Aurora

working to advance road weather information systems technology

Standardized Framework for Winter Weather Road Condition Indices

http://aurora-program.org

Aurora Project 2023-04

Final Report
February 2026

About Aurora

The Aurora program is a partnership of highway agencies that collaborate on research, development, and deployment of road weather information to improve the efficiency, safety, and reliability of surface transportation. The program is administered by the Center for Weather Impacts on Mobility and Safety (CWIMS), which is housed under the Institute for Transportation at Iowa State University. The mission of Aurora and its members is to seek to implement advanced road weather information systems (RWIS) that fully integrate state-of-the-art roadway and weather forecasting technologies with coordinated, multi-agency weather monitoring infrastructures.

Iowa State University Nondiscrimination Statement

Disclaimer Notice

Quality Assurance Statement

Iowa DOT Statements

The preparation of this report was financed in part through funds provided by the Iowa DOT through its "Second Revised Agreement for Management of Research Conducted by Iowa State University for the Iowa Department of Transportation" and its amendments.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
Aurora Project 2023-04		

4. Title and Subtitle	5. Report Date
Standardized Framework for Winter Weather Road Condition Indices	February 2026
	6. Performing Organization Code
7. Author(s)	8. Performing Organization Report No.
Inya Nlenanya, Alireza Sassani, Ahmed AlBughdadi, Adnan Inusah, and Md. Samiullah Chowdhury	InTrans Project 23-858
9. Performing Organization Name and Address	10. Work Unit No. (TRAIS)
Center for Transportation Research and Education Iowa State University 2711 South Loop Drive, Suite 4700 Ames, IA 50010-8664	11. Contract or Grant No.
12. Sponsoring Organization Name and Address	13. Type of Report and Period Covered
Aurora Program Iowa Department of Transportation 800 Lincoln Way Ames, IA 50010 Federal Highway Administration 1200 New Jersey Avenue, SE Washington, DC 20590	Final Report
	14. Sponsoring Agency Code Part of TPF-5(435) and Federal SPR Part II, CFDA 20.205

15. Supplementary Notes

Visit https://aurora-program.org/ for color pdfs of this and other research reports.

16. Abstract

State and local agencies across the United States have developed winter weather road condition indices (WWRCIs) to support decisions related to roadway operations, public information, road closures, and winter maintenance responses based on prevailing conditions. However, the absence of a standardized national framework for WWRCIs has resulted in substantial variation in how road conditions are defined, assessed, and communicated. These inconsistencies can create confusion for travelers and limit the ability of transportation agencies to compare performance, share best practices, and benchmark winter operations effectively.

The objective of this project was to develop a standardized national framework for WWRCIs that reflects both operational realities and safety impacts across diverse climatic and geographic contexts in the United States. The framework is informed by a comprehensive assessment of existing practices, stakeholder input, and advances in data availability, including traditional weather and roadway sensors as well as emerging connected and autonomous vehicle (CAV) data sources. By promoting consistent definitions, indicators, and measurement principles, the proposed framework aims to advance the accuracy, reliability, and usefulness of winter road condition information provided to transportation agencies, policymakers, and the traveling public. Ultimately, this effort supports improved driver safety, reduced crashes and congestion, and more effective and coordinated winter weather response strategies nationwide.

17. Key Words	18. Distribution Statement
road surface conditions—standardized framework—winter maintenance—winter weather road condition index	No restrictions.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. of Pages	22. Price
Unclassified.	Unclassified.	137	NA

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

STANDARDIZED FRAMEWORK FOR WINTER WEATHER ROAD CONDITION INDICES

Final Report
February 2026

Principal Investigator
Inya Nlenanya, Research Scientist
Center for Transportation Research and Education, Iowa State University

Co-Principal Investigators
Alireza Sassani, Research Scientist
Ahmed AlBughdadi, Research Scientist
Center for Transportation Research and Education, Iowa State University

Research Assistants
Adnan Inusah and Md. Samiullah Chowdhury

Authors
Inya Nlenanya, Alireza Sassani, Ahmed AlBughdadi, Adnan Inusah, and Md. Samiullah Chowdhury

Sponsored by
Federal Highway Administration Aurora Program
Transportation Pooled Fund
(TPF-5(435))

Preparation of this report was financed in part
through funds provided by the Iowa Department of Transportation
through its Research Management Agreement with the
Institute for Transportation
(InTrans Project 23-858)

A report from
Aurora Program
Iowa State University
2711 South Loop Drive, Suite 4700
Ames, IA 50010-8664
Phone: 515-294-8103 / Fax: 515-294-0467
https://aurora-program.org/

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

This research was conducted under the Federal Highway Administration (FHWA) Transportation Pooled Fund Aurora program. The authors would like to acknowledge FHWA, the Aurora program partners, and the Iowa Department of Transportation (Iowa DOT), which is the lead state for the program, for their financial support and technical assistance.

EXECUTIVE SUMMARY

State and local agencies across the United States have developed winter weather road condition indices (WWRCIs) to support decisions related to roadway operations, public information, road closures, and winter maintenance responses based on prevailing conditions. However, the absence of a standardized national framework for WWRCIs has resulted in substantial variation in how road conditions are defined, assessed, and communicated. These inconsistencies can create confusion for travelers and limit the ability of transportation agencies to compare performance, share best practices, and benchmark winter operations effectively.

The objective of this project was to develop a standardized national framework for WWRCIs that reflects both operational realities and safety impacts across diverse climatic and geographic contexts in the United States. The framework is informed by a comprehensive assessment of existing practices, stakeholder input, and advances in data availability, including traditional weather and roadway sensors as well as emerging connected and autonomous vehicle (CAV) data sources. By promoting consistent definitions, indicators, and measurement principles, the proposed framework aims to advance the accuracy, reliability, and usefulness of winter road condition information provided to transportation agencies, policymakers, and the traveling public. Ultimately, this effort supports improved driver safety, reduced crashes and congestion, and more effective and coordinated winter weather response strategies nationwide.

CHAPTER 1. INTRODUCTION

Winter weather poses significant challenges to transportation safety and operations, causing increased crash risks, traffic congestion, and elevated maintenance demands. To address these challenges, winter weather road condition indices (WWRCIs) have been developed by state and local agencies across the United States to support decisions related to roadway operations, public information, road closures, and winter maintenance responses based on prevailing conditions. However, the absence of a standardized national framework for WWRCIs has resulted in substantial variation in how road conditions are defined, assessed, and communicated. These inconsistencies can create confusion for travelers and limit the ability of transportation agencies to compare performance, share best practices, and benchmark winter operations effectively. This particularly affects travelers crossing state or regional boundaries.

A standardized national WWRCI framework offers an opportunity to establish a consistent, reliable, and transparent approach for assessing and communicating winter road conditions. Such a framework can improve the accuracy and interpretability of information provided to drivers, enhance operational decision-making, and support cross-agency and cross-state coordination during winter events. In addition, a standardized framework can enable agencies to better evaluate winter maintenance performance, optimize resource allocation, and integrate emerging data sources and technologies as part of modern winter operations.

The objective of this project was to develop a standardized national framework for WWRCIs that reflects both operational realities and safety impacts across diverse climatic and geographic contexts in the United States. The framework is informed by a comprehensive assessment of existing practices, stakeholder input, and advances in data availability, including traditional weather and roadway sensors as well as emerging connected and autonomous vehicle (CAV) data sources. By promoting consistent definitions, indicators, and measurement principles, the proposed framework aims to advance the accuracy, reliability, and usefulness of winter road condition information provided to transportation agencies, policymakers, and the traveling public. Ultimately, this effort supports improved driver safety, reduced crashes and congestion, and more effective and coordinated winter weather response strategies nationwide.

This final report documents the full scope of work completed under the project. Chapter 2 presents the results of a comprehensive literature review and data assessment (Task 1), Chapter 3 describes a national survey of state transportation agencies to capture current practices and priorities related to WWRCIs (Task 2), and Chapter 4 presents an in-depth evaluation of existing indices currently in use across the United States and internationally (Task 3). Findings from these efforts were synthesized and documented in the Phase I Report submitted under Task 4. Building on these foundational analyses, Chapter 5 of this report presents the development of a proposed national standard WWRCI framework and associated implementation guidance (Task 5), and Chapter 6 documents a case study demonstrating application of the framework using real-world data (Task 6). Collectively, these components provide transportation agencies with a practical, flexible, and scalable roadmap for advancing winter weather road condition assessment and communication toward greater consistency and effectiveness at the national level.

CHAPTER 2. LITERATURE REVIEW

The literature review described in this chapter aimed to provide a comprehensive analysis of WWRCIs and the impact of existing indices on driver safety, crash rates, traffic congestion, and winter weather response efficiency. However, no relevant literature was discovered regarding the impact of existing indices. Therefore, the review concentrated on examining how the parameters used in these indices affect driver safety, crash rates, traffic congestion, and efficiency in responding to winter weather.

2.1. Impact of Winter Road Conditions on Traffic Safety and Driver Behavior

Research across various studies highlights the significant impact of road conditions on various aspects of traffic safety. Some studies have focused on the connection between weather and road conditions and the influence of these factors on crash rates, traffic flow, and congestion.

Studies by Wu et al. (2020), Abohassan et al. (2021), and Strong and Shvetsov (2006) delved into the complex interaction between weather and road conditions and their influence on traffic safety. Through critical analysis and empirical findings, these studies shed light on the importance of integrating weather factors into road safety evaluations and maintenance practices.

Wu et al. (2020) provide critical insights into the impact of weather and road conditions on road traffic crashes, noting that adverse weather conditions such as rain, snow, and fog significantly increase the likelihood of crashes by impairing visibility and reducing road grip. Additionally, the study highlights that a majority of crashes occur under dry road conditions, primarily due to speeding and dangerous driving behaviors, but wet and slippery road conditions also pose a considerable risk, particularly in poor weather. The study emphasizes incorporating weather and road condition factors into road safety evaluations and strategies, advocating for targeted interventions like improved road maintenance, enhanced driver education, and the adoption of advanced safety technologies to mitigate these risks.

Abohassan et al. (2021) conducted an in-depth analysis of how winter weather conditions, road maintenance strategies, and road surface states interact to impact road safety. Employing statistical methods to assess the effects of various weather phenomena and maintenance activities on road surface conditions, the research highlights the critical importance of timely and effective maintenance practices in preventing winter-related road accidents. The study suggests that by preserving optimal road conditions in the face of inclement weather, adaptive maintenance tactics, guided by accurate weather predictions, can considerably reduce the probability of crashes. Additionally, the study offers recommendations for optimizing winter maintenance operations to enhance safety.

Strong and Shvetsov (2006) investigated the impact of winter weather conditions on road safety by developing linear models to predict crash rates based on various weather parameters. They provided a tool for traveler information and winter road maintenance planning. The study found correlations between weather severity and crash rates across different regions, and the findings underscore the necessity of integrating weather factors into road safety analysis.

These studies not only highlight the complexity of winter road surface conditions on traffic dynamics but also highlight the potential of winter weather indices to enhance proactive safety measures and optimizing maintenance strategies.

2.2. Monitoring and Predicting Road Surface Condition

Monitoring and predicting road conditions is essential to ensure safety, as it enables sending timely alerts to drivers and authorities about potential hazards. This proactive approach allows for preemptive action to prevent crashes. Additionally, it facilitates efficient traffic management and road maintenance, leading to reduced congestion and optimal resource allocation. This ultimately leads to creating safer, smoother, and more sustainable transportation.

Much research has been conducted to find efficient ways that road conditions can be estimated. Qian et al. (2016) explored the classification of road conditions using images from uncalibrated dashboard cameras, addressing issues such as variability in camera placement, road layout, and weather conditions. The study successfully segmented road surfaces into condition categories using a combination of normalized luminance, texture features, and a probabilistic fusion approach, achieving 80% accuracy for binary classification (bare versus snow/ice) and 68% for three-class scenarios (dry, wet, snow/ice). The dataset comprised 100 images taken under a variety of lighting and weather conditions, highlighting the importance of optimizing feature selection and the region of interest for effective classification. According to the study, further improvements could be made by investigating sophisticated classification approaches, such as convolutional neural networks, to improve the system's feasibility for real road condition estimates.

Utilizing data from Iowa's highways, including weather condition data and vehicle-mounted camera images, Kwon et al. (2021) developed a regression kriging (RK) model combining geostatistical and deep learning techniques to interpolate road surface condition variables like road surface temperature (RST) and slipperiness index between sparse road weather information system (RWIS) stations. The study demonstrated the RK model's effectiveness in capturing spatial road surface condition variability, with the model's accuracy improving alongside increased RWIS density. The study also automated road surface condition classification through a deep learning model, significantly enhancing the efficiency and accuracy of winter road maintenance operations. Future research directions include expanding the study area, integrating additional variables, and optimizing RWIS station placement to refine the system's effectiveness and applicability in real-world winter road maintenance activities.

Gu (2019) expanded on the previous study, using data from highways in Alberta, Canada, in his study. He demonstrated that RK models, enhanced by additional covariates, offer strong predictive capabilities with low estimation errors, leading to optimized RWIS station placements for improved winter road maintenance and safety.

Also using camera images in conjunction with data from RWIS, Jonsson (2011a) presented a novel approach to improve road safety and road maintenance efficiency by accurately identifying road conditions. The study successfully illustrates the model's capability to classify road surfaces as dry, wet, snowy, or icy with an impressive accuracy of 91% to 100%. This classification is crucial for executing timely maintenance actions and for alerting road users about potential hazards, especially in regions susceptible to adverse weather conditions. Jonsson's (2011a) research, which combines meteorological data with advanced image processing, makes an important contribution to the development of expert systems for predicting road slipperiness, providing a competitive alternative to neural network approaches.

A study by Mataei et al. (2016) critically evaluated existing methodologies for assessing pavement friction and skid resistance, emphasizing their significance for road safety, especially in wet conditions. It explored the impact of pavement surface characteristics like microtexture and macrotexture on friction; reviewed various measurement techniques, including field and laboratory methods; and discussed their strengths and limitations. The paper highlights the need for new, more efficient measurement methods that can accurately reflect real-world conditions and suggests potential areas for future research, such as leveraging advanced technology for enhanced assessment of pavement texture and friction properties.

Fu et al. (2017) presented a methodology for classifying and reporting winter road conditions based on the associated risk of collision due to adverse weather and road surface conditions. The study highlights the variability in road surface condition classification and reporting across different regions and proposes a standardized system of road surface condition classification that relates risk to motorists by either averaging relative risk index across different sections or classifying the entire route based on the section with the highest risk. For a given highway section, the relative risk index is the ratio of the crash frequency in adverse conditions to the crash frequency in base conditions. This approach aims to offer a more accurate representation of winter driving hazards. This study advocates extending this risk-based analysis to broader aspects of winter road maintenance and safety, emphasizing the need for further research to develop a universal risk index applicable across larger geographic areas.

Ameddah et al. (2018) introduced a novel approach for monitoring road conditions using a system that integrates smartphone sensors and cloud computing. The study employed a lightweight machine learning algorithm, specifically k-means clustering, to analyze accelerometer and GPS data collected by an Android smartphone application. The system categorizes road conditions into smooth, average, and rough, achieving an accuracy rate of 88.67%. The cloud server plays a crucial role by processing extensive sensor data and sending learning parameters back to the smartphone application, facilitating real-time road condition assessment. This methodology not only enhances the accuracy of road condition monitoring but also offers a cost-effective solution by utilizing existing smartphone technology and cloud resources, making it an innovative contribution to the field of transportation and infrastructure monitoring.

For the era of connected vehicles (CVs), Galanis et al. (2018) presented a unique approach for weather-based road condition estimation to enhance vehicular safety and performance. The study leveraged modern vehicles' advanced computational and connectivity features. These vehicles include visual sensors like stereo cameras, ultrasound sensors and lidars to provide data about the vehicles' environment. These visual sensors can produce high-resolution images and 3D maps used to create a precise representation of the environment. The methodology of the study involved integrating various data sources, particularly weather information from on-vehicle sensors, roadside units, internet and cloud subscription services. These data sources were integrated within a systematic framework to estimate the road surface index (RSI), which in turn influences the dynamic speed recommendations provided to drivers to enhance road safety under different weather conditions. RSI, which ranges from 0.1 (ice-covered roads) to 1.0 (dry roads), quantifies the relationship between weather conditions and road surface status, influencing the recommended speed limit for vehicles. The study demonstrates the effective prediction of road conditions. The practical application of this methodology in real vehicles demonstrates its effectiveness in establishing speed limits that align with the estimated RSI, potentially increasing road safety.

Ito et al. (2017) presented a system designed to enhance road safety by providing real-time information on road conditions to drivers. Utilizing a combination of sensing technologies and vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communications, the system aims to mitigate traffic accidents caused by adverse weather and poor road surfaces. The paper details the system's architecture, including data gathering, analysis, and sharing functionalities, and discusses the outcomes of experimental validations in real-world settings. The research utilized a data gathering car equipped with sensors to monitor different aspects of the vehicle's environment and operation. It also included a data logger for collecting and storing data, an on-board server to process the data from the logger, advanced communication technology for V2I and V2V communication, and a heads-up display system for presenting real-time analyzed road conditions directly to the driver. The research underscores the importance of integrating various sensing and communication technologies to furnish drivers with accurate road condition information, thus contributing to the broader field of intelligent transportation systems.

Li et al. (2020) explored the potential of utilizing data from the controller area network (CAN) bus of vehicles to monitor and improve roadway conditions, particularly during winter. The research leveraged real-time data from vehicle systems such as accelerometers, antilock braking systems (ABS), and traction control systems, combined with GPS coordinates to provide a comprehensive view of roadway conditions during adverse weather events. The study demonstrates the feasibility of extracting and analyzing CAN bus data to identify roadway hazards in real-time, thereby enabling data-driven decision-making for traffic management and road maintenance. Key findings indicate that braking and wheel counter data are crucial for the early detection of deteriorating winter road conditions. However, challenges related to the high volume and velocity of the data were noted, emphasizing the need for efficient data management strategies to handle large datasets from multiple vehicles. The study recommends developing partnerships with CV data providers to integrate essential data points into traffic management center operations. This integration could potentially transform how road conditions are monitored and managed, particularly by utilizing data on hard braking events and traction control activations to inform and enhance winter weather road maintenance practices.

Mahoney and Myers (2003) outlined the development of a maintenance decision support system (MDSS) aimed at improving winter road-maintenance operations. Sponsored by the FHWA's Road Weather Management Program, the MDSS integrates real-time weather forecasts, road conditions models, chemical concentration algorithms, and maintenance practices to optimize treatment strategies, ultimately improving safety and efficiency on roads. Developed through a collaboration between public agencies and private meteorological services, the system leverages a variety of data sources to provide route-specific guidance on treatments such as deicing and plowing. The MDSS represents a significant advancement in leveraging technology to address the complexities of winter road maintenance. Despite its potential, the paper acknowledges challenges such as predicting light precipitation events, managing blowing snow, and incorporating road frost, indicating ongoing efforts to refine and expand the MDSS's capabilities.

Literature has presented promising methods for estimating road conditions, including utilizing dashboard camera images, sensors from CAVs, and a combination of geostatistical and deep learning techniques. These methods enable accurate classification of road surfaces and the prediction of hazardous conditions, resulting in enhanced road maintenance and more effective traffic management strategies.

2.3. Winter Weather Road Condition Indices

Agencies develop indices for winter weather conditions to enhance the efficiency of winter road maintenance operations. These indices are mainly winter severity indices (WSI) or storm severity indices (SSI).

Walker et al. (2019a) provided a foundation for transportation personnel to develop more effective and reliable WSIs. They did this through a detailed investigation into 19 documented WSIs across different states, categorizing them into seven groups based on their development process and characteristics. Their research identified key meteorological variables used by transportation agencies to develop these indices. The 19 WSIs were from the Strategic Highway Research Program (SHRP), Kansas, New Hampshire, Indiana, Minnesota, Wisconsin, Illinois, Maine, Massachusetts, Pennsylvania, Washington, New York, Oklahoma, Utah, Iowa, California, Montana, Oregon, Colorado, and Idaho. The key variables were temperature, snow, wind, and freezing rain. The relevance and application of these variables were discussed. The study suggests that future indices should be dynamic, should be capable of adjusting to changing meteorological conditions, and should efficiently incorporate specific meteorological variables to provide meaningful outcomes for winter maintenance assessments. The study identifies one significant limitation across the existing indices: a lack of sufficient documentation, which hampers reproducibility and adaptation.

In order to develop a plan for deploying a statewide RWIS to support New York State Department of Transportation (NYSDOT) and MDSS applications, a proposed weather severity index was developed (Chien et al. 2014). Drawing from previous research and survey findings, the index incorporates four key parameters: mean wintertime land surface temperature, number of weeks with transitional surface temperature, average annual snowfall accumulation, and average annual duration of freezing rain. Transitional surface temperature refers to the period when temperatures change from below to above freezing. Each parameter was assigned a score on a scale of 1 to 10, with equal weighting applied to all four parameters. However, it was acknowledged that these weights might be subject to adjustment based on future data or evidence. The weather severity index is calculated as the weighted sum of these four parameters.

A study on WSI development by Hoffman et al. (2014) aimed to measure the influence of winter weather on road maintenance activities. It focused on refining a basic WSI by gathering weather data from public sources and the Pennsylvania Department of Transportation's (PennDOT's) maintenance records to construct a WSI equation that was then tested through a pilot program. Through analysis, an equation was developed to assign points to winter weather events, reflecting their severity in terms of maintenance cost impact. Various factors such as snowfall and freezing rain accumulations were considered, with weights applied to indicate their relative significance. The objective was to generate a numerical WSI value for each event and the entire winter season, facilitating comparisons across different periods and regions. The report provides recommendations for short-term actions, such as expanding the pilot program and standardizing data collection, as well as long-term strategies, including implementing a Storm ID system and incorporating additional weather variables. This research highlights the potential of the WSI as a strategic tool for improving the efficiency and effectiveness of winter road maintenance operations, making a substantial contribution to the literature on weather-related transportation planning and management.

A weather severity index developed in a study by Strong and Shvetsov (2006) was used to represent the severity of winter weather conditions for different climatic zones and on a statewide basis. The zones were categorized based on topographical features into mountains (Zone 1), valleys (Zone 2), and plains (Zone 3). Separate indices were created for each climatic zone as well as a comprehensive index for the entire state. These indices were intended to help travelers understand the relative severity of winter weather conditions in different parts of the state and in specific zones. The index was based on the predicted crash rates derived from the study's models, using a scale to translate these rates into index values ranging from 1 to 10, where higher values indicate more severe weather conditions. This approach aimed to make the index straightforward and useful for public communication, offering an easy-to-understand assessment of winter driving risks. For example, if the weather forecast predicts bad weather in the mountains, the index can tell travelers how this compares to usual weather conditions in the mountains and in the entire state. This helps travelers understand whether the current weather is worse than what is normally expected and whether it is bad just in the mountains or across the whole state. Table 1 provides a summary of how the severity index varied across each climatic zone based on the observed and predicted crash rates.

Table 1. Summary of how the severity index varied across each climatic zone

Climatic Zone	Topographical Characteristics	Severity Index Variation
Zone 1	Mountains	Higher index values indicate increased crash rates, reflecting harsher weather conditions in mountainous areas.
Zone 2	Valleys	Clear positive correlation between index value and crashes rates, with a significant increase in crashes as weather worsens.
Zone 3	Plains	Less pronounced correlation, with lower overall crash rates, indicating milder impact of weather on road safety.
Statewide	Combination of zones	General trend of increased index values corresponding to higher crash rates, demonstrating the index's effectiveness across regions.

Source: Strong and Shvetsov 2006

Carmichael et al. (2004) developed a novel winter weather index specifically for Iowa, integrating six years of roadway maintenance budget and climate data. Utilizing artificial neural network techniques, the index was designed to reflect winter maintenance costs more accurately, addressing shortcomings in existing indices' correlations with actual expenses. The new index considered meteorological factors including temperature and precipitation in the form of rain, snow, sleet, and freezing rain. The research demonstrated that the new index significantly outperformed traditional methods like the SHRP index and linear regression models in predicting the Iowa Department of Transportation's (Iowa DOT's) winter road treatment expenses. This offers a methodologically robust tool that could be adapted for use in other regions with similar climatic challenges.

The Missouri Department of Transportation (MoDOT) introduced an advanced WSI that evaluates the impacts of winter weather on surface transportation (Thomas et al. 2021). The report on this WSI incorporates a broad set of variables, including precipitation types (snow, sleet, freezing rain), visibility, wind speed, air temperature, and associated transportation factors like traffic flow impediments and accident rates. These elements are integrated into a comprehensive framework that assesses the financial and operational effects of winter conditions on road maintenance and safety. This innovative approach utilizes a data-driven dashboard for detailed analysis, enabling MoDOT to optimize winter weather response strategies across Missouri's diverse climatic regions.

A study by Walker et al. (2019b) introduced the Nebraska Winter Severity Index (NEWINS), designed to quantify winter storm severity for the Nebraska Department of Transportation (NDOT). NEWINS is an event-driven index that incorporates meteorological data from 2006 to 2016, utilizing variables such as wind speed, visibility, air temperature, snowfall duration and rate, and the affected district area to assess the impact of winter storms across Nebraska. This index offers a nuanced, daily assessment of storm severity, enhancing resource allocation and operational planning for winter road maintenance. By comparing NEWINS with other meteorological and performance data, the study validates its effectiveness and adaptability for other regions, highlighting its potential for broader application in winter weather impact assessments and transportation planning. NEWINS is distinct because it focuses on meteorological conditions at the storm level, unlike other indices that may consider entire winter seasons or different metrics like accident rates.

Dowds and Sullivan (2022) aimed to establish a quantitative relationship between winter severity, road conditions, and snow and ice control (SIC) costs for the Vermont Agency of Transportation (VTrans). Utilizing variables such as the Accumulated Winter Season Severity Index (AWSSI), road surface condition data (grip), and historical SIC expenditure data, they developed a predictive tool for estimating SIC costs under various winter severity scenarios. Grip is a proxy for surface friction calculated from the estimated thickness of water, snow, and ice on the road surface. Key findings include a strong correlation between AWSSI scores and SIC costs, significant regional variability in this relationship, and the potential of grip as a performance measure for SIC activities. The study recommends using AWSSI for more effective planning and budgeting of SIC activities, considering regional differences in cost estimation, and adopting data-driven approaches to improve SIC investment decisions. These insights are pivotal for transportation agencies aiming to optimize winter maintenance strategies and resource allocation.

The Wisconsin Department of Transportation (WisDOT) WSI, established in 1995, is used to assess the severity of winter weather and its impact on road maintenance, helping in resource management for winter road care (WisDOT 2014). This index, ranging from 0 to 100, enables comparisons of winter severity across years and regions (counties), ensuring that resources match actual weather conditions. A statewide WSI is developed by calculating the WSI for each county based on weekly storm reports and using a weighted formula for a statewide average. In 2012–2013, the statewide average WSI was 37.2, 14% higher than the previous 10 winters' average of 32.6. Factors such as number of snow events, number of freezing rain events, total snowfall amount, total storm duration, and total number of incidents contribute to the index. By analyzing these factors, WisDOT is guided in decisions regarding salt usage, equipment deployment, and labor allocation for efficient and effective winter maintenance.

A report by Sturges et al. (2020) provides a thorough analysis of the variables and data sources used in calculating SSIs and WSIs. The authors identify the most commonly used variables in SSI/WSI calculations as atmospheric conditions (air temperature, wind speed), precipitation characteristics (type, accumulation, rate), and pavement-specific factors (road temperature, surface condition). These variables are integral to accurately assessing the impact of winter weather on road maintenance and safety. Key findings indicate that no single data source perfectly satisfies the requirements for SSI/WSI calculations, leading agencies to combine multiple datasets to improve accuracy and reliability. The report recommends a structured approach for agencies aiming to develop or enhance their SSI/WSI, including defining clear objectives, selecting relevant variables and data sources, and continuously evaluating and refining the chosen methodologies. These recommendations aim to assist agencies in effectively using SSIs/WSIs for better winter road maintenance and resource management.

Balasundaram et al. (2012) developed an SSI to quantify various aspects of severe winter weather, specifically for transportation infrastructure. The index encompasses a range of parameters such as temperature, type and intensity of precipitation, accumulation of precipitation, and visibility. The index also makes use of weather prediction models like the Weather Research and Forecasting (WRF) model and the Short-Range Ensemble Forecast (SREF) model for predicting weather conditions relevant to the SSI. The SSI is a sum of two sub-indices: the precipitation index and the base index. The base index includes non-precipitation factors like surface temperature, temperature trend, and wind speed, while the precipitation index covers precipitation-based parameters and their impact on transportation infrastructure. The SSI was tested using historical storm data, and it integrates with the weather prediction models to forecast winter storm severity. This model serves as a valuable tool for making tactical and operational decisions regarding the allocation of winter maintenance resources.

Nixon and Qiu (2005) developed an SSI using three main steps. The first step was classifying storms into categories using six factors, including the type of event (e.g., heavy snow, medium snow, light snow, freezing rain), temperature range, wind speed, early event conditions, surface temperature trends, and post-event weather. The next step involved using a multiple regression model to generate a numerical SSI value between 0 and 1 for each category of storm based on the six factors. The score for each storm was adjusted to ensure that the overall scores fell into a normal distribution, making the index more statistically valid and comprehensive. The final step involved testing the model's accuracy through surveys with winter maintenance garage supervisors from the Iowa DOT, who ranked storms based on their operational difficulty. The initial model was then adjusted according to their feedback to align the SSI scores with the real-world difficulty rankings provided by these experts. This index considers the severity of individual storms and accounts for pre-storm and post-storm conditions and temperatures, setting it apart from other indexes.

The Idaho Transportation Department (ITD) developed a winter performance index (WPI) and an SSI to measure the efficiency of winter maintenance operations (Jensen et al. 2013). Utilizing data from a network of 99 RWIS stations, these indices incorporate parameters like wind speed, precipitation, surface temperature, and road surface friction (grip) to assess storm severity and maintenance performance. The SSI formula combines maximum wind speed, maximum water equivalent layer of precipitation, and minimum surface temperature to rate storm severity. On the other hand, the WPI is derived by utilizing the SSI value within a specific formula that includes the ice-up time (the duration during which pavement grip falls below 0.6, indicative of icy or slippery road conditions). This calculation yields an index value, which is then compared against a performance scale typically ranging from 0.00 to 0.7, with the target being 0.5 or lower. This comparison allows for an assessment of the effectiveness of road treatment efforts and timing as executed by field maintenance personnel.

The Colorado Department of Transportation (CDOT) developed a WPI by integrating SSI values with grip to quantify the severity of winter storm events (Walsh 2016). The SSI, which assesses the severity of winter storms using key atmospheric data like wind speed, precipitation, and surface temperature, helps compare performance across different geographic regions by normalizing the variation in storm severity and duration. Meanwhile, grip, a measure of road surface traction, reflects the condition of the road surface and how well it can support vehicle traction during and after winter storm events. By analyzing grip values in conjunction with the

SSI, the WPI can more accurately determine the effectiveness of maintenance operations in restoring and maintaining safe road conditions during winter storms.

After realizing that existing indices were not fully suitable to Indiana's needs due to the different climatic conditions for which they were developed, the Indiana Department of Transportation (INDOT) opted to develop a specific WSI that did not require extensive data collection (McCullough et al. 2004). Weather data were gathered from different climatic zones within Indiana to reflect the diverse winter weather conditions across the state. Key weather variables included the number of freezing rain events and snow events, total snowfall, average temperatures, storm duration, wind velocity, frost days, and days with snow cover. INDOT used a statistical method to correlate historical weather data with snow and ice removal costs, allowing for a more scientific and less biased approach to developing the WSI. By analyzing these correlations, INDOT was able to assess the impact of different weather events on the costs and efforts associated with snow and ice removal across various climatic zones in Indiana.

The Illinois Department of Transportation (IDOT) tasked the Illinois State Water Survey (ISWS) to forecast a two- to three-month snow removal budget, following IDOT's depletion of its winter maintenance budget before January during the 1978–1979 winter season. This initiative led to the development of a WSI aimed at enhancing preparations for subsequent years (Cohen 1981). The WSI was formulated through correlation analysis to estimate the necessary salt quantities for winter maintenance. This index relies solely on two parameters: the duration of days when temperatures and snowfall meet specific thresholds. Due to its limited use of parameters, this index is best suited for short-term snow removal budget forecasting. It was evident by the conclusion of the project that only projections spanning 12 months or more would benefit annual budget planning.

Qi and Velpur (2024) focused on the development of nonlinear regression models to assess how winter weather variables influence maintenance costs in Illinois. These models consider temperature, wind speed, and snowfall to predict the financial implications of winter weather in terms of the labor, materials, and equipment necessary for winter road maintenance. By considering these parameters, the study aimed to provide a robust methodological approach that allows transportation agencies to effectively forecast and allocate resources, thereby improving their preparedness and response strategies to varying winter conditions. The analysis included regional variations by dividing the state into different climatic zones based on the average annual extreme minimum temperatures, ensuring that the models would be tailored to reflect the distinct weather patterns and maintenance needs of different parts of the state.

2.4. National Standard Development

Establishing national standards is advantageous because it promotes consistency and uniformity across different regions or agencies. However, implementing such standards also comes with certain challenges.

Villwock-Witte et al. (2021) identified several challenges in developing and using weather severity indices, which are crucial tools for assessing winter storm severity and its impact on transportation. The main challenges include the diverse array of methodologies used by existing indices, which hinders comparability, and the lack of flexibility for indices to be applied outside the areas or sets of conditions of their initial development. The study also points out issues with data quality and quantity. The complexity and limited adoption of weather severity indices present further obstacles, alongside difficulties in validating the accuracy of outputs against ground truths. The study proposes some solutions to overcome these challenges, emphasizing automation, integration, collaboration, and innovation. Automating data collection and processing through software development is suggested to simplify weather severity index usage. The integration of diverse data sources to enrich weather severity index datasets and the implementation of spatial variability analysis techniques to address gaps between data collection locations is also proposed. The study emphasizes the need for collaboration between weather experts and transportation agencies to make weather severity indices more effective, suggesting the creation of a team of weather and transportation specialists to tackle and solve the challenges with weather severity indices.

