Relationships Between Weather and Roadway Safety

Final Report
September 2019

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16. Abstract

Much research has attempted to determine the impacts of weather events, specifically winter weather events, on mobility and safety. As more knowledge has been gained, attention has turned to quantifying the impacts of winter maintenance operations on safety.

This project studied the relationships between winter weather, safety, and winter maintenance operations. With detailed data available, a thorough examination of the interactions between these three issues was possible. To demonstrate the interactions between safety, weather, and maintenance operations, visualization tools were implemented to capture as many of the interactions as possible. Additionally, a crash frequency model and a crash severity model were developed to quantify the safety benefits of winter maintenance operations.

Because of the depth of data available, a deeper analysis was also conducted and deeper relationships discovered. An analysis of various ratios produced a clearer picture of the relationship between snowplow parameters and safety.

Ultimately, this project provided a greater understanding of key relationships among winter weather, snowplow operations, and traffic safety. The key findings can help better inform decision makers about how maintenance operations impact safety.

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RELATIONSHIPS BETWEEN WEATHER AND ROADWAY SAFETY

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EXECUTIVE SUMMARY

Objective

The objective of this research was to analyze the relationships between road weather conditions and crash occurrences in Iowa and to develop crash frequency and severity models considering weather-related factors. In particular, the researchers used snowplow automatic vehicle location (AVL) data to examine the effects of winter maintenance operations on roadway safety and mobility.

Background and Problem Statement

Inclement winter weather significantly impacts traffic safety. Between 2010 and 2014, Iowa saw more than 8,000 winter weather-related crashes, including 190 fatalities and serious injuries and 2,200 minor injuries. To mitigate the impacts of winter weather, the Iowa Department of Transportation (DOT) spent 34.6 million dollars on winter maintenance in 2018 and has averaged 29.44 million annually over the last five years.

Much research has attempted to determine the impacts of winter weather events on safety. As more knowledge has been gained, attention has turned to quantifying the impacts of winter maintenance operations on safety.

In recent years, the Iowa DOT has collected large amounts of detailed data pertaining to winter weather, traffic safety, and winter maintenance operations. Because of the amount of detail in the data, a thorough examination of the interactions between all three concerns has become possible.

Research Description

A crash frequency model and a crash severity model were developed to quantify and provide insight into the relationships among winter weather, traffic safety, and winter maintenance operations.

The models utilized data from various sources covering the winters of 2016–2017 and 2017–2018 and eight city centers in Iowa.

Weather data were obtained from automated weather observing system (AWOS) and road weather information system (RWIS) units. These data were fed into the Iowa Environmental Mesonet system, which provides highly granular data across Iowa.

Crash data were extracted from the Iowa DOT crash database.

AVL data from snowplows captured date and time, longitude and latitude, travel speed, plow position, and material spreading rate at approximately 10-second intervals.

The crash frequency model was developed based on snowstorm events. Each winter storm was considered as a sample. The number of crashes associated with each event was analyzed in relation to traffic-, weather-, and snowplow operation-related variables.

The crash severity model was developed by linking each crash with weather- and snowplow operation-related variables. An ordered logit model was used to model crash severity based on the five-tier KABCO numerical categorization system.

Because of the depth of data available, a deeper analysis was conducted involving various ratios between different datasets to further explore the relationship between snowplow parameters and crash risk.

Key Findings

A roughly 50/50 split of winter weather-related crashes occurred during a winter storm (i.e., during precipitation) versus outside of a winter storm. The large proportion of crashes outside of a winter storm may be attributed to the persistence of adverse pavement conditions after the storm ends and possibly drivers' false sense of safety.

Crashes resulting from winter events were found to be less severe than comparable crashes during the same timeframe. Weather-related crashes were found to have a greater proportion of property damage only (PDO) crashes and a lower proportion of major injury and possible injury crashes.

Counterintuitively, higher crash counts and frequencies were correlated with a higher number of snowplow passes (i.e., greater snowplow activity). This is because the number of snowplow passes is directly correlated to storm duration, in that snowplows travel greater distances and spread more material during longer storms.

When controlling for weather variables, normalizing the total solid material that snowplows spread by the total snowfall revealed that the more solid material spread, the greater the safety benefit.

Many winter crashes were found to be temporally located near a snowplow pass either before or after the crash event. Many of these crashes occurred along Interstate routes. Because these routes have multiple lanes and are plowed frequently, Interstate crashes are likely to occur close to a snowplow pass.

Crashes on Iowa routes tended to occur when plow passes were temporally further away from the time of the crash. The crash severity model showed that these routes are less safe than Interstate routes and that both US and Iowa routes had a higher propensity for severe crashes than Interstate routes.

An analysis of expected versus observed crashes showed that almost one-third of all crashes occurred before a snowplow pass, which was significantly higher than the expected proportion. The proportion of observed crashes where several snowplow passes occurred before the crash was significantly lower than the expected proportion. These relationships suggest that the greater the number of snowplow passes early in the storm, the fewer the crashes.

Implementation Readiness and Benefits

The results of this research helped elucidate the key relationships among winter weather, snowplow operations, and traffic safety. These findings can help inform decision makers about how maintenance operations impact safety.

The scope of the study was limited by the number of RWIS sensors, difficulties in quantifying winter storms, and crash data quality. Additionally, non-precipitation based winter weather events were not analyzed in the crash frequency model. For example, blowing snow can cause hazardous driving conditions across Iowa. Because of time and resource constraints, these events could not be incorporated into that part of the study.

The 50/50 ratio of crashes that occurred during versus outside of a storm event may indicate that crashes that occurred after a storm are underrepresented. Examining a longer period after the storm may present a clearer picture of the lasting effects of winter storms. Additionally, the impacts of individual snowplow passes on safety could be clarified by considering snowplow pass frequency in light of the number of lanes on the road.

INTRODUCTION

The Federal Highway Administration (FHWA 2017) states that 70 percent of the US population, as well as 70 percent of roadway networks, experience 5 inches or more of snow per year. The area that receives regular snowfall spans most of the United States, excluding southern states such as Florida, Georgia, Louisiana, Mississippi, and South Carolina. Because so many Americans experience winter driving conditions, it is important to determine how best to approach these winter events in order to provide the greatest utility to the overall public.

Each year, approximately 900 people are killed and 76,000 people are injured during winter weather events nationwide (FHWA 2017). These numbers increase to 1,300 deaths and 116,000 injuries when accounting for crashes caused by seasonal roadway conditions, such as snow- and ice-covered pavements. In Iowa, there were more than 8,000 winter weather-related crashes, 190 fatalities and serious injuries, and 2,200 minor injuries between 2010 and 2014 (Hans et al. 2018). Furthermore, the FHWA estimates that 21 percent of all crashes are related to weather, including rain, fog, and winter conditions.

Not only are there safety implications involved in winter weather, but mobility implications as well. Light precipitation can cause a speed reduction between 3 and 16 percent, while heavy snow can reduce speeds by 64 percent (FHWA 2018). Not only are speeds adversely affected, but the overall flow of traffic is restricted due to weather conditions.

To combat the adverse effects of winter weather events, state and local agencies spend more than 2.3 billion dollars on winter operations annually, which accounts for approximately 20 percent of state department of transportation (DOT) maintenance budgets (FHWA 2017). Furthermore, roadways deteriorate at a faster rate during winter maintenance operations, causing additional economic distress. In 2018, the Iowa DOT spent 34.6 million dollars on winter maintenance and has averaged 29.44 million annually over the last five years (Iowa DOT 2019a).

The objective of this project was to analyze the relationships between road weather conditions and crash occurrences in Iowa and to develop crash frequency and severity models considering weather-related factors. In particular, the researchers used snowplow automatic vehicle location (AVL) data to examine the effects of winter maintenance operations on roadway safety and mobility.

A crash frequency model and a crash severity model were developed to quantify the interacting variables. The crash frequency model was built based on snowstorm events. Each winter storm was considered as a sample. The number of crashes associated with each event was related to traffic, weather, and snowplow operation-related variables. The crash severity model was built by linking each crash with weather and snowplow operation variables. These models aim to provide insight regarding the relationships between weather, winter operations, and safety.

Various data sources were utilized. The main weather data sources included automated weather observing system (AWOS) and road weather information system (RWIS) units. These data were fed into the Iowa Environmental Mesonet system, which provides highly granular data across the state. Traffic volume data were collected from the Iowa DOT's automatic traffic recorders (ATRs) and Wavetronix sensors. In addition, snowplow AVL data were explored to understand the relationships among maintenance operations, winter weather events, and traffic safety.

This report is segmented into four additional chapters, as follows:

- First, the Literature Review chapter contains past work on the subject of winter maintenance operations and winter weather events and their relationships to traffic safety and mobility.

- Second, the Data Collection, Processing, and Quality Assurance chapter provides details on data collection and the method for processing and assuring the quality of the data. This chapter also provides details on the data preparation processes needed for estimating the crash frequency and crash severity models, each of which required a unique approach.

- Third, the Results chapter discusses the crash frequency and crash severity models and the analysis. Each model uses a separate approach even though the data sources for both are the same.

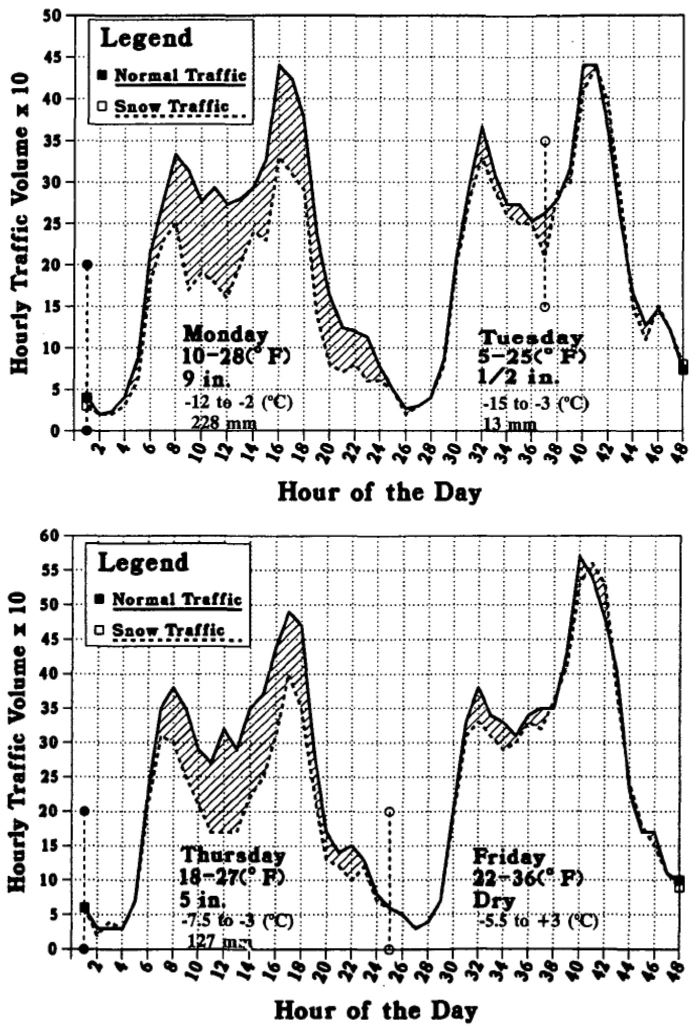
- Fourth, the Conclusions chapter summarizes the findings of this study and discusses future research directions.

LITERATURE REVIEW

In this chapter, we review past work studying how winter weather events impact traffic mobility and safety and examine the role of winter maintenance operations.

