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ARTICLE

Strategic Planning for Equitable RWIS Implementation: A Comprehensive Study Incorporating a Multi-variable Semivariogram Model

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ABSTRACT

This paper extends the previously developed method of optimizing Road Weather Information Systems (RWIS) station placement by unveiling a sophisticated multi-variable semivariogram model that concurrently considers multiple vital road weather variables. Previous research primarily centered on single-variable analysis focusing on road surface temperature (RST). The study bridges this oversight by introducing a framework that integrates multiple critical weather variables into the RWIS location allocation framework. This novel approach ensures balanced and equitable RWIS distribution across zones and aligns the network with areas both prone to traffic accidents and areas of high uncertainty. To demonstrate the effectiveness of this refinement, the authors applied the framework to Maine's existing RWIS network, conducted a gap analysis through varying planning scenarios and generated optimal solutions using a heuristic optimization algorithm. The analysis identified areas that would benefit most from additional RWIS stations and guided optimal resource utilization across different road types and priority locations. A sensitivity analysis was also performed to evaluate the effect of different weightings for weather and traffic factors on the selection of optimal locations. The location solutions generated have been adopted by MaineDOT for future implementations, attesting to the model's practicality and signifying an important advancement for more effective management of road weather conditions.

Keywords: RWIS; Location optimization; Multi-variable semivariogram; Heuristics; Spatial simulated annealing (SSA); Collision rate (CR)

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1. Introduction and background

Road Weather Information System (RWIS) is one of the most crucial highway Intelligent Transportation Systems (ITS) for gathering, analyzing, and distributing road weather and surface condition information. The information derived from RWIS plays a vital role in enabling maintenance authorities to make informed operational decisions prior to, during, and after severe weather events to ensure improved traffic safety, mobility, and operational efficiency, particularly in regions facing adverse weather conditions. By offering real-time road weather and condition updates, RWIS data aid the general public in making informed choices regarding their travel routes and modes of transportation [1,2]. Recognizing the numerous benefits associated with RWIS stations, various transportation agencies in the United States, Canada, Europe and Asia, including the Maine Department of Transportation (Maine DOT), have made significant investments in establishing their own RWIS networks [3,4]. These networks aim to comprehensively cover their highway infrastructure and enhance their existing monitoring capabilities. Nevertheless, there are several drawbacks associated with RWIS. Apart from the significant expenses incurred during installation (US $100K per station) and maintenance (approximately US $10K yearly), RWIS systems only offer point measurements, necessitating additional processing to accurately depict the diverse and expansive road network conditions in Maine [5,6]. Consequently, to optimize the effectiveness of RWIS, it is imperative to strategically and systematically install new RWIS stations, ensuring their synchronization with the existing ones.

In the past few years, a number of studies have attempted to establish a systematic methodological framework for RWIS network planning. In 2005, the U.S. Federal Highway Administration (FHWA) made significant efforts by conducting interviews with multiple states' Department of Transportation (DOTs). The study's findings, which relied heavily on personal insights and expertise from field operators, indicated a recommended spacing of 30 to 50 km (20 to 30 miles) between RWIS stations [6]. Due to the fact that this recommendation was derived from subjective experiences, numerous researchers have sought to establish a more objective approach for quantifying the spatial coverage and determining the optimal placement of RWIS stations [7-12]. Kwon and Fu (2013) conducted a study using a Geographic Information System (GIS) to introduce a framework for evaluating the location of RWIS networks. Their approach incorporated various factors such as surface temperature variability (VST), mean surface temperature (MST), snow water equivalent (SWE), and topographical location attributes. The study's findings demonstrated the potential for developing a systematic methodology for RWIS installation by integrating multiple variables into the location allocation model [13]. Zhao et al. employed a methodology centered around cost-benefit analysis to identify the most advantageous sites for RWIS placement. Their objective was to achieve maximum spatial coverage while considering the variability of weather severity [11]. Jin et al. took a similar approach to maximize spatial coverage, but instead of a cost-benefit analysis, the optimization process involved using a metric called "safety concern index" derived from weather-related crash data [7]. Spatial analysis within GIS platform was also incorporated in several different fields of study, for example, Valjarević et al. (2021) examined the Morava city conurbation in Serbia, utilizing Kriging-based spatial analysis with a particular focus on the interaction between rural and urban areas, traffic connectivity, geographical positioning, and sustainability and profitability [14]. Moreover, Timalsina and Subedi explored the growing significance of open spaces in urban development planning in Nepal. This paper examines the evolution of open space integration in recent urban planning practices in Nepal, highlighting the growing emphasis on sectoral integration with open space development, particularly within Periodic Planning, Integrated Urban Development Planning (IUDP), and Smart City Planning, aiming to create resilient and sustainable cities [15]. However, in a recent study, RWIS network optimization was conducted using kriging-based method, aimed at enhancing monitoring capabilities and minimizing the average kriging variance of hazardous road surface conditions. This study was formulated as a Nonlinear Integer Programming (NIP) problem and showcased its applicability through a case study in the state of Minnesota, U.S. [16].

Although the previously mentioned studies have made valuable contributions to the development of RWIS location models, they focused solely on investigating the spatial characteristics of a single variable, specifically road surface temperature (RST). While RST is undoubtedly an essential measurement, it is important to consider many other weather variables measured by RWIS in the location optimization process.

The primary motivation of this research is to break new ground by concurrently incorporating the spatial characteristics of multiple weather variables. For the first time ever, we are developing an innovative multi-variable semivariogram model that specifically considers critical weather variables, including air temperature (AT), road surface temperature (RST), and dew point temperature (DPT). This novel approach is directed at optimizing RWIS placement by ensuring effective monitoring coverage of the region. Additionally, our method takes into account areas prone to traffic accidents for improved safety, and demonstrates the superiority of the proposed method in ensuring an equitable distribution across different maintenance zones.

In addition to the primary objective, this research encompasses two specific sub-objectives, which are outlined below:

- *Implementation of the developed model for the planning of the regional RWIS network:*
  The RWIS planning tool we developed will be utilized for the region-wide prioritization of potential RWIS sites. Furthermore, we will conduct a comprehensive statewide gap analysis to validate prioritized and potential sites by identifying all new optimal locations.
- *Conducting sensitivity analysis to offer flexibility to decision-makers:*
  Sensitivity analyses will be conducted to explore the effect different weight schemes have on the optimal location. These analyses will provide valuable insights into how variations in weather and traffic factors can influence the selection of additional RWIS locations. The analysis results will provide the flexibility to choose parameter weights based on the decision-maker's needs, considering both weather variables and safety implications related to traffic.

Overall, our proposed multi-variable semivariogram model represents a pioneering step in RWIS location determination. By concurrently considering multiple weather factors and addressing traffic safety in accident-prone areas, we enable planners to tailor the RWIS network to specific needs. This innovation is therefore expected to enhance monitoring capabilities and more effective winter road maintenance decisions.

2. Methodology

2.1 Overview of research procedures

The first phase of this project is data collection, where information about the study area, stationary RWIS data, and traffic data are gathered. In the second step, the collected data is processed by removing missing and erroneous data as per our predefined guidelines [18]. Next, the processed data is merged into a GIS-based platform for further analysis. Moving on to stage three, a highly effective spatial sampling technique called geostatistical analysis is utilized to determine the spatial autocorrelation of the RWIS variables. This technique is designed to enhance the likelihood of capturing spatial variations while minimizing potential biases in the input data. Specifically, semivariogram analysis is conducted here to generate semivariogram clouds for the selected RWIS variables, which are then combined to generate a multi-variable semivariogram model. This multi-variable semivariogram model is then applied in the final stage to optimize the placement of RWIS locations by refining our previously developed location optimization framework. The overall research procedures for this study are summarized in **Figure 1**.