In their endeavor to identify RWIS technologies and assess their cost effectiveness, Boselly et al. (1993) developed an index for specifying winter severity for the different climatic regions in the United States. This was one of the first studies to do so for use in all US states, and most state agencies have used this as a reference in creating their own index due to the huge variations in climatic conditions. Four key parameters were incorporated into this index: temperature index (derived minimum air temperature), snowfall, number of air frosts (days with minimum air temperature below freezing), and temperature range (difference between mean monthly maximum and minimum air temperature). These parameters were aggregated from daily records and then averaged monthly to develop the index. The winter index was then used to analyze spatial and temporal variations in winter severity, its correlation with snow and ice control costs, and the effectiveness of snow and ice control practices. The spatial analysis of the winter index involved comparing the index values across 25 weather stations representing different climatic regions in the United States. This approach allowed for an assessment of how winter severity varied geographically. Stations with higher winter index values indicated regions with more severe winter conditions, requiring potentially greater resources for snow and ice control. The temporal analysis of the winter index focused on examining changes in winter severity over time at the same locations. By analyzing the index values across multiple years, the study identified trends in winter severity. This analysis was instrumental in understanding long-term changes in winter weather patterns, which could impact planning and operational strategies for snow and ice control.

Suggett et al. (2006) developed and assessed two models to gauge the severity of Canadian winters, utilizing meteorological and road weather information. The models, which aim to standardize the impact of winter conditions on road maintenance operations, were based on data from the Meteorological Service of Canada and the Road Weather Information System. Analysis included salt usage across various Canadian regions as the primary metric. The first model, using meteorological data alone, showed a moderate goodness of fit, while the second, incorporating road weather information, achieved slightly better accuracy. The research also involved local calibration for different regions, highlighting the significant role of geographic and climatic variations in winter road maintenance practices. The regions were categorized based on salt usage and climatic zone similarities, i.e., areas with similar weather patterns and road maintenance practices were grouped together. The calibration process then involved either applying a single local calibration factor to the national model results for each area or calibrating the model parameters locally. The findings underscore the complexity of modeling winter severity due to diverse regional practices and weather patterns, suggesting a need for standardized data collection and further refinement of the models.

Kangas et al. (2015) developed a simulation model called RoadSurf, which uses numerical weather forecasts, synoptic and road weather station observations, and radar precipitation measurements to provide accurate, national-scale estimations of road surface conditions and traffic indexes. The model's capabilities extend to predicting RSTs, classifying surface conditions, and forecasting driving conditions and road surface friction, demonstrating its usefulness in a variety of applications from sidewalk condition predictions to supporting intelligent traffic projects. RoadSurf's adaptability and resilience in anticipating weather-related road conditions have shown great potential in enhancing road maintenance methods and safety measures, especially in areas prone to severe winter weather problems.

Boustead et al. (2015) introduced a novel index, AWSSI, designed to assess the severity of winter seasons at specific locations. AWSSI integrates various meteorological parameters such as temperature extremes, snowfall totals, and snow depth into an aggregate score that quantifies winter severity. This index is useful for comparing different winters across locations and time periods, fulfilling the need to provide a standardized method for such comparisons. AWSSI uses temperature, snowfall, and snow depth thresholds to accumulate points throughout the winter season, and it includes a parallel index that uses temperature and precipitation data as proxies for snow where direct snow measurements are unavailable. This tool not only facilitates the analysis of current winter severity but also enables historical comparisons and trend analysis in the context of climatic patterns. The project validated the index using historical data, demonstrating its effectiveness in correlating with known climatic events and trends, thus establishing AWSSI as a valuable resource for operational forecasting.

Clear Roads sponsored a two-phase project (MRCC 2019, 2021) aimed at enhancing the AWSSI tool by adding more locations in each state to better support winter road maintenance decisions. Key enhancements to the already existing index included the ability to compare current winter data with past records directly on the AWSSI graph, predict future winter conditions, and evaluate a specialized version of AWSSI designed specifically for road maintenance. These enhancements help agencies better prepare and respond to winter weather challenges by providing more accurate and useful data for road maintenance planning.

Table 2 shows a summary of the key parameters used in the discussed indices.

Table 2. Summary of current indices and their key parameters

Title	Authors	Year	Agency / State	Index	Key Variables/Indicators
User-Oriented Climatic Information for Planning a Snow Removal Budget	Cohen (1981), Illinois State Water Supply and University of Illinois	1981	IDOT	Winter Severity Index	• Snowfall (no. of days snowfall accumulations greater 0.5 in.) • Temperature (no. of days mean daily temperature between 15°F and 30°F)
Road Weather Information Systems; Volume 1: Research Report	Boselly et al. (1993), SHRP	1993	SHRP	Winter Severity Index	• Temperature • Snowfall • Likelihood of frost
A Winter Weather Index for Estimating Winter Roadway Maintenance Costs in the Midwest	Carmichael et al. (2004), Iowa State University	2004	Iowa	Winter Weather Index	• Daily minimum temperature • Maximum temperature • Precipitation (rain, snow, sleet, and freezing rain) • Snowfall • Snow on the ground
Indiana Winter Severity Index	McCullogh et al. (2004), Purdue University and INDOT	2004	INDOT	Winter Severity Index	• Number of freezing rain events • Snow events • Total snowfall • Average temperatures • Storm duration • Wind velocity • Frost days • Days with snow cover
Developing a Storm Severity Index	Nixon and Qiu (2005), University of Iowa	2005	Iowa	Storm Severity Index	• Type of event (heavy snow, medium snow, light snow, freezing rain) • Temperature range • Surface temperature trends • Wind speed

Title	Authors	Year	Agency / State	Index	Key Variables/Indicators
Development of Winter Severity Indicator Models for Canadian Winter Road Maintenance	Suggett et al. (2006), Various	2006	Canada	Winter Severity Index	• Air temperature • Temperature range (minimum and maximum) • Snow accumulation • Snow occurrence • Freezing rain occurrence • Rain accumulation • Rain occurrence • Blowing snow occurrence
Development of Roadway Weather Severity Index	Strong and Shvetsov (2006), Montana State University	2006	California, Montana, Oregon	Winter Severity Index	• Minimum air temperature • Maximum air temperature • Snowfall • Number of days with minimum air temperature at or below 32°F • Range of monthly maximum and minimum air temperatures
Proactive Approach to Transportation Resource Allocation Under Severe Winter Weather Emergencies	Balasundaram et al. (2012), Oklahoma State University & University of Oklahoma	2012	Oklahoma Transportation Center	Storm Severity Index	• Temperature • Temperature trend • Windspeed • Precipitation type • Precipitation accumulation • Intensity • Visibility
Ensuring and Quantifying Return on Investment Through the Development of Winter Maintenance Performance Measures	Jensen et al. (2013), ITD	2013	ITD	Winter Performance Index & Storm Severity Index	• Max wind speed • Max water equivalent layer of precipitation • Minimum surface temperature • Ice-up time (time duration when
Road Weather Information System Statewide Implementation Plan	Chien et al. (2014), New Jersey Institute of Technology (NJIT)	2014	NYSDOT	Winter Severity Index	• Mean wintertime land surface temperature • Number of weeks with transitional surface temperature • Average annual snowfall accumulation • Average annual duration of freezing rain

Title	Authors	Year	Agency / State	Index	Key Variables/Indicators
Winter Severity Index Development	Hoffman et al. (2014), GHD, Inc.	2014	PennDOT	Winter Severity Index	• Snow accumulation • Temperature at the time of the snow event • Freezing rain
RoadSurf: A modelling system for predicting road weather and road surface conditions	Kangas et al. (2015), Finnish Meteorological Institute	2014	Finnish Meteorological Institute, Finland	Road Surface Condition and Traffic Index	• Relative humidity • Short-wave and long-wave radiation • Temperature (both air and surface) • Wind speed and direction • Humidity • Precipitation type and amount • Specific road surface conditions (ice, snow, or wetness)
Learning to Use Less Salt without Compromising Safety (Annual Winter Maintenance Report)	WisDOT (2014)	2014	Wisconsin Department of Transportation	Winter Severity Index	• Number of snow events • Number of freezing rain events • Total snow amount • Total storm duration • Total number of incidents
The Accumulated Winter Season Severity Index (AWSSI)	Boustead et al. (2015), University of Nebraska	2015	National	Winter Severity Index	• Temperature extremes • Snowfall totals • Snow depth
Winter Maintenance Performance Measure	Walsh (2016), Viasala Inc	2016	CDOT	Winter Performance Index & Storm Severity Index	• Wind speed • Precipitation • Surface temperature
Developing a Department of Transportation Winter Severity Index	Walker et al. (2019b), Various	2019	NDOT	Winter Severity Index	• Wind speed • Visibility • Air temperature • Snowfall duration and rate • Affected district area

Title	Authors	Year	Agency / State	Index	Key Variables/Indicators
Development of a Surface Transportation Impact Factor for Winter Severity Indices	Thomas et al. (2021), Various	2022	MoDOT	Winter Severity Index	• Precipitation types (snow, sleet, freezing rain) • Visibility • Wind speed • Air temperature • Traffic flow impediments • Crash rates
Quantifying Correlations Between Winter Severity, Road Conditions, and VTrans' Snow and Ice Control Activities	Dowds and Sullivan (2022), University of Vermont Transportation Research Center	2022	VTrans	Winter Severity Index	• Min and max daily temperatures • Snowfall • Snow depth • Rain accumulation at low temperatures • Consecutive cold days • Blowing snow (high wind with snowfall) • Pavement ice warnings (from RWIS) • Road surface condition data (grip) • Historical snow and ice control expenditure data
Nonlinear Modelling of The Association Between Winter Weather Severity and Maintenance Expenditures	Qi and Velpur (2024), Southern Illinois University	2024	Illinois	Winter Severity Index Model	• Temperature • Wind speed • Snowfall

2.5. Technology and Mapping Solutions

The key parameters that are used for the discussed indices are measured using various technologies. These technologies, mainly RWIS, are necessary for the accurate recording and observation of data that influence winter weather road conditions.

RWIS refers to a system that senses and gathers on-site weather and road condition data, followed by the processing and sharing of this information as well as the creation and distribution of forecasts for road and weather conditions. RWIS also encompasses individuals, such as meteorologists who provide forecasts and engage with highway agency clients. Many states and agencies have installed RWIS to aid in snow and ice control management (Boselly 1992).

Through research conducted under the Strategic Highway Research Program, Boselly (1992) evaluated the effectiveness of using RWIS in optimizing snow and ice control on highways. RWIS combines meteorological and pavement sensors to provide real-time data on road conditions. Pavement sensors in these systems accurately measure temperature, surface conditions, and deicing chemical concentrations, while atmospheric sensors collect essential meteorological data. The study highlights RWIS's predictive capabilities, particularly its ability to forecast pavement temperatures within a 1°C margin of error 90% of the time, which substantially aids in operational decision-making for snow and ice control. Additionally, road thermography, widely used in Europe, further enhances the accuracy of these temperature measurements. The integration of these technologies enables more precise and effective resource allocation, enhancing both the efficiency and cost-effectiveness of highway maintenance during adverse weather conditions. The study by Boselly (1992) involved field tests and interviews across several US states and Canadian provinces.

Gu et al. (2019) proposed a novel method, a geostatistical approach, to estimate winter RST. The study details the development and application of this method in Alberta, Canada, demonstrating how mobile RWIS data, when combined with GIS and regression kriging, can provide a more accurate and continuous spatial representation of road surface conditions. Key components of the method include using multivariate linear regression to understand the influence of geographic factors on RST and then enhancing the model's accuracy with kriging techniques that factor in spatial correlations resulting in low error values (in terms of root mean square error [RMSE] and mean absolute error [MAE]). The study shows that this combined approach significantly improves the predictive accuracy of RST, which is essential for effective winter road maintenance.

Ding and Kwon (2022) presented an innovative method for estimating winter road friction by leveraging RWIS data. The approach employs a machine learning-based regression tree model that integrates environmental and road condition data to predict road friction. This method combines data from stationary RWIS, which often have large spatial gaps between stations, with mobile RWIS data. To fill these gaps, a kriging interpolator is applied, generating a continuous spatial map of road friction. The resulting model demonstrates an accuracy of 93.3%, effectively identifying hazardous road segments and categorizing them based on risk levels using a colorcoded map. These findings offering significant implications for enhancing road safety and optimizing winter road maintenance operations.

Jonsson (2011b) outlined the development and testing of a cost-effective remote sensor designed to enhance traffic safety by accurately detecting winter road surface conditions, such as dry, wet, snowy, and icy surfaces. The sensor utilizes infrared detectors sensitive to specific wavelengths that correspond to water absorption peaks, enabling the differentiation of surface states based on their infrared signatures. The sensor has proven to be effective in laboratory settings, where it successfully distinguished between dry, wet, icy, and snowy surfaces using a specialized setup that simulates real-world road conditions. The study also discusses the potential for field implementation, suggesting that while the laboratory results are promising, further testing with a ruggedized prototype in outdoor environments is necessary. This would help in understanding the impact of other environmental variables like ambient lighting on the sensor's accuracy and reliability. Overall, the study presents a promising approach towards developing a remote sensing system that could potentially reduce winter road hazards significantly.

CAVs also provide technology for measuring some key parameters or indicators used in WSIs, and these have been discussed in an earlier section.

Several studies have been conducted on the design and implementation of interactive maps or dashboards for communicating road conditions effectively.

Tantillo et al. (2021) conducted an in-depth analysis of the use and implementation of dashboards in transportation management centers (TMCs). Their research covered the evolution of dashboard technologies, their application in monitoring and managing traffic flow, and the significance of data-driven decision-making in transportation network operations. Through a comprehensive review of current practices, the report highlights the diversity in dashboard functionalities, ranging from operational to planning and reporting purposes. It emphasizes the importance of strategic planning, stakeholder engagement, and robust data management in developing effective TMC dashboards. The report also identifies key trends, such as the integration of real-time analytics and the shift towards user-centric designs, offering valuable insights and recommendations for enhancing the efficiency and effectiveness of TMC operations through advanced dashboard systems.

Jamakhandi and Srinivasa (2014) presented an innovative system leveraging internet of things (IoT) principles to monitor and communicate road conditions in real time. Utilizing accelerometers and tilt switches, the system detects road irregularities such as potholes and cracks and uses a combination of GPS and wireless communication to map these on a digital platform through cloud services. This real-time data collection and dissemination system aims to enhance road safety by alerting drivers about upcoming irregularities, allowing for route adjustments and proactive safety measures. The system integrates various technologies to create a feedback loop, offering significant improvements over traditional visual inspection methods for road condition monitoring. The proposed system offers a novel approach to monitoring road conditions and enhancing driver safety and could potentially be expanded for broader applications in vehicle control and infrastructure improvement.

Using images from street and highway cameras across North America, Ramanna et al. (2021) studied the use of convolutional neural networks for near real-time classification of road conditions. The authors developed a comprehensive system integrating image acquisition, classification, and real-time map generation, achieving a high validation accuracy of 90.6% with the EfficientNet-B4 model. Through a multi-phase process of data collection, labeling, and classification, they created a dataset of 47,000 images classified into five classes: dry, wet, snow/ice, poor, and offline. This study demonstrates the potential of deep learning models to significantly enhance road weather monitoring systems by providing extensive, accurate, and timely road condition data.

Magnusson et al. (2019) detailed the creation of a comprehensive road condition map for the European Union, focusing on road friction. Utilizing data from around 500 vehicles over two winter seasons, the study successfully integrated vehicle-derived friction measurements with local weather models to generate a high-resolution friction map. The research found that friction estimations based on longitudinal slip measurements from vehicles are reliable, even in varying weather conditions, and accuracy is enhanced by considering individual vehicle tire characteristics. The study also explored the use of weather models to extend the map's coverage in areas with sparse vehicle data.

In conclusion, the research on technology and mapping solutions for road condition monitoring illustrates significant advancements in data collection, analysis, and dissemination. Studies like those of Tantillo et al. (2021) and Jamakhandi and Srinivasa (2014) demonstrate the evolution of dashboard technologies and IoT-based systems in enhancing transportation management and road safety through real-time data monitoring and communication. The use of advanced techniques, such as convolutional neural networks by Ramanna et al. (2021) and vehicle-derived data for road friction mapping by Magnusson et al. (2019), highlight the move towards more sophisticated and accurate methods of road condition assessment. These studies collectively underscore the potential of technology-driven solutions to revolutionize the way road conditions are monitored, analyzed, and communicated, ultimately contributing to safer and more efficient transportation networks.

CHAPTER 3. SURVEY

3.1. Overview

This chapter presents the comprehensive findings of a survey conducted to understand agencies' stance on WWRCIs and their overall approach to addressing winter weather-related challenges to mobility and safety. The survey, divided into five parts, aimed to gather a broad spectrum of data:

- **Part A** inquired whether the agency deals with any situations caused by or otherwise related to road winter weather conditions.
- **Part B** included general enquiries about agencies' experience in dealing with winter weather road conditions.
- **Part C** asked about agencies' status with respect to the implementation of WWRCIs.
- **Part D** inquired about how agencies are using, managing, or plans to use/manage WWRCIs.
- **Part E** asked how the agency records data on road weather condition indices.

The survey had representation from 24 states. Figure 1 illustrates the states that participated in the survey.

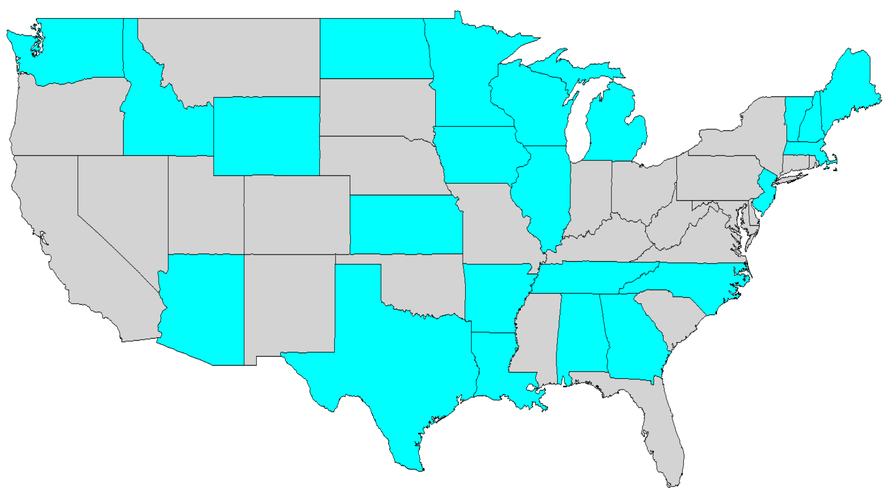


Figure 1. Participating states

The survey included responses from the following states:

- Idaho
- Wisconsin
- Washington
- Alaska
- Tennessee
- Illinois

- Arkansas
- Maine
- Massachusetts
- Texas
- Louisiana
- Michigan
- Minnesota
- Georgia
- Iowa
- North Dakota
- New Hampshire
- New Jersey
- Vermont
- Wyoming
- Kansas
- Alabama
- Arizona
- North Carolina

This chapter details the responses to each question, supported by figures and charts for a clearer understanding of the data.

A summary of survey responses is provided below:

3.2. Part A – Challenge Inquiry

Part A inquired whether the agency deals with any situations caused by or otherwise related to road winter weather conditions.

Q1 - Does your agency deal with any situations caused by or otherwise related to road winter weather conditions?

The survey findings indicated that 100% of the participating state departments of transportation (DOTs) deal with situations caused by or related to road winter weather conditions.

3.3. Part B – Introduction (General Questions)

Part B included general enquiries about agencies' experience in dealing with winter weather road conditions.

Q2 - What road winter weather conditions does you your agency deal with? Please select all that apply.

According to the survey, the most common road winter weather conditions that agencies deal with are **freezing temperatures**, **icy roads**, and **snowfall/snow**. Other conditions also had significant presence in the survey results. Figure 2 shows the distribution of responses.

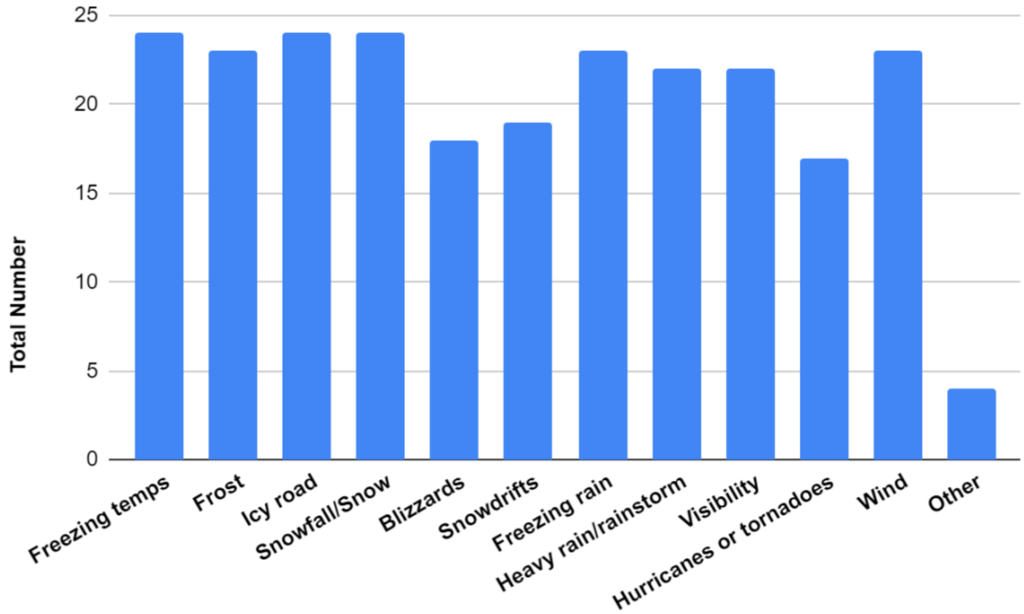


Figure 2. Road winter weather conditions

Respondents were given the option to manually input winter weather conditions that were not included in the question's responses. The following is a list of the inputted conditions:

- Freezing fog
- Flooding (tidal and storm-related)
- Avalanche
- Smoke from wildfires

Q3 - What are the decisions that your agency has to make in response to winter weather conditions? Please select all that apply.

According to the participating agencies, **planning winter maintenance activities** (27%) and **informing the public about winter weather conditions** (26%) were the top decisions they had to make in response to winter weather conditions. Next were **dynamic message sign (DMS)/variable speed limit (VSL) deployment** and **road closures**, making up 25% and 20% of the responses, respectively. Figure 3 shows the distribution of the decisions that agencies make according to the results of the survey.

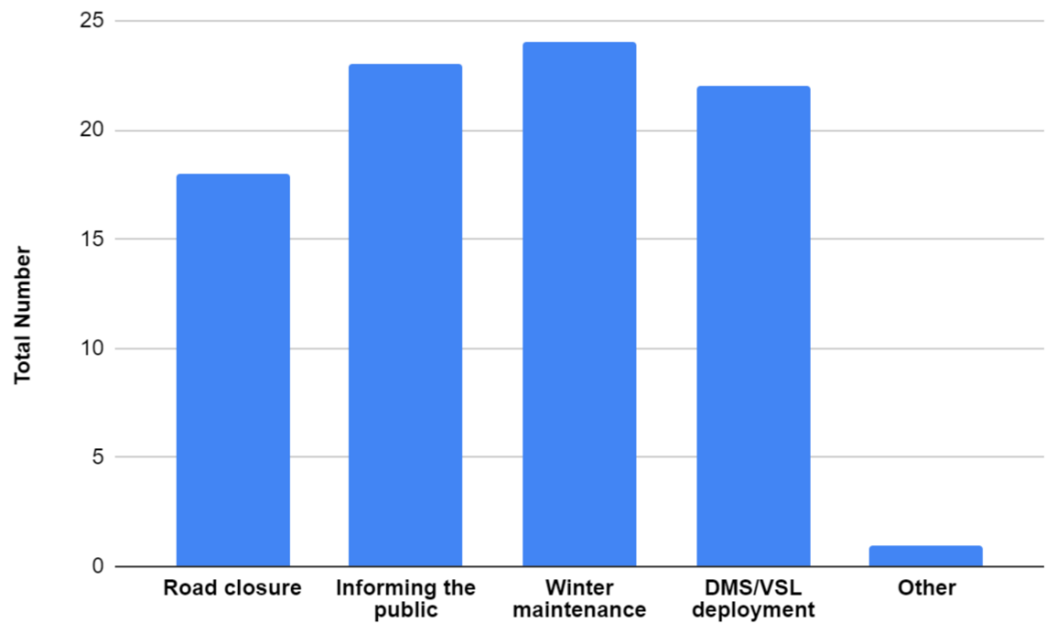


Figure 3. Decisions made in response to winter weather conditions

Respondents were given the option to manually input the decisions their agencies had to make in response to winter weather conditions that were not included in the options. The following is a list of the inputted conditions:

- Snowplows with automatic vehicle location (AVL)

3.4. Part C – Questions about Index

Part C asked about agencies' status with respect to the implementation of WWRCIs.

Q4 - Does your agency implement or is in the process of developing a winter weather road condition index?

Out of the 24 participating agencies, only 6 agencies currently have and are implementing a WWRCI. Eleven agencies indicated that they do not have a WWRCI, while 7 agencies indicated that they are currently in the process of developing their index. Figure 4 shows this distribution.

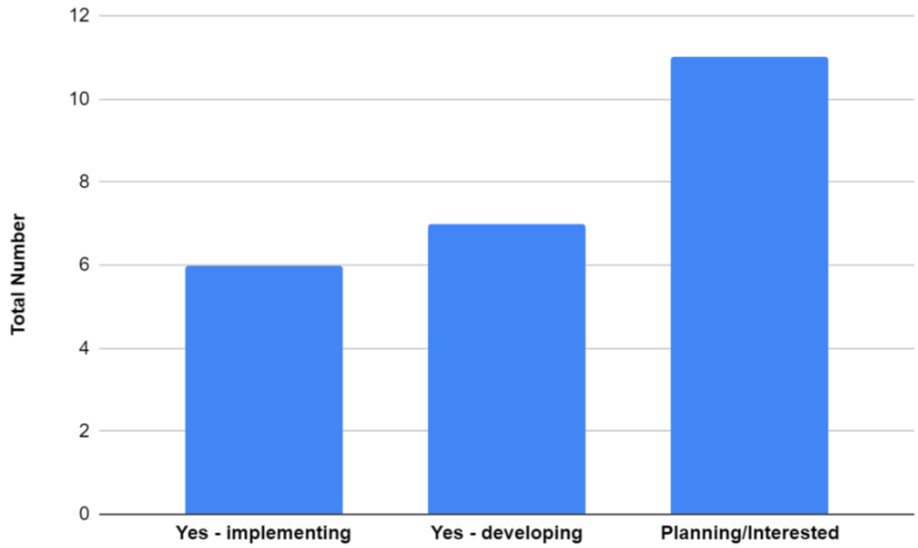


Figure 4. Agencies' status with respect to WWRCIs

Q5 - Which of the following statements best describes your agency's winter weather road condition index?

Of the agencies that participated in the survey, 54% indicated that their condition index was more of a **post-storm index for post-storm analysis and performance measures and to compare with similar storms**, 46% specified that their index was a **during-storm index to monitor winter weather conditions**, and 15% indicated that their index was a **pre-storm index to help prepare for winter weather condition.** Figure 5 shows this distribution.

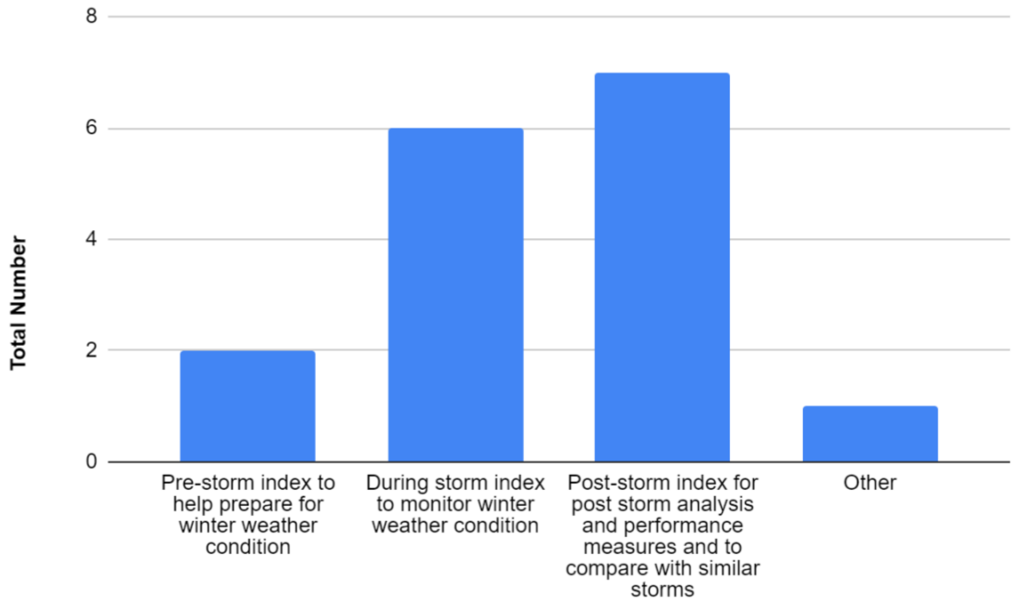


Figure 5. Description of agencies' winter weather condition indices

Respondents were given the option to manually input the best description of their agencies' winter weather condition index that were not included in the options. The following is a list of the additional descriptions:

- Mostly a seasonal index. Also one specifically for salt use.

Q6 - What are the attributes used in your agency's winter weather road condition index? Please select all that apply.

Q7 - What are the attributes that your agency plans to use in the development of the winter weather road condition index? Please select all that apply.

Q11 - If your agency were to implement a winter weather road condition index, what attributes would be of interest to include or cover within the index? Please select all that apply.

With regards to attributes of interest in formulating WWRCIs, **road surface conditions** (20) is the most common attribute, followed by **precipitation type** (18) and **pavement temperature** (18). Agencies do not or are not considering time of day in their indexes. Figure 6 shows the distribution of the attributes of interest.

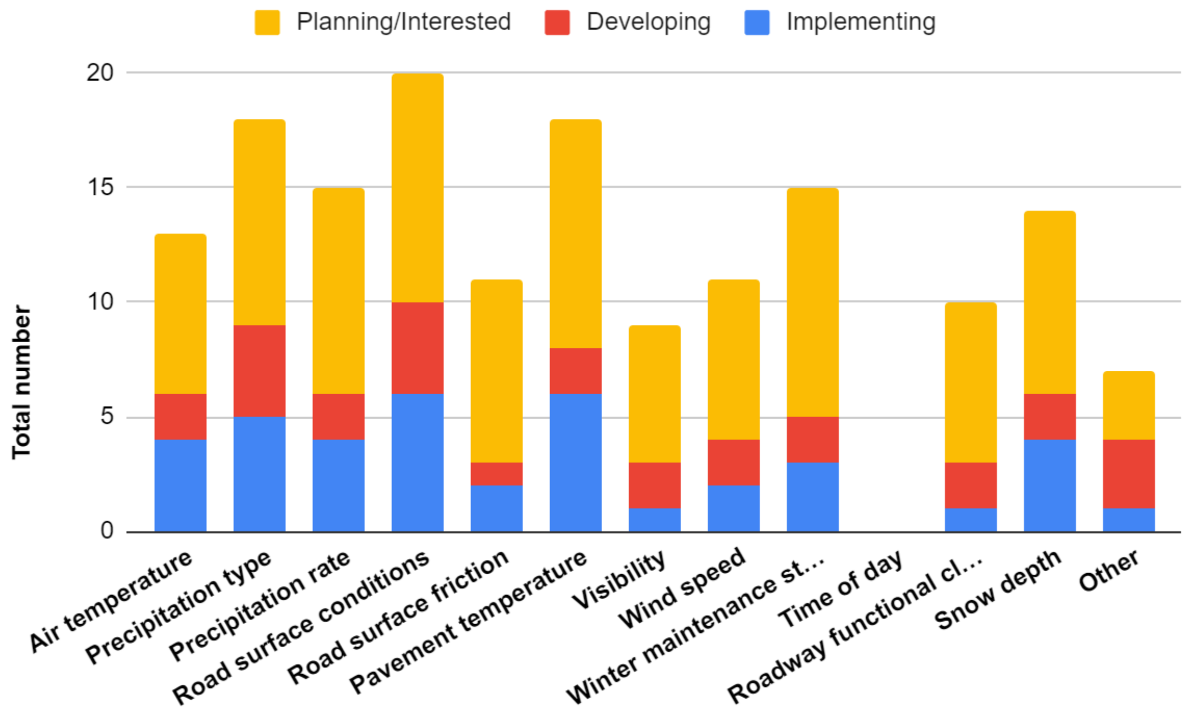


Figure 6. Attributes of agencies' WWRCIs

Out of the agencies that are currently implementing a WWRCI, the most common attributes are **road surface conditions** (6) and **pavement temperature** (6).

For agencies that are in the process of developing a condition index, the most common attributes are **road surface conditions** (4) and **precipitation type** (4).

Road surface conditions (10), **pavement temperature** (10), and **winter maintenance status** (10) are the most common attributes considered by agencies that plan to develop a WWRCI in the future.

Respondents were given the option to manually input the attributes of interest considered when formulating WWRCIs that were not included in the options. The following is a list of the additional descriptions:

- Road images from fixed and plow-mounted cameras
- Speed maintenance (70% of the prevailing speed limit in non-impacted weather on the same road)
- Roadway is included but separately, in a roadway metric. For salt, the weather part and the road part are eventually combined but are separately developed.
- Normalized storm severity

Q8 - What post-storm indicators is your agency using or would be interested in? Please select all that apply.

Q12 - What post-storm indicators would your agency be interested in?

With regards to post-storm indicators that are of interest to agencies, 23 of the respondents selected **resource utilization**, while **road recovery time** and **traffic flow impact** were each selected 18 times. These three post-storm indicators were the most common both for agencies that are currently implementing and developing indices and for agencies that do not currently have indices. Figure 7 shows the distribution of the rest of the responses.