Mobility and Safety

Traffic volumes play an integral role in traffic safety models. Because of the nature of winter storm events, the typical traffic flows might not represent the actual volume traveled during the storm. Early work performed by Hanbali and Kuemmel (1992) demonstrated the effect of winter events on traffic volumes. They investigated the impacts of snowfall on traffic volumes by placing ATR counters throughout the midwestern and northeastern US. The traffic data were then compiled with weather data to observe the effects of weather on traffic volumes. The first finding is that more snowfall results in a greater reduction in traffic volumes, as seen in Figure 1.



Hanbali and Kuemmel 1992

Figure 1. Traffic behavior during weather events

The second finding is that the volume reduction depends on the time of day. The p.m. volumes were found to be less impacted compared to the a.m. peak volumes. This signified that travelers adjusted plans in the morning but were unable to make accommodations later in the day. The difference in volume reductions for weekday peak hours compared to weekday off-peak hours was significant. This suggests that people alter their travel plans when able. However, when schedule adjustment is not possible, many people continue to choose to drive in potentially adverse conditions.

More recent work has expanded the knowledge of changes in traffic patterns due to winter weather events. One study examined 15 years of traffic and weather data in order to enhance the current knowledge on traffic volume variation (Datla et al. 2013). The study found that traffic volumes vary more at the start of the winter season than at the end of the season. This suggests that drivers either adapt to driving in adverse conditions or gain a false perception of the potential safety implications. An alternative possibility is that drivers overestimate their own driving abilities. Specific classifications of roadways, such as Interstates and US highways, were categorized and analyzed. The findings show that commuter routes see the lowest variations in traffic volume and that non-commuter routes experience the largest variations in traffic volumes. Past research has also found that the overall traffic volumes during winter storm events is lower than average volumes. This suggests that individuals postpone trips due to inclement weather and/or that drivers adapt their routes to reflect snowplow activity. This study also inspected the relationships between traffic volume variations and vehicle class. It was found that passenger cars experience a greater volume reduction compared to commercial vehicles. The commercial traffic on main arterials can actually increase during winter weather events. The suggested reason for this was that commercial traffic is required to follow certain schedules. Furthermore, commercial traffic is diverted from minor roadways, where there is little to no maintenance, onto roadways that provide maintenance operations.

Inclement weather also impacts roadway capacity. Agarwal et al. (2005) examined speed and capacity variations for various weather conditions in Minneapolis. Four weather categories for both rain and snow were selected and studied: none, light, medium, and heavy (Table 1).

Table 1. Capacity reductions

		Capacity (percentage change)		
Variable	**Range (in./hr)**	**MSP**	**MIC**	**STP**
Rain	0	0	0	0
	0–0.01	-1.44	-1.17	-3.43
	0.01–0.25	-5.67	-5.94	-10.1
	>0.25	-10.72	-14.01	-17.67
Snow	0	0	0	0
	<=0.05	-3.93	-5.51	-3.44
	0.06–0.01	-8.98	-11.53	-5.48
	0.77–0.5	-7.45	-12.33	-13.35
	>0.5	-19.53	-19.94	-27.82

Source: Agarwal et al. 2005

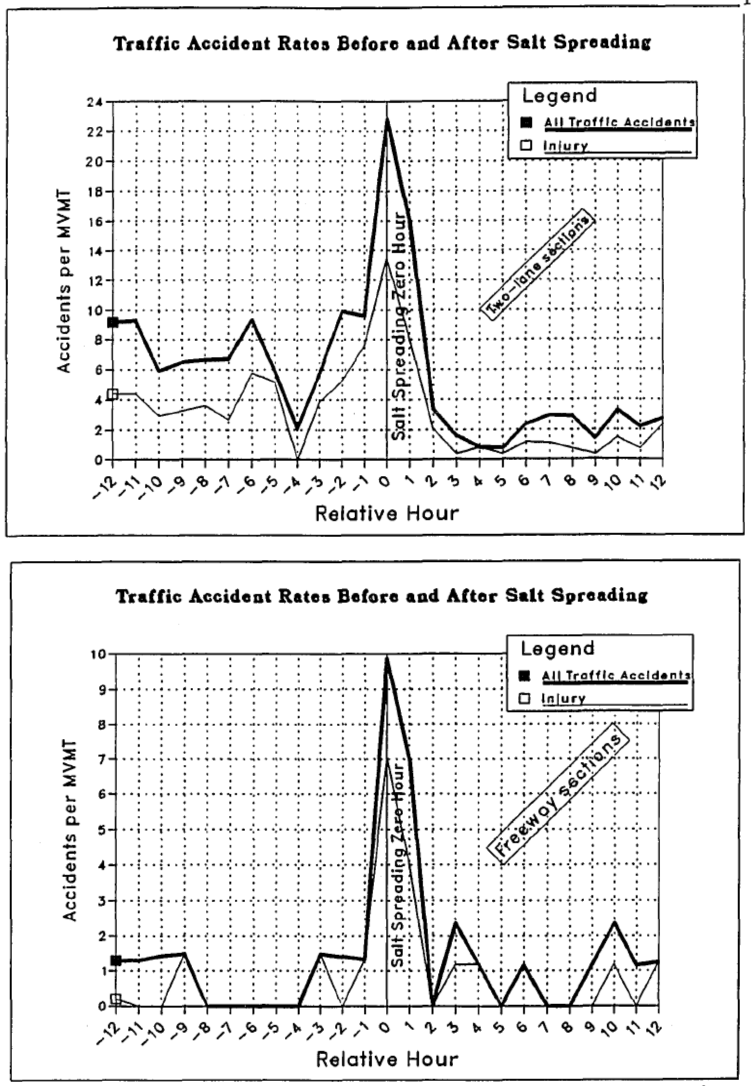
This study was performed over three main regions around Minneapolis using approximately 4,000 pavement sensors. The results for each region proved to be consistent with each other. What is unclear is how much of the capacity reduction is due to reduced speeds and how much is due to deteriorating road conditions. The question is whether snowplow operations would provide a significant increase in roadway capacity or whether the capacity reduction is due to visibility issues.

The safety implications of winter weather events have also been well documented. A study in Iowa performed by Maze et al. (2006) presented clear findings regarding the relationship between winter weather and traffic safety. Traffic counts along I-35 in northern Iowa were collected and aggregated together with weather and crash data. Overall, Iowa experienced an average of 18.2 snow events per year, which equates to 5 percent of the year. The results of a crash analysis showed that although snow events are infrequent, they account for 21 percent of all crashes. Along with this result, the findings reflected past work that found that crash rates increase and crash severities decrease for winter weather events. This is due mainly to the fact that vehicle speeds can be significantly reduced during storm events.

Maintenance Operations

Because winter weather events play a critical role in the roadway network across the nation, much work has been performed to determine the impacts of winter weather on traffic safety and mobility. The next key area of interest regarding the impacts of winter weather is how maintenance operations interact with these other variables to provide a better roadway system.

Though the data necessary to fully comprehend the effects of maintenance operations were not yet available, early attempts were made to quantify the benefits of winter maintenance operations. One of the earliest investigations of winter maintenance operations in the US was performed by Hanbali (1992). This study investigated the links between snowplow spreading times and locations with crash rates for winter events. A before-and-after analysis was performed in regards to when snowplows began spreading material on a specific roadway. This allowed for a comparison of crash rates on the same road with and without salt. The results showed that performing maintenance operations yields significant benefits in terms of traffic safety (Figure 2). While these charts in Figure 2 do not annotate the start of weather events, it can be presumed, based on past literature, that the spike in crash rates is due to winter weather events.



Hanbali 1992

Figure 2. Traffic crash rates before and after salt spreading at hour 0: two-lane highway (top), divided freeway (bottom)

Furthermore, this study presented the findings of a cost-benefit analysis of winter maintenance operations. The findings demonstrate that there are significant economic gains from maintenance operations. This economic benefits stem from less severe crashes, faster travel times, and better fuel efficiency. Hanbali (1992) quantified the effects specifically for the cost of accidents, the cost of time, and operational costs (Table 2).

Table 2. Influence of winter road maintenance on economic costs

	Two-Lane Highways		**Freeways**	
	Icy	**De-Iced**	**Icy**	**De-Iced**
Accident Costs	62.5	7.4	31.6	4.9
Time Costs	22.2	16.6	13.3	11.1
Total	84.7	24.0	44.9	16.

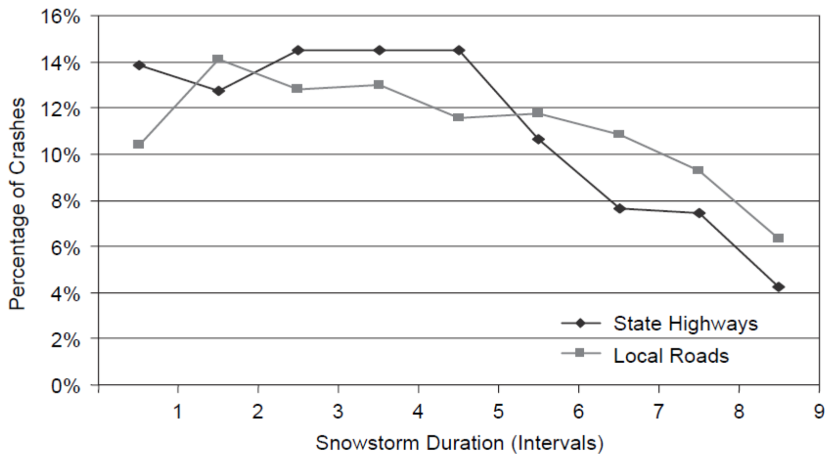
Costs are in cents per vehicle mile.

According to Table 2, the cost savings of maintenance operations are significant. The first savings are due to the reduced cost per accident. The study found a significant drop in fatal crashes, which most likely accounts for the large drop in costs. Because roads are more usable, travelers experience fewer interruptions, which ultimately decreases travel times and the associated costs of fuel and time. The study concluded that winter maintenance operations provided a benefit of $172 per mile for the first hour of salt spreading during a winter event for two-lane highways and $423 per mile for freeway segments.

Usman et al. (2010) examined the major factors determining the effectiveness of snowplow operations and the relationship between snowplow operations and safety. This study was performed in the city of Toronto on several select roadways throughout the city. Throughout Canada, a multitude of road condition weather information system (RCWIS) stations are set up to monitor everything from roadway conditions to precipitation and visibility. Toronto in particular employs a large number of such surveillance systems. Usman et al. (2010) focused on a winter weather event-based analysis. Variables such as road conditions and weather were collected for each storm event. The road conditions variable was meant to indirectly represent the presence of snowplow operations. This is because snowplows improve the surface conditions over time, which therefore means that these factors are correlated. The final model suggests that surface conditions, traffic volumes, and visibility have significant impacts on crash frequency throughout a winter storm. When accounting for all of the variables, surface conditions were found to have a large impact on the crash rate. As road conditions approach bare, the number of accidents drops dramatically.

This same group of researchers furthered their work in establishing a link between road surface conditions and safety (Usman et al. 2012). While their previous study (Usman et al. 2010) focused mostly on the maintenance operations for the entire storm, their later study focused on hourly data and its relationship to the entire storm event. This study was performed in the Ontario region of Canada and spanned six winter seasons. In order to quantify the effects of snowplow operations as a function of time, this study controlled the number of snowplow passes from the start of the storm event. The elapsed times investigated in the study were two, four, and six hours. Each route was designated to have a snowplow pass at one of the times of none, two, four, or six hours from the start of the storm event. The mean number of accidents was plotted along the elapsed time since the start of the storm. An analysis was performed for each of the elapsed time categories: pass times of two, four, and six hours and no pass times. The mean number of accidents dropped at the times when a snowplow pass occurred and then gradually increased as more time elapsed since the snowplow pass. These results indicate that earlier operations produce a prolonged benefit and suggest that earlier mobilization produces a greater impact on safety. Additionally, it was found that visibility, traffic volume, precipitation intensity, wind speed, and air temperature were all major factors affecting crash frequency.

