80 million rows of data; hence VBA scripts were written to process the entire datasets, returning a seasonal and a monthly average of RST stratified by station. These processed datasets will be an input to constructing a semivariogram model on two different temporal units, monthly and seasonal.

For each region, a semivariogram model discussed in the previous sections is constructed to determine the spatial variability of RST, especially, autocorrelation range – a separation distance at which the measurements are no longer correlated to each other. In addition, an optimal RWIS density is determined through an optimization process that minimizes the total condition inference errors across the underlying road network.

To investigate the spatial correlation range of the RWIS measurement, the processed RST data were implemented as per the general modelling guidelines discussed earlier. Locational attributes (i.e., latitude and longitude) of each RWIS station were extracted and implemented to de-trend any existing patterns. Semivariogram models were calibrated using R with packages gstat (Pebesma, 2004) and automap (Hiemstra et al., 2009).

Figure 4-18 shows the sample and fitted semivariogram models using the seasonal RST data and Table 4-3 provides a summary of semivariogram model parameters including sill, nugget, and range, and cross-validation results illustrating the accuracy of the fitted models for both monthly and seasonal data.



(a). Ontario

(b). Iowa

(c). Minnesota

(d). Utah

Figure 4-18: Sample and fitted semivariogram models for four regions

Table 4-3: Summary of Semivariogram Parameters and Cross-validation Using Monthly and Seasonal RST for All Study Sites

State	Month/ Seasonal	Model	Model Parameters			Cross-validation		
			Nugget	Sill	Range (km)	MAE	COR	RMSE
Iowa	Oct	Sph	0.00	1.10	88.96	0.60	0.70	0.98
	Nov	Gau	2.20	3.20	142.71	1.37	0.51	1.70
	Dec	Exp	0.43	5.90	106.08	1.25	0.46	2.19
	Jan	Sph	0.00	2.12	100.16	0.63	0.67	1.02
	Feb	Sph	0.00	1.14	111.63	0.67	0.77	1.02
	Mar	Sph	0.00	1.66	61.95	0.90	0.69	1.33
	Seasonal	Sph	0.00	0.58	***90.48***	0.57	0.86	0.81
Utah	Oct	Gau	0.00	9.70	21.39	2.60	0.42	3.41
	Nov	Sph	0.46	3.42	50.29	1.34	0.55	1.69
	Dec	Gau	2.30	5.40	33.74	1.59	0.42	2.22
	Jan	Gau	0.68	2.40	37.31	1.10	0.55	1.46
	Feb	Gau	0.88	2.70	40.12	1.10	0.63	1.43
	Mar	Gau	1.10	5.90	26.71	1.55	0.62	1.94
	Seasonal	Exp	0.27	2.78	***40.47***	1.24	0.53	1.55
Minnesota	Oct	Sph	0.00	2.70	62.68	1.31	0.60	1.87
	Nov	Sph	0.37	5.00	133.60	1.41	0.25	2.65
	Dec	Gau	0.00	5.50	83.59	1.22	0.68	2.23
	Jan	Sph	1.60	3.50	116.26	1.02	0.60	2.02
	Feb	Sph	0.00	0.47	114.31	0.52	0.90	0.71
	Mar	Sph	0.27	2.80	78.99	1.20	0.59	1.94
	Seasonal	Sph	0.00	0.94	***95.47***	1.15	0.75	2.14
Ontario	Oct	Gau	0.00	6.50	43.21	1.83	0.55	3.07
	Nov	Gau	1.20	4.30	97.29	2.97	0.64	2.49
	Dec	Gau	0.65	3.40	102.50	1.43	0.87	2.01
	Jan	Sph	0.00	1.90	99.29	1.22	0.90	1.64
	Feb	Sph	0.42	1.90	70.28	1.19	0.88	1.76
	Mar	Gau	0.00	2.70	59.76	0.86	0.85	1.10
	Seasonal	Gau	0.12	1.27	***72.84***	1.15	0.72	1.64

MAE and RMSE represents mean absolute error and root mean squared error. COR indicates the correlation between the predicted and observed values (ideally 1). As anticipated, spatial correlation of RST at Iowa and Minnesota (Figure 4-18 (b & c)) having relatively less varied topography is shown to have a longer spatial correlation range suggesting that on average, the RST measurements at those two regions vary less (thus more predictable) when compared to those at Utah, which undergoes a more varied topography. In addition, Ontario, which has a moderate topographic variability, has a spatial correlation range falling between the ranges of other three regions. Likewise, the spatial structure of RST from Utah is less stable and tends to fluctuate in a greater range (in y-axis) as the separation distance increases, whereas the other two regions have a less fluctuation of semivariances contributing to the higher prediction power.

Another inference that can be made by observing the resulting statistics is that for all four regions, the discrepancies tend to be relatively higher for shoulder months (i.e. October and March) than non-shoulder months (i.e. November, December, January, and February). This could be due to the fact that the weather patterns typically vary in a wider range over these shoulder months, making it more difficult to have accurate predictions. Furthermore, during these months, spatial continuity of the weather-related variable (RST) is also affected, resulting in a shorter range. The mean range using the monthly data for Ontario, Iowa, Utah, and Minnesota are found to be 78.72km, 101.91km, 34.93km, and 98.24km, respectively, which generally agree with the average ranges found using the seasonal data (72.84km, 90.48km, 40.47km, and 95.47km for Ontario, Iowa, Utah, and Minnesota, respectively). Slightly different ranges resulted from using the monthly data could be due to the generalization or aggregation of all monthly RST data.

In the next step for determining the optimal density, the proposed optimization model was first implemented in designing an optimal RWIS network using the kriging variance of the seasonal RST data as an optimization criterion (i.e., minimization of kriging variance). For each region, the constrained optimization was run in an iterative fashion by adding one additional RWIS station to the network and its corresponding fitness value was recorded. The optimization continued until the total number of stations reached 350 – an arbitrary number ensuring that the key pattern in error-density relationship is fully revealed. For each study region, the average running time was approximately 3 days by a window operating desktop computer running with a 3.39 GHz processor and 8.00 GB of RAM. ArcGIS 10.2 (ESRI, 2011) and Q-GIS (Quantum GIS Development Team, 2011) were used to process all the geo-spatial data and R (R Development Core Team, 2008) was used as a base platform for running all the optimization in this study

To enforce a valid and fair comparison, the fitness values were normalized and the number of stations added to the network was converted to two distinct measures - the number of stations per unit areas (100km by 100km) and the number of stations per unit highway length (100km). The normalization was necessary because the total area (and length) of each study area was different, thus comparing the fitness value directly to the number of stations added will not be considered valid. The two different density measures considered in this study provide transportation agencies with the freedom of choosing a different measure of units depending upon the type of analyses to be conducted. For instance, if the analysis is intended for a rural area having a smaller size of road network, the use of the number of stations per unit highway length would be considered a more preferable choice as the other measure would suggest an overly high number of stations to be installed.

Figures 4-19 and 4-20 show the comparison of RWIS density charts for all four regions, expressed as a function of the two different analysis units. A quick visual inspection of the two figures shows that Iowa and Minnesota having a similar topographic characteristic (less varied topography) requires a less number of stations per unit area of 10,000km^2 (and per unit length of 100km), while Utah (more varied topography) requires a considerably more number of stations to achieve the comparable objective function values. Likewise, Ontario with moderately varied topographic characteristics requires a higher number of RWIS stations than Iowa and Minnesota but a fewer number than Utah. Another important conclusion that can be drawn is that regions with a longer spatial continuity (Iowa and Minnesota as defined in semivariograms) will require a less number of stations to cover the same area (and the same highway length) than a region with a much shorter spatial continuity (Utah). This makes intuitive sense since the measurements taken at a less varied topographic region will be able to represent a larger area and length.

Given the shape of the all four curves, it is quite challenging to pin point the optimal density. Instead, a rate of change was calculated for every point and when the change was around 5% (again, an arbitrary number selected for a comparison only), the corresponding density was considered as optimal. As a result, Iowa, Minnesota, Ontario would require 2.0, 2.2, and 2.9 stations per every 10,000km^2, respectively, whereas Utah would need 4.5 stations to cover the same area, indicating that a topographically varied region will likely need about 2 times more the number of RWIS stations required by a less varied region. When the unit length is used, Iowa, Minnesota, Ontario would require 0.7, 0.8, and 1.0 stations per every 100km, respectively, whereas Utah would need 1.6 stations to cover the same length of a highway section.

To further test the aforementioned hypothesis, the relationship between the optimal number of RWIS station required per unit area/length and the semivariogram parameter - range is examined, as illustrated in Figures 4-21 and 4-22. Although the relationship relies on a small number of case studies, it reveals a clear linkage between the two measures, demonstrating the usability of the correlation range in any given area (and length) for conveniently determining the station density. For instance, if the analysis of interest is the number of stations per unit area, a region with 60km range (for the given variable of interest) would require, on average, 3.5 RWIS stations per every 10,000 km^2 so as to have an adequate coverage. Similarly, if the analysis of interest is the number of stations per unit length, a region with the same range would require 1.3 RWIS station per every 100 km. There is no doubt that more case studies are required to obtain a promising result, it certainly provides valuable information, particularly for highway authorities initiating a state-wide RWIS implementation plan.

4.4.3.5 Summary

In this section, an innovative framework was introduced for the purpose of locating RWIS stations over a regional highway network. In the proposed method, the weighted sum of average kriging variance of hazardous road surface conditions (HRSC) was used to determine the optimal RWIS network design.

This method relies on a sensible assumption that minimizing the total estimation error would, in due course, contribute to improving the global effectiveness and efficiency of winter road maintenance operations. Road traffic data were also incorporated and weighted to provide a balanced network that considers demands of the traveling public. Case study based on four study regions exemplified two distinct scenarios – redesign and expansion of the existing RWIS network. Findings indicate that optimally redesigned RWIS networks are, on average, 13.58% better than the existing RWIS network. The study further revealed that the deployment of 20 additional RWIS stations would improve the current network, on average, by 15.13%, respectively.

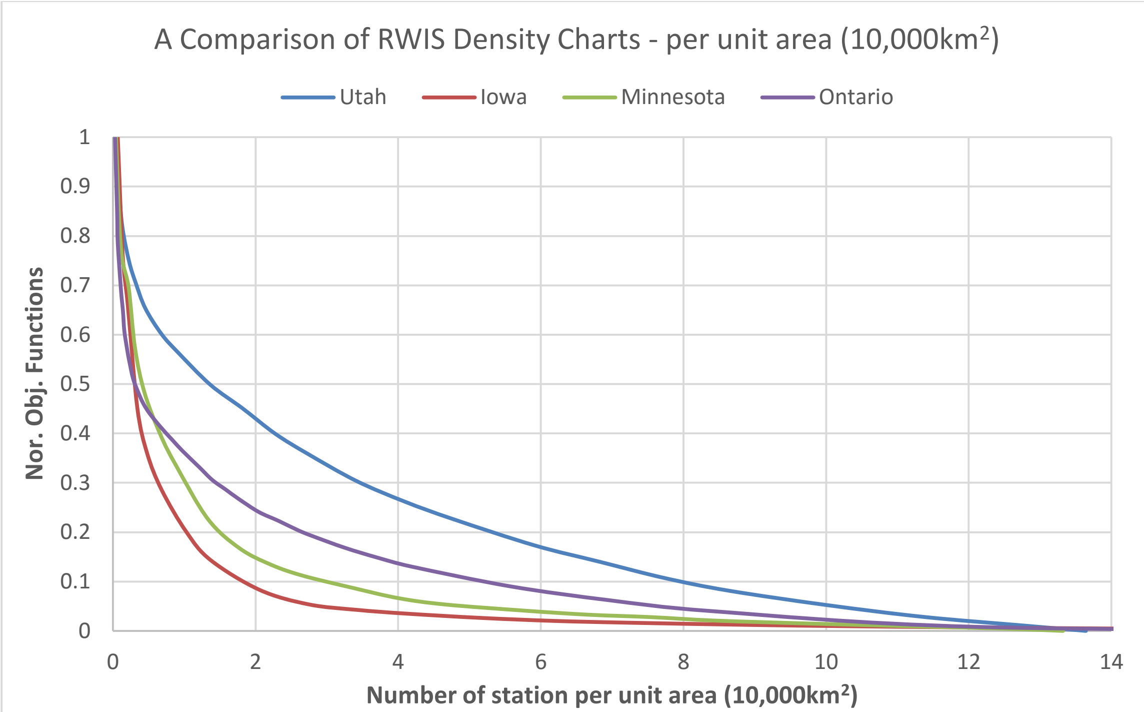


Figure 4-19: A comparison of RWIS density charts – per unit area (10,000km^2)

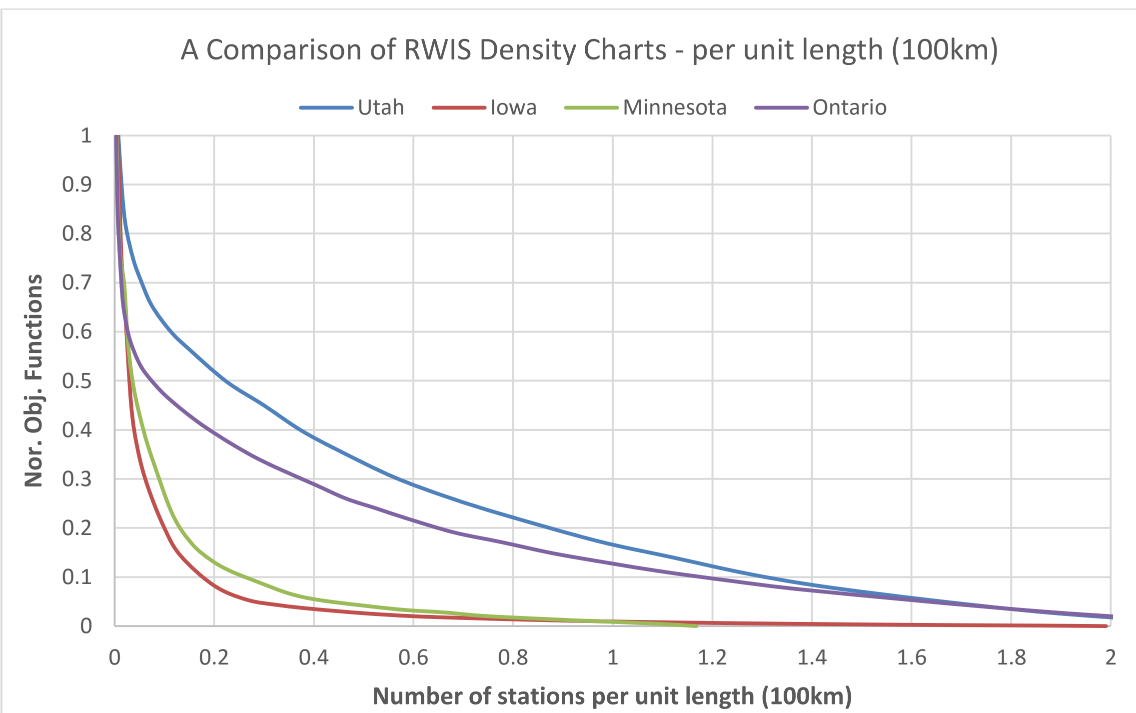


Figure 4-20 : A comparison of RWIS density charts – per unit length (100km)