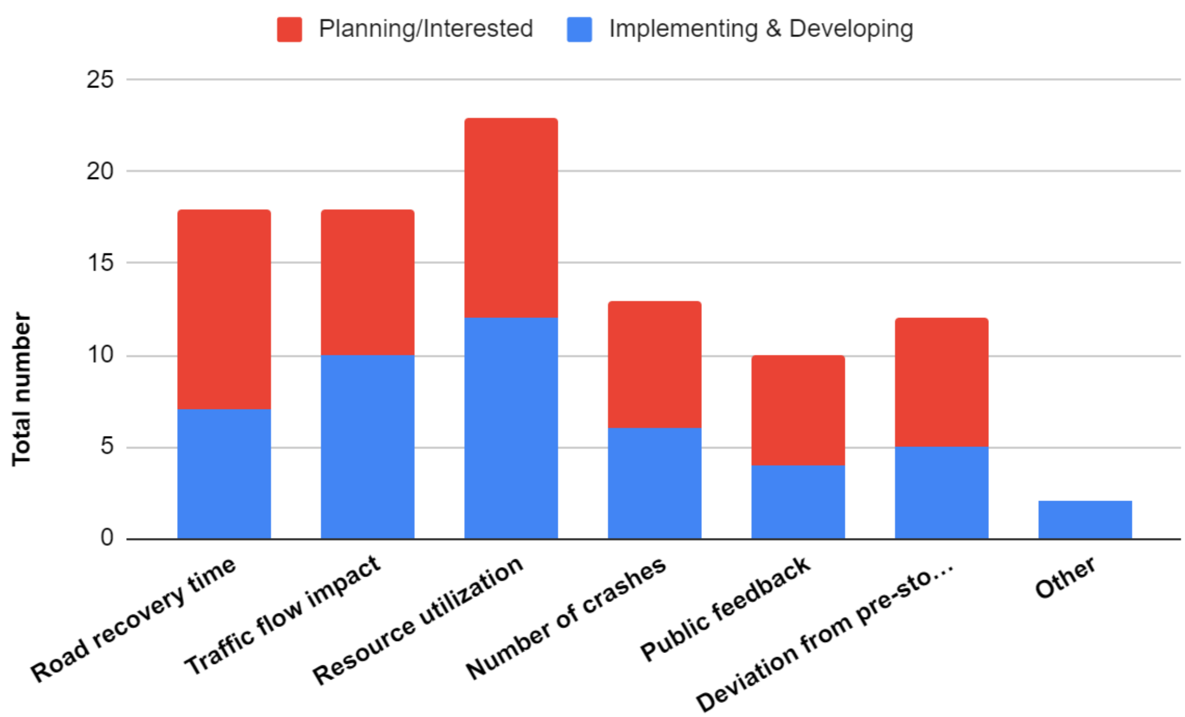


Figure 7. Post-storm indicators

Respondents were given the option to manually input post-storm indicators that were of interest to their agencies that were not included in the options. The following is a list of the additional descriptions:

- Water or ice/snow layer on freezing pavement
- Storm severity and seasonal (winter) severity; we use the latter to index seasonal salt usage

Q9 - What other attributes could be added to your agency's winter weather road condition index to improve it?

Respondents were asked to indicate which attributes they think could be added to their agency's WWRCI in order to improve it. The following are the list of responses:

- Exploring performance metrics related to "performance during storm" and return to normal traffic speeds
- Crowdsourced data from automakers that is making its way to the marketplace
- We are working on an index that can be run on a forecast to quantify expected conditions.
- Freezing rain
- Winter maintenance status (plowed/unplowed/treatment)
- N/A

Q10 - Would your agency consider implementing a national or a regional weather index if it exists? Please provide reason(s) why or why not.

The participants of the survey were asked whether they would consider implementing a national or regional weather index. Fifteen of them indicated that they would consider adopting a **regional weather index** (38%), three indicated that they would consider adopting a **national weather index** (8%) and sixteen, the majority, indicated that they would prefer neither (41%). Figure 8 shows this distribution.

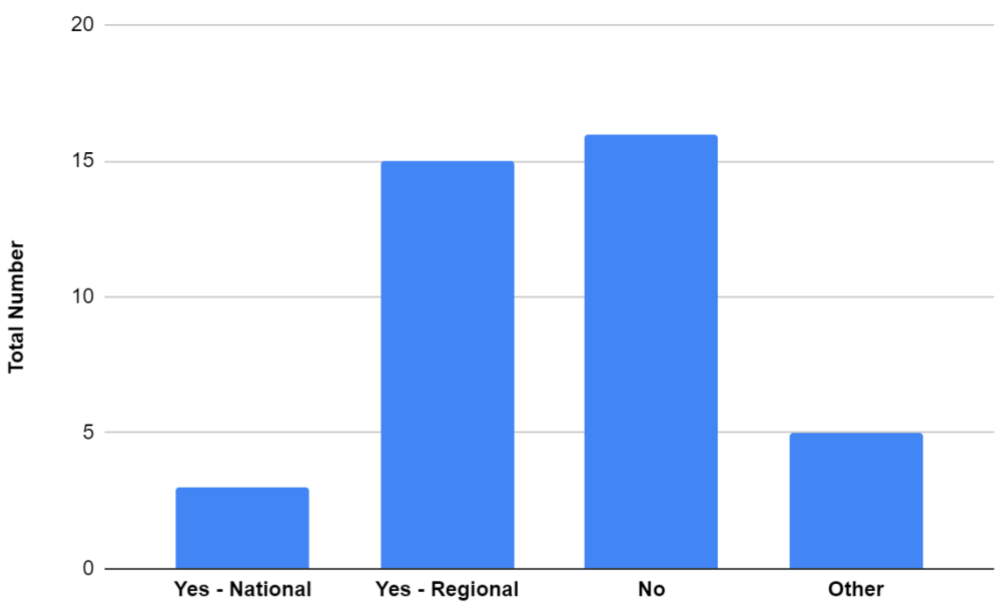


Figure 8. Agencies consideration for adopting a national or regional weather index

The survey required respondents to provide reasons for selecting either option. The following is a list of reasons for considering a national weather index:

- We would be willing to work with other states. Especially with metrics that may assist in benchmarking across our state, region, and nationwide. Also interested in metrics that might improve communications with the public.
- I would prefer a national system because truck drivers are not interested in regional information and only care about true comparisons from one area to another.
- Also or regional. Mainly for context. Would adopt for our own if it outperforms our own.

The following is a list of reasons for considering a regional weather index:

- I believe we are more aligned with our neighbors with weather conditions and expectations.
- National seems far too broad.
- A regional index seems that it would be more applicable than a national index given that there are so many variables across the whole nation.
- Regional makes more sense. Northeast snow is usually different than Midwest snow.
- It is difficult to define a meaningful index.
- We would like to look at it first.
- Potentially region-specific index could be implemented (Midwest).

No reason was provided for choosing not to consider either a national or regional weather index.

The following is a list of reasons for respondents who selected the **other** option:

- Maybe depending on what the index is. We are comfortable with the index we are currently using.
- I believe we are already doing so.
- Georgia winter weather is extremely variable and circumstantial. We would consider a regional implementation but this would be similar to utilizing National Weather Service (NWS) scales and indices.
- We may need an Alaska specific index as our climate zones are maritime to arctic.
- Not familiar with weather index specifically.

3.5. Part D – Index Use and Management

Part D inquired about how agencies are using, managing, or planning to use/manage WWRCIs. It addresses agencies that are currently implementing or are in the process of developing a WWRCI.

Q13 - Which divisions/offices/units of your agency use or plan to use the winter weather road condition index? Please specify.

The following are the responses to the above question:

- All of operations
- Regional traffic management center
- Operations
- Transportation: Maintenance and operations
- TMC
- The Highway Operations and Maintenance division is most interested/applicable.
- Maintenance Bureau is the main user, but is used with field staff, field management, executive management, and one index also has a public page.
- The Bureau of Maintenance. Division of Operations, executive staff with performance measures.
- Maintenance division, district offices, maintenance sections.
- Maintenance.
- Maintenance, districts, communications, transportation systems management and operations (TSMO), TMC.
- Bureau of Operations.
- Traffic operations, maintenance.

Q14 - Who are the primary targeted audience or stakeholders of your agency's winter weather road condition index? Please select all that apply.

According to the survey, the **first responders** (6), **emergency managers** (6), and **511** (6) are the most common primary targeted audience or stakeholders of WWRCIs, closely followed by **truck drivers (5)** and **schools (3).** Figure 9 shows this distribution.

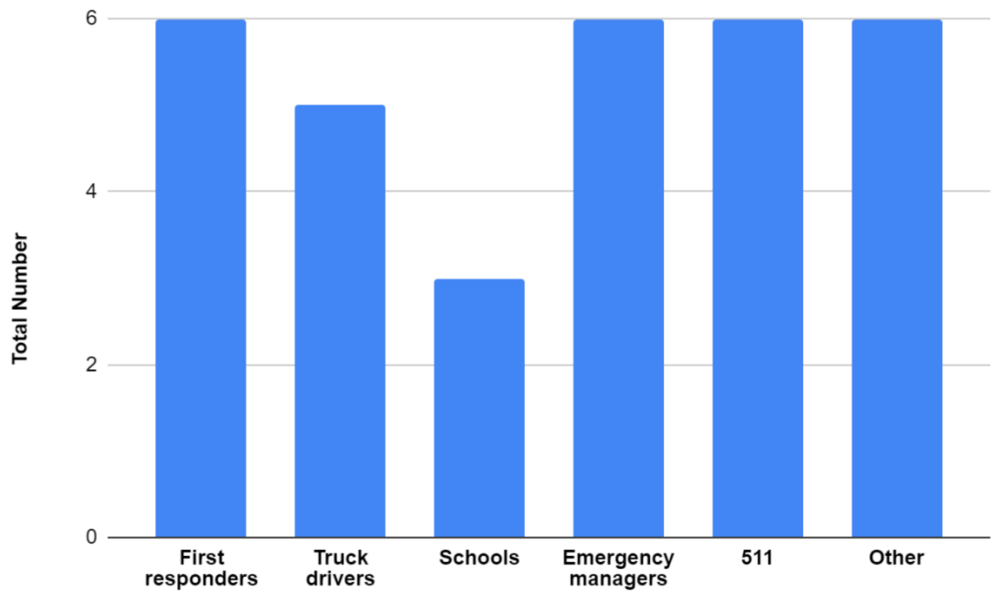


Figure 9. Primary targeted audience for WWRCI

Respondents were given the option to manually input other primary targeted audiences or stakeholders of their agencies' WWRCIs that were not included in the options. The following is a list of the additional primary targeted audiences or stakeholders:

- All drivers
- The index would be useful to keeping track of which roads need attention. I'm more interested in using this information internally to inform maintenance decisions.
- Mostly internal audience, media, or governor's staff.
- Executive staff and performance measures
- New Hampshire Department of Transportation (NHDOT)
- Public

Q15 - In what capacity does/will your agency use the winter weather road condition index?

According to the survey, agencies mainly use their WWRCIs for **advisory** (10) purposes. No respondent chose **regulatory** as a use for its index. Figure 10 shows this distribution.

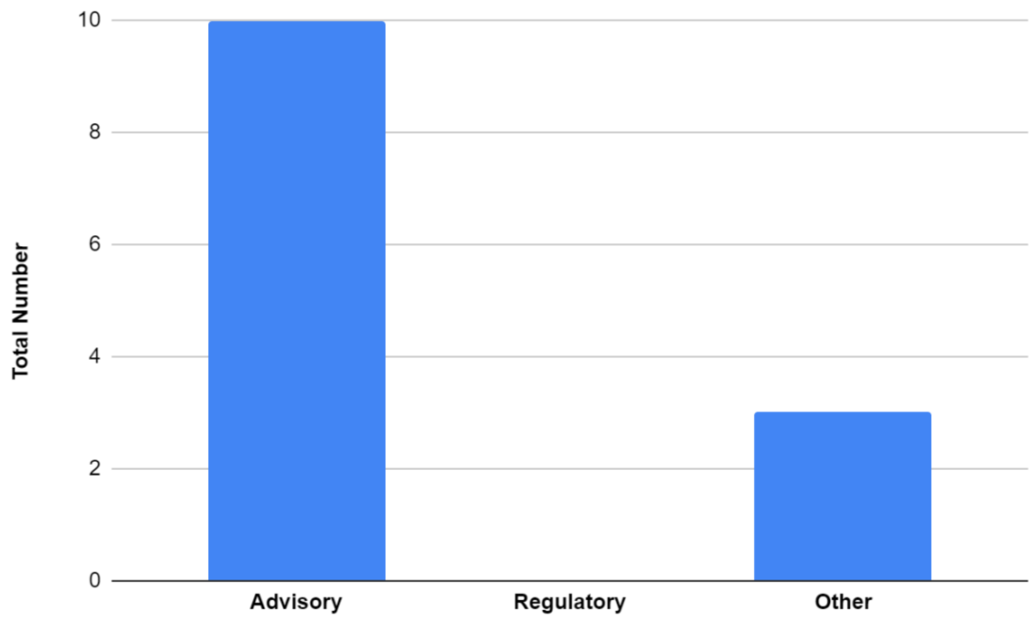


Figure 10. Primary use of WWRCI

Respondents were given the option to manually input other uses for their agencies' weather condition indices. The following is a list of the responses:

- To inform the need for treatment.
- Our index is not required by anyone, but we use it for our own purposes.
- Performance measures.

Q16 - Does your agency monitor/plan to monitor the impact of using its winter weather road condition index on any of the following?

The survey revealed that agencies plan to monitor the impact of using WWRCIs on some factors. According to the survey, the most common factors were **winter weather response efficiency** (5) and **traffic congestion** (4). Figure 11 shows the distribution for all factors.

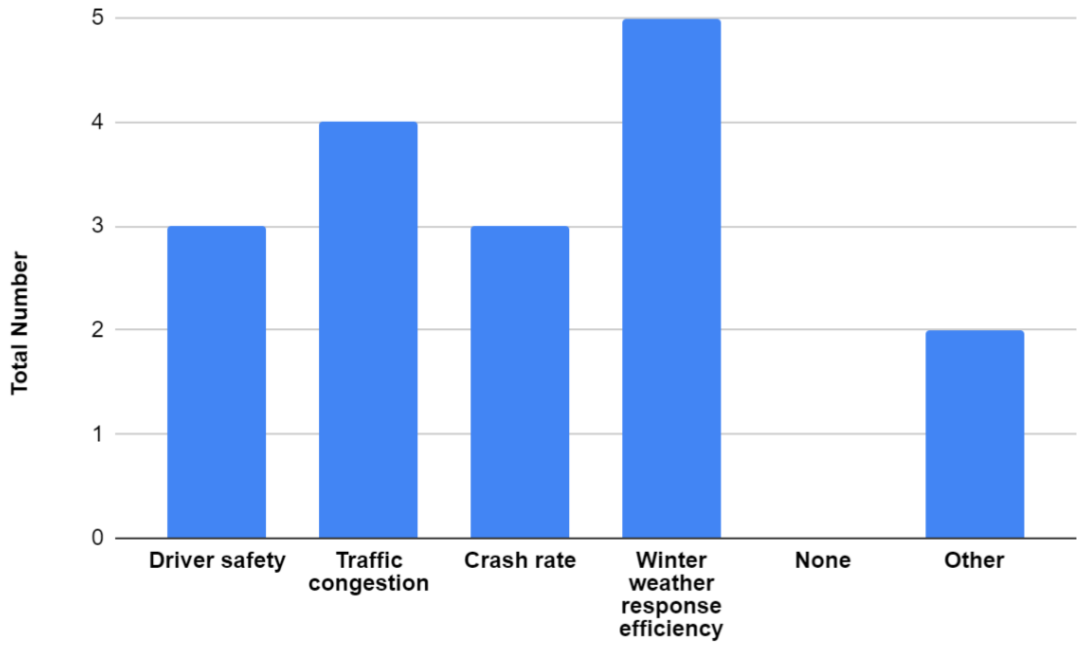


Figure 11. Impact of WWRCI on various factors

Respondents were given the option to manually input other factors that were not included in the options. The following is a list of the responses:

- Budget
- Not sure how we would use it

Q17 - Has your agency received any feedback from the users (or stakeholders) of the winter weather road condition index?

According to the survey, four agencies have received feedback from users or stakeholders on their WWRCIs. Figure 12 shows this distribution.

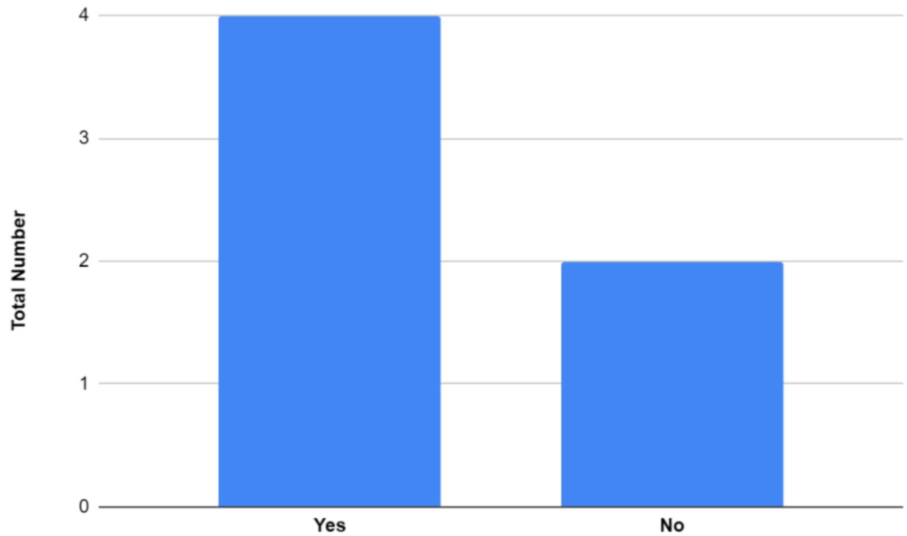


Figure 12. Feedback from users on WWRCI

Q18 - What feedback has your agency received regarding its winter weather road condition index?

According to the survey, out of the four agencies that have received feedback from users or stakeholders on their WWRCIs, all received positive feedback. Figure 13 shows this distribution.

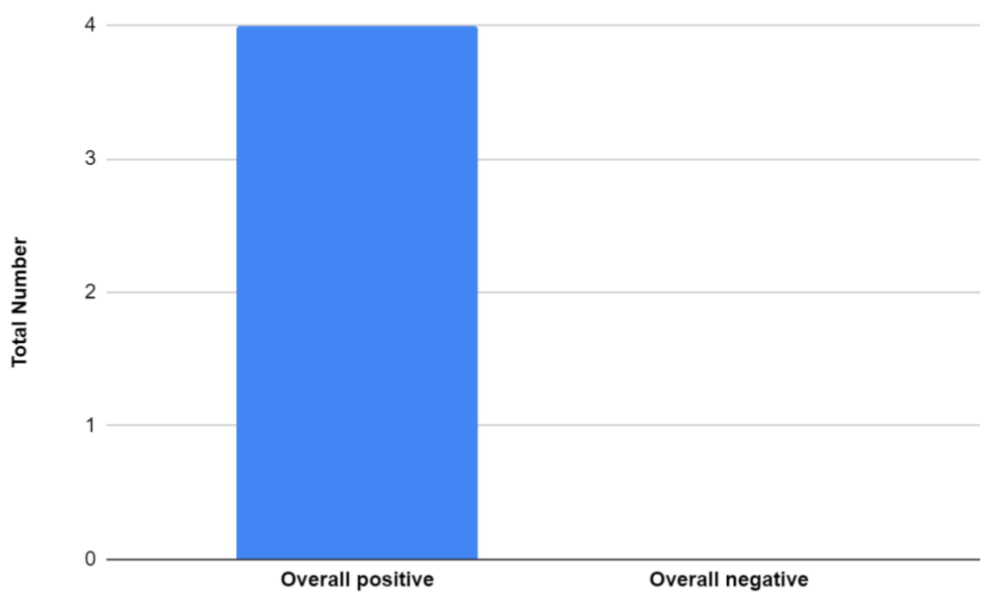


Figure 13. Type of feedback

Q19 - Please select all the options that best describe the received feedback. Feel free to add other relevant feedback in the Other option.

According to the survey, four respondents said their agency's **index was useful**, one said it was **positive yet complicated**, and two said it **needed more attributes**. Figure 14 shows this distribution.

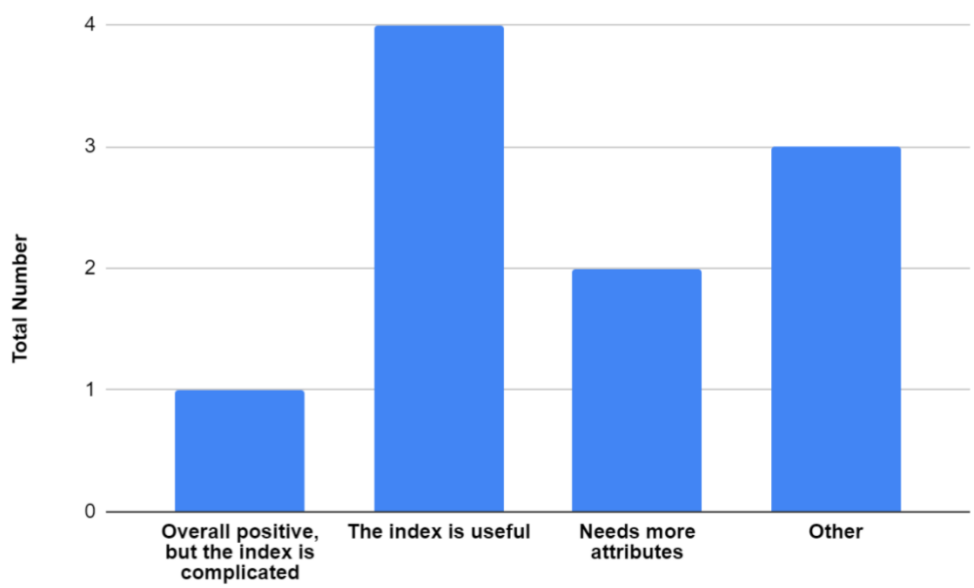


Figure 14. Description of feedback

Three respondents selected the "other" option and were given the opportunity to input their own feedback. The following are the responses received from those respondents:

- Goal is to get to future conditions for travel planning.
- The index depends upon observations that may be dated (up to 2 hours old). We pay attention to real-time RWIS and camera data too.
- We have used it for many years so people are used to it.

Q21 - What attributes were indicated by the users to be added to or used by the index? Please specify

According to the survey, respondents recommended adding the following attributes:

- Plow images
- Varying degrees of impact were requested. Descriptors such as "slippery in spots" were added.

3.6. Part E – Index Documentation

Part E asked how the agency records data on road weather condition indices.

Q22 - Does your agency share data on road winter weather conditions with other state DOTs?

According to the survey, 15 agencies share their road winter weather condition data with other state DOTs, while 9 agencies do not. Figure 15 shows this distribution.

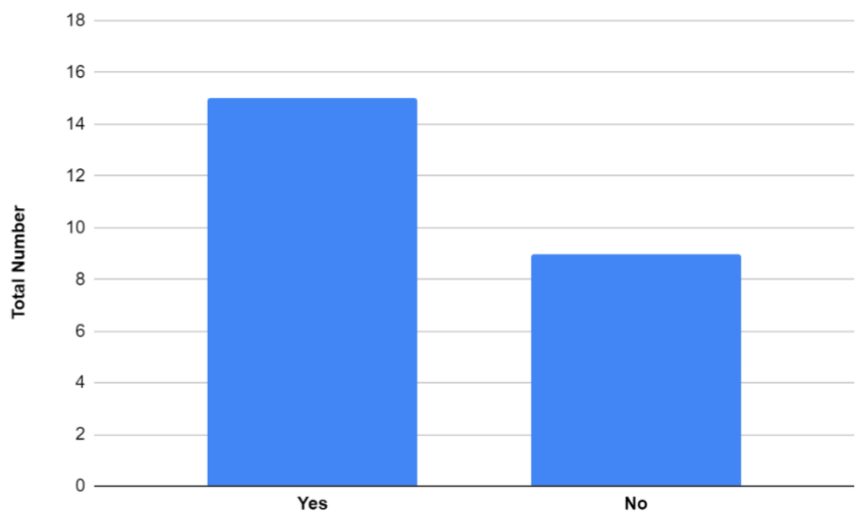


Figure 15. Sharing road winter weather condition data with other state DOTs

Q23 - What type of data or information related to road winter weather conditions does your agency share? Please list.

Respondents were asked to list the type of data or information related to road winter weather that their agencies share. The following is the list of responses:

- RWIS information. Available through weather exchange.
- 511, DMS boards, social media.
- Just road conditions, closures, traffic-related things.
- I would say anything that we have available that would be of interest to other entities.
- We will share anything requested at the state or municipal level.
- All information is available.
- Our RWIS data is shared through Clarus/MADIS.
- 511 road condition data.
- We share the weather data through MADIS with the National Oceanic and Atmospheric Administration (NOAA).

- We share information via peer exchanges but do share live updates such as spring road openings and Alaska highway conditions with our closest neighbor, the Yukon Territory.
- DriveTexas.org road conditions.

Q24 - Is there any available documentation for your agency's index that you could share?

According to the survey, eight agencies had available documentation for their index that they could share. Five agencies did not have documentation that they could share. Figure 16 shows this distribution.

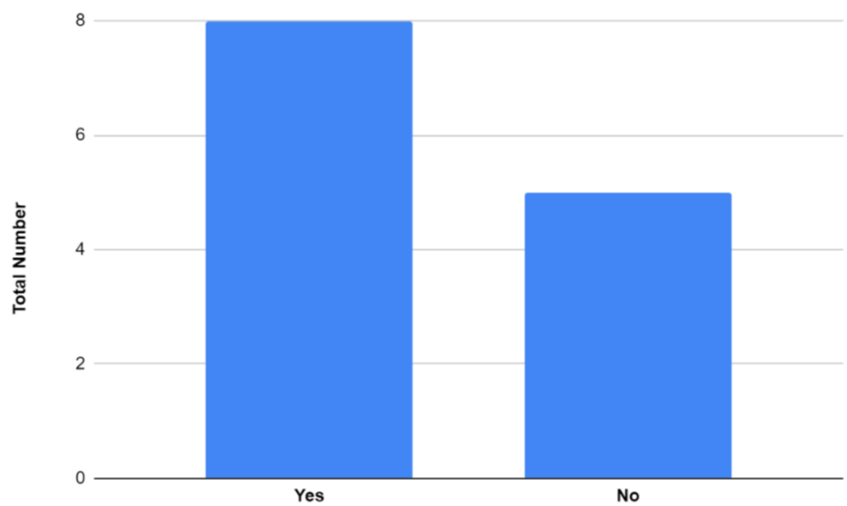


Figure 16. Available documentation on WWRCI that can be shared

Q25 - How could this documentation be shared with us?

According to the survey, **providing contact addresses to request documentation** on the agency's index was the most common mode of sharing the documentation (6). Figure 17 shows the distribution of how documentation can be shared.

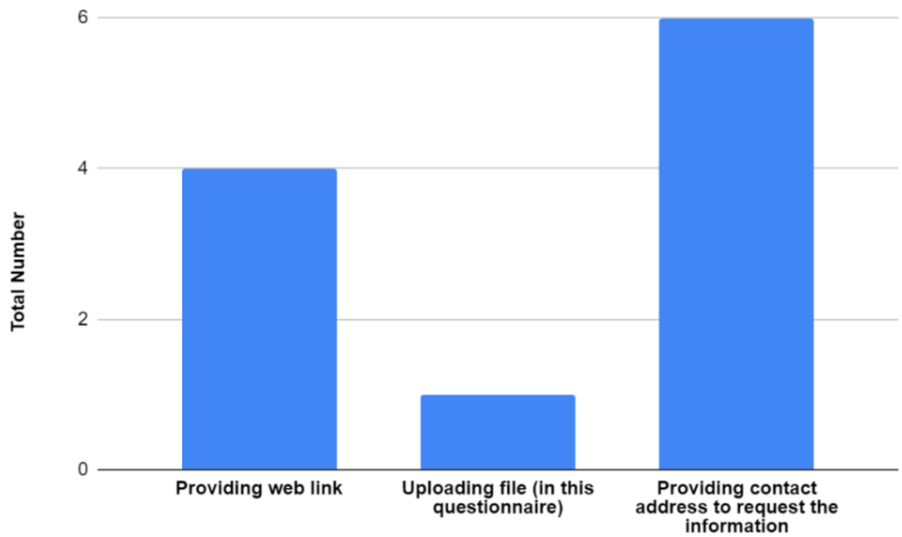


Figure 17. Medium in which WWRCI documentation can be shared

3.7. General Conclusions from the Survey

The purpose of the survey was to evaluate state DOTs' stance on WWRCIs. The study, which encompassed 24 states, focused on a number of important topics, such as challenges associated with winter weather, the implementation and management of road winter weather indices, and the possibility of implementing regional or national indices. The comprehensive results emphasize the state DOTs' broad expertise and variety of strategies for handling winter weather conditions, as well as their decision-making processes, their current status, and their future plans for implementing winter weather condition indices.

The most common challenges resulting from winter road weather conditions were freezing temperatures, icy roads, and snowfall, according to all participating state DOTs. This emphasizes how crucial it is to have efficient plans in place to control how winter weather affects mobility and road safety. The agencies prioritize planning winter maintenance activities and informing the public about current conditions. Decisions such as deploying dynamic message signs, variable speed limits, and road closures are also common, reflecting a proactive approach to mitigating the adverse effects of winter weather.

The survey also focused on the implementation and development of WWRCIs. Though few organizations have an active winter weather condition index at the moment, many are either creating one now or are thinking about implementing one in the future. The indices are used for pre-storm planning, during-storm surveillance, and post-storm analysis. These indices improve road safety and efficiency during winter weather events by assisting agencies in real-time road condition assessment and more efficient response planning.

An important finding from the survey is the preference for regional weather indices over national ones. Many agencies expressed interest in regional indices due to the varied weather conditions across different regions. This preference suggests that regional indices are perceived to be more relevant and applicable to local conditions. Agencies are willing to work together to enhance communication and improve performance metrics. By working together, it may be possible to create more accurate and customized winter weather condition indices that cater to local/regional demands.

The survey also explored the usage and management of these indices. The maintenance and operations divisions within agencies are the primary users of the indices, utilizing them for advisory purposes rather than regulatory enforcement. First responders, emergency management personnel, and the general public are the main stakeholders, highlighting the importance of these indices in ensuring prompt and accurate information distribution during winter weather events.

Data-sharing and documentation practices were also examined. Many agencies share winter weather road condition data with other state DOTs and have documentation available for sharing. This practice facilitates knowledge exchange and the development of best practices across states, contributing to improved winter weather management nationwide.

In summary, the survey reveals the strong engagement of DOTs with winter weather challenges, a growing interest in developing and refining weather condition indices, and a preference for regional collaboration to address the unique weather patterns across different states. The results highlight the significance of ongoing initiatives to strengthen road safety, develop winter weather response plans, and preserve mobility in inclement weather.

CHAPTER 4. EVALUATION OF EXISTING INDICES

4.1. Overview

Building upon the extensive literature review conducted in Task 1 (Chapter 2) and the insightful survey findings from Task 2 (Chapter 3), Task 3 of this project focused on a detailed evaluation of existing WWRCIs. These indices, used across various state and local transportation agencies, are essential for assessing the effectiveness, applicability, and reliability of road condition reporting during winter. The primary goal of this evaluation was to identify the strengths and weaknesses within current indices, exploring their potential for establishing a cohesive, nationwide standard. Such a standard could better support both transportation agencies and the public in managing winter road conditions effectively.

This evaluation systematically reviewed 19 indices, drawn from an extensive set of over 49 studies. Each index reflects specific geographic, operational, or climatic needs, integrating key variables—like temperature, snowfall, wind speed, and visibility—to address distinct winter challenges. Applied at state, regional, and national levels, these indices have evolved from simple models based on basic meteorological data to complex frameworks that leverage sources, such as RWIS and CV data. By analyzing common factors, rating scales, and trigger thresholds, this evaluation aimed to identify the best practices and shared metrics that could form the basis for a reliable and accurate framework. Additionally, the analysis considered each index's adaptability across regions and its suitability in varied weather scenarios, ensuring relevance for stakeholders across different climates. Together, these insights will help establish a foundation for a robust national standard in winter weather road condition assessment.

These 19 indices encompass a broad range of winter severity and weather severity indices developed across various states and regions in the US, as well as Canada and parts of Europe, over several decades. Each index was designed to address specific transportation challenges related to winter weather, focusing on aspects like road safety, maintenance planning, and budget forecasting.

The development of these indices spans from the early 1980s to 2024. They reflect an evolving understanding of winter weather impacts on transportation infrastructure. The earliest studies, such as those in Illinois (Cohen 1981) and under the Strategic Highway Research Program (Boselly et al. 1993), laid foundational models, while later studies like the Vermont Winter Maintenance Performance Index (Dowds and Sullivan 2022) and Illinois Winter Severity Index Model (Qi and Velpur 2024) show the ongoing refinement and sophistication of such indices. The later ones incorporate advancements in data collection technology.

The WSIs and weather impact studies exhibit a diverse geographic scope. They cover multiple US states and entire regions and extend to national applications in Canada and Finland. Many studies are state-specific, such as Illinois' early snow removal budget model, Iowa's winter weather index, and Indiana's climatic zone analysis, which focus on localized factors impacting state DOT operations. Other indices, like New York's Weather Severity Index (Chien et al. 2014), utilize micro-zoning (1 km by 1 km areas) to offer finely tuned data for decision-making across varied regional climates. Canadian studies (Suggett et al. 2006) rely on nationwide data provided by the Meteorological Service of Canada (MSC) and address broad winter maintenance challenges across provinces. Regional indices, such as those in Oklahoma (Balasundaram et al. 2012) and Idaho (Jensen et al. 2013), capture winter's impact on transportation within specific weather patterns, while multi-state studies, including in California, Oregon, and Montana (Strong and Shvetsov 2006), facilitate comparative assessments for wider-reaching transportation strategies. This wide geographical range highlights the importance of tailored winter indices for managing transportation safety and budget forecasting in regions with varied winter climates and weather events.

The indices identified in Task 1 are summarized in Table 3.