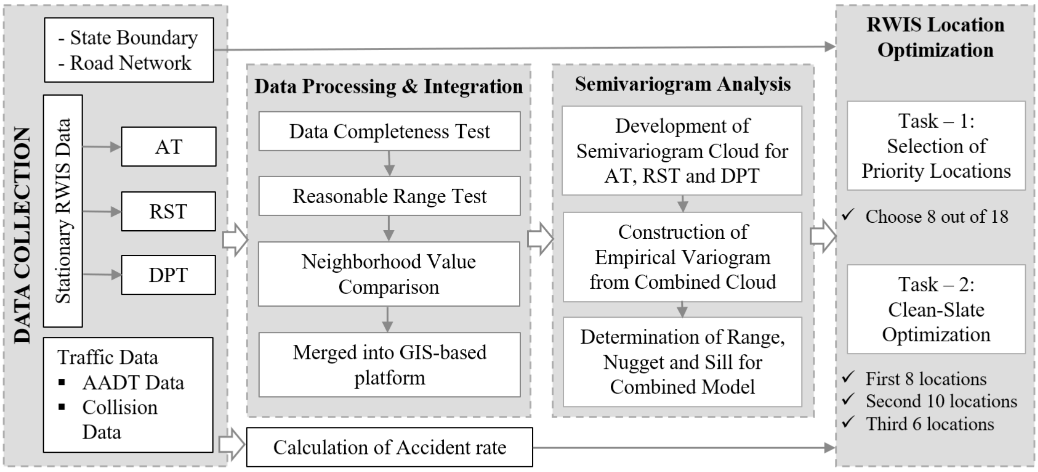

Figure 1. An overview of the research procedure.

2.2 Data collection, processing and integration

As depicted in **Figure 1**, the initial step of our framework involves the collection of the following seven variables: state boundary and road network information, stationary RWIS data (AT, RST, and DPT), and traffic data (AADT and collision). The RWIS measurements obtained from the database undergo several checks to ensure data quality [18]. The processed datasets are then consolidated into a unified GIS database to facilitate spatial analysis.

2.3 Geostatistical semivariogram modeling

In our previous work, we developed a systematic approach for RWIS network planning that utilizes kriging-based optimization to determine the optimal locations for RWIS stations. A key aspect of this framework is the integration of RWIS information for spatial inference [18,19]. To incorporate spatial inference, the geostatistical modeling approach known as semivariogram analysis is utilized to quantify the spatial autocorrelation of RWIS measurements.

A semivariogram is a graphical representation of spatial autocorrelation using a metric called semivariance. Semivariance is a statistical measure that assesses the similarity between two measurements based on their spatial separation distance [20]. It is computed by averaging the squared differences between measurements separated by a designated lag distance. A larger autocorrelation range indicates a higher level of spatial continuity in RWIS measurements, while a smaller range suggests lower continuity. Equation (1) represents the most commonly used method for estimating semivariance:

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(x_i + h) - z(x_i)]^2 \tag{1}$$

In this equation, $\gamma(h)$ represents the semivariance. It is calculated by comparing two measurements, $z(x_i + h)$ and $z(x_i)$, taken at locations x_i and $(x_i + h)$ respectively, with a separation distance of h.

In this research, semivariogram modeling is incorporated to quantify the spatial structure of critical road weather and surface conditions variables. Numerous GIS software packages and programming languages are available for semivariogram modeling, such as ArcGIS, QGIS, R, Python etc. In this research, separate semivariogram clouds are developed primarily for each selected weather variable (i.e., AT, RST, and DPT) and subsequently combined to form a comprehensive semivariogram cloud. By binning the cloud points together, a multi-variable semivariogram model is constructed to capture the spatial autocorrelation of all crucial weather variables. The parameters obtained from the multi-variable semivariogram model serve as critical inputs for optimizing the location of RWIS stations, ensuring that the additional RWIS stations are strategically positioned based on the spatial autocorrelation of the key weather variables.

2.4 RWIS network optimization

In continuation of the geostatistical semivariogram modeling conducted in the previous step, this stage builds upon the previously developed RWIS location allocation framework by incorporating a multi-variable semivariogram model in the location optimization process. The objective is to determine optimal locations for RWIS stations while minimizing spatial inference errors or maximizing spatial coverage across the road network, as demonstrated in previous studies [16-18]. The spatial inference errors are indicative of the requirements for installing RWIS stations to enhance monitoring capabilities and improve the efficiency of winter road maintenance operations. By refining the location allocation model, this study takes into account the spatial impact of multiple road weather variables.

The optimization method employed in this study is Spatial Simulated Annealing (SSA), a popular heuristic algorithm widely recognized for its effectiveness in solving spatial optimization problems [17]. SSA has been extensively used and has a reputation for generating more reliable location solutions [21-24].

In addition to considering various weather variables, the modified network optimization model also incorporates traffic demand distribution by considering the collision and AADT data. The accident rate is calculated using Equation (2) as follows [25].

$$\text{Crash rate, CR} = (\text{number of accident} * 1000000) / (\text{AADT} * 365) \quad (2)$$

In this context, the term "number of accidents" represents the total count of accidents observed during the study period. AADT, on the other hand, represents the average daily traffic volume for a specific road or road section. It serves as a measure of the number of vehicles passing through that area on a daily basis. Consequently, the resulting value of CR obtained from Equation (2) provides an estimate of the frequency of accidents. It indicates the number of accidents that occur per million entering vehicles.

The methodology described above is exemplified through its application in the state of Maine, providing detailed information in the subsequent section.

3. Model Application—Maine, United States

3.1 Study area and RWIS network

This research is primarily based on the expansion plan of the Maine DOT for their RWIS network. Currently, the number of existing stations in Maine (ME) is limited, resulting in insufficient coverage of the road network. To address this, authorities intend to gradually expand the RWIS network by installing a yearly average of 8-10 additional stations, considering budgetary limitations. Given the high costs associated with installation and maintenance, it becomes crucial to determine the precise locations for the placement of these new RWIS stations; so that the additional stations will work collaboratively with existing stations to maximize the value of RWIS information. The outcomes of this research will provide RWIS planners with optimal location solutions for expanding the network, ultimately enhancing the overall monitoring coverage to the best extent possible. Located in the northeastern region of the United States, Maine is positioned as the easternmost state, sharing its border with Canada. Maine exhibits diverse geographical features, encompassing distinctive regions such as uplands, coastal lowlands, mountains, and piedmont areas. Severe winter conditions, including heavy snowfall and freezing temperatures, result in the formation of slippery road surfaces and reduced visibility, consequently rendering winter driving a demanding and challenging task [26,27].

There are, 10 RWIS stations in Maine, with the majority of them strategically positioned along the interstate highway. Due to the limited number of existing stations, RWIS data from a neighboring state, NH (New Hampshire), is also utilized in this analysis. Additionally, ASOS (Automated Surface Observing System) data from both states are also included after conducting data representativeness tests. In the process of assessing the representativeness of NH data for the state of ME, an analysis was conducted on the variation patterns of selected weather variables in both states. According to the assessment, it can be inferred that NH's RWIS and ASOS data are reliable for representing Maine's weather.

The study period selected for this analysis includes three consecutive winter seasons between 2019 and 2022. Within these three years, RWIS and ASOS data collected over a span of five winter months (November to March) are utilized in this analysis. The distribution of RWIS and ASOS stations for the study area is presented in **Figure 2**.

3.2 Data description

This study utilized a comprehensive dataset obtained from the Maine DOT and supplemented with data from adjacent NH to compensate for Maine's lack of RWIS data. The dataset includes state boundary information, road network data, stationary RWIS data, and traffic data. Furthermore, the study incorporated information regarding candidate RWIS sites, which serve as potential locations for future installations of RWIS stations.