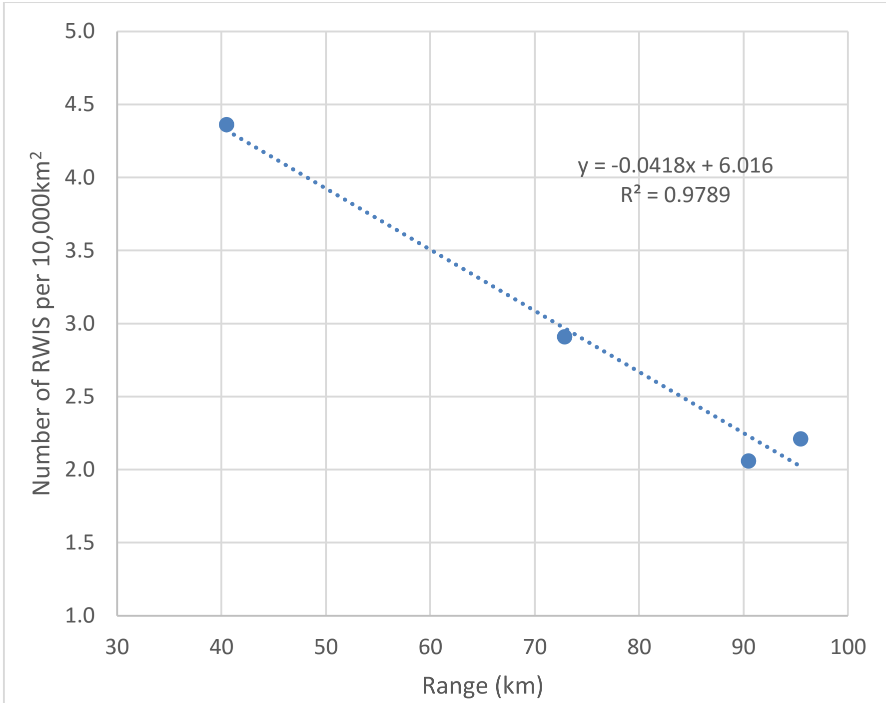


Figure 4-21: A linear relationship of range vs density (per 10,000km²)

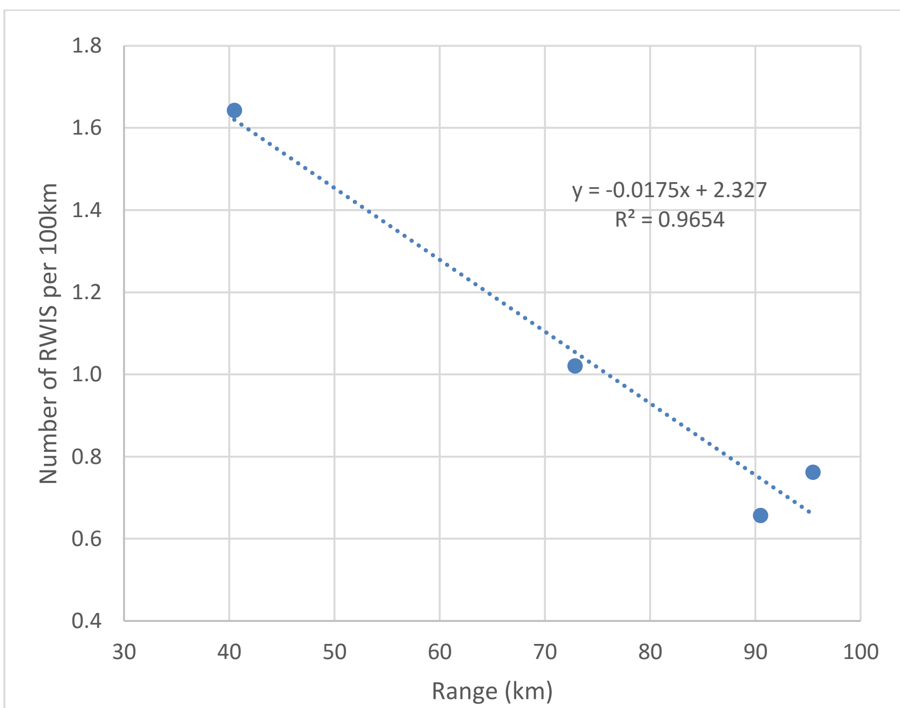


Figure 4-22: A linear relationship of range vs density (per 100km)

Sensitivity analysis was conducted to determine the sensitivity of the optimization parameters including cooling factor (c), absolute temperature (T_a), and probability of accepting an inferior design (p), and further investigate how the change of each parameter would affect the optimization outputs. A synthetic study area was used to locate a total of five RWIS stations. The findings indicate that to maintain the balance between the solutions and the implementation time, the values of c, T_a, and p should be chosen in the ranges of [700, 1000], [300, 500], and [0.2, 0.3], respectively.

Additional study was conducted to determine the spatial continuity of road surface temperature (RST). To do so, the spatial structure of RST for each region was quantified and modelled via semivariogram. The findings suggest that the regions with less varied topography (Iowa and Utah) tend to have a longer spatial correlation range than the region with more varied topography (Utah). As such, a number of RWIS required to have an adequate coverage was found to be 2.0, 2.2, 2.9, and 4.5 per 10,000km^2, and 0.7, 0.8, 1.0, and 1.6 per 100km, for Iowa, Minnesota, Ontario, and Utah, respectively. The results indicate that a more topographically varied region would require a higher number of stations to provide a comparable coverage over a less varied region.

The overall findings of this study show that the new approach is easy and convenient to implement, thus appropriate for real-world applications by integrating key features (road weather and traffic) considered in practice.

Chapter 5
CONCLUSIONS AND FUTURE RESEARCH

Acquiring timely and accurate information on road weather and surface conditions during winter seasons has long been considered indispensable for highway authorities, who are responsible for efficient winter road maintenance (WRM) operations. Better information leads to more effective WRM operations, in return, improve the safety and mobility of road users. Road weather information systems (RWIS) have gained much attention and become popular over the last decade amongst highway authorities for its capability to provide information required to sustain their road network in a safe condition. However, RWIS stations are expensive to install and operate, and thus can only be installed at a limited number of locations. Due to the uncertainties associated with winter road weather and surface conditions, RWIS stations must be placed strategically to ensure that they are most informative in providing the inputs required for stimulating competent winter maintenance operations and provision of timely information to travelers.

This thesis has attempted to tackle this challenging problem of RWIS network planning process by proposing and developing three distinct approaches, providing all-new alternatives dedicated to finding the optimal location and density over a regional highway network. This chapter highlights the main contributions of this research with directions for future research.

5.1 Major Contributions

This section provides a set of major contributions of this research and they are as follows:

- **Synthesization of the current best practice and guidelines for planning RWIS network:** This research provided a detail literature review including a comprehensive and systematic examination and classification of the existing approaches and methods, and survey results based on 25 municipal and provincial transportation agencies, offering new insights into the current best practices and technologies being used in real-world situations.

- **Formalization and implementation of heuristic surrogate measure (SM) based method for locating RWIS stations:** Two types of location ranking criteria are proposed as an attempt to formalize various processes utilized in the current practice, including weather related factors and traffic related factors such as winter average daily traffic, winter accident rate, and highway type. Consideration of these two types of factors captures the needs to allocate RWIS stations to the areas with the most severe weather conditions and having the highest number of traveling public. A total of three location selection alternatives have been evaluated: alternatives 1 and 2 take into account weather and traffic factors. Alternative 3 is a combination of alternatives 1 and 2. The resulting models and solution processes are new in the literature, which generalize the existing methods and are easy to be applied for solving real world problems and be extended with any new decision measures.

- **Development of a cost-benefit (CB) based approach to the RWIS location problem:** The cost-benefit based approach proposed in this thesis is the first of its kind to attempt to formalize the ultimate benefits of RWIS data, namely, improving the efficiency of the winter road maintenance and mitigating the negative impacts of winter weather such as safety and mobility. This approach assumes that data related to weather, traffic and costs of winter road maintenance operations are available for modeling the differences in maintenance costs and road safety between highways covered by RWIS and those without RWIS coverage. A regional RWIS cost-benefit based location optimization model has been developed and used in determining the candidate RWIS station locations, which for the first time provides decision makers with a platform to quantify the benefit-to-cost ratio of any given investment (RWIS installation) and make an explicit trade-off between costs and benefits.

- **Development of a spatial inference (SI) based location optimization approach:** This approach adopts the idea from spatial sampling theory which considers the spatial variability of a measurement (e.g. hazardous road surface and weather conditions) in determining the optimal sampling designs. The application of this sampling idea for determining the RWIS stations provides an all new alternative to the previous two approaches with improved generalization potential. This approach is formulated on the basis of the assumption that an increase in monitoring capability will contribute to enhancing the effectiveness and efficiency of WRM operations. In addition, the method offers unique features of taking into account of the dual criteria representing the value of RWIS information for spatial inferences and travel demand distribution. When estimating the condition of any particular location, the method accounts for spatial interaction of multiple RWIS stations. The method presented herein is the first in the literature targeted at simulating and optimizing RWIS station locations under any given settings, providing decision makers with the freedom to balance the needs of the traveling public, winter road maintenance requirements, and their respective priority in locating RWIS stations.

- **Investigation of spatiotemporal characteristics of road weather condition factors:** An investigation of spatial autocorrelations of road weather condition parameters on two temporal units reveals that the range - a separation distance at which the measurements are no longer correlated to each other, are strongly correlated with unique topographical features of the study areas under analysis. The findings documented herein provide very important piece of information suggesting that the regions with less varied topography tend to have a longer spatial correlation range than the region with more varied topography.

- **Establishment of RWIS sitting guidelines:** The method of determining the optimal density (number of stations required per unit area and per unit length) in a given region required to provide adequate coverage is new – the first of its kind that provides transportation agencies with a tool that helps them determine the optimal density of one of the most important transportation sensor infrastructure - RWIS network. The core research finding is summarized in multiple RWIS density charts providing an easy way of determining the optimal density at a region. Although the relationship relies on a small number of case studies, it reveals a clear linkage between the two measures, demonstrating the usability of the correlation range in any given area for conveniently determining the station density.

- **Development of a web-based RWIS station location allocation optimization service - www.LoRWIS.com:** An application has been created offering unique services to RWIS planning transportation agencies with a user-friendly web environment, as depicted in Figure 5-1. The main service includes RWIS deployment planning, providing all-new optimal RWIS expansion scenarios. It also provides an option of choosing different weights for the optimization criteria considered, and a map tool that gives an easy-to-use visualization option. Other services include weather pattern analysis and traffic data analysis.

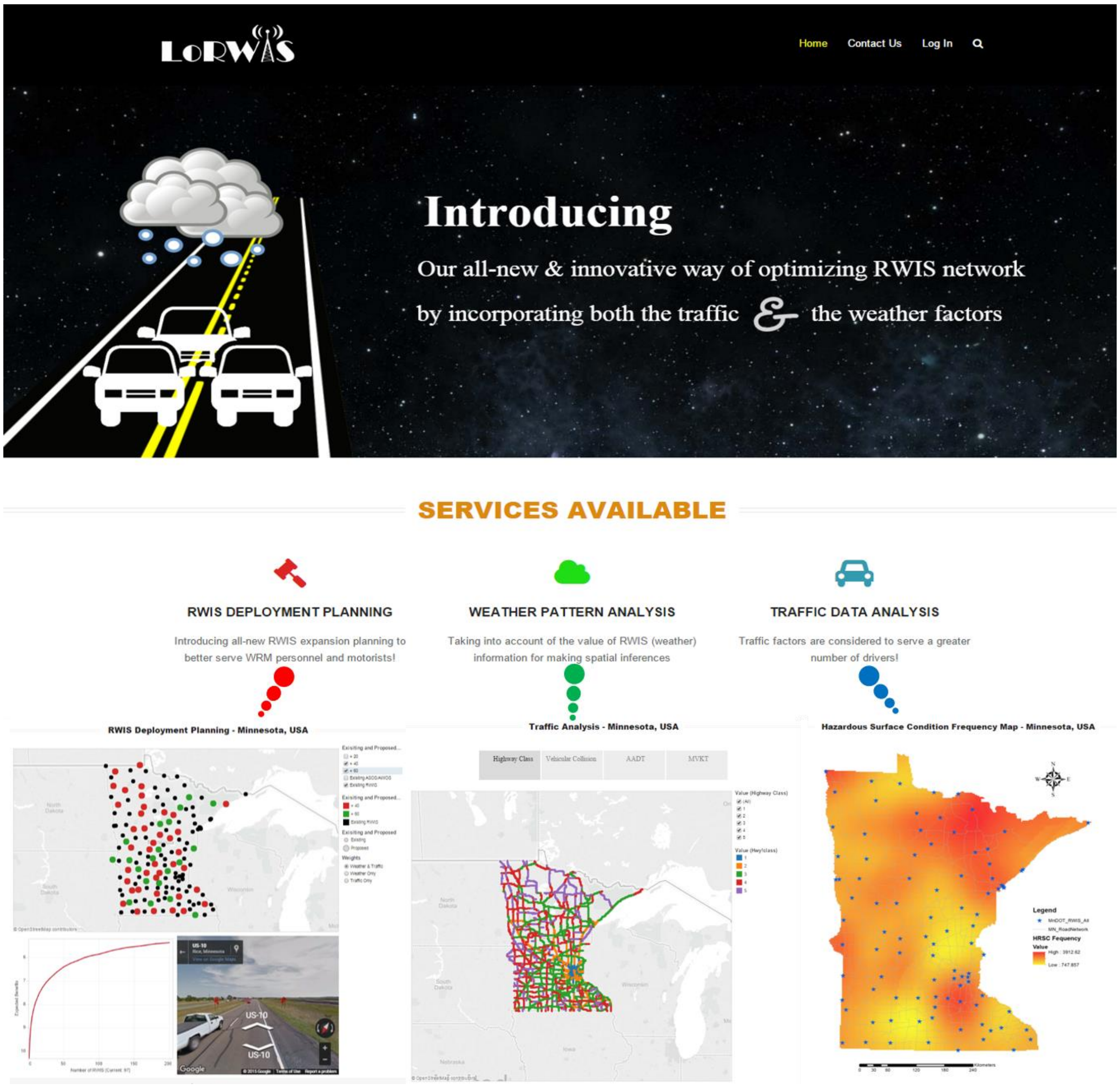


Figure 5-1: A web-based RWIS deployment planning and analyses tool – www.LoRWIS.com

5.2 Recommendations for Future Research

The following is a list of recommendations on the possible extensions to this research.