Table 3. List of indices identified in Task 1

Title	Authors & Affiliation	Year	Geographic Location
User-Oriented Climatic Information for Planning a Snow Removal Budget	Cohen (1981), Illinois State Water Supply and University of Illinois	1981	Illinois (statewide)
Road Weather Information Systems Volume 1: Research Report	Boselly et al. (1993), Strategic Highway Research Program	1993	Nationwide (US)
A Winter Weather Index for Estimating Winter Roadway Maintenance Costs in the Midwest	Carmichael et al. (2004), Iowa State University	2004	Iowa
Indiana Winter Severity Index	McCullough et al. (2004), Purdue and Indiana Department of Transportation	2004	Indiana (four climatic zones)
Developing a Storm Severity Index	Nixon and Qiu (2005), University of Iowa	2005	Iowa
Development of Winter Severity Indicator Models for Canadian Winter Road Maintenance	Suggett et al. (2006), Various	2006	Canada (nationwide with MSC data availability)
Development of Roadway Weather Severity Index	Strong and Shvetsov (2006), Montana State University	2006	California, Oregon, Montana
Proactive Approach to Transportation Resource Allocation Under Severe Winter Weather Emergencies	Balasundaram et al. (2012), Oklahoma State University & University of Oklahoma	2012	Oklahoma
Ensuring and Quantifying Return on Investment Through the Development of Winter Maintenance Performance Measures	Jensen et al. (2013), ITD	2013	Idaho
Road Weather Information System Statewide Implementation Plan	Chien et al. (2014), New Jersey Institute of Technology	2014	New York State (with micro-zones of 1 km by 1 km)
Winter Severity Index Development	Hoffman et al. (2014), GHD, Inc.	2014	Pennsylvania

Title	Authors & Affiliation	Year	Geographic Location
RoadSurf: A modelling system for predicting road weather and road surface conditions	Kangas et al. (2015), Finnish Meteorological Institute	2014	Finland
Learning to Use Less Salt Without Compromising Safety (Annual Winter Maintenance Report)	WisDOT (2014)	2014	Wisconsin
The Accumulated Winter Season Severity Index (AWSSI)	Boustead et al. (2015), University of Nebraska	2015	Nationwide (US)
Winter Maintenance Performance Measure	Walsh (2016), Vaisala Inc.	2016	Colorado
Developing a Department of Transportation Winter Severity Index	Walker et al. (2019b), Various	2019	Nebraska
Development of a Surface Transportation Impact Factor for Winter Severity Indices	Thomas et al. (2021), Various	2022	Missouri
Quantifying Correlations Between Winter Severity, Road Conditions, and VTrans' Snow and Ice Control Activities	Dowds and Sullivan (2022) (University of Vermont Transportation Research Center)	2022	Vermont
Nonlinear Modelling of The Association Between Winter Weather Severity and Maintenance Expenditures	Qi and Velpur (2024), Southern Illinois University	2024	Illinois

4.2. Assessment of Existing Indices

4.2.1. Strengths and Weaknesses

Each index integrates unique parameters and data sources to address the challenges posed by winter conditions, from real-time monitoring to long-term maintenance planning. However, despite their effectiveness at local levels, these indices exhibit both strengths and limitations, which impact their scalability and potential for integration into a standardized national framework.

First, it should be noted that most of the indices listed in Table 3 are better classified as weather condition indices rather than road condition indices, overwhelmingly developed to guide winter maintenance operations. The majority of the discussed indices primarily quantify atmospheric conditions such as snowfall, temperature, wind speed, and storm severity rather than the state of the roadway surface and weather events in their capacity to affect traffic safety and mobility. For instance, indices such as Cohen (1981) and Boustead et al. (2015) focus on winter weather severity, providing insights into climatic trends that impact roadway maintenance but do not measure surface friction, ice accumulation, or roadway traction directly. Similarly, indices like McCullough et al. (2004) and Nixon and Qiu (2005) assess storm severity and winter maintenance costs, but they rely on meteorological inputs rather than real-time or semi-real-time roadway conditions. While some studies, such as Thomas et al. (2021), link winter weather severity to transportation impacts, they still primarily utilize weather-based inputs rather than data elements that represent driving conditions typically obtained from sensors, plow reports, or vehicle traction data. A true road condition index would incorporate both meteorological and road-condition dimensions, incorporating pavement temperature, ice thickness, skid resistance, and friction data besides traditional meteorological data such as wind speed, air temperature, precipitation, humidity, ultraviolet (UV) radiation level, and the like. This approach would enable the index to directly assess hazardous conditions, something that these indices generally lack. Therefore, given these discussions, we can reiterate that these indices are better classified as weather-based severity indices that inform winter maintenance planning rather than roadway conditions for traffic safety and mobility.

In assessing the strengths and weaknesses of existing WWRCIs, we identified several key factors—regional customization, parameter inclusion, data availability, reliability, operational utility, performance measurement, potential biases, and standardization—to structure a thorough evaluation. These factors emerged from insights gathered in Task 1's literature review, where we analyzed a broad range of studies and WWRCI applications, and from Task 2's survey of state agencies, which provided practical feedback on index use and implementation challenges. Subsequently, in Task 3, the in-depth review of the studies from Task 1 highlighted common elements among WWRCIs, such as the critical role of local climate conditions, parameter variability, and data source reliability, in determining each index's effectiveness. This review helped pinpoint where indices have succeeded in addressing winter-specific challenges (e.g., real-time monitoring, integration of RWIS data) and where gaps persist, especially in adaptability and standardization across different regions. Task 2 further informed the selection of factors by revealing agency concerns over limited data coverage and the desire for comprehensive integration of reliable meteorological, traffic, and crash data.

Combining these insights, we structured the evaluation around factors that capture both the practical strengths of WWRCIs in supporting winter maintenance and the barriers to achieving a cohesive, national approach. Table 4 presents these findings, offering a comparative view of how different indices manage challenges and opportunities within their regional contexts. This approach provides a foundation for identifying best practices and areas for improvement as we move toward developing a standardized framework for winter weather road condition assessment across varied climates.

Table 4. Strengths and weaknesses

Assessment Aspect	Strengths	Weaknesses	Examples
Regional Customization	Tailored to local climatic conditions, increasing relevance and effectiveness.	Limited applicability to other regions with different climatic conditions.	**Strength**: Iowa Winter Weather Index (Carmichael et al. 2004); NEWINS (Walker et al. 2019b). **Weakness**: Limited scalability for a national approach.
Comprehensive Parameter Inclusion	Incorporates a broad range of meteorological and operational parameters, giving a holistic view of conditions.	Variability in parameters across indices hinders standardization.	**Strength**: MoDOT WSI (Thomas et al. 2021) includes freezing rain, sleet, snowfall, visibility, and wind speed.
Utilization of Reliable Data Sources	High accuracy and reliability from using authoritative data sources like NWS, RWIS, and automated surface observing system (ASOS) units.	Some indices rely on data sources with gaps or inconsistencies, reducing reliability.	**Strength**: Idaho Winter Maintenance Performance Measures (Jensen et al. 2013); Vermont Winter Maintenance Performance Index (Dowds and Sullivan 2022). **Weakness**: Illinois WSI (Cohen 1981) due to moderate data reliability.
Operational Utility	Provides real-time data, supporting immediate decision-making and response during winter events.	Technological limitations may prevent some regions from fully utilizing advanced data integration, requiring significant infrastructure investment.	**Strength**: RoadSurf system in Finland (Kangas et al. 2015) offers real-time and forecasted data. **Weakness**: Advanced indices pose challenges for agencies with limited infrastructure.
Performance Measurement	Links severity with performance metrics, allowing for winter maintenance evaluation and improvements.	Limited standardization means these performance metrics vary widely across regions, making comparisons difficult.	**Strength**: Idaho Winter Maintenance Performance Measures (Jensen et al. 2013); Vermont Winter Maintenance Performance Index (Dowds and Sullivan 2022).
Potential Biases	-	Indices developed with localized data may introduce biases, potentially reducing accuracy in broader applications.	**Weakness**: Biases could emerge if indices are applied outside their original regional scope.
Lack of Standardization	-	Significant variability in parameters, scales, and thresholds, making integration across regions difficult.	**Weakness**: This variability affects the potential for a standardized national approach.

Task 2 provided valuable insights into the use of existing data sources by state agencies. For instance, the survey revealed that RWIS and meteorological data are commonly employed but often suffer from coverage limitations. Agencies expressed a desire for better data integration and access to more reliable traffic and crash data. These survey insights emphasize the challenges and opportunities identified in this section.

4.2.2. Factors and Scales Used to Rate Road Conditions

Accurately assessing road conditions during winter weather is critical for ensuring driver safety and effective maintenance planning. The effectiveness of WWRCIs relies on a comprehensive set of variables that capture different aspects of winter weather and its impact on road conditions. These variables are categorized into atmospheric, pavement, precipitation, and temporal factors, each playing a vital role in assessing road safety and informing maintenance operations. Integrated through various scaling methods—such as point systems, severity classifications, and composite indices—these factors facilitate efficient communication and action by transportation agencies. Table 5 outlines these variable categories, describes their significance, and provides examples of projects that utilize them.

Table 5. Categorizing variables

Variable Category/Factors	Specific Variables	Description	Example Projects/Indices
Atmospheric Variables	• Air temperature • Wind speed • Visibility • Vertical temperature profile • Gust direction	Variables related to air temperature and atmospheric dynamics affecting winter conditions and safety.	• SHRP Winter Severity Index (WISHRP) (Boselly et al. 1993): Utilizes daily minimum temperatures to assess freezing potential. • Nebraska WSI (Walker et al. 2019b) • Vermont WMI (Dowds and Sullivan 2022) • Indiana WSI (McCullough et al. 2004) • Iowa SSI (Nixon and Qiu 2005) • Pennsylvania WSI (Hoffman et al. 2014) • Oklahoma SSI (Balasundaram et al. 2012) • MoDOT WSI (Thomas et al. 2021)

Variable Category/Factors	Specific Variables	Description	Example Projects/Indices
Pavement Variables	• RST • Surface condition • Friction/grip • Layer thickness	Conditions of road pavement surfaces, including temperature and grip, crucial for driving safety.	• Colorado WSI (Walsh 2016) RoadSurf (Kangas et al. 2015) • Idaho Winter Maintenance Performance Measures (Jensen et al. 2013): Links road conditions to maintenance performance. • Iowa SSI (Nixon and Qiu 2005) • Canadian WSI (MSC + RWIS Data) (Suggett et al. 2006) • Vermont WMI (Dowds and Sullivan 2022): Assesses grip and surface condition.
Precipitation Variables	• Snowfall amount • Snow occurrence • Freezing rain duration • Blowing snow • Snow accumulation	Different types and amounts of precipitation impacting roads, leading to the need for maintenance.	• Iowa WWI (Carmichael et al. 2004): Uses snowfall and freezing rain occurrences. • Canadian WSI (MSC Data Only) (Suggett et al. 2006): Tracks snowfall and freezing rain events. • Illinois WSI (Qi and Velpur 2024) • Indiana WSI (McCullough et al. 2004) • SHRP WISHRP (Boselly et al. 1993) • Vermont WMI (Dowds and Sullivan 2022) • Wisconsin WSI (WisDOT 2014) • MoDOT WSI (Thomas et al. 2021) • Pennsylvania WSI (Hoffman et al. 2014) • Nebraska WSI (Walker et al. 2019b)

Variable Category/Factors	Specific Variables	Description	Example Projects/Indices
Temporal Variables	• Event duration • Frequency of events	Temporal characteristics of weather events, affecting the duration and scheduling of responses.	• Wisconsin WSI (WisDOT 2014) • Vermont WMI (Dowds and Sullivan 2022) • Nebraska WSI (Walker et al. 2019b) • Illinois WSI (Qi and Velpur 2024) • Iowa WWI (Carmichael et al. 2004)
Temperature Parameters	• Daily minimum, maximum, and average temperatures	Assess freezing conditions and snow/ice formation potential.	• SHRP WISHRP (Boselly et al. 1993): Utilizes daily minimum temperatures to assess freezing potential. • AWSSI (Boustead et al. 2015) Maps daily max and min temperatures for severity scoring.
Operational Metrics	• Road surface conditions • Friction/grip • Mobility indices	Evaluate roadway conditions and maintenance efficacy.	• Idaho Winter Maintenance Performance Measures (Jensen et al. 2013): Links road conditions to maintenance performance. • Vermont WMI (Dowds and Sullivan 2022): Assesses grip and surface condition.

Table 6 outlines the different scales and thresholds used in WWRCIs to assess the severity of road conditions. These methods simplify decision-making by categorizing and scoring various weather-related metrics.

Table 6. Scales and thresholds used in indices

Scales	Description
Point Systems	Assigns points based on severity of conditions for metrics like snow accumulation and freezing rain.
Severity Classes	Categorizes conditions into classes (e.g., low, moderate, high) to simplify decision-making.
Composite Indices	Combines multiple parameters into a single score to offer an overall severity rating of road conditions.

While the data elements and variables are generally the same, future indices could be built with access to a more comprehensive toolbox that facilitates obtaining data elements and variables. Recent advancements have introduced tools that facilitate standardization in winter maintenance practices. Among these, the MDSS stands out as a key innovation for enhancing road condition prediction and WWRCI development. MDSS is an automated system that integrates real-time and forecasted weather data with pavement surface conditions, offering a predictive framework for winter road maintenance. Unlike many existing WWRCIs, which primarily rely on atmospheric and precipitation-based factors, MDSS incorporates direct road condition assessments such as pavement temperature, ice accumulation, and surface friction. By merging meteorological data with roadway condition variables, MDSS provides a more holistic approach to evaluating winter road safety, making it a strong foundation for refining and standardizing WWRCIs (Ye et al. 2009, McClellan and Coleman 2009, DTN 2025).

MDSS already integrates several of the data elements (variables) listed in Table 5, including atmospheric variables, pavement variables, precipitation variables, temporal variables, temperature parameters, and operational metrics. By incorporating these data elements, MDSS can support the development of a dynamic WWRCI that more accurately represents road safety hazards and optimizes winter maintenance strategies. MDSS can further contribute to WWRCI development by integrating real-time road condition monitoring with predictive modeling, allowing transportation agencies to optimize their response strategies. Its ability to simulate road condition evolution and assess the effectiveness of different maintenance treatments offers a dynamic approach to index development. By leveraging MDSS's predictive capabilities, future WWRCIs can become more adaptive, reflecting not just weather severity but also its direct impact on road safety. This advancement could lead to more precise and responsive indices, ensuring that winter maintenance decisions are data-driven and aligned with actual roadway conditions. Enhancing data integration, MDSS merges weather forecasts, pavement conditions, and maintenance activities, creating a multi-layered dataset that can inform dynamic index scaling rather than relying solely on historical weather severity. Some critical ways that MDSS can contribute to WWRCI development include the following (Ye et al. 2009, McClellan and Coleman 2009):

- Facilitating real-time road condition assessments: MDSS provides near real-time updates on road surface status, such as snow cover, ice accumulation, and road friction. These variables can be incorporated into a more representative index that directly reflects roadway hazards rather than just meteorological severity.
- Providing predictive capabilities: MDSS uses weather models and road surface physics to forecast how conditions will evolve under different maintenance strategies. This enables proactive adjustments to an index, shifting from a reactive assessment to a predictive tool for resource allocation.
- Enabling maintenance effectiveness evaluation: MDSS records and analyzes past treatment decisions, allowing researchers to correlate maintenance actions with road condition changes. This can refine WWRCIs by incorporating the effectiveness of interventions, such as salt applications and plowing, into severity scoring.
- Facilitating regional adaptation: MDSS is adaptable to different climates and maintenance strategies, allowing indices to be calibrated based on specific regional weather patterns, infrastructure, and operational practices.

4.2.3. Thresholds that Trigger Responses during Winter Weather Events

In examining thresholds that trigger responses during winter weather events, it was observed that these thresholds vary significantly across indices. Each index relies on specific environmental and road condition metrics to determine when maintenance actions, such as pretreatment, plowing, or issuing advisories, should be initiated. This section identifies the most used thresholds: temperature, precipitation accumulation, wind and visibility conditions, and composite severity scores. They play a distinct role in guiding winter maintenance responses. These thresholds were identified through the detailed review in Task 3, where it was analyzed how indices prioritize different conditions to ensure timely and efficient road treatment. For example, sub-freezing temperature thresholds often prompt pretreatment to prevent ice, while specific snowfall levels trigger plowing or the mobilization of resources. Some indices, like Iowa's SSI (Nixon and Qiu 2005), combine multiple factors—including snowfall, RST, wind speed, and storm type—to generate a severity score that directs the level of response required.

Thresholds used to trigger maintenance responses include the following:

- Temperature thresholds: Sub-freezing temperatures often prompt pretreatment of roadways to prevent ice formation.
- Precipitation accumulation: Specific snowfall amounts trigger plowing operations and deployment of resources.
- Wind and visibility conditions: High wind speeds and low visibility conditions may lead to road closures or travel advisories.
- Composite severity scores: Indices use overall severity scores to determine the level of response required, ensuring that resources are allocated efficiently.

Understanding these trigger points provides valuable insight into how a standardized index might balance precision with adaptability, ensuring safe, responsive, and resource-efficient winter road maintenance across regions.

4.2.4. Commonalities and Differences in Approaches

WWRCIs share several foundational elements while also exhibiting distinct variations to accommodate regional needs. This section outlines the common features that unify these indices and highlights the differences in their methodologies, data granularity, and regional applicability.

Commonalities:

- Core parameters: Temperature, precipitation (snowfall, freezing rain), and wind speed are universally recognized as critical factors affecting winter road conditions.
- Objective of enhancing safety and efficiency: All indices aim to improve road safety and optimize maintenance operations during winter weather events.
- Reliance on meteorological data: Use of reliable meteorological data from sources like NWS, RWIS, and ASOS is common across indices.

Differences:

- Parameter weighting and scoring systems: Indices differ in how they weight parameters and calculate severity scores, reflecting regional priorities and operational practices.
- Data granularity: Temporal resolution ranges from hourly (e.g., Roadsurf [Kangas et al. 2015]) to daily or monthly (e.g., Indiana WSI [McCullough et al. 2004]), affecting the responsiveness of the indices.
- Regional focus versus broad applicability: State-specific indices are tailored to local conditions, while national indices like AWSSI (Boustead et al. 2015) provide broader assessments but may lack local specificity.

The survey findings from Task 2 support these observations, as many agencies emphasized the importance of core parameters like temperature, precipitation, and wind speed. The preference for regional indices, driven by varied local weather conditions, further underscores the need for customization. Additionally, Task 2 highlighted differences in parameter weighting and the lack of a standardized national framework, aligning with our findings here.

4.2.5. Practical Approaches for Enhancing Winter Weather Response

Drawing from Task 2 insights on operational methods and regional reliance on specific weather indices, this section highlights effective approaches for improving winter weather response and safety management. These practical recommendations aim to enhance data consistency, operational efficiency, and interagency collaboration:

- Standardization of core parameters and thresholds: Adopting standardized parameters and thresholds facilitates consistency and comparability across regions.
- Real-time data integration: Utilizing real-time data sources improves the timeliness and effectiveness of maintenance responses.
- Advanced analytical techniques: Employing machine learning and predictive modeling can enhance the accuracy of forecasts and severity assessments.
- Regular updates and continuous improvement: Ongoing evaluation and refinement of indices ensure that they remain relevant and effective in changing climatic conditions.

4.3. Investigating the Use of Existing Data

The project evaluated the data sources employed by state agencies to develop their road condition indices, focusing on their strengths, weaknesses, and potential biases. Table 7 provides a comprehensive overview of existing data sources used by state agencies to develop road condition indices, highlighting their reliability, consistency, limitations, and supporting research. Consistency refers to the availability of data over a given period and also accounts for factors such as spatial distribution, data quality, and systematic recording. For example, consider the following:

- RWIS data have low consistency because stations are not evenly distributed, and data quality and measurement standards can vary between locations.
- Meteorological data from NOAA or ASOS have high consistency because they are standardized and systematically recorded across all regions.

Table 7. Existing data sources

Data Source	Description	Data Reliability	Consistency	Limitations	Associated Papers and Indices
RWIS	RWIS provides real-time data on road surface conditions, temperature, and meteorological parameters, essential for assessing road conditions.	High	**Low** – RWIS stations are not evenly distributed, leading to gaps in coverage. Measurement standards and data quality can vary by location.	Limited coverage in rural or remote regions, affecting data comprehensiveness.	• Suggett et al. (2006): Canadian WSI (MSC + RWIS Data) • Jensen et al. 2013): Idaho Winter Maintenance Performance Measures • Walsh (2016): Colorado Winter Maintenance Performance Index • Dowds and Sullivan (2022): Vermont Winter Maintenance Performance Index
Traffic Volume Data	Collected from in-pavement sensors, radar sensors, and cameras, these data track traffic flow and mobility trends, helping agencies understand congestion and prioritize maintenance operations.	Variable	**Low** – Sensor density is inconsistent, particularly in rural areas. Data quality can be affected by maintenance issues and technological discrepancies.	Issues with sensor maintenance can lead to unreliable or incomplete data.	• Strong and Shvetsov (2006): Development of Roadway Weather Severity Index
Crash Data	State crash records give insight into how adverse road conditions affect traffic safety, allowing for correlation analyses between weather severity and crash frequency.	High	**Low** – Inconsistencies in how agencies classify and report crashes can affect comparability. Data quality may vary based on reporting methods.	Delays in data reporting and inconsistencies in record-keeping can impact the analysis.	• Strong and Shvetsov (2006): Development of Roadway Weather Severity Index

Data Source	Description	Data Reliability	Consistency	Limitations	Associated Papers and Indices
Meteorological Data	Comprehensive weather data from sources such as the NWS, NOAA, and local stations. These data are foundational for evaluating winter weather severity and trends.	High	**High** – Data are systematically recorded, standardized, and widely available across regions, ensuring consistency.	Variability in data quality across different regions and stations.	• Boselly et al. (1993): SHRP WISHRP • Hoffman et al. (2014): Pennsylvania WSI • Dowds and Sullivan (2022): Vermont Winter Maintenance Performance Index
ASOS	ASOS stations provide detailed information on atmospheric conditions, including temperature, wind speed, and visibility, supporting real-time assessment of road conditions.	High	**High** – ASOS data are standardized across all stations and systematically recorded, ensuring uniform quality and reliability.	Coverage may be limited in some remote areas, impacting data availability.	• Walker et al. (2019b): Nebraska WSI • Thomas et al. (2021): MoDOT WSI
Neural Network Models	Predictive models for estimating snow and ice thickness, RST, and other parameters. These models support road treatment planning by forecasting hazardous conditions.	High	**High** – Model consistency depends on data inputs, but standardized algorithms and training datasets improve reliability.	Requires advanced computational resources and can be complex to implement.	• Balasundaram et al. (2012): SSI
WRF and SREF Models	Weather forecasting models like the WRF model and SREF model are essential for tracking temperature, precipitation, and wind speeds.	High	**High** – Forecasts are generated using standardized modeling frameworks, but accuracy varies with updates and regional differences.	Forecasting accuracy may vary depending on model updates and regional factors.	• Balasundaram et al. (2012): SSI

Data Source	Description	Data Reliability	Consistency	Limitations	Associated Papers and Indices
RST forecast models	These models predict the temperature of road surfaces based on surface energy balance, atmospheric data, road characteristics, terrain and topography. Atmospheric data elements include air temperature, wind speed, solar radiation, cloud cover, and humidity, possibly along with real-time sensor measurements for increased accuracy. They can forecast hazardous conditions like frost or ice formation.	High	**High** – Similar to weather forecasts, these models run on standardized models but their accuracy varies by data input characteristics.	Can be limited by the accuracy of input weather data, the complexity of modeling surface energy balance, the influence of traffic, the need for extensive real-time data infrastructure, and geographical variability.	• RoadSurf 1.1; Karsisto (2024), FHWA-RD-98-085 (2000), potential use of floating car data in RST forecast models (Hu et al. 2019), and machine learning-based models such as Tabrizi et al. (2021)

Data Source	Description	Data Reliability	Consistency	Limitations	Associated Papers and Indices
CV Data	Data collected from vehicles equipped with sensors, communication systems, and advanced technologies, providing real-time information on speed, acceleration, braking events, wheel slip, and environmental conditions.	High	**High** – When penetration rates are sufficient, data are collected continuously and systematically across wide regions.	Requires sufficient penetration rates of equipped vehicles, secure data-sharing frameworks, and supporting infrastructure.	• Galanis et al. (2018): Weather-based road condition estimation using internet of vehicles (IoV) to establish RSI influencing dynamic speed recommendations. • Li et al. (2020): Utilized CAN bus data from vehicle sensors like ABS and traction control to monitor roadway conditions during adverse weather events. • Wiener et al. (2023): Demonstrated the use of CV friction measurement data in implementing variable speed limits and improving winter maintenance strategies. • Oh and Dong-O'Brien (2025): Explored the impact of winter maintenance operations using CV data, highlighting their role in reducing incident-induced delays and harsh braking events during winter conditions while identifying the importance of improving penetration rates and incorporating real-time data.

* Refers to the availability of data over a given period. Datasets categorized as having low consistency typically contain missing data points at certain collection intervals.

4.3.1. Data Source Assessment

The strengths of the discussed data sources include the following:

- **Comprehensive insights with CV data**: CV data provide unparalleled granularity by capturing real-time metrics like speed, braking events, wheel slip, and environmental conditions. Their dynamic nature allows for timely assessments of road conditions and immediate response to hazards, making them a transformative asset in winter road safety and maintenance. Furthermore, because CV data reflect actual driver behavior and reactions to winter weather (e.g., sudden braking, decelerations, or evasive maneuvers), they serve as a critical indicator to enhance winter road safety and inform more effective maintenance strategies.
- **Robust meteorological and atmospheric data**: Reliable weather data from sources like NOAA, ASOS, and local weather stations form the backbone of winter weather assessments. These authoritative sources provide high-quality and precise observations of temperature, precipitation, and wind conditions.
- **Detailed spatial coverage with traffic volume data**: Traffic sensors and radar systems enhance the understanding of congestion and mobility trends, allowing agencies to prioritize maintenance resources effectively.
- **Real-time monitoring with RWIS**: Despite its limitations, RWIS remains a valuable tool for on-site measurements of pavement temperature, surface conditions, and deicing chemical concentrations. Its integration with other data sources improves the reliability of weather severity indices.
- **Predictive and analytical power**: Data-driven models, such as neural networks and weather forecasting tools like WRF and SREF, enable advanced analytics and predictive insights. These models enhance the accuracy of road condition forecasts and support proactive safety measures.

The main weaknesses of the discussed data sources can be listed as the following:

- **Coverage limitations**:
  - **Connectivity and location constraints**: CV data rely on adequate penetration rates of connected vehicles, which may be low in certain areas. RWIS stations, meanwhile, are fixed and can leave vast rural or remote regions without sufficient monitoring.
  - **Meteorological variability**: Weather data quality can fluctuate by region, leading to patchy coverage and potentially inaccurate assessments in certain locales.
- **Complexity in data integration**:
  - **Diverse formats and methodologies**: Bringing together data from CV systems, RWIS, and various meteorological sources requires standardization and interoperability measures.
  - **Interoperability hurdles**: Incompatible platforms and disparate data structures complicate efforts to produce cohesive, actionable insights.

- **Cost and resource intensity**:
    - **Investment in technology**: Scaling CV data collection infrastructure and RWIS often means investing in new hardware, software, and the integration frameworks that support standardized data exchange.
    - **Technical expertise**: Specialized skill sets are needed to maintain data standards, ensure interoperability, and troubleshoot technological conflicts, tying back to the complexity of integrating multiple data sources.

4.3.2. Summary of Data Source Usage

The integration of multiple data sources, including CV systems, meteorological observations, RWIS, and traffic volume data, builds a robust framework for assessing winter weather road conditions. CV data stand out for their real-time granularity and direct behavioral insights, while RWIS and meteorological sources provide reliable foundational metrics. Traffic data and advanced predictive models complement these systems, offering a holistic understanding of road conditions. However, overcoming limitations in coverage, consistency, and resource allocation will be essential to fully leverage these data sources for WWRCIs. Prioritizing CV data and enhancing their integration with existing systems can lead to more dynamic and adaptive winter maintenance strategies.

4.4. Identifying Gaps and Opportunities

To optimize winter weather management systems, it is essential to recognize current limitations and explore potential improvements. This section outlines key gaps that hinder the effectiveness of existing systems and highlights opportunities to advance data integration, technology adoption, and standardization.

4.4.1. Gaps in Current Systems

The main gaps identified in the systems currently used include the following:

- **Inconsistent data availability:** The uneven distribution of data collection infrastructure creates significant disparities in data quality and coverage, particularly in rural and remote areas. RWIS stations face issues like missing data from sensors. Currently, the reliance on RWIS is significant, yet many regions lack sufficient installations due to funding and logistical challenges, as noted in the survey findings from Task 2. This inconsistency compromises the reliability of weather severity indices, limiting their utility across diverse geographic and climatic conditions. Studies on Vermont’s Winter Maintenance Performance Index and Finland’s RoadSurf emphasize the importance of dense and high-quality data networks, yet these remain sparse in many US states (Sturges et al. 2020, Boselly et al. 1993, Jonsson 2011b). Additionally, gaps in data integration between RWIS and external meteorological sources exacerbate these inconsistencies, as seen in the survey results.
- **Lack of standardization:** A fragmented approach to developing WWRCIs complicates their comparison and integration across states. Variations in parameter weighting, data aggregation

methods, and thresholds hinder efforts to create a cohesive national framework. Sensors from different vendors often come with different sensitivities and thresholds for the output. The survey in Task 2 revealed that many state agencies either lack indices altogether or use vastly different metrics, reducing opportunities for benchmarking and collaboration (Villwock-Witte et al. 2021, Suggett et al. 2006). Villwock-Witte et al. (2021) identified that current indices often fail to address regional climatic variability, rendering them ineffective for universal application.
- **Technological limitations:** Many agencies rely on legacy systems for data collection and analysis, which lack the capacity to adapt to rapidly changing conditions. Indices that do not incorporate real-time data, advanced analytics, or predictive modeling are constrained in their ability to support proactive decision-making (Kwon et al. 2021, Gu et al. 2019). The absence of robust data-sharing mechanisms limits real-time collaboration among agencies, as highlighted in the survey findings.
- **Underutilization of emerging data sources:** CAV data and smartphone-based road condition assessments are promising but remain underutilized. These technologies provide real-time insights and granular road condition data but are not widely adopted due to cost, technical challenges, and a lack of integration with existing systems (Galanis et al. 2018, Walker et al. 2019b). One example from Sturges et al. (2020) funded by the Clear Roads pooled fund program highlights their potential but underscores the need for broader implementation.

4.4.2. Opportunities for Enhancement

The literature and previous practices, while highlighting challenges and concerns in the existing systems, have identified opportunities for improving the effectiveness, efficiency, and usability of these systems. Some key points and recommendations can be listed as follows:

- **Integrated data platforms:** Centralized systems that consolidate data from RWIS, CAVs, IoT devices, meteorological services, and crowdsourced inputs can significantly enhance WWRCI accuracy. Vermont's MDSS demonstrates how integrated platforms can improve the comprehensiveness and timeliness of indices (Kwon et al. 2021). Predictive models from Indiana's WSI illustrate the potential for more accurate assessments using machine learning algorithms (Galanis et al. 2018, Jonsson 2011b).
- **Adoption of advanced technologies:** Leveraging deep learning algorithms, friction mapping technologies, and geostatistical approaches can transform road condition monitoring. Studies have highlighted their ability to provide real-time and predictive insights, enabling proactive winter maintenance strategies (Sturges et al. 2020, Boselly et al. 1993). For example, advanced imaging systems and spatial modeling have shown promise in pilot studies conducted across diverse climatic zones (Suggett et al. 2006).
- **Standardized methodologies:** Developing universal frameworks for data collection, parameter selection, and index calculation would improve comparability and enable cross-state collaboration. Recommendations from the survey include prioritizing common variables such as pavement temperature, precipitation type, and road surface conditions as the foundation for national guidelines (Villwock-Witte et al. 2021, Suggett et al. 2006). Dynamic

indices responsive to meteorological inputs, as suggested by Walker et al. (2019b), could enhance their utility across varied climates.

- **Utilization of emerging data sources:** Incorporating CAV data and IoT-based sensors, as demonstrated in this Aurora project, offers high-resolution, real-time road condition information. These data can complement existing RWIS networks and expand coverage in areas with limited infrastructure (Jonsson 2011b, Sturges et al. 2020).
- **Enhanced collaboration and data sharing:** Expanding data-sharing agreements and implementing interoperable systems can improve situational awareness and foster innovation. The survey revealed that 15 states actively share data through platforms like 511 or social media, suggesting a strong foundation for building collaborative systems (Boselly et al. 1993).

These gaps align closely with the issues reported by DOTs in Task 2. The survey highlighted the uneven distribution of data collection infrastructure, the lack of standardized indices, and the need for modernized technology. The opportunities identified here, such as data integration and the adoption of new technologies, directly address the concerns raised by the agencies surveyed.

4.5. Developing a Data Integration Plan

Creating a cohesive system for assessing winter weather road conditions requires a strategic approach to data integration. This plan emphasizes several key steps:

- **Standardized data formats:** Implement common data formats and protocols to ensure seamless compatibility across different systems and regions, facilitating more efficient data aggregation and analysis. Incorporating the vendors into the system could also streamline the data standardization.
- **Enhance data collection infrastructure:** Utilize existing RWIS networks and integrate emerging data sources like CAVs with them to create a robust network of data collection infrastructure. Nationally available meteorological data sources like NOAA and ASOS can be used with emerging datasets to create a more reliable road weather data infrastructure.
- **Develop data fusion techniques:** Leverage advanced analytics and machine learning methods to combine data from multiple sources, enhancing the accuracy and reliability of weather severity assessments.
- **Implementing interoperable systems:** Design systems that can communicate and exchange information effortlessly, promoting real-time collaboration and more effective decision-making.
- **Establish data governance frameworks:** Define robust policies and procedures for data sharing, privacy, and security to ensure responsible and secure management of integrated data sources.

4.5.1. Usefulness of Existing Data for a New Standardized Approach

The existing data sources provide a solid foundation for developing a new standardized approach but require enhancements to meet the desired objectives:

- **Sufficiency of current data**: While current data sources offer valuable information, gaps in coverage and inconsistencies limit their effectiveness for a comprehensive national standard.
- **Need for additional data sources**: Incorporating emerging data sources like CV data can enrich the dataset and improve assessments.
- **Data quality improvement**: Enhancing data collection methods and ensuring regular maintenance of sensors can address quality issues.

4.6. Use of CV Technology to Support Standardized National Data Collection Framework

Using a standardized data collection practice contributes to developing a standardized framework for WWRCI. Data collected by vehicles possess characteristics that make them a promising source for standardized data, potentially normalizing the attributes used in the standardized WWRCI framework. Using more standardized data sources facilitates comparative analysis across different states. Vehicles collect multiple data elements that could be part of the WWRCI, including barometric pressure, windshield wiper settings, headlight status, ambient air temperature, speed, heading, location, elevation, ABS activation, braking status, stability control, traction control, accelerometer readings, steering angle, differential wheel speed, and yaw/pitch/roll (Drobot et al. 2017). These data elements could be assessed and processed to identify weather events such as precipitation occurrence, precipitation rate and type, and pavement conditions. These weather events could then be included in the standardized weather index. The availability of these data elements by CV original equipment manufacturers (OEMs) and data aggregators is variable at this point.