Understanding the temporal relationship between safety and winter events can provide significant insight into the effectiveness of winter maintenance operations. One study focused on determining this relationship based on data from the state of Wisconsin (Qin et al. 2006). A major finding presented was the relative crash time from the start of the storm. For example, a crash that happened 6 minutes into a 60 minute storm would receive a relative time of 1, or 10 percent. The histogram in Figure 3 shows that most crashes occur earlier in storms and the percentage drops off significantly after about 50 to 60 percent of the storm has passed.



Qin et al. 2006

Figure 3. Crash percentages by storm time interval

In the crash frequency model developed by Qin et al. (2006), it was found that freezing rain, time at which plowing occurs before a storm, storm duration, deicing units per lane mile, salt per lane mile, and wind speed were significant. The results showed conflicting coefficients for deicing units and salt units. The deicing unit coefficient held a negative regression, meaning that the more deicing units used, the fewer crashes recorded. The salt unit coefficient held a positive regression, meaning that using more salt would produce more crashes. It is intuitive that larger storms create a demand for more material, which thus explains the positive relationship between crashes and salt use. Nevertheless, because of the unique nature of each winter event, representing the proper relationship between winter storms and snowplow operations presented many challenges for the study.

DATA COLLECTION, PROCESSING, AND QUALITY ASSURANCE

This chapter describes the data used in the study and quality control and assurance steps taken. Overall, five main categories of data were used:

- Weather data
- Crash data
- Traffic data
- Roadway information data
- Snowplow AVL data

The scope of these data spans two winter seasons from 2016 to 2018. Generally, winters in Iowa span anywhere from October 15 to April 15 of the following year. However, the winter of 2016–2017 was expanded to May 15, 2017. Therefore, we used data from November to May for the 2016–2017 winter season and from November to April for the 2017–2018 winter season. The geographical region of interest encompasses the entire state of Iowa and includes all of the Iowa DOT-maintained roadways (Figure 4). Iowa DOT-maintained roadways include the Interstates, US highways, and Iowa routes across the state.

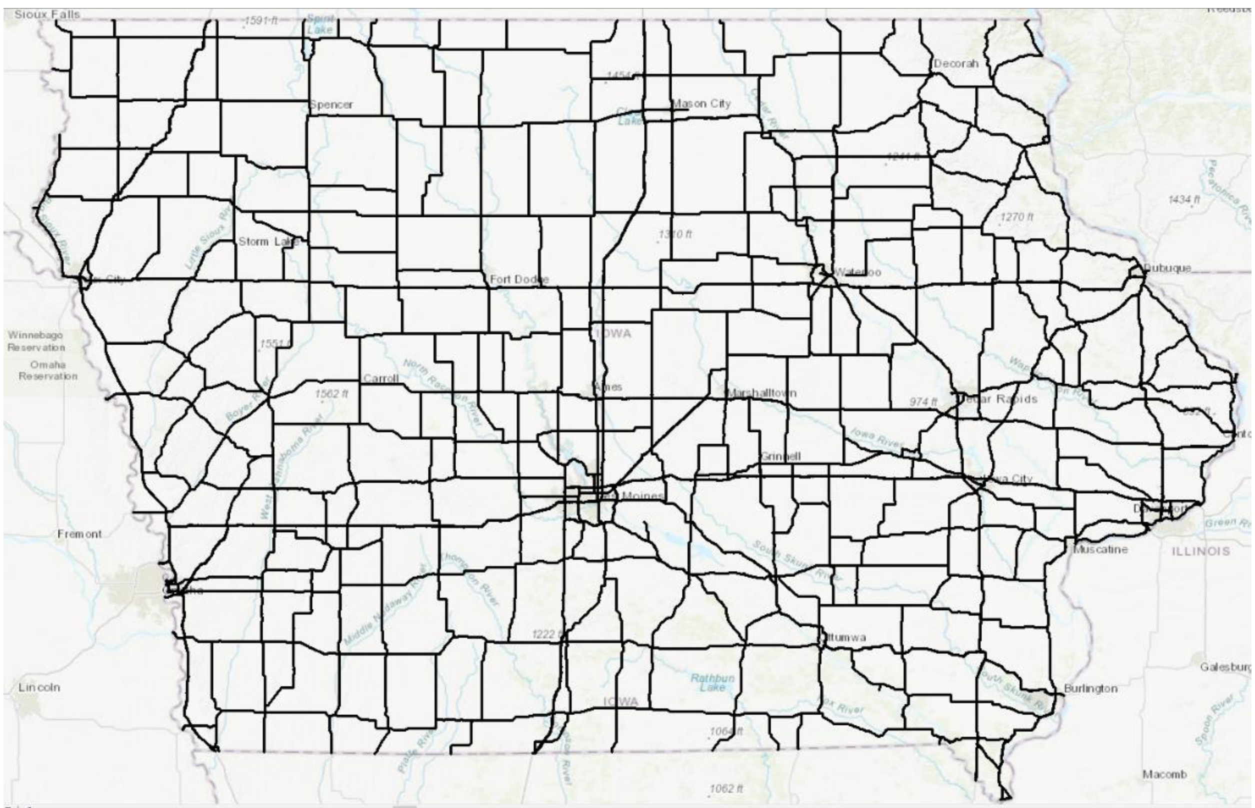


Figure 4. Iowa DOT-maintained roads

For the crash frequency model, eight independent urban city centers were selected for the study:

1. Ames
2. Des Moines
3. Council Bluffs
4. Cedar Rapids
5. Sioux City
6. Waterloo
7. Iowa City
8. Quad Cities

These eight regions encompass many of the large urban areas in the state of Iowa (Figure 5).

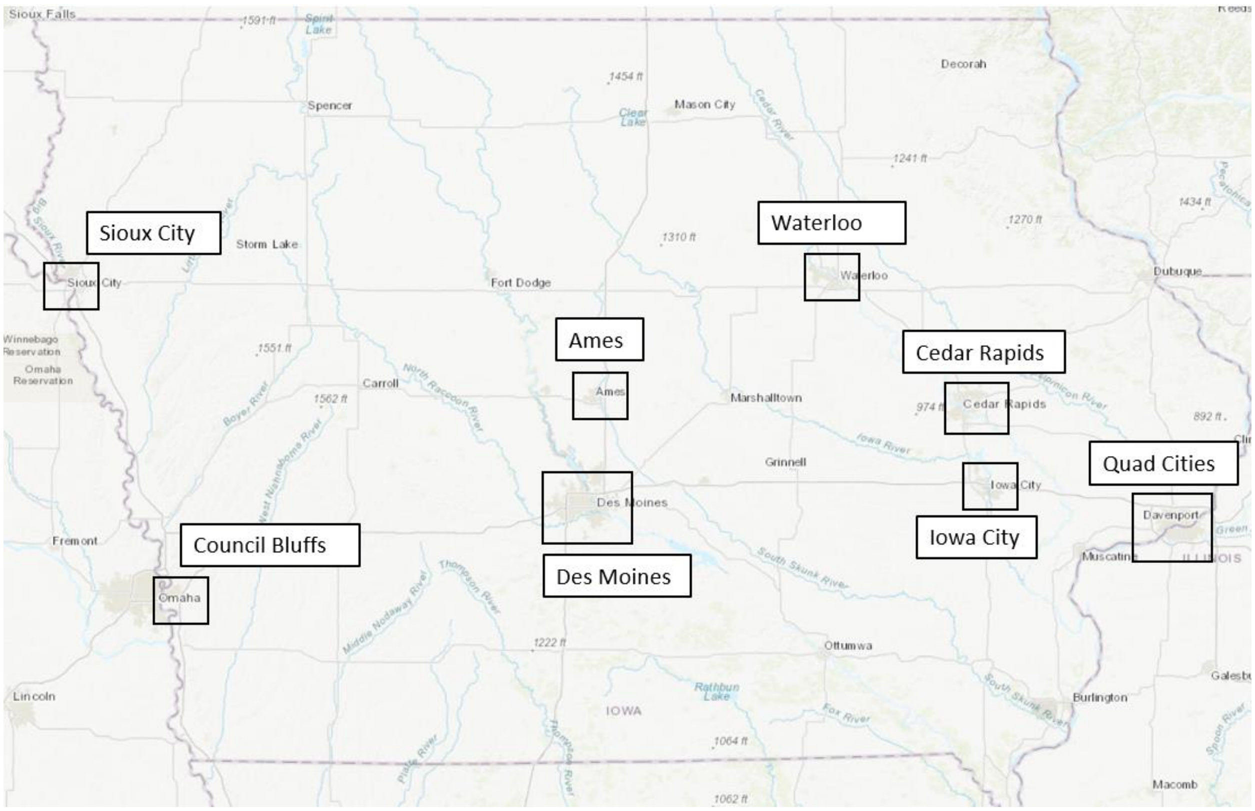


Figure 5. Iowa city centers map

Each of these eight regions also operates snowplow operations independently. In regards to the crash severity model, all available crash locations across the state were eligible samples so long as they fell along Iowa DOT routes.

Weather Data

The weather data were obtained from the Iowa Environmental Mesonet database. Within the mesonet database, there are several weather data programs. One is the Cooperative Observer Program (COOP) database, which measures daily snowfall. There are 123 stations throughout Iowa. Volunteers collect snowfall depth data every morning and report their findings. Another is the AWOS database. There are a total of 47 stations throughout Iowa, mainly at airports. They measure wet precipitation totals, precipitation type, visibility, weather warnings, temperature in Fahrenheit, and wind speed in five-minute aggregation chunks. The Iowa Environmental Mesonet database also partners with National Oceanic and Atmospheric Administration (NOAA) to share weather data. As a result, data from the Multi-Radar/Multi-Sensor (MRMS) project, which combines information from many sources and radar systems to create precise weather conditions, were available for this study. A list of relevant data is provided in Table 3.

Table 3. Weather variables

Weather Variable	Update Interval	Source	Description
Air Temperature (°C)	5 minutes	AWOS	The air temperature 2 meters above the ground
Wind Speed (knots)	5 minutes	AWOS	The average wind speed of the 5 minutes at 10 meters above ground
Hourly Precipitation (in./hr)	5 minutes	AWOS	The measured rate of snowfall
Weather Codes	5 minutes	AWOS	The weather conditions and the precipitation types
Precipitation Accumulation (in.)	5 minutes	NOAA MRMS	The liquid equivalent for the 5-minute interval
Daily Snowfall (in.)	1 day	COOP	Snowfall depth collected by volunteers throughout the state
Hourly Precipitation (in./hr)	5 minutes	AWOS	The current rate of precipitation
Freezing Rain (intensity)	5 minutes	NOAA MRMS / AWOS	Uses weather codes and precipitation totals to extrapolate the freezing rain intensity
Snow (intensity)	5 minutes	NOAA MRMS / AWOS	Uses weather codes and precipitation totals to extrapolate the snow intensity
Visibility (kilometers)	5 minutes	AWOS	The horizontal visibility measured by sensors
Roadway Condition	5 minutes	RWIS	The pavement surface conditions provided by sensors

Because of the scattered geographic nature of the weather variables, one of the initiatives started by the mesonet database was the grid cell identifier (GID) system. The state of Iowa is broken down into approximately 1-mile by 1-mile square blocks. Each square block is populated with the appropriate weather data depending on the current weather conditions across Iowa and its proximity to each respective weather sensor. This provides accurate weather data for the entirety of Iowa. By using the GID system and the five-minute data aggregation together, any location in Iowa has an accurate representation of current weather conditions.

