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# Road Weather Impact Based Decision Support Applications: Developing A Department Of Transportation Winter Severity Index

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# ROAD WEATHER IMPACT BASED DECISION SUPPORT APPLICATIONS: DEVELOPING A DEPARTMENT OF TRANSPORTATION WINTER SEVERITY INDEX

by

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ROAD WEATHER IMPACT BASED DECISION SUPPORT APPLICATIONS: DEVELOPING A DEPARTMENT OF TRANSPORTATION WINTER SEVERITY INDEX

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Adverse weather conditions are responsible for millions of vehicular crashes, thousands of vehicular deaths and billions of dollars in economic and congestion costs. Many transportation agencies utilize a performance or mobility metric to assess how well they are maintaining road access. This research focuses on the development of a winter severity index for the State of Nebraska (NEWINS). NEWINS is an event-driven index that was derived for the Nebraska Department of Transportation (NDOT) and its districts across the state. The NEWINS framework includes a categorical storm classification framework and climatological aspect to capture atmospheric conditions more accurately across diverse spatial regions.

A ten-year (2006-2016) winter season database of meteorological variables for Nebraska was obtained from the National Centers for Environmental Information. Meteorological parameters were grouped into categories that subsequently provided a storm classification database. The NEWINS was based on a weighted linear combination to the collected database to measure severity statewide and across individual districts. The NEWINS results were compared to meteorological variables previously used in winter severity indices. This comparison verified the NEWINS differences observed in the ten-year period. To further validate the developed NEWINS, cluster analyses were

performed on the weather variables and storm classifications. An assessment of the difference between days with observed snowfall versus days with accumulated snowfall revealed a 39% average reduction in days. The NEWINS results for the ten-year period highlight the greater number of events during the 2009-2010 winter season, and the lack of events during the 2011-2012 drought year. The NEWINS also shows strong differences among NDOT districts across the state with the general decrease in events from the western to eastern districts. Furthermore, storm classifications were compared to NDOT winter maintenance operations performance data for a sample winter season. Last, the 2016-17 winter season was computed to provide a testbed for the NEWINS procedure. It is expected that the NEWINS could help transportation personnel to efficiently allocate resources during adverse weather events, while balancing safety, mobility, and available budget. Further, the theoretical and practical contributions provided by the NEWINS can be used by other agencies to assess their weather sensitivity.

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## 1. Introduction

Adverse cold weather conditions**,** most notably snow and ice, threaten surface transportation nationwide and impact roadway safety, mobility and maintenance costs (Pisano et al. 2008; RWMP 2018). During the period from 2005-2014, weather-related vehicular crashes accounted for 22% (1,258,978 crashes) of all reported crashes, resulting in 16% (5,897) of crash fatalities and 19% (445,303) of crash injuries. The United States Department of Transportation (USDOT) National Highway Traffic Safety Administration (NHTSA) estimates the total economic and societal cost of all vehicular crashes in 2010 in the United States was $836 billion (Blincoe et al. 2015; NHTSA 2018). This total includes $242 billion in maintenance and congestion costs and $594 billion from injuries and loss of life. Weather-related vehicular crashes alone may account for approximately $180 billion nationwide, given the relative percentage of such crashes.

Snow and ice reduce pavement friction and vehicle maneuverability, causing slower speeds and reducing roadway capacity. In fact, on snowy or slushy pavement, average arterial speeds decline by 30-40% (RWMP 2018). Highway speeds are reduced by 3-13% in light snow and by 5-40% in heavy snow. In addition to reduction in speed, lanes and roads can be obstructed by snow accumulation, which reduces capacity (i.e., traffic counts; Call 2011) and increases travel time delay. Snow and ice also increase road maintenance costs. Winter road maintenance accounts for roughly 20% of state departments of transportation (DOTs) maintenance budgets. Annually, state and local agencies spend more than $2.3 billion on snow and ice control operations and millions of dollars to repair infrastructure damage caused by snow and ice (RWMP 2018). Given the nature of adverse cold weather events (e.g., snowstorms, ice storms), it is prudent to mitigate the impacts of such events on roadways and allocate resources to reduce their severity.

Evaluating the performance of mitigation strategies implemented as part of winter maintenance operations requires consideration of weather conditions, the state of the road network, the maintenance efforts undertaken for a given storm, the resulting road conditions and the interactions among these factors. The main challenge in evaluating this performance is that weather is inherently variable, and its variability complicates assessments of the relative efficiency and effectiveness of different winter maintenance operations (e.g., meeting levels of service standards, salt reduction, budget targets). Therefore, in pursuit of an evaluation metric for winter maintenance operations, a critical need is to assess the severity of individual storms through a winter severity index (WSI).

This analysis allowed development of a WSI for the Nebraska Department of Transportation (NDOT). This Nebraska Winter Severity Index (NEWINS) incorporates various surface and atmospheric data statewide across a ten-year period from July 2006 through June 2016. Given the intended use of the NEWINS by NDOT, all units used throughout the analysis are English Engineering units and the International System of Units is included for comparison where appropriate. From these data and subsequent analyses, a single, statewide value for each of the ten winter seasons was computed. A winter season is defined as any snowfall occurring between 1 July of the first year and 30 June of the subsequent year. For example, snowfall occurring between 1 July 2006 through 30 June 2007 would represent the 2006-07 winter season. The NEWINS is unique in that it is a meteorologically-based WSI, rather than related to transportation variables (e.g., accident rate) which may or may not be associated with weather conditions; however, the NEWINS framework is developed with consideration of road impacts and winter maintenance operations. The NEWINS was computed for the entire state of Nebraska and individual transportation maintenance districts within the state. Further, the NEWINS is compared to other indices to provide a more robust assessment of its use.

## 2. Background

The available literature documenting existing WSIs is described in the following section. First, transportation specific WSIs (Table 2.1) are considered followed by discussion of additional meteorological WSIs. The transportation WSIs are organized based on their developmental similarities. Then, weather classification schemes are considered for the framework of the NEWINS. Last, winter maintenance operations and meteorological data sets used in existing WSIs and their limitations are considered.

### *a. Existing State Department of Transportation Winter Severity Indices*

The literature documenting existing WSIs depicts a highly variable myriad of approaches typically developed for specific state DOTs. Table 2.1 summarizes the documented state DOT WSIs. In total, 19 states have made available documentation regarding their WSI. The remaining 31 state DOTs have either not made available documentation regarding their WSIs or do not have a WSI. Connecticut and Vermont have winter severity indices presently in development (Kipp and Sanborn 2013; Mahoney et al. 2015). Existing WSIs were often developed with relatively small data sets (e.g., less than six locations) and/or limited time frames (e.g., single month and/or winter season) with some noteworthy exceptions (Strong et al. 2005). Few WSIs have considered a winter storm classification framework, though several weather classification schemes exist (e.g., Fujita 1971; Simpson 1974; Kocin and Uccellini 2004; Cerruti and Decker 2011; Edwards et al. 2013). Automated Surface Observing System (ASOS) stations serve as the primary source for many WSIs in addition to Road Weather Information System

**Table 2.1.** Summary of known documented state DOT WSIs.

| WSI / States | Air Temp. | Road Temp. | Snowfall | Freezing Rain | Wind | Storm-Based | Sub-Regions | Dependent Variable |
|---|---|---|---|---|---|---|---|---|
| Strategic Highway Research Program (SHRP), KS, NH | X | | X | | | | | None |
| IN, MN, WI | X | | X | X | | | X | None |
| IL, MA, ME, PA, WA | X | | X | X | | | | None |
| NY, OK, UT | X | X | X | X | X | X | | None |
| CA, MT, OR | X | | X | | X | | X | Accident Rate |
| CO, ID | | X | X | | X | X | | Grip |
| IA | | X | X | | X | X | | None |

(RWIS) stations (Strong et al. 2005). As such, air and road temperatures, snowfall, wind and freezing rain data are the most common/important variable inclusions in WSI development. Given the literature, it is important for most of these variables to be included, or at least considered, for the NEWINS.

One of the earliest WSIs was developed by the Strategic Highway Research Program (SHRP; Boselly et al. 1993) and has been implemented in Kansas (McCullouch et al. 2004; Farr and Sturges 2012) and New Hampshire (New Hampshire DOT 2012). These studies developed WSIs to help highway agencies efficiently allocate their resources (i.e., labor, equipment and materials) to ensure safety in all weather conditions. The SHRP WSI considers the following variables: temperature, snowfall and likelihood of frost. The parameters in the SHRP WSI are calculated by collecting daily records from the National Weather Service (NWS) and assume that the impact of temperature, snowfall and frost likelihood on maintenance costs are 35%, 35% and 30%, respectively. The SHRP WSI has been widely adopted by other state DOTs for more than two decades (Farr and Sturges 2012), since previous research studies found strong relationships between snow and ice control costs and WSI values. However, one of the major limitations of the SHRP WSI is that it was developed as a general WSI to be used in multiple states. Therefore, this model does not consider the local characteristics that might impact winter maintenance operations in different states. Spatial and temporal examination of the SHRP WSI across the United States has also shown that for a similar latitude, the SHRP WSI provides different values in east, west and central regions that do not always represent the actual conditions on roads. Considering this limitation, some transportation agencies have modified the SHRP WSI to better represent their local weather conditions. One of the prominent examples is the Ontario Ministry of Transportation (MOT) that has substituted freezing rain (number or days recording freezing rain) for likelihood of frost (Andrey et al. 2001). Other transportation agencies, such as Utah DOT, have gone even further to develop their own WSI that consider other meteorological variables rather than use the SHRP WSI (McCullouch et al. 2004; Farr and Sturges 2012).

Wisconsin DOT developed a WSI that included the number of snow events, the number of freezing rain events, the number of incidents (e.g., drifting of snow, cleanup, and frost mitigation), total snow accumulation and total storm duration over the course of an entire season (Cohen 1981; McCullouch et al. 2004; Strong et al. 2005). Wisconsin DOT also investigated potential usage of other variables such as wind speed and direction and pavement temperature; however, these variables were not included in the final model. One of the interesting points about the Wisconsin DOT WSI is that it does not consider temperature. In addition, this index is to be used for a whole season and not event by event. Spatially, severity values are given on both a county-by-county level throughout the state and by Wisconsin DOT maintenance district level. Other states have adopted approaches similar to that of Wisconsin DOT and developed their own WSIs by considering similar variables. For example, Minnesota DOT used a similar approach and removed number of incidents from its framework (Strong et al. 2005). Indiana DOT also has adopted the general framework proposed by Wisconsin DOT. Indiana DOT’s WSI departs from previous models by including three more variables: snow depth, storm intensity (defined by storm duration) and average temperature, as well as developing separate equations for each climate zone in the state of Indiana. These four climate zones are defined arbitrarily by the following locations within the state: South Bend, Fort Wayne, Indianapolis, and Evansville. Indiana DOT also directly correlated its WSI to observed snow removal costs. Indiana DOT's WSI derives a unique WSI value for individual locations within the state representative of its climate regions. While this approach provides the most unique severity value for each location, an important caution is that it can become computationally challenging depending on the amount of meteorological data considered. Further, selection of locations should ideally be as objective as possible. A similar challenge with the development of a WSI in any state is to define representative locations throughout the state from which to obtain meteorological data.

The states of Illinois, Maine, Massachusetts, Pennsylvania and Washington have WSIs which, from a developmental perspective, do not exhibit strong similarity to the aforementioned states. Of this group, Illinois has the oldest winter severity index, which was developed by the Illinois State Water Survey (Cohen 1981; Strong et al. 2005). The Illinois WSI uses daily snowfall and temperature information to define a "salt day," when maintenance operations would be required, for the Illinois DOT. This salt day WSI has also been incorporated into Ontario's WSI as well (Strong et al. 2005). Pennsylvania DOT's WSI incorporates more meteorological variables than Illinois; however, it is also related to the Pennsylvania DOT's maintenance operations in terms of "premium hours," or how many personnel hours are needed to mitigate roadway conditions (Strong et al. 2005). The Pennsylvania WSI is unique because it explicitly considers different snow amounts or intensities. Maine DOT developed a seasonal WSI that is unique for different regions; however, there is no corresponding statewide value (Maine DOT 2009). Maine's

WSI assigns various point values to a derived “freezing rain equivalent” and a “modified daily snowfall.” The Washington State DOT winter frost index is calculated from NWS temperature observations (Boon and Cluett 2002); however, it should be noted that temperature alone is insufficient to capture the severity of winter weather conditions. Aside from the existence of a WSI, Massachusetts DOT does not have robust documentation regarding the parameter details of its index (Massachusetts DOT 2012). In terms of a performance metric, Massachusetts DOT compares its WSI to salt usage throughout the state.

The states of New York, Oklahoma and Utah have considered unique approaches in the development of their WSIs by including surface and air temperature information and by separating non-precipitation from precipitation parameters. New York State DOT has incorporated mean wintertime land surface temperature (LST) information from the National Aeronautics and Space Administration (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) satellite product, surface and air temperature information from the New York State Mesonet, and road pavement temperature from a growing RWIS station network (Chien et al. 2014). Additionally, New York has considered inclusion of data from the North American Model (NAM) of the National Centers for Environmental Prediction (NCEP) particularly for the purpose of determining the duration of freezing rain in its severity score. Oklahoma DOT designed its winter, or “storm,” severity index model with the intention of ensuring compatibility with multiple forecasting models, such as the Weather Research and Forecasting model (WRF) or the Short-Range Ensemble and Forecast (SREF) model (Balasundaram et al. 2012). Oklahoma and Utah initially considered the SHRP WSI and transitioned to an alternative index. Utah's WSI remains in active development and refinement. Unlike the aforementioned states with a WSI presently under development, Utah deserves special mention here due to its similarities with New York and Oklahoma in the unique approach of assimilating more robust and complex meteorological data and techniques. Unlike states that have developed independent WSIs for regions throughout the state (e.g., Indiana), Utah has considered the use of mesoscale analysis systems, such as Real-Time Mesoscale Analysis to account for changes across its complex topography (De Pondeca et al. 2011; Farr and Sturges 2012). Further, Utah has assessed the inclusion of mobile weather observations, such as those from instruments mounted on plow trucks, into its WSI. These unique state DOT WSIs are highlighted to provide the full spectrum of complexity regarding WSIs across the United States. This approach suggests that a WSI with varying levels of complexity will be able to conform to the needs and specifications of the end-user.

California DOT, Montana DOT and Oregon DOT have WSIs that have been correlated to accident rates. They are the only states whose WSI includes a direct transportation safety related variable in the severity index model (Strong et al. 2005). Most state DOT WSIs define some severity values (e.g. SHRP) that are subsequently related to some other performance metrics (e.g. grip, salt usage). Another similarity among the California, Montana and Oregon WSIs is the incorporation of meteorological variables on a daily basis in order to derive a monthly accident rate value. Another unique approach of this group of WSIs is development of an entire statewide model in addition to alternative models for specific geographic regions within the state (i.e., mountains, valleys and plains). The objective of these models is to identify weather conditions that result in increases or decreases in accident rate. That information would subsequently guide mitigation practices on those conditions that increase the accident rate.

Colorado DOT and Idaho Transportation Department (ITD) make use of an identical WSI, and both relate it to a grip-based mobility performance metric (Jensen et al. 2013; Walsh 2016). Both states are interested in reducing the duration over which observed pavement grip falls below a 0.6 threshold. Overall performance is assessed based on severity of weather conditions in addition to how long the measured grip was below the threshold. These two states are among the relative few that explicitly consider individual events in the overall WSI. Most states tend to consider, at best, daily meteorological variables; however, event-based variables more accurately capture what occurs within a particular storm at different times. From event-based variables, it is still possible to derive daily, monthly and seasonal severity index values, though it is difficult to scale downward from a monthly or seasonal value. Also, Colorado and Idaho developed their WSIs for specific points along the road network (e.g., particular mile marker) rather than for statewide, district, or broad geographic regions. Again, this allows for better understanding of how weather conditions are impacting specific areas during a particular event. The benefit of such an approach allows unique consideration of each event in addition to easier identification of target locations for increased mitigation.

Iowa DOT deserves a separate discussion of its WSI, because it is one of the better documented indices (Carmichael et al. 2004; Nixon and Qui 2005; Strong et al. 2005; Qui 2008; Walsh 2016). Iowa's WSI is unique in that it is a storm-based index, rather than monthly or seasonal. Further, individual storms are assigned a type and intensity based on weather conditions before, during and after the storm. This added temporal consideration allows for a more realistic approach to adverse winter weather events. Pre-storm and early-storm behavior allows for consideration of changes in the liquid water equivalent of snow, presence of wet snow, and powdery snowfall. Post-storm conditions allow for consideration of the impact on treatment and mitigation activities of blowing and drifting snow after precipitation has stopped. A WSI that considers changes in meteorological conditions on a storm-scale (i.e., mesoscale) temporal resolution will likely yield better correlation to maintenance and mitigation activities simply due to the level of detail and complexity associated with weather hazards. This is one of the only known WSIs that explicitly incorporates road temperatures; however, while desirable, an important caution is that road temperature data has been shown to exhibit lack of quality control (Walker and Anderson 2016). Table 2.1 summarizes the aforementioned state DOT WSIs.

### b. *Additional Winter Severity Indices*

Many existing WSIs have been developed specifically for transportation-related purposes over relatively short time scales. Non-transportation WSIs have been developed for a wide array of uses such as deer hunting (MNDNR 2018) and are beyond the scope of this work; however, other meteorological WSIs with no specific intended use are mentioned herein. The Accumulated Winter Season Severity Index (AWSSI; Boustead et al. 2015) represents a purely climatology-based meteorological WSI. The AWSSI was developed for over 50 locations in the United States to provide seasonal winter severity values during the period from 1950 through present day (MRCC 2018). Daily points are assigned for specific locations in the AWSSI for predefined thresholds of minimum and maximum air temperatures, snowfall amounts and snow depth. These points are accumulated for an entire winter season to produce a final score that is associated with a given location's winter severity. These final scores are sorted into a categorical range to report final classifications (i.e., mild, moderate, average, severe, extreme). While the AWSSI is a temporally robust WSI, an important limitation is that it is computed on a point-by-point basis. It would be necessary to interpolate winter severity values between points computed by the AWSSI. Another caveat of the AWSSI is that it assesses conditions throughout the entire winter season, not specific to an individual winter storm. This aligns with many of the state DOT WSIs as well; however, winter maintenance operations are more aligned with specific events rather than an entire winter season. A critical discussion during the development of the AWSSI concerned the definition of a winter season. Boustead et al. (2015) note several different definitions for the beginning and end of a winter season. For example, meteorologically / climatologically winter is defined as the months of December, January and February; however, winter events commonly occur outside of this time period. Further, the onset and cessation of winter varies substantially geographically. The AWSSI defined the onset of a winter season once any one of three criteria were met: 1) daily maximum temperature below 32°F (0°C), 2) daily snowfall in excess of 0.1 in. (0.25 cm), or 3) any date after 1 December. Similarly, the AWSSI defines the end of a winter season based on when the last of any four criteria are satisfied: 1) daily maximum temperatures rise above 32°F (0°C), 2) no measurable daily snowfall, 3) snow depth drops below 1.0 in. (2.5 cm), or 4) any date after 1 March. An advantage of this winter season definition is that it provides a concise, strict period for consideration of overall winter severity. A limitation of this definition is that it could omit early/late season snowfalls and/or cold outbreaks. Defining the winter season is crucial for the success of any WSI.

The NWS is experimenting with a prototype Winter Storm Severity Index (WSSI; WPC 2018) to better communicate impacts associated with winter storms as part of its strategic plan calling for an increase in decision support services (Rutz and Gibson 2013). The framework for the WSSI uses a categorical framework to discuss storm severity and impacts (i.e., none, limited, minor, moderate, major and extreme). Unlike the AWSSI and many state DOT WSIs, the WSSI is specific to individual snowstorms. The components of the WSSI include snow amount, blowing snow, ice accumulation, flash freeze and ground blizzard. An event-driven, meteorological index is desirable for the development of the NEWINS and complements the ongoing refinement of the WSSI.

### *c. Weather Classification Schemes*

Meteorological events have been classified to categorize the magnitude of their impacts, including such events as tornadoes (i.e., Fujita and Enhanced Fujita scales; Fujita 1971; Edwards et al. 2013) and hurricanes (i.e., Saffir-Simpson scale; Simpson 1974). In operational forecasting, the NWS Storm Prediction Center (SPC) Convective Outlook Severe Thunderstorm Risk Categories (SPC 2016) and experimental winter storm threat graphics (NWS 2016) use categorical classification approaches to convey potential impacts of hazardous weather. Winter storm classification schemes have not been as widely adopted as those for tornadoes and hurricanes. One reason for the lack of widespread adoption is that existing winter storm classifications have not been performed nationwide, but rather focused on the Northeastern United States. Kocin and Uccellini

(2004) developed a Northeast snowfall impact scale (NESIS) which provides a single classification for a particular winter storm by considering the snowfall amount, area receiving snow and the population density of the region. The NESIS categorical framework classifies events in five categories of increasing impacts: notable, significant, major, crippling and extreme. Extension of the NESIS to other geographic locations is plausible. The joint incorporation of meteorological and societal parameters into the NESIS aligns with the general framework of state DOT WSIs.

Cerruti and Decker (2011) sought to improve on the NESIS by creating a Local Winter Storm Scale (LWSS). Unlike the NESIS, the LWSS only considered meteorological variables in its classification of winter storms and assigned weights to each. Variables considered by the LWSS included sustained wind speeds, wind gusts, snow and ice accumulation and visibility. Wind categories were based on the Beaufort wind scale. Visibility was used as a proxy for precipitation rate. LWSS variable and event classifications included nuisance, moderate, significant, major, crippling, extreme, and catastrophic. While the NESIS used a five-category framework for consistency with tornado and hurricane intensity scales, the LWSS uses a seven-category framework.

None of the state DOT WSIs incorporated a categorical winter storm classification. Some (e.g., Iowa) considered different intensity levels, but never an explicit storm classification. Meteorological WSIs (e.g., AWSSI, WSSI) and storm classifications all considered and incorporated some type of categorical framework into their approaches. An important caveat is that most state DOT WSIs were developed in the absence of meteorological expertise. Similarly, most meteorological WSIs/storm classifications were developed in the absence of transportation officials.

*d. Winter Maintenance Operations and Weather Data*

Existing WSIs and winter storm classifications rely on transportation and meteorological data. Transportation data from state DOTs includes accident rate, personnel hours, winter maintenance operations costs, traffic speeds and counts, and grip measurements (Strong et al. 2005; Jensen et al. 2013; Blincoe et al. 2015; Walsh 2016). State DOTs use their various data sets to assess the performance of their winter maintenance operations. In many instances, these data are also correlated with the state DOTs' WSI. Such WSIs that are closely related to transportation data (e.g., California, Montana, and Oregon; Strong et al. 2005) are limited in their ability to represent the meteorological conditions present. Meteorological WSIs such as the AWSSI and WSSI that exclusively consider surface and atmospheric weather parameters (Boustead et al. 2015; WPC 2018) are more suited to provide a meteorological diagnosis of severity. Such WSIs, though, rely on accurate meteorological data to be reliable.

ASOS station data provides the foundation for meteorological surface-based observations and associated WSIs. ASOS stations can provide high temporal resolution (i.e., one-minute) air temperature, dew point temperature, wind speed and direction, atmospheric pressure, precipitation type and accumulation, sky conditions, and current weather observations (NWS 2018). For WSI development, one of the most critical pieces of information obtainable from an ASOS station is precipitation type. To differentiate precipitation types, ASOS stations use a precipitation identification sensor (PI), also referred to as a Light Emitting Diode Weather Indicator (LEDWI; NWS 2018). As hydrometeors pass through the beam, a spectral analysis determines which hydrometeors are present given the power returned to the sensor. Mixed precipitation can confuse the sensor and is often reported as “unknown precipitation.” For pure rain or snow, the spectral analysis can also derive precipitation intensity (i.e., slight, moderate, heavy). A separate sensor, known as a magnetostrictive oscillator is used to determine freezing rain precipitation and subsequent ice accumulation (NWS 2018). The sensor operates on the principle that as ice accumulates on the sensor, its oscillation frequency will change due to the additional weight of ice. Further, the subsequent magnetization will adjust accordingly. From these changes, freezing rain can be both identified, and accumulation detected. Given the lack of reliable, historical freezing rain observations and ice accumulation data through the entire ten-year study period, freezing rain was not considered in the development of the NEWINS; however, inclusion of freezing rain could be possible in future analyses.

From the literature, the most common meteorological parameters incorporated into state DOT WSIs are temperature, snow, wind and freezing rain. Temperature is one of the most common meteorological parameters used in WSIs. Studies as early as Angot (1914) and Abbe (1914) focused on characterizing winter severity by cumulative freezing degree days, or the sum of minimum temperature departures below 32°F (0°C), for comparison of cities such as Washington, D.C., and Paris, France. Although effective for comparing temperature behavior among sites, this approach neglects any contribution of precipitation. Hulme (1982) was among the first to consider road temperature into an index.

Snow is another critical meteorological parameter for winter maintenance operations and WSIs. Previous studies have shown that road condition/friction is directly related to the amount of snow and/or ice on the road surface (Juga et al. 2013; Kwon et al. 2013). Snow is a complex factor that impacts winter maintenance operations. Estimating the depth of snow/ice on the road surface is difficult since these parameters depend on rapidly changeable factors such as precipitation rate, road treatment actions, traffic flow and surface temperatures (Baldwin et al. 2015). To simplify the problem, previous studies assumed that the amount of snow/ice on the road surface would be proportional to the precipitation rate (Baldwin et al. 2015). Kwon et al. (2013) showed that snowfall rate is linearly related to the percent reduction in free flow speed. In addition, the mass of frozen precipitation is also expected to be an important factor. According to Baldwin et al. (2015), even though low density snow will accumulate quickly and increase the depth of the snowfall much faster than high density, wet snow, the liquid equivalent can be considerably less for the low-density snow. All other conditions being equal, low density snow will melt faster and leave less residual water behind on the road surface than denser snow. Boustead et al. (2015) noted that, for their study, snowfall and snow-depth data were not available through the entire period of record at most stations, and even where available, the quality can be suspect (Robinson 1989; Ryan et al. 2008; Doesken and Robinson 2009).

To address the snow measurement complexity, different methods for measuring snowfall, snow-depth, and respective liquid equivalents, have been developed. Trnka et al. (2010) used an average daily temperature of 32°F (0°C) or less to determine when snow falls, then used thresholds of minimum temperature to further refine the fraction of precipitation that accumulates as snowfall. Kienzle (2008) employed a similar method; however, a threshold temperature at which 50% of precipitation falls as snow and 50%

falls as rain was calculated. The calculations in this approach were considered inadequate for widespread use across a high number of stations and required continual updating. Both approaches provided liquid equivalents, rather than snowfall. Byun et al. (2008) created a snow-liquid ratio based on regression analysis of observed temperature, precipitation and snowfall, but the method required a 3-hourly precipitation rate. The AWSSI is capable of using snow data or precipitation data with snow information derived from precipitation amounts and temperatures. Precipitation measurements during snowfall also can contain errors due to rain gauge under-catch of snowfall (e.g., Goodison 1978; Goodison et al. 1998; Boustead et al. 2015).

Wind, a non-precipitation parameter, might impact traffic conditions both during and after a storm. In the storm, wind has a significant impact on traffic speed and accident risks, whether acting alone or in combination with precipitation (Knapp et al. 2000; Andrey et al. 2001; Liu 2013). In fact, wind-blown snow can reduce visibility, which can impede the ability of drivers to respond to road conditions and potential hazards (Massachusetts DOT 2012). Post-storm winds also significantly impact winter maintenance operations. After a storm, wind can contribute to snowdrifts, reduce plowing effectiveness, cause retention of snow when the pavement is wet, and cause uneven dispersion of de-icing chemicals (McCullouch et al. 2004; Nixon and Qiu 2005; Ye et al. 2009). The wind potential for blowing or drifting snow depends on snow density. In general, a wind speed greater than 20 mph (8.9 m $s^{-1}$) can blow and drift snow (Farr and Sturges 2012). Thus, information on wind speed and direction can support winter maintenance operations and WSI development.