Multiple CV data sources were reviewed to identify available data elements that could potentially be used as attributes in developing a standardized framework for WWRCIs. In light of this, and to investigate the use of CV technology to support a standardized national data collection framework, the research team focused on main attributes such as traffic flow, road surface friction, and precipitation. Speed is one of the CV data elements that is available and could potentially be used to study traffic flow during winter weather. Road surface friction data is also one of the available data elements that could potentially be used to assess drivers' reaction to roadway slipperiness. Wiper state is another data element that could be used to study drivers' reaction to precipitation occurrence.

The impact of rain intensity on traffic flow performance along I-65 in Indiana was studied by Sakhare et al. (2023) using CV data. Using a qualitative example, the study used speed data from CVs in 2022 to generate space-time heatmaps of traffic speeds and high-resolution rapid refresh (HRRR) data published by NOAA to show precipitation rate at one-hour granularity. The study indicated that on a stretch of the studied roadway, one hour (11:00 a.m. to noon) of very heavy rain (>8 mm/hour) and headwind had a high impact on southbound travel speed. However, the impact was lower in the northbound lanes, which experienced tailwind. Based on quantitative analysis, the study indicated that lower speeds were observed when the rain intensity category increased. The mean speed decreased with higher precipitation rate categories, while an interquartile range analysis suggested that speed selection variability increased during rainstorms.

Sakhare et al. (2023) used CV data to study the traffic impacts of a tornado on a section of I-65 over four days. During the tornado, changes in speeds to lower speed bins were observed. Furthermore, a truck rollover due to severe winds during the tornado's movement on the studied stretch of roadway resulted in closure of the interstate for a few hours. Slowdowns due to debris over the following two days were also observed. Camera images and CV data were used to further analyze the rolling slowdowns due to debris clearing operations, with the results indicating an increase in travel time from the usual 19 minutes to 33 minutes behind the slowdown. Additionally, a queue of 2 to 3 miles from the operations was also detected.

Friction measurement data from CVs were utilized by Sehovic et al. (2024) to develop a proof-of-concept tool to detect whether or not studied road segments were slippery in Pennsylvania and Utah, information that has value as an additional layer of information for variable speed limit decision-making. Furthermore, depending on CV coverage, friction signal could provide additional information for removing speed restrictions. The study also analyzed connected vehicle friction measurement (CVFM) data for corridors subjected to a chain law in Colorado, and the method for the variable speed limit case study was applied to the chain law case study to determine the friction signal for slipperiness on selected stretches of I-70 in Colorado. Low friction was detected during snowstorms in winter 2024. The study also calculated key performance indicators (KPIs) for winter storm mitigation on roads using CVFM data.

4.6.1. Analysis of Driver Reaction to Precipitation

Since precipitation rate was identified as one of the high-interest attributes from the survey conducted in Task 2, the research team further investigated the reaction of drivers to precipitation through an analysis of wiper usage data from CVs in Iowa in addition to precipitation accumulation data from the Iowa Environmental Mesonet (IEM).

At this point in the research project, the research team investigated a few qualitative examples showing the high-level reaction of drivers to precipitation through wiper usage.

The following data sources were used:

- **Wejo data.** Wejo data are aggregated from multiple OEMs and include vehicle movement and trajectory data captured in intervals of three seconds or shorter; driver events data such as wiper usage, ABS activation, hard braking, and acceleration changes; and other data elements.
- **IEM data.** The Automated Data Plotter tool from the IEM was used to plot precipitation accumulation maps. Graphs are derived from the processing of multiple data sources performed by the IEM (IEM n.d.). The chart type used was MRMS / PRISM / Stage IV / IFC / IEM Reanalysis Estimated Precip (Multiday summaries/departures) (#84) (IEM n.d.).

The research team created maps that show the locations of wiper usage events from CV data and downloaded precipitation accumulation maps for the same days from the IEM. The qualitative analyses looked at multiple days of wiper usage data for the year 2022. Three examples are presented below for March 18, August 15, and November 4 of 2022.

4.6.1.1. Qualitative Example 1

Figure 18 shows the statewide front wiper usage from CV data for 4,820 journeys with wiper activation events. Figure 19 shows the statewide front wiper usage from CV data for 469 journeys that had at least 20 data points of active wiper usage per journey. Figure 20 shows the statewide precipitation accumulation on March 18, 2022. In Figure 18, it can be observed that the density of wiper usage is higher in the northeastern and southern portions of the state and much lower in the northwestern area of the state. Figure 19 was created to filter out journeys that used wipers for less than one minute (<20 data points, assuming three seconds between data points) and to filter out regular windshield cleaning regardless of precipitation. In Figure 19, it can be observed that there is higher wiper usage in the area to the right of the black dashed line compared to the area to the left of it, the latter of which has limited to no wiper usage. This observation closely aligns with the precipitation accumulation map in Figure 20, which shows precipitation accumulation to the right of the black dashed line and limited to no precipitation accumulation area to the left of the line.

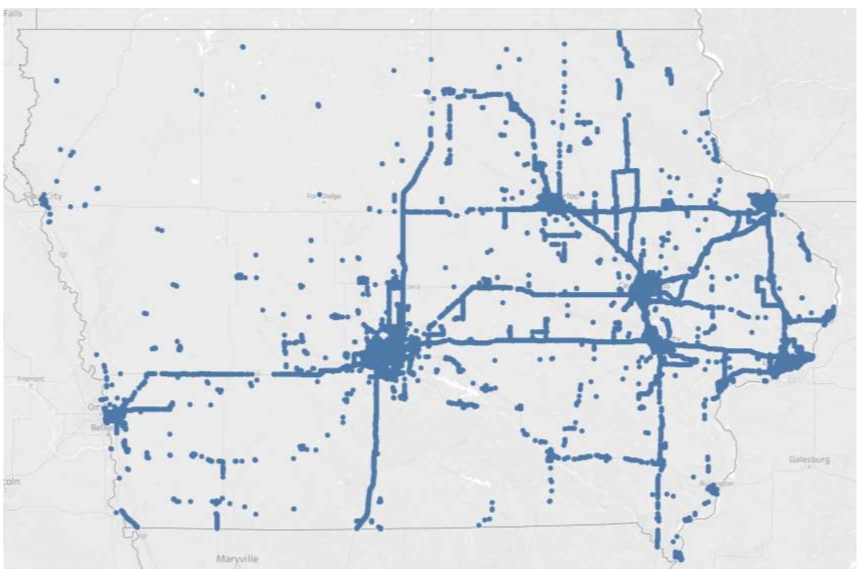


Figure 18. Iowa statewide wiper usage on March 18, 2022

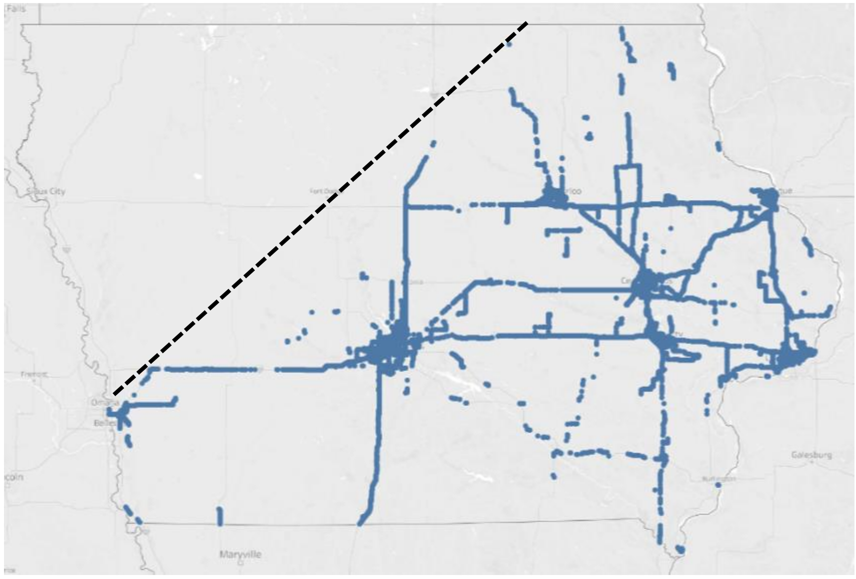
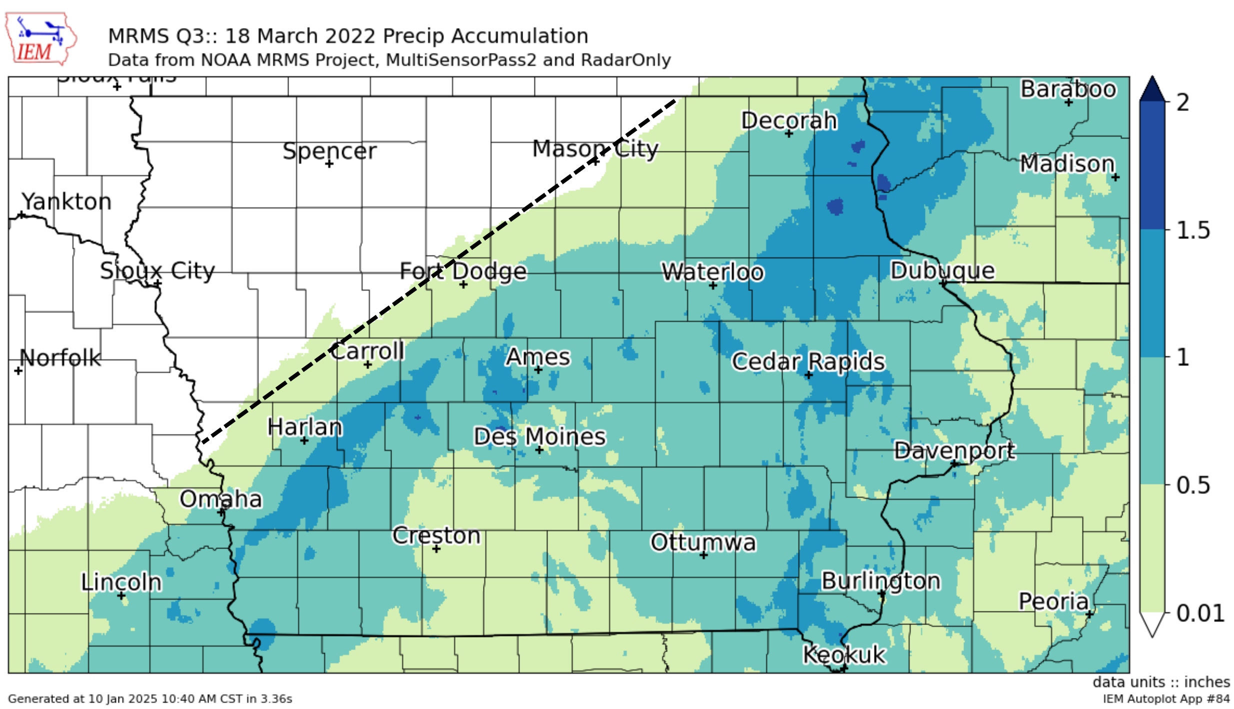


Figure 19. Iowa statewide wiper usage on March 18, 2022, for journeys with at least 20 wiper events



IEM n.d.

Figure 20. March 18, 2022, precipitation accumulation in Iowa

4.6.1.2. Qualitative Example 2

A similar analysis was conducted for August 15, 2022. Figure 21 shows the statewide front wiper usage from CV data for 3,483 journeys with wiper activation events. Figure 22 shows the statewide front wiper usage from CV data for 277 journeys that had at least 20 data points of active wiper usage per journey. Figure 23 shows the statewide precipitation accumulation on August 15, 2022. It can be seen in Figure 21 that the density of wiper usage is higher in the northwestern and southern portions of the state and much lower in the northeastern area. In Figure 22, it can be seen that there is higher wiper usage in the area on the left side of the black dashed line compared to the area on the right side of the line, where no wiper usage is found. This observation closely aligns with the boundary marked by the black dashed line in Figure 23, which divides the area where precipitation accumulation was recorded and the area where no precipitation accumulation was recorded.

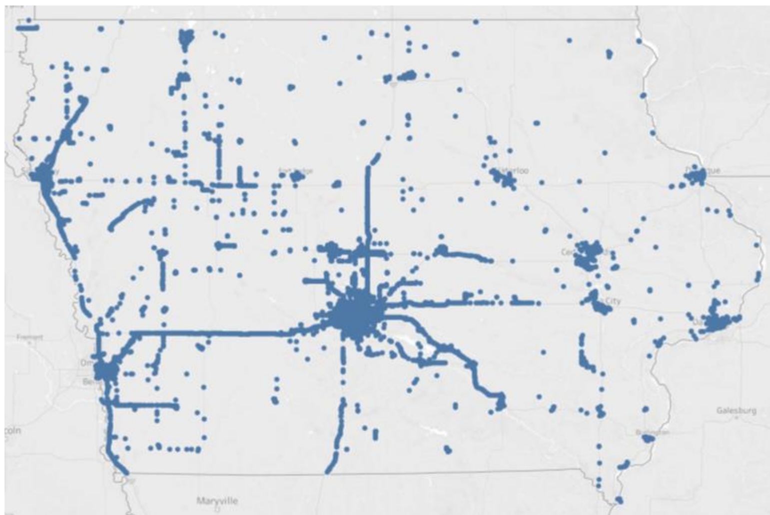


Figure 21. Iowa statewide wiper usage on August 15, 2022

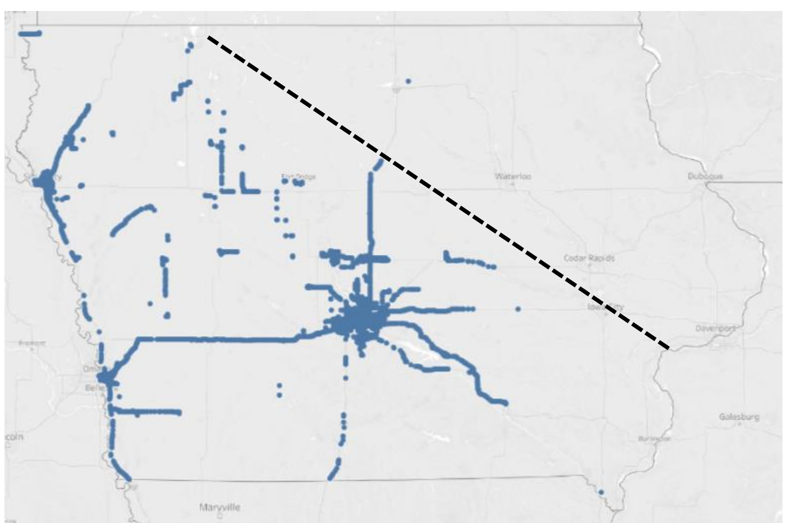
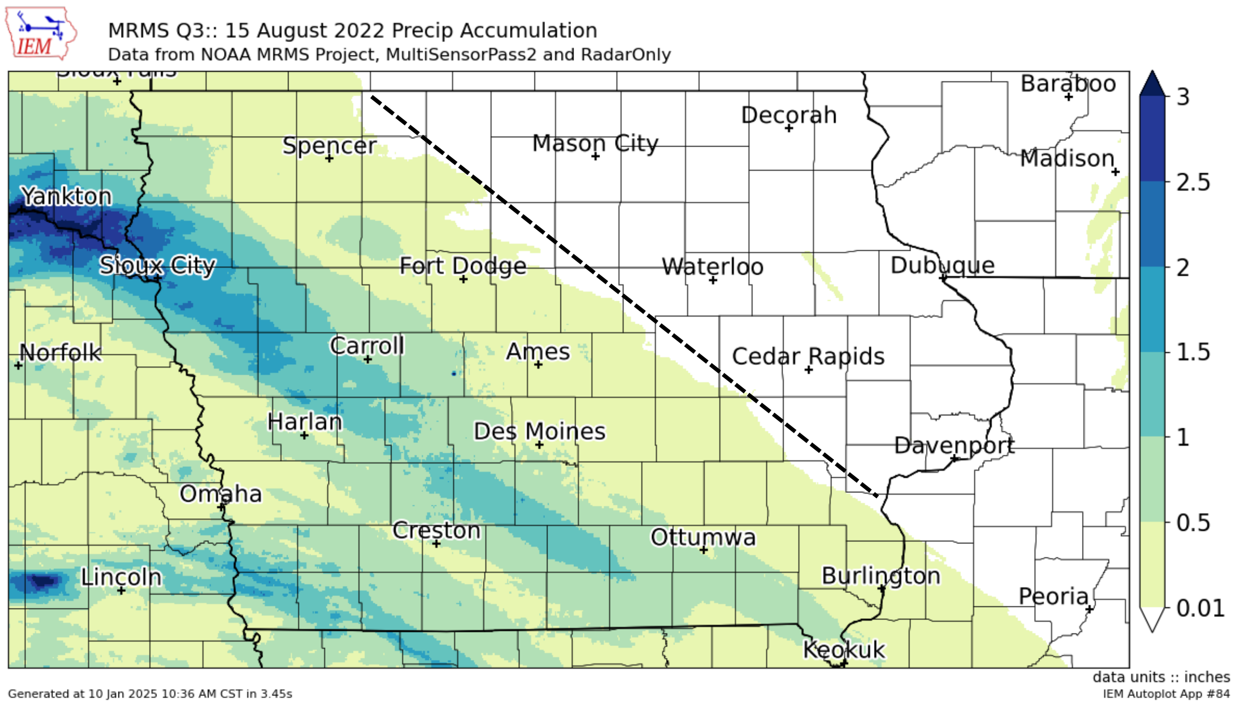


Figure 22. Iowa statewide wiper usage on August 15, 2022, for journeys with at least 20 wiper events



Source (IEM)

Figure 23. August 15, 2022, precipitation accumulation in Iowa

4.6.1.3. Qualitative Example 3

The third qualitative analysis was conducted for November 4, 2022. Figure 24 shows the statewide front wiper usage from CV data for 10,835 journeys with wiper activation events. Figure 25 shows the statewide front wiper usage from CV data for 1,002 journeys that had at least 20 datapoints of active wiper usage per journey. Figure 26 shows the statewide precipitation accumulation on November 4, 2022. In Figure 24, it can be seen that the density of wiper usage is higher in the northeastern and southern portions of the state, while no wiper activation events were observed in the northwestern area. As can be seen in the area labeled *i* in Figure 25, no wiper usage was observed in the northwestern part of the state. That approximate area is overlaid on the precipitation accumulation map in Figure 26, where it coincides with an area that shows 0.01 to 0.5 in of precipitation accumulation. This observation is different from what was observed in the two previous examples, where there was limited to no precipitation accumulation in the areas of limited wiper usage.

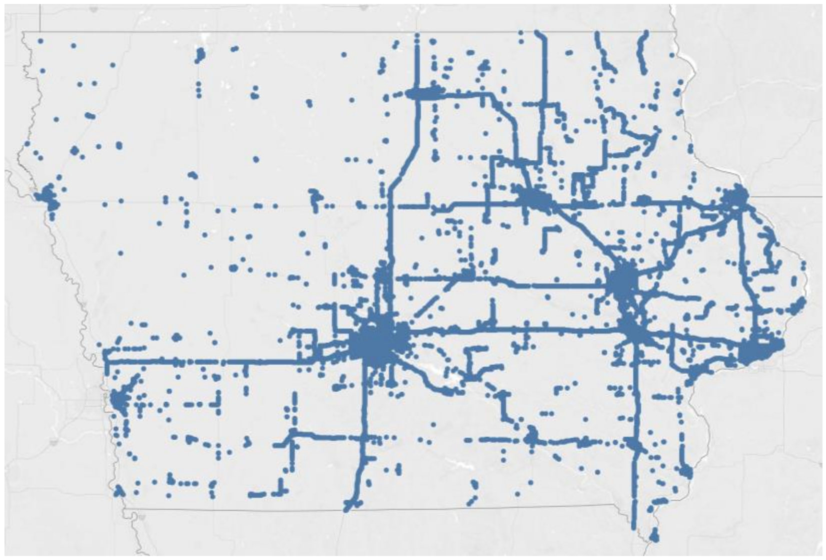


Figure 24. Iowa statewide wiper usage on November 4, 2022

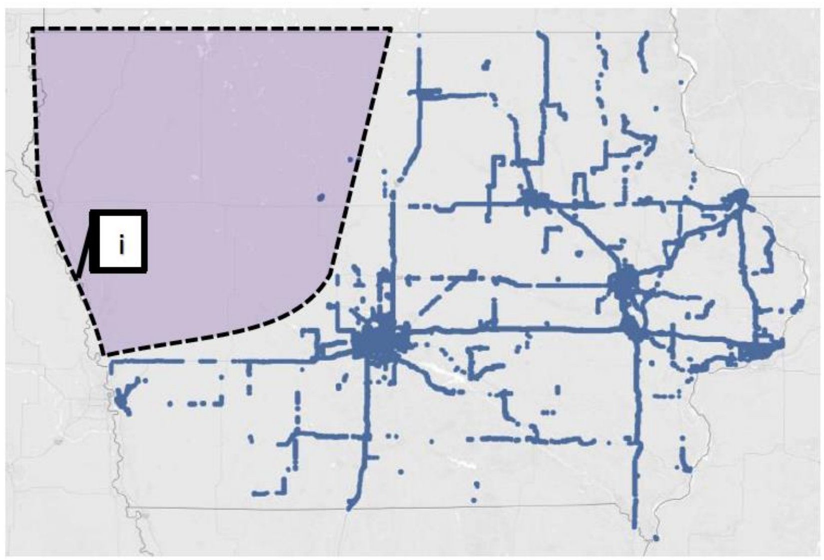
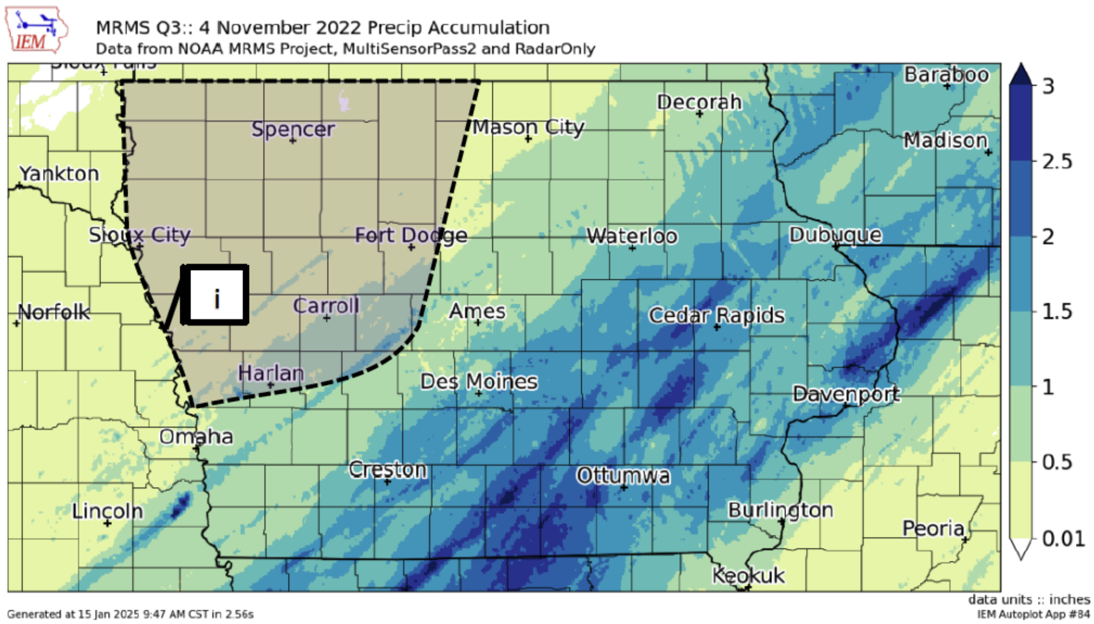


Figure 25. Iowa statewide wiper usage on November 4, 2022, for journeys with at least 20 wiper events



IEM n.d.

Figure 26. November 4, 2022, precipitation accumulation in Iowa

These qualitative examples show the reaction of drivers to precipitation through the use of wiper activation data. Longer intervals of wiper activation could be a strong indication of precipitation. These examples show that CV data have the potential to be used to identify precipitation, which could have an effective impact on the data collection framework for the standardized winter weather condition index. However, these are qualitative examples, and a quantitative analysis is needed to statistically examine this observed correlation. Further analysis of wiper speeds in conjunction with vehicle speeds could potentially help identify drivers' reactions to different precipitation rates.

4.6.2. Discussion

CV data can be a promising resource for better understanding drivers' reactions to various weather events on roadways. In Sakhare et al. (2023), for example, heavy rain was shown to affect drivers' speeds more significantly in one direction than the other, despite ostensibly similar conditions. This discrepancy might be attributed to the wind orientation (e.g., tailwind versus headwind). Additionally, a relationship emerged between mean speed and different rain intensity categories. These findings highlight the potential of using CV data within a standardized winter weather condition index that incorporates driver reactions to weather conditions on the road. Since driver response to weather is a crucial factor for evaluating road safety and mobility, this approach could significantly enhance our ability to gauge and respond to weather-related risks.

Furthermore, CV data can help explain the impact of severe weather events, such as tornados, on roadway traffic and on drivers' reactions in the aftermath of such events, such as during debris clearing operations (Sakhare et al. 2023). This makes CV data valuable as a source of standardized data for these events. Moreover, the use of friction data from CVs, which is discussed in Sehovic et al. (2024), shows potential for detecting road conditions. The qualitative analysis that the research team conducted using wiper activation data from CVs indicates strong potential for using these data to identify precipitation statewide at a network level. This is helpful in. light of the potential use of CVs as a near real-time data source.

The literature review conducted in Task 1 and the analysis conducted in Task 3 highlight the advantages of using CV data to develop a standardized WWRCI. However, CV data are limited in their penetration and availability at this point. Furthermore, the qualitative examples outlined in this section resulted from high-level analyses; a quantitative approach should be used to statistically describe the correlation between precipitation accumulation and wiper usage data from CVs and to perform an hourly, granular-level analysis. A further analysis that identifies other data elements, such as the use of ABS or electronic stability control, should be performed to understand their potential use in a standardized WWRCI framework.

4.7. Implementation and Future Directions

Building a more effective and standardized national framework for WWRCIs necessitates addressing the specific gaps and challenges identified in Task 1 (Chapter 2), Task 2 (Chapter 3), and Task 3 (this chapter). By integrating the lessons learned from these tasks, the implementation strategy can focus on adopting phased improvements, implementing proven methodologies, and fostering collaboration among stakeholders to ensure a robust and adaptable system.

4.7.1. Key Steps for Implementation

- **Phased approach:**
    - **Phase 1: Data standardization:** Begin by standardizing critical variables such as pavement temperature, precipitation type, and road surface condition classifications, as highlighted in Task 1. This ensures consistency in data collection and analysis across regions.
    - **Phase 2: Infrastructure enhancements:** Address the uneven distribution of RWIS and other data collection systems identified in Task 2 by prioritizing investments in under-resourced regions. Develop funding mechanisms to expand infrastructure equitably.
    - **Phase 3: Integration and expansion:** Utilize findings from Task 1 regarding successful international practices (e.g., Finland's RoadSurf [Kangas et al. 2015]) to guide the integration of new technologies, such as IoT devices and CAV data, into regional WWRCIs.
- **Pilot programs:** Launch pilot programs tailored to diverse weather conditions and agency capabilities, as suggested in Task 2. Test the integration of real-time data sources and explore innovative approaches to data collection, such as crowdsourced and CAV inputs, while addressing the logistical challenges noted in the survey responses. Use feedback from these programs to refine strategies and establish replicable models for wider adoption.
- **Collaborative efforts:** Foster partnerships among state DOTs, research institutions, and federal agencies to build on the existing cooperative efforts identified in Task 2. Encourage knowledge sharing through workshops and conferences to disseminate best practices,

focusing on standardized methodologies and scalable solutions. Develop centralized platforms for data sharing, enabling seamless integration and improving situational awareness during winter weather events.

- **Ongoing monitoring and evaluation:** Create performance metrics, such as road safety improvements, reduced closure durations, and cost-effectiveness of maintenance efforts, as emphasized in Task 2. Regularly assess the indices' performance and update them based on real-world feedback, ensuring that they remain aligned with evolving needs and technologies.

4.7.2. Future Directions

4.7.2.1. Data-Driven Decision-Making

Data-driven approaches are at the forefront of modern winter road management, enabling agencies to make informed decisions based on comprehensive and accurate insights. Predictive analytics and machine learning algorithms are revolutionizing maintenance planning by offering tools to analyze complex datasets and forecast road conditions:

- **Enhanced maintenance planning**: Machine learning models can process vast amounts of data from RWIS, CVs, and meteorological inputs to identify patterns and trends. For instance, Illinois' nonlinear modeling studies have shown how such methods can predict snow accumulation, ice formation, and pavement friction loss, enabling preemptive resource allocation and maintenance actions (Qi and Velpur 2024).
- **Crash risk mitigation**: Advanced analytics also support risk assessments by correlating weather severity indices with crash data. These insights allow agencies to prioritize interventions on high-risk corridors, optimizing safety outcomes.

4.7.2.2. Predictive Capabilities

Forecasting tools are critical for preparing agencies to respond effectively to adverse weather conditions. Weather forecasting models like the WRF and SREF models are pivotal in predicting parameters such as snowfall intensity, freezing rain duration, and wind speeds:

- **Timely interventions**: These models provide agencies with early warnings about hazardous conditions, allowing them to mobilize resources proactively. Oklahoma's storm severity projects demonstrated the utility of such tools in triggering responses like pretreatment, plowing, and the issuing of public advisories (Balasundaram et al. 2012).
- **Dynamic resource allocation**: By combining WRF and SREF outputs with operational data, agencies can adapt their strategies in real-time. This capability reduces inefficiencies and ensures that maintenance efforts are directed where they are needed most.

4.7.2.3. Technological Adaptability

As technology evolves, winter weather management must embrace emerging tools to improve road condition assessments and response strategies:

- **Geostatistical modeling**: Tools like geostatistical analysis allow for high-resolution mapping of road conditions, integrating data from multiple sources to create detailed spatial and temporal profiles. RoadSurf applications in Finland demonstrate how these models can predict pavement temperatures, friction levels, and ice formation with remarkable accuracy (Kangas et al. 2015).
- **Smartphone-based assessments**: Innovative approaches, such as using smartphone accelerometers to detect road roughness or hazardous conditions, provide a cost-effective way to supplement existing data sources. These technologies can expand coverage to rural or remote areas with limited infrastructure, bridging critical data gaps.
- **Friction mapping systems**: Real-time friction measurement systems integrated into maintenance vehicles offer granular insights into road slipperiness, enabling precise applications of deicing materials and reducing waste.

4.7.2.4. Regional Customization

While standardization is vital for developing a cohesive national framework, regional variations in climate and infrastructure necessitate adaptable solutions:

- **Localized indices**: Indices tailored to specific climatic zones, such as the indices used in Finland and Canada, address unique challenges like prolonged snow cover, freeze-thaw cycles, and high winds (Suggett et al. 2006, Kangas et al. 2015). These examples highlight the importance of designing indices that incorporate regional weather patterns and operational needs.
- **Climate-specific triggers**: Custom thresholds for triggering maintenance responses, such as snowfall levels or freezing rain durations, ensure that interventions are effective and timely across diverse regions. For example, Vermont's micro-zoning approach for snow and ice control activities allows for precise targeting of resources, minimizing disruptions and costs (Dowds and Sullivan 2022).
- **Interregional collaboration**: Sharing best practices and data across regions with similar challenges fosters innovation and efficiency. Canadian provinces, for instance, have developed cooperative systems that integrate RWIS data nationally, creating a unified platform while accommodating local nuances (Suggett et al. 2006).

4.8. Conclusion

The findings and recommendations presented in this chapter (Task 3) are grounded in the practical insights gained from Task 2 (Chapter 3). By understanding the challenges and preferences of DOTs, our evaluation of existing WWRCIs is not only comprehensive but also tailored to meet the needs of those on the front lines of winter weather management. This connection ensures that our proposed solutions are both relevant and actionable. The evaluation underscores the necessity of a standardized national approach that leverages the strengths of current indices while addressing their weaknesses. By utilizing reliable data sources, adopting best practices, and enhancing data collection and analysis methods, we can develop a robust index that provides accurate and dependable information to drivers and transportation agencies, ultimately improving winter weather response and enhancing driver safety on roadways across the nation.

CHAPTER 5. NATIONAL STANDARD FRAMEWORK FOR WINTER WEATHER IMPACTS ON TRANSPORTATION SYSTEMS

5.1. Overview

This chapter presents the national standard framework for assessing and responding to winter weather impacts on transportation systems. The framework is structured around nine core dimensions that influence road safety, mobility, maintenance operations, and traveler reliability during winter conditions. These dimensions and their associated subdimensions are high-level operational factors representing various phenomena that affect or reflect road conditions. In developing road weather condition indices, agencies may include or exclude factors based on their local relevance and data availability.

The framework was developed through a synthesis of stakeholder engagement—conducted primarily through a national survey of transportation agency priorities and practices—along with best practices, empirical research, and practitioner insights gathered from regional and national transportation agencies. Its purpose is to provide a common structure for evaluating winter weather impacts, regardless of local climate variation or agency size. By establishing consistent definitions, measurable indicators, and thresholds for each dimension, the framework supports more coordinated decision-making and improved performance benchmarking across jurisdictions.

Each of the nine dimensions represents a distinct category of risk or operational concern that can be monitored and analyzed to inform the agency's response. These dimensions span both environmental factors—such as Precipitation-Related, Wind-Related, and Temperature-Related—and operational or user-focused metrics—such as Traffic Flow Impact, Winter Maintenance Status, and Road Recovery Time. For each dimension, the framework includes subdimensions, recommended indicators, underlying rationale, common data sources, timeliness expectations, and a weight consideration reflecting the dimension's relative importance.