RWIS stations provide weather data as well as pavement condition data at sensor locations. In total, there are 86 RWIS stations across the state. RWIS sensors provide qualitative data such as “icy,” “snow covered,” etc. While the weather conditions may give some indication of the roadway surface index, there is not a direct correlation between the two. While RWIS sensors can provide valuable information, each city center only has one or two sensors installed. Because of this, the sensor data can only provide the overall roadway conditions for the area and not the exact conditions at each crash location. Therefore, the RWIS data provided significant information for the crash frequency model but proved to be unusable for the crash severity model because of the geographic spread of the data. Crash data were located across the entire state and were not always near an RWIS sensor.

A categorical assignment method was applied to the road condition data. The RWIS data produced various codes for pavement conditions. Each code was assigned to a categorical number, 1 through 6, with the “Wet” and “Chemically Wet” codes in the same category. The “Other” and “Error” codes were discarded. A category of 1 indicated the best road conditions and 6 indicated the worst.

Crash Data

The crash data originated from the Iowa DOT crash database. The state of Iowa mandates that any crash resulting in injury or damages greater than $1,500 on public roads be reported. Once compiled, the data are split into three levels: the crash, vehicle, and person levels. Multiple person-level or vehicle-level relationships can exist for a single crash level. For the purposes of this research, only the crash-level database was examined.

Each crash is assigned to a geographic location as well as to a specific route with a direction of travel. The crash data include information such as the location, time, crash severity, direction of travel, lighting conditions, and weather conditions that contributed to the crash. Each crash may contain several levels of severity, such as fatal injury or property damage only (PDO), all resulting from a single crash event. Because only the crash-level data were applied to the analysis, a distinction needed to be made among the crash severity levels. Therefore, the highest severity was taken as the crash severity level for that specific event.

Four main fields in the crash reports were used to filter winter weather-related crashes. These are described in Table 4.

Table 4. Crash attributes

Crash Attribute	Description
Environmental Contributing Circumstances	If the environment/weather played role in the crash
Weather1	The primary weather conditions at the time of the crash
Weather2	Any other contributing weather conditions
Surface Conditions	The roadway surface condition at the time of the crash

As long as one of the four fields contained a winter weather-related variable, the crash was included in the analysis. Weather1 and Weather2 provided details of the contributing weather conditions. In the subsequent analysis, crashes with a contributing weather factor of snowfall, freezing rain, or blowing snow were considered.

Additionally, all crashes needed to have occurred along the aforementioned Iowa DOT maintenance routes and within the temporal range for each respective year. Ultimately, 5,089 winter weather-related crashes were identified for the winters of 2016 through 2018 combined (Figure 6).

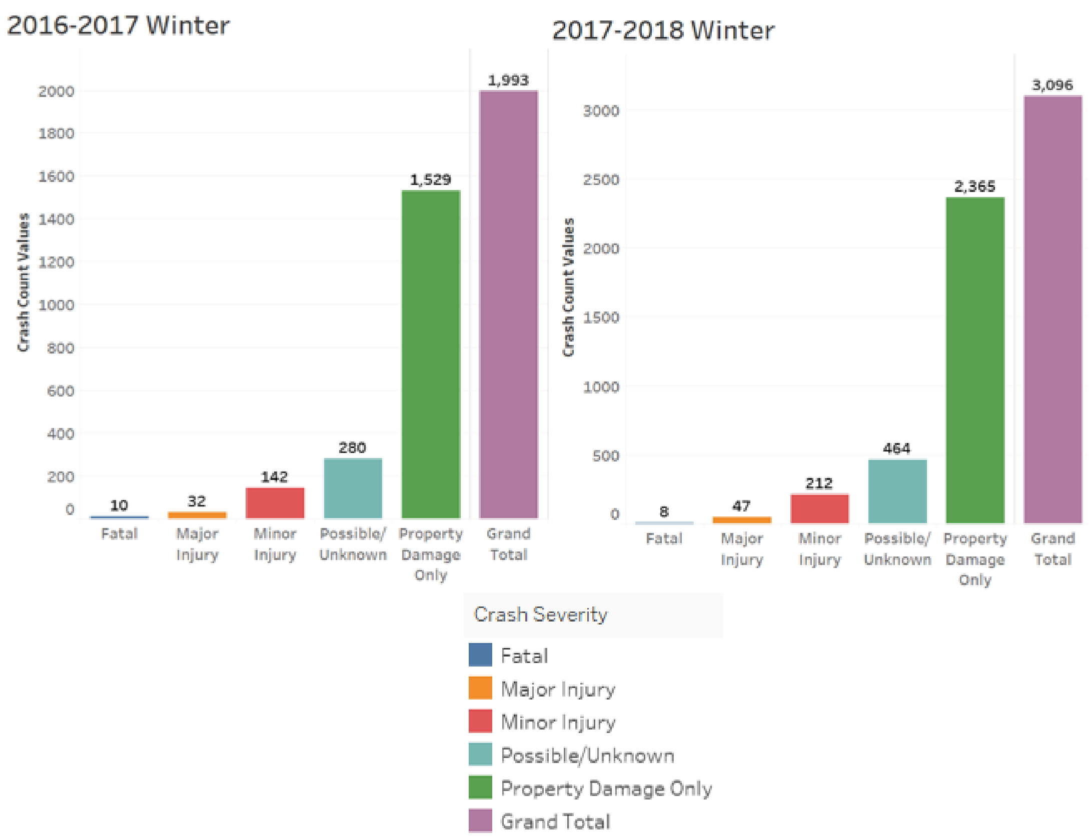


Figure 6. Crash severity breakdown for weather-related crashes on Iowa DOT maintenance routes during the 2016–2018 winters

Consistent with past research, most of the winter crashes identified tended to have low severities. The large jump in the number of crashes from the 2016–2017 winter to the 2017–2018 winter is due to the fact that there were more winter storm events that winter.

Several challenges existed in the crash dataset. First, the recorded crash times might not be accurate. Under normal weather conditions, neither the police nor the parties involved may remember the exact time of the incident. During winter weather events, police response time may be slower and crash reporting may occur significantly later, leading to a decrease in accurate reporting. Another source for error is the direction of travel indicated in the crash report. There are many instances throughout Iowa where a north/south roadway runs east/west or somewhere in between and vice versa. Several roads in Iowa also overlap, one example being I-80/I-35 in Des Moines, where the directionality for each route is not congruent with that of the other route. Attempts were made to correct this issue. However, they proved ineffective. In regards to the crash frequency model, these issues proved insignificant because the direction of travel within cities is not recorded. For the crash severity analysis, a significant portion of crashes along I-80/I-35 on the north side of Des Moines could not be assigned travel directions and therefore were omitted from the analysis.

Traffic Data

The Iowa DOT records and stores traffic data from across the state. The devices used to collect continuous traffic data are ATRs or Wavetronix sensors. ATR sensors cover every type of road class in Iowa in order to provide traffic data and create the seasonal and temporal annual average daily traffic (AADT) adjustment factors. The purpose of Iowa's Wavetronix sensors is to provide real-time traffic data, mainly along Interstate routes in metropolitan areas, to state officials. From these sensors, the five-minute aggregate data of speed, volume, and occupancy were obtained. Most Wavetronix sensors are placed in urban areas and offer significant coverage (Table 5).

Table 5. Wavetronix sensors

City	Number of Wavetronix Sensors
Ames	82
Cedar Rapids	163
Council Bluffs	151
Des Moines	289
Iowa City	78
Sioux City	92
Davenport	46
Waterloo	61

Although Wavetronix sensors are also placed in rural areas, there is not enough coverage to justify their use. For this reason, the Wavetronix data were applied to the crash frequency model but not the crash severity model.

In order to account for erroneous data, a filter was placed on the Wavetronix data to ensure that only accurate information would be used. The Highway Capacity Manual (HCM) states that a base capacity for freeways is 2,400 passenger cars per hour per lane (pcphpl) (TRB 2016). This filtering threshold was adjusted to reflect a five-minute interval and to account for the number of lanes on a particular roadway. For example, for a roadway segment with four lanes, the 5-minute volume cutoff value was set as 840 vehicles. That is, we considered any 5-minute volume less than 210 vehicles per lane as reasonable. These recommended values are based on normal weather conditions and uninterrupted flow, or baseline conditions.

The Iowa DOT offers statewide coverage of the AADT counts, which are updated on a four-year cycle. Because of this range in coverage, the AADT can be used to calculate counts for rural roads that do not have Wavetronix coverage. Through the ATR program, the Iowa DOT provides yearly updates to the temporal and seasonal adjustment factors. These adjustment factors can be applied to the AADT to calculate the traffic volume during winter weather events (Iowa DOT 2019b). Through the AADT and seasonal correction factors, the crash severity model accounted for traffic volumes in this manner.

Roadway Information Data

The Iowa DOT maintains a roadway network information system known as the Roadway Asset Management System (RAMS). This database offers information such as roadway geometry, speed limits, and AADT. One important component of RAMS is its linear reference system (LRS). This system is intertwined with the RAMS network and combines the geometric data with linear reference points. These reference points act like mile markers along a route and are instrumental in combining various data sources. Each similar section of congruent roadway becomes a unique route in the LRS system and contains the linear reference marks. This provides a tool to divide the same route based on different roadway geometric design constraints. Each LRS route is coded by directionality because certain geometric constraints may or may not be present on both sides of the route. Certain data, such as the AVL data, are based on directional flow and need a direction of travel to link data points.

In the crash frequency analysis for this study, two distinct measurements were taken for each city: the total length of roadway miles and the total lane miles (Table 6).

Table 6. City areas and miles

City	Road Miles	Lane Miles
Ames	142	285
Cedar Rapids	199	439
Council Bluffs	153	359
Des Moines	624	1380
Iowa City	227	563
Sioux City	218	517
Davenport	279	597
Waterloo	232	482

The total mileage is the length of all Iowa DOT-maintained roadways. The lane miles variable is the total roadway length multiplied by the number of lanes for each roadway segment.

AVL Data

The Iowa DOT has recorded snowplow AVL data for the past several years. The AVL data include date and time, longitude and latitude, travel speed, plow position (up/down), and spreading rate and are recorded at approximately a 10-second refresh rate for each snowplow truck. The Iowa DOT has more than 900 snowplow trucks distributed across 101 garages. Three types of spreading rates are recorded: solid rate, prewet rate, and liquid rate. While the prewet and liquid materials are measured differently, many snowplow operators apply these materials in tandem. The data collected also include a material set rate and actual spreading rates. Four types of plow wing records are available: front plow, left wing, right wing, and underbelly plow. The truck capacity is 12,000 lbs for single-axle trucks and 24,000 lbs for tandem-axle trucks.

The spreading rate is approximately 200 lbs per lane mile for solid material. The liquid material has varying spreading rates depending on the storm conditions. For anti-icing pre-storm conditions, the spreading rate is approximately 60 gallons per lane mile, and for in-storm conditions, the rate is approximately 10 gallons per lane mile. The service speed of plowing and spreading is about 30 miles per hour, and deadhead speed can be as high as the speed limit. Concerning the variables, plow operators often concurrently deploy the liquid material with the prewet material. For the purposes of this study, both were considered as the liquid rate.

Many variables are involved in the decision to perform maintenance operations. These range from time of day and current snowfall to weather forecasts. Because of these variances, each district is entrusted to make decisions based on their experience and expertise. The Iowa DOT has set guidelines for a snowplow pass frequency minimum for different levels of roads. The actual operation can vary by time of day, storm conditions, and the garage. Certain locations may receive more passes due to their central location and overlaps between snowplow routes.

The AVL data provided for this study had some quality issues. The plow position tracker data proved to be unreliable. Furthermore, multiple data samples had identical timestamp values but displayed different data values. Extensive corrective methods were applied to compile the most accurate dataset possible. Ultimately, a limited number of variables proved reliable for inclusion in the analysis (Table 7).