- For SM approach, first, VST and MST models can be improved by utilizing a geostatistical interpolation technique such as kriging. Several studies have found that kriging would provide a better estimation than regression, especially when variables are spatially dependent on each other

(Hengl et al., 2003; Mesquita and Sousa, 2009). In addition, methodical guidelines need to be established for determining a number of RWIS stations to be allocated within a cell. This is particularly important for DOTs wanting to install more than one RWIS station within, for instance, as used herein minimum spatial unit of 50 km^2 to enhance and extend their monitoring capability and spatial coverage.

- For CB approach, first, savings from other sources such as patrol savings and travel time savings should be quantified and added to the maintenance and safety benefits to facilitate a more complete analysis. Second, road weather and land-use information should be incorporated in the modeling process to take account for the effects of topographical and micrometeorological variations on RWIS benefits and costs. Third, since the use of a buffer zone with a 30-km diameter can be questionable, a geospatial analysis is required to spatially examine the extent to which the effect of an RWIS station would last, and adjust the parameter accordingly. Fourth, as the costs of a single RWIS station could vary depending on many criteria, a range of different values should be tested and validated to see how it would affect the findings.

- For SI approach, first, other variants of kriging, such as regression kriging or universal kriging (Bourennane el al., 2000; Hengl et al., 2004; Amorim et al., 2012), can be used to take into account auxiliary variables in order to obtain more accurate and detailed results in modeling the trend component of the regionalized random variable (e.g., HRSC measurements). Second, other heuristic algorithms including greedy algorithm (Cormen et al., 2001; Baume et al., 2011), genetic algorithm (Arifin, 2010), and tabu search (Glover and Laguna, 1997) should also be explored and tested. Third, in addition to the global performance measure used in this study, it would be worthwhile to use and/or develop another evaluation metric that quantitatively examines the degree of similarities (e.g., spatial/areal overlap analysis) between the optimized and existing network. This will provide a more definite measure of appreciating the similarity or closeness of one network design to another.

- SI approach developed in this thesis deals with a single domain – space, and because almost all environmental variables, including the RWIS measurements, have a strong tendency to vary both in space and time, an incorporation of additional variable namely time is considered important to generate more sensible solutions. The use of this so-called space-time kriging has gained popularity over the past decade due to its renowned capability of capturing the variability of an environmental parameter over two important domains - space and time (Gething et al. (2007); Heuvelink and Griffith (2010); Cressie and Wikle (2011)), and should therefore be explored and implemented in the RWIS station location allocation optimization process.

- Lastly, more case studies should be conducted to investigate the generality and sensitivity of the model results to external conditions including network size, size of grid, and input parameters including use of other traffic variables (accident rates/frequencies, annual average daily traffic), and weather variables (snow intensity, road surface temperature).

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Appendix A - All New Optimized RWIS Network

Locations of All-New RWIS Stations – Single Criterion [Crit1]

Station Number	Ontario		Iowa		Minnesota		Utah	
	x	y	x	y	x	y	x	y
1	-79.1696	43.1603	-94.7426	41.0132	-94.2698	46.8998	-110.3500	39.2990
2	-82.2211	42.3332	-96.3190	42.4893	-92.5713	47.4999	-110.2134	38.9847
3	-74.6003	45.5018	-93.5756	42.1868	-95.6312	44.0682	-111.8595	40.7189
4	-76.0756	45.3178	-93.7795	41.0237	-93.3941	45.6372	-112.1474	39.2278
5	-80.9250	48.5453	-91.8633	42.4528	-94.0561	46.0380	-110.8048	39.5840
6	-82.0626	45.9445	-91.1575	41.6331	-96.5044	47.3391	-112.3288	41.8055
7	-79.7915	47.3496	-95.8723	41.5579	-93.1782	44.8886	-113.0790	37.6956
8	-79.9161	47.8557	-94.2625	42.0192	-95.5340	44.4215	-112.5228	41.8961
9	-94.8048	49.7137	-93.3143	40.7557	-96.6708	46.8749	-112.4241	40.6830
10	-86.0894	49.7849	-93.5416	42.4572	-95.1072	44.0790	-111.8393	39.7463
11	-80.3644	43.6964	-94.3871	41.0720	-96.3427	44.7247	-111.5165	41.0370
12	-75.6209	45.0558	-95.7877	41.2628	-95.9582	47.5165	-109.3815	38.1655
13	-91.9715	48.7256	-95.8046	42.4782	-93.4370	46.2040	-111.9508	40.6931
14	-79.7639	43.6026	-94.2471	43.0730	-91.7646	47.9260	-111.6601	41.0405
15	-80.6232	48.5916	-93.6119	41.5980	-96.3550	43.6170	-111.6452	40.1758
16	-82.6337	42.0680	-91.8498	43.1821	-96.0154	45.7060	-112.6149	38.1469
17	-84.3280	46.6666	-92.6257	43.0792	-92.8989	45.3633	-111.4042	40.9877
18	-81.0655	49.0599	-95.7994	40.6951	-94.0879	43.6611	-111.7088	40.7542
19	-84.2000	49.7437	-93.6226	43.2672	-96.3829	46.0468	-109.5981	40.3884
20	-74.6900	45.0653	-90.6965	42.4353	-94.2228	44.7941	-112.2014	41.7111
21	-92.9553	49.8151	-93.5689	41.4303	-95.6494	43.6356	-112.0143	41.2243
22	-91.5023	48.7121	-92.8879	40.7290	-93.4507	47.8507	-111.8016	40.3691
23	-80.1618	48.0751	-91.7739	43.2894	-95.4494	45.0985	-112.5151	38.8013
24	-93.0823	48.7169	-90.6986	42.5323	-93.0091	44.8817	-109.4841	37.5001
25	-94.2699	49.7302	-91.0958	42.4967	-92.6374	43.5577	-113.2015	40.7225
26	-77.3022	45.8820	-95.3961	41.3257	-94.6815	48.7030	-110.8061	38.8658
27	-78.9587	45.3543	-91.2530	42.0939	-94.4317	44.0355	-111.6134	40.7553
28	-79.9308	43.1536	-95.1903	42.6536	-94.5477	48.3271	-112.6201	38.4877
29	-80.5248	43.4942	-93.4985	41.6198	-91.4869	43.5212	-112.7807	41.9732
30	-79.2357	42.9142	-92.4235	41.0249	-94.0218	44.1479	-111.7283	38.9150
31	-79.3249	44.9605	-92.5617	41.7011	-91.3857	47.1924	-111.1039	39.2567
32	-81.3021	42.8273	-92.4812	42.7275	-92.0098	43.6035	-112.4905	38.5908
33	-86.8901	48.7756	-90.2102	41.8842	-96.2268	47.9952	-112.7002	37.2211
34	-79.7941	45.0686	-93.9002	42.0226	-92.8958	44.5036	-109.2998	37.8717

35	-85.1516	48.5185	-91.1445	40.8222	-90.8559	47.5617	-111.5066	40.7297
36	-76.8740	45.6248	-96.0915	42.9999	-94.9796	43.6221	-112.8828	37.8370
37	-78.3460	44.2657	-95.0045	41.4142	-94.2769	45.5227	-112.2523	39.1190
38	-80.0748	43.9195	-92.6361	41.2960	-91.4020	43.9252	-109.9358	37.6012
39	-80.8631	43.0211	-95.8009	43.2076	-94.7493	47.1094	-112.0380	40.7694
40	-79.8055	43.3141	-91.5672	41.0174	-96.3742	45.2639	-111.7780	41.1327
41	-92.5182	49.6896	-93.7862	41.5911	-92.5213	44.1515	-112.0205	41.1251
42	-93.9156	49.0972	-92.3737	42.4838	-95.5424	45.4745	-112.3751	38.5467
43	-88.6413	48.6780	-92.9218	42.0261	-92.8912	46.9068	-112.3523	38.9495
44	-81.3063	48.5055	-91.3520	42.4736	-93.6648	45.7439	-112.0625	41.5369
45	-84.3571	46.8847	-95.8569	41.2071	-93.9143	44.4729	-109.6077	37.2540
46	-83.6429	49.6864	-90.5826	41.5954	-93.2539	48.6071	-112.7488	40.7569
47	-79.3293	45.5402	-93.2155	43.1337	-95.9270	46.1359	-112.6601	38.3761
48	-82.3371	42.9918	-93.1378	41.3235	-93.0092	45.7728	-111.5130	38.7980
49	-90.7125	49.1160	-94.6906	43.1214	-93.3436	43.6388	-109.6900	38.9514
50	-89.1186	48.8310	-94.1993	42.5062	-94.9220	47.5116	-111.3478	38.7676
51	-78.5391	43.9211	-94.6478	41.5009	-95.4322	44.6938	-111.8294	39.8918
52	-80.9529	43.9501	-93.8470	40.7259	-94.2131	47.8722	-111.2751	41.0681
53	-78.1836	45.4987	-91.5535	41.6388	-92.4071	44.3130	-112.5955	38.6603
54	-79.6482	44.6908	-93.5715	41.7275	-95.3688	45.9103	-111.9092	39.6138
55	-79.6367	44.1218	-95.1697	43.1133	-93.3112	44.5572	-109.0933	39.1904
56	-85.9824	48.6907	-92.8093	43.2958	-92.8484	48.1214	-113.7460	39.0618
57	-84.8049	48.0906	-91.8960	42.6693	-96.3389	43.9956	-109.3432	38.9789
58	-89.8955	48.8025	-93.5739	41.9977	-92.7849	43.8822	-111.9315	38.8792
59	-76.7716	44.2807	-93.7271	42.7263	-96.0206	45.0848	-110.0455	38.9495
60	-90.3334	48.6655	-92.0213	41.6707	-93.2757	45.0434	-111.9916	39.4741
61	-79.5364	43.7142	-95.3361	41.6511	-93.9514	46.7139	-111.9386	41.0156
62	-79.4569	43.1879	-90.6378	42.0559	-93.3559	44.9307	-112.3002	40.6674
63	-94.1851	48.7063	-95.3861	42.0284	-94.9959	45.2153	-109.4397	37.6580
64	-94.0573	49.4282	-92.0502	42.1573	-93.7304	44.8524	-111.7186	40.2786
65	-76.6133	45.4610	-94.2401	42.7219	-95.2652	47.1544	-111.7303	40.0631
66	-79.4215	44.6426	-93.0304	41.7019	-95.7903	48.8435	-109.2258	39.0794
67	-79.9102	43.9602	-94.1447	41.5071	-94.9114	46.1079	-111.9194	40.6385
68	-93.8598	49.8464			-96.2925	46.4814	-112.2412	38.6018
69	-80.1099	43.4452			-96.6989	45.5509	-112.5779	40.7250
70	-87.8214	49.6568			-95.8878	46.8659	-111.0670	38.8452
71	-79.4068	46.1877			-94.6437	44.9239	-111.2578	40.3033
72	-84.5848	47.3109			-93.1280	45.0122	-112.0879	41.6221
73	-94.5394	49.7898			-90.0025	47.8395	-112.1513	38.6854
74	-80.3308	46.4441			-93.3146	45.1783	-109.8899	38.9263

75	-77.7623	44.4603	-93.5249	47.2566	-112.0327	41.3279
76	-81.5602	42.9682	-95.3882	48.1237	-111.6001	38.8821
77	-84.0516	46.3396	-93.4261	44.7729	-112.1787	40.7475
78	-75.5115	44.7302	-94.9370	45.7294	-111.9073	40.4426
79	-86.7070	49.7443	-92.1896	43.7174	-110.4578	38.9305
80	-75.0423	44.9926	-97.0335	48.0237	-112.0840	39.3353
81	-78.7970	44.8006	-94.2572	46.3599	-111.4092	40.8035
82	-94.5870	48.7206	-92.7751	46.4206	-112.1693	41.9104
83	-78.5709	44.1059	-93.3096	44.2601	-109.6659	38.6359
84	-78.9333	44.1024	-94.5486	45.6273	-112.0644	38.8051
85	-79.0889	43.8322	-95.3129	46.4245	-112.1837	39.9339
86	-84.9946	49.7560	-93.8511	45.3106	-112.0475	41.4221
87	-77.1907	44.8664	-94.8902	46.6212	-110.6934	38.3928
88	-81.2088	44.5302	-91.9961	44.1481	-111.1984	39.9308
89	-81.7630	42.5515	-92.1052	46.7953	-111.9069	40.8553
90	-80.8800	48.8850	-92.4601	46.6896	-113.2108	37.5074
91	-92.5999	48.7565	-93.2711	44.0441	-111.8558	38.9371
92	-78.0320	44.9479	-94.8543	44.3805	-111.4053	40.4960
93	-77.3928	44.1937	-93.3101	44.3411	-110.4374	40.1661
94	-79.9814	45.3415	-94.0828	45.4167	-112.6521	38.2716
95	-77.0121	44.2519	-96.8858	48.7307	-113.8214	40.7429
96	-76.2028	44.3386	-92.8151	46.1237	-111.8852	40.5268
97	-82.4340	42.6061	-93.7931	43.8796	-113.5330	37.1250
98	-75.4147	45.3472				
99	-77.7716	44.0733				
100	-79.1250	44.4309				
101	-84.0686	46.3517				
102	-88.2495	49.0388				
103	-82.9040	42.2115				
104	-81.9249	42.9921				
105	-89.3030	48.3752				
106	-89.9002	48.2404				
107	-74.9042	45.3419				
108	-82.1449	49.3403				
109	-80.2492	43.1636				
110	-82.8566	49.5263				
111	-79.8107	46.7437				
112	-81.3828	43.5489				
113	-79.2780	45.2811				
114	-78.0679	46.2235				

115	-80.5678	46.0013
116	-93.9160	48.8285
117	-81.7585	46.2840
118	-81.3875	49.1305
119	-92.8154	49.7865
120	-91.8480	49.4557
121	-80.2984	48.3974
122	-91.3118	49.2991
123	-82.9726	46.1941
124	-81.3147	45.0249
125	-93.3271	49.8413
126	-79.2857	43.9947
127	-80.5075	43.1365
128	-79.0926	46.2726
129	-82.6218	46.3765
130	-79.6576	44.4335
131	-93.6397	48.6191
132	-79.6895	48.1193
133	-79.1551	46.5360
134	-88.0839	49.4895
135	-84.8268	47.7556
136	-89.5638	48.0389
137	-81.3911	46.6082
138	-80.5487	42.8299
139	-89.6360	48.4194
140	-80.9318	43.3705