RWIS Data

Stationary RWIS data for Maine was collected from Maine DOT (https://www.maine.gov/mdot/). RWIS data for NH and ASOS data for Maine and NH were downloaded from Iowa State University (http://mesonet.agron.iastate.edu/RWIS/) and WxDE website (Weather Data Environment: https://wxde.fhwa.dot.gov/). State-wide RWIS data in the form of Excel files were downloaded, containing measurements from multiple parameters including air and surface temperature, visibility, wind speed, and road surface conditions. Likewise, ASOS data encompasses similar weather variables, excluding RST. These measurements are collected at intervals of approximately 15 to 20 minutes. In total, 25 RWIS stations from NH, 10 RWIS stations from Maine, 33 ASOS stations in NH, and 18 ASOS stations in Maine were included in the analysis. A total of 10,800 hours of data was incorporated into the analysis.

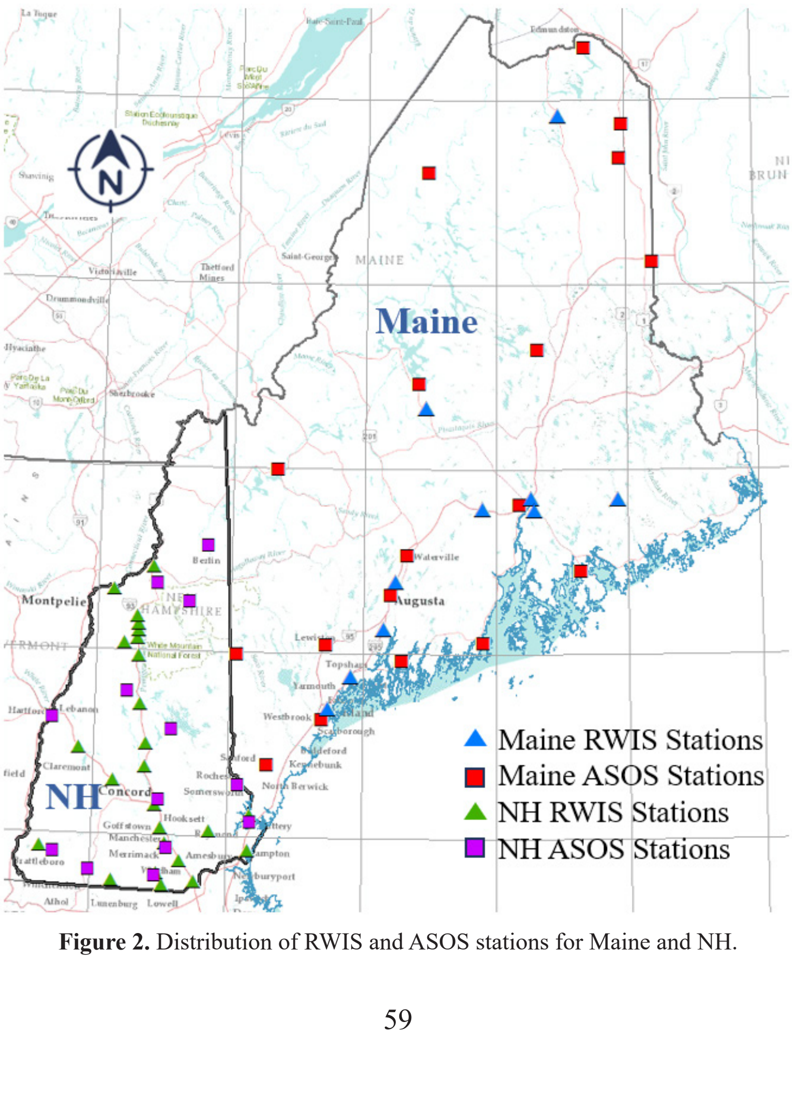

Figure 2. Distribution of RWIS and ASOS stations for Maine and NH.

The weather data underwent a predefined processing procedure to eliminate missing and erroneous data. These steps included a data completeness test, a reasonable range test, cross-checking RST data with AT and DPT data, and analyzing the pattern of weather data [18]. Using this procedure, a total of 60 sets of data were analyzed.

The descriptive statistics of the processed data are summarized in **Table 1**, providing insights into the minimum, average, maximum, and standard deviation values for the data collected from weather stations. Upon closer examination of **Table 1**, it can be observed that the AT exhibits a range of –34.0 ºC to 26.3 ºC throughout the study period, with an average value ranging from –1.2 ºC to –2.3 ºC. The RST varies between –25.9 ºC and 32.1 ºC, with an average value of 0.12 ºC. Furthermore, the DPT ranges from –41.9 ºC to 21.8 ºC, with average values of –6.0 ºC to –6.48 ºC. It is noteworthy that the standard deviation is slightly higher for DPT compared to AT and RST. These statistics provide a comprehensive overview of the temperature variations across the study period and highlight the relative variability among the different variables.

Traffic data

To calculate the accident/crash rate, AADT and collision data were collected for the same 5-year period as RWIS and ASOS data. Then, for the purpose of evaluating collisions during the winter season, only collisions occurring between November and March were considered. Furthermore, to identify collisions caused by adverse weather conditions, several factors were taken into account. These factors included: (i) the contributing factor of the accident, such as road surface conditions like wet, icy, snowy, slushy, etc., (ii) the surface condition during the accident, encompassing ice/frost, snow, slush, mud, dirt, and gravel, and (iii) the type of roadway, focusing on non-intersection collisions. By considering these factors, the study aimed to determine the collision rate (CR) associated with adverse weather conditions.

To create the CR distribution map, the study employed Equation (2) to calculate CR values for square polygons of different sizes generated from Maine's road network data. Smaller polygon sizes resulted in a significant number of polygons with zero CR values, leading to a random CR distribution map that made hotspot identification challenging. After an extensive search process to select the optimal polygon size, the CR map generated with 20 km by 20 km polygons was selected as the most suitable, providing a comprehensive representation of CR and better visualization of high-crash areas. The CR distribution map for Maine with 20 by 20 km square polygons is depicted in **Figure 3**.

3.3 Development of multi-variable semivariogram model

To assess the spatial structure of key road weather and surface condition variables, semivariogram modeling was integrated into this study. The gstat package in R [28,29] was utilized for this purpose. Initially, semivariogram clouds were generated for each weather variable, enabling an examination of the spatial autocorrelation among the recorded sample points. Each point within the cloud represents the variance between a pair of measurements [30,31]. Subsequently, the semivariogram clouds for the weather variables were combined to form a unified semivariogram cloud. By binning the cloud points together, an empirical semivariogram model was constructed that incorporated the spatial autocorrelation of all

Table 1. Descriptive statistics of weather station data for Maine and NH.

Station	**Maine ASOS**		**NH RWIS**			**NH ASOS**	
Weather variable	AT	DPT	AT	RST	DPT	AT	DPT
Minimum temperature	–30.61	–41.89	–29.50	–25.90	–33.00	–34.00	–40.00
Average temperature	–2.32	–6.46	–1.18	0.12	–6.48	–1.22	–5.97
Maximum temperature	24.39	19.00	26.30	32.10	21.80	25.00	21.00
Standard deviation	7.04	7.77	6.82	6.87	7.58	7.10	7.72

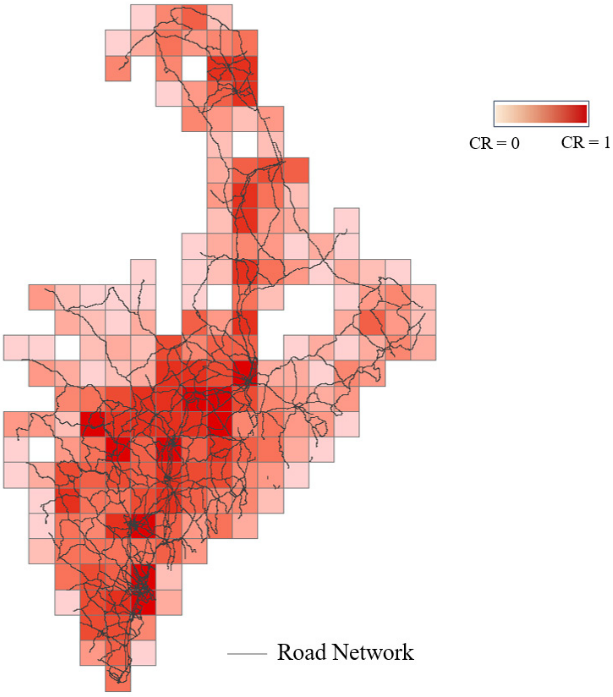

Figure 3. Crash rate (CR) distribution map for the State of Maine.

essential weather variables. **Figure 4** represents the multi-variable semivariogram model developed in this research. Here, the spatial range of autocorrelation was determined to be 145 kilometers, with a sill value of 3.55 and a nugget value of 0.01.

