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Assessment of Winter Maintenance Performance Objectives Using Maintenance Decision Support System

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16. Abstract

It is important for transportation agencies to assess their winter maintenance operations performance to identify areas for improvement and/or resource investment to maintain optimal levels of service, mobility, and safety. This study explores nine winter snowstorms in Nebraska during the 2023-2024 winter season across 20 road segments, 12 of which were along the Interstate-80 corridor. Datasets explored include meteorological information, traffic mobility insights, winter maintenance operations activities, and road conditions before, during, and after the periods of accumulating snowfall. Statistical analyses explored correlations and quantitative relationships among these datasets, while visual dashboards were developed to promote more qualitative considerations of factors that most influenced winter maintenance operations performance.

Across these datasets, time, or duration, was found to be the most meaningful performance metric. The utility of time as a performance metric applied across all considered datasets to include factors such as the duration of snowfall or blowing snow conditions, the duration of speed reductions, road closures, or road condition degradation, and the duration of winter maintenance operation activities such as plowing or chemical applications. Traffic mobility insights, most notably speed disruptions which included speed reductions and road closures, were found to be the most important singular performance metric. Despite this importance, it is imperative to highlight that speed disruptions can result from external factors such as vehicular crashes and congestion associated with adjacent state road closures.

All assessed metrics had strengths and limitations which warrant further scrutiny and caution regarding their use as a sole performance metric. The most important conclusion of this study is that a holistic consideration across multiple metrics offers the greatest benefit in the assessment of winter maintenance operations. The best lens is the broadest assessment which allows for consideration of both individual metrics as well as the relationships among various metrics in both time and space.

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List of Acronyms

ASOS – Automatic Surface Observation System

AVL – Automated Vehicle Location

BLSN – Blowing Snow

DRSN – Drifting Snow

MDSS – Maintenance Decision Support System

NPMRDS – National Performance Management Research Data Set

NOHRSC – National Operational Hydrologic Remote Sensing Center

NWS – National Weather Service

NDOT – Nebraska Department of Transportation

NEWINS-O – Nebraska Winter Severity Index Observed (includes other parameters)

NEWINS-P – Nebraska Winter Severity Index Predictive (includes other parameters)

NA – Not Available

NW – No Wind

PWINO – Precipitation Identifier Sensor Not Available

RITIS – Regional Integrated Transportation Information System

RWIS – Road Weather Information System

TMC – Traffic Message Channel

WSI – Winter Severity Index

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Disclaimer

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This report has been reviewed by the Nebraska Transportation Center for grammar and context, formatting, and compliance with Section 508 of the Rehabilitation Act of 1973.

Executive Summary

It is important for transportation agencies to assess their winter maintenance operations performance to identify areas for improvement and/or resource investment to maintain optimal levels of service, mobility, and safety. This study explores nine winter snowstorms in Nebraska during the 2023-2024 winter season across 20 road segments, 12 of which were along the Interstate-80 corridor. Datasets explored include meteorological information, traffic mobility insights, winter maintenance operations activities, and road conditions before, during, and after the periods of accumulating snowfall. Statistical analyses explored correlations and quantitative relationships among these datasets, while visual dashboards were developed to promote more qualitative considerations of factors that most influenced winter maintenance operations performance.

Across these datasets, time, or duration, was found to be the most meaningful performance metric. The utility of time as a performance metric applied across all considered datasets to include factors such as the duration of snowfall or blowing snow conditions, the duration of speed reductions, road closures, or road condition degradation, and the duration of winter maintenance operation activities such as plowing or chemical applications. Traffic mobility insights, most notably speed disruptions which included speed reductions and road closures, were found to be the most important singular performance metric. Despite this importance, it is imperative to highlight that speed disruptions can result from external factors such as vehicular crashes and congestion associated with adjacent state road closures.

All assessed metrics had strengths and limitations which warrant further scrutiny and caution regarding their use as a sole performance metric. The most important conclusion of this study is that a holistic consideration across multiple metrics offers the greatest benefit in the assessment of winter maintenance operations. The best lens is the broadest assessment which allows for consideration of both individual metrics as well as the relationships among various metrics in both time and space.

Project Highlights

- No singular metric provides a complete assessment of winter maintenance operations performance, and multiple metrics considered together provide greater insights.
- Time, or duration, of various meteorological, mobility, and maintenance parameters are the most important metrics for winter maintenance performance.
- Total speed disruption, or periods of reduced speed and road closures, are important mobility-based impact metrics to assess winter maintenance performance.
- Deicing material applications and maintenance vehicle operation hours are useful to quantify the level of winter maintenance operations effort.
- Road condition data obtained from a variety of sources including traffic camera imagery may warrant future exploration and evaluation as another performance metric.

Chapter 1 Introduction

The Nebraska Department of Transportation (NDOT) has made significant investments in winter maintenance operations including the procurement and evaluation of a Maintenance Decision Support System (MDSS; Anderson et al., 2020), and the development and refinement of a winter severity index (Walker et al., 2018). These resources have improved NDOT's internal operations, coordination with its partners, and its statewide level of service; however, quantifying performance is necessary to sustain and improve NDOT’s level of service to road users. Previously, NDOT explored traffic mobility data to assess performance along the Interstate 80 corridor in terms of speed recovery after a winter storm (Walker et al., 2018; 2019a; NDOT High Street Report personal communication 2025). This metric is useful but limited in quantifying NDOT's winter maintenance operations performance such as its responsiveness to the actions of adjacent state road closures (e.g., Wyoming) and the influence of vehicle congestion when the road initially reopens. Other states have considered metrics such as friction measurements, leveraging camera images to identify time to bare pavement, road condition reports, and more.

Dao et al. (2019), as part of previous NDOT research investments (Walker et al., 2018; Walker et al., 2019a), surveyed 31 Clear Roads consortium states to understand their use of winter maintenance performance metrics and severity indices. They identified improved decision making for snow and ice control as the leading benefit from performance metrics with improved communications and business practices also highly rated. Further, they found that the leading performance metrics used among states included equipment hours, customer satisfaction, time-to-bare pavement, safety information (i.e., crashes) and mobility (i.e., speed) recovery. Dao et al. (2019) also surveyed the methods and technologies used to inform performance measures. In general, most methods relied on manual, human input (e.g., visual inspection, personnel reports, accounting records, and camera inspection).

NDOT, and the transportation community as a whole, presently face unprecedented challenges with staffing shortages, changed travel patterns and preferences in the aftermath of the Covid-19 pandemic, and increasingly variable weather conditions. As such, the ability to quantify winter maintenance performance in ensuring safety and reliability across the transportation network is paramount. This analysis seeks to explore various datasets for use in assessing the performance of winter maintenance operations for a transportation agency across a variety of road and weather conditions.

The purpose of this study is to evaluate how multiple data streams can be integrated to assess NDOT winter maintenance performance at the segment level. Specific objectives are to:

- Assemble and quality-check weather, mobility, maintenance, and road condition datasets for Nebraska snow events.
- Develop time-based performance metrics for each dataset (e.g., snowfall duration, speed disruption duration, maintenance activity duration).
- Quantify relationships among storm severity, maintenance effort, road conditions, and mobility impacts.
- Identify which metrics are most reliable and actionable for NDOT performance tracking and future investment.

The remainder of this report is organized as follows: Chapter 2 summarizes prior work on weather impacts, winter maintenance operations, and performance metrics. Chapter 3 describes the study region, datasets, and analysis methods. Chapter 4 presents results for individual metrics and their combined interpretation. Chapter 5 consolidates findings, limitations, and recommendations for NDOT.

Chapter 2 Literature Review

2.1 Weather Impacts on Transportation Safety and Mobility

Road safety can be greatly impacted by weather, and the statistics on weather-related collisions are alarming. The Federal Highway Administration (FHWA) estimates that weather-related factors account for around 21% of all vehicle accidents in the US, nearly 1,235,000, resulting in over 16% (5,000) of fatalities and 19% (418,000) of injuries yearly (FHWA, 2018; Mathew and Pulugurtha, 2022). Crash events classified as weather-related are those that take place on slick pavement (such as wet pavement, snowy/slushy pavement, or icy pavement) or in adverse weather conditions, such as rain, sleet, snow, fog, strong crosswinds, or blowing snow/sand/debris (Pisano et al., 2008).

2.2 Quantification of Weather Impacts

State Departments of Transportation (DOTs) must be able to evaluate winter seasonal and individual storm severity to lower maintenance costs and the number of accidents caused by winter storms. Additionally, this information can be useful to inform motorists of weather conditions and their potential impacts. Winter severity indices (WSIs) have therefore been developed in many states to assist state DOTs in effectively allocating their labor, material, and equipment resources to ensure roadway safety during the winter or in unusual weather conditions, as well as to provide decision-support systems with an independent baseline to compare material usage/recommendations (Walker et al., 2019b). These models also assist in determining how cost-effective winter maintenance tasks are over the course of a season (Carmichael et al., 2004; Nixon and Qiu, 2005; Strong and Shvetsov, 2006; Walsh, 2016). Past research reported that 19 out of 50 states have well-documented WSIs. The five fundamental factors of these approaches are dependent variables, independent variables, observational levels of data, geographic areas, and mathematical expressions even though each state DOT has chosen different methods to create its own WSIs (Walker et al., 2019a). The characteristics of these state-specific indices determine how well each index evaluates winter maintenance performance, making them appropriate research topics for identifying state DOT best practices (Dao et al., 2019).

One of the tools that helps road authorities with planning, evaluating, and communicating about winter maintenance operations is the winter severity index (WSI). It helps to rate the severity of winter conditions at a specific time period in a specific area. These indices can be used in a variety of ways, including planning maintenance budgets in the context of variable seasonal weather and climate change, and understanding how specific weather conditions or sequences account for unusually high or low maintenance costs (Matthews et al., 2017).

2.3 Winter Maintenance Operations

The lack of resources required is one of the challenges to maintaining roads in the winter. Resources required include machinery and equipment (e.g., plows, trucks, spreaders), maintenance crew, fuels and abrasives, storage depots, and disposal sites. These limitations exacerbate the need to plan for their efficient and effective utilization to achieve the required service level. Winter road maintenance is extremely expensive and accounts for roughly 20% of the state DOTs maintenance budget. Annually, state and local agencies spend more than two billion dollars on snow control operations and millions of dollars to repair the infrastructure damage caused by snow and ice (FHWA, 2018). Therefore, maintenance companies and local governments must develop plans for the most efficient use of resources at their disposal when plowing, spreading abrasives, and loading and disposing of snow. The savings could be applied to other organizational areas or utilized to buy better tools and equipment to improve service delivery.

Due to the availability of all necessary equipment, supplies, laborers, support services, and facilities at the appropriate time when needed, maintenance planning can result in successful and efficient execution of work. Effective planning can greatly reduce the costs of winter road maintenance while delivering the necessary level of service to road users (Ben-Daya et al., 2016). To carry out efficient and effective winter road maintenance, decisions are made at different levels of the organization (i.e., at the strategic, tactical and operational levels) while some decisions can be made in real time. For the required service level to be achieved, right decisions must be made at the right time and should offer minimum operational cost and the highest level of safety (Perrier et al., 2006a; 2006b; 2007; Mbiyana, 2018).

Controlling snow and ice buildup on roadways during winter weather events presents several challenges for winter maintenance personnel. Among these challenges is the need to make effective winter maintenance decisions (treatment types, timing, rates, and locations), as these decisions have a considerable impact on roadway safety and efficiency. Maintenance decision support requires information from various sources including maintenance data, operations data, and data from the suppliers/vendors of the equipment or facility. A decision support system should be able to give information about what, when, where and how to carry out maintenance by utilizing the available data and transforming these data to notify the maintenance crew of the appropriate maintenance actions (Ben-Daya et al., 2016). Additionally, poor decisions can have adverse economic and environmental consequences. To mitigate the challenges associated with winter maintenance decisions, FHWA initiated a program in 2001 aimed at developing a winter road MDSS (National Academies of Sciences, Engineering, and Medicine, 2009).

The FHWA Road Weather Management Program recognized the need to address the difficulties of winter maintenance community professionals faced in using road weather information effectively in the maintenance decision-making process, and in 2000 the idea of the MDSS was conceived. The automated end-to-end decision support system that FHWA envisioned would be capable of offering users diagnostic and prognostic weather and road status information as well as instructions on how to maintain roads both before and during winter weather events. The FHWA started the MDSS project to develop a system that would fulfill this goal. Five national research institutions have contributed to the creation of a prototype MDSS over the course of the project. Cold Regions Research and Engineering Laboratory (CRREL) of the Army, National Center for Atmospheric Research (NCAR), Massachusetts Institute of Technology-Lincoln Laboratory (MIT/LL), National Oceanic and Atmospheric Administration (NOAA), Earth System Research Laboratory (ESRL) and NOAA National Severe Storms Laboratory are among the participating laboratories (Siems-Anderson et al., 2019).

Some studies have investigated certain aspects of winter storm safety. Hanbali (1994) considered the economic impacts of winter road maintenance on roadway users and found a significant decrease in crash rates before and after deicing maintenance activity. The results of several Swedish studies have supported Hanbali's findings and also indicated that severe injury rates on roads with snow and ice can be several times greater than roadways under non-winter conditions (Savenhed, 1995; Scharsching, 1996; Brown and Baass, 1997). Research also found that total injuries and fatalities increased by 25% on snowy days while the rate of injuries and fatalities increased by 100% (Perry and Symons, 1991). A Quebec, Canada study, on the other hand, found that winter months (December to March, inclusive), when compared to summer months, have higher minor and material damage accident rates, but lower severe and fatal accident rates (Brown and Baass, 1997). Several subsequent studies (e.g., Savenhed, 1995; Brown and Baass, 1997; Khattak and Knapp, 2001a; 2001b; Black and Mote, 2015a; 2015b; Tobin et al., 2019; 2021; Walker et al., 2024) confirmed these earlier findings that crash frequency and associated injuries may increase during winter weather conditions; however, overall injury severity decreased. Increases in crash frequency are likely associated with the increased prevalence of all precipitation types during the winter season while the decreases in overall crash severity are likely associated with the slower average speeds typically associated with these same conditions.

One measure of traffic flow mobility is vehicle speed. Several studies (e.g., Hanbali, 1994; FHWA, 2018; Knapp et.al. 2000) explored snow-related speed reductions segmented by road classification and found reductions of 18–42% on two-lane roadways, 13–22% on freeways, and 30–40% on arterial roads. Depending on snow severity, speeds decrease by 3–13% in light snow and by 5–40% in heavy snow (FHWA, 2018). Internationally, a Swedish study found a 10–30% reduction in speed due to snow (Oeberg, 1995). Another study concluded that speed reductions might be determined more by roadway appearance than the actual friction levels provided and that the speed reductions observed are typically higher when slippery roadway conditions are combined with precipitation (Wallman et al., 1997).

2.4 Winter Maintenance Performance

A performance measure is an indicator of how well a system meets and satisfies the expectations of its users and can be quantitative or qualitative. The purpose of measuring performance is to provide a basis for decision making about how resources are used, and ultimately to enhance performance. Performance measures can be used as a basis for resource allocation or to track progress over time toward a goal or an objective (Adams et al., 2003).

Performance measurement assesses progress toward achieving predetermined goals, including information on the efficiency with which resources are transformed into goods and services (outputs), the quality of those outputs (how well they are delivered to clients and the extent to which clients are satisfied) and outcomes (the results of a program activity compared to its intended purpose), and the effectiveness of government operations in terms of their specific contributions to program objectives. Generally, the broad categories of performance measures, including safety, accessibility, mobility, environmental and resource conservation, and operational efficiency were introduced to identify goals for maintenance operations; however, the additional factors, such as the skid-resistance of winter roads or satisfactory public attitudes, could also serve as performance indicators to assess a state DOT's effectiveness. Therefore, determining success against such targets enables a state DOT to measure the outcomes of roadway maintenance (National Academies of Sciences, Engineering, and Medicine, 2009; Dao et al., 2019).

Chapter 3 Data and Methods

3.1 Study Region

The study region for the development of the maintenance performance framework was defined by selecting roadway segments within the state of Nebraska and its eight NDOT districts (Figure 3.1). These MDSS segments (hereafter referred to as “segments”) were used to analyze winter road conditions, maintenance effectiveness, vehicle speed, the severity of snow events, and their impact on traffic safety. These segments were chosen based on multiple criteria to ensure accurate and representative data collection. Proximity to Automatic Surface Observation System (ASOS) weather stations was prioritized to obtain precise weather measurements, allowing for a more reliable assessment of storm severity and road conditions. The distance between the nearest ASOS station and a segment midpoint ranged from 2.5–29.0 miles. Additionally, segments were selected based on the availability of stationary roadside traffic cameras with optimal view angles, enabling a more detailed visual evaluation of snow coverage, vehicle movement, and the effectiveness of maintenance operations. To ensure comprehensive geographic representation, at least one segment from each NDOT district was included, capturing variations in maintenance practices, roadway conditions, and mobility impacts across different regions. Additionally, it was desired to prioritize segments near ASOS stations along Nebraska’s primary interstate corridor, I-80. After applying these criteria, 20 segments were selected across the state, including 12 along I-80 (Figure 3.1 and Table 3.1).

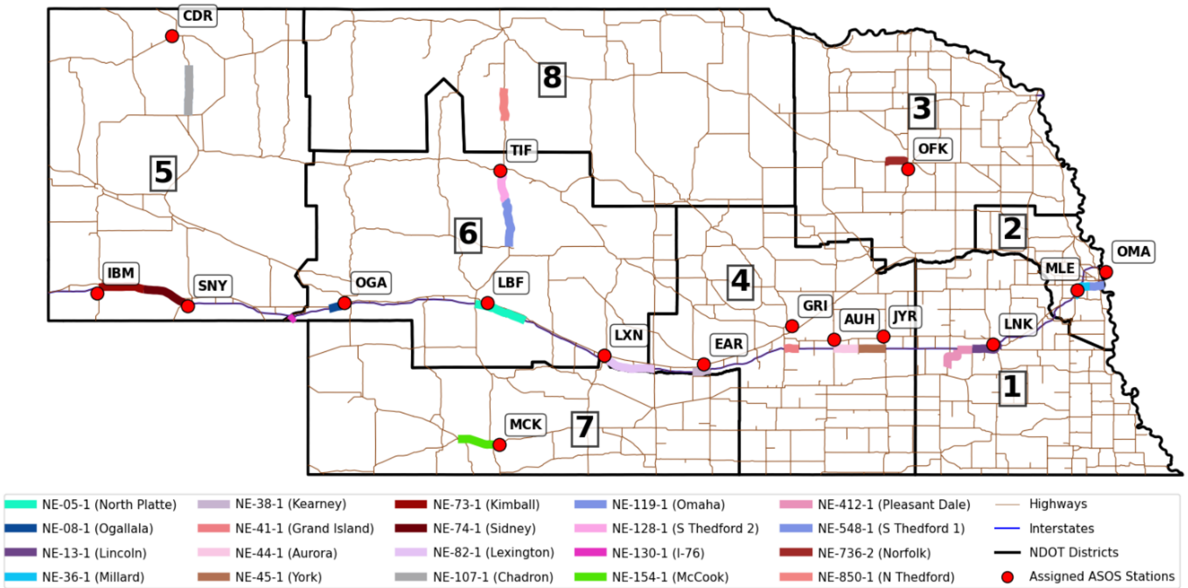


Figure 3.1 The 20 Nebraska road segments (color coded) used for the development of the maintenance performance framework. The 16 red dots represent Automated Surface Observing System (ASOS) weather stations that were assigned to evaluate segment-level weather conditions during each case study, with specific assignments provided in Table 3.1.

Table 3.1 Segment information organized by NDOT maintenance district, including their MDSS segment identification, city and associated ASOS station identified by its three-letter code, and road route designation.

NDOT District	Segments	City (Assigned ASOS Identifier)	Road Route
1	NE-13-1	Lincoln (LNK)	I-80
1	NE-412-1	Pleasant Dale (LNK)	US-6
2	NE-36-1	Millard (MLE)	I-80
2	NE-119-1	Omaha (OMA)	I-80
3	NE-736-2	Norfolk (OFK)	US-275
4	NE-45-1	York (JYR)	I-80
4	NE-44-1	Aurora (AUH)	I-80
4	NE-41-1	Grand Island (GRI)	I-80
4	NE-38-1	Kearney (EAR)	I-80
5	NE-73-1	Kimball (IBM)	I-80
5	NE-74-1	Sidney (SNY)	I-80
5	NE-107-1	Chadron (CDR)	US-385
6	NE-130-1	Big Springs (OGA)	I-76
6	NE-08-1	Ogallala (OGA)	I-80
6	NE-05-1	North Platte (LBF)	I-80
6	NE-82-1	Lexington (LXN)	I-80
6	NE-128-1	South Thedford Dismal River North (TIF)	US-83
6	NE-548-1	South Thedford Dismal River South (TIF)	US-83
7	NE-154-1	McCook (MCK)	US-34
8	NE-850-1	North Thedford (TIF)	US-83

To measure maintenance performance along the segments, an inventory of weather, mobility, traffic camera, and maintenance data were collected for nine case studies during the 2023–24 winter season (Table 3.2). Although these case studies are not a complete database of all systems during the winter season, they represent known impact situations in Nebraska. An important limitation of this study period was that anomalous road weather information system (RWIS) station data were present (NDOT personal communication, 2025). As such, road pavement temperature information is not considered in this study. For weather information, 6-h gridded (1 km [0.6 mi] resolution) observed snowfall data were obtained from the National

Operational Hydrologic Remote Sensing Center (NOHRSC) to describe the severity of snowfall (NOHRSC, 2025). Snowfall data are notoriously complex given a variety of observing networks each with their own unique reporting guidance. For example, the Federal Aviation Administration guidance for airport snowfall observations typically requires them at six-hour intervals (i.e., four times daily). However, community and volunteer weather observer programs require only 24-hour measurements (i.e., once daily). Moreover, there are differences in the time that snowfall may be reported with some recommendations to take an observation immediately at the conclusion of a period of snowfall and others advise taking the measurement at a fixed time each day even if snow technically ended several hours early or remains ongoing through the period. All of these nuances contribute to the strength of the NOHRSC product used in this analysis which is the National Gridded Snowfall Analysis. NOHRSC estimates snowfall by gathering several of these operational observational datasets into a consistent, unified analysis. Put simply, NOHRSC standardizes the snowfall information into a more useful input for this analysis. Beyond NOHRSC, hourly surface weather observation data were obtained from local ASOS stations relative to segments to help determine snow observations, blowing snow, drifting snow, and temperature conditions (Iowa Environmental Mesonet, 2025).

Table 3.2 The nine case studies from the 2023–24 winter season used for this study. Each case study's snowfall start, and end times are provided.

Case Number	Case Study	Snowfall Start Time	Snowfall End Time
1	23–26 November 2023	0600 CST 23 November 2023	1200 CST 26 November 2023
2	2 December 2023	1200 CST 2 December 2023	0000 CST 3 December 2023
3	23–28 December 2023	1800 CST 23 December 2023	1200 CST 28 December 2023
4	7–9 January 2024	1800 CST 7 January 2024	1200 CST 9 January 2024
5	15–16 February 2024	0600 CST 15 February 2024	0000 CST 17 February 2024
6	27 February 2024	0000 CST 27 February 2024	0000 CST 28 February 2024
7	6–8 March 2024	1800 CST 6 March 2024	1800 CST 8 March 2024
8	22–26 March 2024	1200 CST 22 March 2024	0600 CST 26 March 2024
9	6–8 April 2024	1200 CST 6 April 2024	1200 CST 8 April 2024

3.2 Data

3.2.1 Weather Data

To measure the snowfall along each segment, this study uses categorical snowfall severity (NEWINS-O) based on snowfall thresholds as shown in Figure 3.2 (Anderson et al., 2024; Kauzlarich et al., 2025) from NDOT's predictive WSI (NEWINS-P). To expand, NEWINS-O stands for "Nebraska Winter Severity Index – Observed" and uses snow accumulation thresholds (See Figure 3.2) to assign categories across Nebraska. The intent has been to translate individual snow accumulation reports, or ranges of reports, into a "severity" metric for a winter storm. The snowfall severity analysis was conducted within each case study's snowfall period to prevent another system's snowfall from being considered (Table 3.2). The methodology of calculating each case study's snowfall period was adapted from Kauzlarich et al.