Locations of All-New RWIS Stations – Dual Criteria [Crit1+ Crit2]

Station Number	Ontario		Iowa		Minnesota		Utah	
	x	y	x	y	x	y	x	y
1	-79.1696	43.1603	-94.7426	41.0132	-94.2698	46.8998	-111.9041	38.9011
2	-82.2211	42.3332	-96.3190	42.4893	-92.5713	47.4999	-110.2162	38.9832
3	-74.6003	45.5018	-93.5756	42.1868	-95.6312	44.0682	-111.8426	39.7689
4	-76.0756	45.3178	-93.7795	41.0237	-93.3941	45.6372	-111.3226	41.0436
5	-80.9250	48.5453	-91.8633	42.4528	-94.0561	46.0380	-112.2767	40.6827
6	-82.0626	45.9445	-91.1575	41.6331	-96.5044	47.3391	-112.4404	40.6836
7	-79.7915	47.3496	-95.8723	41.5579	-93.1782	44.8886	-109.4732	37.4343
8	-79.9161	47.8557	-94.2625	42.0192	-95.5340	44.4215	-110.7864	39.5795
9	-94.8048	49.7137	-93.3143	40.7557	-96.6708	46.8749	-112.1722	41.9460
10	-86.0894	49.7849	-93.5416	42.4572	-95.1072	44.0790	-113.5865	37.0883
11	-80.3644	43.6964	-94.3871	41.0720	-96.3427	44.7247	-112.7440	40.7544
12	-75.6209	45.0558	-95.7877	41.2628	-95.9582	47.5165	-109.6901	38.9511
13	-91.9715	48.7256	-95.8046	42.4782	-93.4370	46.2040	-111.8983	39.6468
14	-79.7639	43.6026	-94.2471	43.0730	-91.7646	47.9260	-111.8007	40.6872
15	-80.6232	48.5916	-93.6119	41.5980	-96.3550	43.6170	-113.0813	37.6496
16	-82.6337	42.0680	-91.8498	43.1821	-96.0154	45.7060	-109.3372	37.8723
17	-84.3280	46.6666	-92.6257	43.0792	-92.8989	45.3633	-112.9256	37.8126
18	-81.0655	49.0599	-95.7994	40.6951	-94.0879	43.6611	-112.5623	40.7239
19	-84.2000	49.7437	-93.6226	43.2672	-96.3829	46.0468	-111.8295	39.8912
20	-74.6900	45.0653	-90.6965	42.4353	-94.2228	44.7941	-111.8619	41.1397
21	-92.9553	49.8151	-93.5689	41.4303	-95.6494	43.6356	-111.6847	40.0994
22	-91.5023	48.7121	-92.8879	40.7290	-93.4507	47.8507	-111.1111	41.1985
23	-80.1618	48.0751	-91.7739	43.2894	-95.4494	45.0985	-111.9030	40.5749
24	-93.0823	48.7169	-90.6986	42.5323	-93.0091	44.8817	-111.9975	41.1997
25	-94.2699	49.7302	-91.0958	42.4967	-92.6374	43.5577	-111.8574	40.7184
26	-77.3022	45.8820	-95.3961	41.3257	-94.6815	48.7030	-111.3960	40.9149
27	-78.9587	45.3543	-91.2530	42.0939	-94.4317	44.0355	-110.5142	40.1776
28	-79.9308	43.1536	-95.1903	42.6536	-94.5477	48.3271	-112.6188	38.1444
29	-80.5248	43.4942	-93.4985	41.6198	-91.4869	43.5212	-113.7777	40.7395
30	-79.2357	42.9142	-92.4235	41.0249	-94.0218	44.1479	-109.4812	37.6085
31	-79.3249	44.9605	-92.5617	41.7011	-91.3857	47.1924	-112.2876	39.0617
32	-81.3021	42.8273	-92.4812	42.7275	-92.0098	43.6035	-110.7279	40.2060
33	-86.8901	48.7756	-90.2102	41.8842	-96.2268	47.9952	-109.5587	37.1428
34	-79.7941	45.0686	-93.9002	42.0226	-92.8958	44.5036	-111.3488	38.7667
35	-85.1516	48.5185	-91.1445	40.8222	-90.8559	47.5617	-111.6482	40.1865
36	-76.8740	45.6248	-96.0915	42.9999	-94.9796	43.6221	-111.9393	41.0129
37	-78.3460	44.2657	-95.0045	41.4142	-94.2769	45.5227	-111.9499	40.7942

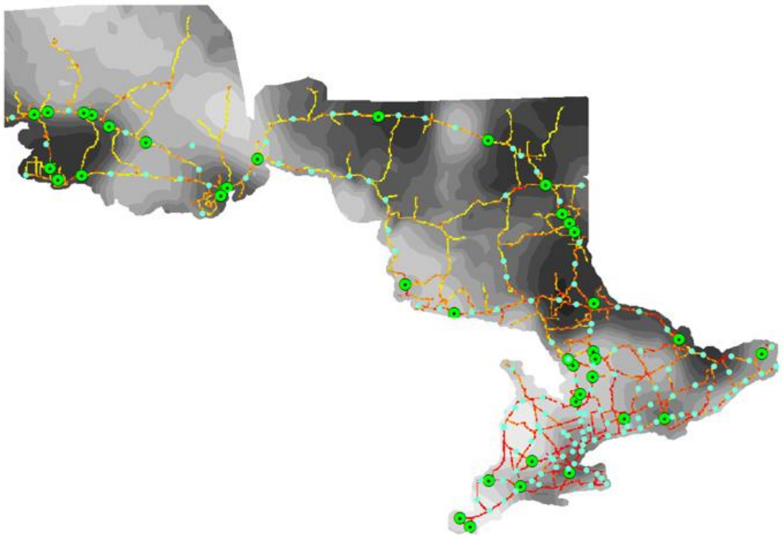
38	-80.0748	43.9195	-92.6361	41.2960	-91.4020	43.9252	-111.7176	40.2755
39	-80.8631	43.0211	-95.8009	43.2076	-94.7493	47.1094	-111.8916	40.9026
40	-79.8055	43.3141	-91.5672	41.0174	-96.3742	45.2639	-111.9548	39.5235
41	-92.5182	49.6896	-93.7862	41.5911	-92.5213	44.1515	-110.8623	38.8596
42	-93.9156	49.0972	-92.3737	42.4838	-95.5424	45.4745	-111.6926	40.7468
43	-88.6413	48.6780	-92.9218	42.0261	-92.8912	46.9068	-112.0278	41.3047
44	-81.3063	48.5055	-91.3520	42.4736	-93.6648	45.7439	-113.1731	40.7257
45	-84.3571	46.8847	-95.8569	41.2071	-93.9143	44.4729	-112.2943	41.7964
46	-83.6429	49.6864	-90.5826	41.5954	-93.2539	48.6071	-110.3745	38.9151
47	-79.3293	45.5402	-93.2155	43.1337	-95.9270	46.1359	-109.5506	38.5690
48	-82.3371	42.9918	-93.1378	41.3235	-93.0092	45.7728	-112.7897	41.9735
49	-90.7125	49.1160	-94.6906	43.1214	-93.3436	43.6388	-111.9557	40.6627
50	-89.1186	48.8310	-94.1993	42.5062	-94.9220	47.5116	-112.1775	41.6979
51	-78.5391	43.9211	-94.6478	41.5009	-95.4322	44.6938	-111.5996	38.8858
52	-80.9529	43.9501	-93.8470	40.7259	-94.2131	47.8722	-111.2197	41.0956
53	-78.1836	45.4987	-91.5535	41.6388	-92.4071	44.3130	-112.7138	38.0296
54	-79.6482	44.6908	-93.5715	41.7275	-95.3688	45.9103	-111.4784	41.0055
55	-79.6367	44.1218	-95.1697	43.1133	-93.3112	44.5572	-112.3572	38.9390
56	-85.9824	48.6907	-92.8093	43.2958	-92.8484	48.1214	-111.9119	40.7833
57	-84.8049	48.0906	-91.8960	42.6693	-96.3389	43.9956	-112.5563	38.7660
58	-89.8955	48.8025	-93.5739	41.9977	-92.7849	43.8822	-111.7632	40.0203
59	-76.7716	44.2807	-93.7271	42.7263	-96.0206	45.0848	-113.3468	37.2466
60	-90.3334	48.6655	-92.0213	41.6707	-93.2757	45.0434	-112.5972	38.6526
61	-79.5364	43.7142	-95.3361	41.6511	-93.9514	46.7139	-113.1903	37.5569
62	-79.4569	43.1879	-90.6378	42.0559	-93.3559	44.9307	-112.0230	41.1302
63	-94.1851	48.7063	-95.3861	42.0284	-94.9959	45.2153	-112.6129	38.5187
64	-94.0573	49.4282	-92.0502	42.1573	-93.7304	44.8524	-112.0463	39.4151
65	-76.6133	45.4610	-94.2401	42.7219	-95.2652	47.1544	-111.7864	39.9642
66	-79.4215	44.6426	-93.0304	41.7019	-95.7903	48.8435	-109.7588	40.3069
67	-79.9102	43.9602	-94.1447	41.5071	-94.9114	46.1079	-111.8326	40.3794
68	-93.8598	49.8464			-96.2925	46.4814	-112.2932	38.5779
69	-80.1099	43.4452			-96.6989	45.5509	-112.0411	38.8228
70	-87.8214	49.6568			-95.8878	46.8659	-112.0605	41.5111
71	-79.4068	46.1877			-94.6437	44.9239	-112.7834	37.9001
72	-84.5848	47.3109			-93.1280	45.0122	-111.4194	40.8060
73	-94.5394	49.7898			-90.0025	47.8395	-112.4461	38.8646
74	-80.3308	46.4441			-93.3146	45.1783	-110.9705	39.2883
75	-77.7623	44.4603			-93.5249	47.2566	-112.1354	38.7127
76	-81.5602	42.9682			-95.3882	48.1237	-113.4082	37.1922
77	-84.0516	46.3396			-93.4261	44.7729	-112.0850	39.3087

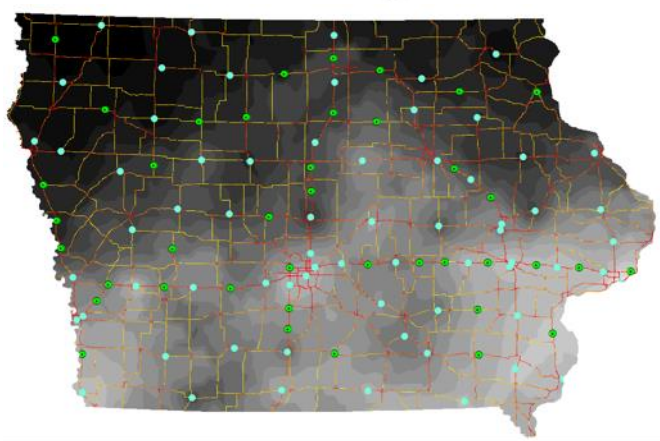
78	-75.5115	44.7302	-94.9370	45.7294	-109.5818	37.2777
79	-86.7070	49.7443	-92.1896	43.7174	-111.5227	40.7216
80	-75.0423	44.9926	-97.0335	48.0237	-111.8333	41.8183
81	-78.7970	44.8006	-94.2572	46.3599	-112.0503	41.4170
82	-94.5870	48.7206	-92.7751	46.4206	-111.7278	41.0781
83	-78.5709	44.1059	-93.3096	44.2601	-111.5940	41.0558
84	-78.9333	44.1024	-94.5486	45.6273	-112.0806	41.6079
85	-79.0889	43.8322	-95.3129	46.4245	-109.5670	40.4402
86	-84.9946	49.7560	-93.8511	45.3106	-112.6509	38.4137
87	-77.1907	44.8664	-94.8902	46.6212	-113.0533	37.7340
88	-81.2088	44.5302	-91.9961	44.1481	-109.4105	37.7339
89	-81.7630	42.5515	-92.1052	46.7953	-111.8968	40.4361
90	-80.8800	48.8850	-92.4601	46.6896	-111.8939	40.5005
91	-92.5999	48.7565	-93.2711	44.0441	-112.6526	38.2800
92	-78.0320	44.9479	-94.8543	44.3805	-111.8108	40.6330
93	-77.3928	44.1937	-93.3101	44.3411	-112.1072	40.7706
94	-79.9814	45.3415	-94.0828	45.4167	-113.2428	37.3978
95	-77.0121	44.2519	-96.8858	48.7307	-112.6913	37.2261
96	-76.2028	44.3386	-92.8151	46.1237	-112.4413	41.8494
97	-82.4340	42.6061	-93.7931	43.8796	-111.1913	38.8176
98	-75.4147	45.3472				
99	-77.7716	44.0733				
100	-79.1250	44.4309				
101	-84.0686	46.3517				
102	-88.2495	49.0388				
103	-82.9040	42.2115				
104	-81.9249	42.9921				
105	-89.3030	48.3752				
106	-89.9002	48.2404				
107	-74.9042	45.3419				
108	-82.1449	49.3403				
109	-80.2492	43.1636				
110	-82.8566	49.5263				
111	-79.8107	46.7437				
112	-81.3828	43.5489				
113	-79.2780	45.2811				
114	-78.0679	46.2235				
115	-80.5678	46.0013				
116	-93.9160	48.8285				
117	-81.7585	46.2840				

118	-81.3875	49.1305
119	-92.8154	49.7865
120	-91.8480	49.4557
121	-80.2984	48.3974
122	-91.3118	49.2991
123	-82.9726	46.1941
124	-81.3147	45.0249
125	-93.3271	49.8413
126	-79.2857	43.9947
127	-80.5075	43.1365
128	-79.0926	46.2726
129	-82.6218	46.3765
130	-79.6576	44.4335
131	-93.6397	48.6191
132	-79.6895	48.1193
133	-79.1551	46.5360
134	-88.0839	49.4895
135	-84.8268	47.7556
136	-89.5638	48.0389
137	-81.3911	46.6082
138	-80.5487	42.8299
139	-89.6360	48.4194
140	-80.9318	43.3705