The use of a multi-variable semivariogram model was expected to yield a more accurate location solution by capturing the variability of multiple weather variables. To evaluate the validity of this hypothesis, single-variable semivariogram models were also employed in the location-allocation algorithm to compare against multi-variable-based solutions. This study utilized R statistical packages to generate separate semivariogram models for AT, RST, and DPT. These models were subsequently employed to determine location solutions for the state of Maine.

Recall that the location optimization process leverages the SSA (Spatial Simulated Annealing) algorithm. The primary objective was to maximize spatial coverage by minimizing estimation variance, represented by a value referred to as 'criterion'. The optimization process involves selecting locations that minimize the 'criterion' value. The resultant solution with the lowest 'criterion' value indicates maximized monitoring coverage. To demonstrate the superiority of the multi-variable model compared to single-variable models, optimization outputs from both approaches were compared.

Figure 5 illustrates the location solutions for eight stations (selected based on planning approaches) and optimization schedules for the three single and multi-variable cases. The optimization schedule displayed the 'criterion' value progression, indicating that the multi-variable model has a notably lower 'criterion' value compared to the single-variable models. This suggests that the multi-variable model offers enhanced monitoring coverage. The parame-

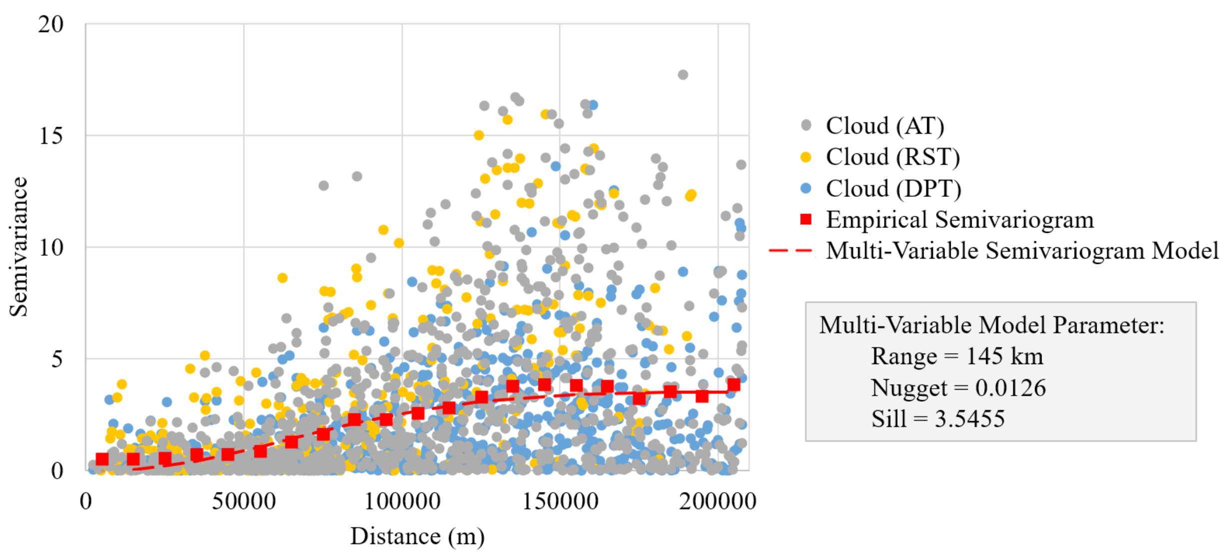

Figure 4. Multi-variable semivariogram model with model parameters.

ters of the multi-variable semivariogram model were then used as inputs in the location optimization process.

3.4 RWIS network expansion

Using the multi-variable semivariogram model developed in the previous step, the study proceeds to assess the effects of spatial demarcation on RWIS planning by constructing various design scenarios. In previous studies, we developed an innovative RWIS location modeling framework where the problem was formulated as an integer programming problem. The objective was to minimize spatial inference error, in other words, maximize spatial coverage across the road network. These spatial inference errors capture the necessity of installing RWIS stations to enhance monitoring capabilities, ultimately improving the effectiveness of winter road maintenance operations [16,18]. In this study, we refined the previously developed location optimization model by incorporating the influence of multiple critical weather variables as well as the distribution of traffic demand.

This study focused on two specific tasks for expanding the RWIS network. A detailed description of the specific tasks is given below.

Task 1: Selection of priority locations out of predetermined sites

A total of 18 potential RWIS locations in Maine have been identified by Maine's regional officers. Our first task was to select 8 priority locations from this pool of predetermined sites. The intent of this analysis was to prioritize RWIS locations based on the constraint that a limited number of RWIS installations can be installed per year. **Figure 6** illustrates the predetermined and existing RWIS stations. The state is divided into five maintenance zones by grey lines. According to **Figure 6**, there are two potential locations identified in zone-1 and zone-2, three locations in zone-3, four locations in zone-4, and seven locations in zone-5.

Both weather and traffic factors were considered to identify priority locations. The aim was to serve a wide range of road users while also effectively capturing weather variability. The weather criteria were incorporated by utilizing multi-variable semivariogram parameters, while the traffic parameters were considered by incorporating CR. In the optimization algorithm, equal weightage was assigned to both weather and traffic factors. This approach aimed to maximize the overall benefit by considering both weather conditions and traffic demands. This result-

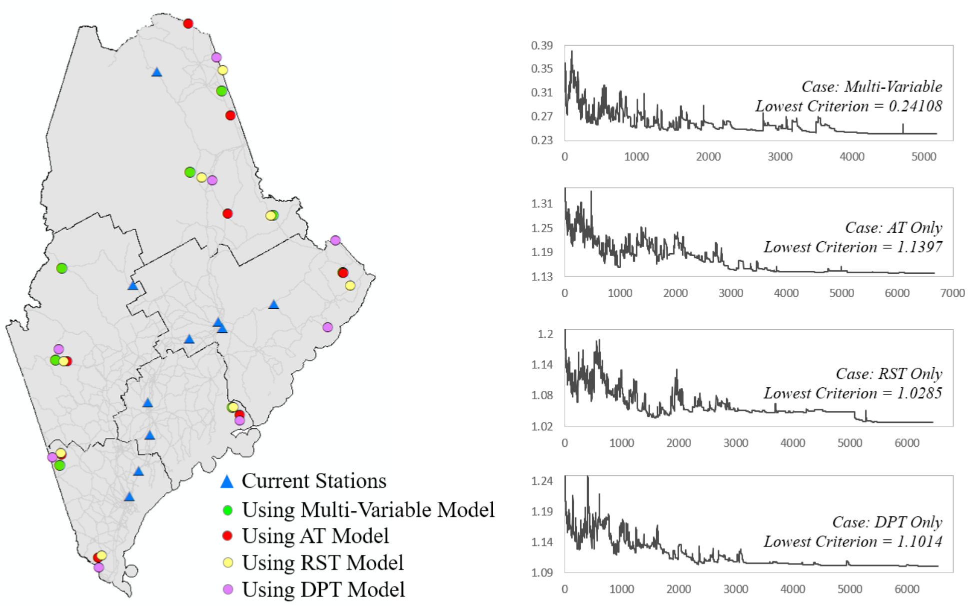

Figure 5. Comparison of single-variable and multi-variable models for network optimization.