(2025) by utilizing statewide snowfall to pinpoint snowfall start and end times. To expand, the start of the snowfall period is defined as the time at which any NOHRSC grid point within Nebraska observed snow accumulation. Similarly, the end of the snowfall period is the last time stamp at which any NOHRSC grid point within Nebraska observed new snow accumulation. Within the snowfall periods, the gridded data were interpolated along each segment to extract their NEWINS-O period, duration, and maximum category, if applicable. The NEWINS-O period was determined by calculating the start and end times of non-zero category segment grid cells. Within this period, the NEWINS-O duration was determined by adding up the number of six-hour intervals with at least one non-zero category segment grid cell. It is important to note that the temporal resolution of the NEWINS-O information is six hours. It is not possible to determine from the NEWINS-O whether the full six-hour period had accumulating snowfall or only a portion thereof. The maximum category was evaluated by taking the segment grid cell that has the greatest category within the NEWINS-O period. It is important to note that each segment was composed of multiple grid points.

Parameter	**NEWINS-O Category**					
	1	**2**	**3**	**4**	**5**	**6**
Snowfall (inches)	< 1.0	< 2.0	< 3.0	< 5.0	< 7.0	≥ 7.0

Figure 3.2 The snowfall categorical thresholds used to develop NEWINS-O, as discussed in Kauzlarich et al. (2025). These amounts are based on total snow accumulation over a six-hour period. The color scale shown is used throughout this study.

In addition to NEWINS-O, surface observations from local ASOS stations were used to further describe segment-level weather conditions such as snow precipitation, blowing and drifting snow, and temperature. To assess these conditions, each segment was assigned an ASOS station to retrieve precipitation, wind, and temperature information (Table 3.1). A segment's assigned ASOS station was determined by choosing the station that was closest to the segment's midpoint. On-the-hour observational data of present weather, wind speed, and temperature for the assigned ASOS stations surrounding each case study's snowfall period were obtained to evaluate pre-storm, in-storm, and post-storm weather conditions.

A more detailed analysis of snow-related weather along the segments was conducted by tallying snow reports based on present weather (i.e., ASOS-reported snow) within each case study's snowfall period. ASOS-reported snow was defined as any present weather that included any combination containing snow, indicating the presence of snow, either alone or in combination with other weather phenomena. The ASOS Precipitation Identification Sensor uses a 50 mm infrared light beam to detect precipitation particles down to the size of a small raindrop or approximately 0.04-inch diameter (NOAA, 1998). The frequency modulations of precipitation particles passing through the beam is interpreted by an algorithm to identify and discern among various types and intensities of precipitation (e.g., light rain, heavy rain, light snow, heavy snow, ice pellets). While the ASOS is the national standard that is compliant with the World Meteorological Organization, there are important limitations as well. Some of the most critical limitations relevant to the current study include less detection sensitivity to mixed phase precipitation (i.e., rain and snow), drizzle that can be interpreted as snow, and strong winds during snowfall. It is for these reasons that the analysis considered a multi-layered suite of weather information and, while ASOS is important, it is not the sole information source. To ensure the accuracy and reliability of these ASOS observations, a quality control process was applied to identify and address any data gaps in the observational datasets. These gaps typically resulted from either complete ASOS station outages, where data were marked as "not available" (NA), or from instances where the automated precipitation sensor was not working, labeled as "Precipitation Identifier Sensor Not Available" (PWINO). The number of NA and PWINO reports within each case study's snowfall periods were documented for further evaluation. By accounting for these reports, the analysis was able to distinguish between actual absences of snow and cases where snow may have occurred; however, it was not recorded due to instrumentation limitations.

In addition to snowfall, blowing and drifting snow and temperature trends are critical for assessing visibility and/or road conditions along each segment. Blowing snow (BLSN) is defined as snowfall that blows when snow is actively precipitating, while drifting snow (DRSN) is defined as pre-existing snowfall that blows when snow is not actively precipitating. As a result, the BLSN and DRSN criteria consider NEWINS-O, surface wind speeds, and/or precipitation type. Wind speed thresholds for BLSN and DRSN were derived from previous studies on critical thresholds for snow transport (Li and Pomeroy, 1997; Baggaley and Hanesiak, 2005) and the NEWINS-P (Kauzlarich et al., 2025). BLSN is recorded when either ASOS-reported snow or a NEWINS-O category is observed concurrently with surface wind speeds of 15 mph or greater during the snowfall period within the case study's snowfall period. Identification of DRSN leverages a method from Kauzlarich et al. (2025) by incorporating past and present NEWINS-O for snowfall information, ASOS-reported snow to confirm the absence of active precipitation, and surface wind speeds. Within each case study's snowfall period and the 24 hours following its end, DRSN is recorded if two specific conditions are met. First, neither ASOS-reported snowfall nor NEWINS-O snowfall can be observed in the current time step; however, NEWINS-O snowfall must have been observed in a previous time step. Second, when the NEWINS-O and

ASOS criteria are satisfied, DRSN is observed if surface wind speeds are greater than or equal to 20 mph. From applying these criteria, the total BLSN and DRSN reports were calculated. Wind sensors occasionally report “no wind” (NW), which may indicate calm conditions. However, instances of prolonged NW were noted during active weather, which may suggest sensor malfunction. The total NW reports within a case study’s snowfall period were documented for quality review. For temperature conditions, the pre-storm, in-storm, and post-storm minimum and maximum hourly temperatures were obtained. The pre-storm period considers observations 24 hours before the start of the NEWINS-O period, while the in-storm and post-storm periods consider observations within the NEWINS-O period and 24 hours after the end of the NEWINS-O period.

In addition to the NEWINS-O and ASOS analyses, weather data were obtained from MDSS to complement the existing datasets and enable cross-examination. Within each case study’s snowfall period, the number of on the hour MDSS snow instances were counted, as well as the number of on the hour snow instances during which the probability of precipitation was at or above 40%, a threshold used to distinguish between accumulating versus non-accumulating snow in MDSS (NDOT personal communication, 2025).

3.2.2 Transportation Mobility Data

The Regional Integrated Transportation Information System (RITIS; Vandervalk et al., 2016) was used to obtain vehicle speed data. All available data across each of the study segments and cases were obtained. Specific variables used from the dataset included: Traffic Message Channel (TMC), geolocation, observation timestamp, the hourly average of instantaneous observed five-minute harmonic speeds of vehicles traveling on a particular TMC, the historical average reference speed, and the speed limit. TMC-segments were aligned with the pre-defined MDSS segments provided by NDOT. Data from these TMC-segments were averaged together to derive a single value for the entire segment at each period, irrespective of travel direction (i.e., eastbound and westbound considered together). Due to variability in traffic volume and associated lack of speed information (e.g., no vehicles traveling overnight) along non-Interstate 80 road segments, speed data were only used for the 12 selected segments along Interstate 80 that generally had vehicles traveling at all times of day, including on holidays. This high-resolution speed dataset provides a foundation for identifying the time of the first speed drop, which serves as an indicator of deteriorating road conditions, detecting the lowest speed point, and ongoing winter maintenance operations, calculating the overall duration of the speed drop, and measuring the magnitude of speed reductions. Additionally, the absence of speed observations along the Interstate 80 corridor was a useful proxy for road closures.

The RITIS-provided historical reference speed was defined as the typical speed for a segment within a 60-minute time bin, calculated separately for each day of the week. To derive these values, the University of Maryland Center for Advanced Transportation Technology (CATT) Laboratory applies a harmonic mean approach, which better represents average traffic flow conditions when vehicle speeds vary, particularly under congested or disrupted conditions. For the 2024 NPMRDS and later versions, the historical averages for all segments were generated using data collected over a three-month period, specifically from March 1 through May 31 of the most recent NPMRDS map year available. This process ensures that the baseline comparison speeds are based on consistent seasonal conditions and are representative of typical, non-storm traffic patterns.

The primary speed metric computed was the reported duration of speed reductions associated with each case along each Interstate 80 segment. These reports quantify the number of hours for a particular case-segment combination in which the hourly observed speeds were greater than 10 mph less than the historical reference speed. For each segment, hourly observed speeds are compared to the historical baseline to identify periods of significant slowdowns, focusing only on instances with a substantial speed gap. Missing data were noted as well as whether the speed reduction period was continuous or discontinuous. Periods of missing data were considered indications of road closure given the observed typical consistency in reported vehicle speeds along Interstate 80. Thus, the reported duration for periods of speed reduction, periods of road closure, and periods of total speed disruption (i.e., speed reductions and closure summed) were identified for each case-segment combination. These metrics provided a measure of the duration of degraded mobility during snow events, emphasizing significant deviations from normal traffic conditions and enabling comparison across different segments and storms. It is important to note that it is not possible to attribute speed disruptions to weather hazards alone relative to other impactful events such as a vehicular crash and/or road congestion and capacity issues associated with closures along adjacent segments and/or states (e.g., Wyoming). To the extent possible, information from Nebraska's 511 traveler information system was utilized to understand the nature and possible causes for possible road closures (Anderson and Bundy, 2022; Bundy et al., 2023; NDOT personal communication, 2025).

3.2.3 Maintenance Operations Data

Winter maintenance operations data were obtained from NDOT's MDSS and its Automated Vehicle Location (AVL) information (NDOT personal communication, 2025). The MDSS provides recommendations for the timing, type of deicing material, and the material application rate. MDSS recommendations include actual treatment material application rates (e.g., 150 pounds per lane mile of pre-wet salt) as well as more general precautionary alerts (e.g., Patrol and Plow). For this analysis, any recommendation of either a specific application rate or a recommendation to Patrol was counted as a recommended maintenance action. The only exclusion was more general advisory language such as “Beware”. The intent here was to focus only on periods with more robust recommended maintenance activities. The start time for maintenance was based on the first on-the-hour instance of a recommended action, and the end time was the hour following the final instance of recommended action. The total on-the-hour reports of recommended maintenance was computed for each case and segment. This maintenance activity period could be continuous or discontinuous (i.e., broken). An important limitation of using these data is that it is only a recommendation and not a verification or validation of what actually occurred from a maintenance perspective, how much material was used, when material was applied, or where material was applied.

The AVL information includes the number of maintenance vehicles, the total miles driven, the amount of material applied, and the duration of a particular maintenance vehicle’s spreader operation mode (i.e., closed loop versus open loop, or more appropriately, automatic versus manual) which provides a confidence quantification of the material amount. For each segment and case, this information was computed. Further, the amount of deicing material applied (solid or liquid) was normalized by the lane miles of each segment to standardize the material information for more meaningful comparisons among segments that might be longer and/or have more traffic lanes such as in the more urban portions of District 2 (i.e., Omaha).

3.2.4 Road Condition Data

Road pavement condition data were obtained from two sources. First, the road condition data were obtained from NDOT’s MDSS. The MDSS defines several unique classifications of road pavement conditions ranging from dry, damp, and wet to snow covered and icy (Figure 3.3). These classifications are based on a combination of observations and model simulations. For simplification and alignment with NDOT’s 511 traveler information system, the raw MDSS road conditions were reclassified into three categories as shown in Figure 3.3: Normal

(Dry/Wet), Partial, and Complete. A degraded road condition was defined as the first instance of either a Partial or Complete road condition report (i.e., any departure from Normal). The first on the hour instance of a degraded road condition was used to identify the start time of degraded road conditions and the final on the last hourly instance of degraded road conditions was used to define the return to Normal road conditions. It was possible for this period of degraded road conditions to be continuous or discontinuous (i.e., broken). The worst indicated road condition category (i.e., Partial or Complete) was noted for each segment and each case. Last, the total number of reported hourly degraded road conditions was computed for each segment and case as well.

The second source for road pavement condition information was a subjective assessment of manually obtained traffic camera images along selective segments for each case. This assessment originated from the desire to serve as an independent baseline for both the MDSS road conditions as well as the observed weather conditions (e.g., start and end times of snowfall). The camera imagery provides the "ground truth". Camera images were generally obtained every 10 minutes with the exception of periods of data loss and Case 4 (i.e., January 2024). For the manual subjective camera assessment, a single image was taken based on its time stamp either being on or as close as possible to an on-the-hour observation (matching the other dataset observations). This single image was only used between 30 minutes before and up to and including the hour, no images were used after the hour to 29 minutes after the hour. Road conditions were subjectively classified as in Figure 3.3. Additionally, related observations such as the presence of snow, blowing snow, drifting snow, crashes, road closures, and other information of interest were noted for each of the images. Images obscured due to low lighting conditions, poor visibility, or any other factor were noted as well. This subjective assessment was only performed on a limited basis due to resource constraints. The assessment considered both the quality of the image (e.g., sun glare, low visibility or lighting conditions, camera obscuration) as well as deriving precipitation and road condition information from the image.

Worst MDSS Road Condition	Grouped MDSS Road Condition (Adapted from NE511 Categories)
Damp, Wet	Normal (Dry/Wet)
Slush, Chemically Wet	Partial
Snowcovered, Compacted Snow, Icy	Complete

Figure 3.3 Categorical classification of MDSS road conditions.

3.3 Analysis Methods

To assess the relationships among the aforementioned datasets in the context of winter maintenance operations performance, a series of exploratory and descriptive statistical analyses were performed. Most of the analyses focused on the Interstate 80 segments given the pairwise completeness and relative consistency of these data across all datasets. The statistical analyses considered included distribution and correlation analyses across individual segments, cases, case-segment combinations, and the entirety of the dataset (including the non-Interstate 80 segments). An important overarching limitation for the analysis is that the MDSS information (i.e., road condition and some maintenance data) is only obtainable from a one-year rolling archive. While the weather, speed, and some maintenance data can be obtained in perpetuity, other datasets were removed after a period of time. Thus, at times, it was challenging to go back and scrutinize datasets further and/or determine if there were more advantageous retrieval protocols.

In addition to the quantitative analyses, a segment-level visual dashboard was developed as a possible tool for NDOT personnel to consider the reinforcing evaluations of the dataset observations as well as the dependencies in assessing winter maintenance performance across all explored datasets (Figure 3.4). In the sample dashboard, from a temporal lens, the dashed vertical black lines represent the time boundaries of the period of accumulating snow across the entire state while the solid vertical black lines indicate the accumulating snow period for a particular segment. The top-most rows contain weather information discussed in Section 3.2.1. The uppermost row includes the six-hour NEWINS-O storm severity metric with colors corresponding to the thresholds shown in Figure 3.2. Empty, or white boxes, indicate periods with no accumulating snow. The second row from the top indicates possible periods of blowing (i.e., BLSN, pink boxes) and/or drifting (i.e., DRSN, gray boxes) snow based on the presence of either falling or accumulating snow and associated wind thresholds. Hatched boxes indicate periods of no wind information. The third row (i.e., ASOS Snow) indicates periods of precipitating snowfall shown as blue boxes. Hatched boxes indicate periods in which the precipitation sensor was not working and missing boxes indicate periods of missing data. The fourth and fifth rows (i.e., MDSS Snow) indicate periods of precipitating snow (once again using blue boxes) from the MDSS at all percentage probability of precipitation and for greater than or equal to 40% probability of precipitation, respectively. The 40% probability of precipitation threshold indicates when snow is anticipated to accumulate on a road surface within MDSS (NDOT personal communication, 2025). The sixth row from the top indicates the road conditions as discussed in Section 3.2.4. and reported from MDSS. Blue boxes correspond to partial coverage classifications while pink boxes correspond to complete coverage classifications. The seventh and eighth rows, if available, indicate road condition and precipitating snowfall observed from a subjective assessment of traffic camera imagery, respectively. These rows use the same color scheme and hatching conventions as MDSS reported road conditions and ASOS-observed precipitating snowfall. The ninth row indicates MDSS recommended maintenance periods with a blue box as discussed in Section 3.2.3. The tenth row indicates periods of speed reductions—discussed in Section 3.2.2.—as brown boxes and closures as missing boxes. Last, the eleventh row indicates whether temperatures were above freezing with values or greater than or equal to 34°F (red boxes), near freezing with values between 20–34°F (lighter blue boxes), or well below freezing with values less than 20°F (darker blue boxes). These dashboards were created for all segments, including those not along Interstate 80, for all cases. A selection of dashboards will be leveraged in the results section to further discussion of the project findings.

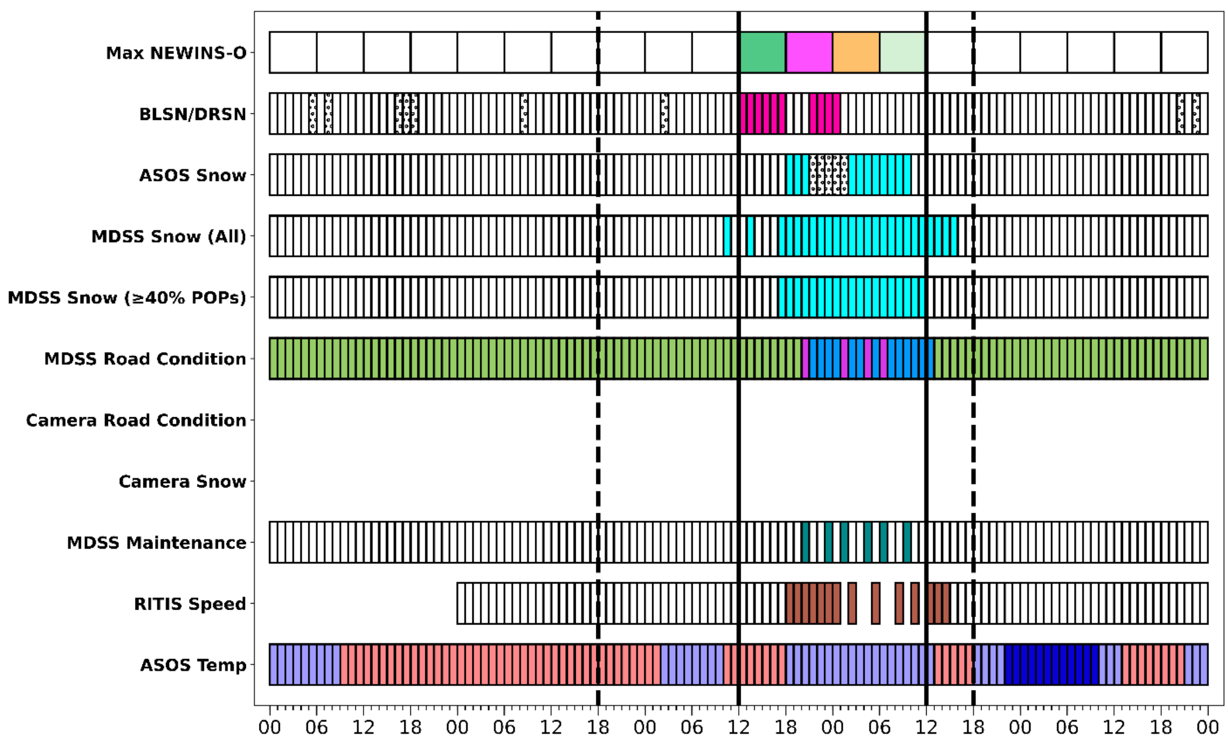


Figure 3.4 A demonstration of a winter maintenance performance temporal dashboard.

Chapter 4 Results

4.1 Overall Performance Parameter Assessment

To assess the value of individual and combined performance parameters, the analysis focused on higher severity events (i.e., Cases 1, 3, 4, 7, and 8). Additionally, the Interstate 80 corridor had the greatest overlap in dataset availability and will be prioritized for the analysis. This section will first consider an independent assessment of each of the parameters. Then, combinations and integrations of parameters will be discussed. This section will conclude with recommendations for each of the parameters given their observed variability, limitations, and noteworthy caveats.

4.1.1 Weather Performance Metrics

Meteorological information serves as a control and reference for assessing the performance of maintenance operations relevant parameters. Through a storm severity lens, the NEWINS-O maximum category distribution for this study mirrors that of past work (e.g., Walker et al., 2019a; Anderson et al., 2024; Kauzlarich et al., 2025). There are relatively more instances of lower severity events and fewer instances of higher severity events for the cases analyzed in this report (Figure 4.1). It is important to note here that the NEWINS-O values are at the segment-level spatially and not at the storm scale (see Figure 3.1). There were 34 instances of no accumulating snow along an entire segment in the dataset (i.e., NEWINS-O Category 0); however, some of these cases may have had falling snow and/or other impacts. Others may have had no impact at all, though are included within the performance analysis dataset for completeness. In terms of snowfall reports, most events in the dataset had less than 10 hours of reported snowfall (Figure 4.2). Relatively few events exceeded 24 hours. Blowing snow reports followed a similar trend (Figure 4.3) with relatively few events longer than 10 hours in duration.

Drifting snow (Figure 4.4) had an even smaller range with most events less than five hours in duration and none above 24 hours in this particular dataset.

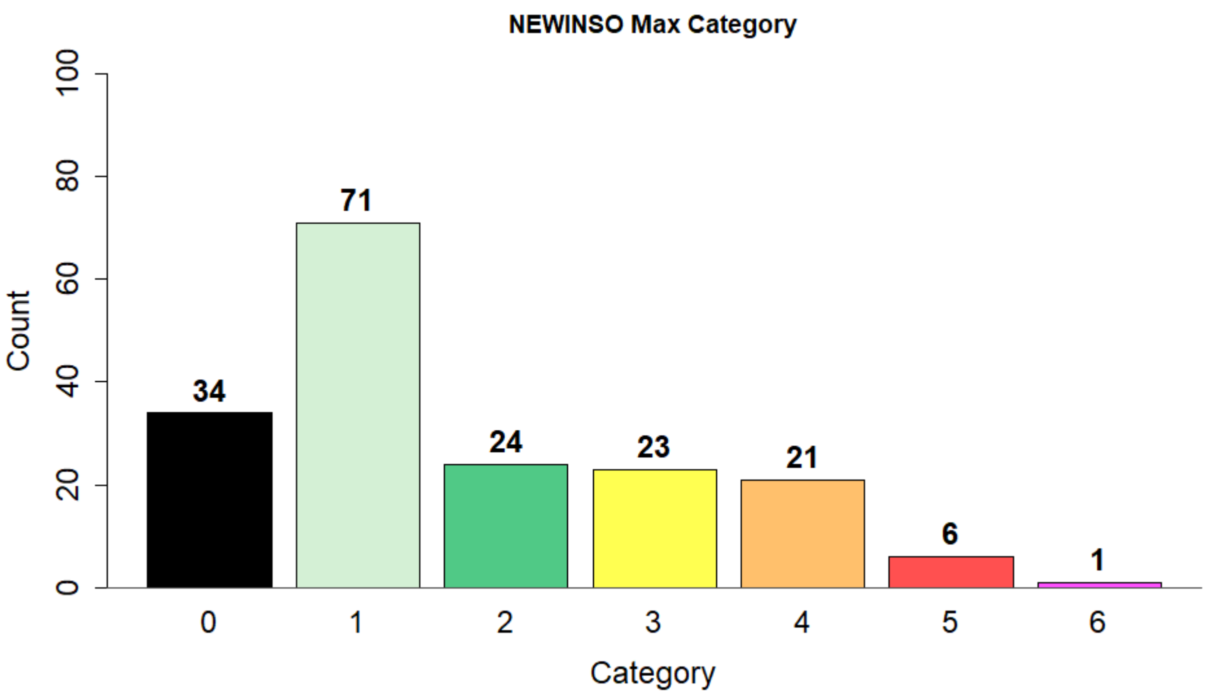


Figure 4.1 Segment-level distribution of NEWINS-O maximum storm severity category.

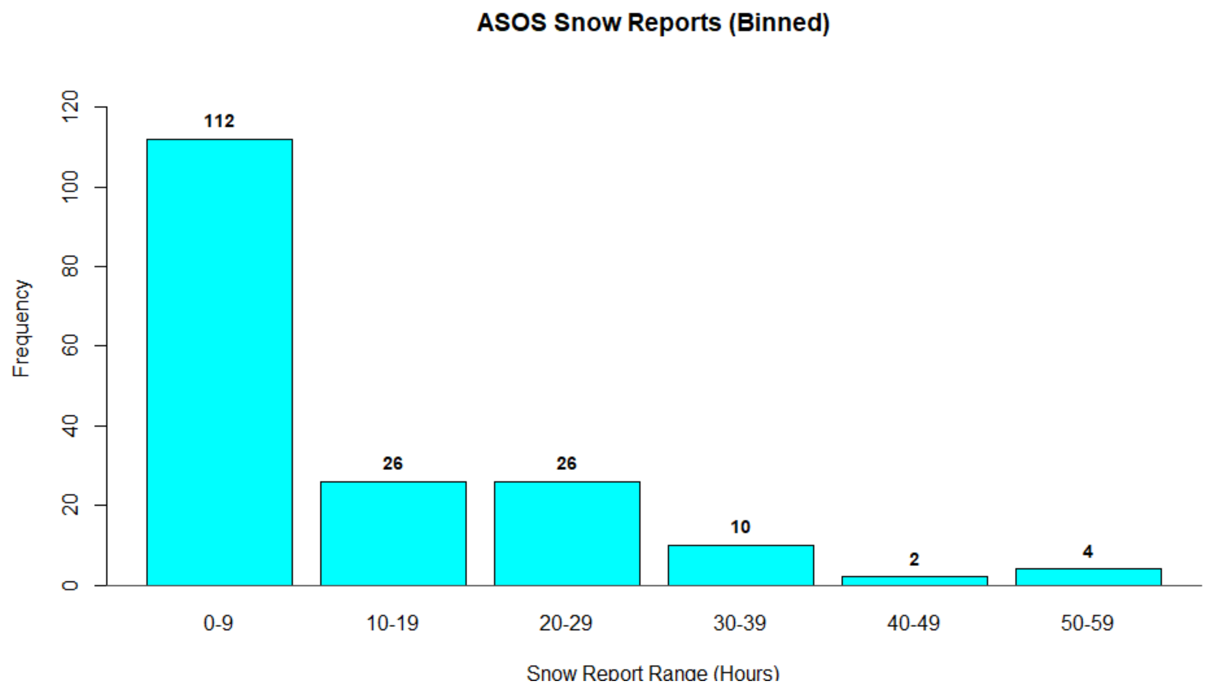


Figure 4.2 Segment-level distribution of reported falling snow duration.