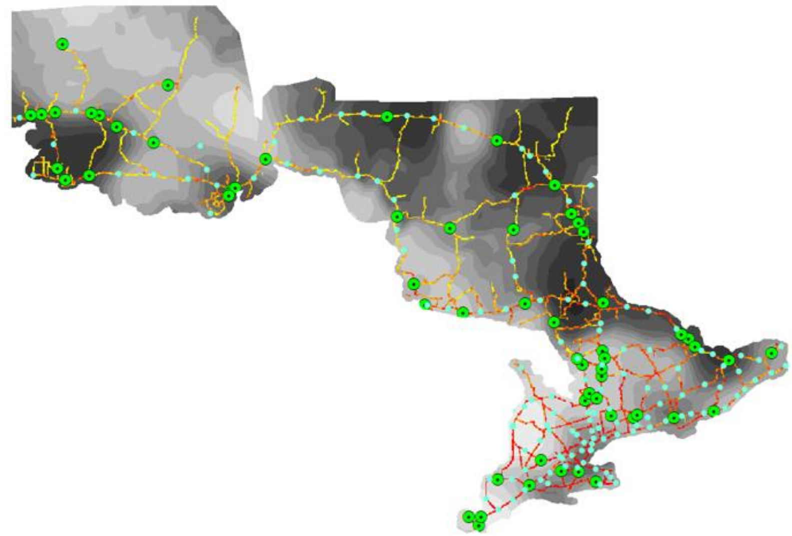
Appendix B – Location Plans for Adding New RWIS Stations

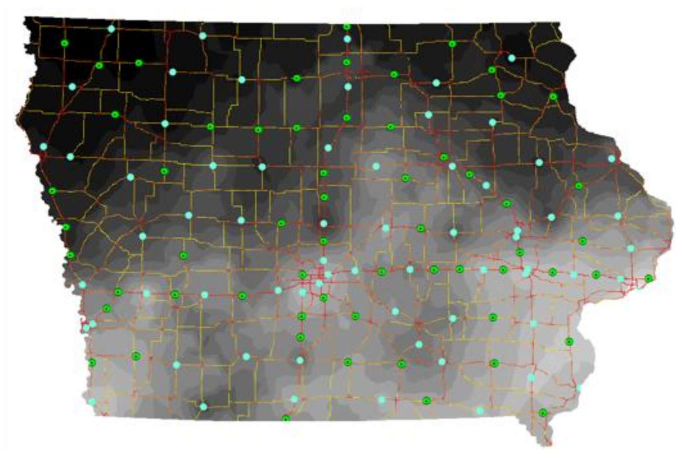
40 Additional Stations



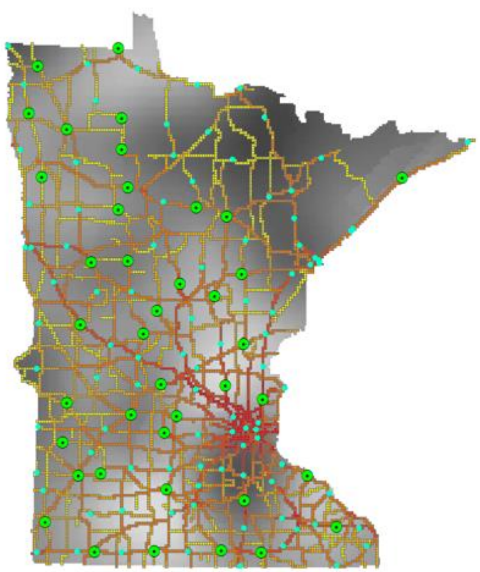


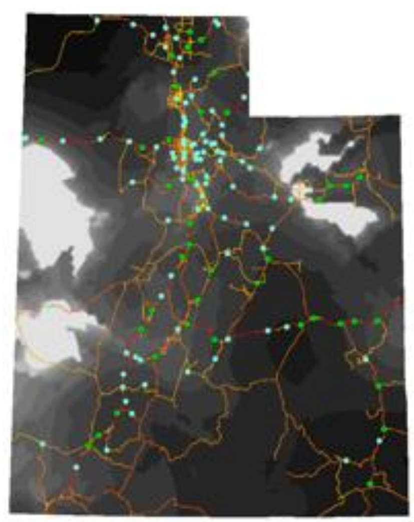
60 Additional Stations



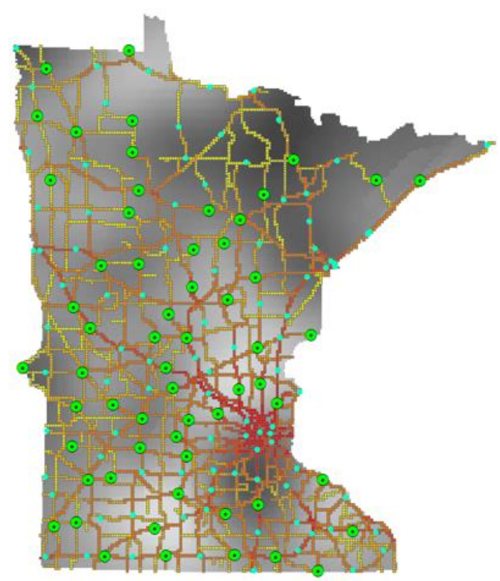


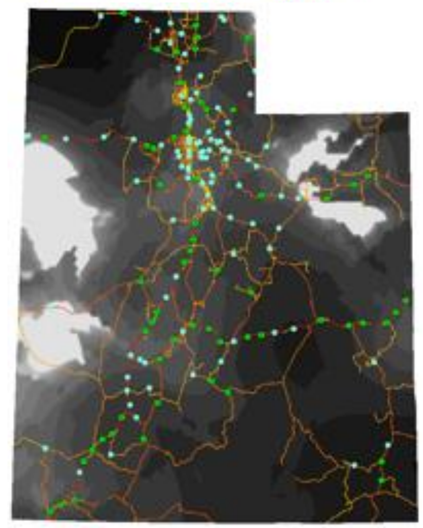
40 Additional Stations





60 Additional Stations





Locations of 20 Additional RWIS Stations

Station Number	Ontario		Iowa		Minnesota		Utah	
	x	y	x	y	x	y	x	y
1	-79.9208	43.1376	-96.2381	42.2266	-90.7397	47.6298	-112.2882	39.0622
2	-82.8731	42.2395	-93.3527	42.8084	-96.7960	48.2711	-111.4833	38.7768
3	-82.6046	42.0682	-90.9113	41.6352	-93.3193	46.6236	-111.8018	40.3696
4	-79.7479	44.5313	-91.9164	41.0027	-95.8441	46.0485	-110.1243	40.1748
5	-81.2538	42.8775	-95.7975	40.9770	-95.3034	47.2865	-112.0795	41.6011
6	-79.6436	44.6787	-94.3597	41.4926	-92.3065	44.4737	-112.4483	40.6817
7	-92.7913	49.7859	-95.6731	41.3749	-94.6463	46.2206	-111.6787	41.0460
8	-89.2200	48.4651	-93.7781	41.3491	-94.4948	44.9291	-111.3293	41.0399
9	-79.2621	46.3839	-96.0991	41.9656	-94.5666	45.4390	-110.2113	38.9856
10	-82.1269	49.3431	-93.3286	41.0151	-94.2937	46.5161	-112.2450	38.6045
11	-89.2984	48.3940	-92.9986	41.6809	-93.5684	47.2371	-112.4339	38.8724
12	-83.0225	46.2066	-93.8496	43.0997	-95.0119	45.1088	-112.9434	37.8067
13	-93.7089	48.6347	-95.5659	41.5008	-93.5713	45.4332	-109.8648	38.9309
14	-79.2827	45.4881	-95.0074	41.4943	-93.6085	43.6832	-112.0989	40.7697
15	-76.9863	45.7154	-94.2241	42.7728	-93.2696	44.2143	-109.5951	40.3876
16	-94.3425	49.7911	-92.4862	41.6930	-95.1243	46.7479	-113.7783	40.7381
17	-78.4518	44.1990	-93.7886	41.1930	-95.2724	47.9287	-113.0761	37.6974
18	-84.3493	46.7330	-92.2371	41.6949	-96.1683	48.1238	-112.0267	41.3041
19	-79.8252	45.2301	-91.2941	42.9517	-96.6982	48.7785	-109.3835	38.9554
20	-79.2981	45.0072	-95.6516	42.8019	-96.0043	45.2163	-111.8120	39.9347

Locations of 40 Additional RWIS Stations

Station Number	Ontario		Iowa		Minnesota		Utah	
	x	y	x	y	x	y	x	y
1	-79.9208	43.1376	-96.2381	42.2266	-90.7397	47.6298	-112.2882	39.0622
2	-82.8731	42.2395	-93.3527	42.8084	-96.7960	48.2711	-111.4833	38.7768
3	-82.6046	42.0682	-90.9113	41.6352	-93.3193	46.6236	-111.8018	40.3696
4	-79.7479	44.5313	-91.9164	41.0027	-95.8441	46.0485	-110.1243	40.1748
5	-81.2538	42.8775	-95.7975	40.9770	-95.3034	47.2865	-112.0795	41.6011
6	-79.6436	44.6787	-94.3597	41.4926	-92.3065	44.4737	-112.4483	40.6817
7	-92.7913	49.7859	-95.6731	41.3749	-94.6463	46.2206	-111.6787	41.0460
8	-89.2200	48.4651	-93.7781	41.3491	-94.4948	44.9291	-111.3293	41.0399
9	-79.2621	46.3839	-96.0991	41.9656	-94.5666	45.4390	-110.2113	38.9856
10	-82.1269	49.3431	-93.3286	41.0151	-94.2937	46.5161	-112.2450	38.6045
11	-89.2984	48.3940	-92.9986	41.6809	-93.5684	47.2371	-112.4339	38.8724
12	-83.0225	46.2066	-93.8496	43.0997	-95.0119	45.1088	-112.9434	37.8067
13	-93.7089	48.6347	-95.5659	41.5008	-93.5713	45.4332	-109.8648	38.9309
14	-79.2827	45.4881	-95.0074	41.4943	-93.6085	43.6832	-112.0989	40.7697
15	-76.9863	45.7154	-94.2241	42.7728	-93.2696	44.2143	-109.5951	40.3876
16	-94.3425	49.7911	-92.4862	41.6930	-95.1243	46.7479	-113.7783	40.7381
17	-78.4518	44.1990	-93.7886	41.1930	-95.2724	47.9287	-113.0761	37.6974
18	-84.3493	46.7330	-92.2371	41.6949	-96.1683	48.1238	-112.0267	41.3041
19	-79.8252	45.2301	-91.2941	42.9517	-96.6982	48.7785	-109.3835	38.9554
20	-79.2981	45.0072	-95.6516	42.8019	-96.0043	45.2163	-111.8120	39.9347
21	-79.9654	45.3326	-92.9147	42.7468	-94.3180	45.1070	-109.3925	38.3035
22	-79.9218	47.8628	-91.3373	41.6628	-95.4485	44.4753	-109.6880	38.9520
23	-79.2334	45.3396	-93.3501	43.2195	-95.5102	43.6407	-112.7135	38.0300
24	-85.0717	49.7570	-91.1887	41.1508	-91.8802	43.9281	-109.7709	40.3068
25	-93.0022	49.8158	-91.7760	42.1711	-93.7509	46.3903	-111.6923	41.7660
26	-93.9810	49.8260	-93.9825	42.0313	-92.9942	45.2924	-111.6999	39.1754
27	-92.3321	49.5833	-92.8796	43.1279	-93.2842	45.8778	-111.5023	41.4452
28	-93.0675	48.7193	-96.1794	43.3146	-95.1561	47.5259	-110.9347	39.3430
29	-80.9321	43.3698	-96.0427	41.7611	-94.0556	47.3299	-110.8019	39.5830
30	-80.1121	48.0324	-92.0791	42.9664	-95.3724	49.0007	-112.1009	40.3079
31	-89.1507	48.4917	-94.9348	41.7782	-95.2848	48.2579	-111.8690	41.6894
32	-80.5697	48.5494	-94.7000	42.7346	-94.8556	45.9788	-111.5295	39.4709
33	-74.7446	45.4359	-93.5693	42.2271	-95.7903	44.4458	-111.8212	39.7278
34	-91.3306	49.3057	-91.9222	41.3389	-96.5416	47.6028	-111.8339	38.9290
35	-88.3234	49.0101	-95.1448	42.3974	-93.0138	43.6626	-111.9114	39.6038
36	-79.7908	47.6970	-93.7734	41.6518	-96.0466	44.7918	-109.9779	40.3044

37	-77.3701	44.2001	-92.1364	42.3936	-96.2716	43.9405	-110.3785	38.9193
38	-93.9172	48.8362	-90.4000	41.5989	-95.7043	46.7213	-109.5185	37.3306
39	-89.3178	48.3502	-91.8135	41.6856	-94.4549	44.3233	-109.3323	37.8720
40	-82.0945	42.9909	-93.5742	42.4008	-94.6189	43.6615	-111.8355	41.8467