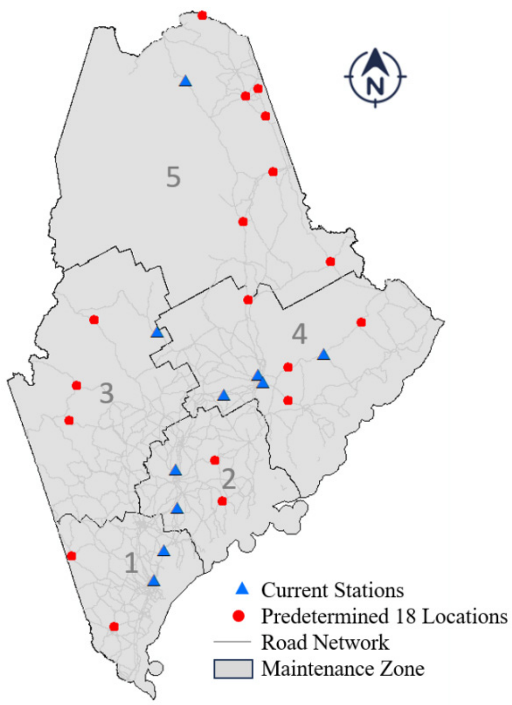

Figure 6. Distribution of current and predetermined locations.

ed in the generation of priority locations, represented by green circles in **Figure 7**.

Figure 7 presents the eight priority locations for RWIS installation, including maintenance zone, estimation error (EE) map, and CR distribution map. The priority locations are evenly distributed throughout the network. The EE map shows varying shades of red, indicating estimation error values computed using ordinary kriging. The kriging interpolation technique utilizes semivariogram parameters to estimate values at unsampled locations, while also providing an assessment of the uncertainty in the estimation, also known as estimation error. The presence of an RWIS station at a particular location results in a lower EE value. As the distance from the station increases, the estimation for unknown locations becomes associated with higher error. This indicates a greater requirement to install a new RWIS station in those areas to bridge the spatial gap and reduce estimation uncertainty. In the optimization process, additional RWIS stations are strategically positioned to minimize EE values and improve network effectiveness. The CR distribution map displays lower CR values in light-colored squares and higher CR values in dark-red squares. The new station locations strike a balance between weather variability and accident-prone areas, with strategic placement near high-traffic and hotspot locations.

Task 2: Clean-slate optimization

At this step, the candidate locations from Task 1 were expanded to encompass all non-interstate corridors in Maine. This extended study corridor includes interstate, freeway, expressway, major collector, principal arterial, and minor arterial roads. The purpose of this analysis was to objectively assess how to best utilize available resources by addressing gaps in

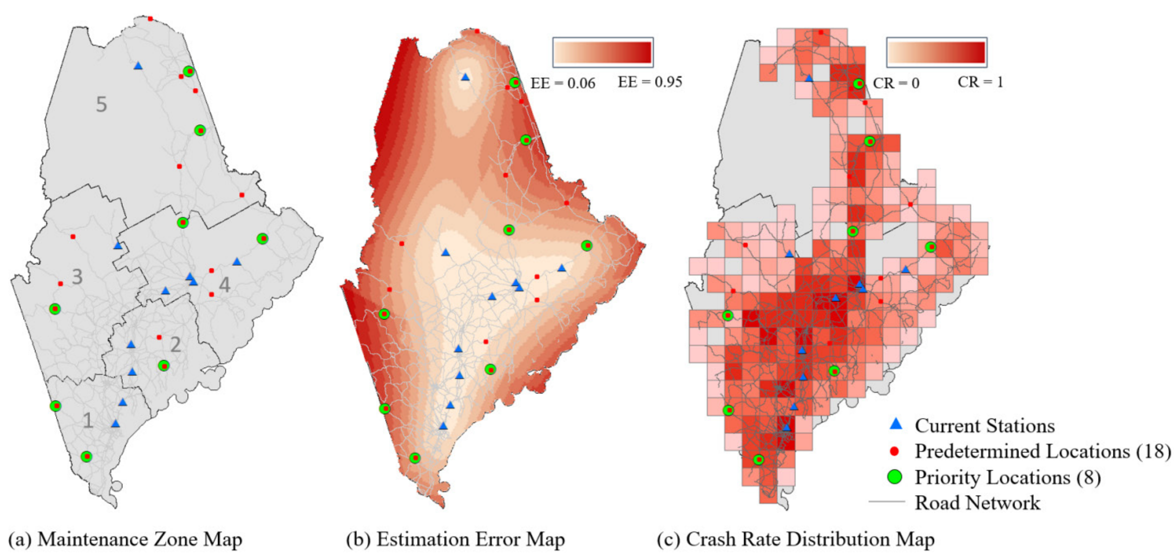

Figure 7. Visualization of priority locations.

the statewide data collection and road weather forecasting network. A constrained optimization process was conducted to determine the optimal locations for RWIS placement, referred to as clean-slate optimization. Three different scenarios were considered during the clean-slate optimization process.

i. Generate the first 8 optimal locations
   Here, 8 optimal locations were generated through clean-slate optimization to compare with 8 priority locations that were identified in Task 1.
ii. Generate the second 10 optimal locations
   To match the 18 predetermined candidate sites, 18 optimal locations were generated, including 10 new sites and 8 initial locations. The aim of this step was to create a direct alignment between the optimal locations and the predetermined candidate sites, ensuring a clear correspondence between the two sets.
iii. Generate the third 6 optimal locations
   The RWIS network expansion plan of Maine DOT aims to install 8 new stations annually for three consecutive years. By the end of this expansion plan, a total of 24 stations will be installed. In this step, an additional 6 optimal stations were generated to reach a total of 24 additional sites (8 + 10 + 6). The outcomes of this step will provide the RWIS planners with a complete set of optimal locations for extending their network.

During the process of determining optimal locations for the three mentioned scenarios, a series of sensitivity analyses were carried out to assess the impact of various weight distributions in kriging-based RWIS location optimization. This step yielded multiple location solutions depending on the weight assigned to weather (W) and traffic (T) factors. These location solutions offer flexibility to network planners and decision-makers, allowing them to choose installation sites based on their specific requirements. For each scenario, a total of 7 sets of weight distributions were considered as follows: Set-1: 0%W, 100%T; Set-2: 20%W, 80%T; Set-3: 40%W, 60%T; Set-4: 50%W, 50%T; Set-5: 60%W, 40%T; Set-6: 80%W, 20%T; and Set-7: 100%W, 0%T.

To generate each set of solutions for each scenario, on average three to five trials were conducted to find a conclusive outcome. In total, clean-slate optimizations were performed over one hundred times. To enhance computational efficiency, a portion of the optimizations in this study were executed using the advanced research computing system called the 'Digital Research Alliance of Canada' (https://alliancecan.ca/en) from the University of Alberta. This system utilized GPUs from the supercomputers "Cedar" and "Graham", each equipped with 12 to 32 GB HBM2 memory. The subsequent sections present comprehensive explanations of various clean-slate optimization scenarios and their outcomes.