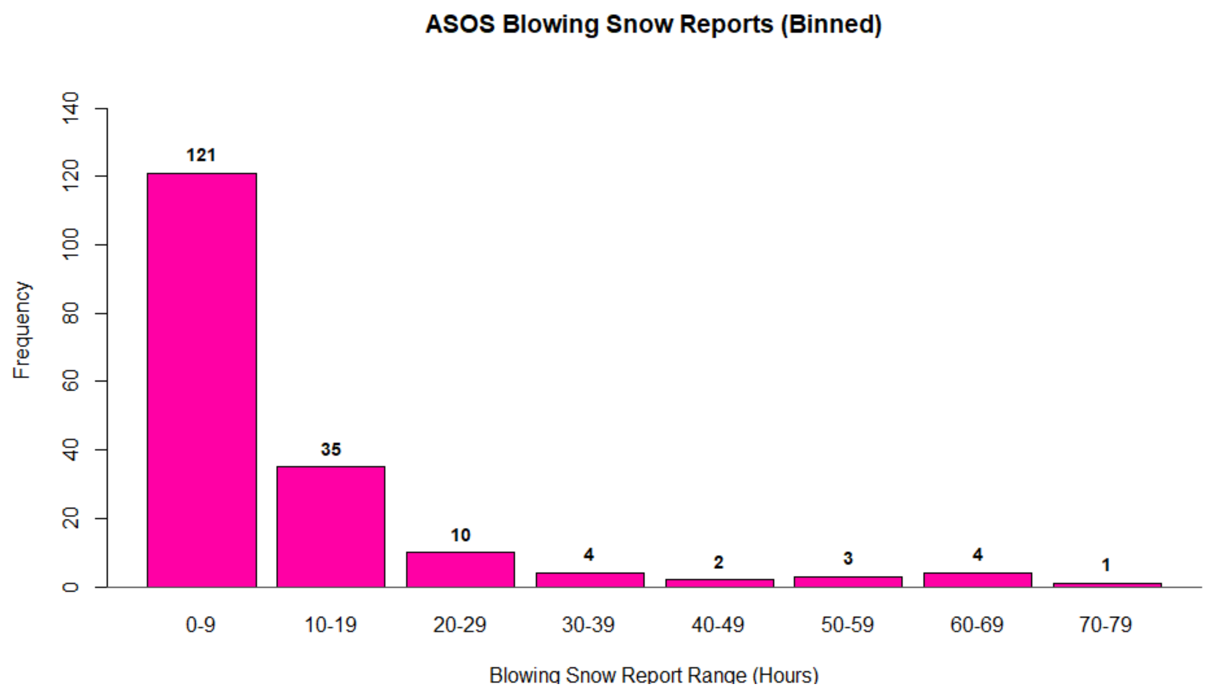


Figure 4.3 Segment-level distribution of derived blowing snow duration.

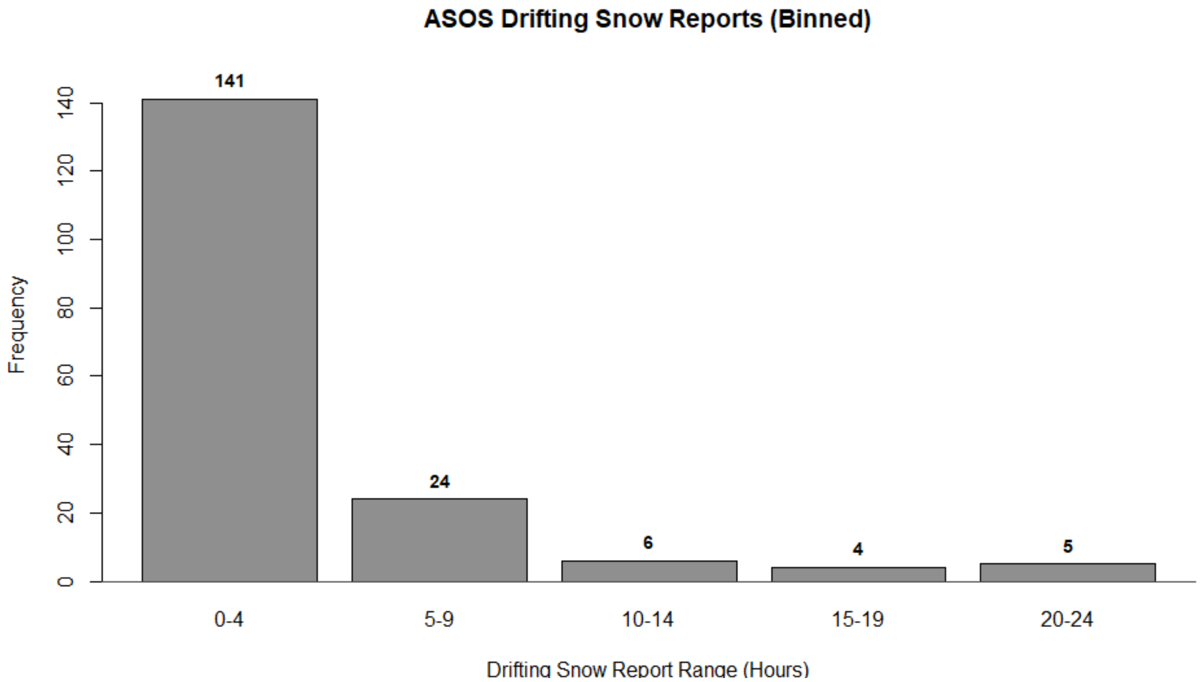


Figure 4.4 Segment-level distribution of derived drifting snow duration.

To visualize the temporal nature of meteorological and winter maintenance operations at each location, a series of dashboard visualizations, discussed in Section 3.3, were developed (Figure 4.5 and Figure 4.6). For Case 7 in North Platte (see Figure 4.5), the dashboard shows a 24-hour period of accumulating snowfall with an intense six-hour period of Category 6 storm severity (uppermost row). This included some periods of blowing snow (second row) and was generally aligned with observed precipitating snow despite some periods of present weather indicator sensor malfunction (third row). Temperatures for this event were generally marginal with near to even slightly above freezing (bottom row). In comparison, for Case 8 in North Platte (see Figure 4.6), the dashboard shows a 30-hour period of accumulating snowfall that begin with two consecutive six-hour periods of Category 3 storm severity (i.e., 12 total hours). Additionally, blowing snow (pink in the second row) was observed for a majority of the accumulating snowfall period and even some drifting snow (gray in the second row) at the conclusion of the event. In this case, the present weather sensor was not operational for the duration of the precipitation period (third row hatched boxes). Last, temperatures in this case were considerably colder (last row dark blue boxes).

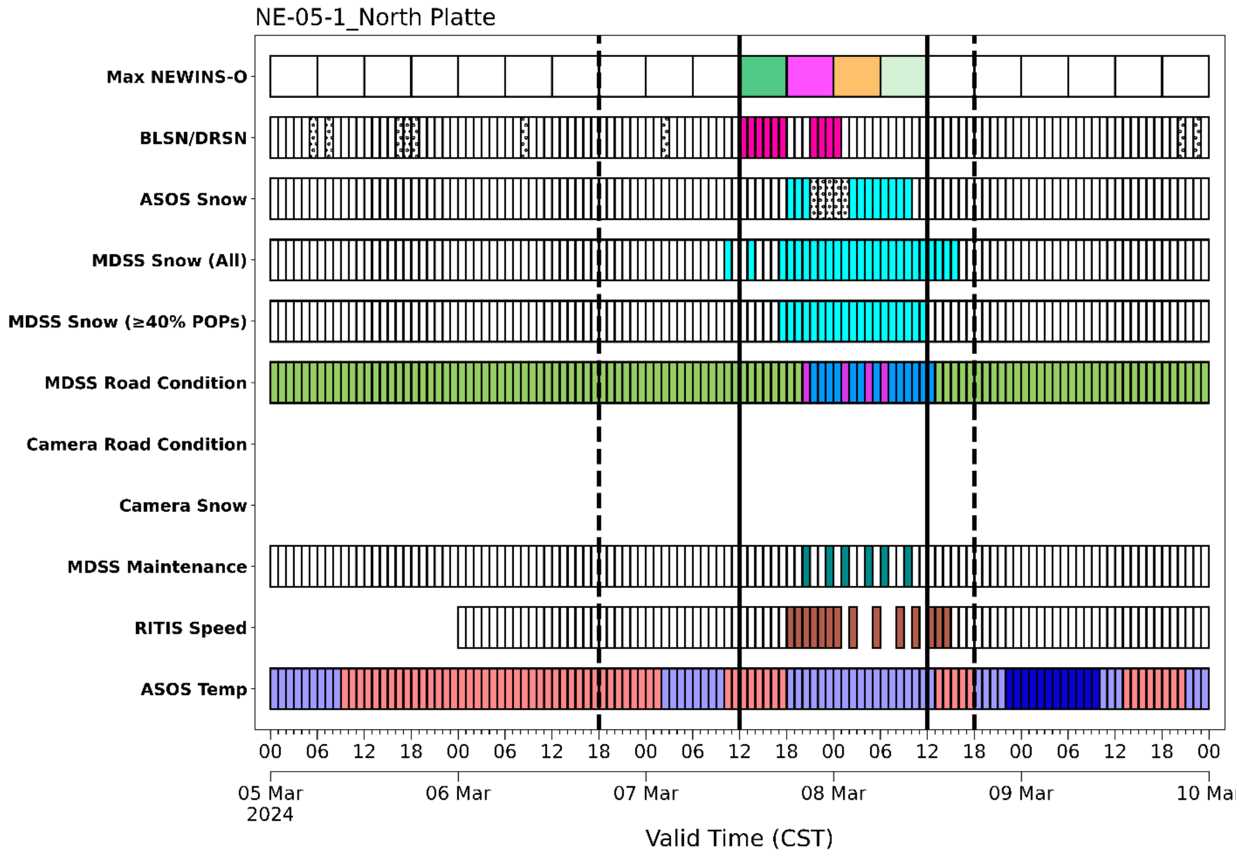


Figure 4.5 North Platte, Case 7 winter maintenance performance dashboard.

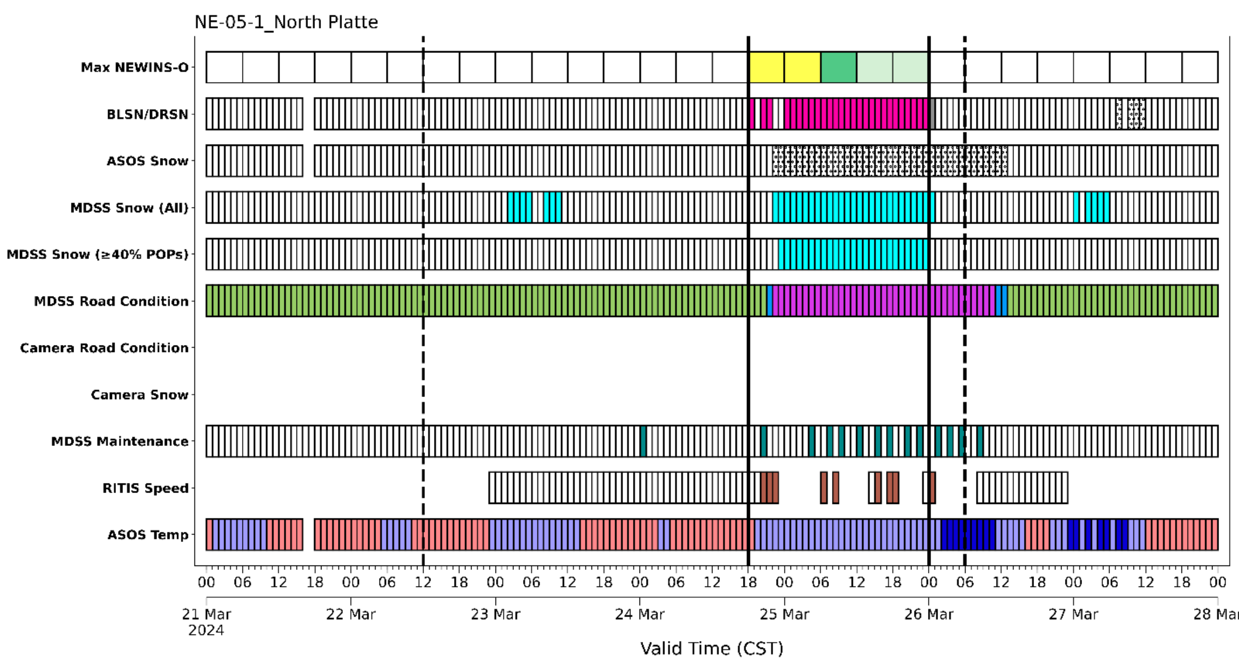


Figure 4.6 North Platte, Case 8 winter maintenance performance dashboard.

To visualize the spatial nature of meteorological impacts across the segments for each case, a series of images were developed displaying the maximum storm severity at each point across all the segments (Figure 4.7–Figure 4.15). Note, these graphics simply show the spatial magnitude of each event without respect to their duration (as shown in the dashboard visualizations). Case 1 was generally more severe across the western portions of the state (e.g., Kimball and Sidney segments in District 5). Case 2 was a relatively minor event with only low severity along portions of central Nebraska (e.g., Aurora). Case 3 was a moderate to strong severity storm impacting the entire state. Similarly, Case 4 was also a moderate to strong severity event though its impacts were concentrated in the eastern half of the state. Case 5 impacted all the state but with relatively low severity along the southern half of the state (i.e., Interstate 80 corridor). Case 6 had relatively minimal severity across most of the state. Case 7 was the most severe storm during the analysis period; however, its impacts were relatively localized to western Nebraska (e.g., North Platte). Case 8 was another moderate to strong severity storm; however, spatially none of the segments analyzed received substantial effects. Case 9 was a relatively small areal extent with severity relegated only to western Nebraska (e.g., Kimball, Sidney in District 5).