For freezing rain, the thickness of the ice layer is determined by the precipitation intensity (Houston and Changnon 2007). This layer of ice creates challenging road conditions during and after a storm (Qiu and Nixon 2009; Wisconsin DOT 2014). Previous studies have found that crash risk is considerably higher during and after freezing rain events compared to dry snow (Andrey et al. 2003). Freezing rain frequency is variable throughout the United States and this phenomenon can increase the difficulty of maintaining safe road conditions. Assessing the risk of freezing rain requires information about its frequency, intensity and duration, along with other weather-related conditions, including the temperature and wind during freezing rain occurrences (Houston and Changnon 2007). The New York State DOT report mentioned that an hour of freezing rain must be considered twice as important as an hour of snowfall due to extra caution required during and after freezing rain (Chien et al. 2014). The Maine DOT collected the opinions of field crews who were involved in winter maintenance operations regarding the difficulty of dealing with freezing rain. They found that maintaining roads during and after freezing rain required additional runs and more materials, and typically costs 20-30% more compared to dry snow removal (Marquis 2009). Based on these results, the Maine DOT suggested increasing its WSI by 25% to account for the additional cost of freezing rain by converting freezing rain information to an equivalent snowfall amount and accumulating it throughout the winter season (Marquis 2009). More recent work (Sanders and Barjenbruch 2016) developed an ice accumulation model based on an analysis of ASOS ice-to-liquid ratios during freezing rain events. Despite these recent advancements, given the historical study period for the development of the NEWINS and lack of reliable/validated freezing rain observations and subsequent ice accumulation, freezing rain was not considered in the development of the NEWINS.

For the development of the NEWINS, temperature, snowfall and wind data will be of critical importance. Road temperature and freezing rain data are omitted from the development of the NEWINS despite their desirability, due to their lack of reliability and availability for the entire ten-year study period. To capture the severity influences of individual events, a categorical storm classification framework (e.g., Kocin and Uccellini 2004; Boustead et al. 2015) is desirable over a seasonal/annual averaged approach (e.g., Strong et al. 2005). Despite Iowa's well documented WSI, it lacked consideration of areal coverage, precipitation rate/intensity, event duration and visibility, all of which were identified by NDOT personnel as desirable for inclusion in the NEWINS. Further, given the desire for the NEWINS to serve as an independent, meteorologically driven WSI, it is developed separate from winter maintenance operations data unlike other WSIs (e.g., California, Montana, Oregon; Strong et al. 2005). The strengths of the NEWINS is that it independently and explicitly considers the individual contribution of select meteorological parameters spatiotemporally during events, and the combined influence of these parameters yield a storm classification frequency distribution that is accumulated throughout a winter season. The NEWINS provides a finer resolution than the most existing WSIs by considering storm-level data. Further, the NEWINS focuses on meteorological conditions and can subsequently be compared independently with transportation and winter maintenance data.

## 3. Methods

The development of the NEWINS first considers the study region and data sets used to define the winter season database. Then, a questionnaire was developed to provide guidance for the development of the NEWINS. Next, data management and quality control criteria were established to ensure a high-quality data set. Individual events were classified in accordance with the NEWINS categorical framework. Last, the NEWINS was computed and validated against winter maintenance performance data and additional meteorological data.

### *a. Study Region and Data*

This research seeks to develop a WSI for NDOT known as the NEWINS. The study region for the development of the NEWINS was defined by the state boundaries of Nebraska. The state of Nebraska is further divided by NDOT into eight maintenance districts (Figure 3.1). NDOT maintenance operations are decentralized and spatially variable among and within the districts. All districts are responsible for their own resource and equipment allocation of personnel, plow trucks, and anti-icing materials. Some districts (e.g., Districts 1 and 2) ensure continuous (i.e., 24-hour) treatment of roads during a snowstorm. This is due, in part, to the urban population centers of Lincoln and Omaha, respectively, with a greater concentration of interstate and expressway road classifications. There is a greater demand on the road network within these two districts. Other districts (e.g., Districts 4, 5 and 6) only maintain continuous maintenance operations on their respective interstate corridor. Secondary and tertiary routes are

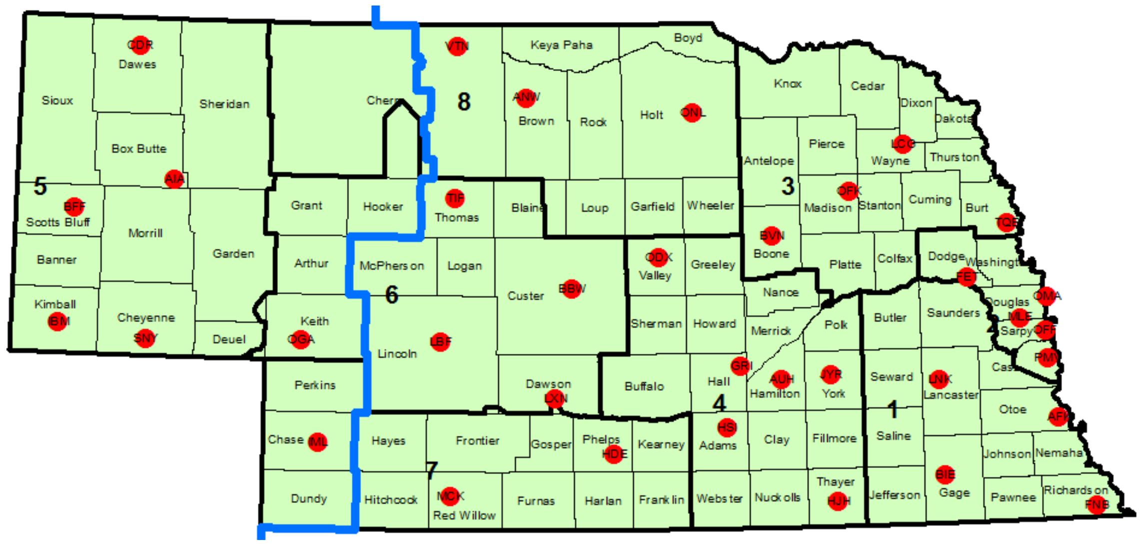


**Figure 3.1.** State of Nebraska counties with eight Nebraska Department of Transportation (NDOT) maintenance districts outlined in the thick black line. The 35 red dots indicate Automated Surface Observing System (ASOS) stations. The blue line represents the demarcation between Central (east, i.e., to the right) and Mountain (west, i.e., to the left) time zones

typically not treated overnight. Last, more rural districts (e.g., Districts 3, 7, and 8) that do not have any interstate highway to maintain also lack any roadways prioritized for continuous winter maintenance operations during a snowstorm.

Atmospheric variables for the NEWINS were obtained from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) for all ASOS stations within Nebraska (NCEI 2017a). Hourly data obtained from the ASOS stations included: station name, station elevation, station latitude, station longitude, wind speed, wind gusts, wind direction, cloud cover, visibility, present observed weather, air temperature, dew point temperature, sea-level pressure, station-pressure, and liquid-equivalent precipitation every hour, six hours, and 24 hours (NCEI 2017a, NWS 2018).

Snowfall observations for the NEWINS were obtained from the Global Historical Climatology Network-Daily (GHCN-D) sites within Nebraska (NCEI 2017b). The GHCN-D sites include data from the Community Collaborative Rain, Hail and Snow Network (CoCoRaHS 2018), the Nebraska Rainfall Assessment and Information Network (NeRAIN 2018), and the NWS Cooperative Observer Network (COOP 2018). The majority of the GHCN-D sites record once-daily 24-hour snowfall amounts measured at approximately 0700 local time (LT); however, there can be some temporal variability in the actual measurement time. Also, while some snowfall measurement networks (e.g., COOP) are more reliable and adhere to strict criteria and quality control, other measurement networks (e.g., CoCoRaHS) are citizen-science based and rely on reports from the public with less stringent quality control, which may result in inaccuracies or inconsistencies due to the measurement approach. Given this variability, it is necessary to define a more consistent daily event period. There are approximately 1000 GHCN-D sites statewide.

### b. *Initial Winter Maintenance Operations and Severity Index Survey*

To complement the literature regarding existing winter severity indices and to guide the development of the NEWINS, a questionnaire available in Dao et al. (2018) was developed to assess state DOT best practices when measuring the performance of winter maintenance operations. Weather and WSI-related questions from the questionnaire are available in Appendix A. Additional questions asked state DOTs about their winter maintenance operations performance measurement and are beyond the scope of the present analysis. One of the major components of the questionnaire was meteorological aspects of winter maintenance operations and WSIs; therefore, a goal of the questionnaire was to document the collection, use, and source of various weather information for consideration in WSIs and winter maintenance operations. The maintenance operations staff of NDOT pilot tested the questionnaire and provided suggested revisions. Subsequently, the questionnaire was approved by the University of Nebraska-Lincoln's Institutional Review Board. The questionnaire contained 25 questions and took approximately 20 minutes for participants to complete. The questionnaire was distributed to the 31 state DOT members of Clear Roads. Clear Roads is a national research consortium for winter maintenance (Clear Roads 2018).

The questionnaire included several sections related to the respondents' demographics, the state DOT decision-making procedures, its performance metrics and data, and the states' WSIs (if applicable). The first section provided general information about the study (e.g., objectives, definitions of technical terms) and obtained demographic information (e.g., work experience) about the respondents. The respondents were then asked to explain the decision-making processes in their agencies (e.g., centralized versus decentralized) regarding winter maintenance operations and storm-preparation activities. Since weather affects both winter maintenance decisions and operations' performance measurements, respondents were asked to rate on a five-point Likert scale (1-"low" to 5-"high") the significance of different weather variables during winter maintenance operations, the importance of different weather-forecast sources at different stages of a storm, and respondents' perception of the accuracy of forecasts for different weather variables. The questionnaire also assessed which performance metrics (e.g., labor hours, lane-miles plowed, quantity of anti-icing materials used) each state implemented. In addition, because performance measurements require data collection, the questionnaire asked state DOT representatives to specify which data were collected regarding roadway winter maintenance operations (e.g., safety, mobility) and how these data were collected (e.g., fixed sensors alongside the road). Participants were also asked whether a state used a WSI to adjust performance measures, and if so, how. Respondents then had to evaluate the benefits of measuring winter maintenance operations' performance and describe their approaches to reporting road conditions and performance measures to the public. Finally, the questionnaire included questions to capture aids and barriers to improving winter maintenance performance.

In total, 44 respondents completed the questionnaire with at least one from each of the 31 states shown in Figure 3.2. To consolidate the data for the states that had more than one respondent, the available responses were combined to create one single data

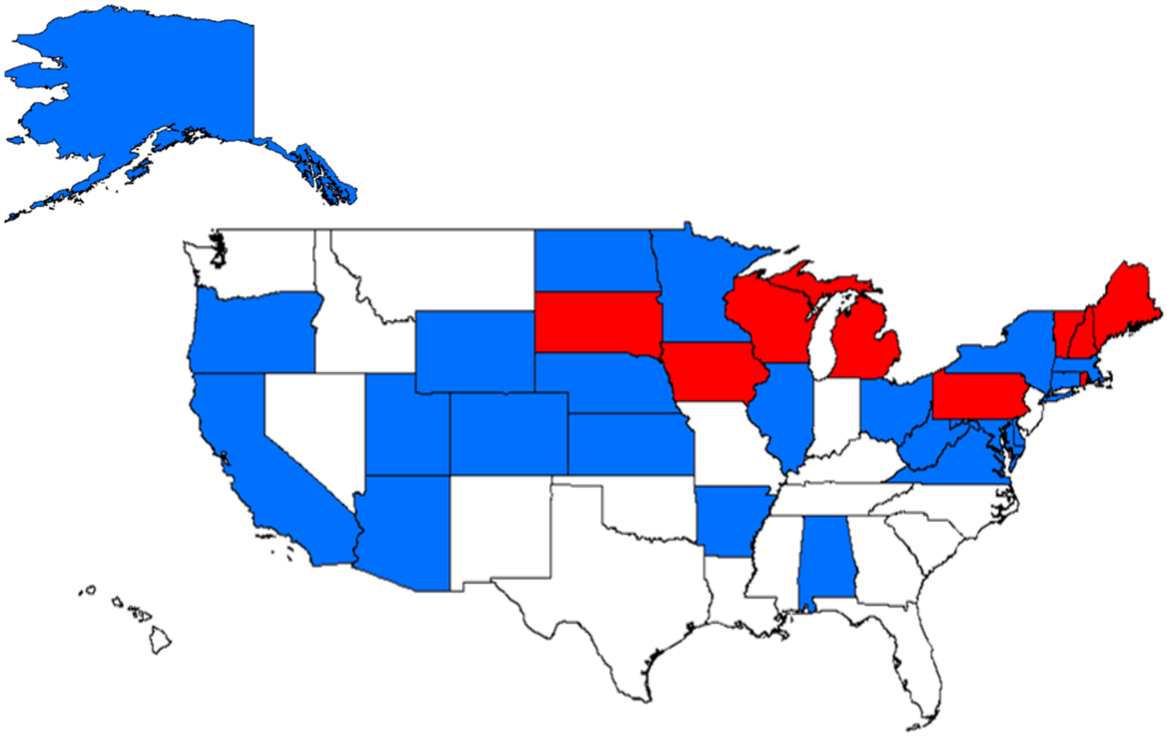

**Figure 3.2.** Thirty-one state (blue) departments of transportation (DOTs) in the United State participated in the first round of data collection and nine state DOTs (red) also participated in the first round and follow-up data collection.

point for each state using the average of the responses. The respondents represented different levels of operation management; including maintenance director, operation supervisor, maintenance superintendent, program specialist, engineer, and business planning coordinator and each had operating experience ranging from 4 to 43 years. To capture more detailed information about WSIs, such as the parameters included, time or spatial scales, and the purposes of using those indices, a follow-up questionnaire was developed (Appendix B), approved and distributed to the state DOTs who had agreed to participate in a follow-up session. Personnel of maintenance operations from nine state DOTs also responded to the follow-up questionnaire (Figure 3.2).

### *c. Data Management and Quality Control*

The abundance of data and having an objective to ensure stringent criteria for the analysis required various quality control procedures prior to the development of the NEWINS. Initially, 39 ASOS stations were included in the analysis; however, the quality control procedures reduced this number to 35 stations. Four ASOS stations were removed from the analysis because either: 1) the station did not have an operational PI, or LEDWI system, for all or part of the ten-year period or 2) the station had missing data for more than one entire winter season (Table 3.1). The ASOS stations in Columbus (KOLU) and Kearney (KEAR) were removed for failing to have an operational PI. ASOS stations in Blair (KBTA) and Wahoo (KAHQ) were removed since their available data did not extend through the entire ten-year period. Plattsmouth (KPMV) and Wayne (KLCG) each had a single winter season in which no data are available; however, the stations were included in the overall analysis. After quality control, the number of ASOS stations per

**Table 3.1.** Automated Surface Observing System (ASOS) station information organized by NDOT Maintenance District. Removed column identifies stations omitted from the analysis after quality control.

| NDOT District | Station ID | City Name | USAF ID | Lat. (°) | Lon. (°) | Elev. (m) | Time Zone | Removed |
|---|---|---|---|---|---|---|---|---|
| 1 | BIE | Beatrice | 725515 | 40.28 | -96.75 | 403 | Central | |
| 1 | FNB | Falls City | 725533 | 40.07 | -95.58 | 300 | Central | |
| 1 | LNK | Lincoln | 725510 | 40.85 | -96.77 | 364 | Central | |
| 1 | AFK | Nebraska City | 725541 | 40.60 | -95.85 | 354 | Central | |
| 1 | AHQ | Wahoo | 720942 | 41.23 | -96.60 | 374 | Central | X |
| 2 | BTA | Blair | 720405 | 41.42 | -96.12 | 396 | Central | X |
| 2 | FET | Fremont | 725564 | 41.45 | -96.52 | 367 | Central | |
| 2 | OFF | Bellevue | 725540 | 41.12 | -95.92 | 319 | Central | |
| 2 | OMA | Omaha | 725500 | 41.32 | -95.90 | 312 | Central | |
| 2 | MLE | Millard | 720308 | 41.20 | -96.12 | 320 | Central | |
| 2 | PMV | Plattsmouth | 722291 | 40.95 | -95.92 | 367 | Central | |
| 3 | BVN | Albion | 723441 | 41.73 | -98.05 | 551 | Central | |
| 3 | OLU | Columbus | 725565 | 41.45 | -97.32 | 440 | Central | X |
| 3 | OFK | Norfolk | 725560 | 41.98 | -97.43 | 470 | Central | |
| 3 | TQE | Tekamah | 725527 | 41.77 | -96.18 | 312 | Central | |
| 3 | LCG | Wayne | 722241 | 42.25 | -96.98 | 436 | Central | |
| 4 | AUH | Aurora | 725513 | 40.88 | -98.00 | 550 | Central | |
| 4 | GRI | Grand Island | 725520 | 40.97 | -98.32 | 561 | Central | |
| 4 | HSI | Hastings | 725525 | 40.60 | -98.43 | 591 | Central | |
| 4 | HJH | Hebron | 722124 | 40.15 | -97.58 | 447 | Central | |
| 4 | EAR | Kearney | 725526 | 40.72 | -99.00 | 649 | Central | X |
| 4 | ODX | Ord | 725524 | 41.62 | -98.95 | 631 | Central | |
| 4 | JYR | York | 725512 | 40.90 | -97.62 | 509 | Central | |
| 5 | AIA | Alliance | 725635 | 42.05 | -102.80 | 1196 | Mountain | |
| 5 | CDR | Chadron | 725636 | 42.83 | -103.10 | 1010 | Mountain | |
| 5 | IBM | Kimball | 725665 | 41.18 | -103.68 | 1501 | Mountain | |
| 5 | BFF | Scottsbluff | 725660 | 41.87 | -103.58 | 1203 | Mountain | |
| 5 | SNY | Sidney | 725610 | 41.10 | -102.98 | 1307 | Mountain | |
| 6 | BBW | Broken Bow | 725555 | 41.43 | -99.63 | 776 | Central | |
| 6 | LXN | Lexington | 725624 | 40.78 | -99.77 | 734 | Central | |
| 6 | LBF | North Platte | 725620 | 41.12 | -100.67 | 847 | Central | |
| 6 | OGA | Ogallala | 725621 | 41.12 | -101.77 | 999 | Mountain | |
| 6 | TIF | Thedford | 722211 | 41.97 | -100.57 | 892 | Central | |
| 7 | HDE | Holdrege | 725628 | 40.45 | -99.32 | 705 | Central | |
| 7 | IML | Imperial | 725626 | 40.52 | -101.62 | 998 | Mountain | |
| 7 | MCK | McCook | 725625 | 40.20 | -100.58 | 782 | Central | |
| 8 | ANW | Ainsworth | 725556 | 42.57 | -100.00 | 789 | Central | |
| 8 | ONL | O'Neill | 725566 | 42.47 | -98.67 | 619 | Central | |
| 8 | VTN | Valentine | 725670 | 42.87 | -100.55 | 788 | Central | |

NDOT district ranged from three stations in Districts 7 and 8 to six stations in District 4 (Figure 3.1). Spatially, the ASOS stations were distributed throughout the NDOT districts to reasonably capture the range of spatial variability in atmospheric conditions.

Hourly ASOS station observations were only incorporated into the analyses if the PI detected frozen precipitation (i.e., snow, ice pellets, mixed precipitation). Freezing rain was not considered in the analyses due to challenges associated with verification of ice accumulation (Changnon and Creech 2003) on spatiotemporal scales necessary for the research objective. For any 24-hour period, it is possible for only a single hour of observations to be included if that was the only instance of frozen precipitation identified. It is also possible for several discontinuous or continuous hours to be included if the precipitation was more intermittent or steady, respectively.

Quality control for these hourly frozen precipitation observations included the computation of dewpoint depression which is the difference between observed air and dewpoint temperatures. Hourly observations were removed from the winter season database if their dewpoint depression exceeded 30°F (16.7°C). As noted by Jiusto and Wieckmann (1973), extreme dewpoint depressions would not yield tremendous moisture availability for frozen precipitation. It is believed that such extreme dewpoint depressions would either be the result of sensor error or indicative of exceptionally light snowfall.

The GHCN-D sites used in the analysis were only selected if the observation was within a 15-km spatial threshold of an ASOS station (Figure 3.3). This was intended to ensure spatial consistency between the observed snowfall and the atmospheric conditions present during the snow accumulation period. Further, given the interest in snowfall amounts that would require a winter maintenance operations response (i.e., plowing of

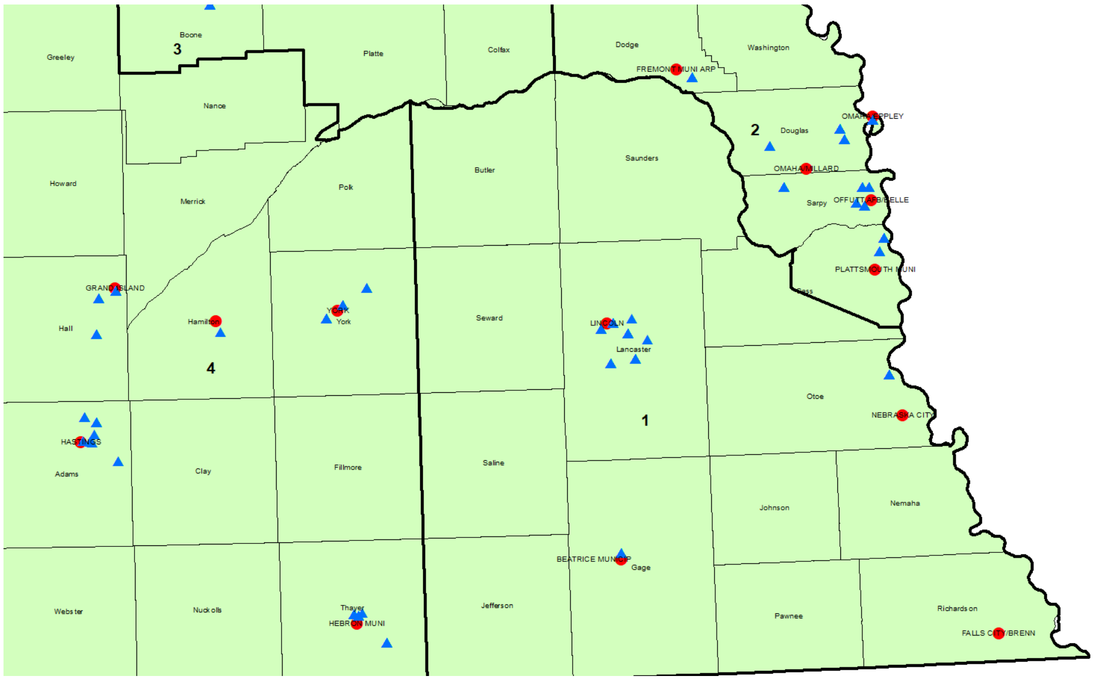


**Figure 3.3.** Southeast Nebraska counties with four Nebraska Department of Transportation (NDOT) maintenance districts visible outlined in the thick black line. The red dots indicate Automated Surface Observing System (ASOS) stations. The blue triangles show Global Historical Climate Network-Daily (GHCN-D) sites within 15 km of the ASOS stations that had sufficient data for the analysis.

measurable snow), GHCN-D sites were removed if the snowfall observations were either missing. To be included in the NEWINS winter season database, GHCN-D sites had to report a measurable snowfall amount .

After quality control, the ASOS station and GHCN-D site data were subsequently merged into a winter season event database. For each date, hourly ASOS station observations in which frozen precipitation was detected were paired with 24-hour snowfall amounts from the GHCN-D sites that adhered to the spatial and temporal criteria. The snowfall observations and number of hours of ASOS station data for each date and location pair were used to derive a snowfall rate variable by dividing snowfall amounts by the number of hours with frozen precipitation observed. Given the derived nature of the snowfall rate variable, rates in excess of 3 in $hr^{-1}$ (7.62 cm $hr^{-1}$) were removed, given the climatological infrequency of such extreme rates in Nebraska as previously documented by Rasmussen et al. (1999). Another derived variable was "district area" to provide a spatial context for the snowfall. District area was computed by dividing the number of ASOS stations reporting frozen precipitation on a given date in a particular NDOT maintenance district by the total number of ASOS stations possible within that district. Statistical parameters (i.e., minimum, maximum, mean, and median) were computed for all of the available variables from the ASOS stations, GHCN-D sites and derived variables.

### *d. Event Classification*

Temporal resolution and discrepancies within the various data sets presented one of the more difficult challenges for the analysis. Nebraska is divided by the Central and

Mountain time zone demarcations (Figure 3.1). Further, daylight savings ends and begins during the winter season on a non-stationary date. While ASOS data are reported in UTC and not impacted by the aforementioned temporal considerations. GHCN-D data are commonly reported in local time. Moreover, snowfall data from the GHCN-D sites are not consistently reported at the same time given the nature of its component programs (i.e., citizen science). In order to accommodate this range of temporal variability among the data sets, a "snow day" was defined as the 24-hour period preceding the reported snowfall observation with some tolerance for up to a two-hour (i.e., one-hour before or after) discrepancy. The latest local time a snowfall observation could be reported to still count for the same snow day would be 0800 LST or 0900 LDT. For most locations throughout Nebraska in the Central time zone, this leads to the definition of a snow day beginning 1400 UTC of the first day and ending through the 1300 UTC observation of the following day in which the snowfall observation would be taken (Table 3.2). For the western Nebraska locations in the Mountain time zone, this snow day definition would range from the 1500 UTC observation of the first day through the 1400 UTC observation of the following day in which the snowfall observation would be taken (Table 3.3). To provide an example of how a snow day would be defined in both time zones for a hypothetical 1 October snow day in which the snow accumulation period extends from 30 September through 1 October where the snow measurement would be taken are given in Tables 3.2 and 3.3. The purpose of these temporal considerations defines the daily boundaries for events in the winter season database. Meteorological variables observed within these temporal bounds are subsequently used to classify individual daily events. This remedy also allowed for the creation of a zero-based "snow hour" variable which

**Table 3.2.** Central Standard/Daylight Time hypothetical comparison with UTC and Snow Date/Hour.

| Snow Date | Snow Hour | Central Standard Time (UTC-6) | Central Daylight Time (UTC-5) | UTC |
|---|---|---|---|---|
| 10/1/2015 | 0 | 09/30/2015 0800 | 09/30/2015 0900 | 09/30/2015 1400 |
| 10/1/2015 | 1 | 09/30/2015 0900 | 09/30/2015 1000 | 09/30/2015 1500 |
| 10/1/2015 | 2 | 09/30/2015 1000 | 09/30/2015 1100 | 09/30/2015 1600 |
| 10/1/2015 | 3 | 09/30/2015 1100 | 09/30/2015 1200 | 09/30/2015 1700 |
| 10/1/2015 | 4 | 09/30/2015 1200 | 09/30/2015 1300 | 09/30/2015 1800 |
| 10/1/2015 | 5 | 09/30/2015 1300 | 09/30/2015 1400 | 09/30/2015 1900 |
| 10/1/2015 | 6 | 09/30/2015 1400 | 09/30/2015 1500 | 09/30/2015 2000 |
| 10/1/2015 | 7 | 09/30/2015 1500 | 09/30/2015 1600 | 09/30/2015 2100 |
| 10/1/2015 | 8 | 09/30/2015 1600 | 09/30/2015 1700 | 09/30/2015 2200 |
| 10/1/2015 | 9 | 09/30/2015 1700 | 09/30/2015 1800 | 09/30/2015 2300 |
| 10/1/2015 | 10 | 09/30/2015 1800 | 09/30/2015 1900 | 10/1/2015 0000 |
| 10/1/2015 | 11 | 09/30/2015 1900 | 09/30/2015 2000 | 10/1/2015 0100 |
| 10/1/2015 | 12 | 09/30/2015 2000 | 09/30/2015 2100 | 10/1/2015 0200 |
| 10/1/2015 | 13 | 09/30/2015 2100 | 09/30/2015 2200 | 10/1/2015 0300 |
| 10/1/2015 | 14 | 09/30/2015 2200 | 09/30/2015 2300 | 10/1/2015 0400 |
| 10/1/2015 | 15 | 09/30/2015 2300 | 10/1/2015 0000 | 10/1/2015 0500 |
| 10/1/2015 | 16 | 10/1/2015 0000 | 10/1/2015 0100 | 10/1/2015 0600 |
| 10/1/2015 | 17 | 10/1/2015 0100 | 10/1/2015 0200 | 10/1/2015 0700 |
| 10/1/2015 | 18 | 10/1/2015 0200 | 10/1/2015 0300 | 10/1/2015 0800 |
| 10/1/2015 | 19 | 10/1/2015 0300 | 10/1/2015 0400 | 10/1/2015 0900 |
| 10/1/2015 | 20 | 10/1/2015 0400 | 10/1/2015 0500 | 10/1/2015 1000 |
| 10/1/2015 | 21 | 10/1/2015 0500 | 10/1/2015 0600 | 10/1/2015 1100 |
| 10/1/2015 | 22 | 10/1/2015 0600 | 10/1/2015 0700 | 10/1/2015 1200 |
| 10/1/2015 | 23 | 10/1/2015 0700 | 10/1/2015 0800 | 10/1/2015 1300 |

**Table 3.3.** Mountain Standard/Daylight Time hypothetical comparison with UTC and Snow Date/Hour.

| Snow Date | Snow Hour | Mountain Standard Time (UTC-7) | Mountain Daylight Time (UTC-6) | UTC |
|---|---|---|---|---|
| 10/1/2015 | 0 | 09/30/2015 0800 | 09/30/2015 0900 | 09/30/2015 1500 |
| 10/1/2015 | 1 | 09/30/2015 0900 | 09/30/2015 1000 | 09/30/2015 1600 |
| 10/1/2015 | 2 | 09/30/2015 1000 | 09/30/2015 1100 | 09/30/2015 1700 |
| 10/1/2015 | 3 | 09/30/2015 1100 | 09/30/2015 1200 | 09/30/2015 1800 |
| 10/1/2015 | 4 | 09/30/2015 1200 | 09/30/2015 1300 | 09/30/2015 1900 |
| 10/1/2015 | 5 | 09/30/2015 1300 | 09/30/2015 1400 | 09/30/2015 2000 |
| 10/1/2015 | 6 | 09/30/2015 1400 | 09/30/2015 1500 | 09/30/2015 2100 |
| 10/1/2015 | 7 | 09/30/2015 1500 | 09/30/2015 1600 | 09/30/2015 2200 |
| 10/1/2015 | 8 | 09/30/2015 1600 | 09/30/2015 1700 | 09/30/2015 2300 |
| 10/1/2015 | 9 | 09/30/2015 1700 | 09/30/2015 1800 | 10/1/2015 0000 |
| 10/1/2015 | 10 | 09/30/2015 1800 | 09/30/2015 1900 | 10/1/2015 0100 |
| 10/1/2015 | 11 | 09/30/2015 1900 | 09/30/2015 2000 | 10/1/2015 0200 |
| 10/1/2015 | 12 | 09/30/2015 2000 | 09/30/2015 2100 | 10/1/2015 0300 |
| 10/1/2015 | 13 | 09/30/2015 2100 | 09/30/2015 2200 | 10/1/2015 0400 |
| 10/1/2015 | 14 | 09/30/2015 2200 | 09/30/2015 2300 | 10/1/2015 0500 |
| 10/1/2015 | 15 | 09/30/2015 2300 | 10/1/2015 0000 | 10/1/2015 0600 |
| 10/1/2015 | 16 | 10/1/2015 0000 | 10/1/2015 0100 | 10/1/2015 0600 |
| 10/1/2015 | 17 | 10/1/2015 0100 | 10/1/2015 0200 | 10/1/2015 0800 |
| 10/1/2015 | 18 | 10/1/2015 0200 | 10/1/2015 0300 | 10/1/2015 0900 |
| 10/1/2015 | 19 | 10/1/2015 0300 | 10/1/2015 0400 | 10/1/2015 1000 |
| 10/1/2015 | 20 | 10/1/2015 0400 | 10/1/2015 0500 | 10/1/2015 1100 |
| 10/1/2015 | 21 | 10/1/2015 0500 | 10/1/2015 0600 | 10/1/2015 1200 |
| 10/1/2015 | 22 | 10/1/2015 0600 | 10/1/2015 0700 | 10/1/2015 1300 |
| 10/1/2015 | 23 | 10/1/2015 0700 | 10/1/2015 0800 | 10/1/2015 1400 |

would subsequently be used in the analysis to compute snowfall duration.