Scenario i: Generate first 8 optimal locations

In order to determine the first eight optimal locations, multiple solutions were generated for seven sets of weight distributions, as mentioned earlier. For the sake of simplicity, we will focus on discussing the three most significant cases: (a) traffic only, (b) equal weightage for weather and traffic, and (c) weather only, as presented in **Figure 8**. For set-1, the selection of locations was based on the ranking of CR values. **Figure 8(a)** illustrates the distribution map of CR, highlighting eight square polygons with higher CR values. It is evident that most of these locations are in close proximity to the interstate and downtown area. **Figure 8(c)** displays the optimal locations along with the EE map (set-7). In this case, the objective was to fill the spatial gap in order to effectively capture weather phenomena. The resultant solution exhibits a uniform distribution of locations, effectively capturing the weather patterns. Lastly, for set-4, optimal locations were determined by considering dual criteria, as depicted in **Figure 8(b)**. Here, the selected locations aimed to strike a balance between capturing weather variability and addressing accident-prone areas. Consequently, we observe some stations located in proximity to hotspot areas, while the overall distribution also captures weather variability by placing stations in areas with higher EE (or areas with high uncertainty).

A comprehensive sensitivity analysis was conducted to assess the sensitivity associated with the optimal locations generated for the seven sets of weight distributions. This analysis aimed to capture how the optimal locations are influenced by different weightage assigned to the weather and traffic factors. To conduct the sensitivity analysis, the EE and CR values for all seven sets of solutions were extracted from the EE map and CR map, respectively, using ArcGIS. **Figure 9** displays the results of the sensitivity analysis. The analysis reveals that higher percentages of the weather factor prioritize locations with higher EE values, while higher percentages of the traffic factor prioritize accident-prone locations with higher CR values. These findings validate the effectiveness of the optimization process and offer insights into the influence of factor weightage on location selection.

Scenario ii: Generate the second 10 optimal locations

In the case of determining the second set of ten optimal locations, the initial eight optimal locations for the dual criteria were treated as existing stations, along with the current RWIS stations. Similar to scenario-i, solutions were generated for seven sets of weight distributions, and the three most significant cases are presented in **Figure 10**. **Figure 10(a)** highlights the top ten square polygons with higher CR values, while the weather-only criterion strategically places RWIS stations in locations with higher EE values to accurately capture weather phenomena. In

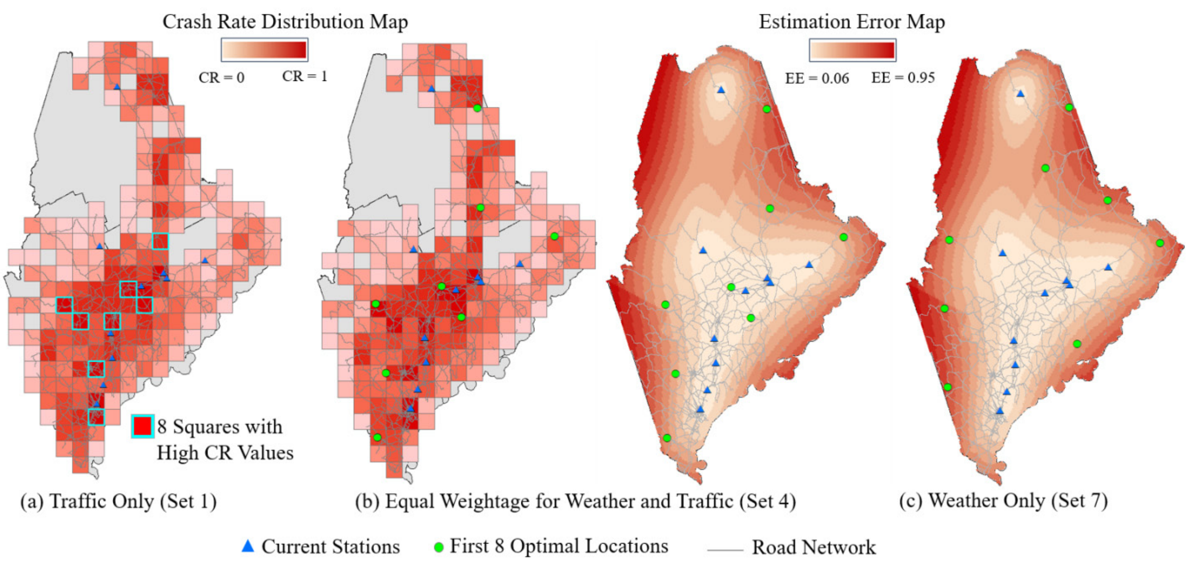

Figure 8. Distribution of first 8 optimal locations for (a) traffic only criterion, (b) dual criteria, and (c) weather only criterion.

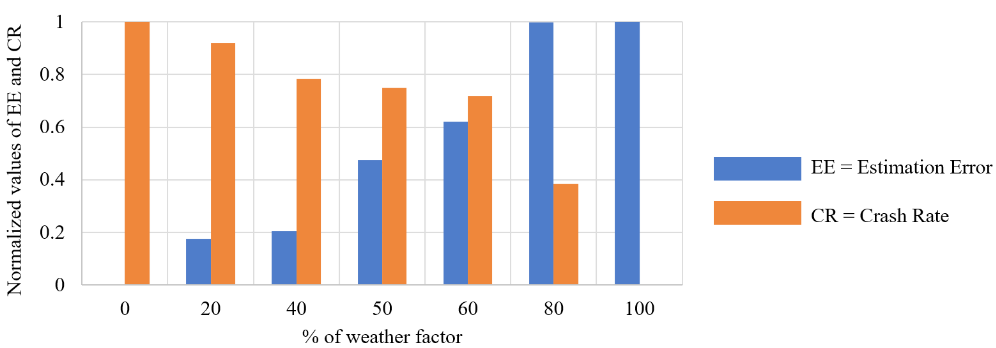

Figure 9. Sensitivity analysis result for first 8 locations: Normalized EE and CR values for 7 sets of optimal location.

the case of the dual scenario, the location solution achieves a balance between capturing weather variability and addressing hotspot areas.

Figure 11 presents the sensitivity analysis results for Scenario-ii, showing near identical pattern to the previous case, demonstrating the clear influence of factor weightage on optimal location selection.

Scenario iii: Generate the third 6 optimal locations

To determine the third set of optimal locations, the first eight and second ten optimal locations for the dual criteria were considered as existing stations, along with the current RWIS stations. Following the methodology employed in previous scenarios, solutions were generated for seven sets of weight distributions. The findings of the three most significant cases are presented in **Figure 12**. Here, in **Figure 12(a)**, the top six square polygons with higher CR values are emphasized, and the weather-only criterion strategically positions RWIS stations in locations with higher EE values to increase interpolation accuracy. The location solution in the dual scenario strikes a balance by effectively capturing weather variability while also addressing accident-prone areas.

Figure 13 displays the sensitivity analysis results for Scenario-iii, which is the same as the two previous cases. This highlights the significant dependency of the optimal locations on the weightage assigned to the weather and traffic factors.

Overall, the sensitivity analysis provides valuable insights into the impact of varying weightage on the selection of optimal locations. These findings under-

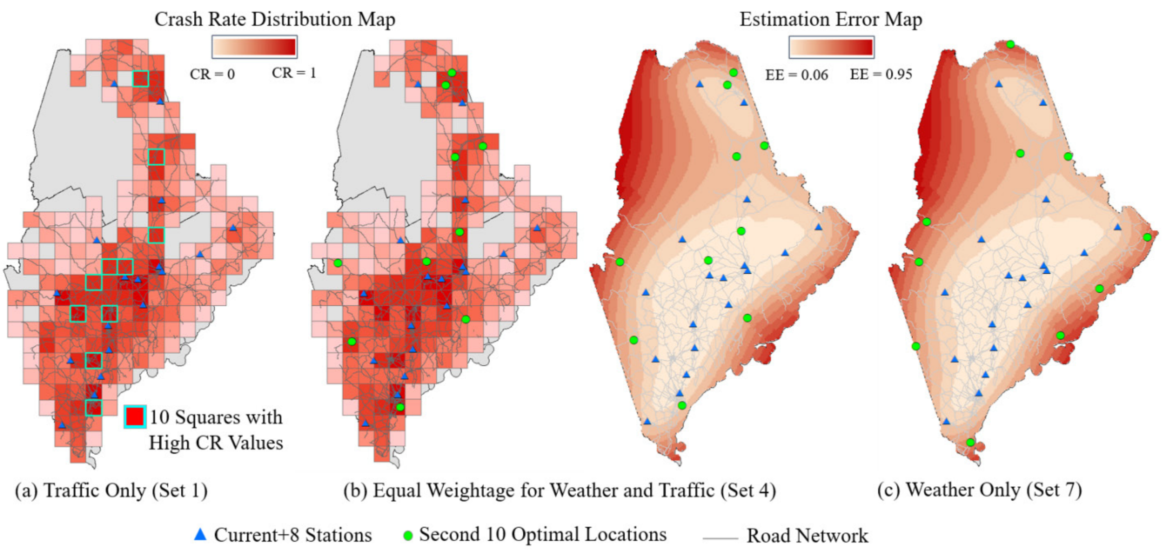

Figure 10. Distribution of the second 10 optimal locations for (a) traffic only criterion, (b) dual criteria, and (c) weather only criterion.