Table 7. AVL parameters

Variable	Unit	Description
LIQUIDRATE	gal/mile	Liquid material spreading rate
PREWETRATE	gal/mile	Prewet material spreading rate
SOLIDRATE	lbs/mile	Solid material spreading ate
PRELIQUID	gal/mile	Prewet and liquid material spreading rates combined
VELOCITY	mph	Vehicle speed
LOGDT	datetime	Timestamp of AVL data
routeId	LRS Route	LRS reference route ID
measure	LRS Reference	LRS route reference point beginning
END_MEASURE	LRS Reference	LRS route reference point ending

METHODOLOGY

This chapter presents the crash frequency model, crash severity model, and the statistical analysis methods used in this study.

Crash Frequency Model

The weather data sources were employed to create a list of storm events occurring between 2016 and 2018. This methodology followed the process used in similar studies (Usman et al. 2012, Usman et al. 2010). Figure 7 displays a representation of the data aggregation timeline used in this study. Data were collected and analyzed between the storm start and storm stop times for all data sources.

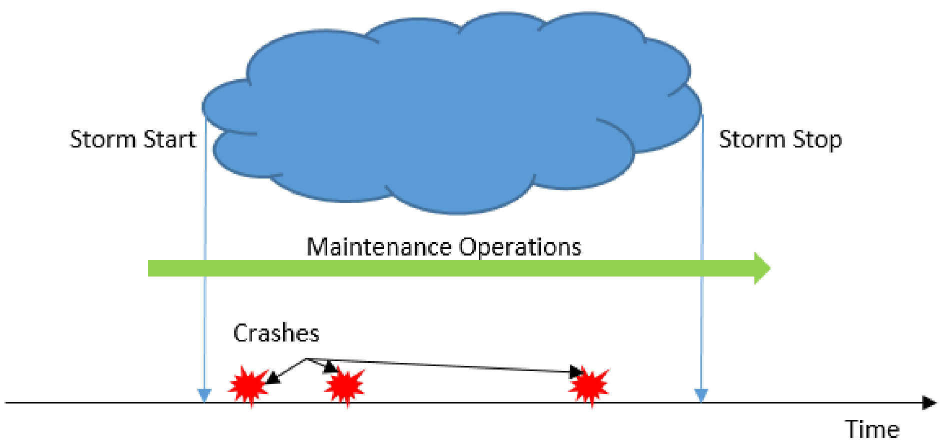


Figure 7. Crash frequency data aggregation timetable

Each of the eight urban centers were analyzed based on their respective weather events. The GID data were overlaid on top of each city in order to determine which GIDs encompassed that city. Base maps in ArcGIS were referenced in order to determine the cities' boundaries. A fence was drawn around each city in order to create the boundaries (Figure 10) (Figure 5). The GID data were intersected with the new bounding box, and a list of GIDs was extracted and aggregated together.

Because city centers are large geographic regions, it is possible that precipitation occurs on only part of the area. The purpose of aggregating the data was to ensure that these scenarios counted towards weather events in the region. A filter was applied to the GID data to extract any timestamps that had a precipitation greater than zero. Because the filtered list contained only precipitation events, a continuous strand of timestamps constituted a winter event. A single storm's start or stop time was then determined by calculating the difference in time between the previous and the subsequent data points. A gap of 20 minutes was used to determine the end of a storm. This was to account for any lulls in a storm event or errors in the weather data. In instances where there was a gap of less than 20 minutes, the two segments of precipitation were counted as the same storm event.

Additional filters were applied in order to determine the final list of snow events:

1. Any continuous time period with a total precipitation greater than 0, a magnitude of snow greater than 0, or a magnitude of freezing rain greater than 0
2. Any continuous time period with a temperature below 41 degrees Fahrenheit
3. Any continuous time period lasting longer than 30 minutes
4. No break in precipitation for longer than 20 minutes

Note that blowing snow events did not count as a winter weather event.

The weather data within each storm were then aggregated to determine the total precipitation, highest hourly precipitation rate, storm duration, average wind speed, and temperature. This process was performed for each city, which allowed for an analysis of variations in weather patterns. The COOP data were compared to the GID data in order to verify the accuracy of the data. Figure 8 displays the breakdown of storm events across both winters by city center.

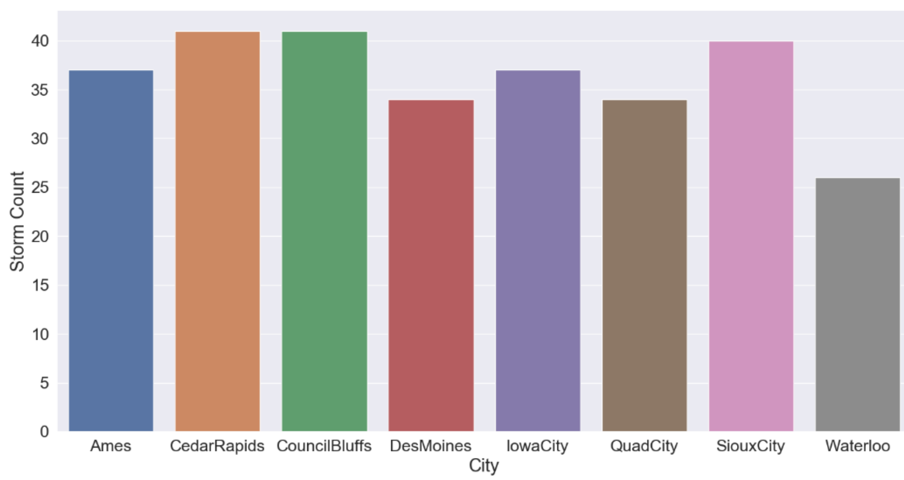


Figure 8. Storm count breakdown by city

While the eight cities are spread across a large geographic area, it was expected that there would be minimal variation among the city centers. When comparing cities that lie directly north and south of each other, the general trend is for more winter storms in the more northern city. For example, Ames is located approximately 30 miles north of Des Moines and received slightly more winter storms during the study period. The same relationship holds for Cedar Rapids and Iowa City. The only exception is the city of Waterloo.

Once the storms' start and stop times were determined, these timestamps were overlaid with the list of Wavetronix sensors from each city center. The associated vehicle count data collected from the Wavetronix were then summed to get the total summation of vehicle counts. Because of the storm-wide approach used in the crash frequency model, accounting for traffic volumes proved difficult. Prior research has proposed a unique method to account for traffic volume

(Usman et al. 2012). This method relies on an exposure count of traffic volumes, as displayed in equation (1).

$$Exposure = AVC \times Miles \tag{1}$$

Exposure accounts for the vehicle miles traveled (VMT) during the storm event, Miles is the road miles listed for each city in Table 6, AVC is the average vehicle count during the storm event. The AVC is the summation of vehicle counts divided by the total number of Wavetronix sensors divided by the total number of five-minute intervals for that respective storm. This results in an average count of vehicles per Wavetronix sensor per time unit interval.

As mentioned previously, the crash data were filtered to capture crashes where winter weather conditions were a contributing factor in the crash. An additional filter was applied to capture crashes where the crash time was within the storm start and end times. For this analysis, crashes after the storm stop time were not considered (Figure 9).

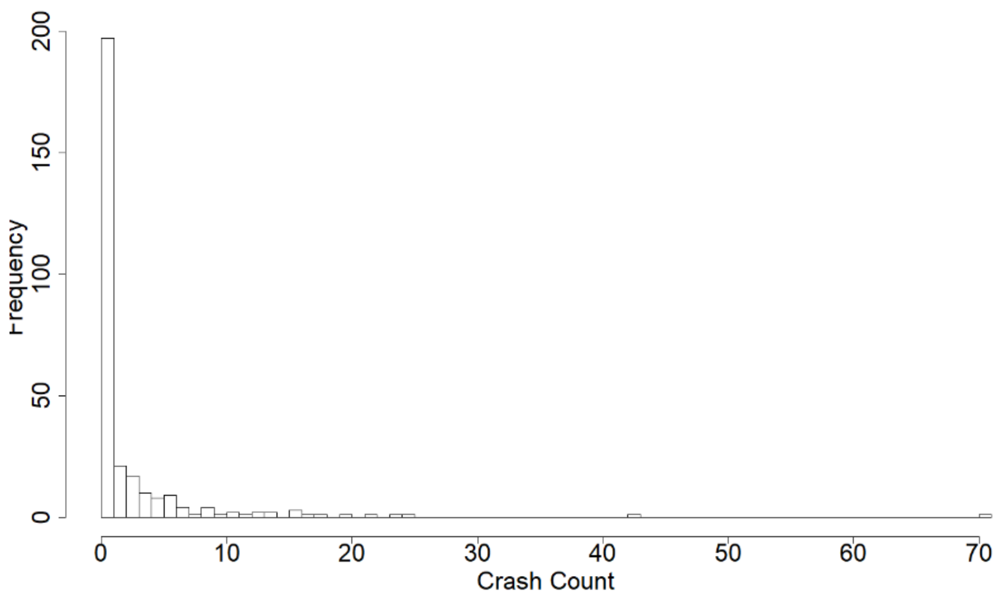


Figure 9. Storm-based crash counts

Many storms yielded zero crashes. However, several large crash counts were observed during a few storms (Figure 9). One storm in particular accounted for over 70 crashes.

Snowplow AVL data from across the state were collected from Iowa DOT-operated snowplows. The AVL data were overlaid with the GID data and the city boundaries in order to restrict data collection to each unique city center (Figure 10).

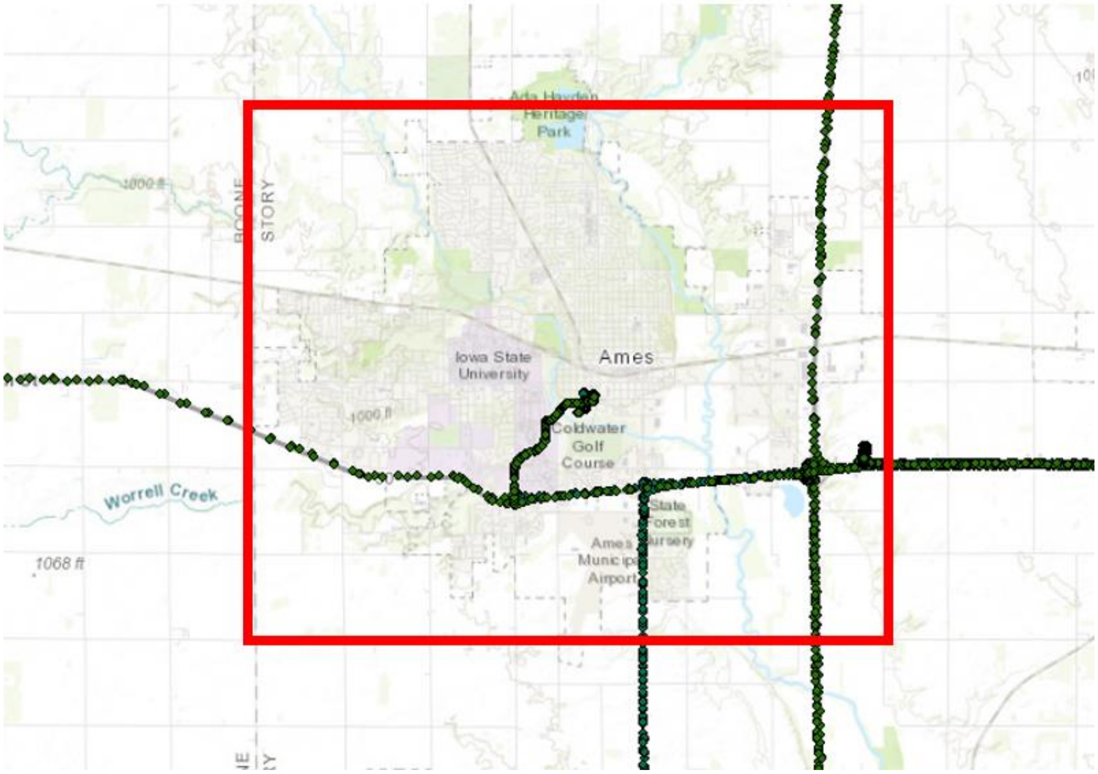


Figure 10. City center AVL boundaries

Once the geographic bounds were set, the AVL location was used to filter pertinent data. A list of snowplows was compiled for each storm event. Additionally, an extension of two hours before and two hours after the storm was created in order to catch a larger operations effect. Each snowplow was aggregated separately. Each data point contained the spreading rate and material being spread. The AVL data also tracked the distance traveled for each data point. This distance traveled was multiplied by the spreading rate of the material to obtain the total material spread for that AVL data ping. During this step, the erroneous material spreading rates were corrected.