In close consultation with the NDOT, the following variables were selected for the primary development of the NEWINS: 1) wind speed, 2) visibility, 3) air temperature, 4) duration of snowfall, 5) snowfall, 6) snowfall rate, and 7) district area. These variables were selected on the basis of their reliability from the instrumentation in addition to their importance / impact on NDOT's winter maintenance operations. For inclusion in the winter season database, these weather variables were averaged across each NDOT maintenance district from the available merged ASOS station and GHCN-D site data for each date. Surface (i.e., RWIS) temperature information was not available for the entire historical ten-year period and was therefore not included in the development of the NEWINS.

The winter season database was further modified for use in a categorical data analysis framework. NDOT communicates extensively with its local NWS offices, and it was desirable to create a winter severity index that mirrored existing and possible future NWS products such as the SPC Convective Outlook Severe Thunderstorm Risk Categories (SPC 2016), experimental winter storm threat graphics (NWS 2016), or experimental winter storm severity index (WPC 2018). To this end, in consultation with NDOT, a categorial road weather and winter maintenance operations framework was developed to serve as the foundation for NEWINS (Table 3.4). The objective was to classify individual events within the winter season database into one of six categories from Category 1: trace, low impact storms, no winter maintenance operations activity to Category 6: high, significant impact storms, maximum winter maintenance operations activity with possible suspensions necessary due to safety concerns. This categorical

**Table 3.4.** NEWINS categorical road / maintenance operations impacts.

| **Variable** | **Category** | | | | | |
|---|---|---|---|---|---|---|
| | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** |
| **Road Access** | No Road Closures | No Road Closures | Minimal Road Closures | Occasional Road Closures | Numerous Road Closures | Significant Road Closures |
| **Road Conditions** | Wet Roads | Wet Roads | Spotty snow and ice-covered roads, otherwise wet | Roads partially covered with snow and ice | Roads completely covered with snow and ice | Impassable roads covered with snow and ice |
| **Traffic Speeds** | No speed reduction | No speed reduction | Minimal speed reduction | Considerable speed reduction | Significant speed reduction | Significant speed reduction |
| **Treatment Operations** | No Deployment | Minimal Deployment | Partial Deployment | Full Deployment | Full Deployment | Full Deployment with Possible Operation Suspension |
| **Winter Maintenance Performance Objective** | Met | Met | Likely Met | Unlikely Met | Not Met | Not Met |

framework was designed with specific consideration given to: 1) road access, 2) road conditions, 3) traffic speeds, 4) treatment operations, and 5) NDOT's winter maintenance performance objective. Road access is defined here as whether the road is open and travel by the public is permitted. Road conditions refers to the amount and type of precipitation accumulation within the driving lanes ranging from wet roads to impassable due to snow and ice coverage. Traffic speeds addresses the likely impact of the weather conditions on free-flow travel speeds. NDOT does not consider specific speed thresholds as a prerequisite to define a meteorological impact as impacts can occur at any speed (NDOT 2016, personal communication). Treatment operations refers to NDOT's winter maintenance operations activities including but not limited to chemical or material applications and mechanical plowing from snow removal. Lastly, NDOT's maintenance performance objective is to return roadway speeds to within 10 mph (16 km $hr^{-1}$) of the posted speed limit within six hours of precipitation cessation (NDOT 2016, personal communication). The likelihood of attaining that objective is incorporated into the NEWINS categorical framework.

From the road weather/maintenance operations framework, the seven weather variables selected for the NEWINS were placed into the same categorical framework (Table 3.5). A subjective, manual sensitivity analysis was performed to identify and refine the distribution based on a modified Delphi method approach (Hallowell and Gambatese 2010). The Delphi method considers the opinion of experts in a discipline to provide reasonably objective data. Further, these opinions are provided in an iterative manner to provide consensus among the group of experts. In this instance, transportation and meteorological experts were consulted to provide input regarding which range of

**Table 3.5.** NEWINS categorical weather variable impacts.

| Variable | Category | | | | | |
|---|---|---|---|---|---|---|
| | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** |
| **Snowfall** | Dusting | Light | Light | Considerable | Heavy | Significant |
| **Snowfall Rate** | Minor | Minor | Elevated | Elevated | Intense | Extreme |
| **Wind Speed** | Light | Light | Moderate | Moderate | Strong | Strong |
| **Air Temperature** | Above Freezing | Near / Below Freezing | Below Freezing | Below Freezing | Below Freezing | Well Below Freezing |
| **District Area** | Single Location | Partial | Less Than Half | More Than Half | Majority | Complete |
| **Duration** | Short | Short | Medium | Medium | Long | Long |
| **Visibility** | Good | Good | Fair | Mid-Range | Poor | Poor |

data, for each meteorological parameter, would yield the corresponding road impacts. Snowfall, air temperature and district area were distributed among the six categories to ensure near-even separation across the range of each variable. For example, each snowfall category range varies between 1-2 in. (2.5-5.1 cm) or each air temperature category contained a 5°F (2.8°C) range, excluding the minimum and maximum categories. Snowfall rate, duration and visibility were distributed among the six categories to ensure near-even frequency of observations within each category. Last, wind speed was distributed among the six categories loosely based on a modified Beaufort wind scale (SPC 2018). Table 3.6 shows the specific distribution of each weather variable and its categorical assignment. Cerruti and Decker (2011) proposed a similar approach in the development of their LWSS.

The NEWINS joins a vast array of WSIs, each with their own respective strengths and caveats. As seen from the SHRP WSI (Boselly et al. 1993), the best approach is for a WSI to be tailored specifically to the needs of the state DOT, since broad, versatile WSIs are often inaccurate due to their simplicity or lack of accounting for localized conditions. Given that the NEWINS was designed with respect to a decadal winter season database, it surpasses the SHRP WSI in terms of considering local and regional weather variability. Further, given the ten-year development period, the NEWINS is surpassed only by the AWSSI (Boustead et al. 2015) in terms of its historical period. Further, with the inclusion of 35 ASOS stations distributed throughout eight transportation districts, the NEWINS provides a greater station density than the AWSSI which considers only approximately 50 locations throughout the United States. Important differences between the NEWINS and AWSSI worth highlighting are that the NEWINS averages conditions across all

**Table 3.6.** NEWINS categorical weather variables sorted into categorical classifications.

| **Variable** | **Category** | | | | | |
|---|---|---|---|---|---|---|
| | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** |
| **Snowfall (in.)** ***(cm.)*** | < 1.0 *(< 2.4)* | < 2.0 *(< 4.9)* | < 3.0 *(< 7.5)* | < 5.0 *(< 12.6)* | < 7.0 *(< 17.5)* | ≥ 7.0 *(≥ 17.5)* |
| **Snowfall Rate (in. $hr^{-1}$)** ***(cm $hr^{-1}$)*** | < 0.2 *(< 0.4)* | 0.2 *(< 0.6)* | 0.3 *(< 0.9)* | 0.4 *(< 1.1)* | < 0.6 *(< 1.5)* | ≥ 0.6 *(≥ 1.5)* |
| **Wind Speed (mph)** ***($ms^{-1}$)*** | ≤ 6.0 *(≤ 2.7)* | ≤ 11.0 *(≤ 4.9)* | ≤ 18.0 *(≤ 8.1)* | ≤ 24.0 *(≤ 10.7)* | ≤ 31.0 *(≤ 13.9)* | > 31.0 *(> 13.9)* |
| **Air Temperature (°F)** ***(°C)*** | > 35 *(> 1.7)* | ≤ 35 *(≤ 1.7)* | ≤ 29 *(≤ -1.7)* | ≤ 25 *(≤ -3.9)* | ≤ 19 *(≤ -7.2)* | < 15 *(< -9.4)* |
| **District Area (Fraction Area)** | ≤ 0.2 | < 0.4 | < 0.5 | < 0.75 | < 1.0 | 1.0 |
| **Duration (hr.)** | ≤ 2.0 | ≤ 3.0 | ≤ 4.0 | ≤ 5.0 | ≤ 8.0 | > 8.0 |
| **Visibility (mi.)** ***(km)*** | > 5.0 *(> 8.0)* | ≤ 5.0 *(≤ 8.0)* | < 4.0 *(< 6.4)* | < 3.5 *(< 5.6)* | < 3 *(< 4.8)* | < 2.5 *(< 4.0)* |

ASOS stations within each district and throughout the state to derive a categorical frequency distribution and subsequent severity value. The AWSSI only computes a severity value for point locations (Boustead et al. 2015). Another important difference is that the AWSSI considers daily conditions throughout the entire winter season whereas the NEWINS only considers the conditions and impacts associated with specific snowstorms. One final difference is that the AWSSI establishes strict criteria to define the beginning and end of a winter season whereas the NEWINS is more flexible and allows for the precipitation type (i.e., frozen precipitation) to dictate the temporal boundaries of the winter season. Both approaches are relatively transferrable to other applications.

### *e. Winter Severity Index Computation and Applications*

An important challenge to overcome with the categorical framework is that for any given event during a winter season, the magnitude of the weather variables can be quite different for a single maintenance district or across several maintenance districts experiencing the same event (Table 3.7). To address this challenge, a subjective, manual sensitivity analysis similar to the Delphi approach of Hallowell and Gambatese (2010) was performed. In consultation with NDOT personnel, appropriate weights for the seven weather variables were developed so that a linear combination would yield a single storm categorical classification (Table 3.4) for each event at the district level. Eq. (1) provides the general form of the NEWINS event category. Each weather variable is averaged across the maintenance district and assigned a category based on Table 3.6. Categories for each weather variable are subsequently used in Eq. (1) in lieu of the raw data. This

**Table 3.7.** NEWINS hypothetical events with differences in weather variables.

| Event | Duration | Air Temp | Wind Speed | Visibility | Snowfall | Snow Rate | District Area | Category |
|---|---|---|---|---|---|---|---|---|
| **Event 1 District 1** | Short | Above Freezing | Moderate | Good | Light | Extreme | Single Location | ? |
| **Event 1 District 2** | Long | Below Freezing | Light | Poor | Considerable | Elevated | Complete | ? |
| **Event 2 District 4** | Long | Near / Below Freezing | Moderate | Poor | Considerable | Elevated | More Than Half | ? |
| **Event 2 District 7** | Short | Near / Below Freezing | Light | Poor | Considerable | Extreme | Single Location | ? |
| **Event 2 District 8** | Long | Well Below Freezing | Strong | Poor | Heavy | Elevated | Majority | ? |
| **Event 3 District 6** | Short | Well Below Freezing | Moderate | Mid-Range | Light | Extreme | Less Than Half | ? |

results in the NEWINS event categorical frequency distribution. Table 3.8 provides the final weights assigned to each weather variable category.

$$Category = \beta_1 \times Snowfall\ Cat + \beta_2 \times Snow\ Rate\ Cat + \beta_3 \times Wind\ Speed\ Cat + \beta_4 \times Air\ Temp\ Cat + \beta_5 \times District\ Area\ Cat + \beta_6 \times Duration\ Cat + \beta_7 \times Visibility\ Cat \quad (1)$$

From the categorical frequency distribution, the final NEWINS value is computed according to Eq. (2).

$$NEWINS = \frac{\sum(Category \times Frequency)}{100} \quad (2)$$

This provides the final statewide NEWINS value for a given season. It can also be used to compute an NEWINS value for each individual NDOT maintenance district which can be summed to yield the same final statewide value. The mathematical linear combination / parameter weighting framework of the NEWINS is similar to that used by Wisconsin, Minnesota, Indiana, Illinois, and Pennsylvania for their respective WSIs (Cohen 1981; Strong et al. 2005). An important difference, though, is that the mathematical framework incorporates a categorical framework. Unlike the aforementioned WSIs, though more similar to Iowa (Carmichael et al. 2004; Nixon and Qui 2005; Strong et al. 2005; Qui 2008; Walsh 2016), the NEWINS is an event-based WSI. It considers specific snowstorms in its computation. Limitations of Iowa’s WSI, though, are that it does not consider a complete set of relevant variables important to winter maintenance operations (e.g., areal coverage, duration, snowfall rate, visibility) unlike the NEWINS. In terms of a dependent variable, the NEWINS is substantially different from the California, Montana, Oregon, Idaho and Colorado WSIs (Strong et al. 2005; Jensen et al. 2013; Walsh 2016) in that it is a pure meteorological index (like the

**Table 3.8.** NEWINS event category linear combination equation weights.

| Parameter | NEWINS Parameter Weight |
|---|---|
| **Snowfall Category ($\beta_1$)** | 0.80 |
| **Snow Rate Category ($\beta_2$)** | 0.05 |
| **Wind Speed Category ($\beta_3$)** | 0.05 |
| **Air Temp Category ($\beta_4$)** | 0.05 |
| **District Area Category ($\beta_5$)** | 0.02 |
| **Duration Category ($\beta_6$)** | 0.02 |
| **Visibility Category ($\beta_7$)** | 0.01 |

AWSSI) and not related to accident rate or grip measurements. It is feasible for future correlation of the NEWINS to transportation-related variables; however, no such data are presently available over the entire historical period.

To ensure the reliability of the NEWINS and its components, several different indices were computed and subsequently compared to the NEWINS. An initial snowfall-based index was computed statewide and for each NDOT maintenance district by comparing the number of days with observed frozen precipitation as identified from the ASOS station data (i.e., snow days) to the number of days with observed snow accumulation as identified from the GHCN-D site data (i.e., snowfall days). A second snowfall-based index was computed statewide and for each maintenance district comparing each winter season's total accumulated snowfall to the ten-year average snowfall accumulation. For an independent climate-based index, temperature and precipitation anomalies were obtained from the NOAA NCEI climate division (Figure 3.4) data (ESRL 2017). Nebraska contains eight climate districts which roughly align with NDOT's eight maintenance districts. Additionally, applications of the NEWINS were performed including a K-means cluster analysis for validation of the storm classification approach, an example correlation of 2015-16 winter season storm classification to available NDOT traffic speed data, and an analysis of a winter season (i.e., 2016-17) beyond the decadal winter season database used for the development of the NEWINS. The NEWINS was not explicitly compared to the AWSSI or LWSS due to lack of available raw data and different spatial resolutions. The NEWINS is computed for entire regions (i.e., statewide, district level), while the AWSSI is point-based.

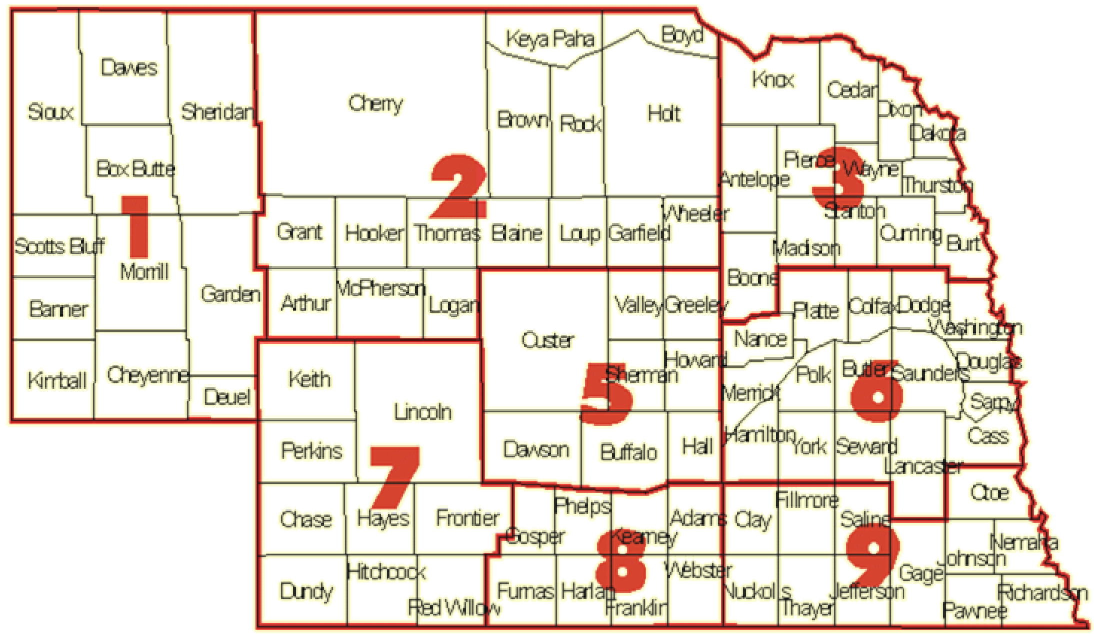


**Figure 3.4.** NOAA NCEI Nebraska climate districts (CPC 2018).

# 4. Results and Discussion

Multiple tasks led to the development of the NEWINS and are presented by subsections within this chapter. The first task was a winter maintenance operations and winter severity index questionnaire which was developed, distributed and will be discussed to aid the formulation of the NEWINS. The second task was the development and refinement of the NEWINS event classification and mathematical formulas. To provide context and highlight the strengths of the NEWINS, the third task was a comparison analysis of various meteorological indices. Furthermore, the fourth task provides a more in-depth consideration of the NEWINS at the statewide and district levels given the intended use of the NEWINS by NDOT. To validate the NEWINS results, the fifth task assessed the NEWINS in the context of a K-means cluster analysis. To apply the NEWINS, the sixth task compared the NEWINS to 2015-16 winter maintenance performance data across Interstate 80 test sections. The final task will ensure the reproducibility of the NEWINS methods by computing and comparing the 2016-17 winter season values to the decadal (i.e., 2006-2016) winter seasons.

## *a. Initial Winter Maintenance Operations and Severity Index Survey*

The primary research objective is attained through the documented creation of the NEWINS. To develop the NEWINS, a questionnaire was developed and distributed to various state DOTs to provide guidance for data collection and variable inclusion considerations. Further, the survey complemented the existing literature documenting other WSIs. The results of the questionnaire (Dao et al. 2018) given to 31 state DOTs that were members of the Clear Roads research consortium yielded a 100% response rate and revealed that, in terms of importance of various weather variables, most respondents rated snowfall, road temperature, and freezing rain as important or very important (Table 4.1). Respondents also mentioned other weather variables that appear to be important to their winter maintenance operations, including frost, cloud cover, storm duration, dew point, humidity, intensity, timing, rate of change, and black ice. Unfortunately, there is no detailed record of freezing rain and black ice, for example, to include these in a WSI. The questionnaire asked respondents for their primary source for weather information, which was in general the NWS before, during, and after a storm (Table 4.2). The next largest response was private weather consulting companies. Results did reveal that it was more common to obtain weather forecast information before a storm rather than during or after an event. Regardless of the specific source and time period for information acquisition, forecasts of air temperature, wind, and snow occurrence were perceived to be most accurate, while forecasts of snow amount and freezing rain were perceived to have the lowest accuracy (Table 4.3).

With respect to how the weather influences their operations, almost all the responding state DOTs (97%) suggested that any forecast of snow would initiate preparations before a storm, and 61% of the responding state DOTs indicated that a forecast for freezing rain, high wind, frost, black ice, freezing fog, or any precipitation with temperatures near or below 32°F (0°C) would also initiate advance preparations. Prior to a storm, 47% of responding state DOTs preferred accurate weather information three days before for winter maintenance operations decisions; 36% of responding state DOTs preferred a two-day lead time; and 17% said the forecast less than one day in

**Table 4.1.** The importance of weather variables for winter maintenance operations. The value represents the number of state DOTs and the percentage of the total respondents.

| Level of importance | Snowfall | Air Temp. | Road Temp. | Wind | Blowing/ Drifting | Freezing Rain |
|---|---|---|---|---|---|---|
| Very Important | 28 (90%) | 12 (39%) | 28 (90%) | 14 (45%) | 13 (42%) | 24 (77%) |
| Elevated Importance | 1 (3.5%) | 8 (26%) | 2 (6.5%) | 9 (29%) | 11 (35%) | 3 (10%) |
| Moderately Important | 2 (6.5%) | 7 (23%) | 1 (3.5%) | 5 (16%) | 5 (16%) | 2 (6%) |
| Less Importance | 0 (0%) | 3 (10%) | 0 (0%) | 1 (3.5%) | 2 (6%) | 2 (6%) |
| Not Important | 0 (0%) | 1 (3%) | 0 (0%) | 2 (6.5%) | 0 (0%) | 0 (0%) |

**Table 4.2.** Sources of weather forecast information used by state DOTs at different stages of a storm. The values represent the number of responses.

| **Weather Information Source** | **Before Storm** | **During Storm (while snowing)** | **Post-Storm** | **Not Used** |
|---|---|---|---|---|
| National Weather Service | 30 | 26 | 18 | 1 |
| Private weather consulting company | 21 | 20 | 16 | 5 |
| Mobile application on smartphone or tablet | 19 | 20 | 15 | 4 |
| Local TV / radio | 19 | 14 | 9 | 5 |
| Maintenance decision support system | 14 | 12 | 11 | 7 |
| Internal meteorologist on staff | 11 | 8 | 7 | 11 |
| The Weather Channel | 11 | 7 | 4 | 10 |
| Newspaper | 3 | 1 | 1 | 16 |

**Table 4.3.** The perception of forecast accuracy for different weather variables. The value represents the number of state DOTs and the percentage of the total respondents.

| Level of Accuracy | Snow Occurrence | Snow Amount | Air Temp. | Road Temp. | Wind | Blowing/ Drifting | Freezing Rain |
|---|---|---|---|---|---|---|---|
| Very Accurate | 5 (16%) | 2 (6%) | 6 (19%) | 3 (10%) | 4 (13%) | 2 (7%) | 2 (7%) |
| Elevated Accuracy | 16 (52%) | 12 (39%) | 20 (65%) | 15 (48%) | 18 (58%) | 15 (50%) | 12 (40%) |
| Moderately Accurate | 9 (29%) | 14 (45%) | 4 (13%) | 10 (32%) | 8 (26%) | 11 (37%) | 12 (40%) |
| Less Accuracy | 1 (3%) | 3 (10%) | 0 (0%) | 1 (3%) | 1 (3%) | 2 (7%) | 4 (13%) |
| Not Accurate | 0 (0%) | 0 (0%) | 0 (0%) | 1 (3%) | 0 (0%) | 0 (0%) | 0 (0%) |

advance was enough time to initiate decisions. Most responding state DOTs (94%) indicated that they pre-treat the roads, though two state DOTs reported that they do not pre-treat roads. Most of the responding state DOTs (75%) indicated that they begin deploying their operation activities (e.g., plowing, material spreading excluding pre-treatment) once snowfall begins; however, some states do not begin deployment until a certain amount of snowfall accumulates on the road surface (e.g., road pavement accumulation of 0.5-1 in. [1.3-2.5 cm] of snow, depending on the event condition and snowfall intensity). Thirty-two percent of the responding state DOTs deployed once they have a request from law enforcement.

Regarding the use of a WSI, 15 out of 31 states responded that they use a WSI for winter maintenance operations. Of the 16 responding states that do not use a WSI, 14 states are interested in developing a WSI. Twenty percent of WSI users rated its accuracy as “Very Accurate,” 53% as “Moderately Accurate,” and 7% rated it as “Minimally Accurate.” With the follow-up questionnaire, state DOTs were asked to provide additional information on WSI practices. Among the nine state DOTs who provided complete responses, four of them responded that the WSIs they are using were developed by their internal staff (Figure 4.1). Four state DOTs reported that the indices had been developed for them by private weather consultants. Only one state reported that they are using a pre-existing WSI to measure their performance, and no states responded that their developed WSI was a part of a university research collaboration. This result highlights the significance of the NEWINS development as fostering groundbreaking collaborations.

The state DOTs were also asked to provide the factors that account for the

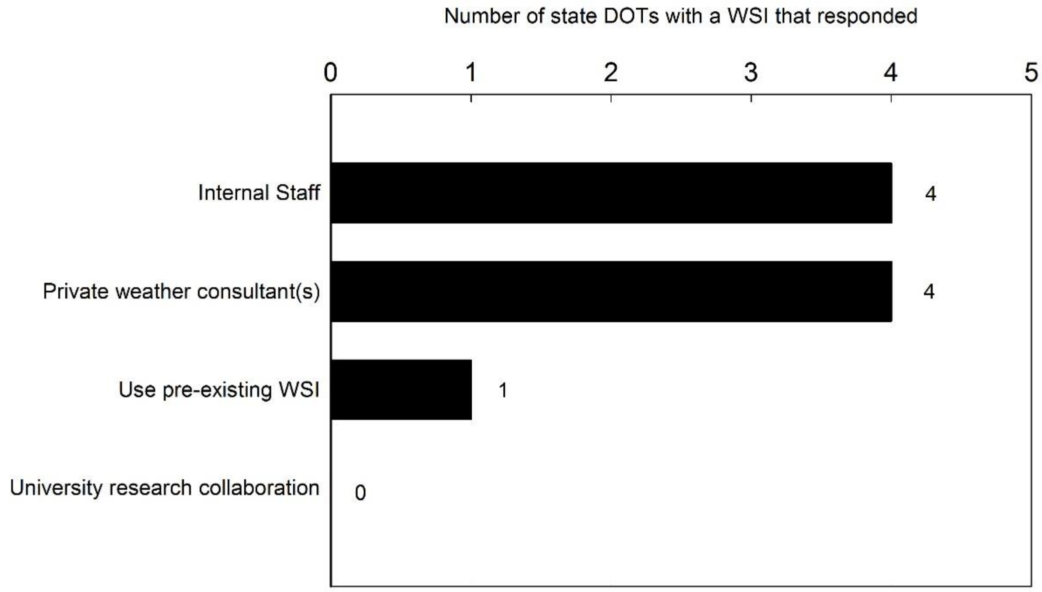


**Figure 4.1.** Organizations which developed the WSI for state DOTs.

accuracy or inaccuracy of their WSIs. The most frequently reported factors accounting for the accuracy of a WSI are air temperature and snowfall amount. For the inaccuracy, three states responded that weather and maintenance operations data are the factor that usually decreases the accuracy of their WSIs, while the other states indicated different factors such as scoring methodology, freezing rain, and visibility.