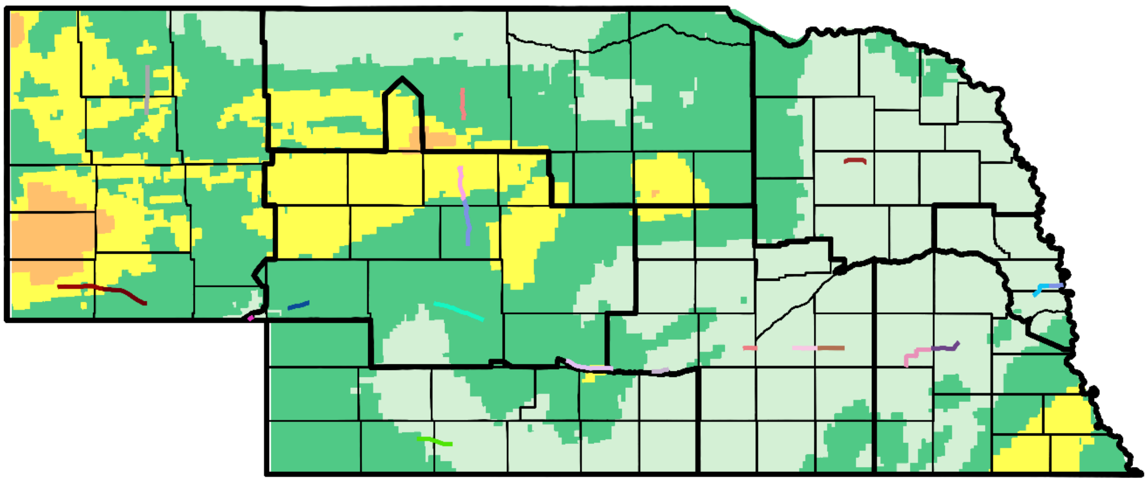


Figure 4.7 Case 1 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

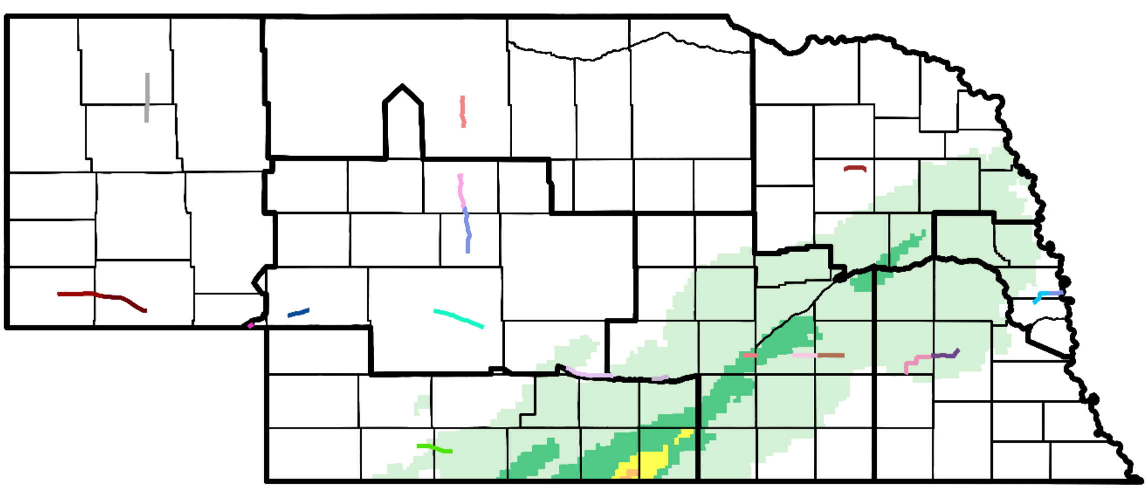


Figure 4.8 Case 2 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

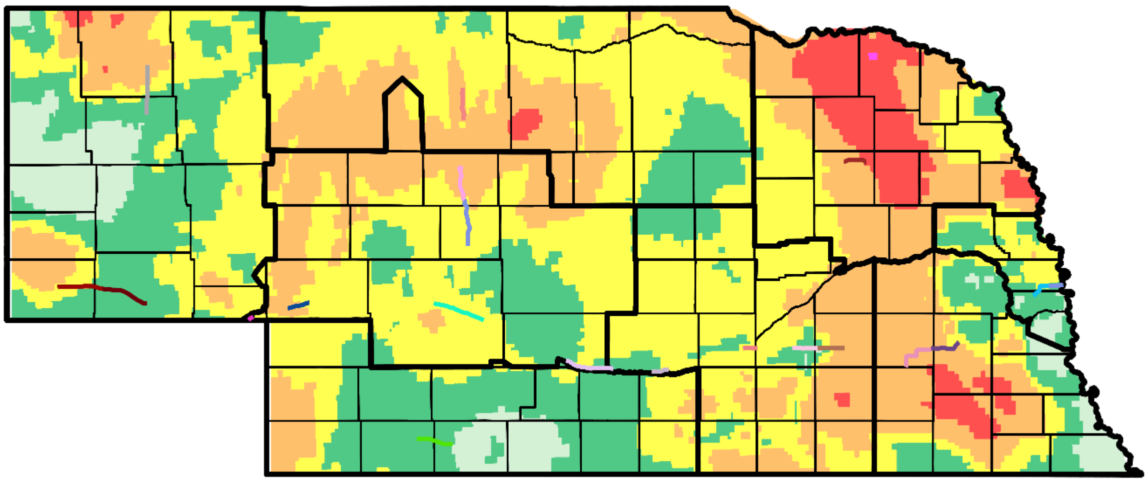


Figure 4.9 Case 3 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

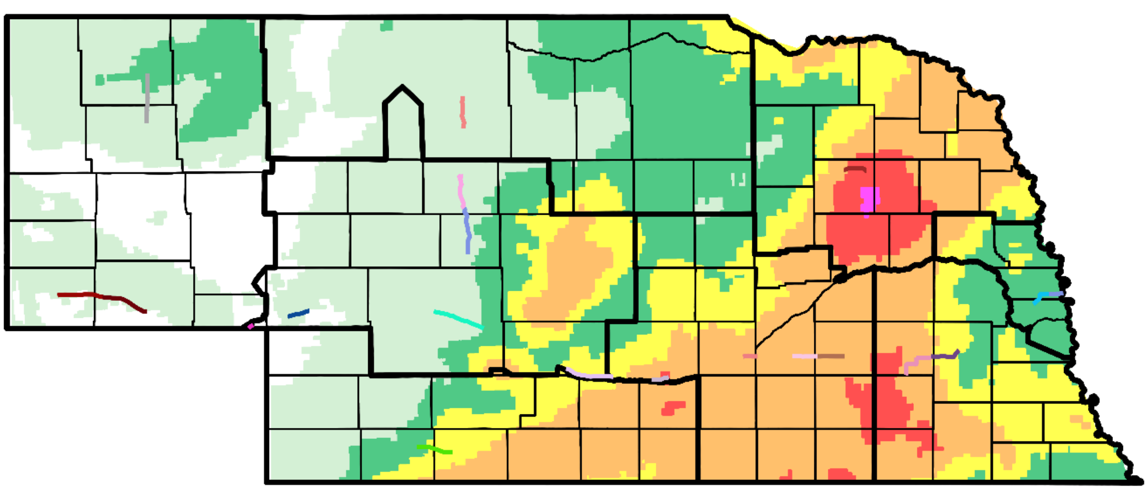


Figure 4.10 Case 4 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

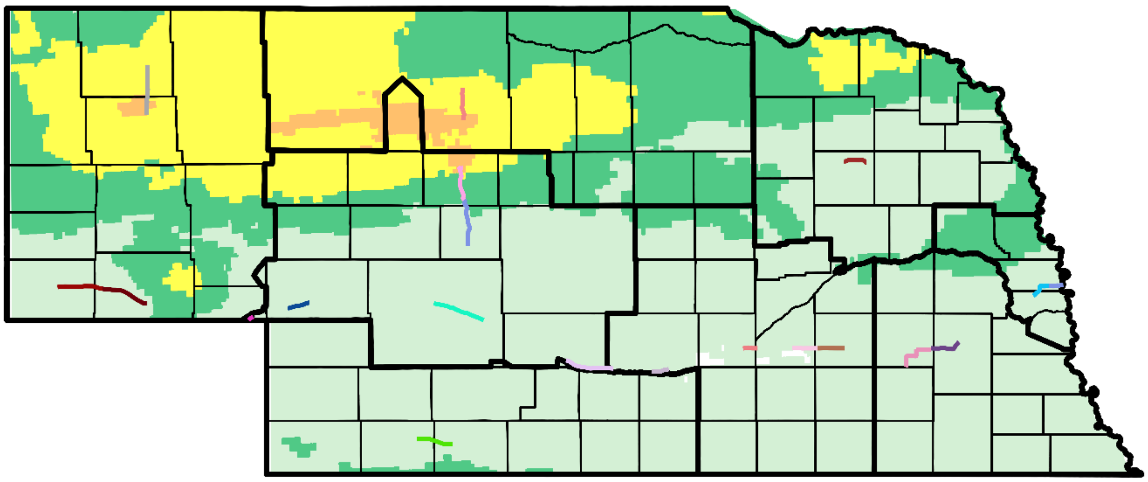


Figure 4.11 Case 5 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

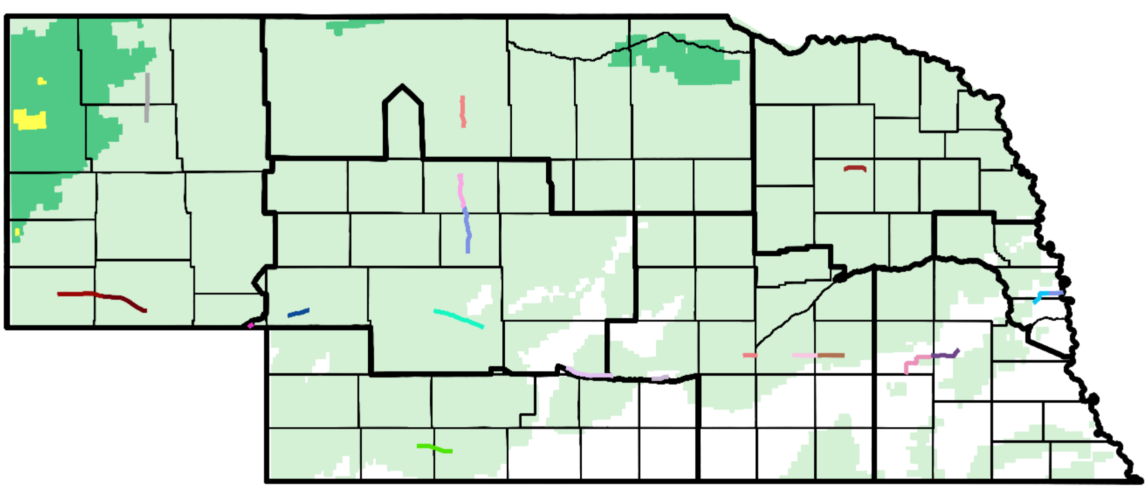


Figure 4.12 Case 6 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

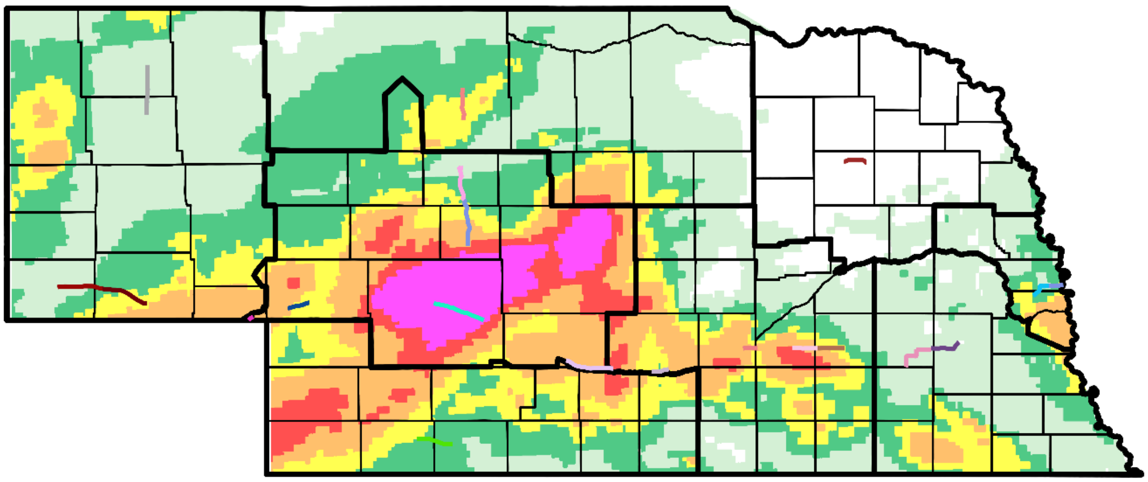


Figure 4.13 Case 7 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

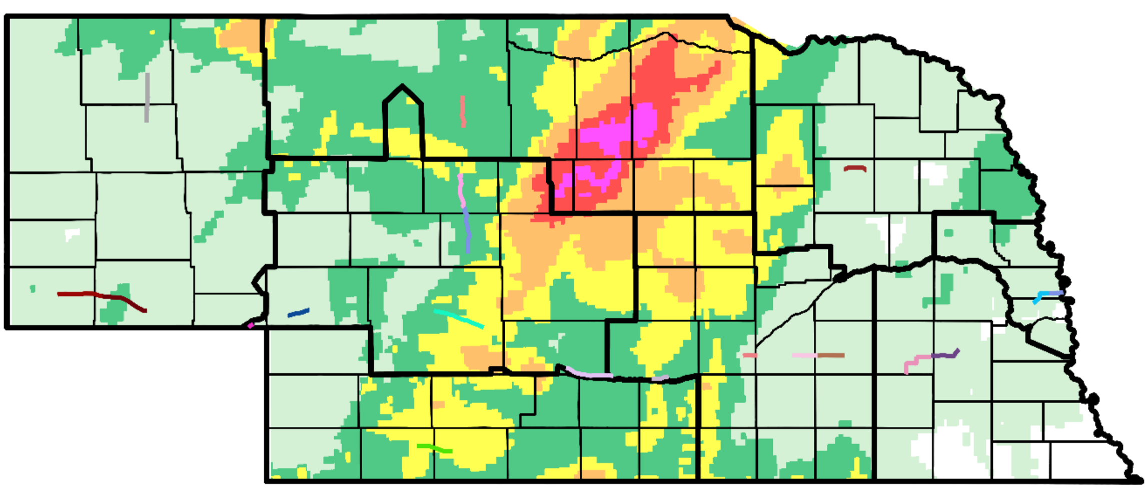


Figure 4.14 Case 8 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

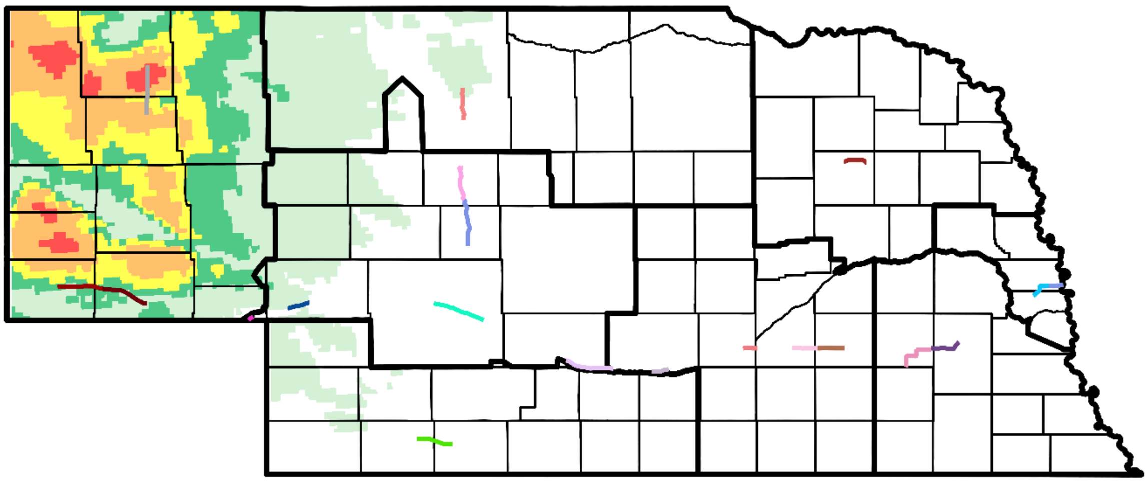


Figure 4.15 Case 9 maximum NEWINS-O storm severity across the entire event. Note road study segments are shown in the same color palette as in Figure 3.1.

4.1.2 Speed Performance Metrics

Overall, speed was an important performance parameter (Figure 4.16). This finding is well aligned with previous studies (e.g., NDOT High Street Report personal communication, 2025). Across cases, longer periods of reduction and/or closure were generally associated with greater storm severity. In Case 1, longer reductions were well aligned with the greater severity in western Nebraska (i.e., Districts 5 and 6). In Case 3, reductions were distributed more across the state with a higher severity and broader areal extent event. Case 4 had longer disruptions across central Nebraska (i.e., District 1, 4, and 6) once again aligned with storm severity. Cases 7 and 8 saw longer speed reductions in central and western Nebraska (i.e., District 6).

Cases 7 and 8 provide a unique opportunity to explore the influence of other weather information such as temperature on speed as a performance parameter (see Figure 4.5 and Figure 4.6). Case 7 had overall greater storm severity; however, its speed reductions were substantially less than those of Case 8. This pattern suggests a temperature-mediated effect; a plausible explanation is the relatively warmer conditions after the most severe Case 7 and colder conditions after the less severe Case 8 event, resulting in greater speed impacts for the latter.

It is important context for speed as a performance parameter to note its sensitivity to external factors such as vehicular crashes and road closures. Crashes often occur due to human error (e.g., driving too fast for conditions, following too closely) and do not accurately reflect the effort of maintenance activities. Partial or complete roadway closures may occur due to these crashes or congestion related to closures in adjacent segments or states (e.g., Wyoming). Crashes and closures both contribute to periods of speed disruptions (i.e., reductions and absence); however, neither scenario may accurately capture the performance, or success, of NDOT's maintenance activities. Moreover, there are additional situations where road conditions are completely dry and yet the road remains closed. To the extent possible, the Nebraska 511 traveler information system data were used to explore these more nuanced closure scenarios.

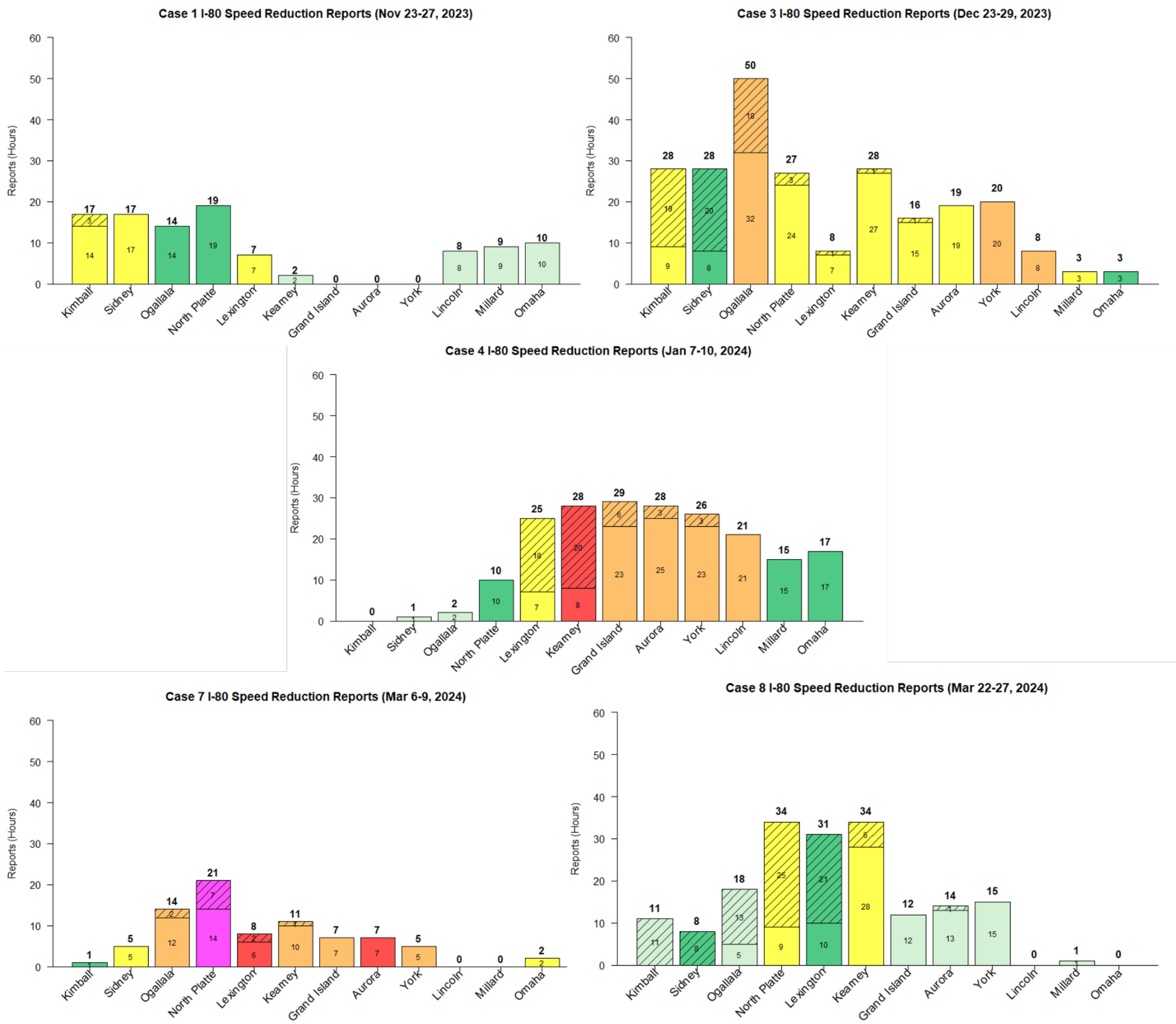


Figure 4.16 Speed disruption (hours) distributions for Interstate 80 segments during Cases 1, 3, 4, 7, and 8 color-coded by maximum NEWINS-O storm severity.

4.1.3 Maintenance Performance Metrics

Maintenance activity is a more complex performance parameter. While normalized material usage (Figure 4.17) and truck operation hours (Figure 4.18) provide useful information, other data such as recommended maintenance periods and the number of trucks or miles driven are less useful. As discussed in Section 3.2.3, an important limitation of using recommended maintenance periods is that these data do not actually reflect when the first maintenance vehicles commenced operations and when the final maintenance vehicles ceased operations during an event. Similarly, using the number of maintenance vehicles and/or the total miles driven among those vehicles does not accurately reflect the level of effort or resources for any given segment. It is possible that a vehicle attributed to a given segment was simply traversing a relatively small portion of that segment on its way to another assignment on a different segment. The inability to isolate the specific subset of maintenance vehicles that are assigned to a particular segment and/or cross-reference different plow routes with study segments presented an analytical barrier in using these data.

Normalized material usage (see Figure 4.17) was not as well-aligned with storm severity as speed was. Across cases, and Case 1 and 4 in particular, eastern Nebraska (i.e., District 2) tended to use a greater amount of material per-lane-mile regardless of storm severity. This is likely due to operational guidance and the more urban, commuter-centric environment. Central Nebraska (i.e., District 6) appeared to use less material regardless of storm severity. For example, despite a Category 5 storm for the Kearney segment during Case 4, relatively less material was used than segments east that had lower storm severity. Western Nebraska (i.e., District 5), seemed to have material variability that was better aligned with storm severity.

Maintenance vehicle operation hours (see Figure 4.18) were perhaps somewhat better aligned with storm severity than normalized material used; however, some similar caveats existed. There were higher operation hours for the more urban District 2. The Kearney segment still exhibited relatively lower operation hours despite higher storm severity. Operation hours for western Nebraska segments better aligned with storm severity.

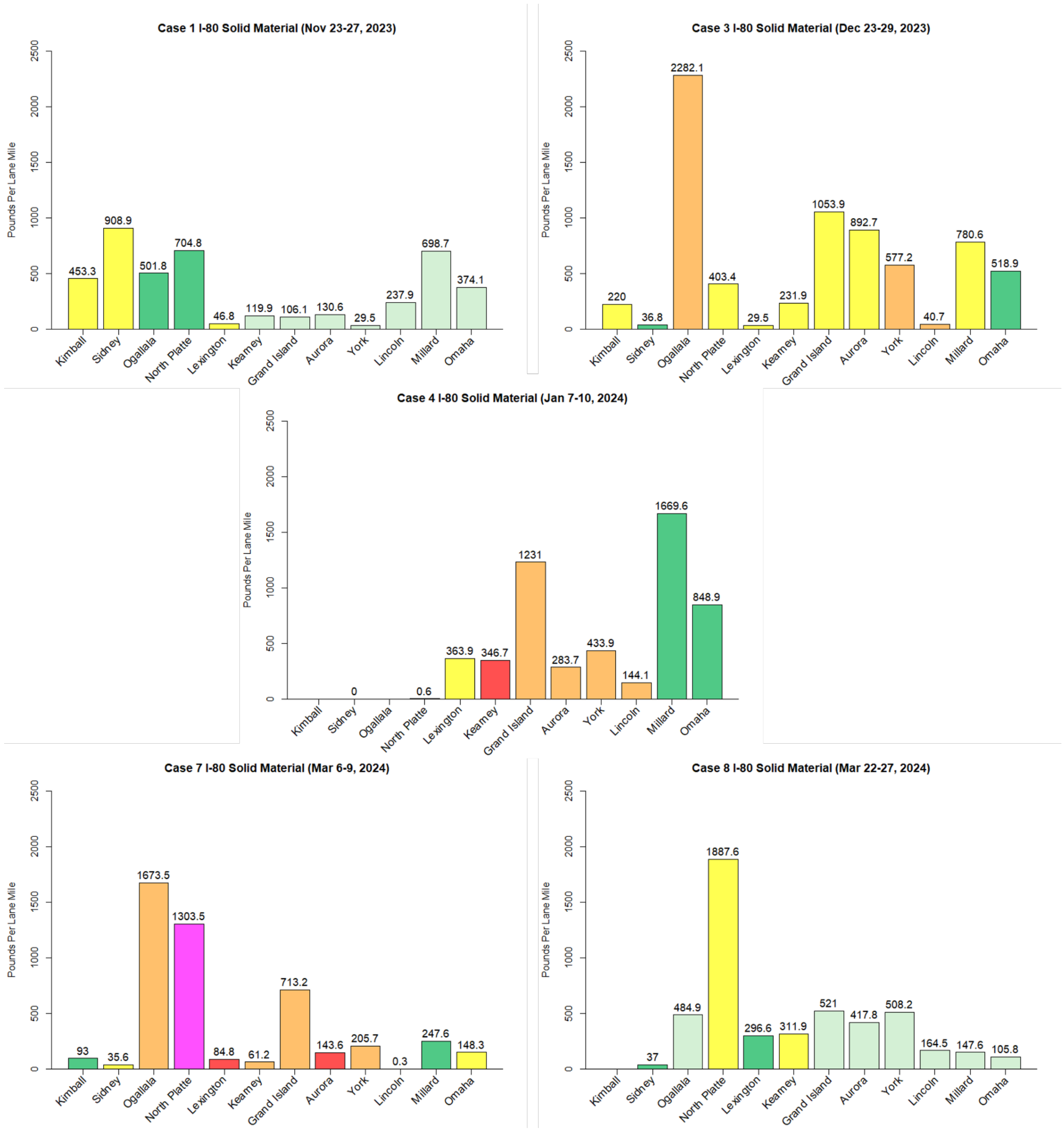


Figure 4.17 Normalized deicing material (pounds per lane mile) distributions for Interstate 80 segments during Cases 1, 3, 4, 7, and 8 color-coded by maximum NEWINS-O storm severity.

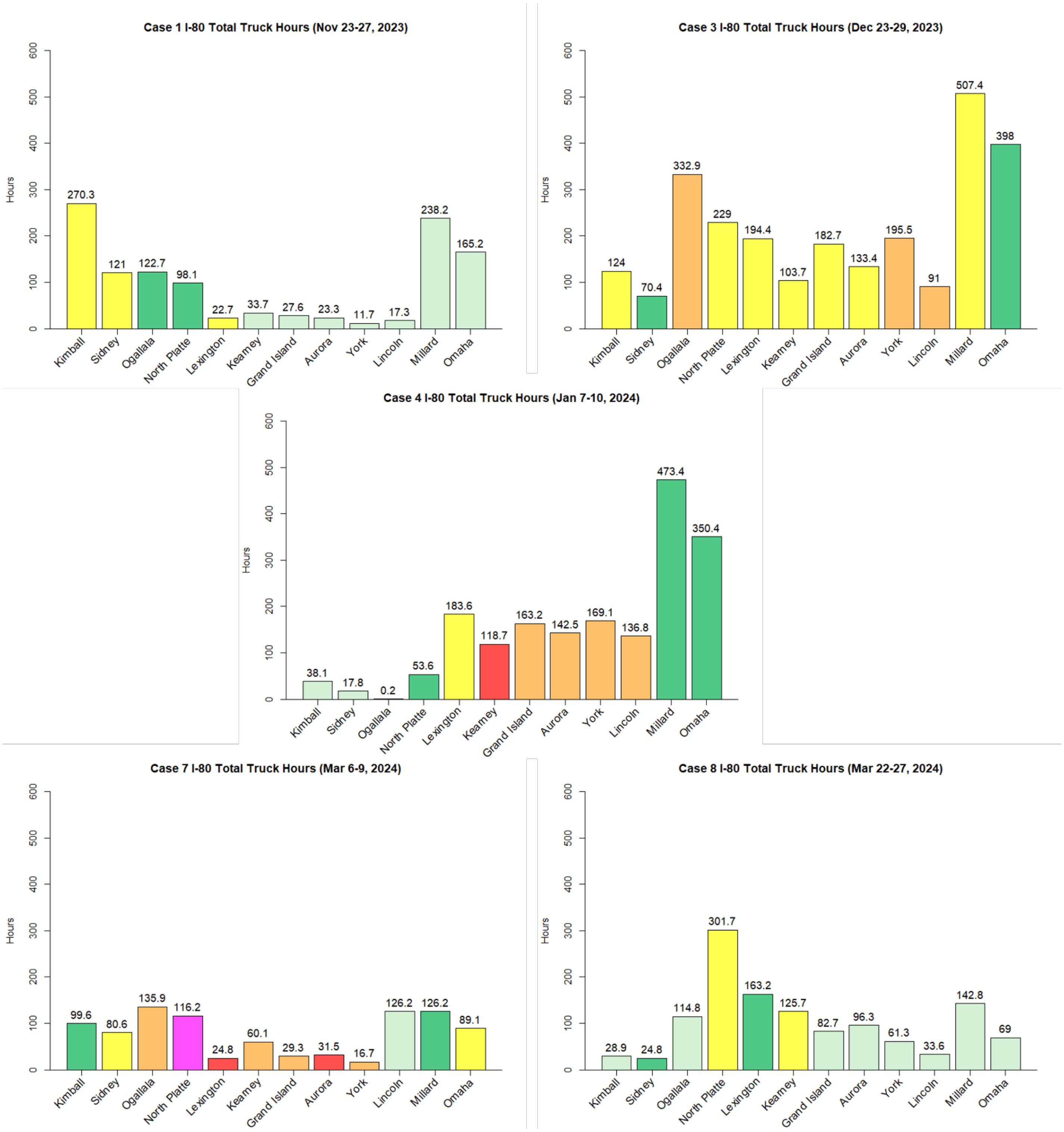


Figure 4.18 Maintenance vehicle operation hour distributions for Interstate 80 segments during Cases 1, 3, 4, 7, and 8 color-coded by maximum NEWINS-O storm severity.

4.1.4 Road Condition Performance Metrics

Road condition, obtained from MDSS, was the least reliable performance parameter in this analysis. For example, the Lincoln segment in Case 1 demonstrates a significant limitation in use of these data (Figure 4.19–Figure 4.21). The MDSS road condition never indicates any level of degraded road conditions despite forecasts of snow greater than 40% probability (see Figure 4.19). The ASOS snow observations from the same period indicate two distinct periods of snow (see Figure 4.19). These two periods of snow are confirmed from the traffic camera images at 1220 CST and 2220 CST on 25 November 2023 (see Figure 4.20 and Figure 4.21). Further, the traffic camera images also show snow accumulation on the road surfaces during both periods of snow. This result requires caution when considering further use of the MDSS road condition information. It is equally important to note that the camera image provides a snapshot at one very specific location and time along a road segment that is several miles in length. The MDSS road condition, on the other hand, must represent the entirety of the road segment.

Case 3 presents further issues with the use of MDSS road condition (Figure 4.22–Figure 4.24). In this instance, road conditions were manually classified from the camera data for the three select segments (i.e., Grand Island, Aurora, and Kimball) alongside the MDSS road conditions for comparison. For Grand Island (see Figure 4.22), the observed road degradation is well aligned with the observed ASOS snow period and the MDSS snow forecast periods. However, the MDSS degraded road condition period commences several hours later than the observed camera period. Perhaps more concerning still, the relative duration of MDSS degraded road conditions is quite similar to that of the observed degraded road conditions even though the actual timing of the situation is different. Meaning the length of degraded roads was similar, though the start and stopping times were very different. A bulk assessment of degraded road condition duration alone without consideration of the timing of degraded road conditions might not identify this inaccuracy in the data. The road condition information are better aligned for Aurora (see Figure 4.23); however, the MDSS degraded road condition continues onward for too long relative to the observed conditions. The Kimball segment (see Figure 4.24) MDSS road condition once again completely misses observed degraded road conditions.