Locations of 60 Additional RWIS Stations

Station Number	Ontario		Iowa		Minnesota		Utah	
	x	y	x	y	x	y	x	y
1	-79.9208	43.1376	-96.2381	42.2266	-90.7397	47.6298	-112.2882	39.0622
2	-82.8731	42.2395	-93.3527	42.8084	-96.7960	48.2711	-111.4833	38.7768
3	-82.6046	42.0682	-90.9113	41.6352	-93.3193	46.6236	-111.8018	40.3696
4	-79.7479	44.5313	-91.9164	41.0027	-95.8441	46.0485	-110.1243	40.1748
5	-81.2538	42.8775	-95.7975	40.9770	-95.3034	47.2865	-112.0795	41.6011
6	-79.6436	44.6787	-94.3597	41.4926	-92.3065	44.4737	-112.4483	40.6817
7	-92.7913	49.7859	-95.6731	41.3749	-94.6463	46.2206	-111.6787	41.0460
8	-89.2200	48.4651	-93.7781	41.3491	-94.4948	44.9291	-111.3293	41.0399
9	-79.2621	46.3839	-96.0991	41.9656	-94.5666	45.4390	-110.2113	38.9856
10	-82.1269	49.3431	-93.3286	41.0151	-94.2937	46.5161	-112.2450	38.6045
11	-89.2984	48.3940	-92.9986	41.6809	-93.5684	47.2371	-112.4339	38.8724
12	-83.0225	46.2066	-93.8496	43.0997	-95.0119	45.1088	-112.9434	37.8067
13	-93.7089	48.6347	-95.5659	41.5008	-93.5713	45.4332	-109.8648	38.9309
14	-79.2827	45.4881	-95.0074	41.4943	-93.6085	43.6832	-112.0989	40.7697
15	-76.9863	45.7154	-94.2241	42.7728	-93.2696	44.2143	-109.5951	40.3876
16	-94.3425	49.7911	-92.4862	41.6930	-95.1243	46.7479	-113.7783	40.7381
17	-78.4518	44.1990	-93.7886	41.1930	-95.2724	47.9287	-113.0761	37.6974
18	-84.3493	46.7330	-92.2371	41.6949	-96.1683	48.1238	-112.0267	41.3041
19	-79.8252	45.2301	-91.2941	42.9517	-96.6982	48.7785	-109.3835	38.9554
20	-79.2981	45.0072	-95.6516	42.8019	-96.0043	45.2163	-111.8120	39.9347
21	-79.9654	45.3326	-92.9147	42.7468	-94.3180	45.1070	-111.8367	38.9315
22	-79.9218	47.8628	-91.3373	41.6628	-95.4485	44.4753	-109.1337	39.1652
23	-79.2334	45.3396	-93.3501	43.2195	-95.5102	43.6407	-110.9689	38.8453
24	-85.0717	49.7570	-91.1887	41.1508	-91.8802	43.9281	-111.9495	39.5520
25	-93.0022	49.8158	-91.7760	42.1711	-93.7509	46.3903	-112.0738	38.7937
26	-93.9810	49.8260	-93.9825	42.0313	-92.9942	45.2924	-112.8190	37.8663
27	-92.3321	49.5833	-92.8796	43.1279	-93.2842	45.8778	-109.4826	37.4157
28	-93.0675	48.7193	-96.1794	43.3146	-95.1561	47.5259	-112.7114	38.0269
29	-80.9321	43.3698	-96.0427	41.7611	-94.0556	47.3299	-111.6322	38.9018
30	-80.1121	48.0324	-92.0791	42.9664	-95.3724	49.0007	-112.3631	40.6627
31	-89.1507	48.4917	-94.9348	41.7782	-95.2848	48.2579	-109.2625	39.0536
32	-80.5697	48.5494	-94.7000	42.7346	-94.8556	45.9788	-113.5724	37.0946
33	-74.7446	45.4359	-93.5693	42.2271	-95.7903	44.4458	-111.7572	41.1140
34	-91.3306	49.3057	-91.9222	41.3389	-96.5416	47.6028	-111.8395	39.7737
35	-88.3234	49.0101	-95.1448	42.3974	-93.0138	43.6626	-113.1731	37.5866

36	-79.7908	47.6970	-93.7734	41.6518	-96.0466	44.7918	-109.6885	38.9501
37	-77.3701	44.2001	-92.1364	42.3936	-96.2716	43.9405	-111.9716	41.0642
38	-93.9172	48.8362	-90.4000	41.5989	-95.7043	46.7213	-111.1427	38.8255
39	-89.3178	48.3502	-91.8135	41.6856	-94.4549	44.3233	-111.9486	40.8282
40	-82.0945	42.9909	-93.5742	42.4008	-94.6189	43.6615	-111.8766	39.6641
41	-77.1631	45.7916	-95.8221	43.1617	-94.3644	45.9740	-109.4774	37.5974
42	-79.3094	45.1377	-91.6763	42.9921	-95.9403	43.9914	-112.7826	41.9735
43	-79.0521	44.2356	-93.5690	41.9011	-92.7255	47.8681	-112.5026	39.3552
44	-76.3068	44.3267	-92.3727	41.6936	-94.6752	45.6525	-113.2736	37.2133
45	-76.8112	45.5711	-93.8439	42.7323	-95.0325	44.7982	-109.7685	40.3071
46	-83.3751	47.7660	-91.0353	41.8875	-93.2406	45.4995	-111.7994	41.7439
47	-90.9487	50.3065	-92.6184	41.9946	-93.8754	45.1748	-111.1487	41.7453
48	-78.3517	44.2585	-92.5674	40.7268	-93.7454	44.1190	-112.3484	38.9608
49	-81.6814	47.7375	-95.3755	41.0314	-95.4521	45.2477	-111.5921	38.3915
50	-82.5553	42.2429	-93.3521	43.4804	-96.8382	45.6018	-112.4346	37.8193
51	-84.0673	46.3523	-95.4262	43.1864	-96.1053	46.2667	-111.5300	39.4734
52	-79.4417	44.5725	-93.4366	42.6979	-91.4266	47.6482	-112.2704	38.1724
53	-84.7915	47.9804	-91.6485	41.8139	-94.3401	44.7247	-113.4449	37.1615
54	-81.3711	46.3722	-93.2577	41.3515	-93.8047	46.9863	-111.3867	38.2812
55	-94.6320	49.7765	-92.7658	42.3647	-94.2825	46.9098	-111.8304	41.8628
56	-80.3906	43.1582	-92.2961	43.3515	-93.2005	47.5020	-112.2762	40.3042
57	-93.7808	51.0061	-91.8846	42.2387	-92.3939	43.5097	-112.3362	41.6263
58	-79.4710	42.9432	-91.0601	42.2947	-94.7929	43.9500	-110.9713	40.2048
59	-80.5915	46.0298	-92.1852	42.4517	-95.9337	45.5797	-111.8325	41.6346
60	-75.8990	45.3123	-93.9236	40.5903	-92.4725	46.0140	-111.1022	39.2584

Appendix C – Survey Results of Current RWIS Sitting Practices

Q1: Current RWIS Deployment: Total number of RWIS Stations

Utah DOT	94 (This includes 7 portable RWIS trailers)
Minnesota DOT	93
Kansas DOT	43 KDOT plus 10 on turnpike
PA DOT	94
Illinois DOT	57
NDDOT	24
Utah DOT	74 permanent RWIS sites, 7 Portable RWIS.
Virginia DOT	82
Ohio dot	173
PEI	5
Ministry of Transportation, B.C.	64
GNWT DOT	1
MTO	140 stations
Alberta Transportation	84 stations are now connected, 17 have been installed and will be connected this year, 17 more will be installed between 2013 and 2016
Alaska DOT	55
Region of Waterloo, Ontario	3 (2 in now , 1 next year)
Illinois DOT	58
UDOT	73
Ohhio DOT	172
NDDOT North Dakota	23
Michigan DOT	23
MDOT/ Michigan	35
KDOT	43
Wisconsin DOT	60
Iowa DOT	68

Q2: Total number of RWIS stations with webcam

Utah DOT	59
Minnesota DOT	85
Kansas DOT	8 KDOT sites
PA DOT	82
Illinois DOT	14
NDDOT	10
Utah DOT	44
Virginia DOT	56
Ohio dot	2
PEI	5
Ministry of Transportation, B.C.	31
GNWT DOT	1
MTO	47
Alberta Transportation	All RWIS stations are equipped with the cameras
Alaska DOT	5
Region of Waterloo, Ontario	1 (2 by next year)
Illinois DOT	8
UDOT	73
Ohhio DOT	1
NDDOT North Dakota	11
Michigan DOT	23
MDOT/ Michigan	35
KDOT	8
Wisconsin DOT	0
Iowa DOT	49

Q3: Total number of RWIS stations with traffic detector

Utah DOT	5
Minnesota DOT	0
Kansas DOT	5 with Groundhog sensors
PA DOT	0

Illinois DOT	12
NDDOT	0
Utah DOT	2 Portable RWIS Trailers
Virginia DOT	3
Ohio dot	100
PEI	0
Ministry of Transportation, B.C.	0
GNWT DOT	0
MTO	2
Alberta Transportation	None
Alaska DOT	4
Region of Waterloo, Ontario	0
Illinois DOT	8
UDOT	0
Ohhio DOT	150
NDDOT North Dakota	0
Michigan DOT	6
MDOT/ Michigan	35
KDOT	0
Wisconsin DOT	0
Iowa DOT	47

Q4: Total number of RWIS stations linked to dynamic message sign

Utah DOT	1
Minnesota DOT	0
Kansas DOT	0
PA DOT	2
Illinois DOT	0
NDDOT	0
Utah DOT	1 is currently being contructed.
Virginia DOT	0
Ohio dot	1
PEI	0

Ministry of Transportation, B.C.	3, 2 more in development
GNWT DOT	0
MTO	0
Alberta Transportation	None but planning to install and integrate RWIS with DMS at two bridge locations
Alaska DOT	0
Region of Waterloo, Ontario	0
Illinois DOT	0
UDOT	0
Ohhio DOT	0
NDDOT North Dakota	0
Michigan DOT	0
MDOT/ Michigan	none directly, several in same vicincity
KDOT	0
Wisconsin DOT	0
Iowa DOT	0

Q5: Total number of RWIS stations with non-intrusive pavement condition sensors

Utah DOT	44 (+7 additional road temperature only sensors would make the total 51))
Minnesota DOT	0
Kansas DOT	1 Lufft
PA DOT	0
Illinois DOT	0
NDDOT	0
Utah DOT	11
Virginia DOT	25
Ohio dot	2
PEI	0
Ministry of Transportation, B.C.	1
GNWT DOT	1
MTO	1

Alberta Transportation	None of the stations use non-intrusive sensors
Alaska DOT	1
Region of Waterloo, Ontario	0
Illinois DOT	3
UDOT	45
Ohhio DOT	2
NDDOT North Dakota	0
Michigan DOT	0
MDOT/ Michigan	2
KDOT	1
Wisconsin DOT	1
Iowa DOT	1

Q6: Total number of RWIS stations linked to Fixed Automated Spray Technology (FAST)

Utah DOT	4 (internal system)
Minnesota DOT	1
Kansas DOT	0
PA DOT	16
Illinois DOT	1
NDDOT	2
Utah DOT	Possibly 3 but they the data is strictly internal to spray system.
Virginia DOT	0
Ohio dot	0
PEI	0
Ministry of Transportation, B.C.	0
GNWT DOT	0
MTO	8
Alberta Transportation	Two,-presently there are two fully functioning integrated RWIS-FAST systems at two bridge locations
Alaska DOT	0
Region of Waterloo, Ontario	0 (1 roughed in for future use if needed on new Fairway Bridge)

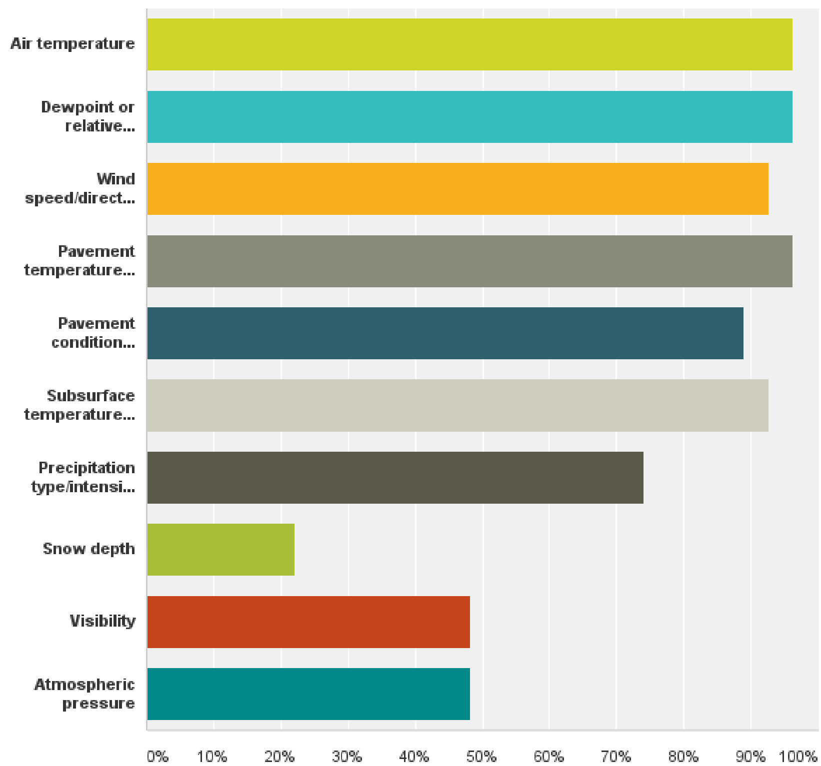
Illinois DOT	1
UDOT	0
Ohhio DOT	0
NDDOT North Dakota	2
Michigan DOT	0
MDOT/ Michigan	1
KDOT	0
Wisconsin DOT	0
Iowa DOT	0

Q7: What are the vendors of your RWIS? (e.g., Vaisala)

Utah DOT	Campbell Scientific, Vaisala, (High Sierra, Lufft - ordered through Campbell)
Minnesota DOT	Vaisala
Kansas DOT	Vaisala and Lufft
PA DOT	Vaisala, SSI, Boschung
Illinois DOT	Vaisala
NDDOT	Vaisala
Utah DOT	Campbell Sci, Vaisala, Lufft, RM Young,
Virginia DOT	Vaisala
Ohio dot	Vaisala
PEI	Vaisala (Approach Navigations Systems Inc)
Ministry of Transportation, B.C.	We build our stations in house with a variety of sensors
GNWT DOT	AMEC Earth & Environmetal
MTO	Vaisala, Campbell Scentific, Lufft, SSI, Boschung
Alberta Transportation	Vaisala (SSI) for older stations and Lufft for all new stations
Alaska DOT	Vaisala
Region of Waterloo, Ontario	Lufft and Vaisala (formerly SSI)
Illinois DOT	Vaisala
UDOT	Campbell Scientific
Ohhio DOT	Vaisala
NDDOT North Dakota	SSI Vaisala
Michigan DOT	Vaisala

MDOT/ Michigan	Vaisala, Lufft, Campbell,
KDOT	Vaisala
Wisconsin DOT	Vaisala, Lufft
Iowa DOT	Vaisala, Zydax, NovaLynx, Sutron, High Sierra

Q8: What are the typical sensor components of your RWIS?



Q9: What is your total annual RWIS maintenance cost?