Regarding the time scale used to compute WSI, most states reported that a daily timeframe is the preferred time scale for their WSI. Some states indicated that even if the mathematical formula of a WSI is daily or hourly, it can be computed whenever needed during the season as well as at the end of a season. The Vermont Agency of Transportation responded that they are using two different indices. Their internal WSI includes daily RWIS data and their external WSI is a private weather consultant's seasonal WSI. Regarding spatial scale, four out of nine states said that their WSI is computed using county regions as the spatial boundary. The five other states used different spatial boundaries for their indices, such as individual road segments, districts, or a single statewide value.

When asked which factors could help to improve their WSI, Pennsylvania DOT reported that omitting the "snow removal cost" portion of the WSI could be helpful due to the variability of snow removal costs such as urban versus rural areas. Additionally, being able to have more granular spatial scale or being able to calculate the WSI more frequently than at seasonal time scales could improve accuracy. This result suggests that the NEWINS should be flexible enough to consider a variety of spatial and temporal resolutions and not necessarily be developed specifically for winter maintenance operations data due to cost variability. More details of weather conditions (e.g., precipitation, blowing snow, visibility) and better accuracy of weather data were also reported as ways to improve a state DOTs performance as these variables are challenging for WSI inclusion.

The follow-up questionnaire results also show that the most important purpose for which state DOTs use WSIs is to improve their performance. Once you improve your performance, the budgetary factors then will change which also corresponds with the next most important parameter, expense verification (Figure 4.2). WSI use varied across the different state DOTs. Some states used their WSI annually as a reference only for internal staff to see how their winter severity compared to different years, while other respondents used the WSIs quarterly, monthly, weekly, or even daily to track the use of maintenance materials. For example, salt use tracking was reported by Iowa DOT. South Dakota DOT reported that their WSI is calculated monthly for statewide related crash rates and at the end of each winter season to calculate a total winter related crash rate. It should be noted that South Dakota and Rhode Island in the questionnaire stated that they had WSIs, though their WSI documentation was not discovered during the literature review. In other states, the WSI is used at times throughout the winter season to do a cost comparison of routes, shops, and other administrative units.

Regarding the weather parameters that are included in the WSIs, the results from the follow-up questionnaire (Figure 4.3) indicate that snow amount is included in most WSIs (7 out of 9 WSIs). Freezing rain is the second parameter that is most frequently used in WSIs; however, its application is poorly documented in the WSI literature. Further, validation of freezing rain observations and ice accumulation data were not available for the NEWINS study period. Other weather parameters were included in

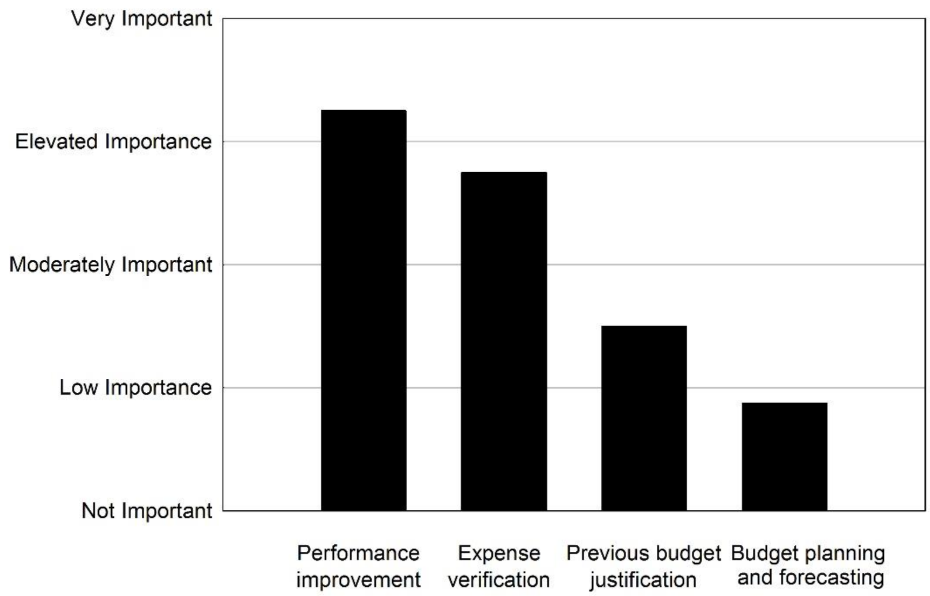


**Figure 4.2.** Purpose of using WSI in Importance Order. The height of the bar represents the relative average score from the respondents for the importance of each option.

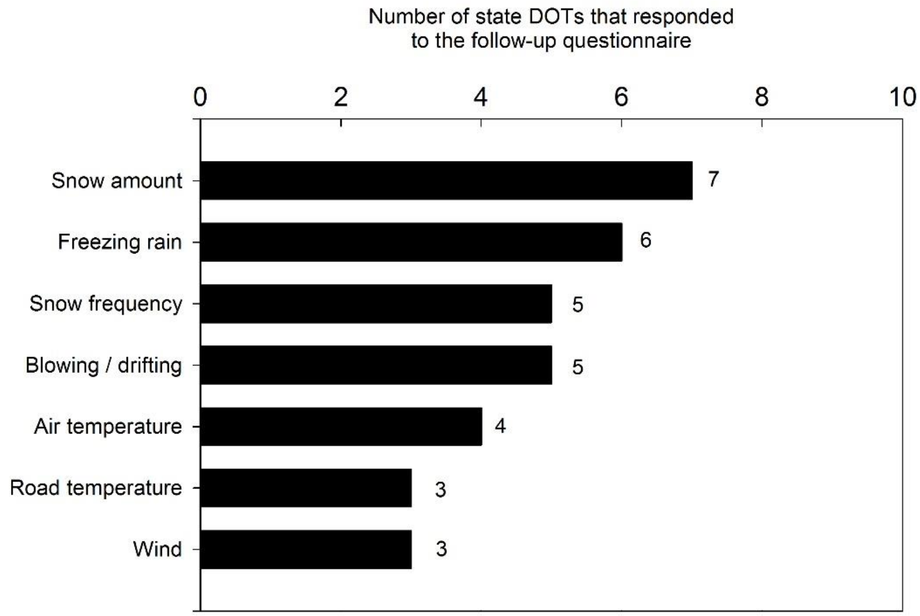


**Figure 4.3.** The number of state DOTs using particular weather parameters included in their WSI, more than one parameter could be chosen.

WSIs a varying number of times. The follow-up questionnaire results show that the most important WSI variable is snow duration, while visibility is ranked the least important WSI variable (Figure 4.4). Calculating the average scores of responses indicated that the order of importance variables that should be included in WSIs are: snow duration, snow intensity, snow amount, air temperature, wind speed, and visibility. While the variables relevant to snow are usually considered to be the most important WSI variables, it is important to note that snow amount is incorporated in the greatest number of WSIs (Figure 4.3); however, the importance of snow amount is not first when the importance of weather variables is considered (Figure 4.4). These results influenced the framework and development of the NEWINS.

Most state DOTs indicated that measuring winter maintenance performance helps them improve decision processes relating to snow and ice control and internal and external communications. According to the questionnaire results, all state DOTs that responded were collecting and using weather data in their planning and decision-making activities for winter maintenance operations, which shows an improvement over the past decade (Maze et al. 2007). While all weather variables are considered important, wind and air temperature exhibit the widest range of responses among the respondents, an outcome reasonably attributed to geographical variation. Additionally, a notable finding indicated that no matter which source generated weather forecast information, most states used the forecast data before a winter storm, with usage decreasing both during and after a storm. This result suggests that state DOTs are more dependent on weather forecast information for planning purposes (e.g., scheduling personnel, loading, and staging equipment) rather than tactical purposes (e.g., specific treatment areas, material

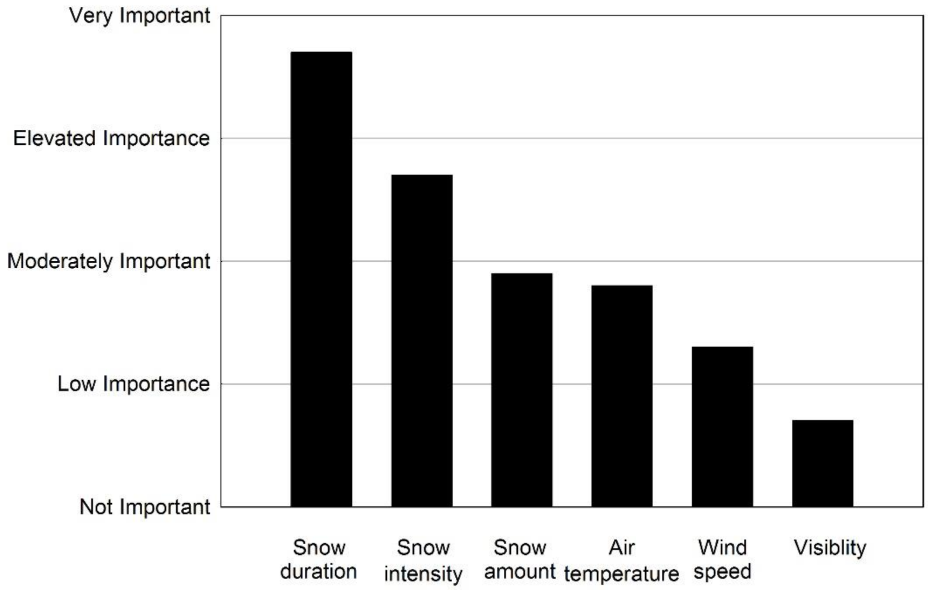


**Figure 4.4.** Importance of weather variables in WSI. The height of the bar represents the average score from the respondents for the importance.

recommendations). The results further corroborate this idea, as most states noted that three days is the preferred timeframe for receiving accurate weather forecast information (Table 4.2). Furthermore, respondents generally viewed weather forecasts as accurate, though they perceived both snow quantity and the occurrence of freezing rain as having the highest inaccuracy. This view implies that a high degree of error still occurs in certain elements of weather forecasts, a fact that can impede state DOT snow and ice control operation plans. The results of this questionnaire suggest that to improve safety and mobility in winter maintenance operations, it might be better for state DOTs to partner with the weather enterprise to obtain more accurate weather data and better interpretation of existing weather data.

Despite the significant reliance on weather information and forecasts, only half of the state DOTs reported that they used a WSI. This result highlights a disconnect in the use of weather information as all state DOTs rely on critical, tactical, in-situ weather information (Tables 4.1-4.3), however, only those state DOTs with a WSI explicitly consider long-term trends and strategic weather information for long-range budget planning, budget justification and performance improvement purposes (Figure 4.2). The weather variables considered within most WSIs (Figures 4.3 and 4.4) were not dissimilar from the critical weather information for winter maintenance operations (Table 4.1). An interesting contradiction was that the state DOTs did highlight the importance of an explicit “visibility” consideration within their WSI; however, visibility was more of a derived quantity from the weather forecast information (i.e., snowfall rate and wind speed). This information is useful for the weather enterprise to ensure forecasts are tailored to address and highlight the needs of its diverse group of end-users. Most of the remaining state DOTs without a WSI did note that there was interest in developing one suited for their operations. These findings underscore future avenues for research and collaboration between state DOTs and the weather enterprise to create new WSIs and refine existing ones. The questionnaire results also suggest that to ensure the success of the NEWINS, NDOT must be consulted extensively before, during and after its development.

*b. Event Classification and Winter Severity Index Development*

A sensitivity analysis refined the parameter weights for event classification to ultimately create the NEWINS. To develop and refine the categorical variable assignment (Table 3.6) in addition to the variable weights (Table 3.8), a subjective, manual analysis following a modified Delphi method approach was performed initially on the 2015-16 winter season, and then the 2009-10 winter season. Initially, nine NDOT personnel manually classified a subset of 16 cases from the two winter seasons and provided preliminary variable weights (Figure 4.5). The specific weights were not incorporated explicitly into the NEWINS; however, the preliminary NDOT weights provided a relative magnitude for each weather variable. After establishing classification consistency between the NDOT personnel and the research team, a panel of three research collaborators manually classified all district-level events for the two winter seasons. This manual classification was iterated three times with the target objective of reaching and maintaining consistency in the categorical frequency distribution of the three researchers. Once consistency was established via the manual classification, sensitivity analyses were performed to identify the appropriate categorical variable assignment and weights.

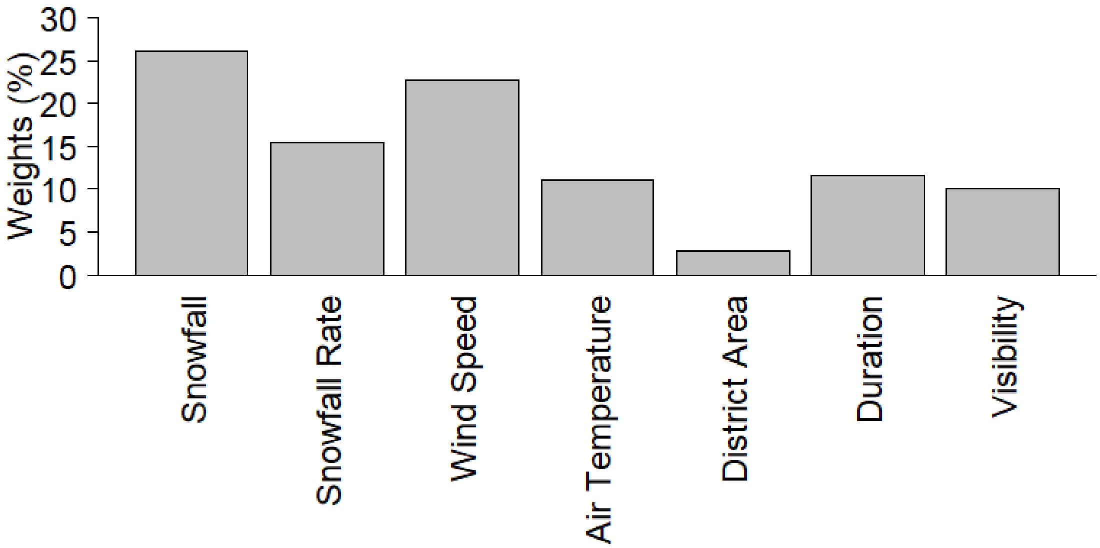


**Figure 4.5.** Nebraska DOT personnel preliminary parameter weights for seven weather variables incorporated into the NEWINS.

Initially, two approaches for categorical variable assignment were conducted. First, variables were assigned in the interest of ensuring equal-sized categories across the range of each variable (Table 4.4). A second technique sought to produce variable assignment in accordance with an equal frequency distribution of observations within each category for each variable (Table 4.5). For both approaches, various parameter weights were attempted in order to match the manually classified distributions (Table 4.6) resulting in eight methods. Methods 1-4were applied to the first categorical variable assignment approach (i.e., equal length distributions, Table 4.4). Methods 5-8 were applied to the second categorical variable assignment (i.e., equal observation distributions, Table 4.5). Methods 1 and 5 assigned equal parameter weights across all seven variables with the only difference being which categorical variable assignment each method was applied to. Similarly, Methods 2 and 6 sought to vary the parameter weights while maintaining consistency with NDOT's recommendation that snow, snow rate, wind speed and temperature had the greatest importance. Methods 3 and 7 sought to modify the weights such that in the event of colder events, the increased likelihood of blowing snow would be represented more significantly while still maintaining an independent weight for temperature itself. Finally, Methods 4 and 8 maintained a conditional parameter weight for wind speed dependent on temperature; however, temperature itself was no longer explicitly considered in the linear combination framework (i.e., parameter weight was assigned zero for air temperature).

Both initial categorical assignment approaches and all eight corresponding parameter weighting methods failed to accurately represent the manually classified distribution (Tables 4.7 and 4.8). The individual researcher classifications and their

**Table 4.4.** NEWINS categorical weather variables sorted into categorical classifications based on subjective equal length distribution for 2015-16 winter season Methods 1-4.

| Variable | Category | | | | | |
|---|---|---|---|---|---|---|
| | Trace (1) | Marginal (2) | Slight (3) | Enhanced (4) | Moderate (5) | High (6) |
| **Snowfall (in.)** ***(cm.)*** | < 1.0 *(< 2.4)* | < 2.0 *(< 4.9)* | < 3.0 *(< 7.5)* | < 5.0 *(< 12.6)* | < 7.0 *(< 17.5)* | ≥ 7.0 *(≥ 17.5)* |
| **Snowfall Rate (in. $hr^{-1}$)** ***(cm $hr^{-1}$)*** | < 0.5 *(< 1.1)* | < 1.0 *(< 2.4)* | < 1.5 *(< 3.7)* | < 2.0 *(< 4.9)* | < 3.0 *(< 7.5)* | ≥ 3.0 *(≥ 7.5)* |
| **Wind Speed (mph)** ***($ms^{-1}$)*** | ≤ 6.0 *(≤ 2.7)* | ≤ 11.0 *(≤ 4.9)* | ≤ 18.0 *(≤ 8.1)* | ≤ 24.0 *(≤ 10.7)* | ≤ 31.0 *(≤ 13.9)* | > 31.0 *(> 13.9)* |
| **Air Temperature (°F)** ***(°C)*** | > 35 *(> 1.7)* | ≤ 35 *(≤ 1.7)* | ≤ 29 *(≤ -1.7)* | ≤ 25 *(≤ -3.9)* | ≤ 19 *(≤ -7.2)* | < 15 *(< -9.4)* |
| **District Area (Fraction Area)** | ≤ 0.2 | < 0.4 | < 0.5 | < 0.75 | < 1.0 | 1.0 |
| **Duration (hr.)** | ≤ 4.0 | ≤ 8.0 | ≤ 12.0 | ≤ 16.0 | ≤ 20.0 | ≤ 24.0 |
| **Visibility (mi.)** ***(km)*** | > 7.0 *(> 11.3)* | ≤ 5.0 *(≤ 8.0)* | ≤ 4.0 *(≤ 4.8)* | < 3 *(< 4.8)* | < 2 *(< 3.2)* | ≤ 1 *(≤ 1.6)* |

**Table 4.5.** NEWINS categorical weather variables sorted into categorical classifications based on equal length observation frequency for 2015-16 winter season Methods 5-8.

| **Variable** | **Category** | | | | | |
|---|---|---|---|---|---|---|
| | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** |
| **Snowfall (in.)** ***(cm.)*** | < 0.3 *(< 0.8)* | < 0.5 *(< 1.1)* | < 0.8 *(< 1.9)* | < 1.2 *(< 3.1)* | ≤ 2.2 *(≤ 5.6)* | > 2.2 *(> 5.6)* |
| **Snowfall Rate (in. $hr^{-1}$)** ***(cm $hr^{-1}$)*** | < 0.2 *(< 0.4)* | 0.2 *(< 0.6)* | 0.3 *(< 0.9)* | 0.4 *(< 1.1)* | < 0.6 *(< 1.5)* | ≥ 0.6 *(≥ 1.5)* |
| **Wind Speed (mph)** ***($ms^{-1}$)*** | ≤ 6.0 *(≤ 2.7)* | ≤ 9.0 *(≤ 4.0)* | ≤ 12.0 *(≤ 5.4)* | ≤ 16.0 *(≤ 7.2)* | ≤ 19.0 *(≤ 8.5)* | > 19 *(> 8.5)* |
| **Air Temperature (°F)** ***(°C)*** | ≥ 33 *(≥ 0.6)* | < 33 *(< 0.6)* | < 31.0 *(< -0.6)* | < 29.0 *(< -1.7)* | < 27.0 *(< -2.8)* | < 23.0 *(< -5.0)* |
| **District Area (Fraction Area)** | ≤ 0.2 | < 0.4 | < 0.5 | < 0.75 | < 1.0 | 1.0 |
| **Duration (hr.)** | ≤ 2.0 | ≤ 3.0 | ≤ 4.0 | ≤ 5.0 | ≤ 8.0 | > 8.0 |
| **Visibility (mi.)** ***(km)*** | > 5.0 *(> 8.0)* | ≤ 5.0 *(≤ 8.0)* | < 4.0 *(< 6.4)* | < 3.5 *(< 5.6)* | < 3 *(< 4.8)* | < 2.5 *(< 4.0)* |

**Table 4.6.** NEWINS event category linear combination equation weights for 2015-16 manual sensitivity analysis various methods.

| Parameter | Method 1 | Method 2 | Method 3 | Method 4 | Method 5 | Method 6 | Method 7 | Method 8 |
|---|---|---|---|---|---|---|---|---|
| **Snowfall Category ($\beta_1$)** | 0.143 | 0.4 | 0.4 | 0.4 | 0.143 | 0.4 | 0.4 | 0.4 |
| **Snow Rate Category ($\beta_2$)** | 0.143 | 0.2 | 0.2 | 0.2 | 0.143 | 0.2 | 0.2 | 0.2 |
| **Wind Speed Category ($\beta_3$)** | 0.143 | 0.2 | If T<25, 0.3 else 0.2 | If T<25, 0.3 else 0.2 | 0.143 | 0.2 | If T<25, 0.3 else 0.2 | If T<27, 0.3 else 0.2 |
| **Air Temp Category ($\beta_4$)** | 0.143 | 0.1 | If T<25, 0.05 else 0.1 | 0 | 0.143 | 0.1 | If T<25, 0.05 else 0.1 | 0 |
| **District Area Category ($\beta_5$)** | 0.143 | 0.04 | If T<25, 0.02 else 0.04 | If T<25, 0.04 else 0.08 | 0.143 | 0.04 | If T<25, 0.02 else 0.04 | If T<27, 0.04 else 0.08 |
| **Duration Category ($\beta_6$)** | 0.143 | 0.04 | If T<25, 0.02 else 0.04 | If T<25, 0.04 else 0.08 | 0.143 | 0.04 | If T<25, 0.02 else 0.04 | If T<27, 0.04 else 0.08 |
| **Visibility Category ($\beta_7$)** | 0.143 | 0.02 | If T<25, 0.01 else 0.02 | If T<25, 0.02 else 0.04 | 0.143 | 0.02 | If T<25, 0.01 else 0.02 | If T<27, 0.02 else 0.04 |

**Table 4.7.** Three researcher (R1-3) 2015-16 winter season database event classifications, their respective averages, median, and corresponding method (M1-8) classifications.

| Category | R1 | R2 | R3 | Avg. | Med. | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 143 | 125 | 140 | 136 | 136 | 6 | 33 | 50 | 22 | 1 | 9 | 10 | 4 |
| **2** | 54 | 81 | 46 | 60 | 61 | 135 | 162 | 147 | 152 | 44 | 49 | 57 | 48 |
| **3** | 27 | 19 | 42 | 30 | 28 | 98 | 41 | 39 | 56 | 85 | 76 | 73 | 68 |
| **4** | 15 | 11 | 19 | 17 | 15 | 15 | 17 | 17 | 20 | 81 | 67 | 63 | 60 |
| **5** | 14 | 12 | 7 | 10 | 13 | 0 | 1 | 1 | 4 | 40 | 43 | 41 | 48 |
| **6** | 1 | 6 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 3 | 10 | 10 | 26 |

**Table 4.8.** Linear combination weighting method frequency distribution (i.e., freq) of differences for 2015-16 winter season from average difference (ADiff) and median difference (MDiff), zero row identifies "success."

| **Method 1** | | **Method 2** | | **Method 3** | | **Method 4** | | **Method 5** | | **Method 6** | | **Method 7** | | **Method 8** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ADiff | Freq | ADiff | Freq | ADiff | Freq | ADiff | Freq | ADiff | Freq | ADiff | Freq | ADiff | Freq | ADiff | Freq |
| -2 | 3 | -2 | 1 | -2 | 1 | -2 | 1 | -2 | 0 | -2 | 0 | -2 | 0 | -2 | 0 |
| -1 | 20 | -1 | 28 | -1 | 29 | -1 | 18 | -1 | 0 | -1 | 0 | -1 | 0 | -1 | 0 |
| 0 | 63 | 0 | 112 | 0 | 129 | 0 | 92 | 0 | 14 | 0 | 18 | 0 | 20 | 0 | 7 |
| 1 | 150 | 1 | 113 | 1 | 95 | 1 | 142 | 1 | 95 | 1 | 90 | 1 | 103 | 1 | 73 |
| 2 | 18 | 2 | 0 | 2 | 0 | 2 | 1 | 2 | 114 | 2 | 120 | 2 | 106 | 2 | 127 |
| 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 31 | 3 | 26 | 3 | 25 | 3 | 45 |
| 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 2 |
| **Method 1** | | **Method 2** | | **Method 3** | | **Method 4** | | **Method 5** | | **Method 6** | | **Method 7** | | **Method 8** | |
| MDiff | Freq | MDiff | Freq | MDiff | Freq | MDiff | Freq | MDiff | Freq | MDiff | Freq | MDiff | Freq | MDiff | Freq |
| -2 | 6 | -2 | 2 | -2 | 2 | -2 | 2 | -2 | 0 | -2 | 0 | -2 | 0 | -2 | 0 |
| -1 | 18 | -1 | 29 | -1 | 30 | -1 | 19 | -1 | 0 | -1 | 0 | -1 | 0 | -1 | 0 |
| 0 | 61 | 0 | 110 | 0 | 127 | 0 | 90 | 0 | 18 | 0 | 20 | 0 | 22 | 0 | 7 |
| 1 | 151 | 1 | 113 | 1 | 95 | 1 | 142 | 1 | 90 | 1 | 89 | 1 | 102 | 1 | 77 |
| 2 | 18 | 2 | 0 | 2 | 0 | 2 | 1 | 2 | 115 | 2 | 119 | 2 | 105 | 2 | 122 |
| 3 | 0 | 3 | 0 | 3 | 0 | 3 | 0 | 3 | 31 | 3 | 26 | 3 | 25 | 3 | 46 |
| 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 0 | 4 | 2 |

respective averages and medians suggest a target frequency distribution that is right-tailed, with highest frequencies for Category 1 events and lowest frequencies for Category 6 events. A similar distribution was observed by Cerruti and Decker (2011) in their LWSS. The methods all failed to produce a similar distribution to the manual distribution, with the greatest frequencies on average observed in the intermediate Category 2 and 3 events. An assessment of the average difference between the categories produced among the methods and the average/median of the manually classification revealed a consistent error of at least one category (Table 4.8). Methods 3 and 4 performed the best of the various approaches; however, there were still substantial instances of categorical assignment error.

To overcome these assignment errors a hybrid categorical variable assignment approach was developed. Snowfall, wind speed, air temperature, and district area were distributed according to the first approach maintaining equal length distributions. Snowfall rate, duration and visibility were distributed according to the second approach maintaining equal observation distributions. This categorical variable assignment was eventually selected to represent the frequency distribution for the final NEWINS (Table 3.6). To determine appropriate parameter weights, a simple linear regression was performed on the average of the manual classifications from the three researchers to determine a suitable weight for the variables (Method 9; Table 4.9). Then, only the parameter weight for snowfall from the simple linear regression was utilized and the remaining weights were determined in consultation with NDOT to ensure the weights summed to one (Method 10; Table 4.9). The distributions of both approaches were highly similar and aligned well with the manually classification distributions (Table 4.10).

**Table 4.9.** Second round linear combination equation weights.

| Parameter | Method 9 | Method 10 |
|---|---|---|
| **Intercept ($\beta_0$)** | -0.30 | 0.00 |
| **Snowfall Category ($\beta_1$)** | 0.80 | 0.80 |
| **Snow Rate Category ($\beta_2$)** | 0.02 | 0.05 |
| **Wind Speed Category ($\beta_3$)** | 0.09 | 0.05 |
| **Air Temp Category ($\beta_4$)** | 0.04 | 0.05 |
| **District Area Category ($\beta_5$)** | 0.09 | 0.02 |
| **Duration Category ($\beta_6$)** | -0.04 | 0.02 |
| **Visibility Category ($\beta_7$)** | 0.01 | 0.01 |

**Table 4.10.** Three researcher (R1-3) 2015-16 winter season database event classifications, their respective averages, median, and corresponding second round method (M9-10) classifications.

| Category | R1 | R2 | R3 | Avg. | Med. | M9 | M10 |
|---|---|---|---|---|---|---|---|
| **1** | 143 | 125 | 140 | 136 | 136 | 132 | 132 |
| **2** | 54 | 81 | 46 | 60 | 61 | 64 | 64 |
| **3** | 27 | 19 | 42 | 30 | 28 | 29 | 25 |
| **4** | 15 | 11 | 19 | 17 | 15 | 20 | 19 |
| **5** | 14 | 12 | 7 | 10 | 13 | 9 | 12 |
| **6** | 1 | 6 | 0 | 1 | 1 | 0 | 2 |

Given the similarity between the two approaches, the simplicity of Method 10's final equation, and its greater accuracy classifying higher end (i.e., Category 6) events, Method 10 was selected to move forward for the final NEWINS (Table 3.8). To further validate the decision to proceed with Method 10 as the NEWINS, corresponding NEWINS values were computed from the individual and average classifications of three researchers for the 2009-10 and 2015-16 winter seasons (Table 4.11). The NEWINS results show relatively minor variability which provides sufficient evidence to move forward with comparing the NEWINS to additional indices for further validation and discussion.