In the literature (e.g., Dao et al., 2019), road condition is a common performance parameter across transportation agencies. In the current analysis, the available road condition data obtained from NDOT's MDSS cannot be recommended. However, with refinements to either the road condition observation network and/or the road condition modeling, it may be possible to improve this. Further, road condition assessment from traffic camera imagery has been documented in the literature (e.g., Welch, 2021; Wiener et al., 2023; Sutter et al., 2025) and may warrant further consideration by NDOT.

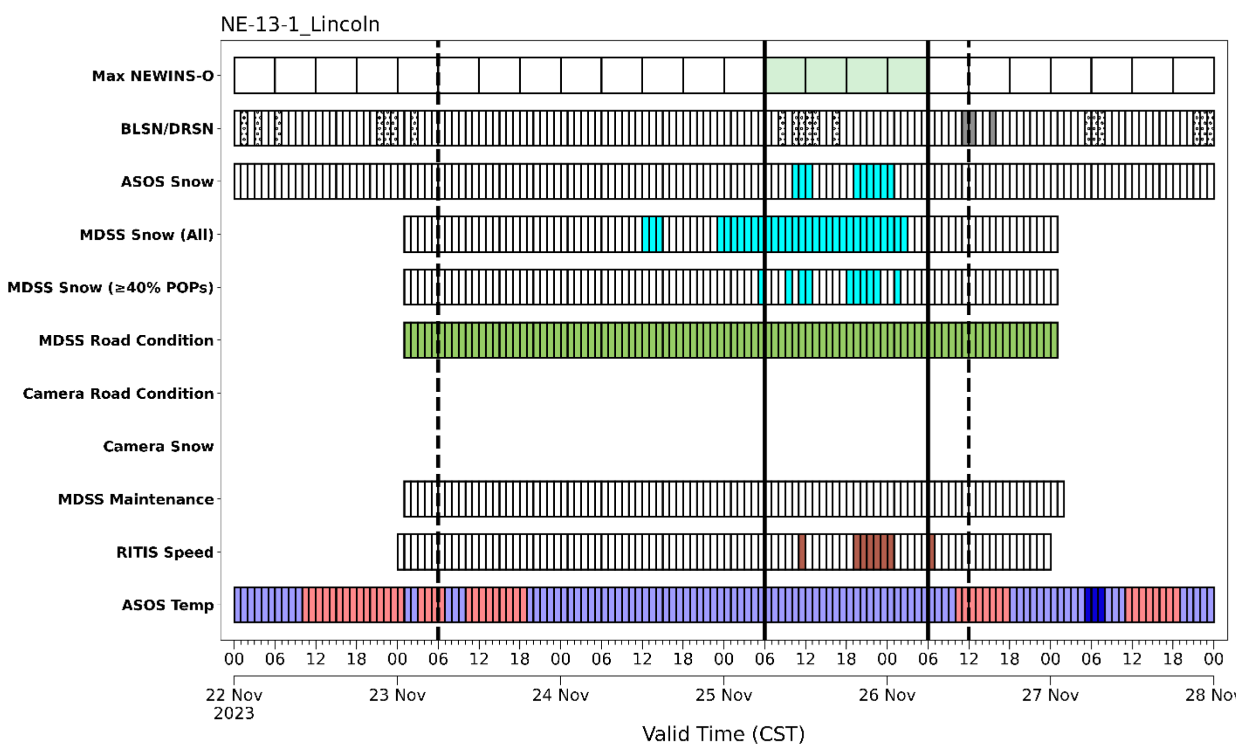


Figure 4.19 Lincoln, Case 1 winter maintenance performance dashboard.

Figure 4.20 Lincoln segment, Case 1 traffic camera image at Exit 399 at 1220 CST on 25 November 2023.

Figure 4.21 Lincoln segment, Case 1 traffic camera image at Exit 399 at 2220 CST on 25 November 2023.

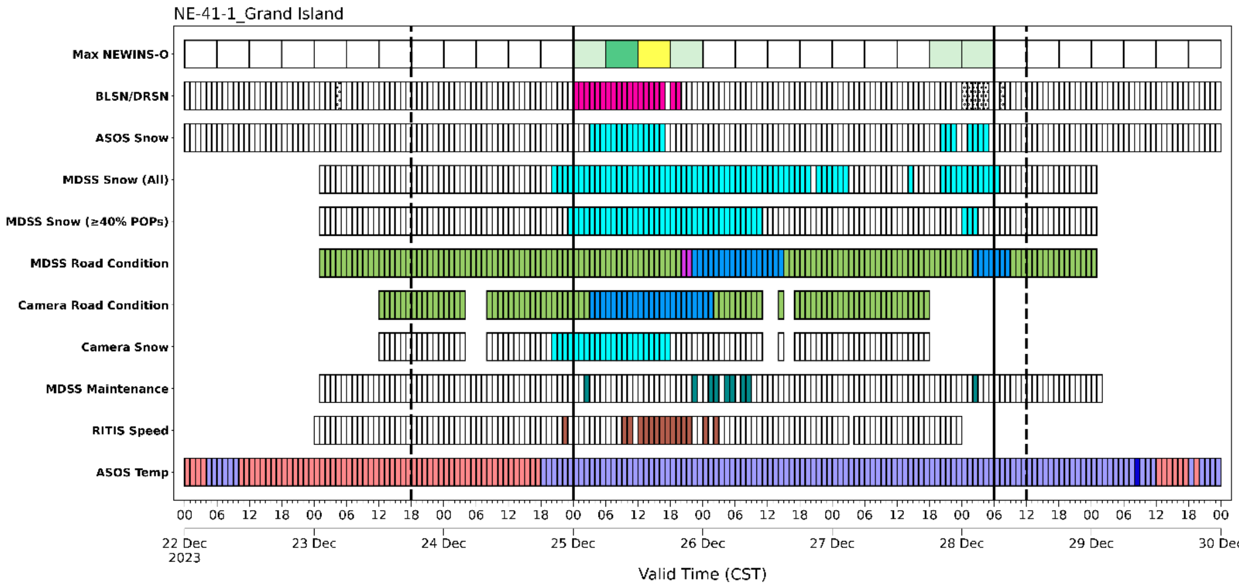


Figure 4.22 Grand Island, Case 3 winter maintenance performance dashboard (top) and Grand Island segment, Case 3 traffic camera image at Exit 314 at 1155 CST on 25 December 2023.

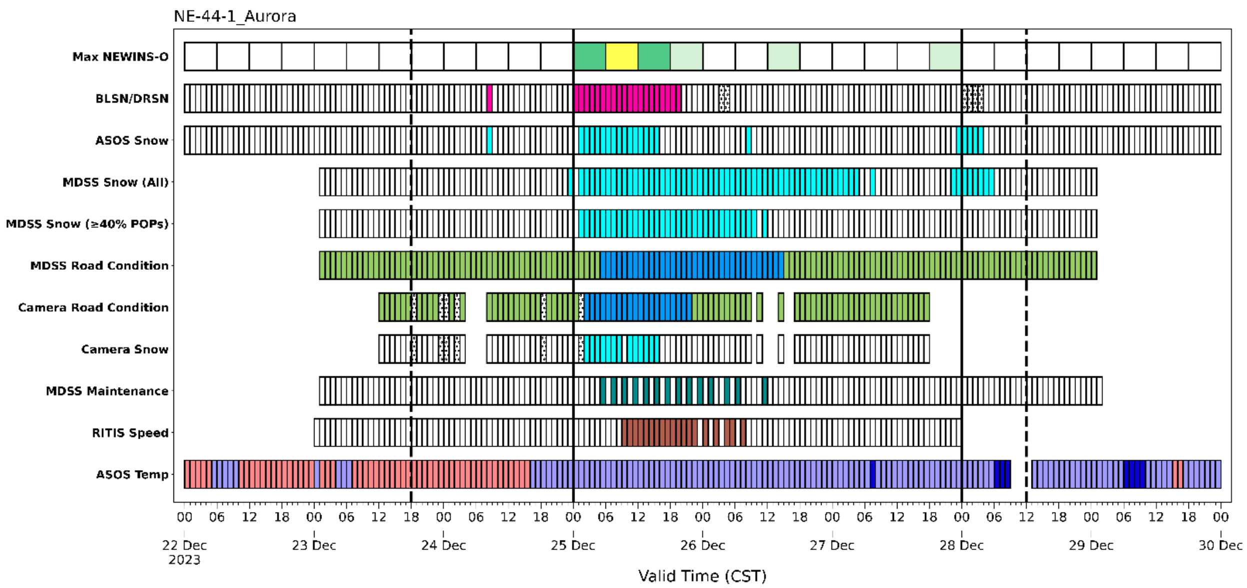


Figure 4.23 Aurora, Case 3 winter maintenance performance dashboard (top) and Aurora segment, Case 3 traffic camera image at Exit 332 at 0855 CST on 25 December 2023 (bottom).

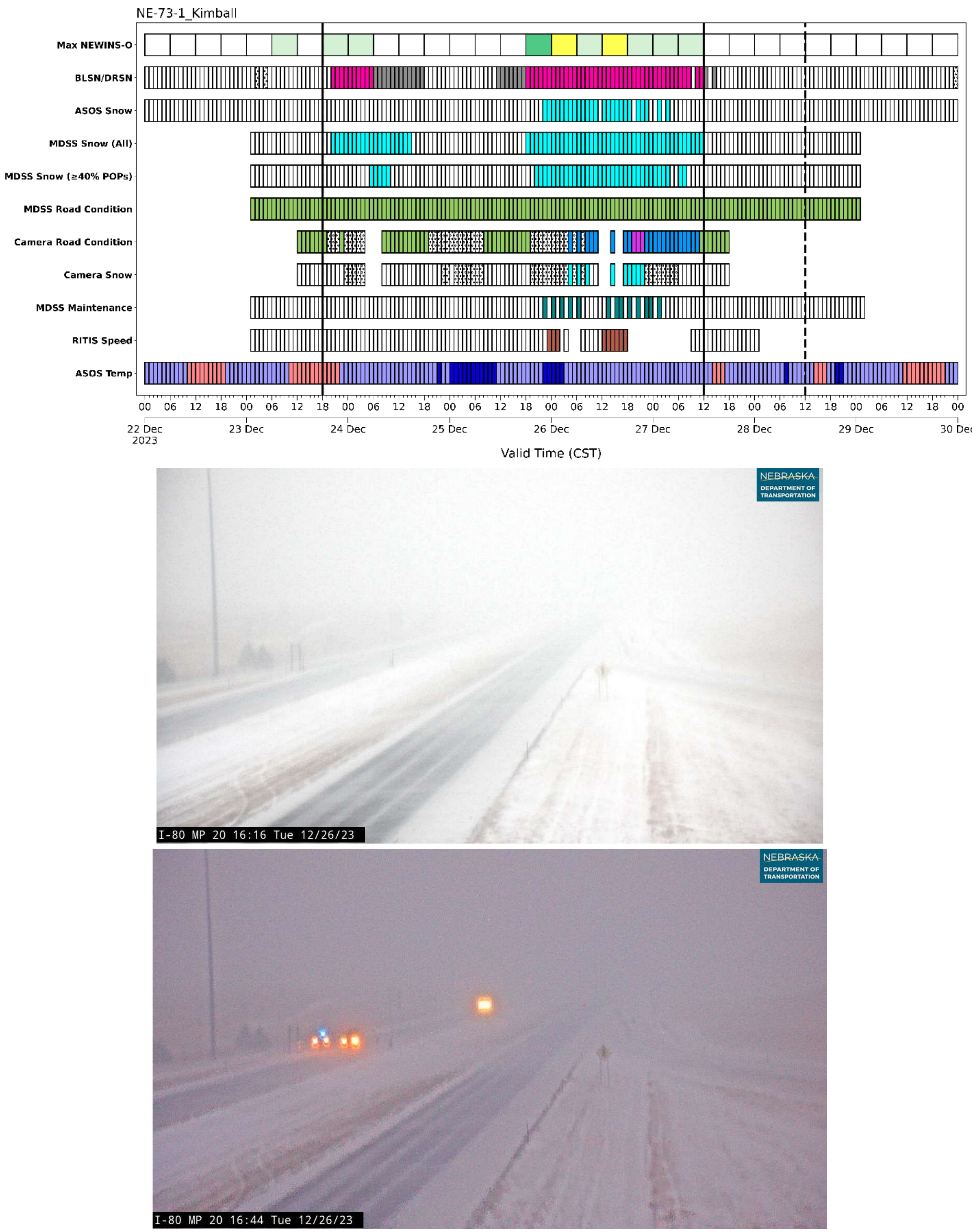


Figure 4.24 Kimball, Case 3 winter maintenance performance dashboard (top), Kimball segment, Case 3 traffic camera image at Exit 20 at 1616 MST on 26 December 2023 (middle), and 1644 MST showing a road closure being implemented (bottom).

4.2 Aggregate Analysis

This section will assess the various performance parameters at each location along Interstate 80 beginning in western Nebraska (i.e., Kimball) and ending in eastern Nebraska (i.e., Omaha). Then, correlations and relationships among the performance parameters for all cases and segments, including those not along Interstate 80, will be assessed in a bulk, or aggregate, manner to discuss overall implications of the research findings.

4.2.1 Interstate 80 Segment Performance Metric Analysis

Kimball was impacted by all events except Case 2 (Figure 4.25–Figure 4.26). From a storm severity lens, Case 1 and 3 were the most severe storms. As a result, Case 1 required the greatest material usage as well as the greatest number of maintenance vehicle operation hours. Despite similar severity, Case 3 had the greatest total disruption to vehicle speeds with Case 1 following. Lower severity storms in Cases 8 and 9 had a fair number of speed disruptions despite relatively less maintenance effort. These may be circumstances where disruptions were more attributable to downstream impacts and road closure decisions (e.g., Wyoming) rather than a direct reflection of NDOT performance. Case 5 had a fair amount of material usage despite the relatively lower maintenance vehicle operation hours and minimal speed disruption. Looking at associated temperatures (see Figure 4.26), Case 5 had the coldest minimum temperatures following the event suggesting that more material was needed to achieve the desired level of service.

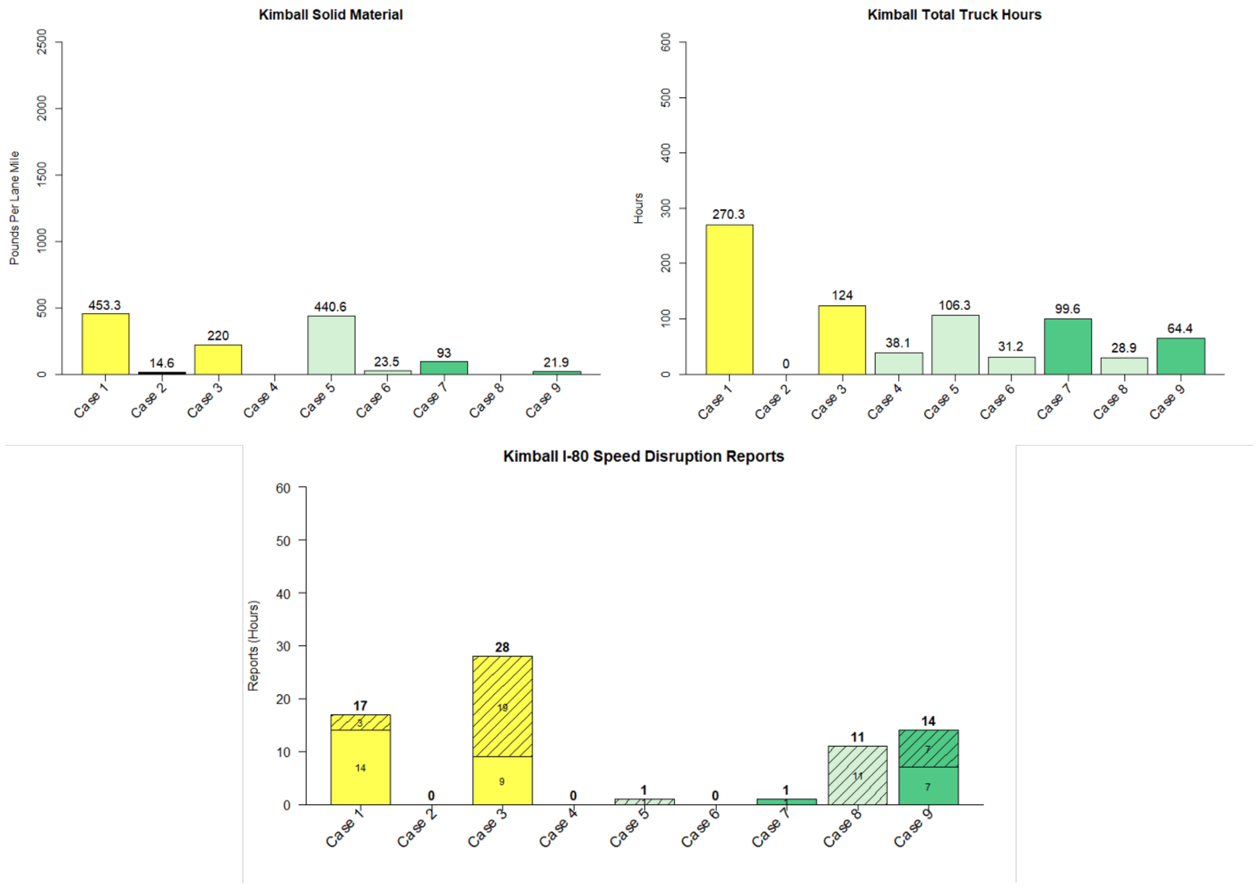


Figure 4.25 Kimball segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-73-1	1	Kimball	42	3	37	1	0	48	22	28	10	32	12	453	270	71	14	3	17
2 NE-73-1	2	Kimball	0	0	0	0	0	NA	NA	NA	NA	NA	NA	15	0	0	NA	0	0
3 NE-73-1	3	Kimball	54	3	25	51	21	49	21	44	12	36	20	220	124	56	9	19	28
4 NE-73-1	4	Kimball	12	1	10	14	10	34	11	22	14	25	11	NA	38	14	NA	0	0
5 NE-73-1	5	Kimball	30	1	20	0	0	34	24	34	11	31	0	441	106	49	NA	1	0
6 NE-73-1	6	Kimball	18	1	3	13	0	61	27	28	15	51	15	24	31	13	NA	0	0
7 NE-73-1	7	Kimball	36	2	21	0	0	56	21	37	19	39	16	93	100	26	1	0	1
8 NE-73-1	8	Kimball	12	1	9	17	11	56	28	36	22	26	14	NA	29	11	NA	11	0
9 NE-73-1	9	Kimball	24	2	12	24	10	71	40	49	32	46	26	22	64	34	7	7	14

Figure 4.26 Kimball segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Similar to Kimball, Sidney was impacted by all events except Case 2 (Figure 4.27–Figure 4.28). From a storm severity lens, Case 1 and 7 were the most severe storms. As a result, Case 1 required the greatest material usage as well as the greatest number of maintenance vehicle operation hours. Despite storm severity, Case 3 had the greatest total disruption to vehicle speeds with Case 1 following. Case 7 speed disruptions were relatively minimal. Similar to Kimball, lower severity storms in Cases 8 and 9 had a fair number of speed disruptions as well despite relatively less maintenance effort. The remaining cases did not have substantial impacts along this particular segment.

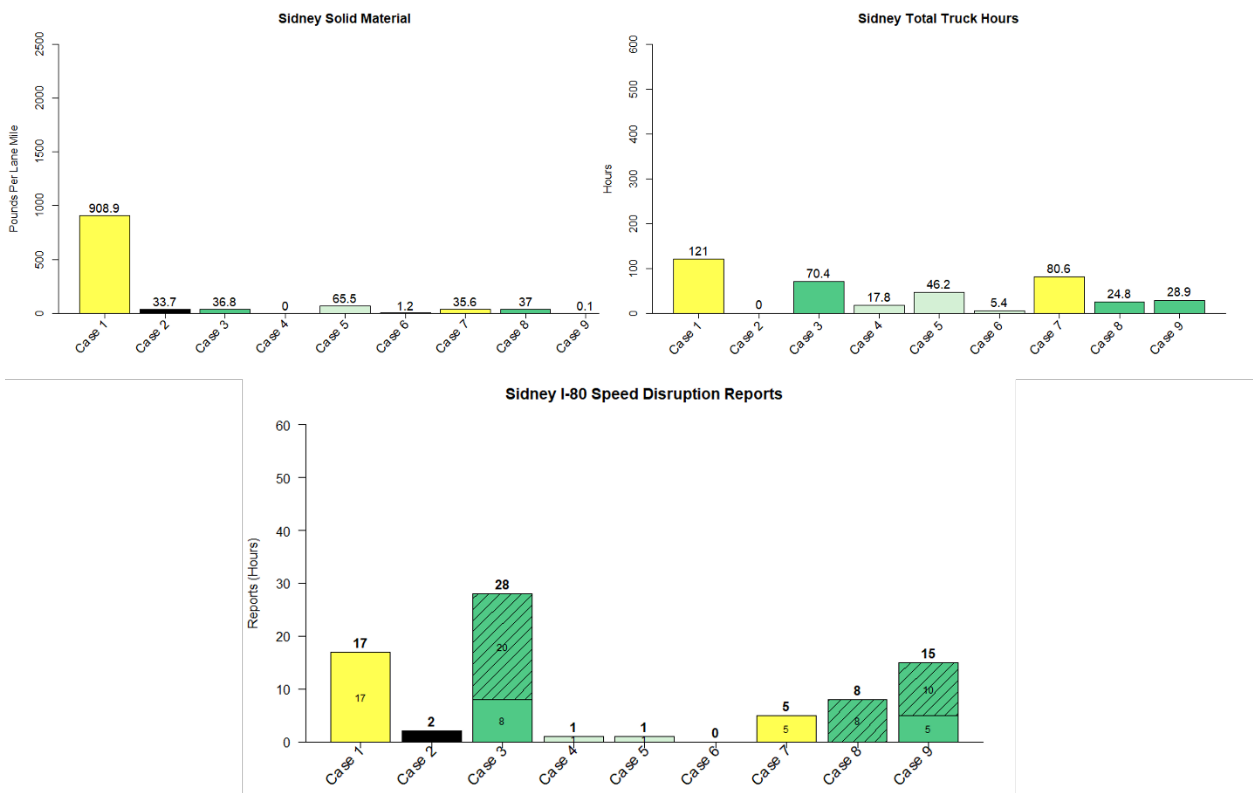


Figure 4.27 Sidney segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-74-1	1	Sidney	42	3	28	1	5	54	24	29	13	34	13	909	121	50	17	0	17
2 NE-74-1	2	Sidney	0	0	0	0	0	NA	NA	NA	NA	NA	NA	34	0	0	2	0	2
3 NE-74-1	3	Sidney	54	2	27	54	16	48	23	36	18	39	20	37	70	18	8	20	28
4 NE-74-1	4	Sidney	12	1	7	12	10	31	12	24	16	26	10	0	18	6	1	0	1
5 NE-74-1	5	Sidney	30	1	19	2	0	41	23	35	12	34	3	66	46	23	1	0	1
6 NE-74-1	6	Sidney	18	1	2	13	0	65	27	31	12	51	8	1	5	2	NA	0	0
7 NE-74-1	7	Sidney	42	3	26	0	0	61	25	38	21	45	13	36	81	9	5	0	5
8 NE-74-1	8	Sidney	12	2	2	10	16	50	28	36	22	27	17	37	25	6	NA	8	0
9 NE-74-1	9	Sidney	24	2	9	12	0	71	45	62	33	NA	NA	0	29	10	5	10	15

Figure 4.28 Sidney segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Like Kimball and Sidney, Ogallala was impacted by all events except Case 2 (Figure 4.29–Figure 4.30). From a storm severity lens, Case 3 and 7 were the most severe storms. As a result, Case 3 required the greatest material usage as well as the greatest number of maintenance vehicle operation hours followed by Case 7. Aligning with the severity, Case 3 had the greatest number of speed disruptions for any case and segment across the entire analysis. Despite lower relative severity, Case 8 had the second most speed disruptions for Ogallala.