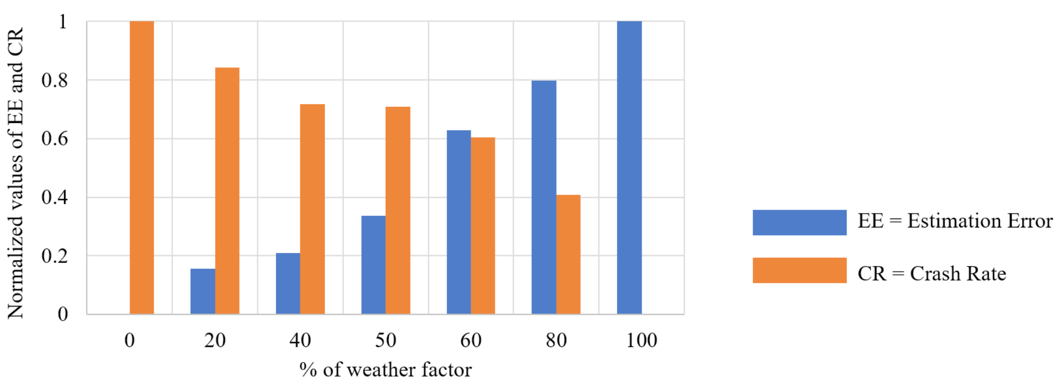

Figure 11. Sensitivity analysis result for the second 10 locations: Normalized EE and CR values for 7 sets of optimal locations.

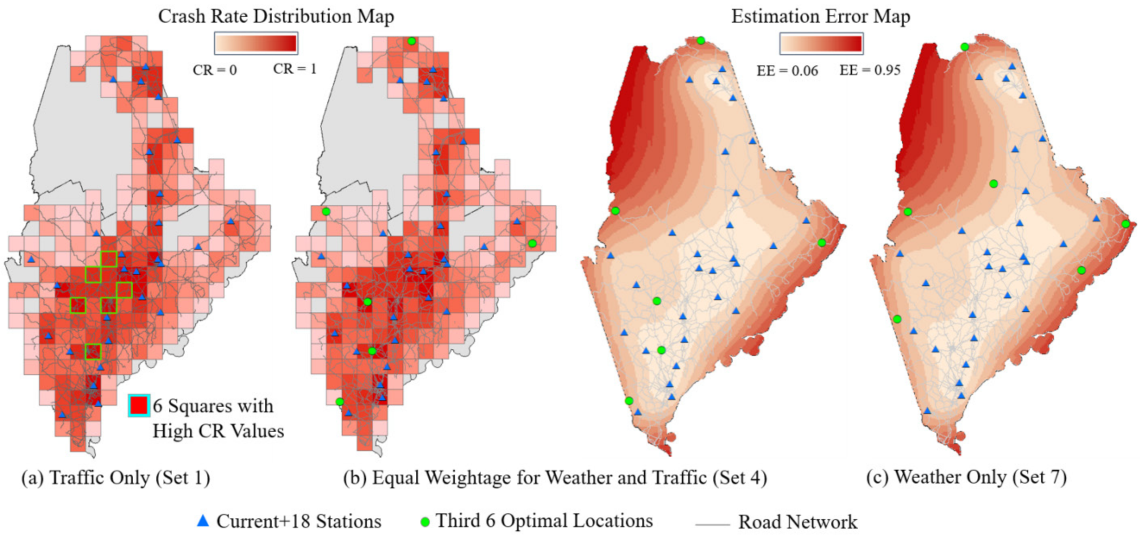

Figure 12. Distribution of the third 6 optimal locations for (a) traffic-only criterion, (b) dual criteria, and (c) weather-only criterion.

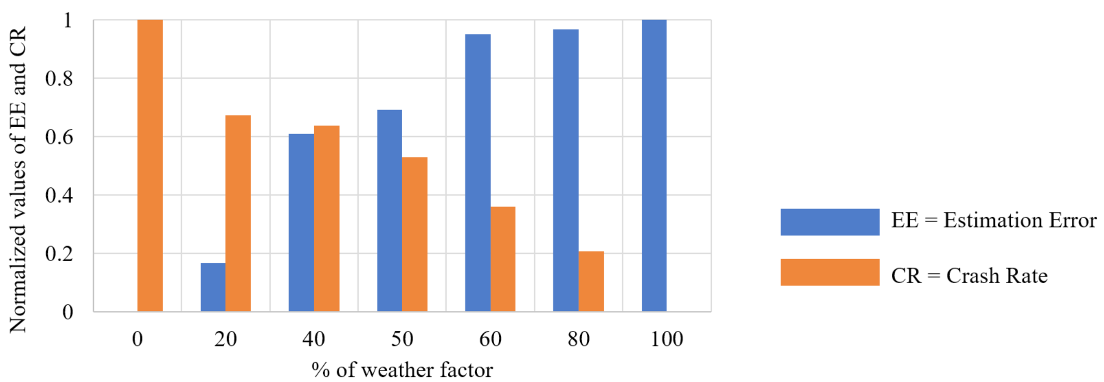

Figure 13. Sensitivity analysis result for third 6 locations: Normalized EE and CR values for 7 sets of optimal location.

score the importance of carefully considering and adjusting the weightage assigned to different factors when determining optimal RWIS locations.

3.5 RWIS density, equity and performance analysis

After identifying the optimal locations through clean-slate optimization, the study embarked on a comparative analysis with the 8 priority and 18 predetermined locations within Maine's five maintenance zones. Within this framework, the density of RWIS stations was determined based on the length of roads in each zone and the number of existing and new RWIS stations. The analysis was also aimed not just at validating the predetermined locations but also delved into an equity assessment to ensure that the RWIS stations are distributed fairly across the five distinct zones.

The results, presented in **Table 2**, indicate that the RWIS densities for both the priority and optimal locations remain consistent across eight stations. This consistency provides evidence supporting the validity of the selected priority locations. When comparing the 18 predetermined and 18 optimal locations, similar numbers of stations are observed in most regions, with minor differences between Zone 1 and 5. The evaluation of standard deviation values unveils that the predetermined case is characterized by a slightly higher variability (1.29), contrasting with the more streamlined standard deviation found in the optimal case (0.979). From an equity perspective, this numerical difference underscores a more refined alignment of the RWIS stations within the optimal

Table 2. RWIS density comparison between priority and predetermined locations with optimal locations.