### *c. Comparison Indices*

Comparison indices were computed to provide additional context for the NEWINS. Some severity indices (e.g., Cohen 1981; Kocin and Uccellini 2004; Strong et al. 2005) consider the spatial distribution of accumulated snowfall throughout an event or entire winter season. Therefore, snowfall-based indices were computed statewide and for each NDOT maintenance district by comparing the annual frequency distribution between the number of days with observed frozen precipitation as identified from the ASOS station data (i.e., snow days) and the number of days with observed snow accumulation (i.e., snowfall days; frozen precipitation accumulation of 0.1 in. [0.25 cm] or greater) as identified from the GHCN-D site data within 15 km of an ASOS station (i.e., snowfall days) for each winter season (Figure 4.6 and Table 4.12). An important caveat to note with this approach is that snow reported at a single ASOS station or GHCN-D site within a NDOT District of any duration would be sufficient to count as a

**Table 4.11.** Statewide seasonal NEWINS for 2009-10 and 2015-16 winter seasons from three researcher classifications (R1-3), their average and selected method (M10).

| Winter Season | R1 | R2 | R3 | Avg. | M10 |
|---|---|---|---|---|---|
| **2009 – 2010** | 6.06 | 6.05 | 6.18 | 6.10 | 6.15 |
| **2015 – 2016** | 4.68 | 4.84 | 4.69 | 4.74 | 4.83 |

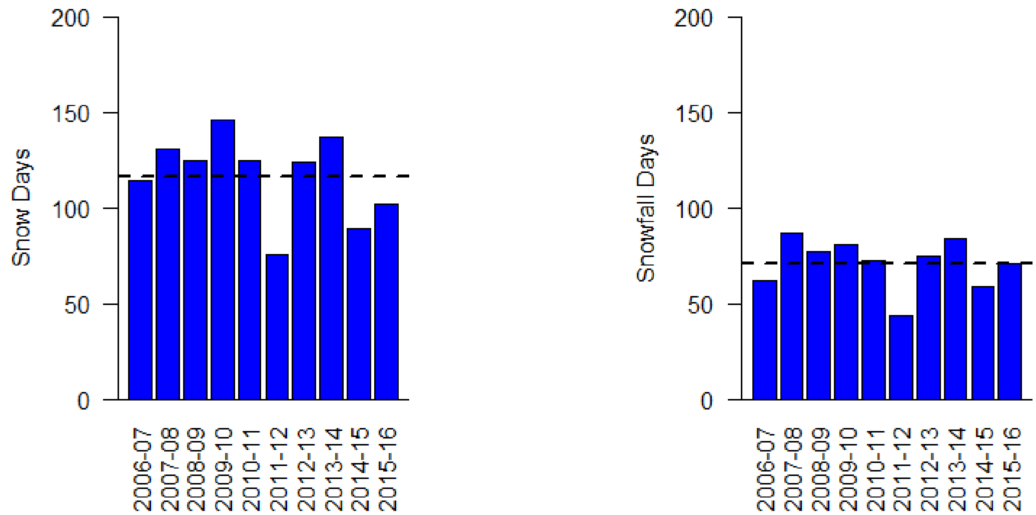


**Figure 4.6.** Snow (i.e., frozen precipitation identified by ASOS stations) days (left) and snowfall (i.e., accumulation measured by GHCN-D sites) days (right) with respective averages (dashed line).

**Table 4.12.** District and statewide total snow (i.e., frozen precipitation reported by ASOS) days.

| | Snow Days | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **Statewide** |
| **2006-07** | 36 | 40 | 59 | 53 | 67 | 57 | 42 | 67 | 114 |
| **2007-08** | 60 | 61 | 68 | 78 | 86 | 77 | 51 | 67 | 131 |
| **2008-09** | 48 | 55 | 65 | 64 | 71 | 67 | 46 | 75 | 125 |
| **2009-10** | 60 | 70 | 64 | 81 | 84 | 75 | 61 | 67 | 146 |
| **2010-11** | 49 | 60 | 63 | 53 | 80 | 61 | 43 | 67 | 125 |
| **2011-12** | 28 | 22 | 31 | 35 | 50 | 39 | 27 | 34 | 76 |
| **2012-13** | 51 | 58 | 69 | 63 | 77 | 65 | 44 | 66 | 124 |
| **2013-14** | 42 | 59 | 62 | 70 | 94 | 75 | 52 | 77 | 137 |
| **2014-15** | 33 | 39 | 42 | 41 | 61 | 48 | 36 | 45 | 89 |
| **2015-16** | 37 | 44 | 53 | 44 | 71 | 52 | 43 | 56 | 102 |
| **Decade Average** | 44.4 | 50.8 | 57.6 | 58.2 | 74.1 | 61.6 | 44.5 | 62.1 | 116.9 |

snow or snowfall day, respectively. Statewide, the decade average number of snow days was 116.9 days (Figure 4.6 and Table 4.12). This indicates that for the ten-year period, on average, somewhere within the state receives snowfall nearly one-third of the year. The annual variability in snow day frequency ranged from 76 days during the 2011-12 winter season to 146 days during the 2009-10 winter season. By this measure, it can be stated that 2009-10 was the most severe winter season in the ten-year winter season database and 2011-12 was the least severe if only number of days that snow was observed is taken into consideration. At the NDOT maintenance district level, the decade average snow day frequency ranged from 44.4 days in District 1 (i.e., southeast Nebraska) to 74.1 days in District 5 (i.e., western Nebraska). Inter-annual variability in snow day frequency can be seen among the maintenance districts as well. For example, District 3's highest snow day frequency occurred during the 2012-13 winter season whereas the statewide highest was the 2009-10 winter season (Table 4.12). All districts observed their lowest snow day frequency during the 2011-12 winter season. This consistency among the districts suggests that the 2011-12 winter season was a lower frozen precipitation year relative to the others. Snow day anomalies (Table 4.13) were computed statewide and for each district as well. Statewide, the largest positive snow day anomaly occurred during the 2009-10 winter season and the largest negative snow day anomaly occurred during the 2011-12 winter season. For the maintenance districts, while the largest negative anomalies were consistent with the 2011-12 winter season, the positive anomalies were more variable. For example, District 1's largest positive snow day anomalies occurred in both the 2007-08 and 2009-10 winter seasons (Table 4.13). Similarly, District 8's largest positive anomaly occurred during the 2013-14 winter season (Table 4.13).

**Table 4.13.** District and statewide snow day anomalies. Blue denotes positive anomalies and gold denotes negative anomalies. The largest positive anomalies are bold, and the largest negative anomalies are italicized.

| Snow Days Anomalies | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **Statewide** |
| **2006-07** | -8.4 | -10.8 | 1.4 | -5.2 | -7.1 | -4.6 | -2.5 | 4.9 | -2.9 |
| **2007-08** | **15.6** | 10.2 | 10.4 | 19.8 | 11.9 | **15.4** | 6.5 | 4.9 | 14.1 |
| **2008-09** | 3.6 | 4.2 | 7.4 | 5.8 | -3.1 | 5.4 | 1.5 | 12.9 | 8.1 |
| **2009-10** | **15.6** | **19.2** | 6.4 | **22.8** | 9.9 | 13.4 | **16.5** | 4.9 | **29.1** |
| **2010-11** | 4.6 | 9.2 | 5.4 | -5.2 | 5.9 | -0.6 | -1.5 | 4.9 | 8.1 |
| **2011-12** | *-16.4* | *-28.8* | *-26.6* | *-23.2* | *-24.1* | *-22.6* | *-17.5* | *-28.1* | *-40.9* |
| **2012-13** | 6.6 | 7.2 | **11.4** | 4.8 | 2.9 | 3.4 | -0.5 | 3.9 | 7.1 |
| **2013-14** | -2.4 | 8.2 | 4.4 | 11.8 | **19.9** | 13.4 | 7.5 | **14.9** | 20.1 |
| **2014-15** | -11.4 | -11.8 | -15.6 | -17.2 | -13.1 | -13.6 | -8.5 | -17.1 | -27.9 |
| **2015-16** | -7.4 | -6.8 | -4.6 | -14.2 | -3.1 | -9.6 | -1.5 | -6.1 | -14.9 |

Snow days considered only observed frozen precipitation whereas snowfall days considered frozen precipitation accumulation. Snowfall days statewide averaged 71.3 days during the decade (Figure 4.6 and Table 4.14). The statewide range in snowfall day frequency was a minimum of 44 days during the 2011-12 winter season and 87 days during the 2007-08 winter season. By this measure, the 2007-08 winter season was the most severe during the period, while the 2011-12 winter season was the least severe. This difference would suggest that while there was a higher frequency of days with snow during the 2009-10 winter season, that snow tended not to accumulate on all days. Further, this difference in the most severe winter season between the two methodologies highlights the necessity of a more robust winter severity index that assesses details regarding individual storms. Among the districts, decadal average snowfall day frequency ranged from 22.9 days in District 1 to 47.0 days in District 5. This result paired with the snow day frequency demonstrates that the eastern part of the state receives on average approximately half the number of snow/snowfall days as the western part of the state. This quantification could be beneficial to NDOT for the purposes of budgetary planning among the different maintenance districts. Snowfall day anomalies (Table 4.15) further agree with the 2011-12 winter season as the least severe during the period with the largest negative anomaly. The snowfall day anomalies would rank the 2007-08 winter season as the most severe and the 2009-10 winter season, which observed the largest positive anomalies in snow day frequency, would be ranked third behind the 2013-14 winter season.

The percentage reduction between snow and snowfall days is an important statistic for winter maintenance operations (Table 4.16). NDOT personnel state that their

**Table 4.14.** District and statewide total snowfall (i.e., accumulation) days.

| | Snowfall Days | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **Statewide** |
| **2006-07** | 17 | 21 | 21 | 26 | 41 | 26 | 28 | 24 | 62 |
| **2007-08** | 33 | 36 | 43 | 48 | 57 | 35 | 27 | 30 | 87 |
| **2008-09** | 24 | 31 | 43 | 34 | 45 | 31 | 28 | 21 | 77 |
| **2009-10** | 32 | 38 | 43 | 45 | 49 | 39 | 31 | 28 | 81 |
| **2010-11** | 28 | 37 | 38 | 32 | 51 | 32 | 23 | 38 | 73 |
| **2011-12** | 9 | 14 | 15 | 16 | 30 | 20 | 16 | 14 | 44 |
| **2012-13** | 21 | 25 | 28 | 37 | 50 | 38 | 28 | 30 | 75 |
| **2013-14** | 24 | 35 | 27 | 37 | 61 | 36 | 25 | 23 | 84 |
| **2014-15** | 18 | 22 | 24 | 24 | 44 | 30 | 24 | 21 | 59 |
| **2015-16** | 23 | 28 | 31 | 31 | 42 | 35 | 31 | 33 | 71 |
| **Decade Average** | 22.9 | 28.7 | 31.3 | 33.0 | 47.0 | 32.2 | 26.1 | 26.2 | 71.3 |

**Table 4.15.** District and statewide snowfall day anomalies. Blue denotes positive anomalies and gold denotes negative anomalies. The largest positive anomalies are bold, and the largest negative anomalies are italicized.

| Snowfall Days Anomalies | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **Statewide** |
| **2006-07** | -5.9 | -7.7 | -10.3 | -7 | -6 | -6.2 | 1.9 | -2.2 | -9.3 |
| **2007-08** | **10.1** | 7.3 | **11.7** | **15** | 10 | 2.8 | 0.9 | 3.8 | **15.7** |
| **2008-09** | 1.1 | 2.3 | **11.7** | 1 | -2 | -1.2 | 1.9 | -5.2 | 5.7 |
| **2009-10** | 9.1 | **9.3** | **11.7** | 12 | 2 | **6.8** | **4.9** | 1.8 | 9.7 |
| **2010-11** | 5.1 | 8.3 | 6.7 | -1 | 4 | -0.2 | -3.1 | **11.8** | 1.7 |
| **2011-12** | *-13.9* | *-14.7* | *-16.3* | *-17* | *-17* | *-12.2* | *-10.1* | *-12.2* | *-27.3* |
| **2012-13** | -1.9 | -3.7 | -3.3 | 4 | 3 | 5.8 | 1.9 | 3.8 | 3.7 |
| **2013-14** | 1.1 | 6.3 | -4.3 | 4 | **14** | 3.8 | -1.1 | -3.2 | 12.7 |
| **2014-15** | -4.9 | -6.7 | -7.3 | -9 | -3 | -2.2 | -2.1 | -5.2 | -12.3 |
| **2015-16** | 0.1 | -0.7 | -0.3 | -2 | -5 | 2.8 | **4.9** | 6.8 | -0.3 |

**Table 4.16.** District and statewide percent reduction between snow (i.e., precipitation) and snowfall (i.e., accumulation) days.

| | Snow-Snowfall Days Percentage Reduction | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **Statewide** |
| **2006-07** | 52.8 | 47.5 | 64.4 | 50.9 | 38.8 | 54.4 | 33.3 | 64.2 | 45.6 |
| **2007-08** | 45.0 | 41.0 | 36.8 | 38.5 | 33.7 | 54.5 | 47.1 | 55.2 | 33.6 |
| **2008-09** | 50.0 | 43.6 | 33.8 | 46.9 | 36.6 | 53.7 | 39.1 | 72.0 | 38.4 |
| **2009-10** | 46.7 | 45.7 | 32.8 | 44.4 | 41.7 | 48.0 | 49.2 | 58.2 | 44.5 |
| **2010-11** | 42.9 | 38.3 | 39.7 | 39.6 | 36.3 | 47.5 | 46.5 | 43.3 | 41.6 |
| **2011-12** | 67.9 | 36.4 | 51.6 | 54.3 | 40.0 | 48.7 | 40.7 | 58.8 | 42.1 |
| **2012-13** | 58.8 | 56.9 | 59.4 | 41.3 | 35.1 | 41.5 | 36.4 | 54.5 | 39.5 |
| **2013-14** | 42.9 | 40.7 | 56.5 | 47.1 | 35.1 | 52.0 | 51.9 | 70.1 | 38.7 |
| **2014-15** | 45.5 | 43.6 | 42.9 | 41.5 | 27.9 | 37.5 | 33.3 | 53.3 | 33.7 |
| **2015-16** | 37.8 | 36.4 | 41.5 | 29.5 | 40.8 | 32.7 | 27.9 | 41.1 | 30.4 |
| **Decade Average** | 48.4 | 43.5 | 45.7 | 43.3 | 36.6 | 47.7 | 41.3 | 57.8 | 39.0 |

operations prepare for a forecast threat of snow and deploy once snow begins (i.e., operations deploy on snow days). The statewide decadal average percentage reduction between snow and snowfall days suggests that 39.0% of the times it snows, the snow does not accumulate. From a winter maintenance operations standpoint, this could equate to a savings in unnecessary deployment expenses. The statewide percentage reduction ranges from 30.4% during the 2015-16 winter season to 45.6% during the 2006-07 winter season. At the district level, decadal percentage reductions range from 36.6% in District 5 to 57.8% in District 8. The high variability in these results further highlights the need for a winter severity index which captures individual events during the winter season rather than a frequency distribution of days with snow falling versus accumulating.

One final snowfall-based index was to observe the winter seasonal accumulated snowfall (Table 4.17). The decadal average statewide snowfall was 42.6 in. (108.2 cm) with a range from 24.1 in. (61.2 cm) during the 2011-12 winter season to 60.2 in. (152.9 cm) during the 2009-10 winter season. This result aligns with the snow day frequency distribution that would suggest the most severe winter season was 2009-10 and the least severe was 2011-12. The average decadal snowfall at the district level ranged from 30.3 in. (76.9 cm) in District 1 to 68.12 in. (173.0 cm) in District 5. This result also aligns with the snow/snowfall day distribution between the eastern and western regions of the state. Snowfall anomalies (Table 4.18) illustrate further spatial variability using snowfall-based winter severity indices. Statewide, the largest positive anomaly occurred during the 2009-10 winter season and the largest negative anomaly occurred during the 2011-12 winter season. However, at the district level, while large negative anomalies

**Table 4.17.** District and statewide total seasonal snowfall.

| | Snowfall Accumulation (in.) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **State Average** |
| **2006-07** | 36.6 | 37.0 | 32.8 | 26.0 | 61.4 | 46.3 | 47.7 | 31.8 | 40.0 |
| **2007-08** | 36.5 | 30.6 | 46.1 | 43.2 | 75.0 | 38.6 | 42.7 | 42.1 | 44.3 |
| **2008-09** | 23.1 | 32.5 | 46.6 | 40.1 | 57.0 | 40.9 | 40.4 | 41.0 | 40.2 |
| **2009-10** | 57.7 | 63.5 | 63.4 | 66.7 | 87.6 | 60.6 | 49.9 | 31.9 | 60.2 |
| **2010-11** | 38.5 | 51.4 | 54.3 | 53.0 | 66.5 | 53.2 | 41.4 | 59.6 | 52.2 |
| **2011-12** | 15.6 | 28.8 | 21.1 | 24.9 | 31.2 | 23.0 | 30.8 | 17.6 | 24.1 |
| **2012-13** | 27.2 | 40.2 | 37.6 | 47.9 | 74.2 | 51.3 | 53.6 | 52.1 | 48.0 |
| **2013-14** | 21.7 | 22.6 | 24.2 | 33.5 | 82.7 | 40.6 | 36.4 | 32.9 | 36.8 |
| **2014-15** | 22.8 | 22.1 | 26.6 | 33.9 | 69.9 | 27.6 | 25.1 | 30.3 | 32.3 |
| **2015-16** | 23.0 | 34.6 | 59.5 | 42.6 | 75.7 | 47.5 | 49.4 | 51.8 | 48.0 |
| **Decade Average** | 30.3 | 36.3 | 41.2 | 41.2 | 68.1 | 43.0 | 41.7 | 39.1 | 42.6 |

**Table 4.18.** District and statewide snowfall anomalies. Blue denotes positive anomalies and gold denotes negative anomalies. The largest positive anomalies are bold, and the largest negative anomalies are italicized.

| | Snowfall Accumulation Anomalies (in.) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **State Average** |
| **2006-07** | 6.3 | 0.7 | -8.4 | -15.2 | -6.7 | 3.3 | 5.9 | -7.3 | -2.6 |
| **2007-08** | 6.2 | -5.7 | 4.9 | 2.0 | 6.9 | -4.4 | 0.9 | 3.0 | 1.7 |
| **2008-09** | -7.2 | -3.8 | 5.4 | -1.1 | -11.1 | -2.0 | -1.3 | 1.9 | -2.4 |
| **2009-10** | **27.4** | **27.2** | **22.2** | **25.5** | **19.5** | **17.6** | 8.1 | -7.2 | **17.6** |
| **2010-11** | 8.2 | 15.1 | 13.1 | 11.8 | -1.6 | 10.2 | -0.4 | **20.5** | 9.6 |
| **2011-12** | *-14.7* | -7.5 | *-20.1* | *-16.3* | *-36.9* | *-20.0* | -10.9 | *-21.5* | *-18.5* |
| **2012-13** | -3.1 | 3.9 | -3.6 | 6.7 | 6.1 | 8.3 | **11.9** | 13.0 | 5.4 |
| **2013-14** | -8.6 | -13.7 | -17.0 | -7.7 | 14.6 | -2.4 | -5.4 | -6.2 | -5.8 |
| **2014-15** | -7.5 | *-14.2* | -14.6 | -7.3 | 1.8 | -15.4 | *-16.7* | -8.8 | -10.3 |
| **2015-16** | -7.3 | -1.7 | 18.3 | 1.4 | 7.6 | 4.5 | 7.7 | 12.7 | 5.4 |

were consistent across all eight districts for the 2011-12 winter season, District 8 observed a negative anomaly during the 2009-10 winter season while the remainder of the districts had large positive anomalies. While the spatial variability in snowfall-based indices supports a more robust, event-oriented approach, it also highlights the worthwhile consideration of climate (i.e., temperature and precipitation) anomalies across the state for the ten-year period as well.

In order to consider a longer, climatology-based index, temperature and precipitation anomalies were obtained from the NOAA NCEI climate division data (ESRL 2017). Nebraska contains eight climate districts which roughly align with NDOT's eight maintenance districts. Due to the lack of a perfect alignment; however, the temperature and precipitation anomalies were accumulated across the eight climate districts to provide a statewide value for each winter season. These anomalies would subsequently be compared with the aforementioned snowfall-based winter severity indices and the final NEWINS.

For a climate-based index, precipitation and temperature anomalies were obtained from the eight climate districts within the state of Nebraska (Figure 3.4) from October through April of each winter season and averaged statewide (Table 4.19). For severity purposes, the anomalies are ranked and larger positive precipitation anomalies (i.e., more snowfall possible) while larger negative temperature anomalies (i.e., colder winter) are associated with a higher winter severity. For precipitation anomalies, the 2015-16 winter season observed the largest positive anomaly (4.30 in.; 10.92 cm) while the 2014-15 winter season observed the largest negative anomaly (-2.02 in.; -5.13 cm). From the snowfall data, the most severe 2009-10 winter season ranks third in the precipitation

**Table 4.19.** Average statewide decadal temperature and precipitation anomalies. For precipitation, blue denotes positive anomalies and gold denotes negative anomalies. For temperature, blue denotes negative anomalies (i.e., colder, more severe conditions) and gold denotes positive anomalies (i.e., warmer, less severe conditions). The largest positive anomalies are bold, and the largest negative anomalies are italicized.

| Winter Season | Precip. Anomaly (in.) | Precip. Anomaly Rank | Temp. Anomaly (°F) | Temp. Anomaly Rank |
|---|---|---|---|---|
| **2006-2007** | 2.84 | **2** | 0.68 | **7** |
| **2007-2008** | 0.74 | **5** | -0.58 | **3** |
| **2008-2009** | 1.97 | **4** | 0.43 | **6** |
| **2009-2010** | 2.71 | **3** | -1.21 | **2** |
| **2010-2011** | -1.57 | **9** | -0.23 | **4** |
| **2011-2012** | -0.10 | **6** | **5.18** | **10** |
| **2012-2013** | -1.52 | **8** | -0.16 | **5** |
| **2013-2014** | -1.34 | **7** | *-1.46* | **1** |
| **2014-2015** | *-2.02* | **10** | 1.66 | **8** |
| **2015-2016** | **4.30** | **1** | 4.57 | **9** |

anomalies and the least severe 2011-12 winter season ranks sixth in precipitation anomalies. These results provide stark contrast to the snowfall-based indices. However, while the 2015-16 winter season may have observed an abundance of precipitation, it was not in the form of snow. For temperature anomalies, the 2013-14 winter season observed the largest negative anomaly (-1.46 °F; -0.81°C) while the 2011-12 winter season observed the largest positive anomaly (5.18°F; 2.88°C). This result agrees with the previous ranking of the 2011-12 winter season as the least severe season from the snowfall data. The 2009-10 winter season ranks second in the temperature anomalies (-1.21°F; -0.67°C) which is more in agreement with the snowfall-based index as well. Given the misalignment between climate districts and maintenance districts, it was not feasible to conduct a district level anomaly comparison. The snowfall and climate-based indices support the use of a hybrid approach which considers snowfall and temperature, in addition to other weather variables at the level of individual events.

### *d. Nebraska Winter Severity Index (NEWINS)*

The first component of the NEWINS produced a categorical (Table 3.4) frequency distribution of classified events statewide and at the district level (Figure 4.7 and Tables 4.20-4.28) for each of the ten winter seasons within the study period. Statewide, the average number of events was 246.7 (Table 4.20). The 2011-12 winter season had the fewest events with 134, and the 2007-08 and 2009-10 winter seasons were tied for the most events with 305. From the categorical framework, the distribution of events across all winter seasons was right-skewed/tailed (Figure 4.7). Trace (i.e., Category 1) events were the most frequent while high (i.e., Category 6) events were rare with several winter

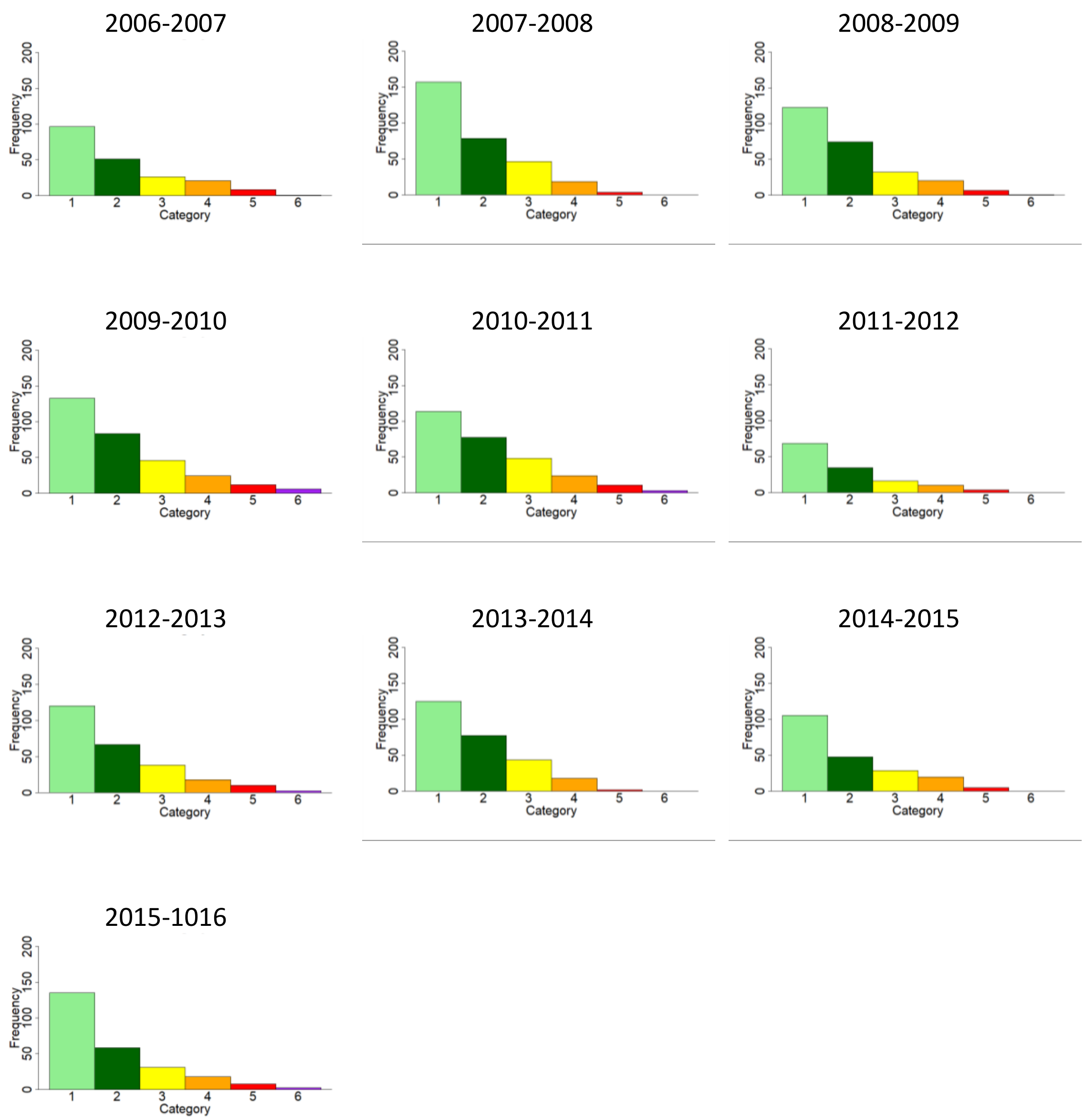


**Figure 4.7.** NEWINS winter season categorical event distribution.

**Table 4.20.** Statewide categorical classification frequency distribution.

| | Categorical Event Frequency | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 98 | 51 | 21 | 23 | 10 | 1 | 204 |
| **2007-2008** | 155 | 85 | 41 | 22 | 2 | 0 | 305 |
| **2008-2009** | 123 | 88 | 22 | 18 | 6 | 0 | 257 |
| **2009-2010** | 129 | 96 | 39 | 25 | 13 | 3 | 305 |
| **2010-2011** | 114 | 92 | 37 | 23 | 11 | 1 | 278 |
| **2011-2012** | 65 | 35 | 15 | 12 | 7 | 0 | 134 |
| **2012-2013** | 113 | 74 | 35 | 21 | 13 | 0 | 256 |
| **2013-2014** | 136 | 80 | 36 | 13 | 2 | 0 | 267 |
| **2014-2015** | 112 | 54 | 19 | 20 | 2 | 0 | 207 |
| **2015-2016** | 127 | 67 | 24 | 22 | 12 | 2 | 254 |
| **Decade Average** | 117.2 | 72.2 | 28.9 | 19.9 | 7.8 | 0.7 | 246.7 |