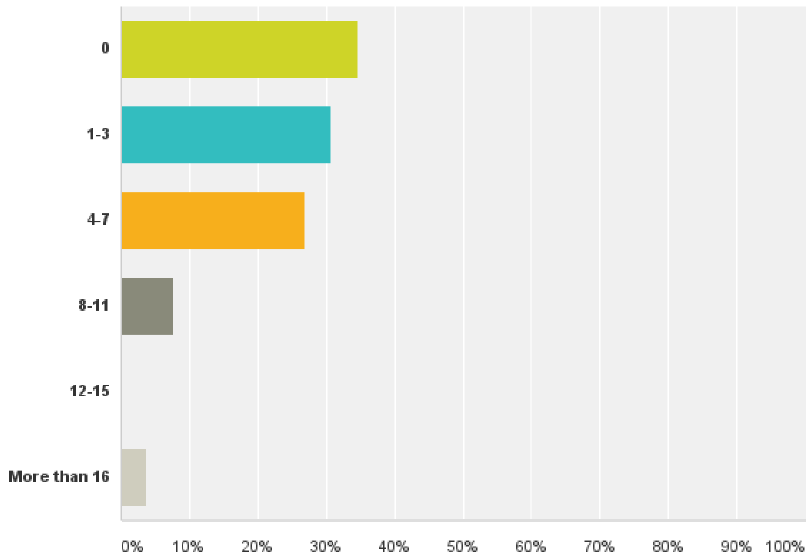
Utah DOT	$77,651.16 - FY14, $53,082.00 - FY15, $204,487.52 - Proposed FY16. FY16 budget allows for replacement parts to address an aging system..
Minnesota DOT	175000
Kansas DOT	$150,000 for repair and upgrades
PA DOT	400000
Illinois DOT	250000
NDDOT	75000

Utah DOT	$69,556.84 for response maintenance and preventative maintenance. Unknown cost for parts at this time.
Virginia DOT	300000
Ohio dot	+/- $630k
PEI	$27,500 for operation and maintenance of 5 units
Ministry of Transportation, B.C.	approx $500K
GNWT DOT	40000
MTO	approx. $500,000
Alberta Transportation	The RWIS infrastructure is managed under two contracts: first contract - for 80 existing stations with an operations/maintenance summer cost of app. $600 per station per month and winter cost of app. $2,000 per station per month, second contract: for the newly installed and future stations with a monthly cost of $800 per station per month throughout the year plus $250 per station per month for forecasting services only during the winter months Oct. 15- March 31.
Alaska DOT	$350K
Region of Waterloo, Ontario	A field visit to clean and inspect. Very little.
Illinois DOT	250000
UDOT	110000
Ohhio DOT	620000
NDDOT North Dakota	We don't have funds set aside, I would guess near the $50,000 but our system is very old and needs many repairs. It is being pieced together to keep running right now.
Michigan DOT	143000
MDOT/ Michigan	3,800/site/year, plus traffic control and spare parts
KDOT	50000
Wisconsin DOT	130000
Iowa DOT	$163,200 for maintenance contract plus ~$40,000 unscheduled maintenance

Q10: What is the average installation cost per station?

Utah DOT	40000
Minnesota DOT	90000
Kansas DOT	30000
PA DOT	40000
Illinois DOT	80000
NDDOT	120000
Utah DOT	$50,000 with Non-invasive Road Sensors.
Virginia DOT	50000
Ohio dot	$2k
PEI	55000
Ministry of Transportation, B.C.	$55K
GNWT DOT	200000
MTO	75000
Alberta Transportation	Based on the recent contract: $132,000 pe station, RWIS installations at interchanges varied from $135,000 to $180,000 due to long cable connections (to the bridge sensors), power provisions. Integrated RWIS -DMS at the bridge sites will be in the order of $250,000
Alaska DOT	This is a wide variance due to the geographic extent of Alaska and the type of site being installed. An average cost over the lifetime of the RWIS network would be $125K
Region of Waterloo, Ontario	80,000 for new fully loaded site
Illinois DOT	50000
UDOT	30000
Ohhio DOT	40000
NDDOT North Dakota	Currently nearly $80,000, new specification hopefully near $30,000 or less
Michigan DOT	107000
MDOT/ Michigan	130000
KDOT	30000
Wisconsin DOT	35000
Iowa DOT	~$60,000

Q11: How many RWIS stations do you plan to deploy next year?

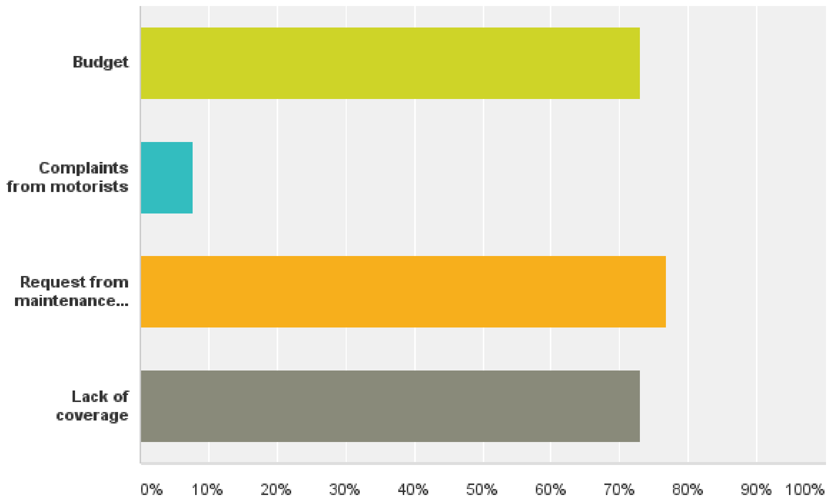


Q12: How many RWIS stations do you plan to deploy in next 5 years?

Utah DOT	Around 30 to 40 sites.
Kansas DOT	No full sites, possibly some mini sites at existing ITS message boards.
Illinois DOT	60
Utah DOT	20
PEI	0
GNWT DOT	4 to 7
MTO	0
Alberta Transportation	8 more stations will be deployed: 1 in 2014 and 7 in 2016
Alaska DOT	10, but there may be some installs of very limited sensor arrays, aka temperature and camera only
Region of Waterloo, Ontario	2
Illinois DOT	15
UDOT	8
NDDOT North Dakota	We are currently updating our specifications and hope to have all our sites updated to a new system in the next 5 to 10 years depending on funding.
Michigan DOT	Unknown

MDOT/ Michigan	Just 16 next year
KDOT	0
Iowa DOT	3

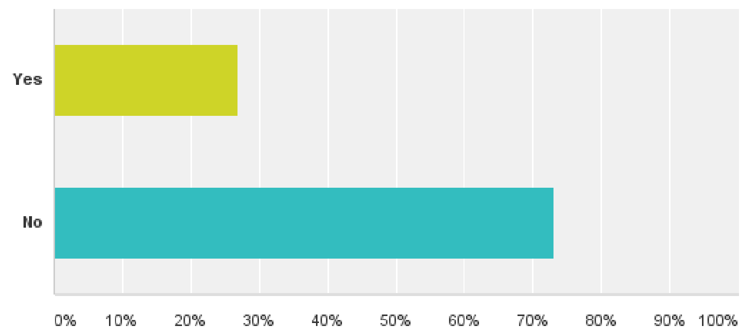
Q13: How do you make decisions on the number of RWIS to be deployed?



Utah DOT	We currently are addressing regional spacing concerns. Construction projects dictate some new sites.
Alberta Transportation	We have taken into consideration climate and meteorological conditions, safety and operational problems. Initial RWIS network plan included NHS and the need to create a Canada wide RWIS network along the major national highways, some key provincial highways were also included in the initial deployment. Budget was another consideration which mainly had an impact on the schedule - after we determined the need for the RWIS stations. New RWIS program which is being implemented now was based on the need to provide coverage for other areas in the province to improve forecasting and provide RWIS observations along the remaining major provincial highways. An expansion study was conducted which also looked at safety and traffic volumes and several stations were also recommended for "hot spots".
Alaska DOT	meet Department strategic goals
Region of Waterloo, Ontario	Based on weather zone report and field experience

UDOT	New roads or road projects that have need and funding for RWIS.
MDOT/ Michigan	jurisdictional changes on a route
Wisconsin DOT	Highway improvement projects

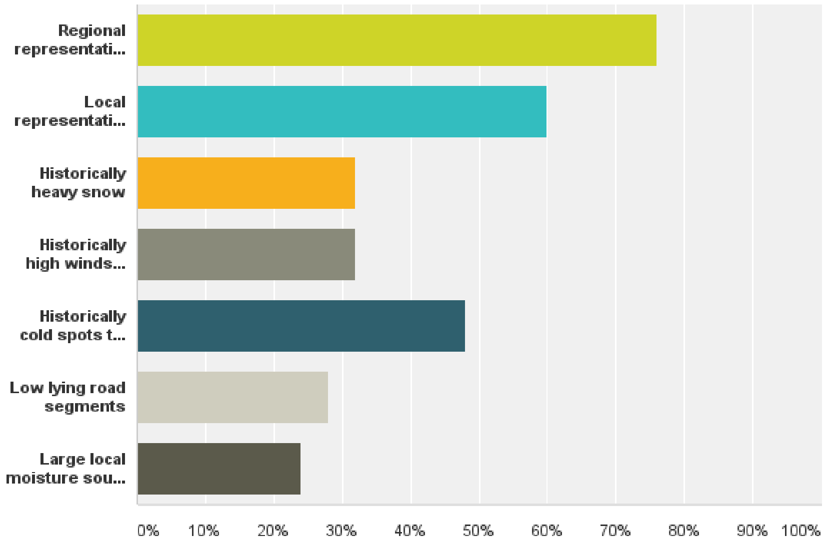
Q14: Do you have a pre-defined spacing requirement? (e.g., RWIS at every 50 km)



Utah DOT	Our current plan is to have a RWIS site every 50 miles on US highways and Interstate routes and within every 10 miles within variable speed limit projects. We hope to fulfill these goals with in the next few years.
NDDOT	We try to use a 30 mile radius for spacing
Ohio dot	Every 30 miles
Ministry of Transportation, B.C.	Not applicable in mountainous terrain with many micro-climates
Alberta Transportation	In general, the minimum requirement for spacing between the stations is at least 50 km .
Alaska DOT	based on maintenance station needs. A typical need is to know that is going on at the maintenance station boundaries. A second requirement would be a particular area that has challenging weather conditions.
Region of Waterloo, Ontario	20km range
UDOT	But it is less distance-based, and more phenomenon-based. In complex topography, you have to hit the points that have particular need of observation, or that can be representative of a large area.
Ohio DOT	30 miles

Wisconsin DOT	We do prefer one every 30 miles, but it's not a requirement

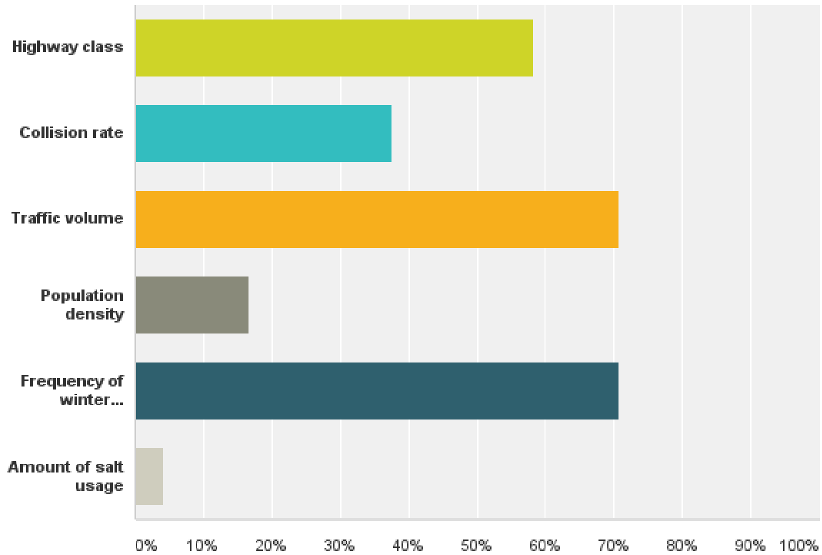
Q15: What are the main factors (or considerations) for deciding the location of RWIS stations at both local and regional scales?



Utah DOT	Areas of high traffic crashes, research projects, seasonal road closures and traffic management.
Minnesota DOT	When possible, we try to pick areas that are representative of general atmospheric conditions in the surrounding area. MnDOT's RWIS network was carefully selected using input from multiple sources including meteorologists, maintenance supervisors, and through thermal mapping. MnDOT conducted a series of interviews with representatives from all maintenance operations offices within the Department. These in-person meetings allowed the Department to identify those potential locations which are subject to impaired travel conditions such as reduced visibility or hazardous pavement conditions (wet or frozen pavement, frost, blowing snow etc.). In addition, the Regional Weather Information Center (RWIC) of the University of North Dakota, in conjunction with MnDOT, conducted site assessment and evaluation of potential RWIS sites throughout the State of Minnesota. These sites were evaluated as to whether the information from those sites could be used as inputs to mesoscale weather forecasting models or would be used only for detection of localized conditions. Also the sites were evaluated in respect to their

	location to the nearest National Weather Service Automated Weather Observing System (AWOS) site. Consideration was given to obstructions, both natural and man-made, which may affect atmospheric and road sensing capabilities.
Utah DOT	Heavily weighted to weather forecaster needs and shed maintenance supervisor needs. Like to place them near shed maintenance boundaries.
Virginia DOT	ESS Warrent
Ministry of Transportation, B.C.	Locations where winter maintenance is most challenging
MTO	Weather zones
Alberta Transportation	Regional climate and meteorological patterns were analyzed (based on input from meteorologists and regional/local staff) to determine areas which needed more RWIS coverage (more observations to fill in the gaps to improve forecasting capabilities). Also collisions, historical winter road conditions and traffic patterns were analyzed (historical data plus input from local/regional staff) to select the worst road segments which needed accurate RWIS observations from the sensors and cameras - to improve maintenance responses. At the micro scale local staff was very helpful in determining which locations met the FHWA guidelines for selecting the sites (shading, proximity to water and traffic, etc.).
Alaska DOT	travel corridors, maintenance station boundaries, other agency needs, e.g., railroad, FAA
Region of Waterloo, Ontario	Representative conditions ex. One on a bridge, one in snow belt, west side of region etc.
MDOT/ Michigan	change in maintenance areas,
Wisconsin DOT	Improvement project locations

Q16: What other non-weather related factors do you consider when deciding the candidate locations?



	Other (please specify)
Utah DOT	Out of view of private residences, available communication, available solar power (canyons, etc), favor bridges (first to freeze)
Kansas DOT	None of these are strong factors in our siting considerations.
Utah DOT	The greater the distance away from the maintenance shed, the better.
Ohio dot	budget
Iowa DOT	Access to power and communications, distance from maintenance facility

Q17: Do you have any standardized guidelines that help you identify the candidate locations?

Utah DOT	RWIS siting reports/guidelines are performed on most RWIS sites.
Minnesota DOT	See answer to question 13 above. More documentation may be available as well.
Utah DOT	We do in terms of the vicinity considerations. A full siting reports is done within 5 miles of the desired location with power, communication and obstruction considerations.
Virginia DOT	ESS Warrant
MTO	MTO Guidelines/ TAC guidelines
Alberta Transportation	We use North American guidelines and practices from other jurisdictions.