Maintenance zone		**1**	**2**	**3**	**4**	**5**
Road length (1000 km)		2.245	1.725	1.623	2.049	1.63
8 priority locations	Number of priority and existing RWIS	4	3	2	6	3
	Density per 1000 km of road	1.782	1.739	1.232	2.928	1.84
First 8 optimal locations	Number of optimal and existing RWIS	4	3	2	6	3
	Density per 1000 km of road	1.782	1.739	1.232	2.928	1.84
18 predetermined locations	Number of predetermined and existing RWIS	4	4	4	8	8
	Density per 1000 km of road	1.782	2.319	2.465	3.904	4.908
First 8 + Second 10 optimal locations	Number of optimal and existing RWIS	5	4	4	8	7
	Density per 1000 km of road	2.227	2.319	2.465	3.904	4.294

solution, reflecting a concerted effort to evenly balance the distribution across different zones. Consequently, the optimal case not only illustrates the efficacy of the selected locations but also emphasizes a more harmonized and equitable distribution of RWIS stations across the maintenance zones.

The impact of incorporating additional RWIS stations into Maine's network was also evaluated by analyzing the 'objective function' values associated with each set of solutions during the optimization process. The findings, depicted in **Figure 14**, quantify the percentage improvement in monitoring coverage. The infusion of the first 8 and second 10 stations show substantial improvement, while the improve-

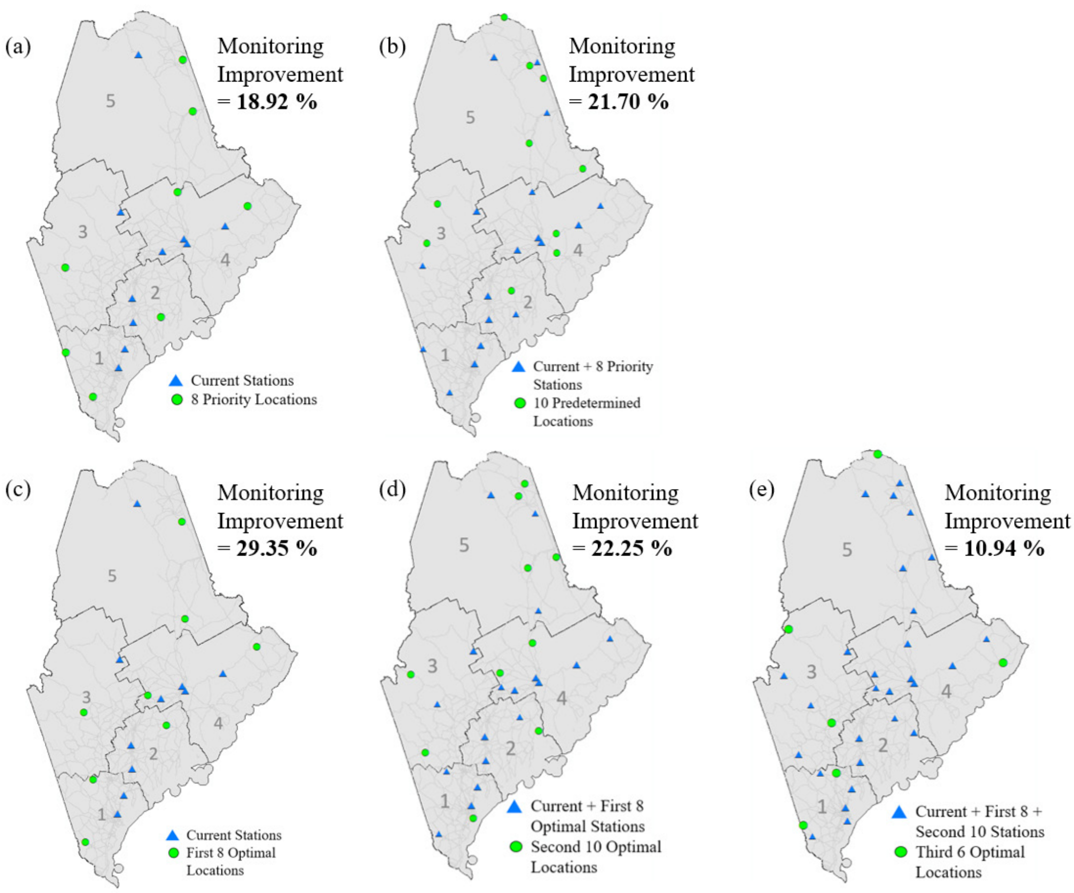

Figure 14. Enhanced network monitoring: The impact of additional RWIS stations.

ment for the third set of 6 stations is relatively lower, indicating that the network is nearing saturation. The monitoring improvement for optimal locations surpasses that of the proposed locations. This is because the entire road network of Maine was utilized as a study corridor for the optimal case, leading to more favorable outcomes. While the improvement for 8 priority locations is slightly lower than the optimal case, the second set of 10 locations demonstrates similar improvements. These findings confirm the effectiveness and validity of the predetermined locations proposed by Maine DOT in optimizing the RWIS network.

4. Conclusions and recommendations

This paper demonstrates the importance of incorporating the effect of multiple weather variables in optimizing the placement of RWIS. By refining the location-allocation algorithms and utilizing a multi-variable semivariogram model, we have developed a novel optimization framework for determining optimal solutions for RWIS network expansion, a valuable contribution to the field. The refined location allocation framework was applied in regional RWIS network planning for the state of Maine, where we carried out a comprehensive state-wide gap analysis to determine the most suitable locations. To further assess the selection of optimal locations, a sensitivity analysis was conducted to examine the effects of assigning different weightings to weather variability and traffic factors.

The key contribution of this research is listed below.

- This research has made significant strides in the optimization of RWIS station placement by introducing an innovative multi-variable semivariogram model that considers essential road weather variables. The comparative study between single and multi-variable semivariogram models demonstrates that employing the multi-variable approach leads to more precise location solutions by effectively capturing the variability of multiple weather variables, resulting in significantly improved monitoring coverage compared to single-variable models.
- Through the application of this refined framework to Maine's existing RWIS network, we model prioritized strategic locations for installing RWIS stations, ensuring equitable and balanced distribution across various zones, and statewide coverage. The location solutions generated are currently being adopted by MaineDOT for future implementations, demonstrating the practicality and robustness of our approach.
- A total of 24 locations were generated using the optimization model for the annual installation of RWIS stations, aligning with the requirements of Maine DOT. These generated locations serve as evidence of the validity and effectiveness of the proposed locations. Additionally, the sensitivity analysis allowed us to assess the impact of different weightings for weather and traffic factors on the selection of optimal station locations. This information empowers decision-makers to tailor the model according to specific monitoring requirements.
- Overall, the utilization of the multi-variable semivariogram model marks a crucial step forward in the optimization of RWIS station placement, providing a reliable and adaptable tool for decision-makers in the field of road weather management. As the model continues to be embraced and applied, it holds promise for contributing to safer, more efficient road systems in Maine and beyond.

Recommendations for further research are given below:

This research opens up several promising directions for future investigations, outlined below:

- *Development of an empirical optimal density model:*
  This extension aims to determine the optimal number of RWIS stations needed for sufficient monitoring coverage in Maine. Factors like geographical distribution, road network characteristics, and desired monitoring accuracy

will be considered.

- *Designing a bi-level sequential optimization model:*
  Another advancement involves creating a novel bi-level sequential optimization model to determine both locations and types of RWIS stations (regular and mini-RWIS). This comprehensive approach will enhance the efficiency and effectiveness of the RWIS network deployment.
- Lastly, incorporating a larger and more diverse sample size in this research could enhance the methodology's robustness and reliability.

In conclusion, this research serves as a fundamental guide and critical foundation for devising a long-term RWIS deployment strategy in the state of Maine. The outcomes of this study will greatly benefit winter travelers by enhancing safety, mobility, and environmental sustainability through an optimized RWIS network.

Author Contributions

The authors confirm their contribution to the paper as follows: study conception and design: S. Biswas, T. J. Kwon; data collection: S. Biswas; analysis, interpretation of results and draft manuscript preparation: S. Biswas, T. J. Kwon. All authors reviewed the results and approved the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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