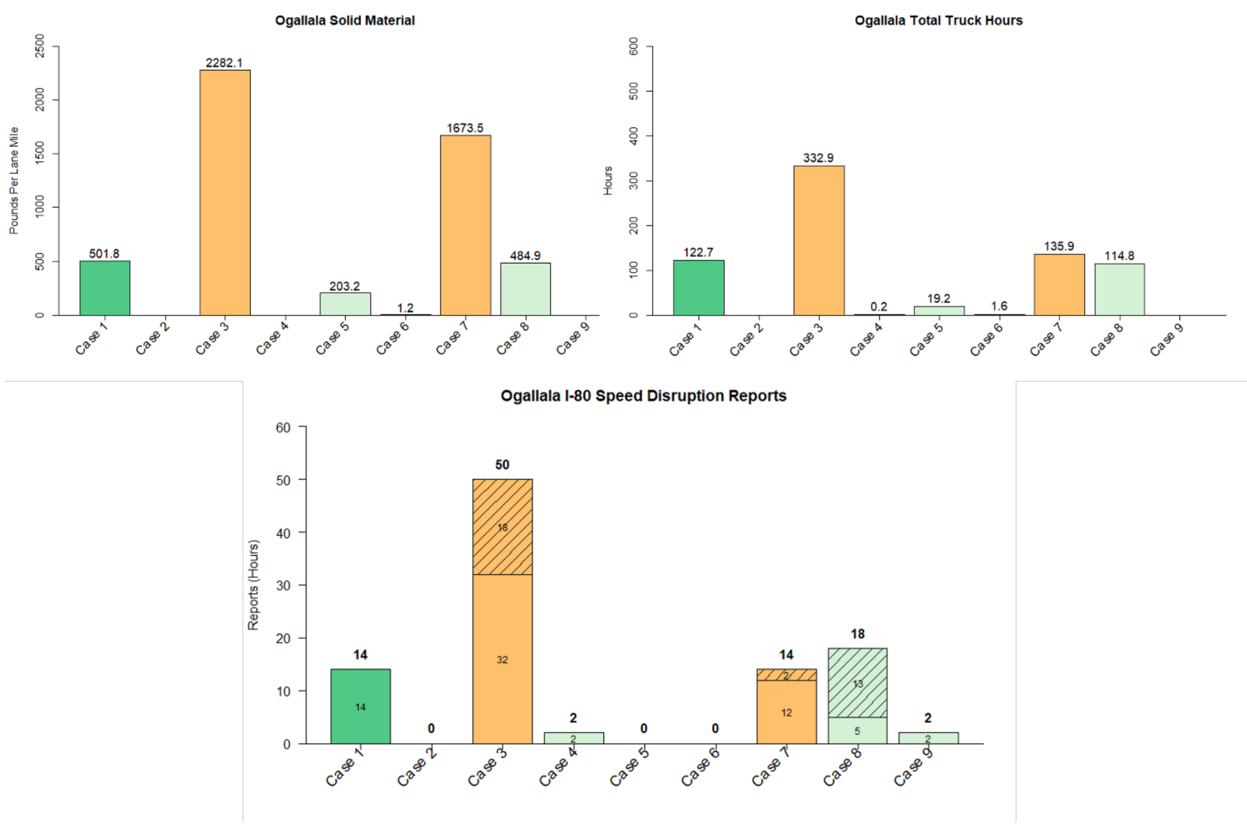


Figure 4.29 Ogallala segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-08-1	1	Ogallala	36	2	30	2	6	50	28	30	15	31	4	502	123	118	14	0	14
2 NE-08-1	2	Ogallala	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0	0
3 NE-08-1	3	Ogallala	66	4	40	60	3	45	22	40	20	35	22	2282	333	303	32	18	50
4 NE-08-1	4	Ogallala	6	1	0	1	19	30	9	28	27	27	13	NA	0	0	2	0	2
5 NE-08-1	5	Ogallala	18	1	7	1	0	34	25	33	19	34	3	203	19	19	NA	0	0
6 NE-08-1	6	Ogallala	6	1	1	6	3	69	26	35	21	38	7	1	2	2	NA	0	0
7 NE-08-1	7	Ogallala	30	4	21	2	0	62	32	34	24	33	14	1673	136	134	12	2	14
8 NE-08-1	8	Ogallala	30	1	0	0	0	46	24	38	38	NA	NA	485	115	104	5	13	18
9 NE-08-1	9	Ogallala	12	1	0	12	22	72	52	46	37	48	30	NA	NA	NA	2	0	2

Figure 4.30 Ogallala segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

North Platte was impacted by all events except Cases 2 and 9 (Figure 4.31–Figure 4.32). This particular segment was impacted by the sole Category 6 event within the entire analysis dataset. Despite the severity, Case 8 was an overall more impactful storm for this particular segment with higher material usage and truck operation hours as well as a greater number of speed disruptions compared to Case 7. Similarly, Case 3 which had the same severity as Case 8, was also fairly impactful for this segment with the third highest material usage after Cases 7 and 9, the second highest truck operation hours falling between Cases 7 and 8, and the second highest speed disruptions once again falling between Cases 7 and 8. This result indicates that storm severity alone can be more nuanced from a performance and impact lens. Possible explanations for these observed discrepancies may be the relatively longer duration of impacts (e.g., accumulating snow and blowing snow) during Cases 3 and 8 relative to Case 7. Practically, we might conclude that Case 7 was a relatively “quick” albeit “heavy-hitter” type of event whereas Cases 3 and 8 were longer duration events with greater overall impacts as a result.

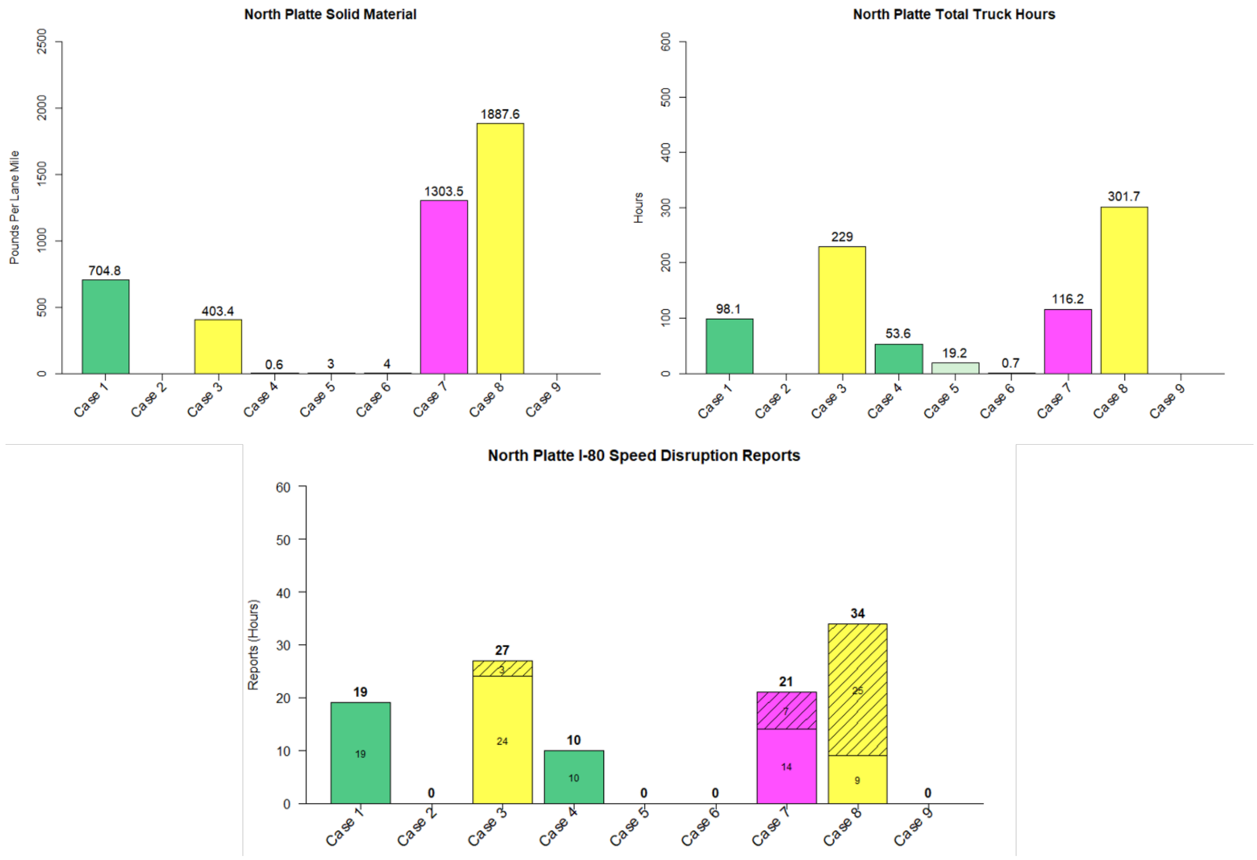


Figure 4.31 North Platte segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-05-1	1	North Platte	54	2	28	0	0	45	25	25	11	36	8	705	98	95	19	0	19
2 NE-05-1	2	North Platte	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0	0
3 NE-05-1	3	North Platte	78	3	15	48	8	53	31	46	23	34	13	403	229	228	24	3	27
4 NE-05-1	4	North Platte	18	2	8	18	0	35	11	29	19	37	5	1	54	33	10	0	10
5 NE-05-1	5	North Platte	18	1	2	1	0	36	23	30	18	27	4	3	19	12	NA	0	0
6 NE-05-1	6	North Platte	6	1	1	6	1	72	24	22	16	51	3	4	1	1	NA	0	0
7 NE-05-1	7	North Platte	24	6	11	10	0	61	32	42	24	37	9	1303	116	104	14	7	21
8 NE-05-1	8	North Platte	30	3	0	27	1	47	33	34	22	39	11	1888	302	241	9	25	34
9 NE-05-1	9	North Platte	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0	0

Figure 4.32 North Platte segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Lexington was impacted by all events except Case 9 (Figure 4.33–Figure 4.34). Similar to North Platte, despite the greater severity of Case 7 relative to others along this segment, the greatest impacts from a performance perspective were noted in other Cases. For material usage, Cases 4 and 8 had greater use. From an operation hours standpoint, Cases 3, 4, and 8 all had greater duration than Case 7. Last, from a speed disruption lens, once again Case 8 had the most for the Lexington segment followed by Case 4.

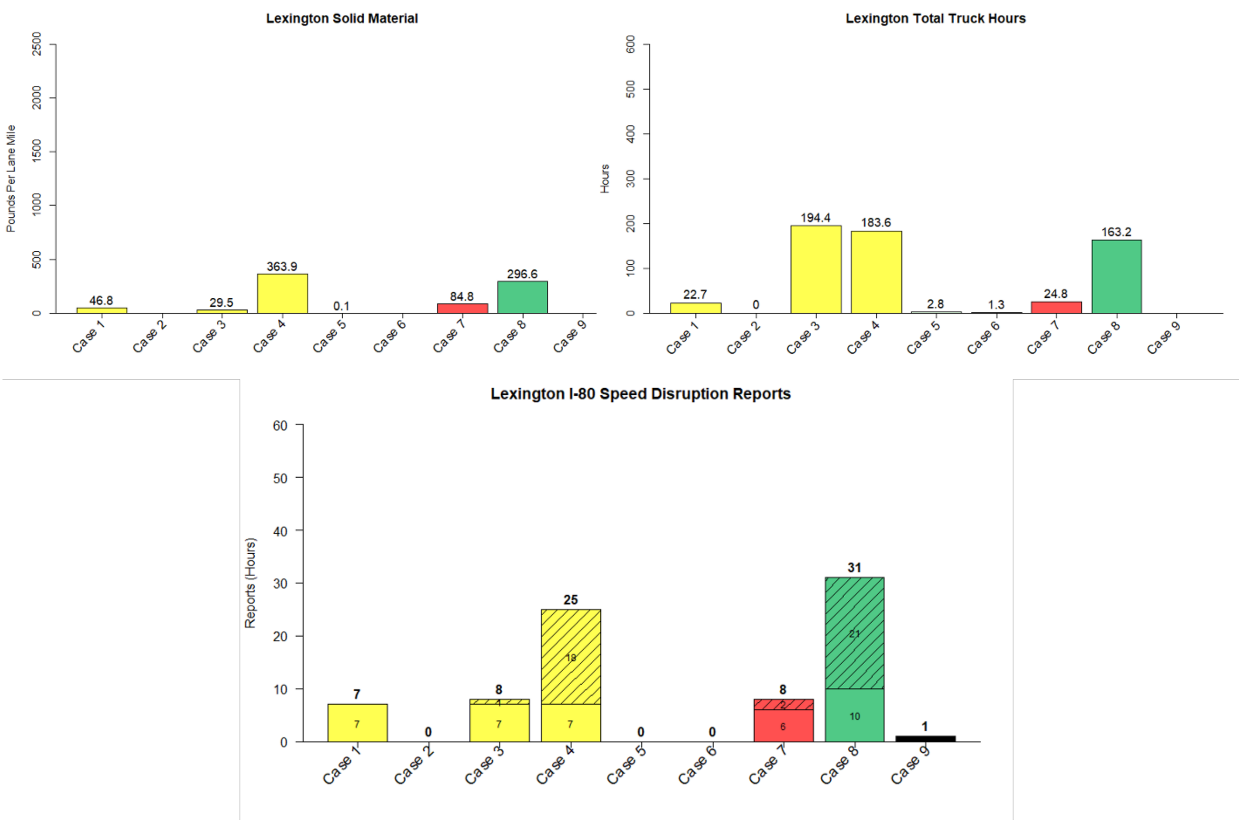
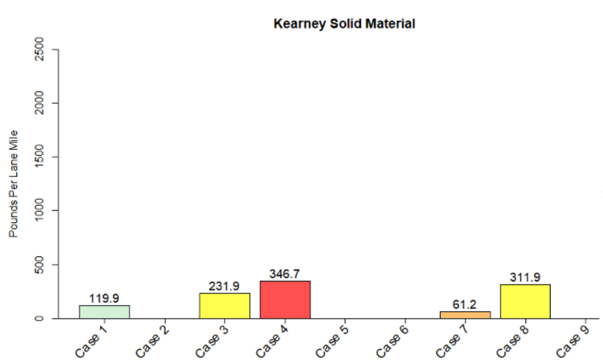


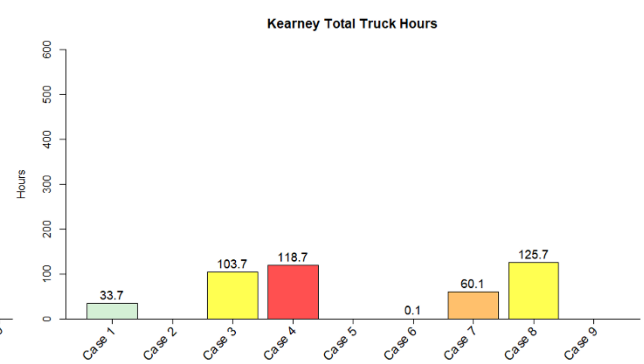
Figure 4.33 Lexington segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-82-1	1	Lexington	36	3	18	0	1	38	24	25	17	37	14	47	23	10	7	0	7
2 NE-82-1	2	Lexington	6	1	0	0	4	36	19	35	27	44	20	NA	0	0	NA	0	0
3 NE-82-1	3	Lexington	84	3	36	59	0	54	33	37	24	32	19	30	194	150	7	1	8
4 NE-82-1	4	Lexington	30	3	11	18	7	33	13	33	18	32	16	364	184	152	7	18	25
5 NE-82-1	5	Lexington	6	1	2	2	0	32	26	29	24	28	10	0	3	3	NA	0	0
6 NE-82-1	6	Lexington	6	1	1	6	2	74	27	30	19	50	7	NA	1	1	NA	0	0
7 NE-82-1	7	Lexington	24	5	13	17	0	56	31	42	26	51	16	85	25	24	6	2	8
8 NE-82-1	8	Lexington	42	2	20	35	5	46	25	44	19	33	15	297	163	108	10	21	31
9 NE-82-1	9	Lexington	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	NA	NA	1	0	1

Figure 4.34 Lexington segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Kearney was impacted by all events except Cases 6 and 9 (Figure 4.35–Figure 4.36). The greatest severity storm for this segment was Case 4 followed by Case 7. Similar to North Platte and Lexington, many of the aforementioned caveats with Case 7 remain. Unique for Kearney, though, is that despite variable storm severity, there was not substantial variability in material usage nor in total maintenance vehicle operation hours. This might suggest that maintenance along this particular segment is fairly consistent regardless of storm severity or any other impact enhancements such as blowing snow. Speed disruptions were also similar among Cases 3, 4, and 8 despite variable severity. This underscores the potential importance of local practices in evaluating overall performance. Another important caveat is that there are several other additional factors that are difficult to evaluate their influence such as time of day, time of year, sun angle, day of week, holidays, and any other special events (e.g., road work, football game).





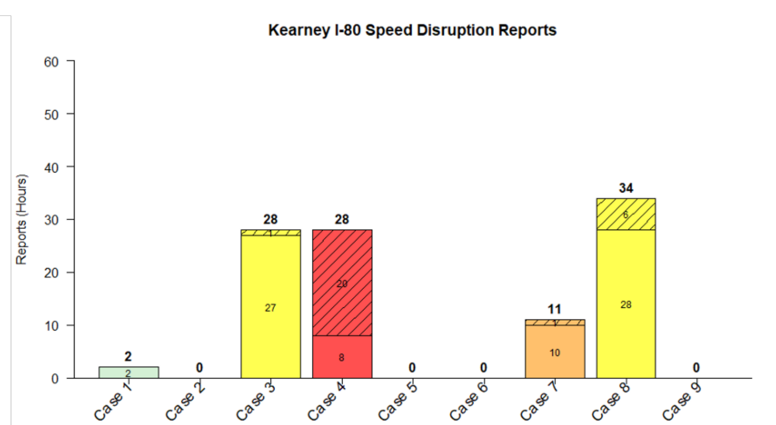


Figure 4.35 Kearney segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-38-1	1	Kearney	30	1	14	1	4	37	21	27	19	38	17	120	34	15	2	0	2
2 NE-38-1	2	Kearney	12	1	2	0	2	33	17	39	24	44	21	NA	NA	NA	NA	0	0
3 NE-38-1	3	Kearney	60	3	51	29	0	54	32	31	23	33	19	232	104	59	27	1	28
4 NE-38-1	4	Kearney	24	5	23	22	1	33	11	32	16	30	14	347	119	60	8	20	28
5 NE-38-1	5	Kearney	12	1	11	8	0	34	25	29	22	27	9	NA	NA	NA	NA	0	0
6 NE-38-1	6	Kearney	0	0	1	1	0	NA	NA	NA	NA	NA	NA	NA	0	0	NA	0	0
7 NE-38-1	7	Kearney	18	4	13	14	0	49	28	35	25	51	18	61	60	35	10	1	11
8 NE-38-1	8	Kearney	36	3	29	33	7	44	22	53	20	31	13	312	126	70	28	6	34
9 NE-38-1	9	Kearney	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0	0

Figure 4.36 Kearney segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Grand Island was impacted by all events except Case 9 (Figure 4.47–Figure 4.48). Cases 4 and 7 represented the greatest severity events for this particular segment with similar caveats regarding Case 7 overall impacts like segments to the west. Cases 4, followed by 3, had the greatest material usage; however, their relative magnitudes were flipped in terms of total maintenance vehicle operation hours. For speed disruptions, there was alignment with the material usage with Case 4 surpassing Case 3.

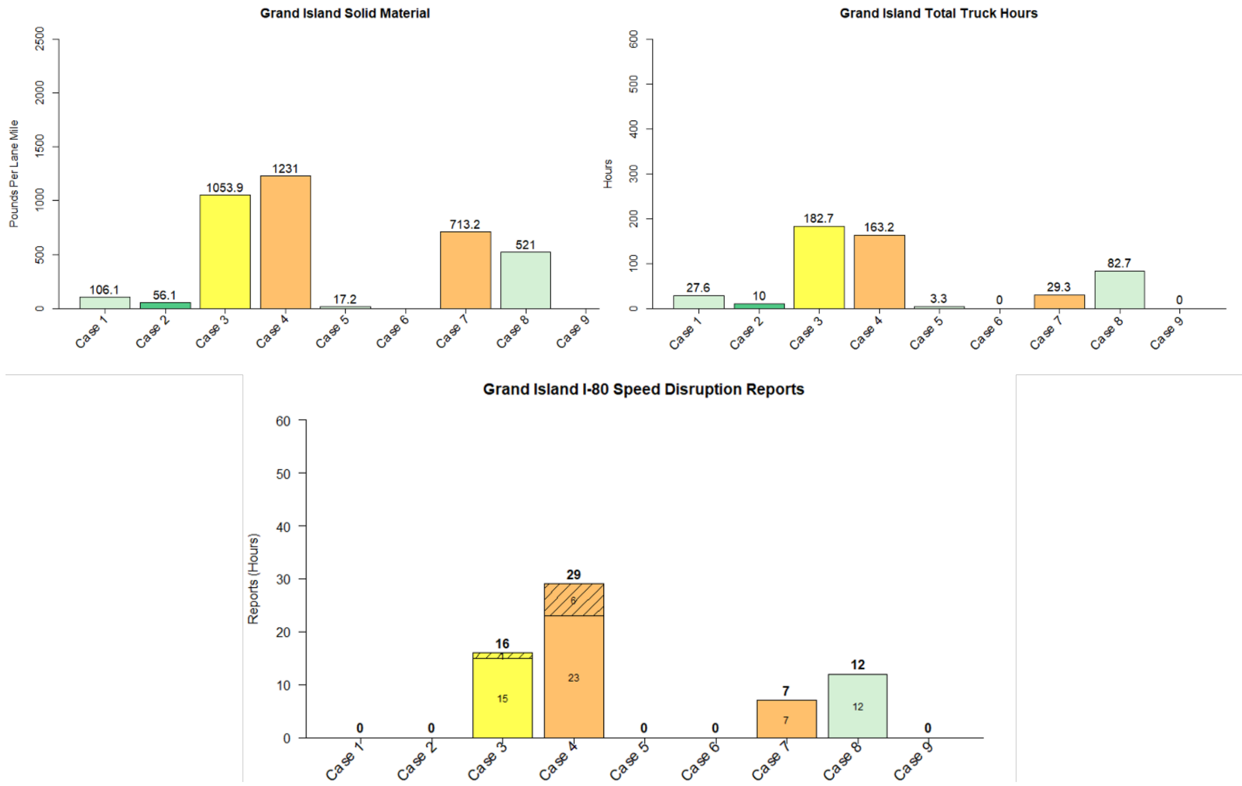


Figure 4.37 Grand Island segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-41-1	1	Grand Island	24	1	5	0	3	25	21	25	20	38	17	106	28	17	NA	0	0
2 NE-41-1	2	Grand Island	18	2	3	0	1	36	20	35	20	41	23	56	10	0	NA	0	0
3 NE-41-1	3	Grand Island	36	3	21	19	0	55	31	31	24	34	20	1054	183	162	15	1	16
4 NE-41-1	4	Grand Island	30	4	18	22	3	33	14	33	18	26	12	1231	163	157	23	6	29
5 NE-41-1	5	Grand Island	6	1	2	3	2	37	25	29	24	27	8	17	3	3	NA	0	0
6 NE-41-1	6	Grand Island	6	1	2	6	6	77	31	31	17	44	6	NA	0	0	NA	0	0
7 NE-41-1	7	Grand Island	18	4	11	15	0	52	28	40	26	53	20	713	29	29	7	0	7
8 NE-41-1	8	Grand Island	36	1	18	30	12	42	26	53	22	29	17	521	83	82	12	0	12
9 NE-41-1	9	Grand Island	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	0	0	NA	0	0

Figure 4.38 Grand Island segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Aurora was impacted by all events except Case 9 (Figure 4.39–Figure 4.40). As with other central Nebraska segments, Case 7 was Aurora's greatest severity though not its greatest impacts. Similar to Kearney, there was much less variability noted across the material and operation hours metrics in the context of severity. Case 3 had greater material usage despite lower severity than Cases 4 and 7. Cases 3 and 4 had similar maintenance vehicle operation hours. In terms of speed disruptions, Case 4 had the most for Aurora followed by Case 3. Interestingly, Case 8, with relatively low severity, had greater speed disruption than even the highest severity Case 7.