**Table 4.21.** NDOT District 1 categorical classification frequency distribution.

| Categorical Event Frequency District 1 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 6 | 4 | 2 | 4 | 1 | 0 | 17 |
| **2007-2008** | 22 | 3 | 3 | 5 | 0 | 0 | 33 |
| **2008-2009** | 15 | 6 | 1 | 2 | 0 | 0 | 24 |
| **2009-2010** | 13 | 10 | 3 | 3 | 3 | 0 | 32 |
| **2010-2011** | 13 | 8 | 2 | 5 | 0 | 0 | 28 |
| **2011-2012** | 3 | 2 | 2 | 2 | 0 | 0 | 9 |
| **2012-2013** | 12 | 4 | 3 | 1 | 1 | 0 | 21 |
| **2013-2014** | 16 | 4 | 2 | 2 | 0 | 0 | 24 |
| **2014-2015** | 11 | 3 | 1 | 3 | 0 | 0 | 18 |
| **2015-2016** | 12 | 6 | 5 | 0 | 0 | 0 | 23 |
| **Decade Average** | 12.3 | 5.0 | 2.4 | 2.7 | 0.5 | 0.0 | 22.9 |

**Table 4.22.** NDOT District 2 categorical classification frequency distribution.

| Categorical Event Frequency District 2 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 11 | 3 | 1 | 4 | 2 | 0 | 21 |
| **2007-2008** | 27 | 4 | 2 | 3 | 0 | 0 | 36 |
| **2008-2009** | 19 | 8 | 2 | 1 | 1 | 0 | 31 |
| **2009-2010** | 19 | 9 | 3 | 4 | 2 | 1 | 38 |
| **2010-2011** | 19 | 7 | 8 | 2 | 0 | 1 | 37 |
| **2011-2012** | 6 | 3 | 1 | 1 | 3 | 0 | 14 |
| **2012-2013** | 15 | 3 | 2 | 2 | 3 | 0 | 25 |
| **2013-2014** | 25 | 9 | 0 | 1 | 0 | 0 | 35 |
| **2014-2015** | 16 | 3 | 2 | 0 | 1 | 0 | 22 |
| **2015-2016** | 16 | 6 | 1 | 4 | 1 | 0 | 28 |
| **Decade Average** | 17.3 | 5.5 | 2.2 | 2.2 | 1.3 | 0.2 | 28.7 |

**Table 4.23.** NDOT District 3 categorical classification frequency distribution.

| Categorical Event Frequency District 3 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 11 | 3 | 2 | 4 | 1 | 0 | 21 |
| **2007-2008** | 18 | 17 | 6 | 2 | 0 | 0 | 43 |
| **2008-2009** | 23 | 15 | 1 | 3 | 1 | 0 | 43 |
| **2009-2010** | 21 | 14 | 2 | 3 | 2 | 1 | 43 |
| **2010-2011** | 14 | 17 | 4 | 2 | 1 | 0 | 38 |
| **2011-2012** | 8 | 3 | 2 | 1 | 1 | 0 | 15 |
| **2012-2013** | 14 | 6 | 6 | 1 | 1 | 0 | 28 |
| **2013-2014** | 15 | 9 | 3 | 0 | 0 | 0 | 27 |
| **2014-2015** | 14 | 6 | 1 | 3 | 0 | 0 | 24 |
| **2015-2016** | 13 | 7 | 7 | 1 | 2 | 1 | 31 |
| **Decade Average** | 15.1 | 9.7 | 3.4 | 2.0 | 0.9 | 0.2 | 31.3 |

**Table 4.24.** NDOT District 4 categorical classification frequency distribution.

| Categorical Event Frequency District 4 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 16 | 7 | 2 | 0 | 1 | 0 | 26 |
| **2007-2008** | 30 | 11 | 5 | 1 | 0 | 0 | 47 |
| **2008-2009** | 16 | 12 | 3 | 2 | 1 | 0 | 34 |
| **2009-2010** | 22 | 11 | 6 | 4 | 1 | 1 | 45 |
| **2010-2011** | 12 | 10 | 5 | 3 | 2 | 0 | 32 |
| **2011-2012** | 9 | 2 | 3 | 1 | 1 | 0 | 16 |
| **2012-2013** | 19 | 10 | 5 | 2 | 1 | 0 | 37 |
| **2013-2014** | 21 | 11 | 4 | 1 | 0 | 0 | 37 |
| **2014-2015** | 11 | 8 | 3 | 2 | 0 | 0 | 24 |
| **2015-2016** | 15 | 12 | 2 | 0 | 2 | 0 | 31 |
| **Decade Average** | 17.1 | 9.4 | 3.8 | 1.6 | 0.9 | 0.1 | 32.9 |

**Table 4.25.** NDOT District 5 categorical classification frequency distribution.

| Categorical Event Frequency District 5 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Winter Season | Trace (1) | Marginal (2) | Slight (3) | Enhanced (4) | Moderate (5) | High (6) | Total |
| **2006-2007** | 21 | 10 | 5 | 4 | 0 | 1 | 41 |
| **2007-2008** | 20 | 18 | 14 | 2 | 0 | 0 | 54 |
| **2008-2009** | 18 | 20 | 3 | 4 | 0 | 0 | 45 |
| **2009-2010** | 15 | 15 | 11 | 8 | 0 | 0 | 49 |
| **2010-2011** | 24 | 15 | 7 | 4 | 1 | 0 | 51 |
| **2011-2012** | 16 | 11 | 1 | 2 | 0 | 0 | 30 |
| **2012-2013** | 18 | 18 | 10 | 2 | 2 | 0 | 50 |
| **2013-2014** | 25 | 20 | 11 | 2 | 2 | 0 | 60 |
| **2014-2015** | 17 | 15 | 7 | 4 | 1 | 0 | 44 |
| **2015-2016** | 20 | 11 | 2 | 4 | 4 | 1 | 42 |
| **Decade Average** | 19.4 | 15.3 | 7.1 | 3.6 | 1.0 | 0.2 | 46.6 |

**Table 4.26.** NDOT District 6 categorical classification frequency distribution.

| Categorical Event Frequency District 6 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 12 | 5 | 3 | 4 | 2 | 0 | 26 |
| **2007-2008** | 18 | 12 | 2 | 2 | 1 | 0 | 35 |
| **2008-2009** | 15 | 8 | 5 | 3 | 0 | 0 | 31 |
| **2009-2010** | 16 | 15 | 5 | 0 | 3 | 0 | 39 |
| **2010-2011** | 11 | 11 | 5 | 1 | 3 | 0 | 31 |
| **2011-2012** | 10 | 7 | 2 | 1 | 0 | 0 | 20 |
| **2012-2013** | 17 | 13 | 3 | 5 | 0 | 0 | 38 |
| **2013-2014** | 19 | 9 | 6 | 2 | 0 | 0 | 36 |
| **2014-2015** | 19 | 7 | 1 | 3 | 0 | 0 | 30 |
| **2015-2016** | 18 | 11 | 2 | 3 | 1 | 0 | 35 |
| **Decade Average** | 15.5 | 9.8 | 3.4 | 2.4 | 1.0 | 0.0 | 32.1 |

**Table 4.27.** NDOT District 7 categorical classification frequency distribution.

| Categorical Event Frequency District 7 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 10 | 11 | 3 | 1 | 3 | 0 | 28 |
| **2007-2008** | 7 | 10 | 6 | 4 | 0 | 0 | 27 |
| **2008-2009** | 11 | 12 | 3 | 1 | 1 | 0 | 28 |
| **2009-2010** | 10 | 12 | 4 | 3 | 2 | 0 | 31 |
| **2010-2011** | 7 | 10 | 2 | 2 | 2 | 0 | 23 |
| **2011-2012** | 6 | 3 | 3 | 2 | 2 | 0 | 16 |
| **2012-2013** | 9 | 9 | 3 | 5 | 2 | 0 | 28 |
| **2013-2014** | 8 | 10 | 5 | 2 | 0 | 0 | 25 |
| **2014-2015** | 15 | 5 | 3 | 1 | 0 | 0 | 24 |
| **2015-2016** | 19 | 6 | 2 | 2 | 2 | 0 | 31 |
| **Decade Average** | 10.2 | 8.8 | 3.4 | 2.3 | 1.4 | 0.0 | 26.1 |

**Table 4.28.** NDOT District 8 categorical classification frequency distribution.

| Categorical Event Frequency District 8 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 11 | 8 | 3 | 2 | 0 | 0 | 24 |
| **2007-2008** | 13 | 10 | 3 | 3 | 1 | 0 | 30 |
| **2008-2009** | 6 | 7 | 4 | 2 | 2 | 0 | 21 |
| **2009-2010** | 13 | 10 | 5 | 0 | 0 | 0 | 28 |
| **2010-2011** | 14 | 14 | 4 | 4 | 2 | 0 | 38 |
| **2011-2012** | 7 | 4 | 1 | 2 | 0 | 0 | 14 |
| **2012-2013** | 9 | 11 | 3 | 3 | 3 | 0 | 29 |
| **2013-2014** | 7 | 8 | 5 | 3 | 0 | 0 | 23 |
| **2014-2015** | 9 | 7 | 1 | 4 | 0 | 0 | 21 |
| **2015-2016** | 14 | 8 | 3 | 8 | 0 | 0 | 33 |
| **Decade Average** | 10.3 | 8.7 | 3.2 | 3.1 | 0.8 | 0.0 | 26.1 |

seasons observing none (Table 4.20). Slight (i.e., Category 3) and enhanced (i.e., Category 4) events exhibited higher variability in their frequency distributions. Some winter seasons observed more enhanced events than slight (e.g., 2006-07, 2014-15 winter seasons), where others contained very similar frequencies (e.g., 2008-09, 2011-12, and 2015-16 winter seasons) between the two. Given the categorical assignment (Table 3.4) and Eq. (1), the middle events are likely to overlap with one another as very subtle changes could alter their classification. The extreme events (i.e., trace and high) are more distinct from one another and therefore do not exhibit any degree of overlap. This is an important caveat to note in both the frequency distribution and eventual final NEWINS seasonal values as well. At the district level (Tables 4.21-4.28), District 1 overall had the fewest events with a decadal average of 22.9 while District 5 had the most with a decadal average of 46.6 events. This spatial distribution aligns with the previous snowfall-based data (Tables 4.12-4.18).

To further confirm the NEWINS storm classification frequency distribution beyond comparison with additional snowfall and climate-based indices, an independent Delphi-based method was performed with seven new research collaborators who were undergraduate and graduate meteorology students. These seven new researchers were asked to perform the same manual classification of events that led to the development of the NEWINS. The initial NEWINS was based on manual classification of two winter seasons. These seven researchers manually classified events across all ten winter seasons in the database with multiple iterations. The objective was to ensure consistency in the frequency distribution between this new manually classified winter season database and the NEWINS winter season database. Further, with a greater number of researchers manually classifying the seasons, it was important to ensure that their individual departures from the group mean (Table 4.29) and standard deviations (Table 4.30) were minimized, hence the multiple iterations as needed. Overall, the results from the seven researchers aligned with those of the NEWINS quite well (Table 4.31). The distributions were right-skewed/tailed across all ten winter seasons for the manual classifications. The categorical frequency distribution and event classification component of the NEWINS builds on the framework in the development of the NESIS (Kocin and Uccellini 2004) and LWSS (Cerruti and Decker 2011). Cerruti and Decker (2011) observed a similar right-tailed/skewed frequency distribution with higher category (i.e., impact) events exhibiting far lower frequencies relative to lower category events. Also, while the parameter weights differed between the NEWINS and LWSS, both approaches gave the most weight to the snowfall amount parameter. As noted, freezing rain data lacked availability through the ten-year study period and was omitted during the development of the NEWINS, unlike the LWSS which considered freezing rain events. Future refinement of the NEWINS could ensure freezing rain is incorporated into the WSI. These additional improvements could also make the NEWINS framework a candidate for NWS consideration in its WSSI (WPC 2018). The consistency between these results and the literature confirm the NEWINS frequency distribution and its components given the similarities to a manual classification with a more numerous, independent set of researchers.

The final NEWINS was computed via Eq. (2) to provide a single value for each winter season statewide and at the NDOT maintenance district level (Figures 4.8-4.9 and Table 4.32). The statewide decadal average NEWINS value was 4.77. Based on the

**Table 4.29.** Departures for each researcher from the group average frequency distribution. Blue represents overestimates (positive values) where gold represents underestimates (negative values).

| Winter Season | R1 | R2 | R3 | R4 | R5 | R6 | R7 |
|---|---|---|---|---|---|---|---|
| **2006-2007** | 0.21 | -0.50 | 0.08 | 0.07 | 0.39 | 0.00 | -0.17 |
| **2007-2008** | 0.21 | -0.40 | 0.12 | -0.05 | 0.32 | -0.04 | -0.19 |
| **2008-2009** | 0.25 | -0.47 | 0.07 | -0.10 | 0.37 | 0.01 | -0.20 |
| **2009-2010** | 0.43 | 0.26 | 0.12 | -0.36 | -0.07 | -0.07 | -0.19 |
| **2010-2011** | 0.32 | -0.67 | 0.29 | -0.11 | 0.26 | 0.09 | -0.20 |
| **2011-2012** | 0.40 | -0.49 | 0.07 | -0.07 | 0.34 | 0.14 | -0.07 |
| **2012-2013** | 0.41 | -0.49 | 0.11 | -0.31 | 0.38 | 0.13 | -0.06 |
| **2013-2014** | 0.40 | -0.46 | 0.23 | -0.28 | 0.27 | 0.12 | -0.16 |
| **2014-2015** | 0.44 | -0.47 | 0.24 | -0.19 | 0.43 | 0.13 | -0.05 |
| **2015-2016** | 0.27 | 0.26 | -0.13 | -0.01 | -0.03 | -0.02 | -0.24 |

**Table 4.30.** Researcher standard deviations for Delphi approach.

| Winter Season | R1 | R2 | R3 | R4 | R5 | R6 | R7 |
|---|---|---|---|---|---|---|---|
| **2006-2007** | 0.45 | 0.66 | 0.53 | 0.51 | 0.61 | 0.42 | 0.57 |
| **2007-2008** | 0.42 | 0.61 | 0.51 | 0.53 | 0.50 | 0.37 | 0.44 |
| **2008-2009** | 0.44 | 0.57 | 0.42 | 0.55 | 0.50 | 0.23 | 0.45 |
| **2009-2010** | 0.57 | 0.55 | 0.39 | 0.60 | 0.40 | 0.35 | 0.46 |
| **2010-2011** | 0.47 | 0.70 | 0.61 | 0.49 | 0.47 | 0.37 | 0.56 |
| **2011-2012** | 0.49 | 0.67 | 0.46 | 0.44 | 0.50 | 0.41 | 0.52 |
| **2012-2013** | 0.51 | 0.61 | 0.42 | 0.50 | 0.50 | 0.39 | 0.49 |
| **2013-2014** | 0.56 | 0.61 | 0.49 | 0.46 | 0.44 | 0.36 | 0.45 |
| **2014-2015** | 0.54 | 0.66 | 0.54 | 0.46 | 0.52 | 0.40 | 0.40 |
| **2015-2016** | 0.48 | 0.52 | 0.37 | 0.53 | 0.32 | 0.31 | 0.50 |

**Table 4.31.** Average categorical classification frequency distribution from seven researchers who manually classified each winter season for Delphi approach.

| | Categorical Event Frequency | | | | | | |
|---|---|---|---|---|---|---|---|
| **Winter Season** | **Trace (1)** | **Marginal (2)** | **Slight (3)** | **Enhanced (4)** | **Moderate (5)** | **High (6)** | **Total** |
| **2006-2007** | 97 | 56 | 28 | 11 | 12 | 0 | 204 |
| **2007-2008** | 159 | 103 | 38 | 7 | 2 | 0 | 309 |
| **2008-2009** | 131 | 87 | 22 | 10 | 6 | 1 | 257 |
| **2009-2010** | 151 | 79 | 40 | 17 | 6 | 12 | 305 |
| **2010-2011** | 122 | 105 | 33 | 9 | 10 | 0 | 279 |
| **2011-2012** | 76 | 34 | 11 | 8 | 3 | 2 | 134 |
| **2012-2013** | 133 | 72 | 28 | 10 | 12 | 2 | 257 |
| **2013-2014** | 155 | 83 | 24 | 4 | 2 | 0 | 268 |
| **2014-2015** | 120 | 57 | 19 | 8 | 2 | 1 | 207 |
| **2015-2016** | 136 | 59 | 29 | 15 | 6 | 9 | 254 |
| **Decade Average** | 128 | 73.5 | 27.2 | 9.9 | 6.1 | 2.7 | 247.4 |

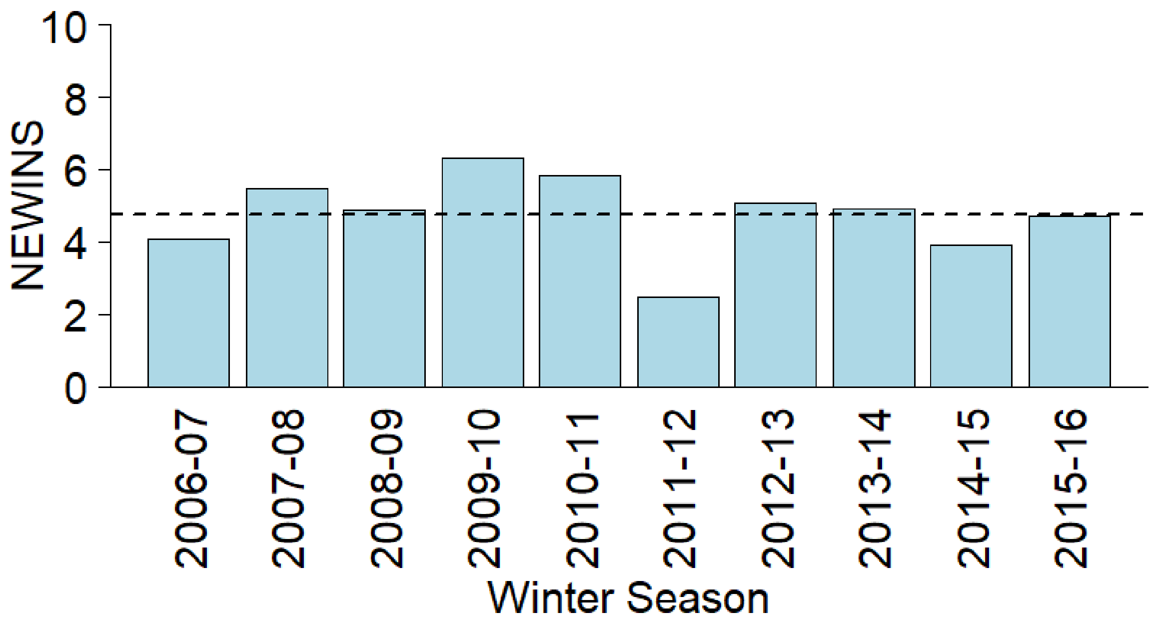


**Figure 4.8.** NEWINS winter season values with decadal average (black dashed line).

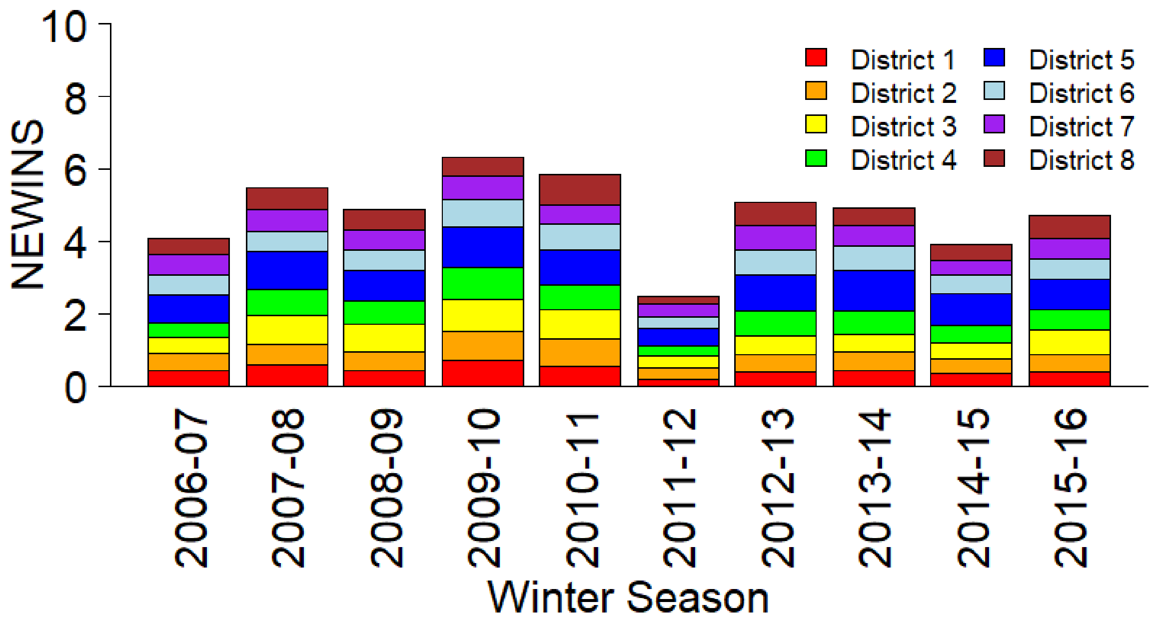


**Figure 4.9.** NEWINS winter season values with each district's contribution.

**Table 4.32.** NEWINS district and statewide seasonal values.

| | NEWINS Values | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **Statewide** |
| **2006-07** | 0.44 | 0.46 | 0.43 | 0.43 | 0.74 | 0.56 | 0.58 | 0.43 | 4.08 |
| **2007-08** | 0.59 | 0.58 | 0.79 | 0.72 | 1.02 | 0.58 | 0.60 | 0.60 | 5.47 |
| **2008-09** | 0.41 | 0.53 | 0.78 | 0.63 | 0.84 | 0.58 | 0.56 | 0.54 | 4.87 |
| **2009-10** | 0.69 | 0.81 | 0.88 | 0.88 | 1.11 | 0.76 | 0.66 | 0.53 | 6.33 |
| **2010-11** | 0.56 | 0.75 | 0.79 | 0.69 | 0.98 | 0.70 | 0.55 | 0.83 | 5.84 |
| **2011-12** | 0.19 | 0.33 | 0.29 | 0.30 | 0.46 | 0.32 | 0.35 | 0.24 | 2.49 |
| **2012-13** | 0.38 | 0.48 | 0.52 | 0.68 | 1.00 | 0.71 | 0.65 | 0.65 | 5.07 |
| **2013-14** | 0.42 | 0.54 | 0.46 | 0.63 | 1.15 | 0.66 | 0.55 | 0.51 | 4.93 |
| **2014-15** | 0.36 | 0.38 | 0.46 | 0.49 | 0.88 | 0.49 | 0.42 | 0.45 | 3.92 |
| **2015-16** | 0.38 | 0.51 | 0.66 | 0.55 | 0.84 | 0.60 | 0.55 | 0.66 | 4.73 |
| **Decade Average** | 0.44 | 0.54 | 0.61 | 0.60 | 0.90 | 0.60 | 0.55 | 0.54 | 4.77 |

NEWINS values, the least severe winter season was 2011-12 with a value of 2.49 while the most severe winter season was 2009-10 with a value of 6.33 (Figure 4.8 and Table 4.32). These results generally align with the snowfall-based winter severity indices. At the district level, the NEWINS value summed across all districts would yield the statewide value. District 1 has the smallest contribution on average for the decade (0.44) while District 5 has the largest contribution for the decade (0.90) of any one single district (Table 4.32). This result is to be expected given the relative differences in event frequency and snow/snowfall days between the eastern and western parts of the state. A more detailed consideration of the district level NEWINS values also reveals that while the 2009-10 winter season was the most severe for the entire state, individual districts' most severe winter seasons can be different. For example, District 8's most severe was the 2010-11 winter season with an NEWINS value of 0.83 (Figure 4.9 and Table 4.32). Similar differences between districts were observed in the snowfall-based winter severity indices and it is important that the NEWINS also be able to capture the same level of variability to be reliable. Moreover, this result further highlights the challenge and difficulty of representing an entire state's winter season with a single severity index value.

The advantages of the NEWINS become more apparent when the NEWINS anomalies (Figure 4.10) are compared with the aforementioned snowfall-based and climate-based index anomalies ranked from most severe to least severe for each respective index (Tables 4.33-4.34). For the snowfall-based anomalies (i.e., snowfall amounts, snow days and snowfall days), there is fair agreement that the 2011-12 winter season was the least severe in the decade and the 2009-10 winter season was the most

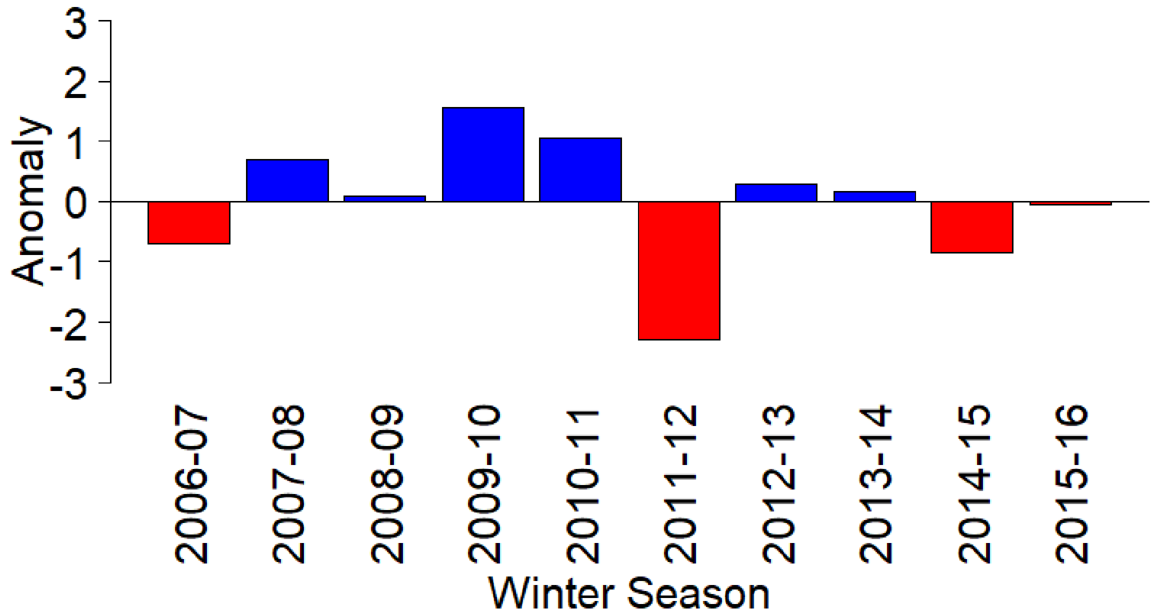


**Figure 4.10.** NEWINS winter season anomalies with positive (blue) and negative (red).

**Table 4.33.** NEWINS statewide seasonal anomalies ranked from lowest (i.e., most severe) to highest (i.e., least severe) versus snowfall, snow day, and snowfall day anomalies. Blue denotes positive anomalies and gold denotes negative anomalies

| Statewide NEWINS, Snowfall, Snow Days and Snowfall Days | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **NEWINS** | **NEWINS Anomaly** | **NEWINS Anomaly Rank** | **Average Snowfall (in.)** | **Snowfall Anomaly (in.)** | **Snowfall Anomaly Rank** | **Snow Days** | **Snow Days Anomaly** | **Snow Days Anomaly Rank** | **Snowfall Days** | **Snowfall Days Anomaly** | **Snowfall Days Anomaly Rank** |
| **2009-10** | 6.3 | 1.6 | **1** | 60.2 | 17.6 | **1** | 146 | 29.1 | **1** | 81 | 9.7 | **3** |
| **2010-11** | 5.8 | 1.1 | **2** | 52.2 | 9.6 | **2** | 125 | 8.1 | **4** | 73 | 1.7 | **6** |
| **2007-08** | 5.5 | 0.7 | **3** | 44.3 | 1.7 | **5** | 131 | 14.1 | **3** | 87 | 15.7 | **1** |
| **2012-13** | 5.1 | 0.3 | **4** | 48.0 | 5.4 | **3** | 124 | 7.1 | **6** | 75 | 3.7 | **5** |
| **2013-14** | 4.9 | 0.2 | **5** | 36.8 | -5.8 | **8** | 137 | 20.1 | **2** | 84 | 12.7 | **2** |
| **2008-09** | 4.9 | 0.1 | **6** | 40.2 | -2.4 | **6** | 125 | 8.1 | **4** | 77 | 5.7 | **4** |
| **2015-16** | 4.7 | 0.0 | **7** | 48.0 | 5.4 | **3** | 102 | -14.9 | **8** | 71 | -0.3 | **7** |
| **2006-07** | 4.1 | -0.7 | **8** | 40.0 | -2.6 | **7** | 114 | -2.9 | **7** | 62 | -9.3 | **8** |
| **2014-15** | 3.9 | -0.9 | **9** | 32.3 | -10.3 | **9** | 89 | -27.9 | **9** | 59 | -12.3 | **9** |
| **2011-12** | 2.5 | -2.3 | **10** | 24.1 | -18.5 | **10** | 76 | -40.9 | **10** | 44 | -27.3 | **10** |

**Table 4.34.** NEWINS statewide seasonal values, snowfall, temperature and precipitation anomalies. For NEWINS, snowfall and precipitation anomalies, blue denotes positive anomalies and gold denotes negative anomalies. For temperature, blue denotes negative anomalies (i.e., colder, more severe conditions) and gold denotes positive anomalies (i.e., warmer, less severe conditions).

| Statewide NEWINS, Snowfall, Temperature and Precipitation | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **NEWINS** | **NEWINS Anomaly** | **NEWINS Anomaly Rank** | **Average Snowfall (in.)** | **Snowfall Anomaly (in.)** | **Snowfall Anomaly Rank** | **Precip. Anomaly (in.)** | **Precip. Anomaly Rank** | **Temp. Anomaly (°F)** | **Temp. Anomaly Rank** |
| **2009-10** | 6.3 | 1.6 | **1** | 60.2 | 17.6 | **1** | 2.7 | **3** | -1.3 | **2** |
| **2010-11** | 5.8 | 1.1 | **2** | 52.2 | 9.6 | **2** | -1.6 | **9** | -0.2 | **4** |
| **2007-08** | 5.5 | 0.7 | **3** | 44.3 | 1.7 | **5** | 0.7 | **5** | -0.5 | **3** |
| **2012-13** | 5.1 | 0.3 | **4** | 48.0 | 5.4 | **3** | -1.5 | **8** | -0.2 | **5** |
| **2013-14** | 4.9 | 0.2 | **5** | 36.8 | -5.8 | **8** | -1.3 | **7** | -1.4 | **1** |
| **2008-09** | 4.9 | 0.1 | **6** | 40.2 | -2.4 | **6** | 2.0 | **4** | 0.4 | **6** |
| **2015-16** | 4.7 | 0.0 | **7** | 48.0 | 5.4 | **3** | 4.3 | **1** | 4.5 | **9** |
| **2006-07** | 4.1 | -0.7 | **8** | 40.0 | -2.6 | **7** | 2.8 | **2** | 0.7 | **7** |
| **2014-15** | 3.9 | -0.9 | **9** | 32.3 | -10.3 | **9** | -2.0 | **10** | 1.6 | **8** |
| **2011-12** | 2.5 | -2.3 | **10** | 24.1 | -18.5 | **10** | -0.1 | **6** | 5.2 | **10** |

severe in the decade. The exception is that for the snowfall days anomaly, the 2009-10 winter season is ranked as the third most severe winter season. While there is less consistency on the rank of each winter season's severity, there is fair agreement between the cutoff threshold between positive (i.e., more severe) and negative (i.e., less severe) anomalies for each winter season. The exception to this is with the snowfall anomalies, particularly during the 2015-16 winter season which did have a positive snowfall anomaly (ranked third most severe) but average (i.e., zero anomaly) NEWINS, snow day and snowfall day anomalies (ranked seventh or eighth most severe).