Alaska DOT	The initial sites were installed based on extensive stakeholder interviews. Since then we have done targeted updates with the maintenance and operations staff. These documents are available if you would like.
Region of Waterloo, Ontario	Yes
UDOT	We decide general location using the aforementioned factors, and have a 5-year deployment plan that meets those factors. We also have siting reports that are written up for each siting area that specifies the best exact spot for the site.
Ohio DOT	fhwa
MDOT/ Michigan	FHWA siting guidelines
KDOT	FHWA -HOP-05-026 RWIS ESS Siting Guidelines

Q18: What are the common procedures/practices being undertaken prior to deciding the optimal location of RWIS stations?

Utah DOT	Identify weather patterns and micro climates. Consider shed boundaries. Street lighting for low light cameras. Traffic/crash data. Local bridges.
Minnesota DOT	MnDOT's RWIS network was carefully selected using input from multiple sources including meteorologists, maintenance supervisors, and through thermal mapping. MnDOT conducted a series of interviews with representatives from all maintenance operations offices within the Department. These in-person meetings allowed the Department to identify those potential locations which are subject to impaired travel conditions such as reduced visibility or hazardous pavement conditions (wet or frozen pavement, frost, blowing snow etc.). In addition, the Regional Weather Information Center (RWIC) of the University of North Dakota, in conjunction with MnDOT, conducted site assessment and evaluation of potential RWIS sites throughout the State of Minnesota. These sites were evaluated as to whether the information from those sites could be used as inputs to mesoscale weather forecasting models or would be used only for detection of localized conditions. Also the sites were evaluated in respect to their

	location to the nearest National Weather Service Automated Weather Observing System (AWOS) site. Consideration was given to obstructions, both natural and man-made, which may affect atmospheric and road sensing capabilities.
Kansas DOT	Existing sites only.
PA DOT	Under Development
Illinois DOT	Asking experienced field staff in the area.
NDDOT	We will meet with the district and often times have a field review prior to choosing the final location.
Utah DOT	A full siting report is done within 5 miles of a desired location. Shed supervisors and weather forecasters are surveyed.
Virginia DOT	If it warrants one.
Ohio dot	site surveys
PEI	Discussions with regional staff on locations that would best represent weather patterns for a specific area.
Ministry of Transportation, B.C.	Discussion with maintenance personnel, investigation of accident history, thermal mapping
GNWT DOT	No standard procedures are presently in place for determining general location of RWIS stations.
MTO	Reviewing of existing RWIS stations within Weather Zones and spacing between stations
Alberta Transportation	We conducted an RWIS expansion study which looked at various factors and aspects - as described above.
Alaska DOT	DOT needs Availability of power and comm Repsentativeness of the site (aka RWIS Siting Guidelines) Maintenance
Region of Waterloo, Ontario	Availability of Land, Site conditions that are appropriate, priority of location based on traffic, winter conditions, topography, lack of existing site owned by MTO, etc.
Illinois DOT	Work with experienced district staff, they know where their needs are.
UDOT	Required siting is done at each proposed area. Proposed areas are a combination of maintenance, road project needs, public need, weather forecaster need, etc.
Ohio DOT	traffic volume
NDDOT North Dakota	We work with each district to find out their problem areas as well as looking at the current density and try to obtain a 30 mile radius density.

MDOT/ Michigan	A concept of operations for that area. Stakeholder meetings,
Wisconsin DOT	Determine need in coordination with local maintenance folks. Include in improvement project plans.
Iowa DOT	Our RWIS Committee collects site requests from area supervisor. The requests are analyzed by the committee and a few are selected, per the budget.

Q19: Do you think a computer software tool for locating new RWIS stations would be necessary and useful?

	If yes, please describe
Utah DOT	It would be helpful but it would not dictate where RWIS is located. Often terrain and weather patterns ultimately dictate where RWIS stations are installed.
Minnesota DOT	I believe that a computer software tool could be very useful if it incorporates all the needed factors like how will the site fit in with weather forecasting, etc.
PA DOT	If used in conjunction with local maintenance management input
Ohio dot	possibly. depending on the agency need
MTO	Only if it takes into account new technologies (ie. thermal mapping, Intelldrive, mobile tracking)
Alberta Transportation	It would be beneficial to have Canadian guidelines and perhaps a computer program incorporating every aspects both at the macro and micro levels.
Region of Waterloo, Ontario	If the model took into consideration the types of storms, traffic volumes, other available sites, etc.
MDOT/ Michigan	not sure.... could be just a manual
KDOT	It could provide guidance for installations based on facts not opinions
Wisconsin DOT	It would have to be climate based.
Iowa DOT	not necessary, but maybe helpful

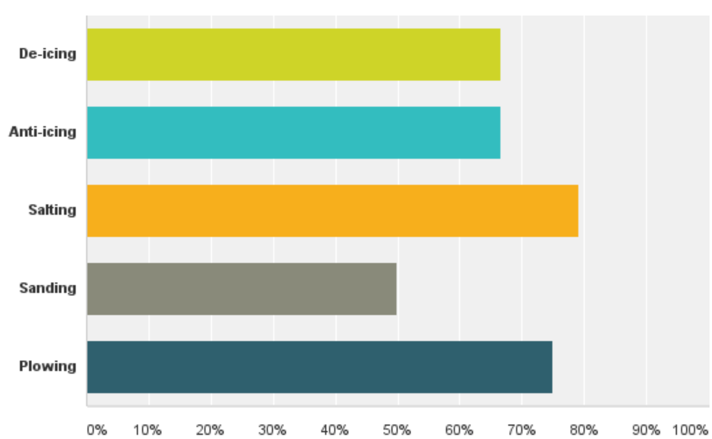
Q20: In general, what are the greatest challenges that you often encounter when locating RWISs?

Utah DOT	Power sources and communications. Cell phone coverage is limited in a rural and mountainous state such as Utah. Balancing operational distance of non-invasive road sensors and clear zone requirements. Occasionally right of way is a concern, especially bordering NFS and BLM lands. Soil conditions.
Minnesota DOT	Funding, access to power and good communication for the data stream.
Kansas DOT	Not a current issue for us.
PA DOT	Suitability of desired location, access to power and communication (wired or wireless)
Illinois DOT	Funding has been our greatest challenge.
NDDOT	Trying to balance the density vs. problem areas. If you focus on problem areas your data becomes skewed to a worse degree.
Utah DOT	Communication. Cell phone coverage can be limited in rural areas. Right of way, especially BLM and NFS land.
Virginia DOT	Cost
Ohio dot	Construction planning
PEI	Finding the balance between regional coverage and ideal locations for capturing all weather patterns.
Ministry of Transportation, B.C.	Communications options for data retrieval in remote locations, availability of AC power (reliance on solar power problematic at many locations)
GNWT DOT	Local and regional representation, winter maintenance operations, budget constraints, and availability of power and communication.
MTO	Power, and ROW limitations
Alberta Transportation	At the macro level - it is a time consuming process to gather and analyze the historical data, also the process requires input from many professionals. Consolidating the data and making decisions without clear guidelines. At the micro level - it would be helpful to have a clear procedure with a clearly described process for the field staff.
Alaska DOT	Power and communication Priority maintenance and O&M
Region of Waterloo, Ontario	Since we only have installed weather stations in rural locations, acquiring land was very time consuming. Picking the preferable site was the next toughest along with determining our needs.

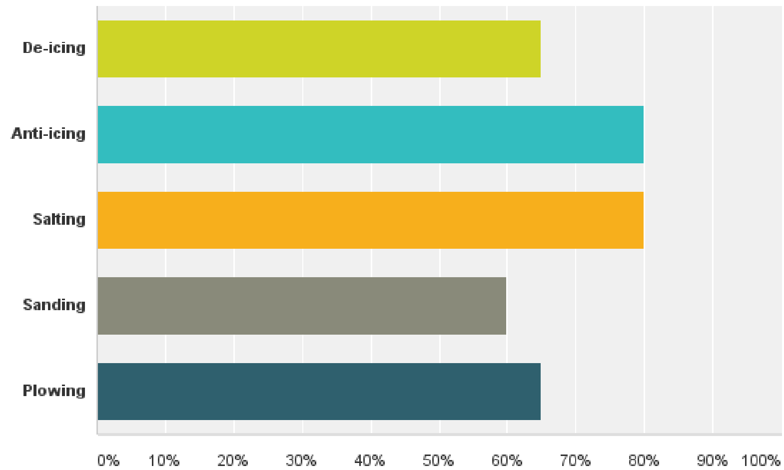
Illinois DOT	Lack of budget
UDOT	Lack of communication to the site. Utah has areas of no cell coverage, and many of these are frequently hazardous weather locations.
Ohio DOT	none
NDDOT North Dakota	Most often we would like to deploy in remote areas that lack power and communications. This creates cost issues.
MDOT/ Michigan	budget - installation and maintenance costs.
Wisconsin DOT	Cost.
Iowa DOT	Weighing all the pros and cons. There never seems to be a perfect site all around.

Q21: What winter maintenance operations do you perform using real-time (e.g., current observation) RWIS data?

	Other (please specify)
Minnesota DOT	Maintenance operational planning and deploying crews.
Kansas DOT	Camera images
Ministry of Transportation, B.C.	Sweeping
Region of Waterloo, Ontario	Occasionally
UDOT	Probably all of these.
Ohhio DOT	storm tracking
MDOT/ Michigan	in general maintenance staff do not access the real time data.



Q22: What winter maintenance operations do you perform using near-future (e.g., forecast) RWIS data?



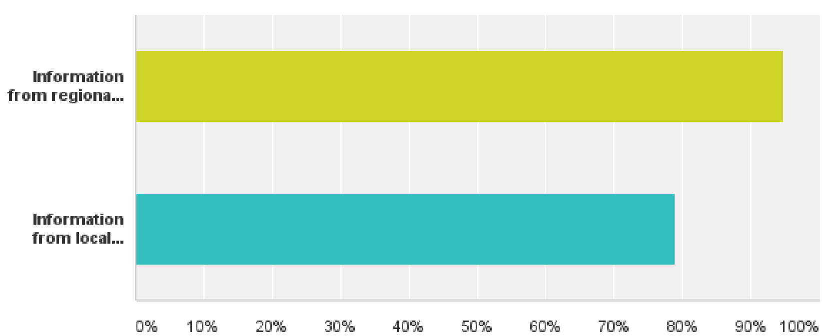
	Other (please specify)
Utah DOT	Weather group provides forecast tools for operational decision makers.
Minnesota DOT	Maintenance operational planning and deploying crews.
Utah DOT	We have no site specific RWIS forecasts rather a detailed forecast for the entire route.
Alaska DOT	seasonal weight restrictions primarily
UDOT	Our maintenance activities use forecasts from human forecasters.
Ohio DOT	storm tracking

Q23: Do you use RWIS (forecast) data for a resource planning and preparation (e.g., staff, equipment, and material)?

	If yes, please describe what RWIS data (e.g., near-future pavement temperature) you use
Utah DOT	Weather Group supports in house weather briefings and conference calls to all decision makers within UDOT.
Minnesota DOT	forecasted wind, pavement temperature, precipitation, air temp, dew point, RH, etc.
Kansas DOT	Standby and crew call out based on pavement forecast data.

NDDOT	The RWIS data is used by Meridian to aid in their forecasting.
Utah DOT	We have no site specific RWIS forecasts rather a detailed forecast for the entire route. The RWIS data helps verify and adjust short term forecasts.
Ohio dot	pavement temperature. sub-surface temperature, precip
PEI	near future pavement temperature, precipitation type, road conditions, wind speed
Ministry of Transportation , B.C.	Hwy Maintenance is privatized - the contractors do this.
GNWT DOT	snowfall amounts, air temperature, pavement temperature
MTO	Its one of the tools that our AMC contractors use.
Alberta Transportation	I am not directly involved in Maintenance. I can provide contact information for your further inquiries.
Alaska DOT	pavement and sub-surface temperatures, camera images
Illinois DOT	pavement temperature forecast
Ohio DOT	pavement temperature
NDDOT North Dakota	RWIS Data is used by MDSS
MDOT/ Michigan	pavement temps and precipitation (ie to prevent an ice bond from forming)
Iowa DOT	pavement temperature, wind, visibility, humidity, precip probability, precip type

Q24: What other sources of information (other than from RWIS) do you incorporate for initiating the winter maintenance operations?



	Other (please specify)
Utah DOT	Weather Group uses all available weather data at their disposal. The Weather Group is under the Traffic Management Division and not under Road Maintenance. Weather Group supports the entire state DOT.
Minnesota DOT	Maintenance Decision Support System (MDSS)
PA DOT	Paid private weather forecast service
Illinois DOT	Forecast from contracted weather service
Utah DOT	We often use NWS locations. We will use local weather data when trusted by the meteorologist in areas of sparse data.
Ohio dot	Private weather consultants
Ministry of Transportation , B.C.	Winter Maintenance Specifications (contract documents)
MTO	Patroller observations
Alberta Transportation	EC, Local weather networks
Alaska DOT	FAA Weather Cameras, other weather cameras, We have a good cooperative relationship with the National Weather Service and the Federal Aviation Administration (FAA has installed two web cameras at RWIS sites and will do another in 2013). We also have cooperative agreements with the National Park Service and River Forecast Center (NWS), and the Depart of Fish and Game. See Alaska Weather Links on our web site.
Region of Waterloo, Ontario	Intellicast and other websites that show large storms (clippers and Colorado lows,etc) forming days away. Presence of salt residual on road.
UDOT	Not sure the distinction here.
Ohio DOT	consultants
MDOT/ Michigan	past experience of weather conditions in that area
Wisconsin DOT	MDSS
Iowa DOT	communications from other maintenance supervisors

Q25: Please feel free to leave any comments or suggestions on the RWIS site selection process.

Minnesota DOT	It is very important to include Meteorologists in the decision to make sure your RWIS system is able to be used to help on a broader scale (weather forecasting models), but also to find out which atmospheric sensors you will actually need since you don't want to double up if there is another weather station close to the area you are considering for an RWIS. You may just need to have pavement information and camera and no or limited atmospherics needed.
Kansas DOT	RWIS and information it provides through our weather service provider are tools used by our Maintenance decision makers.
Illinois DOT	If citing is a concern portable RWIS sites could be used to help with gathering data to make a decision.
Virginia DOT	What you see on the road is a environmental sensor station not an RWIS
Ohio dot	this would be a good tool for developing users
Ministry of Transportation , B.C.	In complex mountainous terrain there is no optimal spacing of stations. Site selections are based on operational needs for data to support local decision making.
Alaska DOT	I invite you to take a look at the information we provide to travelers and the maintenance engineers (for seasonal weight restrictions) on our RWIS public web site at http://roadweather.alaska.gov. The Alaska Weather Links demonstrates the partnerships that DOT has developed. Also note the cooperative observations we provide (Mentasta Pass, Klondike)
Ohio DOT	any rwis activity needs front line user buy in or it is a not worth the effort