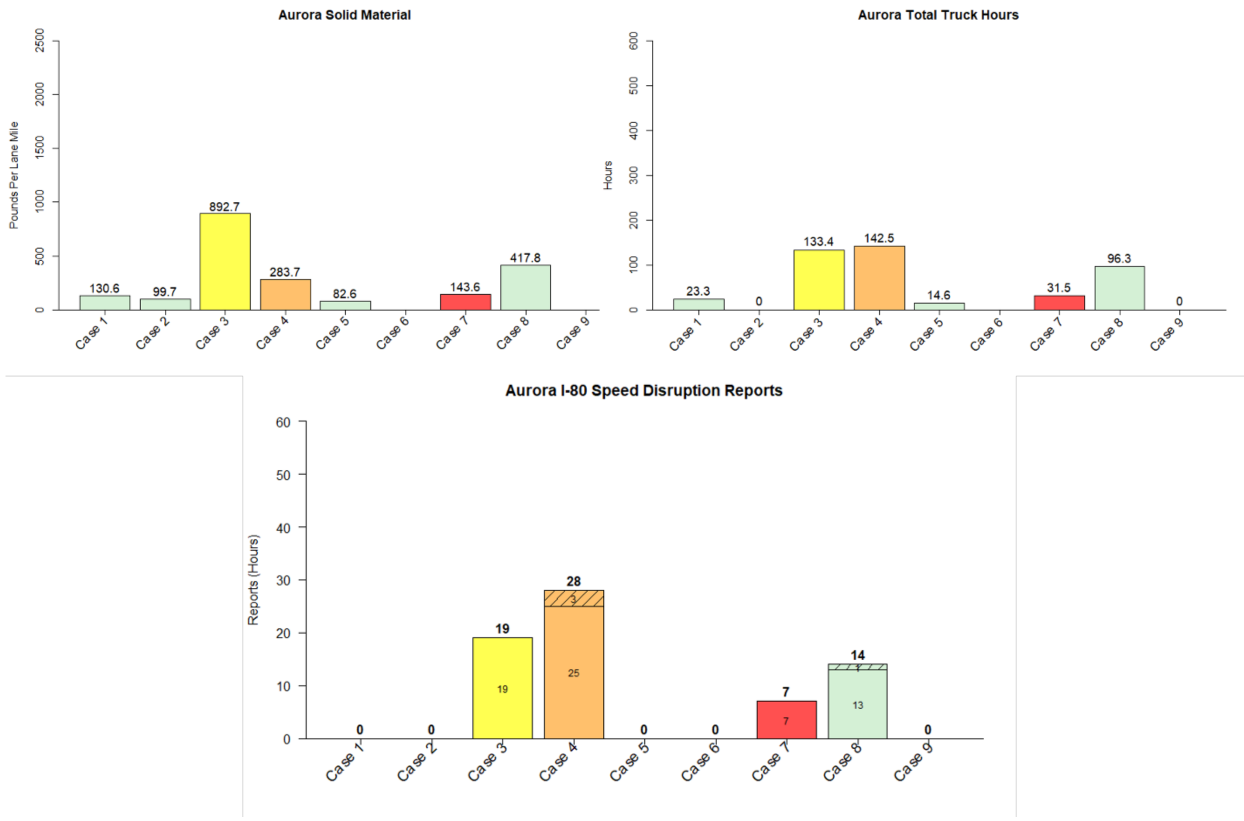


Figure 4.39 Aurora segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-44-1	1	Aurora	18	1	6	0	4	26	20	25	20	37	21	131	23	19	NA	0	0
2 NE-44-1	2	Aurora	18	1	2	0	0	34	18	33	16	41	20	100	0	0	NA	0	0
3 NE-44-1	3	Aurora	36	3	22	21	0	54	30	30	16	31	13	893	133	97	19	0	19
4 NE-44-1	4	Aurora	18	4	10	10	11	33	11	32	18	25	10	284	143	104	25	3	28
5 NE-44-1	5	Aurora	6	1	3	3	1	37	25	28	24	27	8	83	15	12	NA	0	0
6 NE-44-1	6	Aurora	6	1	2	7	6	77	32	31	16	40	3	NA	NA	NA	NA	0	0
7 NE-44-1	7	Aurora	18	5	3	16	0	51	29	39	26	52	17	144	32	23	7	0	7
8 NE-44-1	8	Aurora	30	1	4	18	22	39	29	51	21	29	18	418	96	78	13	1	14
9 NE-44-1	9	Aurora	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	0	6	NA	0	0

Figure 4.40 Aurora segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

York was impacted by all events except Case 9 (Figure 4.41–Figure 4.42). For York, Cases 3, 4, and 7 all had its greatest severity with similar caveats already discussed for Case 7 in terms of overall impacts. From a material usage perspective, York had the greatest usage in Case 3 followed by Case 8 despite the relatively minimal severity of the latter. Maintenance vehicle operation hours better aligned with storm severity for the top two events in Cases 3 and 4. Similarly, speed disruptions were the greatest for Case 4 followed by Case 3.

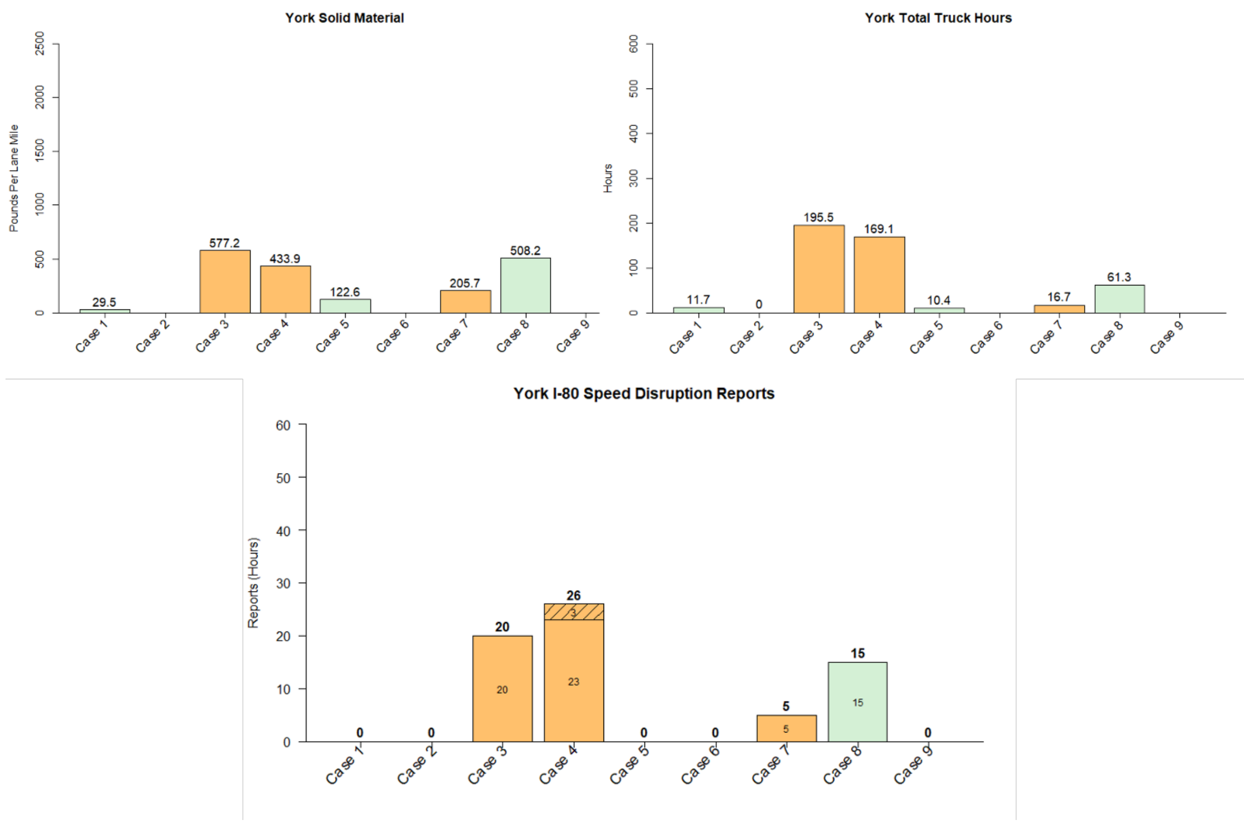


Figure 4.41 York segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-45-1	1	York	18	1	6	0	5	25	19	25	21	37	23	29	12	8	NA	0	0
2 NE-45-1	2	York	18	1	0	0	0	37	19	34	14	41	18	NA	0	0	NA	0	0
3 NE-45-1	3	York	42	4	21	23	0	55	37	37	23	30	19	577	196	158	20	0	20
4 NE-45-1	4	York	24	4	23	0	0	34	16	32	19	23	7	434	169	137	23	3	26
5 NE-45-1	5	York	6	1	5	0	0	37	25	28	23	27	9	123	10	10	NA	0	0
6 NE-45-1	6	York	6	1	2	7	3	77	34	34	18	39	5	NA	NA	NA	NA	0	0
7 NE-45-1	7	York	12	4	6	12	0	54	28	37	27	43	21	206	17	9	5	0	5
8 NE-45-1	8	York	30	1	11	15	8	43	28	50	23	28	18	508	61	43	15	0	15
9 NE-45-1	9	York	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0	0

Figure 4.42 York segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Lincoln was impacted by all events except Cases 6 and 9 with Cases 3 and 4 having both the greatest severity and general impacts for the segment (Figure 4.43–Figure 4.44). Similar to Kearney and Aurora, there was generally less variability in maintenance parameters despite storm severity. There were also some nuances for the Lincoln segment. Case 1 had the greatest material usage despite minimal severity. Case 4 had the greatest maintenance vehicle operation hours; however, Case 7 was the second most once again despite relatively minimal severity at this segment. Speed disruptions in Lincoln were greatest for Case 4 with Cases 1 and 3 tied for second place. It is important to note that Case 1 did have two observed vehicle crashes during the period (see Figure 4.20–Figure 4.21) which likely contributed to disruption and underscore the importance of controlling speed disruptions for crashes in future work.

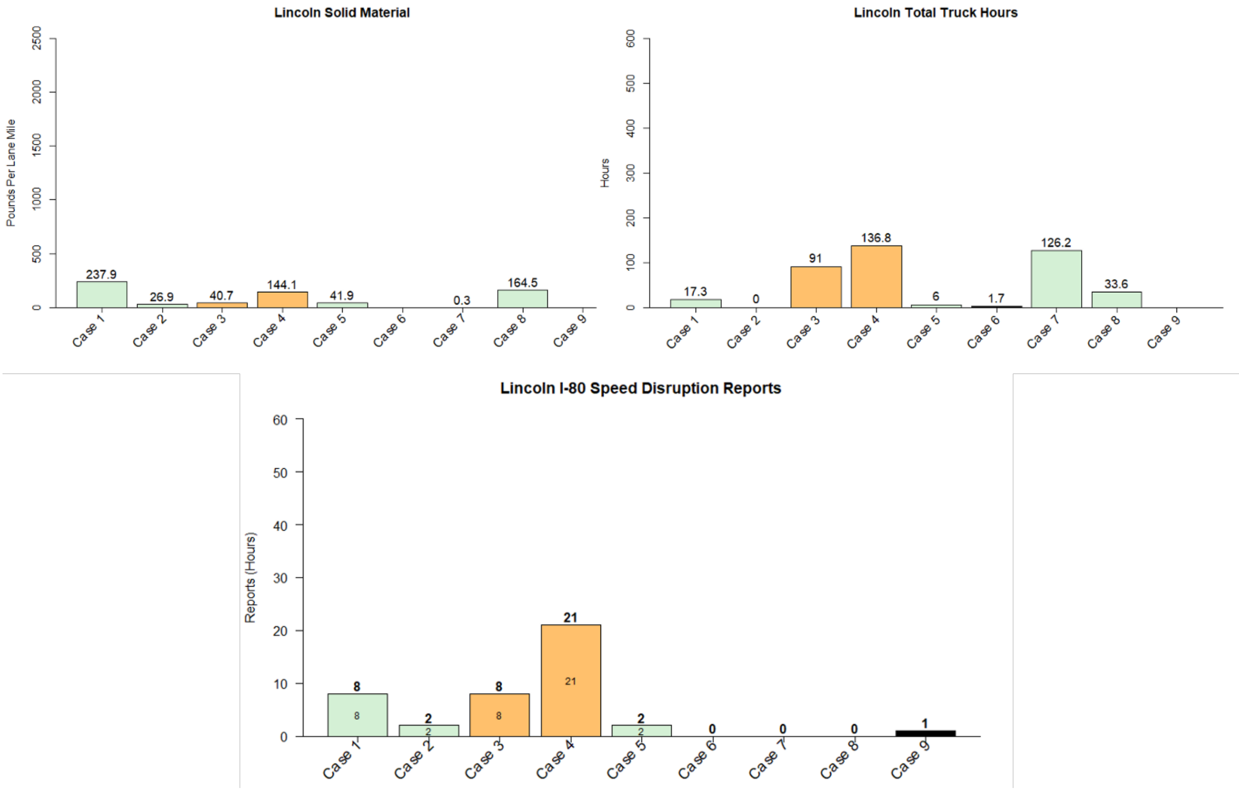


Figure 4.43 Lincoln segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-13-1	1	Lincoln	24	1	9	0	3	30	23	29	23	41	19	238	17	8	8	0	8
2 NE-13-1	2	Lincoln	6	1	0	0	0	42	14	40	36	40	20	27	0	0	2	0	2
3 NE-13-1	3	Lincoln	60	4	22	19	0	58	38	37	26	33	22	41	91	28	8	0	8
4 NE-13-1	4	Lincoln	30	4	26	13	5	36	23	35	24	24	11	144	137	50	21	0	21
5 NE-13-1	5	Lincoln	6	1	2	2	2	41	23	32	27	31	10	42	6	1	2	0	2
6 NE-13-1	6	Lincoln	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	2	0	NA	0	0
7 NE-13-1	7	Lincoln	12	1	2	9	2	56	31	41	30	47	19	0	126	94	NA	0	0
8 NE-13-1	8	Lincoln	18	1	4	6	22	40	28	53	28	35	17	165	34	19	NA	0	0
9 NE-13-1	9	Lincoln	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	NA	0	1	0	1

Figure 4.44 Lincoln segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Millard was impacted by all events except Cases 2, 6, and 9 (Figure 4.45–Figure 4.46). Case 3 was its greatest storm severity. In general, Millard had higher magnitudes of maintenance parameters suggesting potential regional differences in levels of service with the more urban and commuter-oriented nature of NDOT’s District 2. Case 4 had greater material usage than Case 3 despite its relatively lower severity while Case 3 had higher maintenance operation hours. As aligned with material, Case 4 had the greatest speed disruptions for the Millard segment across all cases.

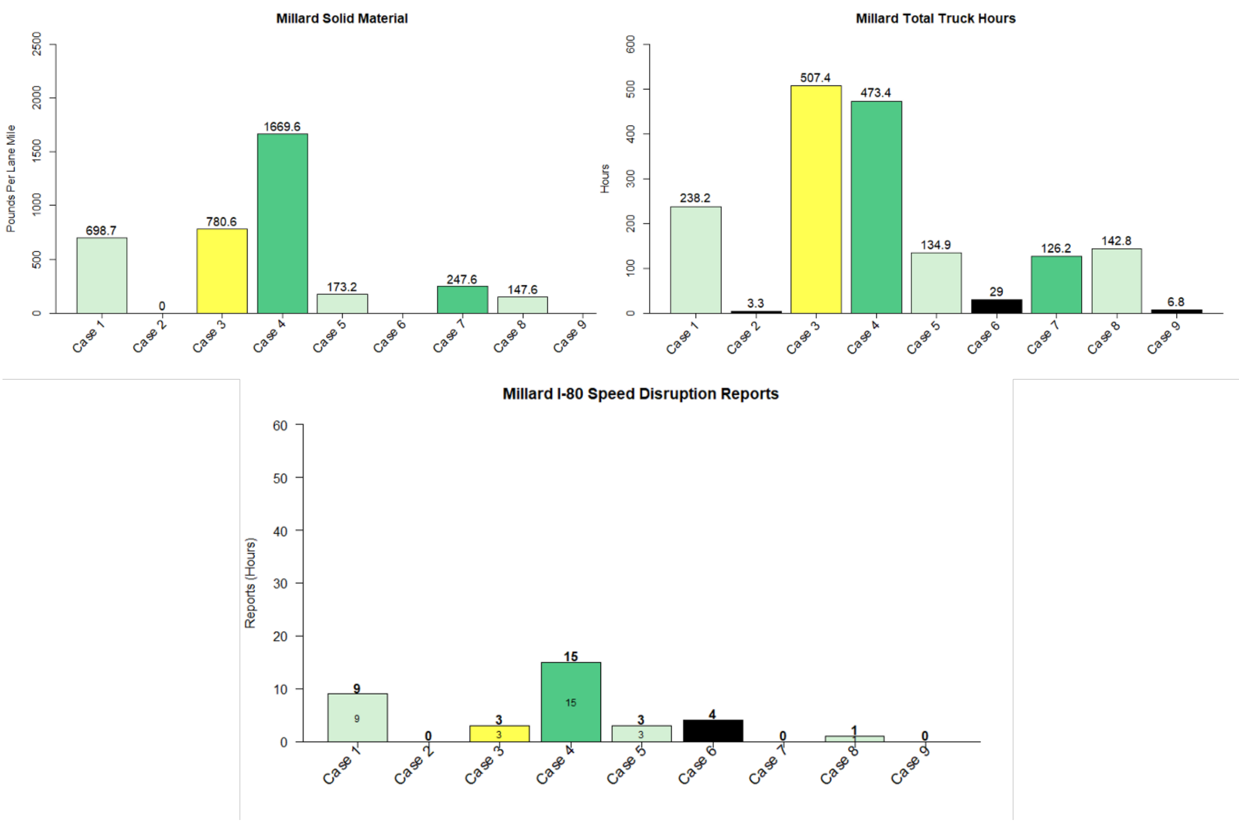


Figure 4.45 Millard segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1 NE-36-1	1	Omaha/Millard	24	1	8	0	1	29	23	28	25	37	19	699	238	196	9	0	9
2 NE-36-1	2	Omaha/Millard	0	0	0	0	0	NA	NA	NA	NA	NA	NA	0	3	0	NA	0	0
3 NE-36-1	3	Omaha/Millard	36	3	21	3	0	57	34	34	27	33	29	781	507	405	3	0	3
4 NE-36-1	4	Omaha/Millard	36	2	18	2	0	32	26	34	21	23	13	1670	473	423	15	0	15
5 NE-36-1	5	Omaha/Millard	12	1	4	0	0	38	24	31	25	30	10	173	135	110	3	0	3
6 NE-36-1	6	Omaha/Millard	0	0	1	1	0	NA	NA	NA	NA	NA	NA	NA	29	21	4	0	4
7 NE-36-1	7	Omaha/Millard	12	2	7	0	0	56	38	37	28	41	23	248	126	94	NA	0	0
8 NE-36-1	8	Omaha/Millard	12	1	1	3	2	36	26	55	28	31	20	148	143	108	1	0	1
9 NE-36-1	9	Omaha/Millard	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	7	7	NA	0	0

Figure 4.46 Millard segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Like Millard, Omaha was impacted by all events except Cases 2, 6, 9 (Figure 4.47–Figure 4.48). Case 7 was Omaha’s greatest severity but as discussed at other locations the impacts were relatively minimal. In terms of material, Case 4 was Omaha’s greatest event followed by Case 3. For maintenance vehicle operation hours, Case 3 was Omaha’s greatest event followed by Case 4. In terms of speed disruptions, Case 4 was Omaha’s greatest followed by Case 1. In terms of speed overall, it is important to note that Omaha had no complete closures associated with the cases in the database attributable to its urban nature and level of service.

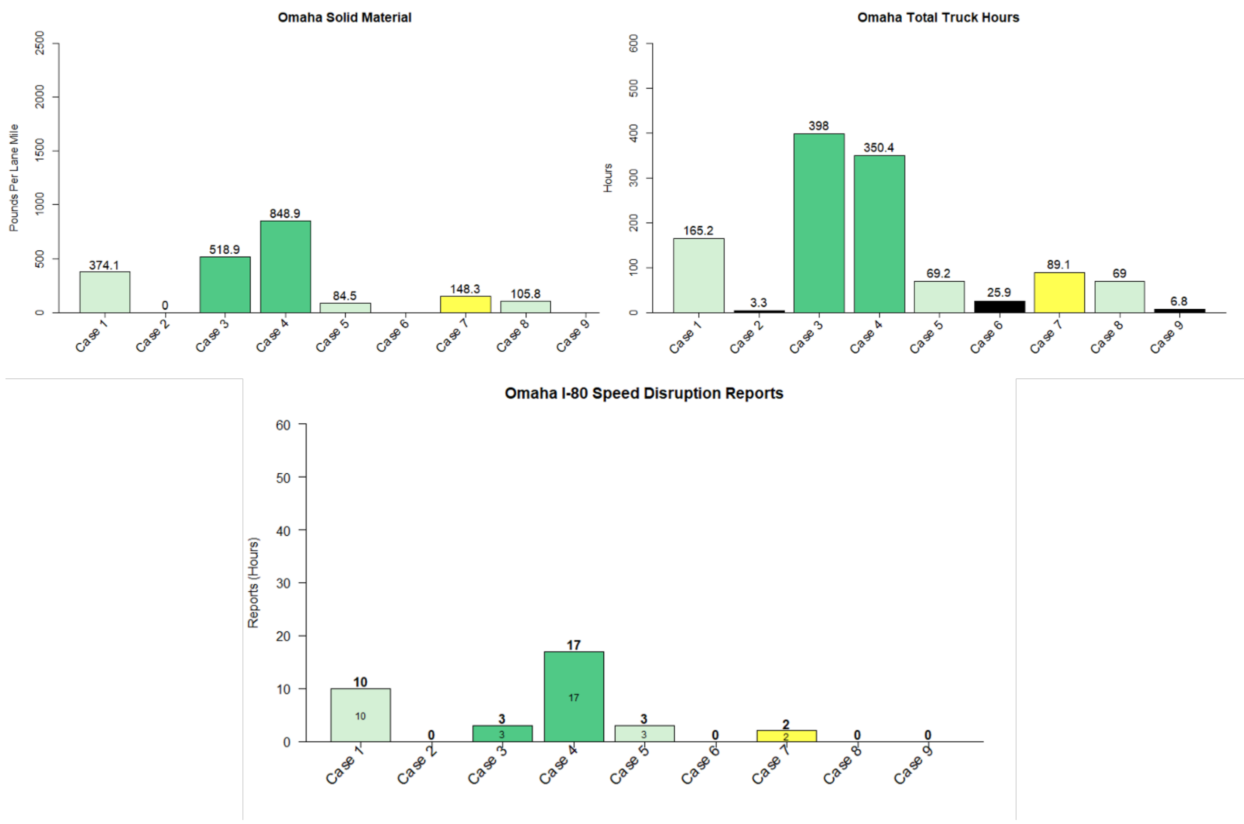


Figure 4.47 Omaha segment normalized deicing material application (pounds per lane mile), maintenance vehicle operation hours, and speed disruption distributions for all Cases color-coded by maximum NEWINS-O storm severity.

	ID	Case	City	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Closed Loop	Speed	Closure	Disruption
1	NE-119-1	1	Omaha	24	1	12	0	2	29	22	28	24	36	17	374	165	119	10	0	10
2	NE-119-1	2	Omaha	0	0	0	0	0	NA	NA	NA	NA	NA	NA	0	3	0	NA	0	0
3	NE-119-1	3	Omaha	36	2	24	14	0	57	34	34	27	33	28	519	398	323	3	0	3
4	NE-119-1	4	Omaha	30	2	25	12	4	33	24	34	22	23	11	849	350	262	17	0	17
5	NE-119-1	5	Omaha	6	1	7	1	4	41	22	29	25	30	7	85	69	48	3	0	3
6	NE-119-1	6	Omaha	0	0	1	1	0	NA	NA	NA	NA	NA	NA	NA	26	20	NA	0	0
7	NE-119-1	7	Omaha	12	3	8	13	0	57	30	36	28	39	22	148	89	64	2	0	2
8	NE-119-1	8	Omaha	6	1	2	6	7	58	33	32	29	30	20	106	69	54	NA	0	0
9	NE-119-1	9	Omaha	0	0	0	0	0	NA	NA	NA	NA	NA	NA	NA	7	7	NA	0	0

Figure 4.48 Omaha segment performance dataset information for all Cases color-coded by maximum NEWINS-O storm severity.

Considering the findings across Interstate 80, western and central portions of Nebraska generally had more material usage and maintenance vehicle operation hours combined with greater speed disruptions. This may be indicative of generally greater storm severity among the observed cases and/or differences in treatment practice. Additionally, western Nebraska mobility disruptions may be more associated with road closures in adjacent states (e.g., Wyoming) and capacity issues for motorists and commercial vehicles. The next section will consider all cases and segments, both along and beyond Interstate 80.