As suggested from the frequency distributions, while there is consistency among the least and most severe winter seasons between the NEWINS and snowfall-based anomalies, the greatest variability is in the middle where subtle differences in the variables of interest can influence the rank of the winter seasons. While the NEWINS and snowfall-based anomalies both exhibit this intermediate variability, one advantage is that the NEWINS considers additional variables (Table 3.6) and not simply event frequency or snowfall amounts exclusively. For the climate-based index anomalies (Table 4.34), temperature anomalies also exhibited a clear cut-off between negative (i.e., more severe in the case of temperature) and positive (i.e., less severe in the case of temperature) anomalies for the corresponding NEWINS anomalies. The precipitation anomalies, though, did not exhibit any clear pattern that was in line with the observed NEWINS or snowfall anomalies. A reason for this is that precipitation anomalies consider both liquid and frozen precipitation; however, the NEWINS and other approaches are only interested in the frozen precipitation. A "wet" or "dry" winter season from the climatological precipitation standpoint can be very different than a "snowy" winter.

*e. NEWINS Storm Classification Cluster Analysis*

A K-means cluster analysis was performed to further illustrate the separation of individual variables within the NEWINS storm classifications and to strengthen results of the NEWINS. K-means is one of the most widely applied clustering algorithms (Kanungo et al. 2002; Jain 2010). K-means is well-applicable in situations when all the attributes are quantitative, the dissimilarity measure is the squared Euclidean distance (Hastie et al. 2009), and there is an adequate knowledge about the number of clusters (Pena et al. 1999). Being a prototype-based method, K-means would develop clusters in which each observation is closer to its prototype (i.e., average or centroid with quantitative variables) than to the prototypes of other clusters (Zhang et al. 2005). K-means works as follows: (1) select K points randomly as the initial cluster centroids, (2) assign each observation to the closest centroid and form K clusters such that the within-cluster sum of squares is at its minimum, (3) calculate the new centroids and assign the observations to their closest centroids with, again, the goal of minimizing the within-cluster sum of squares, and (4) repeat steps 2 and 3 until centroids and consequently cluster assignments remain unchanged or until only 1% of points change clusters. It is apparent from the algorithm that the final clusters are sensitive to the selection of the initial centroids. While there are many methods to select the initial points, this study would rely on the results of Pena et al. (1999) and choose the initial points randomly. The R function kmeans() from the stats package was used for the analysis. This function applies a method introduced by Hartigan and Wong (1979). Given the six-category framework of the NEWINS, six clusters were selected to perform the K-means cluster analysis using the seven weather variables. The seven weather variables were standardized via the scale() R function which centers each column with its mean and then scales by dividing each column by its standard deviation. The identified clusters were subsequently compared to the storm classification assignment.

Cluster numbers were assigned to match NEWINS storm classification categories (e.g., Cluster 1 represents Category 1, Cluster 2 represents Category 2, etc.). From consideration of the centroid distribution for each weather variable among the clusters (Table 4.35), reasonable alignment with the NEWINS classifications can be seen. For example, the centroid for duration is highest in Cluster 6 and lowest in Cluster 5. Air temperature is coldest in Clusters 2 and 4 and similar in the remaining four clusters. Wind speeds are highest in Cluster 3. Visibilities are lowest in Cluster 6 and highest in Cluster 2. Snowfall amount and rate are both maximized in Cluster 6. Last, district area is high in both Clusters 4 and 6.

From the consideration of variable centroids among the clusters, the clusters can be defined in terms of the NEWINS storm classifications. Cluster 1 contains the lowest wind speeds, low snowfall amounts, short durations, moderate air temperature, low to mid-range visibility, and small district area which would likely be associated with Category 1 events. Cluster 2 contains low snowfall amount with high visibility, short durations, and some of the coldest temperatures which would likely align with Category 2 events. Cluster 3 contains the highest wind speeds and air temperatures, second lowest average visibility; however, snowfall amount and rate are not as impressive in other clusters likely associating these with Category 3 events. Cluster 4 contains mid to long duration, the coldest temperatures, low wind speeds, medium snowfall with low snow rates and the largest district area which would align with Category 4 events. Cluster 5

**Table 4.35.** Cluster analysis centroid for each weather variable.

| | Cluster Number | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **1** | **2** | **3** | **4** | **5** | **6** |
| **Duration (hr.)** | 3.70 | 3.88 | 5.40 | 9.14 | 2.34 | 13.23 |
| **Air Temperature (°F)** | 26.35 | 18.93 | 27.39 | 18.25 | 27.36 | 24.19 |
| **Wind Speed (mph)** | 8.43 | 11.25 | 21.94 | 11.43 | 14.54 | 15.68 |
| **Visibility (mi.)** | 2.75 | 5.87 | 2.48 | 2.98 | 3.08 | 1.91 |
| **Snow Fall (in.)** | 0.73 | 0.46 | 1.00 | 1.52 | 2.30 | 4.94 |
| **Snow Rate (in. $hr^{-1}$)** | 0.23 | 0.16 | 0.22 | 0.19 | 1.21 | 0.44 |
| **District Area (Fraction Area)** | 0.37 | 0.38 | 0.48 | 0.85 | 0.39 | 0.81 |

contained the highest snow rates, second highest average snowfall amounts, short duration, high temperature (second highest average), mid-range wind speed and visibility likely associating these with Category 5 events. Last, Cluster 6 represents the most severe Category 6 events with the highest snow amount, longest average duration, lowest visibility, mid-range to high wind speed, high snow rate, and the second highest district area.

From a cluster-based distribution of the NEWINS storm classifications (Table 4.36) Cluster 6 contains the highest number of Category 4, 5 and 6 events providing further evidence that this cluster contains the most severe, (i.e., high impact) storms. Cluster 5 contains the second highest number of combined Category 4 and 5 storms suggesting that these are the second most severe (i.e., moderate impact) storms. The remaining clusters and storm classifications exhibit overlap; however, Cluster 1 contains the highest number of Category 1 events likely associating this with the least severe (i.e., trace impact) events while Cluster 2, having few events above Category 2 is likely associated with these marginal impact events. From the observed distribution, Cluster 4 events are likely slightly more severe than Cluster 3 events, which suggests these two clusters are associated with Category 4 (i.e., enhanced) and Category 3 (i.e., slight) events, respectively. The results show overlap among the variables and categorical assignment which underscores the difficulty in defining an event in a single category; however, the results also indicate there are similarities among the clusters and event classifications. Future inclusion of winter maintenance operations data may allow for increased separation of events among the clusters, though the cluster analysis does show reasonable separation among the events with expected high variability in the

**Table 4.36.** Cluster analysis centroid for each weather variable.

| | Storm Classification Category | | | | | |
|---|---|---|---|---|---|---|
| **Cluster Number** | **1** | **2** | **3** | **4** | **5** | **6** |
| **1** | 449 | 170 | 31 | 5 | 0 | 0 |
| **2** | 316 | 38 | 4 | 1 | 0 | 0 |
| **3** | 249 | 164 | 60 | 7 | 0 | 0 |
| **4** | 153 | 287 | 147 | 37 | 0 | 0 |
| **5** | 5 | 62 | 37 | 34 | 8 | 0 |
| **6** | 0 | 1 | 10 | 115 | 70 | 7 |

intermediate ones where subtle differences can modify categorical classification. The same variability was observed in the manual event classifications as well.

### *f. NEWINS 2015-16 Winter Season Maintenance Performance Comparison*

NDOT's performance objective for its winter maintenance operations is to maintain traffic speeds along the Interstate 80 corridor at or above 65 mph (29.1 m $s^{-1}$) for both directions (i.e., eastbound and westbound) within six hours of the precipitation ending (NDOT 2016, personal communication). The 2015-16 winter season NDOT performance data was available for 15 events throughout the state (Table 4.37). Of these 15 events, seven resulted in the performance objective not being met. Reasons for the performance objective not being met range from truly severe weather conditions to vehicular crashes and necessary road closures. Their performance data for the 2015-16 winter season was related to the individual NEWINS storm classifications for each of the Interstate 80 districts (Table 4.37). The results show that, in general, the performance objective was met for lower impact Category 1-3 events (e.g., 16 November 2015, 16 January 2016), but not for higher impact Category 4-6 events (e.g., 15 December 2015, 1 February 2016). Some important caveats were identified in this comparison analysis. First, NDOT's event definition is based on precipitation that causes a maintenance response (e.g., wet snow, freezing rain, potential for icy roads) regardless of the final snowfall accumulation (NDOT 2016, personal communication). Given that the NEWINS only considers events with accumulated snowfall, this results in events included in NDOT's maintenance database that are missing from the NEWINS database (e.g., "NA" on 16 November 2015; Table 4.37). Future alignment of event definitions is

**Table 4.37.** Interstate 80 corridor district-level 2015-16 winter maintenance performance evaluation. NDOT's event criteria (i.e., green and red boxes) was precipitation that resulted in maintenance activity (NDOT 2016, personal communication). Green boxes indicate where the performance objective was met. Red boxes indicate where the performance objective was not met. The numbers within the boxes represent the 2015-16 winter season NEWINS storm classification and "NA" denotes the storm failed NEWINS criteria. This could be due to several reasons; for example, lack of accumulation (i.e., snow days versus snowfall days), snow melted before observation time, or freezing rain events which were omitted from the NEWINS.

| Storm Date | District 5 | District 6 | District 4 | District 1 | District 2 |
|---|---|---|---|---|---|
| 11/10/2015 | *2* | - | - | - | - |
| 11/16/2015 | *1* | *1* | *NA* | *NA* | *NA* |
| 11/17/2015 | - | - | - | *NA* | - |
| 11/26/2015 | *1* | *NA* | *2* | *NA* | *1* |
| 11/29/2015 | - | *2* | - | - | *3* |
| 12/1/2015 | - | - | *1* | - | - |
| 12/12/2015 | *2* | *1* | *1* | *1* | *2* |
| 12/15/2015 | *6* | *4* | *2* | - | - |
| 12/22/2015 | *NA* | *1* | - | *2* | *1* |
| 12/25/2015 | *5* | *2* | *1* | *3* | *4* |
| 12/29/2015 | - | - | *1* | *1* | *1* |
| 1/7/2015 | - | - | *2* | *1* | *2* |
| 1/16/2016 | *1* | - | *1* | - | - |
| 1/18/2016 | - | - | - | *1* | *2* |
| 2/1/2016 | *4* | *5* | *5* | *3* | *4* |

necessary to improve the usefulness of the NEWINS. An additional caveat is that some low events result in performance objectives not being met (e.g., 26 November 2015, District 5). Upon discussion with NDOT, it was revealed that this was due to the Wyoming DOT closing its roads due to significantly worse weather conditions creating a backup of traffic into Nebraska (NDOT 2016, personal communication). This is an important consideration as the NEWINS is a pure meteorological index and does not consider transportation-related incidents (e.g., road closures, highway crashes). NEWINS did exhibit skill in identifying higher impact/severity storms associated with more numerous road instances of road closures.

### *g. NEWINS 2016-17 Winter Season Application*

The 2016-17 winter season NEWINS was computed to provide further validation and verification of the methods. From a categorical frequency distribution perspective (Figure 4.11), the 2016-17 winter season was very similar to the 2011-12 winter season (Figure 4.7). Both winter seasons had a relatively low number of events. Consideration of the statewide and district NEWINS values (Figures 4.12 and 4.13) shows that 2016-17 was well below average and rivaled the 2011-12 winter season for the lowest severity. Last, consideration of the NEWINS anomalies (Figure 4.14) provides further confirmation of the 2016-17 winter season's place as the second least severe winter after the 2011-12 winter season. An important consideration regarding the addition of a new winter season is whether or not the average NEWINS value should be fixed based on the decadal period or adjusted to accommodate additional winter seasons. In the decadal anomalies (Figure 4.10), the 2015-16 winter season is slightly below average; however,

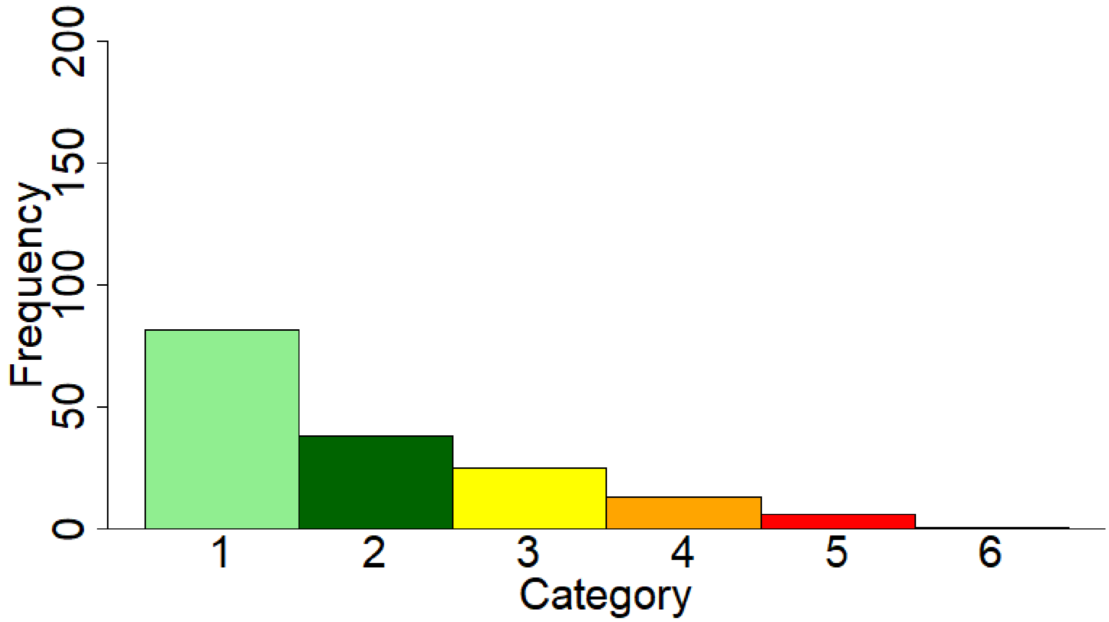


**Figure 4.11.** NEWINS 2016-2017 winter season categorical event distribution.

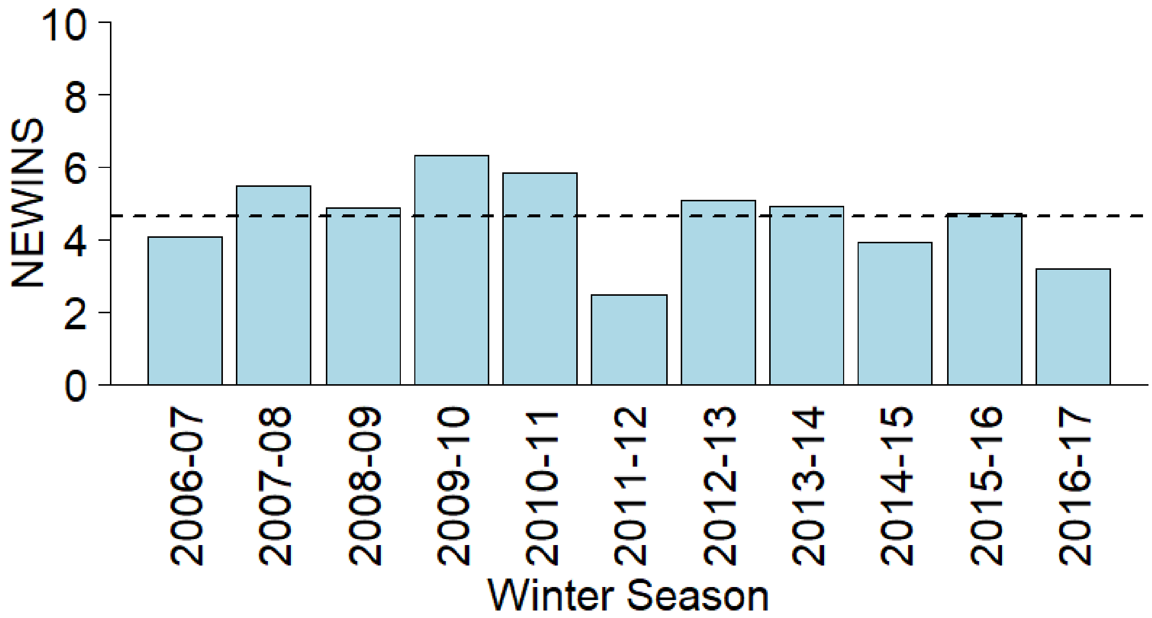


**Figure 4.12.** NEWINS winter season values with decadal (i.e., 2006-2016) average (black dashed line).

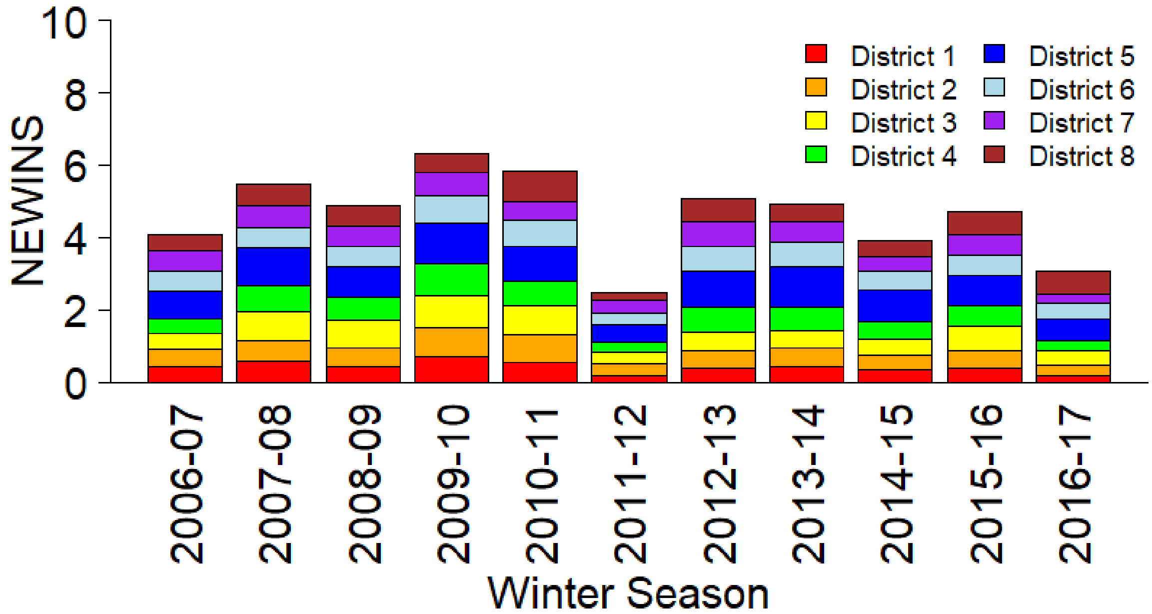


**Figure 4.13.** NEWINS winter season values with each district's contribution.

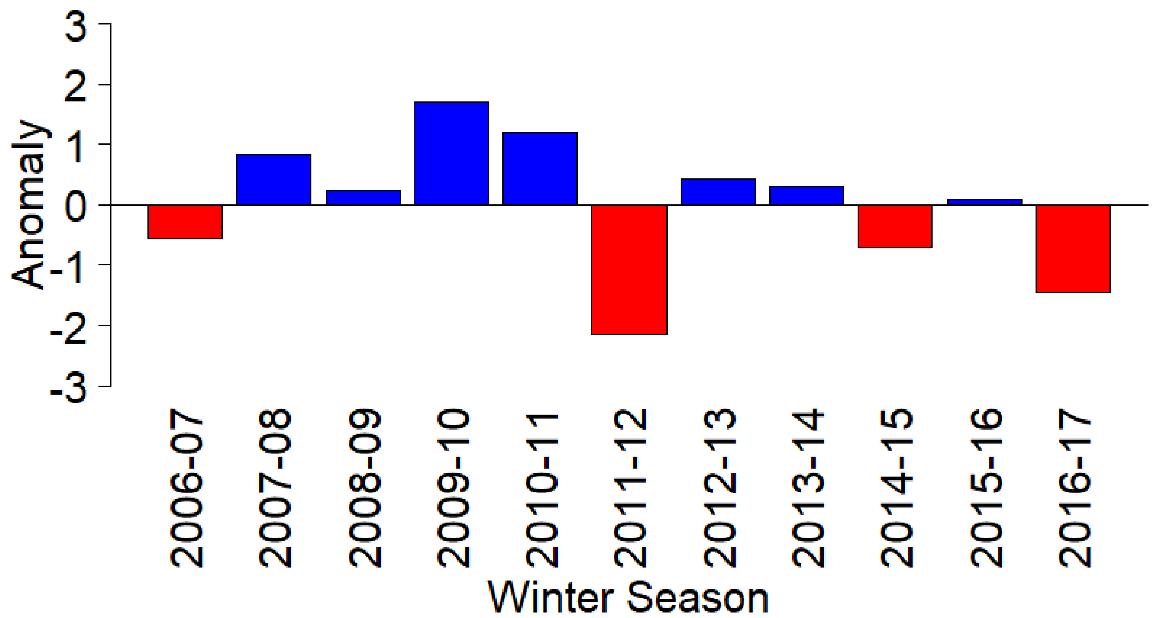


**Figure 4.14.** NEWINS winter season anomalies based on 11-year average with positive (blue) and negative (red).

when considering the 11-year anomalies with an adjusted average, the 2015-16 winter season is slightly above average (Figure 4.14). This discrepancy is also apparent when considering a snowfall accumulation-based index and comparing decadal versus 11-year averages (Table 4.38). To prevent such variation as more winter seasons are incorporated into the NEWINS, it is recommended that the decadal average be fixed, and subsequent winter seasons compared to it. Only after an additional decade has passed should the average be considered based upon either the new decade or the entire two-decade period.

The snowfall accumulation-based index also yields an interesting result when comparing the least and greatest amounts at the district level. For the 2016-17 winter season, Districts 1, 2, 4 and 7 observed their least snowfall amounts in the 11-year period. Districts 3, 5, 6, 8 and the entire state, though, observed the least snowfall amounts during the 2011-12 winter season which has previously been identified as the least severe. District 8, however, had its highest seasonal snowfall amount during the 2016-17 winter season while all other districts observed markedly lower amounts (Table 4.38). This is also apparent in the district NEWINS values where District 8 has a larger contribution to the overall severity during the 2016-17 winter season (Figure 4.13). This finding further supports the use of the NEWINS in lieu of snowfall-based indices given such high variability in seasonal meteorological conditions that must be captured.

**Table 4.38.** Decadal and 11-year district and statewide total snowfall.

| Snowfall Accumulation (in.) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Winter Season** | **District 1** | **District 2** | **District 3** | **District 4** | **District 5** | **District 6** | **District 7** | **District 8** | **State Average** |
| **2006-07** | 36.6 | 37.0 | 32.8 | 26.0 | 61.4 | 46.3 | 47.7 | 31.8 | 40.0 |
| **2007-08** | 36.5 | 30.6 | 46.1 | 43.2 | 75.0 | 38.6 | 42.7 | 42.1 | 44.3 |
| **2008-09** | 23.1 | 32.5 | 46.6 | 40.1 | 57.0 | 40.9 | 40.4 | 41.0 | 40.2 |
| **2009-10** | 57.7 | 63.5 | 63.4 | 66.7 | 87.6 | 60.6 | 49.9 | 31.9 | 60.2 |
| **2010-11** | 38.5 | 51.4 | 54.3 | 53.0 | 66.5 | 53.2 | 41.4 | 59.6 | 52.2 |
| **2011-12** | 15.6 | 28.8 | 21.1 | 24.9 | 31.2 | 23.0 | 30.8 | 17.6 | 24.1 |
| **2012-13** | 27.2 | 40.2 | 37.6 | 47.9 | 74.2 | 51.3 | 53.6 | 52.1 | 48.0 |
| **2013-14** | 21.7 | 22.6 | 24.2 | 33.5 | 82.7 | 40.6 | 36.4 | 32.9 | 36.8 |
| **2014-15** | 22.8 | 22.1 | 26.6 | 33.9 | 69.9 | 27.6 | 25.1 | 30.3 | 32.3 |
| **2015-16** | 23.0 | 34.6 | 59.5 | 42.6 | 75.7 | 47.5 | 49.4 | 51.8 | 48.0 |
| **2016-17** | 8.5 | 15.0 | 34.6 | 12.7 | 54.1 | 29.4 | 18.4 | 61.6 | 29.3 |
| **Decade Average** | 30.3 | 36.3 | 41.2 | 41.2 | 68.1 | 43.0 | 41.7 | 39.1 | 42.6 |
| **11-Year Average** | 28.3 | 34.4 | 40.6 | 38.6 | 66.8 | 41.7 | 39.6 | 41.2 | 41.4 |

## 5. Summary and Conclusion

The winter severity index developed specifically for NDOT is known as the NEWINS. The NEWINS serves an integral role in providing an independent, meteorological baseline for ten winter seasons beginning in July 2006 through June 2016 for the state of Nebraska. Further, through the development of the NEWINS, a winter event categorical classification framework was developed. This classification framework allowed for a weighted linear combination of seven key weather variables to create a frequency distribution of events for each winter season. This frequency distribution ultimately resulted in the final seasonal NEWINS value. The NEWINS values were also compared alongside snowfall-based and climate-based index approaches.

A literature review and survey results highlight best practices for state DOTs regarding their needs, sources, perceptions, and use of weather information in addition to the existence and application of WSIs. The survey results highlight the need for a continuous close partnership between the transportation community and the weather enterprise to ensure forecast accuracy and WSIs are always refined, tailored to the needs of the end-user and caveats communicated. State DOTs rely on weather information typically in advance of a storm for preparation purposes, while tactical weather information during/after a storm is generally of lesser importance. These findings advocate for future research to focus on the forecasting aspect and allow WSIs to have predictive capabilities.