In defining the dimensions and their associated subdimensions, care was taken to minimize overlap between subdimensions across different dimensions. This was done to promote clear distinction between contributing factors and to facilitate the development of condition indices that rely on weighted aggregation. As a result, subdimensions are mutually exclusive across dimensions, with one exception: temperature-related elements. While temperature appears in both the Temperature-Related and Wind-Related dimensions, it reflects different aspects—such as air temperature, pavement temperature, and wind chill effects—thereby preserving conceptual separation. At the same time, the framework also supports cross-cutting analysis. For example, a snowstorm event may simultaneously trigger metrics under the Precipitation-Related, Visibility-Related, Surface Condition, and Resource Utilization dimensions. This multidimensional view enables agencies to track cascading impacts, prioritize resources, and assess operational effectiveness more holistically. The aforementioned separation of dimensions ensures that metrics activated across multiple dimensions during a single event can be traced and interpreted distinctly, rather than redundantly. This structure allows agencies to observe not only that an event occurred but also how it propagated through various facets of the transportation system.

Importantly, the framework is intended not as a rigid standard but as a flexible tool that agencies can tailor to their capabilities and data infrastructure. Smaller jurisdictions may choose to prioritize a subset of high-impact dimensions, while larger agencies may fully implement all nine. The framework's emphasis on data fusion—from weather sensors to maintenance dashboards to CV data—also aligns with current trends toward integrated, real-time operational intelligence.

5.2. Framework Dimensions and Key Components

The following dimensions represent the standardized categories that transportation agencies should monitor to evaluate winter-related hazards and support operational decision-making:

- **Precipitation-Related:** The characteristics and impacts of winter weather events involving different precipitation types and intensities
- **Resource Utilization:** Quantification of operational effort and deicing materials in response to weather
- **Road Recovery Time:** Time required for road to return to safe conditions after storm
- **Surface Condition:** Physical condition of pavement due to winter events; includes weather conditions that reduce friction, weather events that cause foreign object accumulation (e.g., snow, ice, frost, water, or ash), wet condition (hydro-climatic) threats, including water and erosion impacts
- **Temperature-Related:** Ambient thermal conditions influencing road surface states
- **Traffic Flow Impact:** Congestion or slowdown resulting from weather; impact of winter conditions on traffic mobility and reliability
- **Visibility-Related:** Visual range for drivers under adverse winter weather
- **Wind-Related:** Wind events influencing snow drift, visibility, and vehicle stability
- **Winter Maintenance Status:** Status of winter maintenance operations on the roadway; DOT response activities that affect surface state

Each dimension is described using a standardized set of table columns designed to provide a comprehensive and actionable profile. These columns work together to support interpretation, prioritization, and operational planning:

- **Subdimension**: Captures specific aspects within each dimension that require monitoring (e.g., snowfall rate, surface slipperiness). These serve as more detailed areas of focus within the broader dimension.
- **Indicators**: These measurable metrics associated with each subdimension provide quantifiable variables that signal the presence or severity of an operational factor (i.e., dimension or subdimension). These can include sensor readings and physical measurements, qualitative thresholds (e.g., visibility below 0.25 miles), or categorical or binary markers (e.g., road classified as plowed or unplowed).
- **Rationale**: Justifies the inclusion of each dimension based on its impact on safety, mobility, operational response, or resource allocation. It highlights how each dimension contributes to real-world decision-making.

- **Data sources**: Lists the most common sources of information for each indicator, including RWIS, NWS feeds, operator logs, or CV data. These help agencies align existing infrastructure with required inputs.
- **Weight consideration**: Reflects the relative importance or criticality of the dimension. For example, direct safety risks like ice presence may be marked “High,” while post-event metrics like recovery time may be “Medium to High.” This aids prioritization during resource-constrained scenarios.
- **Refresh frequency**: Indicates how frequently the data should be updated (e.g., real-time, hourly, post-event). Timeliness helps determine the role of each metric in proactive monitoring versus retrospective analysis.
- **References**: Where available, scientific or empirical references can be cited to validate indicator relevance and methodology. This enhances credibility and encourages standardization.

By interacting across these columns, the framework enables agencies to do the following:

- Evaluate winter events comprehensively across environmental, operational, and mobility dimensions
- Tailor monitoring protocols to available data infrastructure
- Benchmark performance over time and across regions
- Prioritize high-impact conditions with real-time operational consequences

5.3. Implementation Steps for Transportation Agencies

The following step-by-step approach is recommended for applying the framework within agency operations:

5.3.1. Step 1: Assess Current Capabilities

- Review the full list of framework dimensions and assess their applicability to the agency’s operational environment, geography, and risk profile. Consider factors such as typical winter hazards, crash history, available data infrastructure, and stakeholder priorities.
- Retain dimensions that align with agency goals (e.g., reduce crash rates, improve response time, ensure mobility) and deprioritize those with limited relevance or feasibility.
- Inventory existing data collection systems (e.g., RWIS, intelligent transportation systems [ITS], NWS feeds).
- Identify which dimensions are already monitored and which require additional infrastructure or integration.

5.3.2. Step 2: Align with Standardized Metrics

- Adopt the indicators and thresholds associated with each dimension.

- Use the rationale column to prioritize dimensions based on operational or safety relevance. For example, highlight indicators with strong predictive value or direct interpretability.
- Record any gaps in available indicators and identify potential proxy metrics.

5.3.3. Step 3: Integrate Data Sources and Platforms

- Connect real-time, periodic, and post-event data into a centralized analytics platform.
- Enable data fusion between weather feeds, CV data, maintenance logs, and traffic sensors.

5.3.4. Step 4: Classify Event Severity and Operational Readiness

- Use the weight consideration (e.g., "High—direct safety impact") to inform response prioritization. Scoring logic should be defined at this stage, establishing scoring criteria or thresholds for each indicator (e.g., "Wind gust > 30 mph = moderate hazard").
- Weights can be assigned to the selected factors (dimensions or subdimensions) using expert judgement or data-driven models.
- Incorporate benchmark ranges for indicators such as snowfall rate, visibility threshold, or salt usage.
- Develop a method for aggregating scores across indicators and operational factors. This can involve a variety of techniques, such as simple summation, weighted average, and rule-based classification, given that they enable intuitive index values such as a 1–10 scale or low-medium-high severity levels.

5.3.5. Step 5: Evaluate and Refine

- Conduct post-event reviews using the Resource Utilization, Traffic Flow Impact, and Road Recovery Time dimensions.
- Update thresholds and response protocols as technology and climate conditions evolve.

5.4. Example Use Cases for Decision-Making

The following use cases demonstrate how the framework's structure can be applied across key phases of winter weather management (namely, pre-event planning, in-event operations, and post-event evaluation) and link operational factors with measurable indicators and data sources. Each example reflects a different combination of dimensions (e.g., Snowfall, Visibility, Resource Utilization) and shows how agencies can interpret real-time or historical data to inform actionable decisions:

- **Example 1: Pre-storm Resource Allocation.** An agency anticipates a winter storm event with high snowfall rates and freezing rain. By using real-time indicators from the **Precipitation-Related** and **Temperature-Related** dimensions, combined with the **Storm Severity** forecast, the agency can proactively allocate salt and brine, stage plows, and deploy early alerts to travelers. The high weight consideration of these dimensions signals that immediate action is warranted.

- **Example 2: Dynamic Traffic Management during an Event.** As visibility drops below the 0.25-mile threshold and wind gusts exceed safe limits, data from the **Visibility-Related** and **Wind-Related** dimensions are triggered. The agency activates message signs, lowers speed limits, and coordinates with law enforcement for high-risk areas. Concurrent data from **Traffic Flow Impact** provide real-time feedback on congestion, allowing traffic signal timing adjustments or rerouting plans.
- **Example 3: Post-event Effectiveness Review.** Following a major storm, the agency evaluates its response using the **Winter Maintenance Status**, **Resource Utilization**, and **Road Recovery Time** dimensions. It reviews clearance times, salt usage logs, and traffic sensor data to measure how quickly roads returned to safe conditions. Lessons learned are documented and thresholds adjusted based on findings.

As these examples highlight, the integrated use of the framework supports both strategic planning and tactical response, promoting safer roads and more efficient winter operations. By defining indicators and thresholds for each operational factor, the framework enables agencies to respond not only to individual data points but also to broader patterns of road condition deterioration or system stress. The ability to track indicator activation across multiple dimensions during a single event (e.g., a snowstorm triggering snowfall, surface condition, and traffic flow impact metrics) allows for a more comprehensive understanding of event severity and system performance.

Detailed tables of indicators, data sources, and scientific references supporting each dimension are maintained in the Framework spreadsheet (Dimension worksheet) developed under this project. This worksheet presents the complete matrix for each winter weather dimension, with structured details on subdimensions, indicators, rationale, data sources, weight consideration, timeliness, and references. Table 8 presents a summary of this information.

This matrix is intended to support implementation consistency and performance tracking. Agencies may tailor specific indicators and thresholds based on regional climate, operational capacity, and data availability.

Table 8. Detailed indicator-level framework matrix

Dimension	Subdimension	Indicators	Data Sources
Precipitation-Related	Snowfall (incl. Heavy Snow, Blizzards, Lake Effect Snow)	Precipitation type	NWS, NWS current conditions, RWIS, SNODAS (NSIDC), road cameras, CV data, DOT weather logs, plow sensor logs
		Precipitation rate	
		Precipitation duration	
		Snow accumulation (in.)	
		Visibility	
		Wind speed	
		Wind gusts	
		temperature	
	Rain	Precipitation rate	NWS, NWS current conditions, RWIS, road cameras, CV data, DOT weather logs
		Precipitation duration	
		Visibility	
		Temperature	
	Fog	Visibility	RWIS, NWS current conditions, road cameras, CV data
		Temperature	
		Humidity	
		Dew point	
		Wind speed	
	Freezing Precipitation & Ice-Related Events (e.g., Frost)	Precipitation type	RWIS, Road cameras, CV data, plow sensor logs, SNODAS (NSIDC), DOT weather logs
		Precipitation rate	
		Ice accretion (in. or mm)	
		Ice detection	
		Temperature	
		Surface friction	
	Storm Events	Precipitation type	NWS, RWIS, CV data, DOT weather logs, road cameras
		Precipitation rate	
		Wind speed	
		Wind gusts	
		Temperature	
		Visibility	
	Storm Severity	SSI (composite)	RWIS, CV data, DOT weather logs, plow sensor logs, SNODAS (NSIDC)
		Wind gusts	
		Precipitation rate	
		Ice detection	
		Surface friction	
	Storm Duration	Precipitation duration	RWIS, CV data, DOT weather logs
		SSI (composite)	
		Wind gusts	
	Storm Transition Type	Precipitation type transitions	NWS current conditions, RWIS, road cameras, CV data
		Temperature	
		Wind speed	
		Visibility	

Dimension	Subdimension	Indicators	Data Sources
Resource Utilization	Material Usage	Salt usage (tons/event)	Maintenance reporting systems, salt tracking dashboards, operator logs
		Brine usage (tons/event)	
		Sand usage (tons/event)	
	Labor Effort	Crew hours (hours)	Maintenance reporting systems, operator logs
	Equipment Utilization	Equipment operation hours	Maintenance reporting systems, operator logs
		Cost per lane-mile ($/mi)	
Road Recovery Time	Clearance Timeline	Time to bare/wet pavement	DOT logs, RWIS, operator inputs, sensor data, ITS
		Reopen time for closures	
		Reduction in treatment frequency	
	Traffic Speed and Volume (Traffic Normalization)	Traffic speed	Regional Integrated Transportation Information System (RITIS), CV and probe vehicle data, traffic sensors, RWIS, ITS
		Traffic volume/flow	
		Queue length/formation	
Surface Condition	Surface Traction	Road surface friction	RWIS (incl. cameras and friction), ITS and road sensors, operator logs, AVL data, CV data, DOT incident logs
		Black ice detection	
		Ice presence	
		Frost occurrence	
		Frost depth	
		Sleet	
		Slushy surface	
		Hydroplaning potential	
		Ice patches	
		Black ice reports	
	Surface Hazards and Clearance	Ash presence	RWIS, ITS and road sensors, roadside cameras, operator logs, DOT incident logs
		Debris presence	
		Whiteouts	
		Snow accumulation	
		Salt residue on roads	
		Wet surface	
		Road submersion	
	Surface Moisture State Parameters	Pavement surface temperature	RWIS, NWS, flood sensors, roadside cameras, CV data, AVL data
		Soil temperature	
		Air temperature	
		Dew point	
		Humidity	
		Precipitation type	
		Precipitation rate	
		Freezing precipitation/Freezing rain	
		Water level	
		Flash flood warnings	

Dimension	Subdimension	Indicators	Data Sources
Temperature-Related	Air Temperature	Air temperature	RWIS, ASOS/AWOS, NWS
		Dew point	
		Freezing point differential (ΔT between surface and dew point)	
	Pavement Temperature	Pavement temperature	
		Dew point	
		Freezing point differential (ΔT between surface and dew point)	
Traffic Flow Impact	Speed (Reduction of Speed)	Traffic speed	ITS, RITIS, CV and probe vehicle data, traffic sensors
		Queue length/formation	
	Volume (Reduction of Volume)	Traffic volume/flow	
		Queue length/formation	
Visibility-Related	Fog and Obscuration (including Smoke)	Visibility distance (miles/km)	NWS, RWIS (visibility sensors), road cameras
		Visibility threshold	
		Fog detection	
		Snow squalls	
		Blowing snow reports	
	Precipitation-Induced Visibility Loss	Visibility distance (miles/km)	
		Precipitation rate combined with wind speed	
		Blowing snow reports	

Dimension	Subdimension	Indicators	Data Sources
Wind-Related	Wind Characteristics (Speed)	Wind speed & gusts (mph or km/h)	NWS, RWIS, ASOS/AWOS
		Crosswind index (vehicle stability hazard score)	
		Air temperature	
	Wind Characteristics (Temperature)	Wind chill index (°F or °C)	
		Surface cooling rate (°F/hour)	
		Frost point versus surface temperature differential	
		Air temperature	
	Wind Characteristics (Direction)	Wind direction	
		Crosswind index	
	Wind Events – Blowing Snow	Snow drift reports / likelihood (categorical or binary)	
		Wind speed & gusts	
		Whiteout probability	
	Wind Events – Wind Chill	Wind chill index (°F or °C)	
		Surface cooling rate	
		Frost point versus surface temperature differential	
	Wind Events – Wind Gusts	Wind speed & gusts (mph or km/h)	
		Crosswind index	
	Wind Events – Snow Drift Potential	Snow drift reports / likelihood (categorical or binary)	
		Crosswind index	
		Whiteout probability	
Winter Maintenance Status	Treatment/Plow Status	Plow status (pass/no pass per route)	AVL data, MDSS logs, operator logs, maintenance dashboards
		% of network treated	
	Maintenance Response Time	Time since last treatment (minutes/hours)	
	Coverage Quality	% of network treated	
		Resource utilization metrics*	
	Residual Salt Level	Resource utilization metrics*	

CHAPTER 6. CASE STUDY APPLICATION OF THE WINTER WEATHER ROAD CONDITION INDEX FRAMEWORK

6.1. Overview and Approach

The development of a standardized national framework for WWRCIs requires not only conceptual and technical consistency but also demonstrable applicability under real-world conditions. Tasks 1 through 5 of this project established the theoretical foundation, investigated stakeholder priorities, evaluated existing indices, and developed the proposed national framework and implementation guidance. Task 6, described in this chapter, focused on validating the practicality, flexibility, and interpretability of the framework through an applied case study. The case study aimed at translating the framework from a conceptual standard into an operationally meaningful tool that transportation agencies can realistically implement using available data and resources.

The rationale for conducting this case study was primarily based on the notion that winter weather events are inherently complex and multidimensional, with impacts that vary temporally, spatially, and operationally. A case study would allow the framework to be tested against an actual winter storm event and demonstrate how multiple dimensions, such as precipitation, temperature, wind, visibility, surface condition, and traffic impacts, and the subdimensions, indicators, and parameters associated with them, can be systematically identified, quantified, and aggregated to produce a meaningful road condition index. Moreover, the case study aimed to show how the framework can be applied in a flexible manner, allowing dimensions, subdimensions, and indicators to be selected based on data availability while still maintaining internal consistency and alignment with the national standard. This is particularly useful given that agencies across the country differ in data availability, technological maturity, and institutional capacity.

This task applied the framework to a documented winter weather event to demonstrate the end-to-end process of framework implementation. The case study approach included selecting a severe winter weather event and using the framework developed in this project to obtain a WWRCI for a selected county immediately before, during, and immediately after the event. The process involved mapping the event characteristics to relevant framework dimensions, identifying available data sources and indicators, processing and harmonizing data across multiple sources, and calculating a daily WWRCI for the selected county. The analysis evaluated conditions before, during, and after the event, thereby illustrating the framework's ability to capture event evolution, operational impacts, and recovery dynamics over time.

The description of the case study in this chapter is structured in a stepwise and transparent manner to support reproducibility by transportation agencies. It begins with event identification and justification, followed by selection of applicable framework dimensions and indicators based on the event narrative and data availability. Subsequent sections describe data acquisition, data processing and treatment methods, index calculation procedures, and interpretation of results. This structure mirrors the implementation guidance developed in Task 5 and is intended to serve as a practical reference for agencies seeking to operationalize the framework.

Data and resources used in the case study included nationally available and commonly used datasets such as weather observations, RWIS, publicly available climatological data, and CV-based traffic performance metrics. By relying on data sources that are accessible or increasingly available to transportation agencies, the case study emphasizes feasibility and scalability rather than specialized or experimental data requirements. Where data gaps exist, the case study documents how alternative indicators or proxy measures can be used.

To ensure that the WWRCI reflects the true impact of winter events on safety and mobility, the framework incorporates a hierarchical weighting system. This approach recognizes that not all environmental factors contribute equally to hazardous driving conditions; for example, the presence of ice on the roadway generally poses a more immediate threat to vehicle control than a minor reduction in visibility. Therefore, weights are applied at multiple levels of the framework, starting with individual indicators (e.g., ice versus frost) and aggregating up to the subdimensions (e.g., Surface Traction) and to the primary dimensions (e.g., Surface Condition, Visibility-Related). This multi-tiered weighting process ensures that the final index is a balanced and operationally relevant composite score, preventing less critical data points from disproportionately skewing the assessment of overall severity. Agencies may select these weights based on a range of factors, including applicable guidance, established policies, institutional experience, input from subject matter experts, and stakeholder engagement.

The primary products of Task 6 include a documented example of framework application, sample calculations of a WWRCI over a defined event period, and visual and tabular outputs that illustrate how index results can support operational awareness and post-event assessment.

6.2. Event Selection

In an effort to showcase the use of the framework, the research team identified a winter weather event that occurred in Story County in 2022. The research team also decided to calculate the WWRCI on each day before, during, and after the winter weather event.

The weather event that was selected was a blizzard that took place on December 23, 2022. Figure 27 shows the blizzard event information from NOAA's National Centers for Environmental Information.

NOAA NATIONAL CENTERS FOR ENVIRONMENTAL INFORMATION
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION

Home Contact Us About NCEI Help

NCEI > Storm Events Database (Select State) > (Select Date/County/Event) > (Search Results)

Storm Events Database

Data Access
- Search
- Bulk Data Download (CSV)
- Storm Data Publication

Documentation
- Database Details
- Version History
- Storm Data FAQ
- NOAA's NWS Documentation
- Tornado EF Scale

External Resources
- NOAA's SPC Reports
- NOAA's SPC WCM Page
- NOAA's NWS Damage Assessment Toolkit
- NOAA's Tsunami Database
- ESRI/FEMA Civil Air Patrol Images
- SHELDUS
- USDA Cause of Loss Data

Storm Events Database

Search Results

Event Details:

Event	**Blizzard**
State	**IOWA**
County/Area	**STORY**
WFO	**DMX**
Report Source	**ASOS**
NCEI Data Source	**CSV**
Begin Date	**2022-12-23 08:00 CST-6**
End Date	**2022-12-23 20:00 CST-6**
Deaths Direct/Indirect	**0/0** (fatality details below, when available...)
Injuries Direct/Indirect	**0/0**
Property Damage	**0.00K**
Crop Damage	**0.00K**
Episode Narrative	**A large winter system impacted Iowa and much of the Midwest in the days leading up to Christmas 2022. Snow began to fall across Iowa on the 21st and lasted through the morning of the 22nd, blanketing most of the state in a widespread depth of two to four inches. At the same time, temperature began to plummet with wind chills across the area dropping into the minus 30s and minus 40s by the morning of the 22nd. As the system began to shift east the tight pressure gradient and strong cold air advection allowed winds to increase, gusting to over 40 mph in many locations by the 23rd. A few places even recorded wind gusts of 50 to 58 mph. The strong winds and fresh snow resulted in blizzard conditions across portions of central and all of northern Iowa on the 23rd with visibility near zero. Winds gradually eased overnight with significant improvement to visibility by Christmas Eve morning. Conditions significantly impacted holiday travel with dozens of car accidents reported and a closure of interstate 35. This was a historic event. While extreme cold occurs with regularity in Iowa, the duration of this arctic outbreak set this event apart. The combination with blizzard conditions resulted in especially dangerous conditions putting anyone stranded at severe risk.**
Event Narrative	

Source: NOAA

Figure 27. Blizzard event information

Although the blizzard occurred on December 23, 2022, the episode narrative indicates that snowfall as well as other winter weather elements began on December 21, 2022. Therefore the event duration was considered to be from December 21, 2022, to December 24, 2022; the pre-event weather was considered to have occurred on December 20, 2022; and the post-event weather was considered to have occurred on December 25, 2022.

6.3. Acquiring and Processing Available Data for the Related Framework Dimensions

Applying the standardized WWRCI framework to a real-world event requires the systematic acquisition and processing of data that correspond to the framework's defined dimensions, subdimensions, and indicators. Because winter weather events involve multiple interacting environmental and operational factors, this step is critical for translating observed conditions into quantifiable inputs that support consistent index calculation and interpretation. The purpose of this section is to describe how available data were identified, aligned with the framework structure, and prepared for use in the case study analysis.

The framework developed in Task 5 is intentionally flexible to accommodate varying levels of data availability across agencies and regions. Accordingly, data acquisition in this case study follows a hierarchical approach: when direct information, or, as we refer to it, weather intelligence, was available at the dimension level, those data were used. When dimension-level direct information was unavailable, the analysis relied on subdimensions and, where necessary, specific indicators to represent the associated framework components.

Data sources for the case study were selected based on three primary criteria:

- Relevance to the identified winter weather event
- Reliability and documentation of the data
- Accessibility to transportation agencies across different states and levels

Priority was given to nationally or regionally available datasets commonly used in winter operations, including weather observations, RWIS, and transportation system performance data. These sources provide the environmental, roadway, and traffic-related inputs required to assess winter impacts across multiple framework dimensions.

Once acquired, raw data were processed to ensure temporal consistency, comparability across sources, and suitability for index calculation. Processing steps included filtering data to the defined event period, converting observations to consistent time intervals, aggregating metrics as needed (e.g., daily summaries), and translating raw measurements into standardized indicators consistent with the framework thresholds. Where necessary, proxy measures and binary indicators were used to represent framework elements that could not be directly measured with available data.

6.3.1. Mapping Event to the Framework (Identifying Relevant Dimensions)

Based on the event episode narrative from Figure 27, the weather event included snowfall, low temperatures, windchills, strong cold air, tight pressure, wind gusts, visibility near zero, and a roadway closure. From these descriptions of the weather event, relevant dimensions of the framework were identified. These dimensions included the following:

- Visibility-Related
- Precipitation-Related
- Temperature-Related
- Wind-Related
- Traffic Flow Impact

- Surface Condition

Table 9 presents the first step in applying the framework to a weather event, which is to identify the main parameters for the weather event.

Table 9. Identifying event descriptors

Narrative	Keywords/Descriptors
"A large winter system impacted Iowa and much of the Midwest in the days leading up to Christmas 2022. Snow began to fall across Iowa on the 21st and lasted through the morning of the 22nd, blanketing most of the state in a widespread depth of 2 to 4 in. At the same time, temperature began to plummet with wind chills across the area dropping into the minus 30s and minus 40s by the morning of the 22nd. As the system began to shift east the tight pressure gradient and strong cold air advection allowed winds to increase, gusting to over 40 mph in many locations by the 23rd. A few places even recorded wind gusts of 50 to 58 mph. The strong winds and fresh snow resulted in blizzard conditions across portions of central and all of northern Iowa on the 23rd with visibility near zero. Winds gradually eased overnight with significant improvement to visibility by Christmas Eve morning. Conditions significantly impacted holiday travel with dozens of car accidents reported and a closure of Interstate 35. This was a historic event. While extreme cold occurs with regularity in Iowa, the duration of this arctic outbreak set this event apart. The combination with blizzard conditions resulted in especially dangerous conditions putting anyone stranded at severe risk." [https://www.ncei.noaa.gov/stormevents/eventdetails.jsp?id=1068072]	Snowfall Low temperature Windchills Strong cold air Tight pressure Wind gusts Visibility near zero Closure of Interstate 35

Table 10 shows the next step, in which the relevant dimensions associated with the event description are identified. Dimensions marked with an asterisk (*) are the ones that were selected to move forward with the analysis. Unmarked dimensions, such as Resource Utilization, were not selected because of data availability; however, if state agencies have these data, it is recommended that the data be used to calculate the index.

Table 10. Identifying relevant dimensions

Keywords/Descriptors	Dimension	Description
Snowfall, Low temperature, Windchills, Strong cold air, Tight pressure, Wind gusts, Visibility near zero, Closure of Interstate 35	**Precipitation-Related***	The characteristics and impacts of winter weather events involving different precipitation types and intensities.
	Resource Utilization	Quantification of operational effort and deicing materials in response to weather.
	Road Recovery Time	Time required for road to return to safe conditions after storm.
	Surface Condition*	Physical condition of pavement due to winter events; includes weather conditions that reduce friction, weather events that cause foreign object accumulation (e.g., snow, ice, frost, water, or ash), wet condition (hydro-climatic) threats including water and erosion impacts.
	Temperature-Related*	Ambient thermal conditions influencing road surface states.
	Traffic Flow Impact*	Congestion or slowdown resulting from winter weather condition impacts on traffic mobility and reliability.
	Visibility-Related*	Visual range for drivers under adverse winter weather.
	Wind-Related*	Wind events influencing snow drift, visibility, and vehicle stability.
	Winter Maintenance Status	Status of winter maintenance operations on the roadway; DOT response activities that affect surface state.

6.3.2. Identifying Data Sources

Each dimension includes a set of recommended subdimensions and indicators that are used to calculate the dimension's impact within the road weather condition index. When no data are available at the dimension level, subdimensions are used, and when no data are available for the subdimensions, indicators are used to assess the associated subdimensions and then the subdimensions are used to assess the primary dimension. The user can select the most relevant subdimensions or indicators associated with the event based on the hierarchical structure and data-availability principles defined in the standardized framework. Tables 11, 12 and 13 show examples of dimensions for which available data were identified at the dimension level (Table 11), at the subdimension level (Table 12) and at the indicator level (Table 13).

Table 11. Dimension with available data at the dimension level

Dimension	Subdimension	Indicators
Visibility-related	Fog and Obscuration (including Smoke)	Visibility distance (miles/km)
		Visibility threshold
		Fog detection
		Snow squalls
		Blowing snow reports
	Precipitation-Induced Visibility Loss	Visibility distance (miles/km)
		Precipitation rate combined with wind speed
		Blowing snow reports

Table 12. Dimension with available data at the subdimension level

Dimension	Subdimension	Indicators
Precipitation-related	**Snowfall (incl. Heavy Snow, Blizzards, Lake Effect Snow)**	Precipitation type
		Precipitation rate
		Precipitation duration
		Snow accumulation (in)
		Visibility
		Wind speed
		Wind gusts
		Temperature
	Rain	Precipitation rate
		Precipitation duration
		Visibility
		Temperature
	Fog	Visibility
		Temperature
		Humidity
		Dew point
		Wind speed
	Freezing Precipitation & Ice-Related Events (e.g., Frost)	Precipitation type
		Precipitation rate
		Ice accretion (in or mm)
		Ice detection
		Temperature
		Surface friction
	Storm Events	Precipitation type
		Precipitation rate
		Wind speed
		Wind gusts
		Temperature
		Visibility
	Storm Severity	SSI (composite)
		Wind gusts
		Precipitation rate
		Ice detection
		Surface friction
	Storm Duration	Precipitation duration
		SSI (composite)
		Wind gusts
	Storm Transition Type	Precipitation type transitions
		Temperature
		Wind speed
		Visibility

Table 13. Dimension with available data at the indicator level

Dimension	Subdimension	Indicators
Surface Condition	Surface Traction	Road surface friction
		Black ice detection
		Ice presence
		Frost occurrence
		Frost depth
		Sleet
		Slushy surface
		Hydroplaning potential
		Ice patches
		Black ice reports
	Surface Hazards and Clearance	Ash presence
		Debris presence
		Whiteouts
		Snow accumulation
		Salt residue on roads
		Wet surface
		Road submersion
	Surface Moisture State Parameters	Pavement surface temperature
		Soil temperature
		Air temperature
		Dew point
		Humidity
		Precipitation type
		Precipitation rate
		Freezing precipitation/Freezing rain
		Water level
		Flash flood warnings

Table 14 shows the third step, which is to identify framework elements for which data are available. In this case study, the Precipitation-Related dimension was calculated based on snowfall rate, while the severity of the Surface Traction subdimension was calculated using ice presence and frost occurrence. On the other hand, the severity of the Surface Hazards and Clearance subdimension was calculated using the snow accumulation (snow depth) indicator. Both subdimensions (Surface Traction, and Surface Hazard and Clearance) were used to calculate the severity of Surface Condition dimension.

Table 14. Identifying framework elements with available data

Dimension	Subdimension	Indicator
Precipitation-Related	Snowfall	-
Temperature-Related	Air Temperature	-
Wind-Related	Wind Events – Wind Gusts	-
Visibility-Related	-	-
Traffic Flow Impact	Speed (Reduction of Speed)	-
	Volume (Reduction of Volume)	-
Surface Condition	Surface Hazards and Clearance	Snow accumulation
	Surface Traction	Ice presence
		Frost occurrence

To populate the identified framework dimensions, subdimensions, and indicators, the case study relied on a combination of nationally available, regionally maintained, and operational transportation datasets that are commonly used by state and local agencies for winter weather monitoring and performance assessment. Weather- and atmosphere-related variables, including visibility, air temperature, and wind gusts, were obtained from publicly accessible meteorological observation networks, while precipitation characteristics such as snowfall rate and snow accumulation (snow depth) were sourced from nationally archived climatological datasets. Road surface condition indicators, including ice presence and frost occurrence, were derived from RWIS observations to capture pavement-level impacts that directly influence roadway safety. Traffic performance indicators reflecting changes in speed and traffic volume were developed using connected vehicle–based data to quantify mobility impacts associated with the winter event. Together, these data sources enable consistent calculation of dimension-level severities while demonstrating how agencies can integrate diverse, yet readily available, data resources within a standardized WWRCI application. Some notable publicly available data sources used in the case study include the following:

- **Iowa Environmental Mesonet** (IEM n.d.), used for the following:

  1. Visibility
  2. Air temperature
  3. Wind events/wind gusts
  4. Ice presence
  5. Frost occurrence

- **NOAA's Global Historical Climatology Network - Daily (GHCN-Daily), Version 3 dataset**, used to obtain snowfall and snow accumulation (snow depth) (Menne et al. 2012)
- **CV data**, including vehicle movement datasets from Wejo, used to obtain traffic speed and traffic volume/flow

6.3.3. Data Treatment and Processing

The research team calculated the daily averages of snowfall and snow depth from multiple meteorological stations. Furthermore, daily averages of temperature and wind gusts were calculated from available data. Daily minimum visibility was calculated and used to represent visibility. Ice watch and frost occurrences were used to represent ice and frost indicators, respectively. Figure 28 shows the daily average snowfall (Avg. Snow) and snow depth (Avg. Snwd) during the analysis period. Figure 29 shows the minimum visibility (Min. Vsby), average temperature (Avg. Tmpf), and average wind gusts (Avg. Gust Mph) during the analysis period. Figure 30 shows the ice watch and frost occurrences during the analysis period. Changes in speed and traffic volume between the analysis period in 2022 and the same weekdays in 2021 were calculated using CV data from Wejo. Figure 31 shows a comparison of the number of journeys and the overall county-level average speeds between December 21–26, 2021, and December 20–25, 2022. The percent changes in speed and traffic volume were calculated for each of the weekdays and were used in the framework to represent the Speed (Reduction of Speed) and Volume (Reduction of Volume) subdimensions.