In order to find the outliers for each truck, the material set rate value was taken and increased by 25 percent to provide a buffer region. This new maximum value was used as the filter value for each individual material spreading rate. For example, if a truck has a set rate of 200 lbs/mile for solid material, the maximum allowable value for the material rate for that truck is set as 250 lbs/mile. A similar calculation was performed for the liquid material.

These calculations were performed on every snowplow data point and then repeated for each snowplow that operated within the geographic bounds of the city center. Because the set rate for each material can change throughout a storm, applying a dynamic filter for every data point provided better accuracy. An error range of 25 percent was selected in order to provide an adequate buffer for possible actual spreading rates. A buffer was installed because of discrepancies between the set rate by the computer system and the actual material spreading rates.

Several variables were derived from the processed data, the first being Laps (previous Table 6). The Laps variable was calculated by dividing the total snowplow distance traveled by the Lane Miles for the city. Because the size of each city's roadway network varies, comparing the total distance traveled between storms would have skewed the data. For example, a smaller city such as Ames may take 20 hours to spread the same amount of material or travel the same amount of truck distance as Des Moines does in 4 hours. The variable Solid/Liquid per Lane Mile appeared in past research (Qin et al. 2006). This variable represents the intensity of the spreading of material for each city and in this study allowed for a normalized comparison.

Several major assumptions were made for this procedure. First, the snowplows provided equal coverage across all lanes. Although the distance traveled was recorded, no distinction was made as to which lanes were traversed. This also assumes that all lanes contain similar weather and road surface conditions. Because the RWIS sensors were so sparse, some discrepancy may exist in the actual roadway conditions in different parts of each city. Furthermore, no distinction was made as to the roadway type traversed. In practice, Interstate routes would receive more maintenance treatment than other routes, thus leading to a difference in maintenance service levels. In general, this analysis reports the overall and general performance of snowplow operations for the city center as a whole. Therefore, no distinction could be made in regards to the route type.

According to past work, crash frequency models tend to be over-dispersed (Lord and Mannering 2010). Because of this over-dispersion, typical Poisson regression models become invalid. In order to correct these issues, a negative binomial (NB) model is employed. The NB model can be written as follows:

$$Y_i \sim NB(\mu_i, \alpha) \tag{2}$$

where Y_i is the number of incidents during a winter storm event $i, (i = 1, \ldots, n)$, μ_i stands for the mean crash frequency, and α is the over-dispersion parameter. It is assumed that μ_i is a function of explanatory variables such that

$$\mu_i = \exp(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_k + \beta_{k+1} Ln(Average\ Exposure_i)) \tag{3}$$

where x_{ij} represents the jth variable in event i. $\beta_0, \beta_1, \ldots, \beta_{k+1}$ is a vector of regression parameters. Because each storm event has different traffic characteristics, $Ln(Average\ Exposure_i)$ acts as the offset variable.

Crash Severity Model

The crash severity model followed a similar methodology as the crash frequency with some minor variances. Each crash represented an individual event for this analysis. As such, filtering the pertinent crash data was the first priority. Each crash contained a latitude and longitude. This information allowed each crash to be linked to the RAMS LRS and receive a linear reference distance mark. For example, crash A was linked to I-80 at reference mark 21.3. The direction of travel for the crash was needed to clarify which route reference direction to assign. In this regard, a stretch of crashes along I-80/I-35 in Des Moines proved unusable due to the fact that they did not have correct direction assignments.

Once the LRS route assignment for each crash was made, traffic variables could be added. The Iowa DOT maintains a database of AADTs throughout the state and links them to RAMS, and thus the LRS. This allowed the seasonal adjustment factors to be applied to each crash location for this study. With the LRS code, the route speed limit, route type, and an urban or rural designation were also attached.

Each AVL data point contains a reference to the LRS system. This marks the route ID, the reference distance start point, and the reference difference stop point. Therefore, each plow point covers a geographic as well as a temporal range along a specific route. The snowplow parameters, such as spreading rate, apply to that entire region of roadway. The snowplow parameters and the LRS reference are then updated in the ensuing data point. This successive process continues for the duration of the plow operations, providing continuous coverage of the traversed roadways. Figure 11 presents a visual of the AVL data overview.

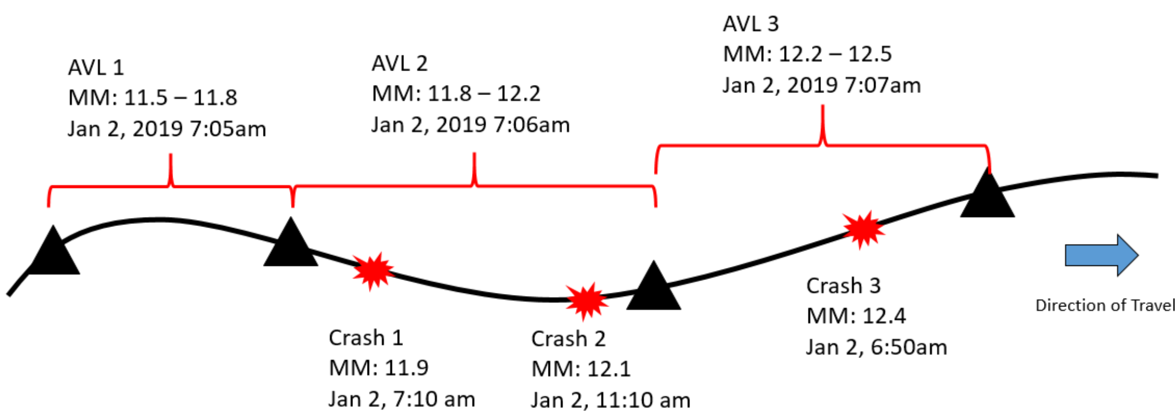


Figure 11. Snowplow crash point connection

Since both the AVL and crash data contained the LRS data, these datasets were prepared so that they could be joined. Because the LRS provided route IDs with direction and reference points and continuous coverage, the data were connected in a straightforward fashion using several criteria:

- Crash and AVL direction match and route IDs match
- Crash falls within AVL reference distance mark
- AVL passes come within two hours before or two hours after the crash

In order to match the AVL and crash points, the route ID and direction of travel needed to match. This would ensure that AVL points from the opposite direction of travel on the same road would not count towards that crash and vice versa. Figure 11 displays the process implemented to connect the data. Each AVL point contains a range for the reference distance mark, while each crash point contains a single reference distance mark. The first step in filtering was to find where the crash reference distance mark fell within the range of AVL reference distance marks. In Figure 11, Crash 1 and Crash 2 fall within the second AVL point, while Crash 3 falls within the third AVL point. As stated previously, the Iowa DOT maintains a two-hour pass frequency rate for its maintenance routes. The absence of a plow pass within two hours, plus or minus, signifies that AVL operations are not currently operating. There may be instances where plow pass frequency is delayed by the intensity of the storm, causing travel delays. Another scenario might be that the storm's intensity is insufficient to necessitate standard maintenance operations. In either case, observing a plow pass more than two hours before or after a crash likely has little impact on the events of the crash. It is under this assumption that a filter of two hours before or after a crash was applied to the AVL data points. In Figure 11, Crash 1 occurred 4 minutes after the most recent plow pass, and Crash 3 occurred 17 minutes before the most recent plow pass. Meanwhile, Crash 2 occurred approximately 4 hours after the most recent plow pass and was therefore not matched with the AVL data. Certain locations across Iowa experience a plow pass frequency greater than two hours. In these instances, the totality of the data was compiled and aggregated. The total before and after passes were counted, and the ratio of before passes to after passes was calculated.

Using a four-hour window for the effect of snowplow operations may exclude several important factors. Detailing the relationship between the time of a crash and the timeline of AVL operations can provide insight into their relationship. Past research has suggested that winter storm crashes occur early in the event and that road surface conditions play an important role in crash safety (Qin et al. 2006). By identifying the start time and duration of snowplow operations in relation to each crash, the entirety of the operations could be analyzed. AVL data for the 24 hours both before and after the crash were filtered in order to determine the relevant operational events. As long as there were consistent plow operations or a pass frequency of approximately two hours, AVL data were considered part of the same operational event. Once the plow operation event was determined, the relative relationship between the crash time and the plow operations start time was derived by equation (4).

$$Relative\ Time = {}^{CT - OS}\!/_{OE - OS} \tag{4}$$

Relative Time is a normalized scale for the crash time occurrence. CT stands for crash time, OS stands for operation start, and OE stands for operation end. By placing all crashes on a normalized scale, it becomes possible to compare the relative crash times in relation to the snowplow operations.

In addition to examining the AVL operations as a whole, the investigation of individual plow passes may provide further insight. The count of total passes represents the overall frequency of passes for a specific location. Consequently, this does not fully represent the temporal relationship between plow passes and crashes. A location with a high number of total passes may simply have multiple roadway lanes. Alternatively, many plow passes may have occurred at the two hours before or after mark. By examining the temporal proximity of snowplow passes to each crash, these biases can be corrected. For each crash, the nearest AVL pass both before and after was marked. By identifying these values, the plow pass proximity conditions at the time of the crash can be better understood.

Each single crash was linked to the GID cell in which it was located. Once a GID cell was assigned to each event, the weather data could be aggregated. A list of storms for each location was compiled. If a crash fell within a storm, the relative time in relation to the storm was determined following equation (4). In this case, however, the operation start and end times were replaced with the storm start and end times. Not all crashes fell within a winter storm. Various crashes occurred immediately before or immediately after the winter event. If a crash did not occur during a winter storm, the time since the previous storm and the time until the next storm were calculated. By determining the proximity of crashes to weather events, the temporal relationship between winter storms and crashes can be better understood.

In the literature, ordered probit and logistic regression models have typically been used to model crash severity. The KABCO system is a five-tier numerical categorization (Table 8) for describing crash severity (Iowa DOT 2014).

Table 8. KABCO scale

Symbol	Injury	Description
K	Fatal	Results in death within 30 days
A	Suspected serious/incapacitating	Injury prevents victim from continuing activities
B	Suspected minor/non-incapacitating	Injury present but continues activities
C	Possible	Non-visible injury or complaint
O	Uninjured	Property damage only

Often, the number of fatal and serious injury crashes is insufficient for individual analysis. In these cases, the various injury levels can be combined to provide adequate samples for analysis.

Ultimately, a proportional odds model, or an ordered logit model, was applied to the crash severity data (equation [5]).

$$z = \beta X + \varepsilon \tag{5}$$

where z is a latent variable that is predicted by the generalized linear equation, β represents a vector of coefficients that can be estimated, X is a vector of predictor variables, and ε is a random disturbance term. A threshold equation is then created (equation [6]).

$$y = 1 \; if \; z \leq \mu_0$$
$$y = 1 \; if \; \mu_0 < z \leq \mu_1$$
$$y = \cdots$$
$$y = n \; if \; z \geq \mu_{n-1} \quad (6)$$

where μ is defined as the threshold parameter that defines y, or the injury severity level, and n represents the integer number of responses, or the number of injury levels.