4.2.2 All Segment Performance Metric Analysis

From an overall perspective of relating the various performance parameters explored, their correlation (Figure 4.49–Figure 4.50) indicates their relative strength and importance in serving as a potential metric for winter maintenance performance. As discussed in the previous sections, speed disruptions (i.e., reductions, closures, and total disruptions) and maintenance activities (i.e., material per lane mile and maintenance vehicle operation hours) were the primary metrics explored. Weather information serves as an important control in assessing these performance parameters.

In terms of speed reductions alone, their strongest overall correlation was a positive association with the number of observed snow reports (0.6). This indicates that the longer it snows, the longer speeds will be reduced. This direct relationship makes sense and is well aligned with expectation. Similarly, speed reductions have a strong positive correlation with the accumulating snow duration (0.53) which is closely related to the duration of snowfall (0.84). A moderately strong direct relationship is seen between speed reductions and material usage (0.48) which suggests that more material is needed for longer duration events that contribute to more speed impacts. The duration of blowing snow was also found to have a moderate direct relationship with speed reductions (0.41) indicating that reduced visibility and potential refreezing associated with blowing slow can further extend speed reductions beyond falling snow alone. The strongest inverse relationships for speed reductions were observed with temperature (e.g., post-storm maximum temperature had a correlation coefficient of -0.37 while in-storm minimum temperature has a correlation coefficient of -0.36). This finding indicates that colder temperatures are more likely to be associated with longer periods of speed disruptions. It also aligns with the result that longer speed reductions are associated with greater material usage.

Closures had the strongest direct relationship with the duration of blowing snow (0.59). This indicates that while less important for general speed reductions, the presence of blowing snow is more likely to induce road closures. This is likely associated with either visibility impacts and/or operational protocols to temporarily suspend winter maintenance activities during particularly adverse conditions that would threaten personnel safety and equipment. Closures were not found in this dataset to have as strong a relationship with the duration of snow and/or temperatures as speed reductions alone.

In terms of total speed disruptions (i.e., speed reductions and closures), trends were similar to features from both speed reductions and closures. The strongest overall relationship for total speed disruption was associated with blowing snow reports (0.63) which aligns with the closure data. Similar to speed reductions alone, total speed disruptions also had moderately strong direct relationships with accumulating snow duration (0.54), material used (0.51), and accumulating snow duration (0.51). Storm severity had a moderately strong direct relationship with total speed disrupts as well (0.48). Similar to speed reductions, the in-storm minimum temperature had the largest inverse relationship with total speed disruptions (-0.35).

From the maintenance lens, material had its strongest direct relationship with storm severity (0.34). However, this is not a strong overall relationship indicating that storm severity is a more nuanced parameter. As discussed previously, material usage overall had a much stronger relationship with parameters such as total speed disruption (0.51). Material did not have any strong inverse relationships with its relatively strongest indirect association with post-storm maximum temperature (-0.16). Paired with the maintenance vehicle operation hours, material had a relatively strong direct relationship (0.6).

Maintenance vehicle operation hours had their strongest direct relationship with falling snow duration (0.42) followed closely by accumulating snow duration (0.40). Moderate direct relationships are also noted with storm severity (0.36). Operation hours had a weak-moderate inverse relationship with post-storm maximum temperature (-0.26) aligning with the previous discussion that colder conditions during or after an event were associated with the greatest disruptions and maintenance needs.

There are several key relationships that can be explored among the data. The relationship between material and speed disruption (Figure 4.51) shows that there is a fair amount of noise in using storm severity as a discriminator. Also, while the general trend is that more material usage is associated with a greater magnitude of speed disruptions there are many other nuances where disruptions around 30 hours are associated with relatively low material applications (under 500 pounds per lane mile). It may be in such situations that less material is used if a road is simply closed and maintenance operations are temporarily suspended. The relationship between blowing snow duration and the duration of speed disruption (Figure 4.52) demonstrates a direct relationship. Generally, more hours of blowing snow results in increased speed disruptions. This is likely associated with the travel difficulty presented by such situations. The relationship between minimum temperature and speed disruption is an inverse one (Figure 4.53). Colder temperatures are associated with greater disruption while warmer temperatures typically have less disruption. This aligns with the likely greater difficulty for winter maintenance operations at colder temperatures. Last, the relationship between the duration of snow periods and maintenance vehicle operations (Figure 4.54) generally demonstrates that longer duration snowfall requires longer maintenance actions.

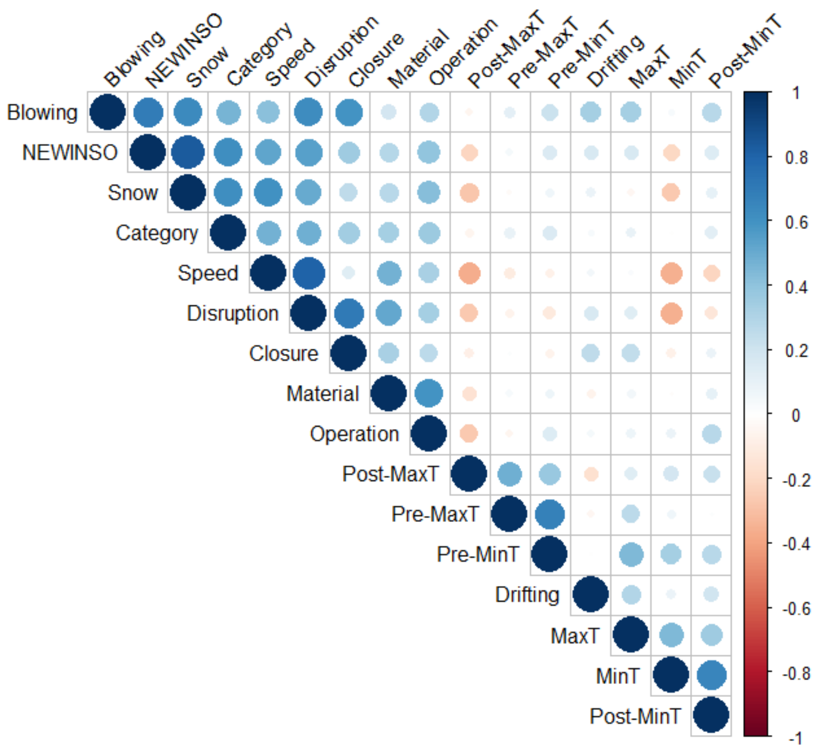


Figure 4.49 Correlation plot of entire performance metric dataset. Larger correlations are shown as larger circles with blues representing positive, or direct, correlation and reds representing negative, or indirect, correlation.

	NEWINSO	Category	Snow	Blowing	Drifting	Pre-MaxT	Pre-MinT	MaxT	MinT	Post-MaxT	Post-MinT	Material	Operation	Speed	Closure	Disruption
NEWINSO	1	0.61	0.84	0.69	0.17	0.05	0.15	0.17	-0.21	-0.22	0.15	0.29	0.4	0.53	0.36	0.54
Category	0.61	1	0.61	0.46	0.03	0.09	0.16	0.09	-0.01	-0.06	0.12	0.34	0.36	0.47	0.35	0.48
Snow	0.84	0.61	1	0.63	0.08	-0.02	0.07	-0.04	-0.26	-0.27	0.11	0.27	0.42	0.6	0.26	0.51
Blowing	0.69	0.46	0.63	1	0.33	0.11	0.21	0.33	0.03	-0.05	0.27	0.18	0.3	0.41	0.59	0.63
Drifting	0.17	0.03	0.08	0.33	1	-0.04	0	0.3	0.08	-0.16	0.2	-0.06	0.04	0.05	0.26	0.16
Pre-MaxT	0.05	0.09	-0.02	0.11	-0.04	1	0.68	0.27	0.06	0.49	0.01	0.04	-0.05	-0.1	0.01	-0.07
Pre-MinT	0.15	0.16	0.07	0.21	0	0.68	1	0.45	0.34	0.37	0.27	0.07	0.14	-0.07	-0.07	-0.12
MaxT	0.17	0.09	-0.04	0.33	0.3	0.27	0.45	1	0.45	0.14	0.35	0.05	0.07	0.02	0.24	0.14
MinT	-0.21	-0.01	-0.26	0.03	0.08	0.06	0.34	0.45	1	0.19	0.65	-0.01	0.09	-0.36	-0.07	-0.35
Post-MaxT	-0.22	-0.06	-0.27	-0.05	-0.16	0.49	0.37	0.14	0.19	1	0.22	-0.16	-0.26	-0.37	-0.08	-0.26
Post-MinT	0.15	0.12	0.11	0.27	0.2	0.01	0.27	0.35	0.65	0.22	1	0.1	0.27	-0.22	0.09	-0.14
Material	0.29	0.34	0.27	0.18	-0.06	0.04	0.07	0.05	-0.01	-0.16	0.1	1	0.6	0.48	0.33	0.51
Operation	0.4	0.36	0.42	0.3	0.04	-0.05	0.14	0.07	0.09	-0.26	0.27	0.6	1	0.33	0.27	0.34
Speed	0.53	0.47	0.6	0.41	0.05	-0.1	-0.07	0.02	-0.36	-0.37	-0.22	0.48	0.33	1	0.14	0.8
Closure	0.36	0.35	0.26	0.59	0.26	0.01	-0.07	0.24	-0.07	-0.08	0.09	0.33	0.27	0.14	1	0.7
Disruption	0.54	0.48	0.51	0.63	0.16	-0.07	-0.12	0.14	-0.35	-0.26	-0.14	0.51	0.34	0.8	0.7	1

Figure 4.50 Correlation values across entire performance metric dataset.

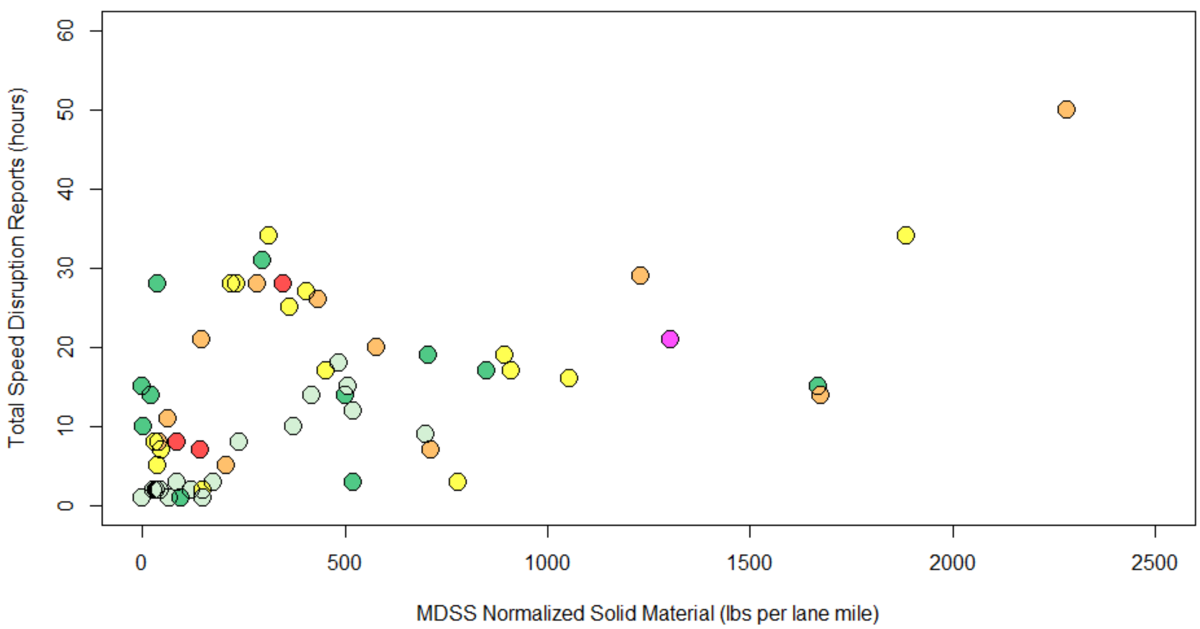


Figure 4.51 Scatterplot of normalized solid material (pounds per lane mile) on the horizontal axis and total speed disruption (hours) on the vertical axis color-coded by NEWINS-O maximum storm severity.

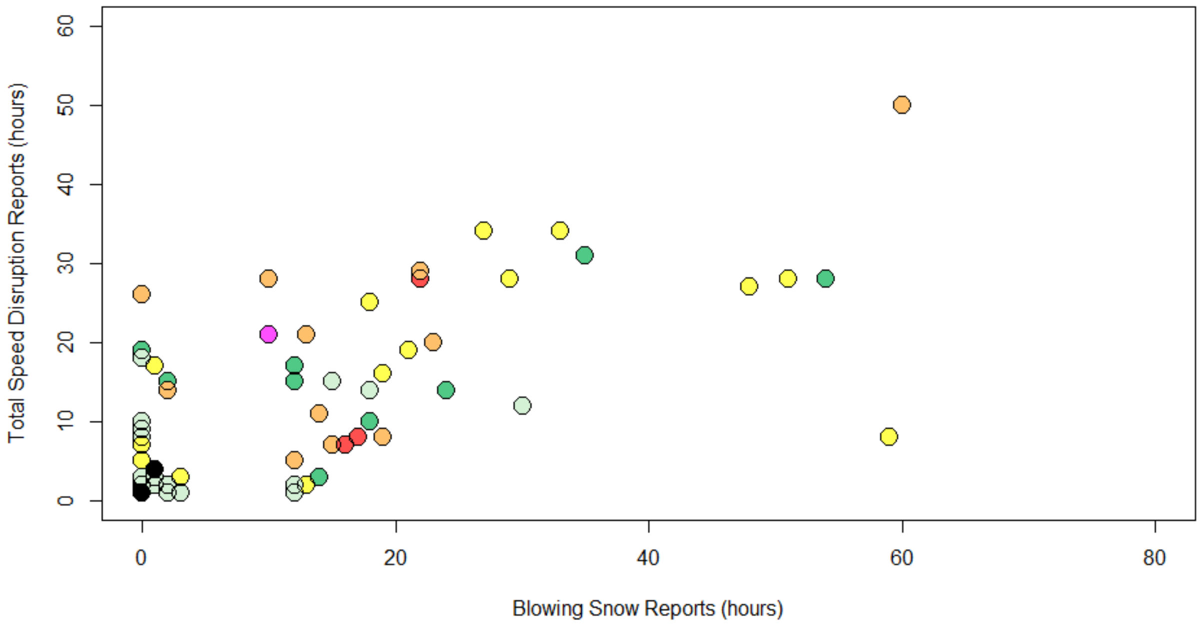


Figure 4.52 Scatterplot of blowing snow reports (hours) on the horizontal axis and total speed disruption (hours) on the vertical axis color-coded by NEWINS-O maximum storm severity.

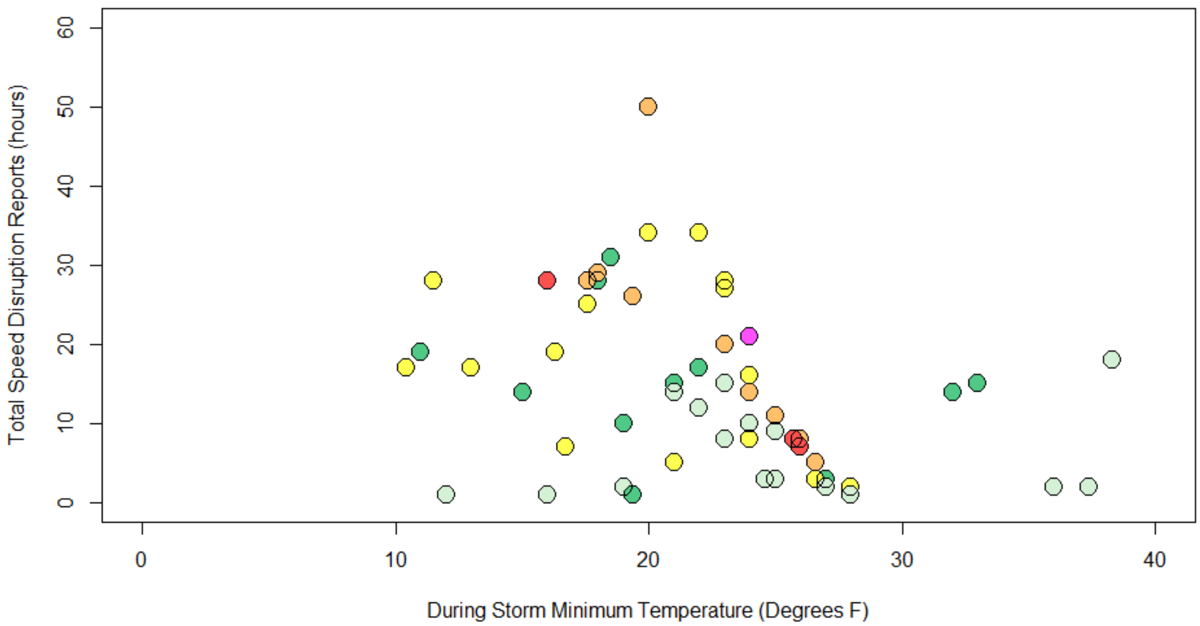


Figure 4.53 Scatterplot of minimum temperatures during a storm (°F) on the horizontal axis and total speed disruption (hours) on the vertical axis color-coded by NEWINS-O maximum storm severity.

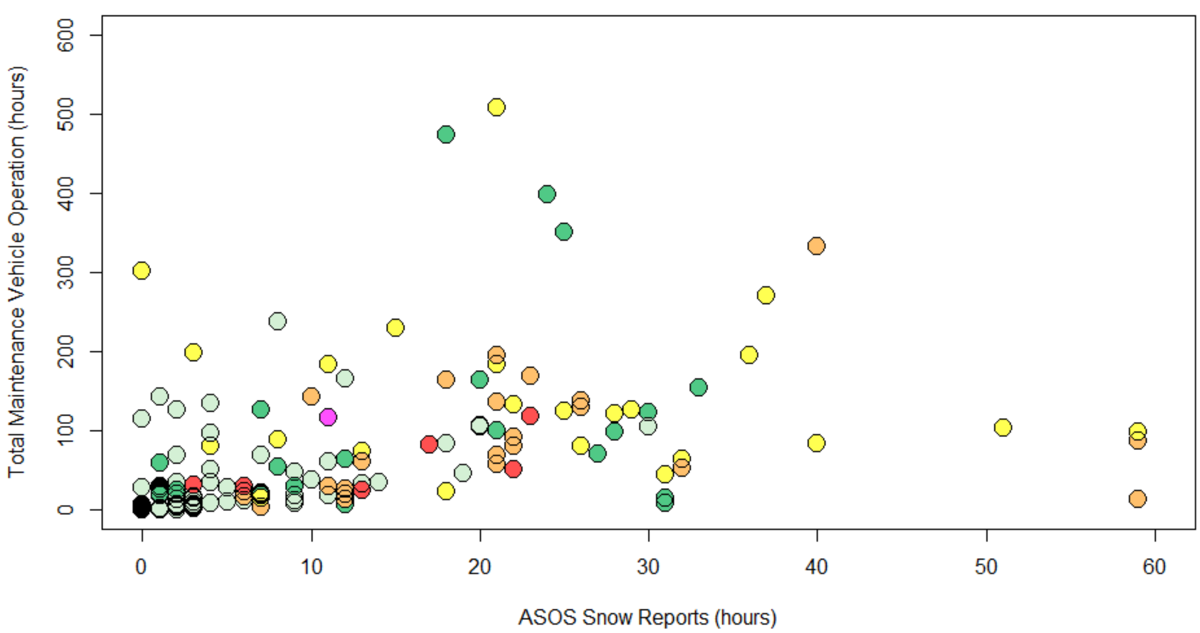


Figure 4.54 Scatterplot of precipitating snow reports (hours) on the horizontal axis and total maintenance vehicle operation (hours) on the vertical axis color-coded by NEWINS-O maximum storm severity.

Chapter 5 Summary

In summary, this analysis demonstrated the utility and feasibility of assessing the performance of winter maintenance operations across a variety of datasets including weather, speed, maintenance operations, and road conditions. The most important conclusion from this analysis is that no singular metric provides a complete assessment of winter maintenance operations performance. Each metric, and its interactions with others, offers insights into overall performance, though each with their own strengths and limitations. If a singular metric is desired, it can be surmised that "time," or the duration that various parameters are in effect (e.g., snowfall, speed reductions, maintenance vehicle operations), is the most important performance variable. Throughout the dataset, time (i.e., duration) was well correlated across the explored metrics with longer duration snowfalls and longer instances of blowing snow associated with longer duration speed disruptions and longer maintenance vehicle operation hours.

Weather information represents an important control on assessing winter maintenance performance. Weather demonstrated substantial variability across the cases and segments which yields more nuance in assessing its relative importance and impact on winter maintenance performance. Indeed, it was found that the duration of snowfall and the presence of blowing snow were all associated with greater speed disruptions, more material application, and longer maintenance vehicle operation periods. The effect of temperature and storm severity, or the total amount of accumulated snowfall, were less clear due, in part, to a relatively small sample size of events considered in this analysis.

Speed, after time, is likely the second most important parameter for assessing winter maintenance operations performance. It represents a direct measure of mobility impacts, and the lack of speed observations is a proxy well suited for indications of road closure along high-volume corridors such as Interstate 80. Beyond the interstate, the utility of speed is lower given the lack of good historic reference information and the diurnal patterns of speeds along lower volume roads (i.e., few, if any, vehicles at night and generally slower speeds due to visibility challenges and potential motorist concerns regarding vehicle-wildlife conflicts). Even along the interstate, speed as a performance metric has limitations given its sensitivity to non-meteorological or winter maintenance operations events such as vehicle crashes and congestion associated with adjacent state closures. To use speed as a meaningful performance metric, it will be important to isolate only the disruptions associated with weather and maintenance conditions and control for these external factors. This can be challenging with limits in documenting when and where crashes or other closures occur and, most importantly, when the road reopens.

Maintenance information, similar to weather data, represents another important control for assessing winter maintenance performance. Knowing the precise timing, location, and type of maintenance activity (e.g., plowing or material application rate) is crucial to determine whether winter maintenance operations succeeded in improving the level of service and reducing the disruption associated with a particular storm. Further, it would be beneficial for NDOT to determine the degree to which recommendations of maintenance from tools like MDSS actually align with actual maintenance actions. This would serve two-purposes: first, ensuring that the forecast and guidance from NDOT's investment in MDSS accurately aligns with the meteorological hazards and treatment needs of a particular event, and second, ensuring the efficiency goals of having a MDSS in the first place are realized with reasonable alignment between maintenance vehicle operations and MDSS recommendations. If future evaluations show that maintenance actions occur independent of input from MDSS, then there are more cost-effective weather forecast solutions available that may warrant further NDOT consideration.

Last, road conditions warrant further scrutiny beyond the scope of the current analysis. It was anticipated that this would be among the most important and useful performance parameters. However, the available MDSS-derived road condition datasets were found to be less reliable. Traffic camera imagery demonstrated some utility but similarly had limitations particularly at night and during poor visibility conditions. Moreover, the volume and quantity of traffic camera data represented a limitation in analytical capacity for this particular analysis. An entire separate project could be dedicated to image processing and automated recognition of road conditions. Regardless of the information source, road conditions are still nuanced by non-maintenance factors such as seasonality (e.g., early/late winter season event with relatively warm conditions and high daytime sun angles versus a middle of winter event) which can influence how quickly road conditions recover after an event regardless of the amount of materials used or the duration of maintenance activity.

Looking ahead, it would be prudent for NDOT, and other transportation agencies, to consider which winter maintenance operations performance metrics are most suitable for their unique needs. Then, NDOT and other agencies should prioritize strategic investments in the datasets and sensor infrastructure to ensure they are obtaining the most reliable information possible for assessing their performance. For example, if road condition information is deemed important and desirable, investment in road weather information system stations would be warranted and serve to ensure robust road condition data are available that are less reliant on simulated conditions from MDSS or traffic cameras with poor image quality or road surface viewing angles. Moreover, good weather and maintenance information are essential to serve as important controls for winter maintenance performance. While weather information is often available at high-quality external to transportation agencies, it is important for maintenance information, such as spreader calibration and maintenance vehicle geolocation, to be of similarly high-quality so that the maintenance activities of each vehicle can be assessed in a meaningful manner in context with other datasets.

Ultimately, assessing winter maintenance performance will always be bound by the limitation that correlation does not automatically equal causality. It requires holistic consideration of various information sources combined to understand the broader picture of how weather conditions, mobility, road, and maintenance information relate to performance. Thus, it would be prudent for NDOT and other agencies to continue strategic investments in ensuring the broadest lens possible when assessing the performance of their winter maintenance operations. A narrower scope or focus can result in critical omissions or reasonable-seeming outcomes for inaccurate reasons.

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