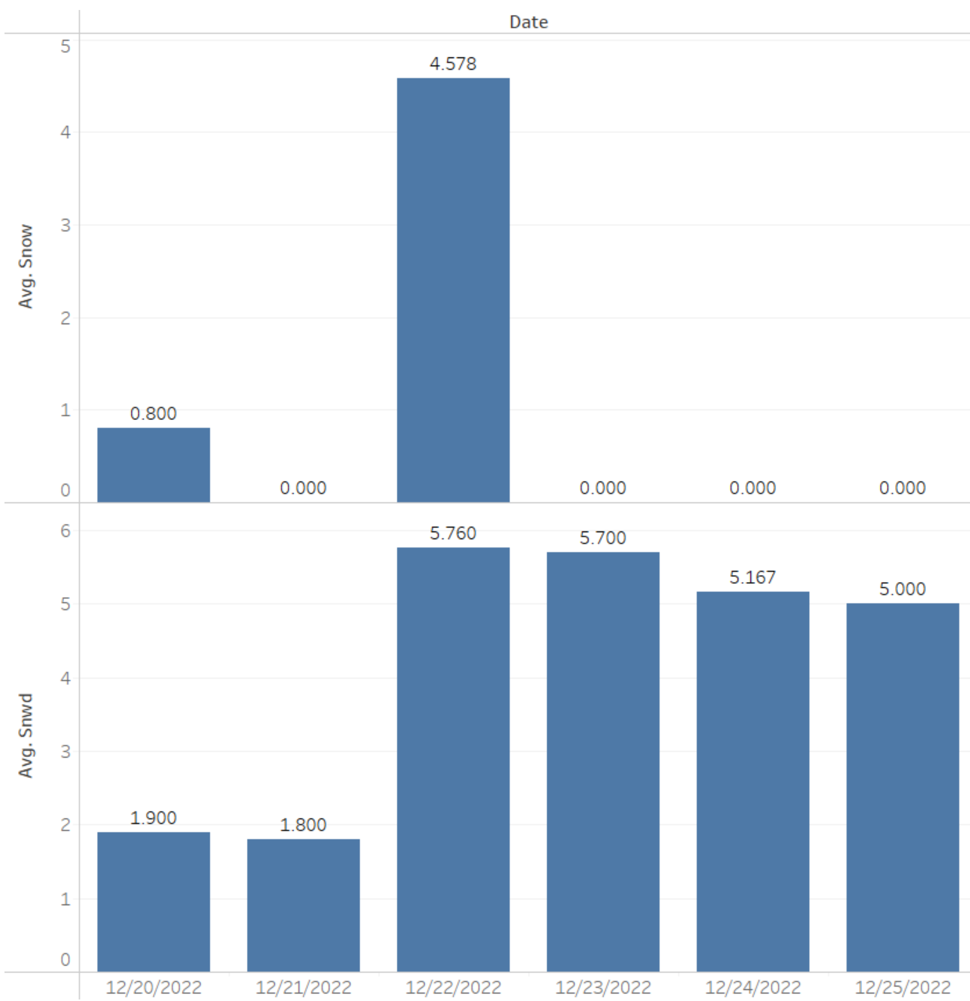


Figure 28. Snowfall data for each date during the case study period

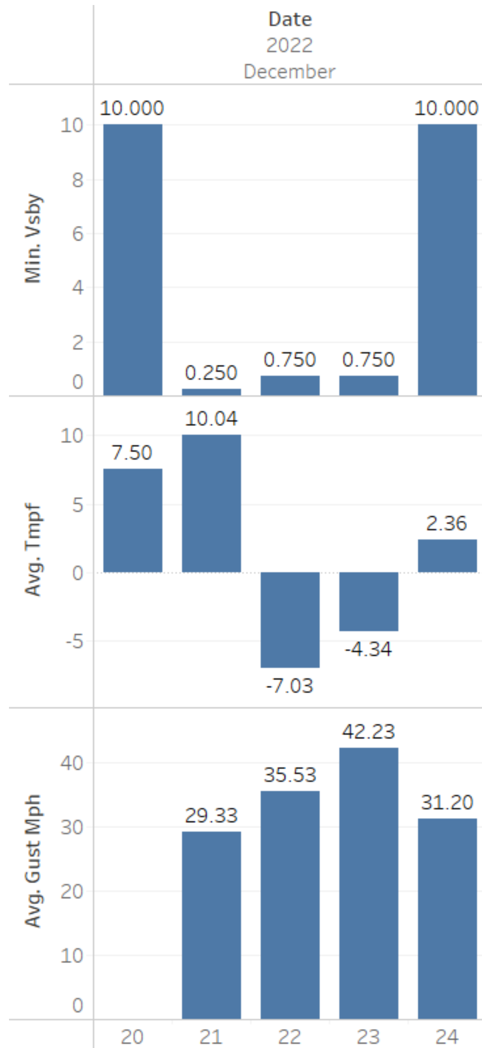


Figure 29. Minimum visibility data, average temperature, and average wind gust during the analysis period

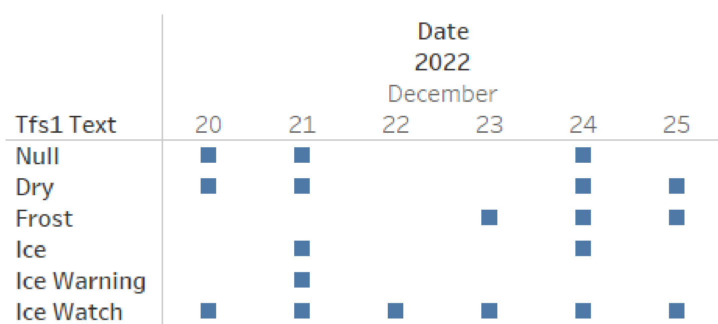


Figure 30. Ice watch and frost occurrence during the analysis period

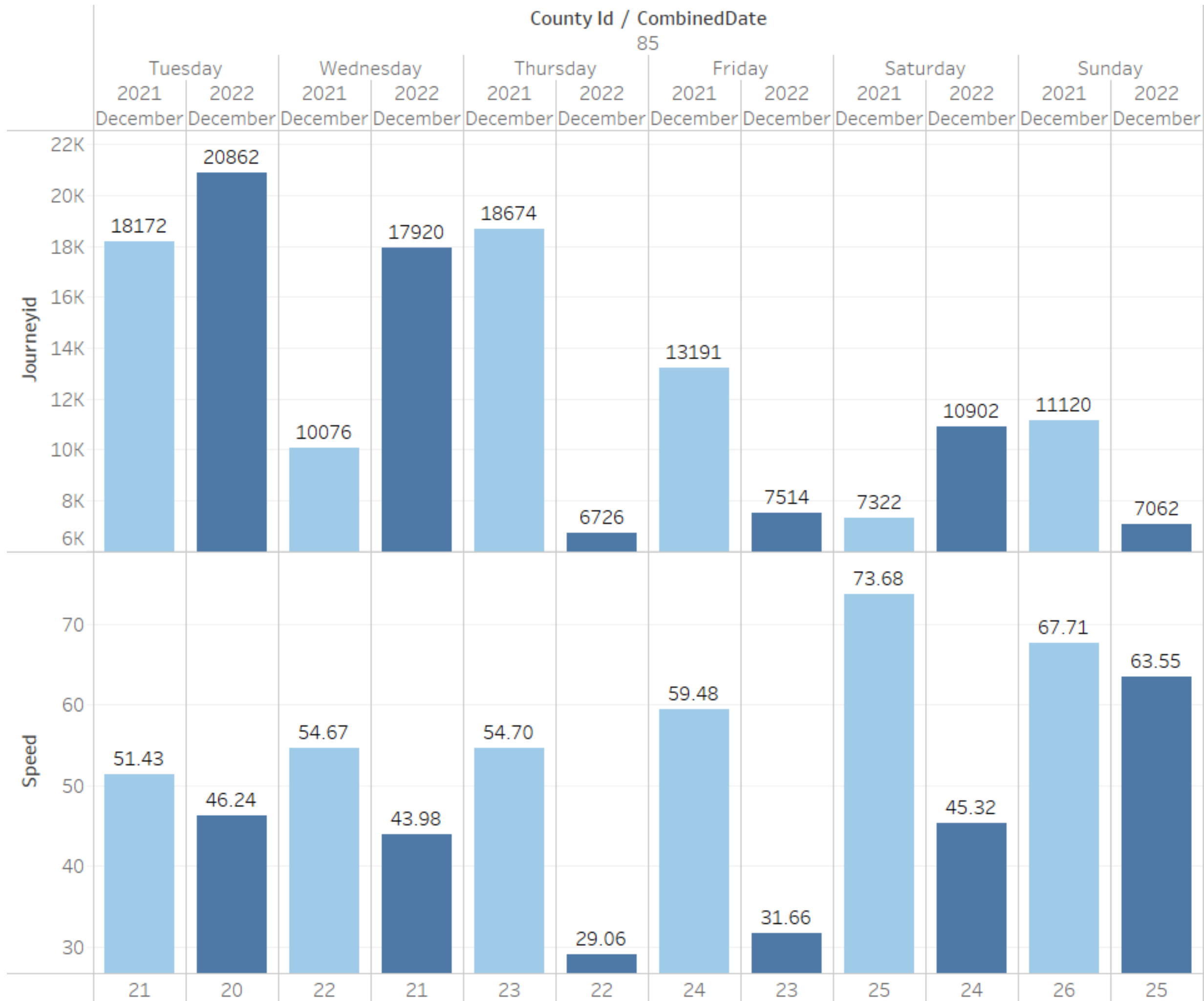


Figure 31. Speed and traffic volume for December 21–26, 2021, and December 20–25, 2022

Tables 15, 16, and 17 show the fourth step in calculating the WWRCI, which includes populating the values from the data processing and treatment steps for each of the framework elements of the case study. Table 15 shows the dimension values for each day of the analysis period, while Table 16 shows the values for the subdimensions and Table 17 shows the values for the indictors.

Table 15. Dimension-level values used in the WWRCI calculation (pre-, during-, and post-event periods)

Dimension	Pre-event (12/20/2022)	During-event (12/21-24/2022)				Post-event (12/25/2022)	Unit
	Dimension Value	Dimension Value	Dimension Value	Dimension Value	Dimension Value	Dimension Value	
Precipitation-Related	-	-	-	-	-	-	-
Temperature-Related	-	-	-	-	-	-	-
Wind-Related	-	-	-	-	-	-	-
Visibility-Related	10	0.25	0.75	0.75	10	M	mile
Traffic Flow Impact	-	-	-	-	-	-	-
Surface Condition	-	-	-	-	-	-	-

Table 16. Subdimension-level data inputs and severity values for the winter weather event

Dimension	Subdimension	Pre-event (12/20/2022)	During-event (12/21-24/2022)				Post-event (12/25/2022)	Unit
		Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value	
Precipitation-Related	Snowfall	0.8	0	4.6	0	0	0	in.
Temperature-Related	Air Temperature	7.5	10	-7	-4.3	2.4	M	F
Wind-Related	Wind Events – Wind Gusts	Missing	29.3	35.5	42.2	31.2	M	mph
Visibility-Related	-	-	-	-	-		-	-
Traffic Flow Impact	Speed (Reduction of Speed)	-10%	-20%	-47%	-47%	-38%	-6%	pct change
	Volume (Reduction of Volume)	15%	78%	-64%	-43%	49%	-36%	pct change
Surface Condition	Surface Hazards and Clearance	-	-	-	-		-	
	Surface Traction	-	-	-	-	-	-	-

Table 17. Indicator-level observations used to derive subdimension and dimension severity values

Dimension	Subdimension	Indicator	Pre-event (12/20/2022) Indicator Value	During-event (12/21-24/2022) Indicator Value	Indicator Value	Indicator Value	Indicator Value	Post-event (12/25/2022) Indicator Value	Unit
Precipitation-Related	Snowfall	-	-	-	-	-	-	-	-
Temperature-Related	Air Temperature	-	-	-	-	-	-	-	-
Wind-Related	Wind Events – Wind Gusts	-	-	-	-	-	-	-	-
Visibility-Related	-	-	-	-	-	-	-	-	-
Traffic Flow Impact	Speed (Reduction of Speed)	-	-	-	-	-	-	-	-
	Volume (Reduction of Volume)	-	-	-	-	-	-	-	-
Surface Condition	Surface Hazards and Clearance	Snow accumulation	1.9	1.8	5.8	5.7	5.2	5	in.
	Surface Traction	Ice presence	y	y	y	y	y	y	issued/not issued
		Frost occurrence	n	n	n	y	y	y	issued/not issued

6.4. Calculating the Index

After obtaining the data for the selected framework elements of the case study, a transformation step was initiated to transform the data values to a common scale. To achieve this, the research team conducted a literature review to identify thresholds for the selected framework elements. Think of these severity thresholds as a set of rules for road maintenance crews. The NWS Warning Criteria (e.g., 7 in. of snow in 24 hours) serve as the major rule that stops public traffic and triggers a maximum response. The Plowing Initiation Threshold (e.g., 2 in. of accumulation) is a lesser emergency condition that triggers routine maintenance deployment. The Surface Traction Threshold (e.g., grip below 0.6) is a technical measure of operational performance. If the road surface performance scores are too low, the crew has failed to keep up, regardless of the initial weather inputs.

6.4.1. Establishing Severity Thresholds

Assigning quantitative values to each index parameter, i.e., dimensions, subdimensions, or indicators as needed, requires establishing severity thresholds that allow the mapping of the weather event to the selected index rating. This process involves defining quantitative breakpoints that map observed values of dimensions, subdimensions, or indicators to discrete severity levels. Thresholds were established to align with commonly recognized operational triggers, safety benchmarks, and performance expectations used by transportation agencies.

Rather than relying on a single source, thresholds were derived through a synthesis of prior research, agency practices, national guidance (such as NWS Warning Criteria), and transportation operations literature. This approach ensures that severity classifications are both technically defensible and practically interpretable. Where dimension-level data were available, thresholds were applied directly at the dimension level. When only subdimension- or indicator-level data were available, thresholds were applied at those levels and then propagated upward to assess the associated framework components. This hierarchical application preserves internal consistency while accommodating variations in data availability.

The tables presented in this section summarize the severity thresholds used to translate observed data values into standardized severity levels across dimensions, subdimensions, and indicators. For each framework element represented in the case study, the tables define threshold ranges, associated severity classifications, and corresponding units of measurement. Together, these tables establish a consistent basis for transforming heterogeneous data inputs into comparable severity scores that support aggregation within the WWRCI. By applying these thresholds uniformly across the pre-event, during-event, and post-event periods, the framework captures the progression of winter impacts and supports a transparent, reproducible index calculation without requiring element-specific narrative explanations for each threshold table.

6.4.1.1. Snowfall/Snow Accumulation

Thresholds for snowfall severity (Table 18) depend on whether the criteria are based on total accumulation (for warnings/plowing initiation) or rate (for operational planning).

Table 18. Summary of snowfall/snow accumulation thresholds from the literature

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
Winter Storm Warning (NWS National)	≥5 in. in a 12-hour period OR ≥7 in. in a 24-hour period (snow/sleet)	Defines "heavy snow" and triggers a public warning.	NOAA (n.d.-b)
Winter Storm Warning (NWS Regionally Adjusted)	≥6 in. in a 12-hour period OR ≥8 in. in a 24-hour period (snow/sleet)	Higher criteria used in regions routinely subjected to severe winter weather.	NOAA (n.d.-b)
Heavy Snow (Iowa SSI)	>6 in. in 24 hours	Highest category of snowstorm type.	Nixon and Qiu (2005); Qi and Velpur (2024)
Medium Snow (Iowa SSI)	2~6 in.	Mid-range snow accumulation category.	Nixon and Qiu (2005); Qi and Velpur (2024)
Light Snow (Iowa SSI)	<2 in.	Lowest category of snow accumulation.	Nixon and Qiu (2005); Qi and Velpur (2024)
Plowing Initiation (DOT Operational Minimum)	2 in. (Aledo, IL) or 3 in. (El Dorado County, CA)	Minimum accumulation triggers for initiating plowing of collector routes.	NHDOT (n.d.); El Dorado County (n.d.); City of Aledo (n.d.)
Deployment Start (Some States)	0.5~1 in.	Maintenance operations (plowing/spreading) begin when this amount accumulates.	Dao et al. (2019)
Snow Accumulation Rate (Planning Baseline, Arizona DOT)	1 in./hour	Used as a planning basis for level of service analysis.	Boselly et al. (2005)
Snow Accumulation Rate (Utah Winter Road Weather Index [WRWI] Threshold)	1 in./hour	Snowfall rate value (SRV) is 0 when the road is snow covered. UDOT's target for snow removal is 1 in. of snow per hour.	Sturges et al. (2020; Williams (n.d.); Fay et al. (2020)
Snow Accumulation Rate (Walker Method, Highest Severity)	≥0.6 in./hour	Assigned Category 6 (highest severity).	Sturges et al. (2020)
AWSSI Daily Snowfall	0.1~0.9 in.	Scores 1 point.	Dowds and Sullivan (2022); Boustead et al. (2015)
AWSSI Daily Snowfall	>12 in.	Scores 15 points.	Dowds and Sullivan (2022)
AWSSI Current Snow Depth	1 in.	Scores 1 point.	Dowds and Sullivan (2022)
AWSSI Current Snow Depth	>30 in.	Scores 45 points.	Dowds and Sullivan (2022); Boustead et al. (2015)

6.4.1.2. Air Temperature

Air temperature thresholds (Table 19) are critical for determining the operational requirements related to freezing and deicing materials.

Table 19. Summary of air temperature thresholds from the literature

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
Subfreezing Weather (General)	Maximum temperatures averaging lower than 0°C (~32°F)	Characterizes winter in northern Midwest.	Carmichael et al. (2004)
RST Activation	RST less than 35°F	Triggers the calculation of the Utah WRWI.	Sturges et al. (2020); Williams (n.d.)
Chemical Efficacy Threshold	Pavement temperatures decline below about 20°F (−6.7°C)	Most ice control chemicals become very inefficient below this temperature.	McCullough et al. (2004)
Road Temperature Inflection Point (Utah Method)	22°F	Point where severity scoring increases sharply due to extra effort/different materials needed at lower temperatures.	Sturges et al. (2020)
Mid-range Storm Temperature (Iowa SSI)	25°F to 32°F	Mid-range operational temperature category.	Nixon and Qiu (2005); Qi and Velpur (2024)
Cold Storm Temperature (Iowa SSI)	<25°F	Cold operational temperature category (assigned high severity score).	Nixon and Qiu (2005); Qi and Velpur (2024)
Illinois "Salt Day" (Mean Daily Temperature)	Between 15°F and 30°F	Threshold used to define a day requiring maintenance operations.	Qi and Velpur (2024); Walker et al. (2019b)
AWSSI Daily Low Temperature	≤−35°F	Scores 20 points (highest scoring tier).	Dowds and Sullivan (2022)
MDOT SHA Extreme Cold	−10°F	Identified as a severe winter condition in some maintenance districts.	Fay et al. (2020)

6.4.1.3. Wind Chill, Wind Gusts

While specific wind chill thresholds (Table 20) are not explicitly provided, thresholds for wind speed and wind gusts used in conjunction with low temperatures are documented.

Table 20. Summary of wind-related thresholds from the literature

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
Wind Restriction (Commercial Motor Vehicle Safety)	Sustained or frequent gusts of ≥35 mph	Critical threshold triggering restrictions or warnings for high-profile vehicles.	(NOAA (n.d.-b); El Dorado County (n.d.; City of Aledo (n.d.); CRST (2025); Freedom Heavy Haul (2025); Loeffler (2021)
High Wind Warning (NWS)	Sustained wind speeds of 40 mph or greater (for ≥1 hour) OR winds of 58 mph or greater (any duration)	Used for high winds outside of severe local storms or winter storms.	NOAA (n.d.-a)
Wind Advisory (NWS)	Sustained wind speeds of 31~39 mph (for ≥3 hours) OR wind gusts of 46~57 mph	Advisory criteria.	NOAA (n.d.-a)
Utah WRWI Wind Gust	≥20 mph	Threshold for wind gust inclusion in the WRWI calculation.	Williams (n.d.), directly from UDOT presentation and discussed in MDOT report (Fay et al. 2020)
Drifting Snow Risk (Operational/Iowa)	Cross-wind speeds in excess of about 12 to 15 mph	Speed range that may cause drifting snow problems.	Nixon and Qiu (2005)
Drifting Snow Day (Indiana WSI)	Wind speeds >15 mph	Used as a factor to define drifting days.	Walker et al. (2019b); Thomas et al. (2021)
Ground Blizzard (Wyoming)	Winds exceeding 25 mph	Condition used to describe the presence of blowing snow that strongly correlates with icy road conditions.	Mentioned in Indiana's report (McCullough et al. 2004)

6.4.1.4. Visibility

Visibility thresholds (Table 21) are defined based on NWS warnings and DOT operational standards for limited visibility conditions.

Table 21. Summary of visibility thresholds from the literature

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
Blizzard Warning (NWS)	Visibility ≤ ¼ mi (≤400 m), for ≥3 hours	Critical visibility threshold used in combination with wind speed and snow.	NOAA (n.d.-a)
Snow Squall Warning	Visibility reduced to less than ¼ mi	Issued during heavy snow squalls.	NOAA (n.d.-a)
Wyoming DOT Reduced Visibility	Visibility of less than 400 ft	DOT definition for reduced visibility conditions.	WYDOT (n.d.)
MoDOT/WSI Low Visibility Event	0.25 mi (¼ mi)	Threshold used to analyze low visibility events with no precipitation.	Thomas et al. (2021)
Nebraska WSI	<2.5 mi	Most severe visibility category (Category 6) used in the index calculation.	Sturges et al. (2020); Walker et al. (2019b)
Accident Risk (Highest Fatality)	Visibility ≤50 m	Visibility condition associated with the highest number of fatalities in a single accident.	Wu et al. (2020)

6.4.1.5. Clearance or Reopen Time for Closures

DOTs use level of service (LOS) targets to define maximum clearance or regain times for roads to achieve specific conditions (e.g., bare pavement). Thresholds are shown in Table 22.

Table 22. Summary of thresholds from the literature relevant to clearance and reopen time

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
High Traffic Roads LOS (MnDOT Priority 1, AADT >30,000)	0~3 hours	Target timeframe for clearing snow and ice after a winter event.	NOAA (n.d.-b); Dao et al. (2019)
Secondary Roads LOS (MnDOT Priority 4, AADT <800)	9~36 hours	Target timeframe for clearing snow and ice after a winter event.	Dao et al. (2019)
Priority Routes (South Dakota)	80% clear of snow/ice within 2 hours	Required frequency of achieving desired pavement condition.	Dao et al. (2019)
Nonpriority Routes (South Dakota)	80% clear of snow/ice within 18 working hours	Required clearance time.	Dao et al. (2019)
Low-volume service roads (South Dakota)	80% clear of snow/ice within 36 working hours	Required clearance time.	Dao et al. (2019)
Ice-Up Time Duration (Idaho/Colorado WPI)	>1/2 hour (or 30 minutes)	Duration when road friction (grip) is below the 0.6 threshold, used to calculate WPI.	Sturges et al. (2020); Jensen et al. (2013)

6.4.1.6. Traffic Speed/Traffic Volume/Flow

Severity is often rated based on the reduction in speed or capacity caused by the weather event. Specific quantitative thresholds (Table 23) define these reductions.

Table 23. Summary of traffic flow-related thresholds from the literature, relevant to weather event conditions

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
Speed Reduction (General adverse weather)	3% to 40%	Range of average speed reductions from adverse winter weather.	Dao et al. (2019)
Traffic Volume Reduction (General adverse weather)	5% to 44%	Range of average traffic volume reductions from adverse winter weather.	Dao et al. (2019)
Roadway Capacity Reduction (General adverse weather)	4% to 30%	Range of average roadway capacity reductions.	Dao et al. (2019)
Low Visibility Flow Reduction	10% to 12%	Quantifiable reduction in freeway traffic flow capacity due to low visibility.	FHWA (2025)

6.4.1.7. Surface Hazards and Clearance (Layer Thickness)

Surface hazards relate directly to the accumulation of snow, ice, or slush on the pavement, often measured by layer thickness sensors. Thresholds are shown in Table 24.

Table 24. Summary of thresholds from the literature relevant to surface hazards

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
Maximum Loose Accumulation (LOS Condition 3)	Up to 5 cm (2 in.)	Maximum accumulation of loose snow or slush allowed on the pavement surface while roads are considered passable with moderate delays.	McCullough et al. (2004)
Maximum Wheel Track Accumulation (LOS Condition 4)	Up to 4 cm (1.5 in.)	Maximum slush or unpacked snow allowed in wheel tracks.	McCullough et al. (2004)
Excessive Loose Snow (LOS Condition 6)	Over 5 cm (2 in.)	Amount of loose or wind-transported snow indicating significant buildup of packed snow and ice.	McCullough et al. (2004)
Slick Road Section (Wyoming DOT)	Greater than 50% of the road section is icy or snow packed	Definition for a “slick” road segment.	WYDOT (n.d.)
Water Equivalent Layer (Idaho SSI)	Measured in millimeters	Used as a component of the SSI formula.	Jensen et al. (2013)
Blowing Snow (Wyoming DOT)	Snow propelled by wind at least 1 ft above the ground	Definition of “blowing snow.”	WYDOT (n.d.)

6.4.1.8. Surface Traction

Pavement friction coefficients (μ or grip) provide the clearest numerical definition of road hazard severity. Thresholds are shown in Table 25.

Table 25. Summary of surface traction thresholds in the literature applied to winter weather conditions

Event Metric	Threshold Value (μ or Grip)	Operational Significance / Severity Rating	Source(s)
Dry Pavement (Baseline)	≈0.8 (or 0.9–1.0)	Represents the baseline driveable condition.	Loeffler (2021); Gu (2019)
Maintenance Goal (Post-Treatment)	≈0.6	Target coefficient for maintenance crews aiming to restore safe winter roads.	Loeffler (2021)
Critical Performance Threshold	Below 0.6	Duration below this value constitutes “ice-up time” (Idaho/Colorado WPI).	Sturges et al. (2020); Jensen et al. (2013)
Slush or Ice Forming (Idaho)	0.5 to 0.6	Indicates immediate hazard conditions.	Jensen et al. (2013)
Snow Covered	0.25~0.49	RSI range for snow-covered conditions.	Gu (2019)
Snow Packed/Icy (Idaho)	0.4 to 0.5	Indicates severe slipperiness.	Jensen et al. (2013)
Black Ice (Extreme Hazard)	≈0.2 (or 0.1–0.15)	Critically low stability; extreme hazard condition.	Loeffler (2021) [Gu (2019) for the 0.1–0.15 value]
Heavy Snow (Lowest Documented Friction)	≈0.17	Lowest documented average friction coefficient found on winter roads.	Salimi et al. (2016)

6.4.1.9. Ice Presence

Thresholds for ice presence are shown in Table 26.

Table 26. Summary of ice presence thresholds found in the literature

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
Ice Storm Warning (NWS)	≥½ in. of ice accumulation	Issued when accumulation is sufficient to cause damage to trees or powerlines. Note: Some criteria depend on location (0.25 in. or 0.50 in.).	NOAA (n.d.-a, n.d.-b, n.d.-c)
Freezing Rain Advisory (NWS)	Trace accumulation of freezing rain (there was not a definitive value)	Issued for minimal accumulation that causes travel impacts.	NOAA (n.d.-c)
Freezing Rain Severity (Iowa SSI)	Freezing rain modifies the severity index (see Table 1 in Nixon and Qiu [2005])	In most studies, it has been given a high score (e.g., 0.72), reflecting operational difficulty, compared to heavy snow (1.0) or medium snow (0.52).	Nixon and Qiu (2005)

6.4.1.10. Frost Occurrence

Frost events are typically identified based on the occurrence of freezing temperatures in combination with pavement or dew point temperature conditions. Thresholds are shown in Table 27.

Table 27. Summary of thresholds relevant to frost occurrence found in the literature

Event Metric	Threshold Value	Operational Significance / Severity Rating	Source(s)
Frost Day/Air Frost	Minimum air temperature at or below 32°F (0∘C)	Used as a parameter reflecting frost likelihood.	Sturges et al. (2020); Strong and Shvetsov (2006)
Frost Cycle (Pennsylvania WSI)	Maximum daily air temperature above 32°F and minimum daily air temperature below 32°F	Days when temperature crosses freezing point, increasing frost risk.	Walker et al. (2019b)
Frost Mitigation Trigger (Indiana WSI)	Minimum temperature at or below 32°F and minimum dew point at or below 32°F	Criteria used to define a frost day.	Walker et al. (2019b)

6.4.1.11. Selected Threshold Values for Index Calculation

Table 28 was developed to help identify the thresholds for the framework elements.

Table 28. Selected thresholds for each parameter used in the case study

Indicator	Severity Level	Thresholds
Snowfall *(Snowfall Rate)*	**High**	**≥1 in./hour** (Arizona, Utah WRWI, Walker Method Category 6 ≥0.6 in./hour)
	Medium	**0.25–1.0 in./hour**
	Low	**<0.25 in./hour**
Snow Accumulation *(Snow Depth)*	**High**	**>6 in. in 24 hours** (Iowa SSI, NWS 6–7 in. thresholds)
	Medium	**2–6 in.**
	Low	**<2 in.**
Air Temperature	**High**	**>32°F**
	Medium	**25–32°F**
	Low	**<25°F**
Visibility	**High Severity**	**≤0.25 mile** (NWS Blizzard & Snow Squall Warning)
	Medium	**0.25–2.5 miles** (Used by NE index, Category 6 <2.5 mi)
	Low	**>2.5 miles**
Traffic Speed / Traffic Volume / Flow	—	**Five severity levels already defined**
Ice Presence	Binary	**Yes/No** (Trace = advisory; ≥0.5" = Ice Storm Warning)
Frost Occurrence	Binary	**Yes/No** (Air temp ≤32°F + dew point ≤32°F)
Wind Events – Wind Chill	—	**Not a standalone threshold in literature; depends on temperature + wind speed**
Wind Events – Wind Gusts	**High**	**≥35 mph** (vehicle restriction threshold; blizzard criteria)
	Medium	**20–34 mph** (Utah WRWI ≥20 mph gust threshold)
	Low	**<20 mph**
Clearance or Reopen Time for Closures	**High Severity Roads**	**MnDOT Priority 1: 0–3 hours**
	Medium	**South Dakota Priority: 2–18 hours**
	Low Priority Roads	**9–36 hours** (MnDOT Priority 4)
Surface Hazards & Clearance	—	**Up to 2 in. loose snow**, **1.5 in. wheel-track depth**, **>2 in. = hazard**
Surface Traction	—	**Dry ≈0.8**, **Maintenance target ≈0.6**, **Black ice ≈0.2**, **Snow packed 0.25–0.49**
Surface Traction – Severity Mapping	High	**μ < 0.4**
	Medium	**0.4–0.6**
	Low	**>0.6**

6.5. Applying the Severity Thresholds to Index Parameters

6.5.1. Initial Mapping to Framework Scales

The data acquisition and processing workflow described in the previous sections established the foundation for applying the framework to the selected winter weather event. The purpose of establishing this foundation was to ensure that the subsequent steps, i.e., identifying relevant dimensions, computing dimension-level severities, and producing the final road condition index, would be grounded in transparent, reproducible, and operationally realistic data practices.

The first step in calculating the index for the selected winter weather event involved mapping the processed data from the case study (December 20–25, 2022) to the severity scales defined in the framework. This mapping assigned an initial integer value (e.g., 1 to 3 or 1 to 5; the greater the number, the greater the potential impact) to each element based on the established thresholds. The results for the dimension, subdimension, and indicator levels are presented in Tables 29, 30, and 31, respectively. These tables show the scaled values for each of the framework elements of the case study.

Table 29. Initial severity mapping for dimension-level elements

	Pre-event (12/20/2022)	During-event (12/21-24/2022)				Post-event (12/25/2022)	
Dimension	Dimension Value	Dimension Value	Dimension Value	Dimension Value	Dimension Value	Dimension Value	Scale
Precipitation-Related	-	-	-	-	-	-	-
Temperature-Related	-	-	-	-	-	-	-
Wind-Related	-	-	-	-	-	-	
Visibility-Related	1	3	2	2	1	Missing	1–3
Traffic Flow Impact	-	-	-	-	-	-	-
Surface Condition	-	-	-	-	-	-	-

Table 30. Initial severity mapping for subdimension-level elements

		Pre-event (12/20/2022)	During-event (12/21-24/2022)				Post-event (12/25/2022)	
Dimension	Subdimension	Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value	Scale
Precipitation-Related	Snowfall	1	1	2	1	1	1	1–3
Temperature-Related	Air Temperature	3	3	3	3	3	Missing	1–3
Wind-Related	Wind Events – Wind Gusts	Missing	2	3	3	2	Missing	1–3
Visibility-Related	-	-	-	-	-		-	-
Traffic Flow Impact	Speed (Reduction of Speed)	1	1	3	3	2	1	1–5
	Volume (Reduction of Volume)	1	1	4	3	1	2	1–5
Surface Condition	Surface Hazards and Clearance	-	-	-	-	-	-	-
	Surface Traction	-	-	-	-	-	-	-

Table 31. Initial severity mapping for indicator-level elements

Dimension	Subdimension	Indicator	Pre-event (12/20/2022)	During-event (12/21-24/2022)				Post-event (12/25/2022)	Scale
			Indicator Value	Indicator Value	Indicator Value	Indicator Value	Indicator Value	Indicator Value	
Precipitation-Related	Snowfall	-	-	-	-	-	-	-	
Temperature-Related	Air Temperature	-	-	-	-	-	-	-	
Wind-Related	Wind Events – Wind Gusts	-	-	-	-	-	-	-	
Visibility-Related	-	-	-	-	-	-	-	-	
Traffic Flow Impact	Speed (Reduction of Speed)	-							
	Volume (Reduction of Volume)	-							
Surface Condition	Surface Hazards and Clearance	Snow accumulation	1	1	2	2	2	2	1–3
	Surface Traction	Ice presence	1	1	1	1	1	1	0–1
		Frost occurrence	0	0	0	1	1	1	0–1

It is worth noting here that the scale developed for the percent change in overall speed and volume for the county was based on the notion that a negative percent change is considered to have a higher potential impact. Therefore, a five-point scale was established for which any positive percent change in addition to a negative percent change up to 20% was assigned a score of 1. Additional negative changes were grouped into four bins with ranges of 20%. The highest impact would be 5, corresponding to a change between -80% and -100% in number of journeys or average speed.

Since the framework elements utilize different scales (e.g., 1–3 for visibility, 1–5 for traffic impact), a normalization step was performed to standardize all values to a common 0 to 1 scale. This ensured that no single parameter disproportionately would influence the final index due to its scale range.

The following equation was used for normalization:

where

- S^{norm} is the normalized severity value (0 to 1).
- S_i is the initial mapped value from Step 5.
- S_{min} is the minimum value of the scale (typically 1 or 0).
- S_{max} is the maximum value of the scale (e.g., 3 or 5).

The normalized values for each framework element are presented in Tables 32, 33, and 34.

Table 32. Normalized severity scores for dimension-level elements

Dimension	Pre-event (12/20/2022)	During-event (12/21-24/2022)				Post-event (12/25/2022)
	Dimension Value	Dimension Value	Dimension Value	Dimension Value	Dimension Value	Dimension Value
Precipitation-Related	-	-	-	-	-	-
Temperature-Related	-	-	-	-	-	-
Wind-Related	-	-	-	-	-	-
Visibility-Related	0	1	0.5	0.5	0	Missing
Traffic Flow Impact	-	-	-	-	-	-
Surface Condition	-	-	-	-	-	-

Table 33. Normalized severity scores for subdimension-level elements

Dimension	Subdimension	Pre-event (12/20/2022)	During-event (12/21-24/2022)				Post-event (12/25/2022)
		Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value	Subdimension Value
Precipitation-Related	Snowfall	0	0	0.5	0	0	0
Temperature-Related	Air Temperature	1	1	1	1	1	Missing
Wind-Related	Wind Events – Wind Gusts	Missing	0.5	1	1	0.5	Missing
Visibility-Related	-	-	-	-	-		-
Traffic Flow Impact	Speed (Reduction of Speed)	0	0	0.5	0.5	0.25	0
	Volume (Reduction of Volume)	0	0	0.75	0.5	0	0.25
Surface Condition	Surface Hazards and Clearance	-	-	-	-		-
	Surface Traction	-	-	-	-	-	-

Table 34. Normalized severity scores for indicator-level elements

Dimension	Subdimension	Indicator	Pre-event (12/20/2022)	During-event (12/21-24/2022)				Post-event (12/25/2022)
			Indicator Value	Indicator Value	Indicator Value	Indicator Value	Indicator Value	Indicator Value
Precipitation-Related	Snowfall	-	-	-	-	-	-	-
Temperature-Related	Air Temperature	-	-	-	-	-	-	-
Wind-Related	Wind Events – Wind Gusts	-	-	-	-	-	-	-
Visibility-Related	-	-	-	-	-	-	-	-
Traffic Flow Impact	Speed (Reduction of Speed)	-	-	-	-	-	-	-
	Volume (Reduction of Volume)	-	-	-	-	-	-	-
Surface Condition	Surface Hazards and Clearance	Snow accumulation	0	0	0.5	0.5	0.5	0.5
	Surface Traction	Ice presence	1	1	1	1	1	1
		Frost occurrence	0	0	0	1	1	1

6.5.2. Identification of Extreme Values for Analysis Periods

The next step in calculating the index involved aggregating the time-series data into three distinct analysis frames: pre-event, during-event, and post-event. To capture the maximum potential impact within each period, the most extreme (maximum) normalized severity value observed during that timeframe was selected. Table 35 summarizes these extreme values for all framework elements.