An important component to severity analysis is to compute the marginal effects. The marginal effects for categorical variables represent the discrete change, or how the predicted probabilities change as the category varies (Williams 2018). Each crash severity level has the potential to interact differently.

Statistical Tests

Making comparisons between datasets provides many challenges. Establishing comparisons between two datasets that have the same mean and standard deviation and that are normally distributed is fairly straightforward. However, datasets are often not of the same size and distribution. Two common methods of determining the difference are the difference of proportions test and the t-test of mean differences.

The difference of proportions test is employed to determine the proportion of data that passes certain criteria for two separate datasets (Penn State Eberly College of Science 2018). These proportions are then compared to each other with the intent to determine if the difference in proportions is statistically significant. For example, a proportions test is able to determine whether a specific location experiences a higher rate of property damage crashes compared to other locations.

The null hypothesis for this analysis states that the proportions between the data bins are equal. Simply put, the difference between the two is assumed to be zero (equation [7]).

$$p_1 = p_2 \quad (7)$$

where p_1 represents the proportion from data bin 1 and p_2 represents the proportion from data bin 2. The alternative hypothesis for this test is that p_1 does not equal p_2. In order to reject the null hypothesis, the proportions test must return a result that is statistically significant. Statistical significance is defined as having a p-value of 0.05 or less. The p-value is derived from a z-score, which is calculated by using the proportions from the two datasets (equation [8]).

$$Z = \widehat{p_1} - \widehat{p_2} \Big/ \sqrt{\dot{p} \times (1 - \dot{p}) \times (\frac{1}{n_1} + \frac{1}{n_2})} \quad (8)$$

where $\hat{p}$ portrays the observed proportions from each dataset, n is the sample size of the respective data, and $\dot{p}$ describes the pooled proportion between the samples. In essence, the pooled proportion is the average proportion between the data. Equation (9) depicts the derivation of the pooled proportion.

$$\dot{p} = {}^{x_1 + x_2}\!/_{n_1 + n_2} \tag{9}$$

In equation (9), x simply portrays the total count of data in the respective category, while n depicts the sample size.

For this analysis, a two-sided z-score was calculated in order to determine the p-value. This is because the proportions for dataset 1 are able to be higher or lower than the proportion for dataset 2. In the scenarios where the dataset 1 proportion is designated as being higher or lower than the dataset 2 proportion, a one-sided z-score was computed (Penn State Eberly College of Science 2018).

In contrast to the difference of proportions is the t-test. The t-test was designed with the purpose of examining the mean and distribution between two data samples. Previously, the difference of proportions test was implemented in this study to determine if specific ratios in the data existed. Not all data is segmented in this fashion, however, and therefore the t-test is needed. For example, determining the difference in mean traffic volume between two locations requires a t-test. Generally, the t-test assumes that the variance of the data samples is the same and that they are normally distributed. Not all of the data examined in this study met those conditions. Therefore, a variation of the t-test called Welch's t-test is required. Welch's t-test does not require that data samples be normally distributed, nor that their variances be equal.

As with the difference of proportions, a null and alternative hypothesis are needed. The null hypothesis is that the means of the two samples are equal. The alternative hypothesis is that the means of the two samples are not equal. The next step dictates that a t-value be calculated using equation (10).

$$T = {}^{\mu_1 - \mu_2}\Big/_{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{10}$$

where μ values represent the mean for each respective sample set, s represents the variances of the respective datasets, and n signifies the sample sizes. With the t-value calculated, the p-value can be determined. A p-value of 0.05 once again signifies statistical significance.

RESULTS

This chapter highlights the key findings of this study.

Crash Frequency Analysis

The weather, traffic, crash, and AVL data for each winter storm were combined to create the dataset for the crash frequency analysis. In total, there were 232 eligible storms. Only two of the storms did not contain AVL data. Because they met the winter storm criteria, however, it was decided to include them in the study. The summary statistics for the dataset are shown in Table 9.

Table 9. Summary statistics of winter storm dataset

	Mean	Std. Dev	Minimum	Maximum
Crash Count (crashes)	1.84	3.41	0	22
Average Vehicle Count (veh)	3,995	4,707	24	44,155
Ln(Exposure)	13.35	1.03	10.82	15.53
Road Condition	3.39	1.23	1	5.21
Hourly Precipitation (in./hr)	0.01	0.01	0	0.06
Total Precipitation (in.)	0.78	1.58	0	10.05
Freezing Rain (mm)	0.02	0.06	0	0.37
Snow (in.)	0.56	0.33	0.02	1.88
Visibility (miles)	5.38	2	1.2	9.92
Temperature (°F)	22.82	9.43	-2.02	37.31
Wind Speed (knots)	9.97	4.35	0.71	24.49
Storm Duration (hours)	9.95	7.73	0.58	37.33
Truck Laps Traveled	4.6	3.82	0	22.59
Truck Liquid Spreading Rates (gal/mile)	27.84	11.13	0	102.96
Truck Solid Spreading Rates (lbs/mile)	180.78	39.53	0	297.2
Truck Prewet Spreading Rates (gal/mile)	3.59	2.95	0	13.95

N = 232 storm events

The Truck Laps Traveled is the total truck distance divided by the lane miles. This was presented in lieu of the total truck distance traveled in order to normalize the scale among the cities. Storms of equal impact for separate cities resulted in drastically different miles traveled. Because all of the city networks were of different sizes, the results became skewed and needed to be corrected.

To examine the interaction between weather, snowplow operations, and crashes, several plots were developed. Figure 12 depicts the relationship between snowfall, truck laps, and storm duration.

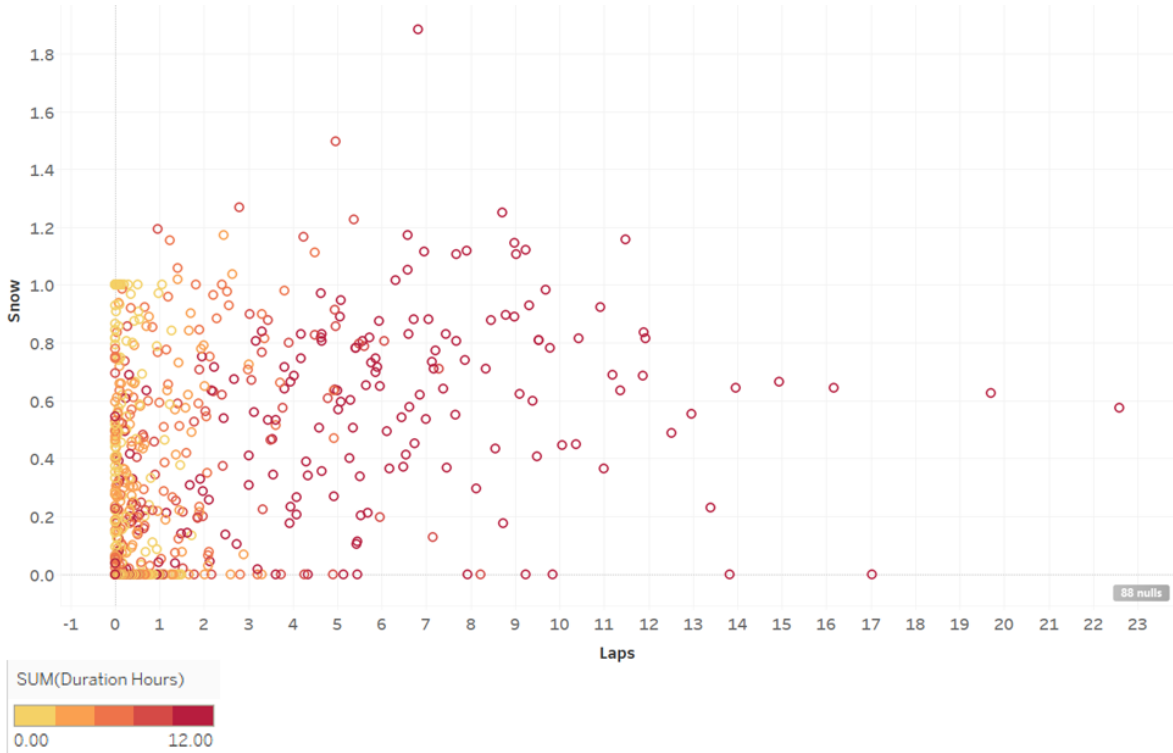


Figure 12. Snowfall versus truck laps

The snowfall variable is in inches while the laps variable is in truck laps for each respective city. The color scheme indicates the duration in hours of the storm. The darker the red, the longer the storm. Conversely, the lighter the yellow, the shorter the storm. The initial expectation was that the snowfall verse laps comparison would demonstrate a clear relationship where the more snowfall there was, the more truck laps would be taken. The y-axis at near 0 laps consists of numerous high-snowfall storms. These data points simultaneously exhibit short storm durations. Several of the storms with the highest number of truck laps by no means correlate to the storms with the highest snowfall amounts. This shows that the storm duration plays a greater role in snowplow distance traveled than total snowfall. With that being said, very few high-truck lap storms exhibit near 0 snowfall. Overall, the correlation between snowfall and truck laps is not significantly clear.

Figure 13 shows the interactions between precipitation and snowplow laps.

Figure 13. Worst snowfall versus truck laps

The Worst Snow variable is categorized into several possible values, with 1 being the lightest snowfall and 3 being the heaviest snowfall. The color scheme and x-axis remain the same as in Figure 12. Many of the storms in category 0 tend to be shorter storms that result in fewer truck laps. This trend continues for the storms in category 3, which mostly includes long-duration storms and very storms few having a low number of truck laps. This suggests that the more intense the snowfall, the longer the storm duration. Moreover, the longer that snow falls, the longer that snowplows are out plowing in order to improve traffic operations.

When examining the implications of both Figure 12 and Figure 13, it appears that storm duration plays a significant factor in AVL operations and in storm intensity. This assumption was validated by the plotting of Figure 14.