Consideration of the annual distribution of days with observed snowfall (i.e., snow days) versus days with observed snowfall accumulation (i.e., snowfall days) revealed an average 39% reduction between the two for the ten-year period. These results also revealed that the western part of Nebraska receives twice as many days with snowfall compared to the eastern part of the state. From a snowfall accumulation perspective, the western part of Nebraska receives more than twice the amount of snowfall as the eastern part. A consideration of snow day, snowfall day and snowfall amount anomalies underscore the spatial and temporal variability that the NEWINS must consider. The snow data (i.e., days and amount) suggest the 2011-12 winter season was the least severe compared to the 2009-10 winter season which was the most severe.

Climatological liquid precipitation and temperature anomalies provided an additional context for the NEWINS results. Liquid precipitation anomalies were not well aligned with the snow anomalies and NEWINS results, likely due to the combination of both rain and snow events in precipitation data. The temperature anomalies showed better alignment with the snow data and NEWINS results, including a clear separation between positive and negative anomalies when compared to different winter season severities.

The NEWINS results highlight the 2011-12 winter season as the least severe and the 2009-10 winter season as the most severe during the study period. These two winter seasons were also identified similarly by the other index measures. The NEWINS also highlights the spatial differences in winter severity, especially between eastern and western regions of Nebraska. More substantial differences and inconsistency arose between the NEWINS and other (i.e., snowfall-based and climate-based) index approaches during the intermediate winter seasons where subtle differences could alter a particular season’s ranking. Inclusion of the 2016-17 winter season identified important considerations for an overall average, or baseline, NEWINS value. A fixed average NEWINS ensures that the inclusion of future winter seasons (e.g., 2016-17) does not influence the anomalies of existing winter seasons (e.g., 2015-16). The average should only be adjusted upon the addition of several (e.g., five to ten) new winter seasons.

The overall strengths of the NEWINS are that it 1) considers a wide range of surface, ASOS-based meteorological variables, 2) incorporates a categorical frequency distribution framework related to weather impacts on road conditions and winter maintenance operations, 3) is robust and flexible enough to be computed easily at the statewide and district levels, 4) can be continuously and easily modified to include additional parameters such as freezing rain and road temperature, and 5) can be easily correlated to available transportation data (e.g., traffic speeds, winter maintenance operations costs) once available.

The benefits of the NEWINS are that it allows NDOT to assess the performance of its winter maintenance operations activities, resource allocations and other expenses with respect to the severity, or magnitude, of each winter season. NDOT's goal is to efficiently maintain safety and mobility for the public and commercial transportation interests. This information can be used to increase efficiency in resource allocation and maintenance operations, in addition to the identification of conditions which would prompt the need for increases or reductions in assets. Further, the NEWINS considers multiple weather variables across spatiotemporal scales to provide the best resolution of true winter severity in a framework that can be tailored to the end-user needs. Moreover, it is flexible and robust enough to be transferred to other regions and applications (e.g., modification of variables and weight sensitivity for different industries).

Future avenues for research include adding a predictive, forecasting value to the NEWINS so that it can be used as a planning tool in addition to a post-winter season assessment. To this end, machine and deep learning algorithms can take advantage of the categorical frequency distribution framework component of the NEWINS for future studies. Additional prospects for the NEWINS include correlation to more robust winter maintenance operations data such as salt usage, personnel hours, lane miles plowed, crash data or costs. To accomplish this, the NEWINS could be tailored to specific locations and/or road segments for more meaningful correlation with maintenance data. Given the present lack of freezing rain data in the NEWINS framework, further work could include incorporation of these data to allow for consideration of all winter weather precipitation types. Last, the NEWINS framework can be adaptive to provide meteorological guidance for diverse sectors (e.g., renewable energy, agriculture) and end-users (e.g., insurance adjusters, weather derivative traders) to quantify their exposure and sensitivity to atmospheric conditions.

**References**

Abbe, C., Jr., 1914: Washington and Paris winters. *Monthly Weather Review*, **42**, 626–628, doi: 10.1175/1520-0493(1914)42,626:WAPW.2.0.CO;2.

Andrey, J., J. Li and B. Mills, 2001: A Winter Index for Benchmarking Winter Road Maintenance Operations on Ontario Highways. *Presented at 80th Annual Meeting of the Transportation Research Board,* Washington, D.C.

Andrey, J., B. Mills, M. Leahy, and J. Suggett, 2003: Weather as a chronic hazard for road transportation in Canadian cities. *Natural Hazards*, **28**, 319-343.

Angot, A., 1914: On a method for classifying winters. *Monthly Weather Review*, **42**, 625, doi: 10.1175/1520-0493(1914)42,625:OAMFCW.2.0.CO;2.

Balasundaram, B., S. Bukkapatnam, Z. Kong, and Y. Hong, 2012: Proactive Approach to Transportation Resource Allocation under Severe Winter Weather Emergencies. Report No. OTCREOS9.1-02-F. Oklahoma Transportation Center, Midwest City, OK, 77 pp.

Baldwin, M. E., D. Snyder, C. Miller, and K. Hoogewind, 2015: Road weather severity based on environmental energy. Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2015/13. West Lafayette, IN: Purdue University. doi: 10.5703/1288284315710.

Blincoe, L. J., T.R. Miller, E. Zaloshnja, and B. A. Lawrence, 2015: The economic and societal impact of motor vehicle crashes, 2010. Report No. DOT HS 812 013. Washington, DC: National Highway Traffic Safety Administration, 304 pp.

Boon, C.B., and C. Cluett, 2002: Road Weather Information Systems: Enabling Proactive Maintenance Practices in Washington State. Report No. WA-RD 529.1. Washington State Transportation Center, Seattle, WA, 126 pp.

Boselly, S.E., J.E. Thornes, and C. Ulberg, 1993: Road Weather Information Systems Volume 1: Research Report. Report No. SHRP-H-350. National Research Council, Washington, D.C., 219 pp.

Boustead, B., S.D. Hilberg, M.D. Shulski, and K.G. Hubbard, 2015: The Accumulated Winter Season Severity Index (AWSSI). *Journal of Applied Meteorology and Climatology*, **54**, 1693-1712, doi: 10.1175/JAMC-D-14-0217.1.

Byun, K., J. Yang, and T. Lee, 2008: A snow-ratio equation and its application to numerical snowfall prediction. *Weather Forecasting*, **23**, 644–658, doi:10.1175/2007WAF2006080.1.

Call, D.A., 2011: The Effect of Snow on Traffic Counts in Western New York State. *Weather, Climate and Society*, **3**, 71-75, doi: 10.1175/WCAS-D-10-05008.1.

Carmichael, C.G., W.A. Gallus Jr., B.R. Temeyer, and M.K. Bryden, 2004: A Winter Weather Index for Estimating Winter Roadway Maintenance Costs in the Midwest. *Journal of Applied Meteorology*, **43**, 1783–1790, doi: 10.1175/JAM2167.1.

Cerruti, B.J., and S.G. Decker, 2011: The Local Winter Storm Scale: A Measure of the Intrinsic Ability of Winter Storms to Disrupt Society. *Bull. Amer. Meteor. Soc.*, **92**, 721–737, https://doi.org/10.1175/2010BAMS3191.1.

Changnon, S.A., and T.G. Creech, 2003: Sources of Data on Freezing Rain and Resulting Damages. *Journal of Applied Meteorology*, **42**, 1514–1518, https://doi.org/10.1175/1520-0450(2003)042<1514:SODOFR>2.0.CO;2.

Chien, S., J. Meegoda, J. Luo, P. Corrigan, L. and Zhao, 2014: Road weather information system statewide implementation plan. Final Report, New York State Department of Transportation. Accessed 1 July 2016. [Available online at https://www.dot.ny.gov/ divisions/engineering/technical-services/trans-r-and-d-repository/C-11-54%20Final%20Report_4-2014.pdf]

Clear Roads, 2018: The Clear Roads Research Program. Accessed 10 March 2018. [Available online at http://clearroads.org/]

Climate Prediction Center [CPC], 2018: Nebraska Climate Divisions. Accessed 19 March 2018. [Available online at http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/CLIM_DIVS/nebraska.gif]

Cohen, S.J., 1981: User Oriented Climatic Information for Planning a Snow Removal Budget. *Journal of Applied Meteorology*, **20**, 1420–1427, https://doi.org/10.1175/1520-0450(1981)020<1420:UOCIFP>2.0.CO;2.

Community Collaborative Rain, Hail, and Snow Network [CoCoRaHS], 2018: Welcome to CoCoRaHS! Accessed 15 January 2018. [Available online at https://www.cocorahs.org/.]

Cooperative Observer Network [COOP], 2018: Cooperative Observer Program. Accessed 15 January 2018. [Available online at http://www.nws.noaa.gov/om/coop/.]

Dao, B., S. Hasanzadeh, C.L. Walker, D. Steinkruger, B. Esmaeili, and M.R. Anderson, 2018: Current practices in measuring the performance of winter maintenance operations. *Journal of Cold Regions Engineering*, in review.

De Pondeca, M.S., G.S. Manikin, G. DiMego, S.G. Benjamin, D.F. Parrish, R.J. Purser, W. Wu, J.D. Horel, D.T. Myrick, Y. Lin, R.M. Aune, D. Keyser, B. Colman, G. Mann, and J. Vavra, 2011: The Real-Time Mesoscale Analysis at NOAA's National Centers for Environmental Prediction: Current Status and Development. *Weather Forecasting*, **26**, 593–612, https://doi.org/10.1175/WAF-D-10-05037.1.

Doesken, N.J., and D.A. Robinson, 2009: The challenge of snow measurements. Historical Climate Variability and Impacts in North America. Springer, 251–274.

Earth Systems Research Laboratory [ESRL], 2017: Location of US Climate Divisions. Accessed 1 January 2017. [Available online at https://www.esrl.noaa.gov/psd/data/usclimdivs/data/map.html#Nebraska%20.]

Edwards, R., J.G. LaDue, J.T. Ferree, K. Scharfenberg, C. Maier, and W.L. Coulbourne, 2013: Tornado intensity estimation: Past, present, and future. *Bulletin of the American Meteorological Society*, **94**, 641–653, doi:10.1175/BAMS-D-11-00006.1.

Farr, W.C., and L.J. Sturges, 2012: Utah Winter Severity Index: Phase 1. Report No. UT-12.12. Utah Department of Transportation Weather Operations, Salt Lake City, UT, 56 pp.

Fujita, T.T., 1971: Proposed characterization of tornadoes and hurricanes by area and intensity. University of Chicago Satellite & Mesometeorology Research Project Research Paper 91, 42 pp. Accessed on 11 March 2018. [Available online at https://ia600509.us.archive.org/12/items/nasa_techdoc_19720008829/19720008829.pdf.]

Goodison, B.E., 1978: Accuracy of Canadian Snow Gage Measurements. *Journal of Applied Meteorology*, **17**, 1542–1548, https://doi.org/10.1175/1520-0450(1978)017<1542:AOCSGM>2.0.CO;2.

Goodison, B.E., P.Y.T. Louie, and D. Yang, 1998: WMO solid precipitation measurement intercomparison. Instruments and Observing Methods Rep. 67 (WMO/TD 872), World Meteorological Organization, Geneva, Switzerland, 212 pp.

Hallowell, M.R., and J.A. Gambatese, 2010: Qualitative Research: Application of the Delphi Method to CEM Research. *Journal of Construction Engineering and Management*, **136**, 99-107, 10.1061/_ASCE_CO.1943-7862.0000137.

Hartigan, J.A., and M.A. Wong, 1979: Algorithm AS 136: A k-means clustering algorithm. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, **28**, 100-108.

Hastie T., R. Tibshirani, and J. Friedman, 2009: *The elements of statistical learning* 2nd ed. New York, NY: Springer-Verlag, 545 pp.

Houston, T.G., and S.A. Changnon, 2007: Freezing rain events: a major weather hazard in the conterminous US. *Natural Hazards*, **40**, 485-494.

Hulme, M., 1982: A New Winter Index and Geographical Variations in Winter Weather, *Journal of Meteorology*, **7**, 294-300.

Jain, A.K., 2010: Data clustering: 50 years beyond K-Means. *Pattern Recognition Letters*, **31**, 651-666, doi: 10.1016/j.patrec.209.09.011.

Jensen, D., B. Koeberlein, E. Bala, and P. Bridge, 2013: Development of Winter Maintenance Performance Measures. Idaho Transportation Department, 6 pp.

Jiusto, J.E., and H.K. Weickmann, 1973: Types of Snowfall. *Bulletin of the American Meteorological. Society*, **54**, 1148–1162, https://doi.org/10.1175/1520-0477(1973)054<1148:TOS>2.0.CO;2.

Juga, I., P. Nurmi, and M. Hippi, 2013: Statistical modeling of wintertime road surface friction. *Meteorological Applications*, **20**, 318–329, doi: 10.1002/met.1285.

Kanungo, T., D.M. Mount, N.S. Netanyahu, C.D. Piatko, R. Silverman, and A.Y. Wu, 2002: An Efficient k-Means Clustering Algorithm: Analysis and Implementation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **24**, 881-892.

Kienzle, S.W., 2008: A new temperature based method to separate rain and snow. *Hydrological Processes*, **22**, 5067–5085, doi:10.1002/hyp.7131.

Kipp, W., and D. Sanborn, 2013: Identifying Performance Based Measures for Winter Maintenance Practices. Report No. 2013-02. Montpelier, VT: Vermont Agency of Transportation, 15 pp.

Knapp, K.K., L.D. Smithson, and A.J. Khattak, 2000: Mobility and safety impacts of winter storm events in a freeway environment (No. TR-426). Center for Transportation Research and Education, Iowa State University.

Kocin, P.J., and L.W. Uccellini, 2004: A Snowfall Impact Scale Derived from Northeast Storm Snowfall Distributions. *Bulletin of the American Meteorological Society*, **85**, 177–194, https://doi.org/10.1175/BAMS-85-2-177.

Kwon, T.J., L. Fu, and C. Jiang, 2013: Effect of winter weather and road surface conditions on macroscopic traffic parameters. *Transportation Research Record*, **2329**, 54–62.

Liu, Y. 2013: Weather Impact on Road Accident Severity in Maryland. Accessed on 11 March 2018. [Available online at https://drum.lib.umd.edu/handle/1903/14263]

Mahoney, J., E. Jackson, D. Larsen, T. Vadas, K. Wille, and S. Zinke, 2015: Winter Highway Maintenance Operations: Connecticut. Report No. CT-2289-F-15-1. Rocky Hill, CT: Connecticut Academy of Science and Engineering, 248 pp.

Maine Department of Transportation [Maine DOT], 2009: A Winter Severity Index for the State of Maine. Technical Report No. 09-1. 53 pp.

Massachusetts Department of Transportation (Massachusetts DOT) (2012). MassDOT Snow & Ice Control Program. 2012 Environmental Status and Planning Report. Report No. EOEA 11202. Boston, MA: MassDOT Highway Division, 125 pp. Accessed 1 July 2016. [Available online at https://www.massdot.state.ma.us/ Portals/8/docs/environmental/ EnvironStatus_PlanningRpt_0212.pdf.]

Marquis, B. 2009: A Winter Severity Index for the State of Maine. No. ME 09-01. Final Report, Maine State Department of Transportation. Accessed 1 July 2016. [Available online at https://trid.trb.org/view/1238126.]

Maze, T.H., C. Albrecht, D. Kroeger, and J. Wiegand, 2007: Performance Measures for Snow and Ice Control Operations. NCHRP Web-Only Document 136, Transportation Research Board, National Cooperative Highway Research Program, Washington D.C.

McCullouch, B., D. Belter, T. Konieczny, and T. McClellan, 2004: Indiana Winter Severity Index. *Transportation Research Circular Sixth International Symposium on Snow Removal and Ice Control Technology*, 7-9 June, Spokane WA

Midwestern Regional Climate Center [MRCC], 2018: Research: Accumulated Winter Season Severity Index (AWSSI). Accessed on 11 March 2018. [Available online at http://mrcc.isws.illinois.edu/research/awssi/indexAwssi.jsp]

Minnesota Department of Natural Resources [MNDNR], 2018: Deer reports & statistics. Accessed 18 March 2018. [Available online at https://www.dnr.state.mn.us/ mammals/deer/management/statistics.html]

National Centers for Environmental Information [NCEI], 2017a: Data Access. Accessed 1 January 2017. [Available online at https://www7.ncdc.noaa.gov/CDO/ cdoselect.cmd.]

NCEI, 2017b: Data Access. Accessed 1 January 2017. [Available online https://www. ncdc.noaa.gov/cdo-web/search.]

National Highway Traffic Safety Administration [NHTSA], 2018: New NHTSA Study Shows Motor Vehicle Crashes Have $871 Billion Economic and Societal Impact on U.S. Citizens. Accessed 10 March 2018. [Available online at https://www.nhtsa.gov/press-releases/new-nhtsa-study-shows-motor-vehicle-crashes-have-871-billion-economic-and-societal]

National Weather Service [NWS], 2016: Experimental Winter Storm Threat Graphics. Accessed 1 July 2016. [Available online at http://www.weather.gov/lwx/ ExperimentalWinterStormThreat.]

NWS, 2018: Automated Surface Observing System. Accessed 15 January 2018. [Available online at http://www.nws.noaa.gov/asos/.]

Nebraska Rainfall Assessment and Information Network [NeRAIN], 2018: Welcome to the Nebraska Rainfall Assessment and Information Network. Accessed 15 January 2018. [Available online at https://nednr.nebraska.gov/nerain.]

New Hampshire Department of Transportation [New Hampshire DOT], 2012: Effective Resource Management – 2012. 2 pp.

Nixon, W., and L. Qiu, 2005: Developing a storm severity index. *Transportation Research Record: Journal of the Transportation Research Board*, **1911**, 143-148.

Pena, J.M., J.A. Lozano, and P. Larranaga, 1999: An empirical comparison of four initialization methods for the k-means algorithm. *Pattern Recognition Letters*, **20**, 1027-1040.

Pisano, P.A., L.C. Goodwin, and M.A. Rosetti, 2008: U.S. Highway Crashes in Adverse Road Weather Conditions. *Proceedings of the 88th Annual American Meteorological Society Meeting*, 20-24 January, New Orleans, LA.

Qui, L., 2008: Performance measurement for highway winter operations. Accessed 10 March 2018. [Available online at http://ir.uiowa.edu/etd/28/]

Qiu, L., and W.A. Nixon, 2009: Performance measurement for highway winter maintenance operations. No. IHRB Project TR-491. IIHR Hydroscience and Engineering, University of Iowa.

Rasmussen, R.M., J. Vivekanandan, J. Cole, B. Myers, and C. Masters, 1999: The Estimation of Snowfall Rate Using Visibility. *J. Appl. Meteor.*, **38**, 1542–1563, https://doi.org/10.1175/1520-0450(1999)038<1542:TEOSRU>2.0.CO;2.

Road Weather Management Program [RWMP], 2018: How Do Weather Events Impact Roads? Accessed 10 March 2018. [Available online at https://ops.fhwa.dot.gov/weather/q1_roadimpact.htm]

Robinson, D.A., 1989: Evaluation of the collection, archiving, and publication of daily snow data in the United States. *Physical Geography*, **10**, 120–130, doi:10.1080/02723646.1989.10642372.

Rutz, J.J. and C.V. Gibson, 2013: Integration of a Road Surface Model into NWS Operations. *Bulletin of the American Meteorological Society*, **94**, 1495–1500, https://doi.org/10.1175/BAMS-D-12-00037.1.

Ryan, W.A., N.J. Doesken, and S.R. Fassnacht, 2008: Evaluation of ultrasonic snow depth sensors for U.S. snow measurements. *Journal of Atmospheric and Oceanic Technology*, **25**, 667–684, doi:10.1175/2007JTECHA947.1.

Sanders, K.J., and B.L. Barjenbruch, 2016: Analysis of Ice-to-Liquid Ratios during Freezing Rain and the Development of an Ice Accumulation Model. *Weather and Forecasting*, **31**, 1041-1060, doi: 10.1175/WAF-D-15-0118.1.

Simpson, R.H., 1974: The hurricane disaster-potential scale. *Weatherwise*, **27**, 169–186, doi:10.1080/00431672.1974.9931702.

Storm Prediction Center [SPC], 2016: SPC Products. Accessed 1 July 2016. [Available online at http://www.spc.noaa.gov/misc/about.html#Severe%20Weather%20Risks.]

Storm Prediction Center [SPC], 2018: Beaufort Wind Scale. Accessed 15 January 2018. [Available online at http://www.spc.noaa.gov/faq/tornado/beaufort.html.]

Strong, C., Y. Shvetsov, and J. Sharp, 2005: Development of roadway weather severity index. Final Technical Report, U.S. Department of Transportation, 76 pp. [Available online at https://westerntransportationinstitute.org/research_projects/development-of-a-roadway-weather-severity-index-showcase-evaluation-16/.]

Trnka, M., E. Kocmankova, J. Balek, J. Eitzinger, F. Ruget, H. Formayer, P. Hlavinka, A. Schaumberger, V. Horakova, M. Mozny, and Z. Zalud, 2010: Simple snow cover model for agrometeorological applications. *Agricultural and Forest Meteorology*, **150**, 1115–1127, doi: 10.1016/j.agrformet.2010.04. 012.

Walker, C.L. and M.R. Anderson, 2016: Cloud Impacts on Pavement Temperature and Shortwave Radiation. *Journal of Applied Meteorology and Climatology,* **55**, 2329–2347, doi: 10.1175/JAMC-D-16-0094.1.

Walsh, C., 2016: Winter Maintenance Performance Measure. Report No. CDOT-2016-02. Louisville, CO: Vaisala Inc., 22 pp.

Weather Prediction Center [WPC], 2018: Winter Storm Severity Index. Accessed 15 January 2018. [Available online at http://www.wpc.ncep.noaa.gov/wwd/wssi/wssi.php.]

Wisconsin Department of Transportation [Wisconsin DOT], 2014: ANNUAL WINTER MAINTENANCE REPORT 2013-2014: Keeping Wisconsin Moving During the Polar Vortex. Division of Transportation System Development, Bureau of Highway Maintenance, Winter Operations Unit.

Ye, Z., C.K. Strong, L. Fay, and X. Shi, 2009: Cost benefits of weather information for winter road maintenance. Final Report, Iowa Department of Transportation. Accessed 1 July 2017. [Available online at https://westerntransportationinstitute.org/wp-content/uploads/2016/08/4W1576_Final_Report.pdf]

Zhang, D., S. Chen, and K. Tan, 2005: Improving the robustness of online agglomerative clustering method based on kernel-induce distance measures. *Neural Processing Letters*, **21**, 45-51.

## APPENDIX A: Weather-Related Initial Survey Questions

1. Please rate each of the following weather variables based on the importance for winter maintenance operations.

| Weather Variable | Not Important | | Moderately Important | | Very Important | Do not know |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | |
| **Snowfall** | O | O | O | O | O | O |
| **Air Temperature** | O | O | O | O | O | O |
| **Road Temperature** | O | O | O | O | O | O |
| **Wind** | O | O | O | O | O | O |
| **Blowing/drifting** | O | O | O | O | O | O |
| **Freezing Rain** | O | O | O | O | O | O |
| **Other (Please specify) ____________** | O | O | O | O | O | O |

2. How do you obtain your weather forecast at different stages of a storm? (Please check all that apply)

| Weather Information Source | Before Storm | During Storm (While Snowing) | Post-Storm | Not Used |
|---|---|---|---|---|
| **The Weather Channel** | ☐ | ☐ | ☐ | ☐ |
| **National Weather Service** | ☐ | ☐ | ☐ | ☐ |
| **Local TV / Radio** | ☐ | ☐ | ☐ | ☐ |
| **Newspaper** | ☐ | ☐ | ☐ | ☐ |
| **Mobile Application on Smartphone or Tablet** | ☐ | ☐ | ☐ | ☐ |
| **Private Weather Consulting Company** | ☐ | ☐ | ☐ | ☐ |
| **Maintenance Decision Support System** | ☐ | ☐ | ☐ | ☐ |
| **Internal Meteorologist on Staff** | ☐ | ☐ | ☐ | ☐ |
| **Other (Please specify) __________** | ☐ | ☐ | ☐ | ☐ |

3. Please rate each of the following weather variables based on your perception of forecast accuracy.

| Weather Variable | Not Accurate | | Moderately Accurate | | Very Accurate |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| **Snow Occurrence** | O | O | O | O | O |
| **Snow Amount** | | | | | |
| **Air Temperature** | O | O | O | O | O |
| **Road Temperature** | O | O | O | O | O |
| **Wind** | O | O | O | O | O |
| **Blowing/drifting** | O | O | O | O | O |
| **Freezing Rain** | O | O | O | O | O |
| **Other (Please specify) __________** | O | O | O | O | O |

4. What weather information triggers your preparation (including pre-treatment) for a storm? (Please check all that apply)
☐ Any forecast threat of snow
☐ Forecast for specific amount of snow (If selected, please specify amount) __________
☐ Forecast for other specific weather conditions (e.g., high winds, if selected please specify conditions) ______________
☐ Wait until snow begins
☐ Others (please specify) ________________

5. How far in advance does the weather forecast influence your decision-making for winter maintenance operations?
   - O Less than 1 day
   - O 1 day
   - O 2 days
   - O 3 days
   - O 4 days
   - O 5 days
   - O 6-7 days
   - O More than 1 week
   - O Others (please specify) ________________

6. Does your agency pre-treat the roads (e.g., brine)?
   - O Yes
   - O No

7. What triggers deployment activities for a storm (e.g., plowing, material spreading excluding pre-treatment)? (Please check all that apply)
   - ☐ Snowfall begins
   - ☐ Certain amount of snowfall accumulation on road surface (If selected, please specify amount) ________
   - ☐ Snowfall expected to begin within a particular time frame (If selected, please specify time frame) __________
   - ☐ Accident reports
   - ☐ Request from law enforcement
   - ☐ Others (please specify) ______________

8. Does your agency use a winter severity index (WSI) for winter maintenance operations?
   - O Yes
   - O No

   a. If yes, please rate how well you feel the WSI accurately captures what happened?

| Level of Accuracy | Not Accurate | | Moderately Accurate | | Very Accurate |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| **Winter Severity Index** | O | O | O | O | O |

   b. If you are not using a WSI, would you be interested in developing a WSI to support your winter maintenance operations?
   - O Yes
   - O No

9. Are you willing to be contacted to provide follow-up information?
   - O Yes
   - O No

**APPENDIX B: Weather and Winter Severity Index Follow-up Survey Questions**

1. What factors account for the accuracy of your agency's WSI?

   ______________________________________________________________

   ______________________________________________________________

2. What factors account for the inaccuracy / error of your agency's WSI?

   ______________________________________________________________

   ______________________________________________________________

3. Who developed your WSI?
   - Internal staff
   - Private weather consultant(s)
   - University research collaboration
   - Use pre-existing WSI
   - Others (please specify) _______________

4. At what time scale is your WSI computed?
   - Hourly
   - Daily
   - Weekly
   - Monthly
   - Seasonal
   - Annual
   - Others (please specify) _______________

5. At what spatial scale is your WSI computed?
   - Sensor Location
   - Road Segment
   - City
   - County
   - District
   - Statewide
   - Others (please specify) _______________

6. What do you believe would improve your agency's WSI?

   ______________________________________________________________

   ______________________________________________________________

7. Please rank each of the following, from 1 = most important, how your agency uses its WSI?
_ __Budget planning and forecasting
_ __Previous budget justification
_ __Expense verification
_ __Performance improvement
_ __Others (please specify) _______________
_
8. Please explain how often your agency uses its WSI?

______________________________________________________________________________

______________________________________________________________________________

9. Suppose the following seven (7) weather variables are possible in your agency's WSI. Please rank each of the following, from 1 = most important to 7 = least important.
_ __Snow duration
_ __Snow amount
_ __Snow intensity
_ __Area receiving snowfall
_ __Air temperature
_ __Wind speed
_ __Visibility
_
10. Please indicate which weather parameters are included in your WSI, or if they are not used.

| Weather Parameter | Winter Severity Index | Not Used |
|---|---|---|
| **Air Temperature** | ☐ | ☐ |
| **Road Temperature** | ☐ | ☐ |
| **Wind** | ☐ | ☐ |
| **Freezing Rain** | ☐ | ☐ |
| **Snow Amount** | ☐ | ☐ |
| **Snow Frequency** | ☐ | ☐ |
| **Snow Amount** | ☐ | ☐ |
| **Blowing / Drifting** | ☐ | ☐ |
| **Other (Specify)** | ☐ | ☐ |

a. Which additional weather parameters would you like to see included in your WSI?

______________________________________________________________________________

______________________________________________________________________________

11. Please upload a copy of your agency’s WSI documentation or provide a current reference so we can obtain your documentation.