Table 35. Extreme normalized severity values by analysis timeframe

Dimension	Timeframe	Severity	-	-	-	-	-	-
Visibility-Related	Before	0	-	-	-	-	-	-
	During	1	-	-	-	-	-	-
	After	Missing	**Subdimension**	**Timeframe**	**Severity**	-	-	-
Precipitation-Related			Snowfall	Before	0	-	-	-
				During	0.5	-	-	-
				After	0	-	-	-
Temperature-Related			Air Temperature	Before	1	-	-	-
				During	1	-	-	-
				After	Missing	-	-	-
Wind-Related			Wind Events – Wind Gusts	Before	Missing	-	-	-
				During	1	-	-	-
				After	Missing	-	-	-
Traffic Flow Impact			Traffic Speed	Before	0	-	-	-
				During	0.5	-	-	-
				After	0	-	-	-
			Traffic Volume/Flow	Before	0	-	-	-
				During	0.75	-	-	-
				After	0.25	**Indicator**	**Timeframe**	**Severity**
Surface Condition			Surface Hazards and Clearance			Snow accumulation	Before	0
							During	0.5
							After	0.5
			Surface Traction			Ice presence	Before	1
							During	1
							After	1
						Frost occurrence	Before	0
							During	1
							After	1

6.5.3. Calculation of Weighted Dimension Severities

The next step in calculating the index included calculating the primary dimension severities. When a primary dimension is represented through subdimensions, the weights of the subdimensions under the primary dimension are multiplied by the subdimension severities. The results are then added to represent the dimension severity for each timeframe. The weights of these subdimensions under the primary dimension could be assigned based on guidance policies or experience. In this case study, these weights were selected as a function of the number of subdimensions used to describe the primary dimension; however, it is recommended that these weights be assigned based on expert judgment and stakeholder engagement.

Similarly, when a primary dimension is represented by indicators, the weights of the indicators under each subdimension are multiplied by the indicator severities. The results are then added to represent each subdimension severity for each timeframe. Afterwards, the weights of each subdimension under the main dimension are multiplied by the calculated subdimension severities. The results are then added to represent the dimension severity for each timeframe. Table 36 details this calculation, showing the contribution of each element to the final dimension severities for the pre-event, during-event, and post-event periods.

Table 36. Weighted dimension and subdimension severity calculation

Dimension	Time frame	Dimension Severity	Dimension Weight in Index	Subdimension	Time frame	Subdimension Severity	Subdimension Weight	Indicator	Time frame	Indicator Severity	Indicator Weight
Visibility-Related	Before	0	0.2	-	-	-	-	-	-	-	-
	During	1	0.2	-	-	-	-	-	-	-	-
	After	-	0.2	-	-	-	-	-	-	-	-
Precipitation-Related	Before	0	0.15	Snowfall	Before	0	1	-	-	-	-
	During	0.50	0.15		During	0.5	1	-	-	-	-
	After	0	0.15		After	0	1	-	-	-	-
Temperature-Related	Before	1	0.05	Air Temperature	Before	1	1	-	-	-	-
	During	1	0.05		During	1	1	-	-	-	-
	After		0.05		After	Missing	1	-	-	-	-
Wind-Related	Before		0.1	Wind Events – Wind Gusts	Before	Missing	1	-	-	-	-
	During	1	0.1		During	1	1	-	-	-	-
	After		0.1		After	Missing	1	-	-	-	-
Traffic Flow Impact	Before	0	0.2	Traffic Speed	Before	0	0.5	-	-	-	-
					During	0.5	0.5	-	-	-	-
	During	0.625	0.2		After	0	0.5	-	-	-	-
				Traffic Volume / Flow	Before	0	0.5	-	-	-	-
	After	0.125	0.2		During	0.75	0.5	-	-	-	-
					After	0.25	0.5	-	-	-	-
Surface Condition	Before	0.25	0.3	Surface Hazards and Clearance	Before	0.0	0.5	Snow accumulation	Before	0	1
					During	0.5	0.5		During	0.5	1
					After	0.5	0.5		After	0.5	1
	During	0.75	0.3	Surface Traction	Before	0.5	0.5	Ice presence	Before	1	0.5
									During	1	0.5
					During	1.0	0.5		After	1	0.5
	After	0.75	0.3					Frost occurrence	Before	0	0.5
					After	1.0	0.5		During	1	0.5
									After	1	0.5

6.5.4. Handling Data Gaps

Real-world data collection is rarely perfect, and the WWRCI framework is designed to adapt when sensors fail or data are unavailable. To demonstrate this resilience, the Story County case study required adjustments in weight during two specific timeframes. In the pre-event phase, the wind-related dimension (originally weighted at 0.1) was missing. Consequently, this 0.1 value was distributed equally among the remaining five dimensions. Similarly, during the post-event (after) phase, data were unavailable for three dimensions: wind, temperature, and visibility. These combined original weights totaled 0.35, which was then redistributed to the remaining operational dimensions. Table 37 details these specific weight adjustments.

Table 37. Adjusted dimension weights due to missing data in pre- and post-event scenarios

Dimension	Weight	Adjusted Weights due to Missing Data: Before	Adjusted Weights due to Missing Data: After
Precipitation-Related	0.15	0.17	0.27
Temperature-Related	0.05	0.07	
Wind-Related	0.1		
Visibility-Related	0.2	0.22	
Road Recovery Time	0.2	0.22	0.32
Surface Condition	0.3	0.32	0.42

By applying these adjusted weights, the final index remains a valid reflection of the available data. Table 38 presents a comparison of the calculated index results with and without these weight adjustments.

Table 38. Comparison of WWRCI values with and without weight adjustments

Timeframe		Before	During	After
No Weight Adjustments	Aggregated Dimension Severities	0.125	0.775	0.25
	Calculated Road Weather Condition Index	1.5	4.1	2
	Road Weather Condition Index	**2**	**4**	**2**
With Weight Adjustments	Aggregated Dimension Severities	0.15	0.775	0.352
	Calculated Road Weather Condition Index	1.6	4.1	2.408
	Road Weather Condition Index	**2**	**4**	**2**
Excluded Dimensions		Excludes wind gusts		Excludes visibility, wind gusts, and temperature

6.5.5. Final Road Weather Condition Index Calculation

The final step involved calculating the overall WWRCI. The calculated dimension severities from Step 8 were multiplied by their dimension weights and summed. The result was then linearly scaled to a 1–5 index, where 1 represents light winter weather conditions and 5 represents extreme conditions.

Table 39 presents the final WWRCI results for the case study. The index accurately reflects the progression of the storm, showing a peak severity of **4.1** during the event, consistent with the blizzard conditions observed in Story County.

Table 39. Final WWRCI for case study

Feature	**Index (1-5)**		
Timeframe	**Before**	**During**	**After**
Aggregated Dimension Severities	0.125	0.775	0.25
Calculated Road Weather Condition Index	1.5	4.1	2
Road Weather Condition Index	**2**	**4**	**2**
Excluded Dimensions	Excludes wind gusts	-	Excludes visibility, wind gusts, and temperature

6.6. Conclusions from the Case Study

The application of the standardized WWRCI framework to the December 2022 blizzard in Story County, Iowa, demonstrates the framework's viability. By processing real-world data through the defined steps, the case study enabled several conclusions regarding the framework's performance:

1. **Reasonable representation of event progression:** The calculated index values successfully captured the temporal evolution of the winter storm. The WWRCI rose from a baseline of 2 (minor/moderate) during the pre-event phase to a peak of 4 (severe) during the storm's height, before returning to 2 in the post-event recovery phase. This numerical progression aligns well with the qualitative narrative of the event, which involved blizzard warnings, whiteout, and significant travel disruptions. The framework was found capable of distinguishing between the warning phase, the active hazard phase, and the recovery phase.

2. **Resilience to data gaps:** A significant finding from the case study is the framework's flexibility in handling missing data. During the "post-event" analysis period, critical meteorological data for visibility, wind, and temperature was unavailable (labeled as "missing" in the source data). Despite these gaps, the framework allowed for the exclusion of these specific dimensions without invalidating the entire index. By adjusting the aggregation weights to focus on the available indicators (precipitation, traffic flow, and surface condition), the system still produced a coherent and actionable index value.

3. **Integration of operational and physical metrics:** The case study validated the importance of a multidimensional approach. While meteorological data (snowfall) indicated severity, the inclusion of Traffic Flow Impact (speed and volume reductions) provided a proxy for the actual operational reality experienced by road users. For instance, the "during-event" phase

showed significant reductions in traffic volume (severity 0.75) and speed (severity 0.625), further strengthening the weather data to justify the high index score of 4.1.

4. **Feasibility of implementation:** The successful execution of this case study using standard data sources such as NWS archives, RWIS sensor readings, and commercially available traffic data, confirms the framework's feasibility. The methodology does not require experimental or cost-prohibitive technology; rather, it standardizes the use of data already possessed by most transportation agencies.

6.7. Limitations

Several limitations were identified in the development and application of the framework. These include challenges associated with identifying appropriate weights for indicators within their respective subdimensions, as well as assigning weights to subdimensions within their associated primary dimensions. In addition, the weights of the primary dimensions within the road weather condition index were not derived from established or standardized criteria but rather were determined through internal research team discussions regarding the relative importance of each selected primary dimension within the index.

Other limitations are related to data availability. As a result of limited data, not all nine dimensions included in the conceptual framework were applied in the case study. For example, the Resource Utilization and Winter Maintenance Status dimensions were not incorporated due to a lack of sufficient data. Furthermore, some of the primary dimensions included in the case study were represented by only a subset of their associated subdimensions or indicators rather than the complete set originally defined in the framework.

It is also important to note that certain dimensions are not solely influenced by weather event factors. For instance, the traffic flow may be affected by other operational factors, such as reduced travel demand during holidays. In this case study, lower traffic volumes observed on December 25 cannot be attributed exclusively to weather conditions, as the day coincided with a national holiday. A comparison with the same holiday in the previous year, during which no weather event occurred, revealed a similar pattern of reduced traffic volumes.

Finally, the application of the framework to a single case study represents a limitation in itself. Additional case studies, further testing and validation, and increased engagement with relevant stakeholders are recommended to strengthen the robustness and generalizability of the framework.

CHAPTER 7. CONCLUSION AND PATH FORWARD

7.1. Project Summary

This project successfully addressed the critical need for a standardized national approach to winter road assessment. Through a comprehensive literature review (Task 1) and a national survey of transportation agencies (Task 2), the research identified significant inconsistencies in how winter weather impacts are currently measured and communicated. In response, this project developed a standardized national framework for WWRCIs (Task 5). The operational viability of this framework was validated through a case study of the December 2022 blizzard in Story County, Iowa (Task 6), which demonstrated the framework's ability to accurately capture event severity and resilience to data gaps. However, the transition from a retrospective case study to a proactive, national operational standard requires a structured pilot implementation plan. Future research should focus on three critical phases of development—technological integration, operational refinement, and institutional standardization—to ensure the framework's scalability and effectiveness.

7.2. Recommendations for Future Implementation

To transition this framework from a validated concept to a robust national standard, it is recommended that future work center on a pilot application designed to calibrate the index for real-world decision-making, validate its flexibility across diverse regions, and produce actionable training deliverables. A proposed pilot application should address the following critical areas:

1. **Calibrating the WWRCI for decision-making:** To ensure that the index drives actionable operational decisions, such as salt allocation or road closures, pilot agencies should calibrate the framework's scoring logic to their specific operational realities. Considerations for this critical area include the following:

    - **Threshold standardization:** Pilot agencies should establish and test quantitative breakpoints for indicators. Future research should rigorously test these thresholds to ensure that they align with safety benchmarks and performance expectations across different jurisdictions.
    - **Blueprint for stakeholder-driven weighting:** Determining the relative importance of dimensions (e.g., Is ice presence more critical than wind speed?) requires consensus. Future efforts should develop a weighting blueprint: a structured guide for conducting stakeholder workshops and surveys. This blueprint would allow future users to systematically derive weights based on their local operational priorities and expert judgment.

2. **Capturing different regions, practices, and capacities:** A core requirement of the framework is scalability. A pilot application should demonstrate that the framework functions effectively for both large state DOTs with advanced infrastructure and smaller local agencies with limited resources. Considerations for this critical area include the following:

- **Regional customization:** The pilot should include agencies from diverse climatic zones to address unique hazards, such as “micro-zoning” needs in mountainous regions or ice storm prevalence in southern states.
- **Operational scalability:** Future research should evaluate the framework’s “flexible tool” design, confirming that agencies can successfully monitor a subset of high-impact dimensions (e.g., Surface Condition) when full data suites are unavailable, without compromising the index’s utility.

3. **Validating framework flexibility and technology integration:** A pilot application would serve as a stress test for the framework’s resilience, specifically its ability to handle data gaps and integrate emerging technologies. Considerations for this critical area include the following:

   - **Sensitivity analysis:** Future research should test the sensitivity of the framework to minor fluctuations in input data. By varying indicator values and weights, the pilot could quantify the stability of the final index score, ensuring that the WWRCI does not react to volatility due to insignificant data noise or minor sensor errors.
   - **Resilience to data gaps:** As observed in the Story County case study, real-world data are often incomplete. The pilot should validate protocols for redistributing weights when specific dimensions (e.g., wind sensors) go offline, ensuring that the index remains coherent.

4. **Advanced integration: MDSS and emerging technology:** To maximize utility, the WWRCI should not exist in isolation but should integrate with existing decision support and data systems. Considerations for this critical area include the following:

   - **Linking results to MDSS:** The pilot should explore how WWRCI outputs can be fed directly into MDSS platforms. By integrating real-time road condition assessments with MDSS predictive modeling, agencies could shift from reactive monitoring to proactive resource allocation, utilizing the index to validate past treatment effectiveness and refine future maintenance strategies.
   - **CV data fusion:** The pilot should rigorously test the integration of diverse data sources, specifically fusing traditional RWIS sensor readings with CV data. Research is needed to quantitatively validate the correlation between CV metrics (e.g., wiper usage, ABS activation) and ground truth road conditions.

5. **Deliverables: Training modules and revised guidelines:** Insights gained from a pilot would directly inform the final toolkit provided to transportation agencies, supporting widespread adoption. Considerations for this critical area include the following:

   - **Revised implementation guide:** The step-by-step implementation approach—assessing capabilities, aligning metrics, integrating data, and classifying severity—should be refined based on pilot feedback.

- **Training modules:** Comprehensive training materials should be developed to teach staff how to map local data to the standardized 1–5 index scale and interpret multi-dimensional scores for strategic planning.

By executing a pilot application, the WWRCI framework can evolve from a theoretical model into a practical, standardized tool. This process would not only validate the framework's adaptability to varying regional and operational capacities but also establish the necessary data governance and training structures to support a safer, more coordinated national response to winter weather impacts on transportation systems.

REFERENCES

Abohassan, A., K. El-Basyouny, and T. J. Kwon. 2021. Exploring the associations between winter maintenance operations, weather variables, surface condition, and road safety: A path analysis approach. *Accident Analysis and Prevention*, Vol. 163 (December 2021). doi: 10.1016/j.aap.2021.106448.

Ameddah, M. A., B. Das, and J. Almhana. 2018. Cloud Assisted Real-Time Road Condition Monitoring System for Vehicles. 2018 IEEE Conference on Global Communications (GLOBECOM), December 9–13, 2018.

Balasundaram, B., S. T. S. Bukkapatnam, Z. Kong, and Y. Hong. 2012. *Proactive Approach to Transportation Resource Allocation under Severe Winter Weather Emergencies*. Oklahoma Transportation Center. https://rosap.ntl.bts.gov/view/dot/27048.

Boselly III, E. S. 1992. Road Weather Information Systems: What Are They and What Can They Do for You? *Transportation Research Record*, Vol. 1387, pp. 191–195.

Boselly III, E. S., R. R. Blackburn, and D. E. Amsler. 2005. *Procedures for Winter Storm Maintenance Operations*. FHWA-AZ-05-461. Arizona Department of Transportation.

Boselly III, E. S., E. J. Thornes, and C. Ulburg. 1993. *Road Weather Information Systems Volume 1: Research Report*. SHRP-H-350. Strategic Highway Research Program. https://onlinepubs.trb.org/onlinepubs/shrp/shrp-h-350.pdf.

Boustead, B. E. M., S. D. Hilberg, M. D. Shulski, and K. G. Hubbard. 2015. "The Accumulated Winter Season Severity Index (AWSSI)." *Journal of Applied Meteorology and Climatology* 54 (8): 1693–712. https://doi.org/10.1175/JAMC-D-14-0217.1.

Carmichael, C. G., W. A. Gallus, B. R. Temeyer, and M. K. Bryden. 2004. A Winter Weather Index for Estimating Winter Roadway Maintenance Costs in the Midwest. *Journal of Applied Meteorology*, Vol. 43, No. 11, pp. 1783–90. https://doi.org/10.1175/JAM2167.1.

Chien, S., J. Meegoda, J. Luo, P. Corrigan, and L. Zhao. 2014. *Road Weather Information System Statewide Implementation Plan*. New York State Department of Transportation.

City of Aledo. n.d. Winter Maintenance Plan. City of Aledo, Illinois. https://www.aledoil.gov/267/Winter-Maintenance-Plan.

Cohen, S. J. 1981. User-Oriented Climatic Information for Planning a Snow Removal Budget. *Journal of Applied Meteorology*, Vol. 20, No. 12, pp. 1420–1427.

CRST. 2025. High Wind Driving for Truckers: When to Stop and Safety Tips. Life On the Road. CRST, April 1, 2025. https://www.crst.com/blog/high-wind-driving-for-truckers-when-to-stop-safety-tips/.

Dao, B., S. Hasanzadeh, C. L. Walker, D. Steinkruger, B. Esmaeili, and M. R. Anderson. 2019. Current Practices of Winter Maintenance Operations and Perceptions of Winter Weather Conditions. *Journal of Cold Regions Engineering*, Vol. 33, No. 3. https://doi.org/10.1061/(ASCE)CR.1943-5495.0000191.

Ding, X., and T. J. Kwon. 2022. Winter Road Friction Estimations via Multi-Source Road Weather Data—A Case Study of Alberta, Canada. *Future Transportation*, Vol. 2, No. 4, pp. 970–987, doi: 10.3390/futuretransp2040054.

Dowds, J., and J. Sullivan. 2022. *Quantifying Correlations Between Winter Severity, Road Conditions, and VTrans' Snow and Ice Control Activities*. 2021-06. Vermont Agency of Transportation.

Drobot, S., W. P. Mahoney III, E. Schuler, G. Wiener, M. Chapman, P. A. Pisano, P. Kennedy, B. B. MvKeever, and A. Stern. 2017. *IntelliDrive(SM) Road Weather Research & Development – The Vehicle Data Translator*. Federal Highway Administration. https://ops.fhwa.dot.gov/weather/resources/publications/itsapaper9005/itsapaper9005.pdf.

DTN. 2025. Maintenance Decision Support System Multi-State Pooled Fund Study. DTN. https://mdss.dtn.com/.

El Dorado County. n.d. Frequently Asked Snow Removal Question. El Dorado County, California. https://www.eldoradocounty.ca.gov/files/assets/county/v/1/documents/land-use/transportation/snow-removal-final-faqs.pdf.

Fay, L., N. Villwock-Witte, K. Clouser, and D. Veneziano. 2020. *Severe Weather Index*. MD-20-SP809B4G. State Highway Administration, Maryland Department of Transportation. https://www.roads.maryland.gov/OPR_Research/MD-20-SP809B4G_SevereWeatherIndex_Report.pdf.

FHWA. 2025. How Do Weather Events Affect Roads? Road Weather Management, Federal Highway Administration. https://ops.fhwa.dot.gov/weather/roadimpact.htm.

Freedom Heavy Haul. n.d. *Understanding Wind Restrictions for Oversize Hauls*. 2025. Freedom Heavy Haul. https://freedomheavyhaul.com/wind-restrictions-for-oversize-hauls-explained/.

Fu, L., L. Thakali, T. J. Kwon, and T. Usman. 2017. A risk-based approach to winter road surface condition classification. *Canadian Journal of Civil Engineering*, Vol. 44, No. 3, pp. 182–191. doi: 10.1139/cjce-2016-0215.

Galanis, I., P. Gurunathan, D. Burkard, and I. Anagnostopoulos. 2018. Weather-based road condition estimation in the era of Internet-of-Vehicles (1oV). 2018 IEEE International Symposium on Circuits and Systems (ISCAS), May 27–30, 2018.

Gu, L. 2019. Developing Models for Estimating Winter Road Weather and Surface Conditions-An Empirical Investigation. MS Thesis. University of Alberta, Canada. https://doi.org/10.7939/R3-M864-KJ06.

Gu, L., T. J. Kwon, and T. Z. Qiu. 2019. A geostatistical approach to winter road surface condition estimation using mobile RWIS data. *Canadian Journal of Civil Engineering*, Vol. 46, No. 6, pp. 511–521. https://doi.org/10.1139/cjce-2018-0341.

Hoffman, B., D. White, and M. Taylor. 2014. *Winter Severity Index Development*. E02978 WO2. The Pennsylvania Department of Transportation. https://www.pa.gov/content/dam/copapwp-pagov/en/penndot/documents/research-planning-innovation/research-projects/winter_severity_index_final%20report.pdf.

IEM. n.d. Automated Data Plotter. Iowa Environmental Mesonet. Department of Agronomy, Iowa State University. https://mesonet.agron.iastate.edu/plotting/auto/?q=84.

Ito, K., G. Hirakawa, K. Hashimoto, Y. Arai, and Y. Shibata. 2017. Road surface condition understanding and sharing system using various sensing technologies. *Proceedings of the 31st IEEE International Conference on Advanced Information Networking and Applications Workshops, WAINA 2017*. Institute of Electrical and Electronics Engineers, pp. 655–658. doi: 10.1109/WAINA.2017.76.

Jamakhandi, H. A., and G. K. Srinivasa. 2014. Internet of Things Based Real Time Mapping of Road Irregularities. International Conference on Circuits, Communication, Control and Computing, November 21–22, 2014.

Jensen, D., B. Koeberlein, E. Bala, and P. Bridge. 2013. 2013. Ensuring and Quantifying Return On Investment Through The Development of Winter Maintenance Performance Measures. 20th ITS World Congress Tokyo 2013, October 14–18, 2013, Tokyo, Japan. https://www.vaisala.cn/sites/default/files/documents/WEA-RDS-G-Performace%20Measures_2014.pdf.

Jonsson, P. 2011a. Classification of Road Conditions From Camera Images and Weather Data. 2011 IEEE International Conference on Computational Intelligence for Measurement Systems and Applications (CIMSA), September 9–21, 2011.

Jonsson, P. 2011b. Remote sensor for winter road surface status detection. SENSORS, 2011 IEEE, October 28–31, 2011. https://doi.org/10.1109/ICSENS.2011.6127089.

Kangas, M., M. Heikinheimo, and M. Hippi. 2015. RoadSurf: A modelling system for predicting road weather and road surface conditions. *Meteorological Applications*, Vol. 22, No. 3, pp. 544–553. https://doi.org/10.1002/met.1486.

Kwon, T. J., M. Wu, and L. Fu. 2021. Optimal RWIS Sensor Density and Location – Phase III. Aurora Project 2019-01. Aurora Program, Iowa Department of Transportation. https://www.intrans.iastate.edu/wp-content/uploads/2021/08/optimal_RWIS_sensor_density_and_location_phase-III_w_cvr.pdf.

Li, H., E. Saldivar-Carranza, J. K. Mathew, W. Kim, J. Desai, T. Wells, and D. M. Bullock. 2020. *Extraction of Vehicle CAN Bus Data for Roadway Condition Monitoring*. Joint Transportation Research Program, Purdue University. https://doi.org/10.5703/1288284317212.

Loeffler, B. 2021. Understanding Friction Testing. *Ice Slicer*, December 21, 2021. https://blog.iceslicer.redmond.com/understanding-friction-testing.

Magnusson, P., H. Frank, T. Gustavsson, and E. Almkvist. 2019. Real-time high-resolution road condition map for the EU. *Proceedings of the 9th International Munich Chassis Symposium 2018*, pp. 851–875. https://doi.org/10.1007/978-3-658-22050-1_56.

Mahoney, W. P., and W. L. Myers. 2003. Predicting Weather and Road Conditions. *Transportation Research Record*, Vol. 1824, pp. 98–105.

Mataei, B., H. Zakeri, M. Zahedi, and F. M. Nejad. 2016. Pavement Friction and Skid Resistance Measurement Methods: A Literature Review. *Open Journal of Civil Engineering*, Vol. 06, No. 04, pp. 537–565. doi: 10.4236/ojce.2016.64046.

McClellan, T., and M. A. Coleman. 2009. *Maintenance Decision Support System (MDSS): Indiana Department of Transportation (INDOT) Statewide Implementation*. Indiana Department of Transportation.

McCullough, B., D. Belter, T. Konieczny, and T. McClellan. 2004. Indiana Winter Severity Index. *Transportation Research Circular Number E-C063: Sixth International Symposium on Snow Removal and Ice Control Technology*, pp. 167–207. Transportation Research Board. https://onlinepubs.trb.org/onlinepubs/circulars/ec063.pdf.

Menne, M. J., I. Durre, B. Korzeniewski, S. McNeill, K. Thomas, X. Yin, S. Anthony, R. Ray, R. S. Vose, B. E. Gleason, and T. G. Houston. 2012. Global Historical Climatology Network - Daily (GHCN-Daily), Version 3. National Climatic Data Center, National Oceanic and Atmospheric Administration. https://doi.org/10.7289/V5D21VHZ.

MRCC. 2019. *AWSSI Enhancements in Support of Winter Road Maintenance*. Clear Roads Project 16-02. Midwestern Regional Climate Center, University of Illinois. https://www.clearroads.org/project/16-02/.

MRCC. 2021. *AWSSI Enhancements, Phase II*. Clear Roads Project 20-07. Midwestern Regional Climate Center, University of Illinois. https://www.clearroads.org/project/20-07/.

NHDOT. n.d. Levels of Service Summary for Snow Removal & Ice Control by Road Way Types. New Hampshire Department of Transportation. https://www.dot.nh.gov/document/levels-service-summary-snow-removal-ice-control-road-way-types.

NOAA. n.d.-a. Warning Criteria. National Weather Service, National Oceanic and Atmospheric Administration. https://www.weather.gov/car/Warning_Criteria.

NOAA. n.d.-b. Watch/Warning/Advisory Definitions. National Weather Service, National Oceanic and Atmospheric Administration. https://www.weather.gov/lwx/warningsdefined.

NOAA. n.d.-c. Definitions, Thresholds, Criteria for Warnings, Watches and Advisories. National Weather Service, National Oceanic and Atmospheric Administration. https://www.weather.gov/ctp/wwacriteria.

Nixon, W. A., and L. Qiu. 2005. Developing a Storm Severity Index. *Transportation Research Record*, Vol. 1911, pp. 143–148. https://doi.org/10.1177/0361198105191100114.

Oh, M., and J. Dong-O'Brien. 2025. Assessing the Safety Impacts of Winter Road Maintenance Operations Using Connected Vehicle Data. *Accident Analysis and Prevention*, Vol. 209 (January 2025), 107837. https://doi.org/10.1016/j.aap.2024.107837.

Qi, Y., and V. R. Velpur. 2024. Nonlinear modelling of the association between winter weather severity and maintenance expenditures. *Canadian Journal of Civil Engineering*, Vol. 51, No. 4, pp. 409–422. https://doi.org/10.1139/cjce-2023-0203.

Qian, Y., E. J. Almazan, and J. H. Elder, 2016. Evaluating features and classifiers for road weather condition analysis. 2016 IEEE International Conference on Image Processing (ICIP), September 25–28, 2016.

Ramanna, S., C. Sengoz, S. Kehler, and D. Pham. 2021. Near Real-time Map Building with Multi-class Image Set Labeling and Classification of Road Conditions Using Convolutional Neural Networks. *Applied Artificial Intelligence*, Vol. 35, No. 11, pp. 803–833. doi: 10.1080/08839514.2021.1935590.

Sakhare, R. S., J. Desai, W. Woker, H. Li, J. K. Mathew, J. Mahlberg, E. D. Saldivar-Carranza, D. Horton, and D. M. Bullock. 2023. *Connected Vehicle-Centric Dashboards for TMC of the Future*. FHWA/IN/JTRP-2023/17. Joint Transportation Research Program, Purdue University. https://doi.org/10.5703/1288284317642.

Salimi, S., S. Nassiri, A. Bayat, and D. Halliday. 2016. Lateral Coefficient of Friction for Characterizing Winter Road Conditions. *Canadian Journal of Civil Engineering*, Vol. 43, No. 1, pp. 73–83. https://doi.org/10.1139/cjce-2015-0222.

Sehovic, F., B. Zachrisson, and J. Petersson. 2024. *Assessment of Connected Vehicle Friction Measurement Data on DOT Winter Maintenance Use Cases*. Aurora Project 2023-01. Aurora Program, Iowa State University.

Strong, C., and Y. Shvetsov. 2006. Development of Roadway Weather Severity Index. *Transportation Research Record*, Vol. 1948, pp. 161–169. https://doi.org/10.1177/0361198106194800118.

Sturges, L., L. Fay, K. Clouser, and N. Villwock-Witte. 2020. *Evaluation of SSI and WSI Variables*. CR 18-03. Clear Roads Pooled Fund, Minnesota Department of Transportation https://rosap.ntl.bts.gov/view/dot/73440.

Suggett, J., A. Hadayeghi, B. Mills, J. Andrey, and M. G. Leach. 2006. Development of Winter Severity Indicator Models for Canadian Winter Road Maintenance. *TAC/ATC 2006 – 2006 Annual Conference and Exhibition of the Transportation Association of Canada: Transportation Without Boundaries, Charlottetown, Prince Edward Island*, pp. 1–20.

Tantillo, M., K. Smith, C. Packard, T. Lomax, and S. Dhuri. 2021. *Transportation Management Center Performance Dashboards*. FHWA-HOP-20-032. Federal Highway Administration. https://rosap.ntl.bts.gov/view/dot/57982.

Thomas, R., R. Bennett, D. Hassan, Y. Adu-Gyamfi, and P. Edara. 2021. *Development of a Surface Transportation Impact Factor for Winter Severity Indices*. MoDOT Research Report CMR 22-003. Missouri Department of Transportation.

Villwock-Witte, Y., C. Walker, L. Fay, S. Landolt, G. Wiener, and K. Clouser. 2021. *Weather Severity Indices – Key Issues and Potential Paths Forward*. Aurora Project 2020-03. Aurora Program, Iowa Department of Transportation. https://www.intrans.iastate.edu/wp-content/uploads/2021/01/weather_severity_indices_key_issues_and_paths_white_paper_w_cvr.pdf.

Walker, C. L., S. Hasanzadeh, B. Esmaeili, M. R. Anderson, and B. Dao. 2019a. Developing a winter severity index: A critical review. *Cold Regions Science and Technology*, Vol. 160 (April), pp. 139–149. https://doi.org/10.1016/j.coldregions.2019.02.005.

Walker, C. L., D. Steinkruger, P. Gholizadeh, S. Hasanzedah, M. R. Anderson, and B. Esmaeili. 2019b. Developing a department of transportation winter severity index. *Journal of Applied Meteorology and Climatology*, Vol. 58, No. 8, pp. 1779–1798. doi: 10.1175/JAMC-D-18-0240.1.

Walsh, C. 2016. *Winter Maintenance Performance Measure*. Colorado Department of Transportation. https://rosap.ntl.bts.gov/view/dot/29725.

Wiener, G., L. Fay, T. Brummet, S. Landolt, J. Lentz, S. Linden, and B. Petzke. 2023. *Roadway Friction Modeling : Improving the Use of Friction Measurements in State DOTs*. Aurora Project 2020-04. Aurora Program, Iowa State University.

Williams, J. n.d. UDOT Weather Operations Road Weather Index / Performance Metric. Presentation Slides.

WisDOT. 2014. *Annual Winter Maintenance Report Acknowledgments: Learning to Use Less Salt Without Compromising Safety*. Wisconsin Department of Transportation.

Wu, G. F., F. J. Liu, and G. L. Dong. 2020. Analysis of the Influencing Factors of Road Environment in Road Traffic Accidents. 2020 4th Annual International Conference on Data Science and Business Analytics (ICDSBA), September 5–6, 2020, Changsha, China, pp. 83–85. https://doi.org/10.1109/ICDSBA51020.2020.00028.

WYDOT. n.d. *Blow Over Hazards*. Brochure. Wyoming Department of Transportation. https://www.dot.state.wy.us/files/live/sites/wydot/files/shared/Public%20Affairs/brochures/blow-over%20brochure.pdf.

Ye, Z., C. K. Strong, X. Shi, and S. M. Conger. 2009. Analysis of Maintenance Decision Support System (MDSS) Benefits and Costs. No. SD2006-10-F. Office of Research, South Dakota Department of Transportation. https://rosap.ntl.bts.gov/view/dot/77543.

THE INSTITUTE FOR TRANSPORTATION IS THE FOCAL POINT FOR TRANSPORTATION AT IOWA STATE UNIVERSITY.

InTrans centers and programs perform transportation research and provide technology transfer services for government agencies and private companies;

InTrans contributes to Iowa State University and the College of Engineering's educational programs for transportation students and provides K–12 outreach; and

InTrans conducts local, regional, and national transportation services and continuing education programs.

INSTITUTE FOR TRANSPORTATION

IOWA STATE UNIVERSITY

Visit **InTrans.iastate.edu** for color pdfs of this and other research reports.