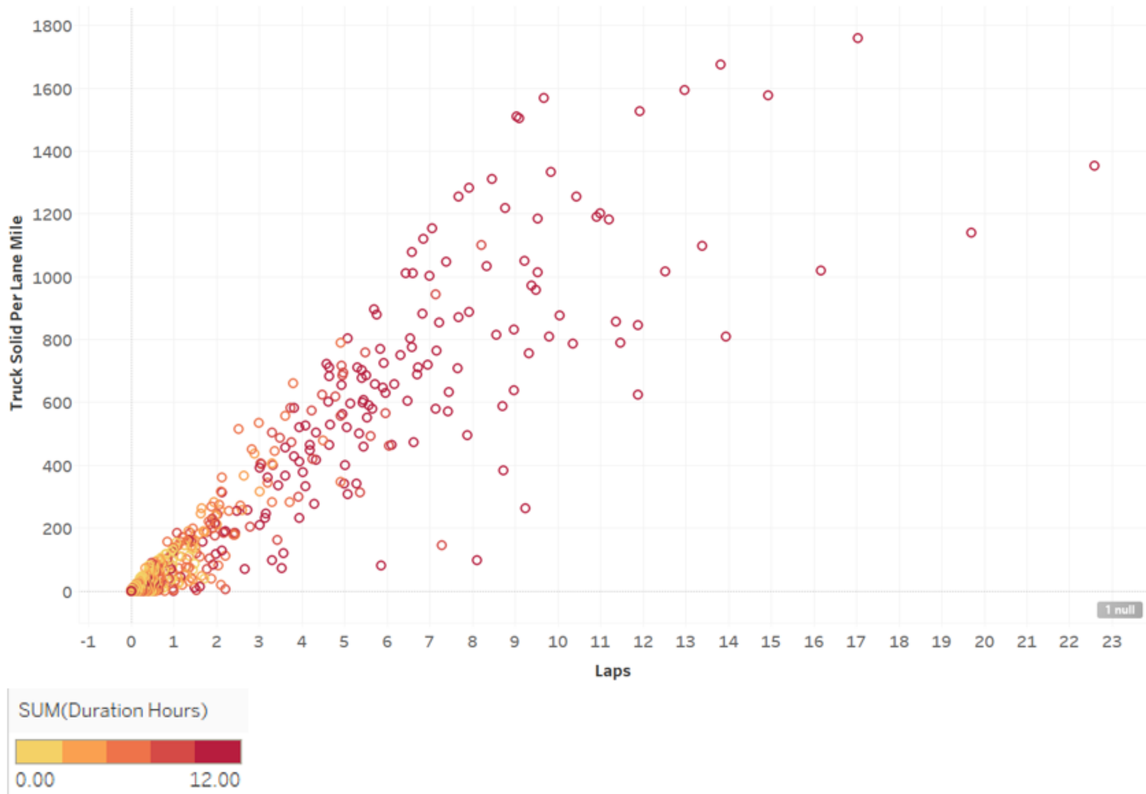


Figure 14. Truck solid per lane miles versus truck laps

The color scheme and x-axis remain unchanged from the previous two figures. In Figure 14, snowfall is replaced by the Truck Solid Per Lane Mile metric. This is the amount of solid material spread divided by the total lane miles for the urban region. This unit is in pounds per lane mile. The relationship here suggests that the longer the storm duration, the more plowing and more material spreading that occurs. Because of the correlation between the solid and liquid materials, a similar plot would exist independent of the material type displayed.

When controlling for the storm duration, a new trend emerged. The total solid material spread per lane mile was divided by the time of the storm in order to observe a comparable variable between events. Figure 15 displays the normalized spreading rate compared to truck laps traveled.

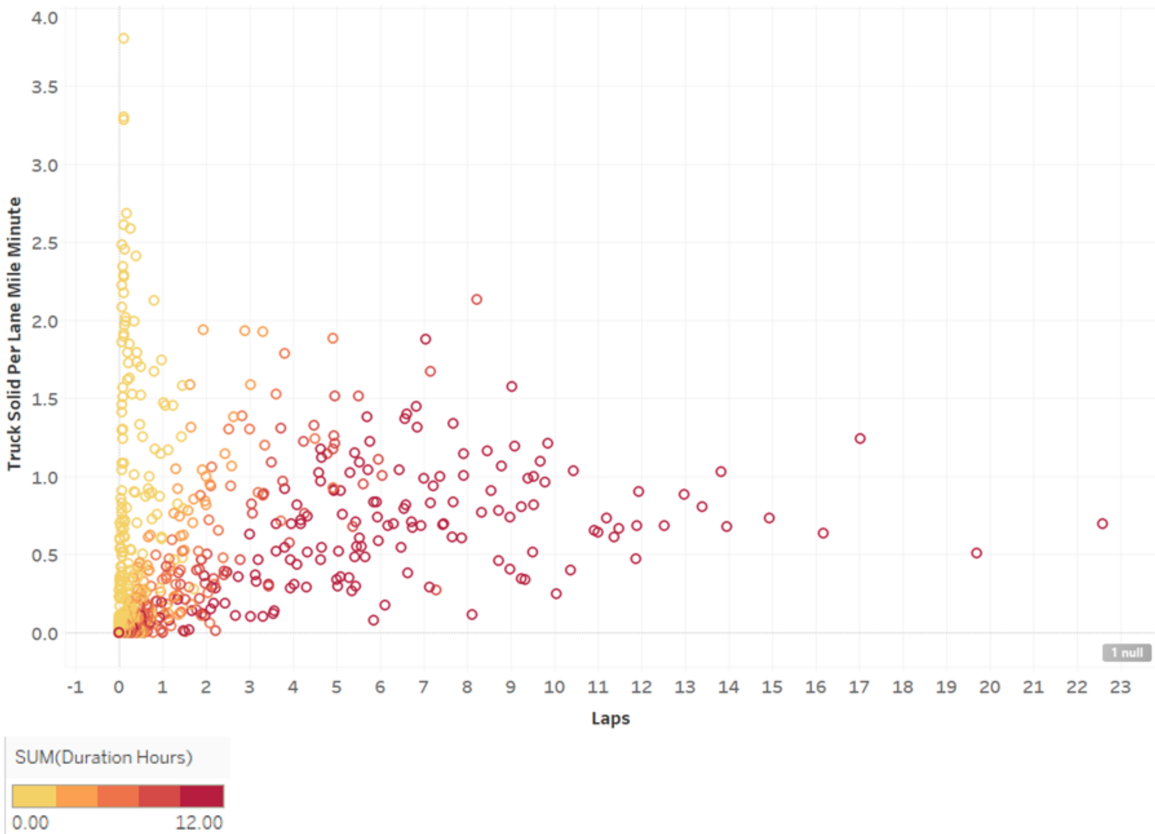


Figure 15. Truck solid per lane mile minute versus truck laps

Along the y-axis are many short-duration storms that also provided a high rate of material spreading. This trend indicates that the longer the storm duration, the more laps there were and the lower the normalized spreading rates. This suggests that maintenance operations for short-duration storms may concentrate on providing preventative maintenance by spreading material while longer-duration storms require more time plowing roadways instead of spreading material.

Investigating the relationships between weather and snowplow operations paved the way for further understanding of the impacts of winter weather events. An important factor that has not yet been considered is the effect that these variables have on crash safety and traffic operations. A fourth dimension, crashes, was added to the figures presented above. The crash variable was normalized by the exposure, or traffic counts, in each city. Figure 16 and Figure 17 demonstrate the end result of the incorporation of the crash variable.

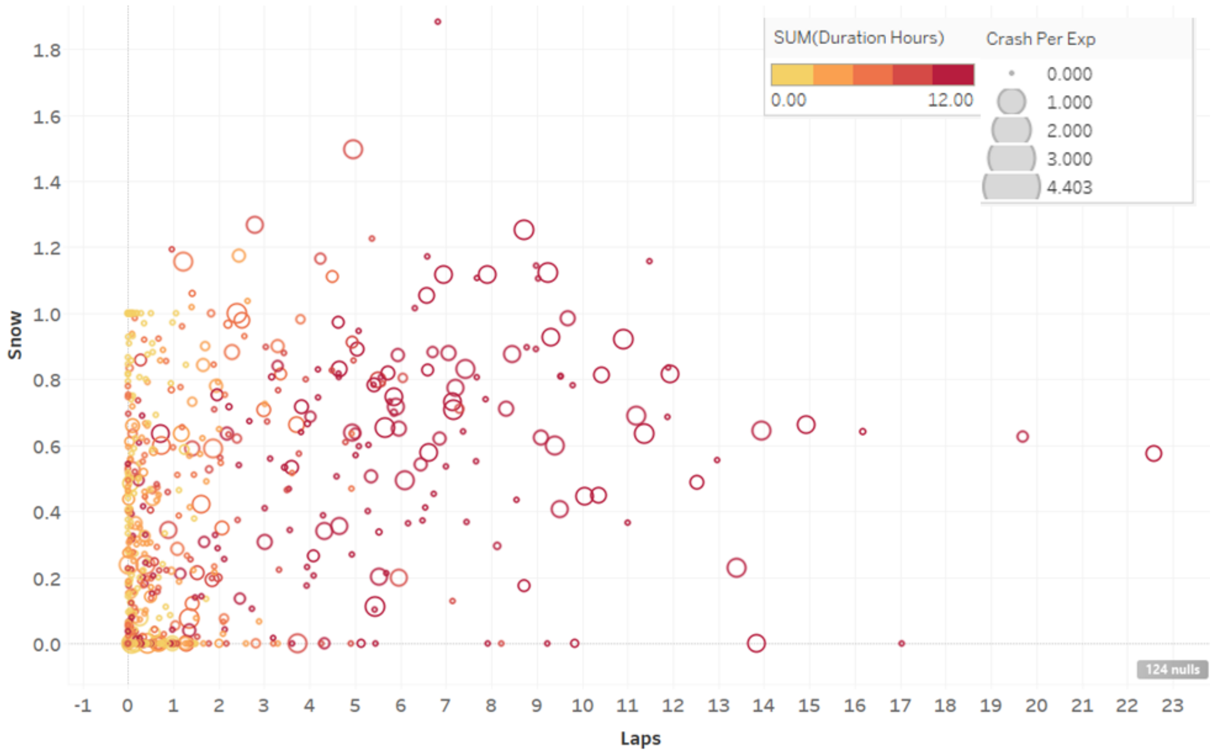


Figure 16. Snowfall versus truck laps – crash

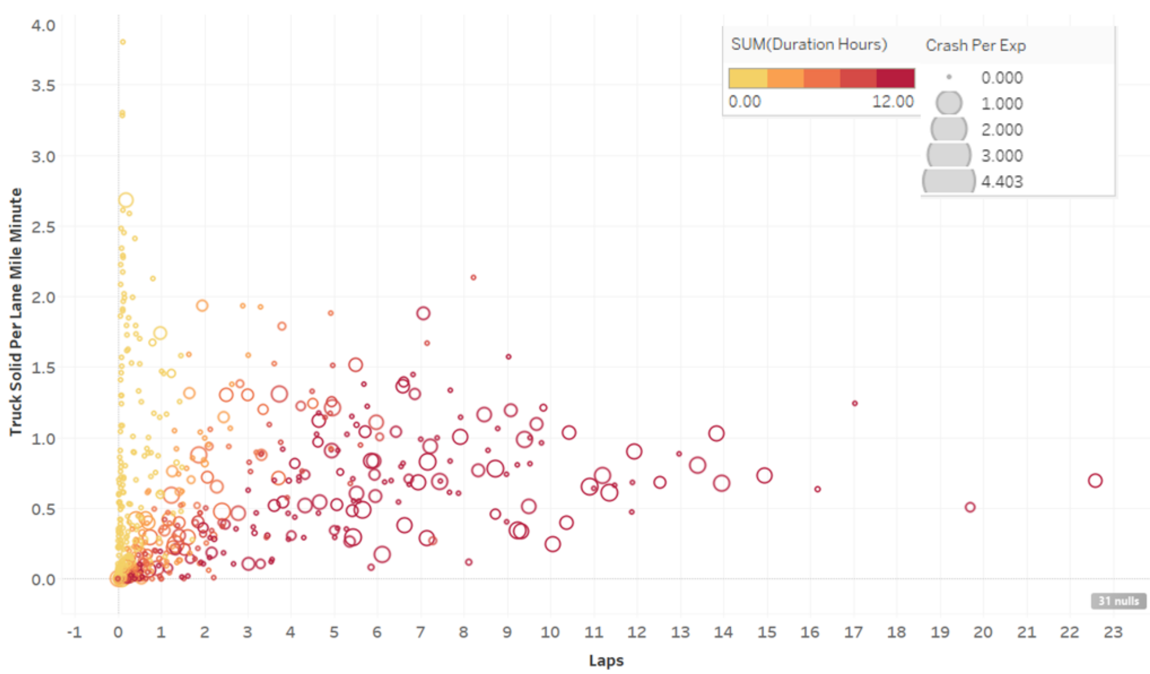


Figure 17. Truck solid per lane mile minute versus truck laps – crash

In both graphs, the size of the circle represents a higher crashes per exposure count. In both of these plots, the longer-duration storms tend to have higher crash rates than the shorter-duration storms. The initial conclusions from the analysis suggest that the more snowplowing that occurs, the higher the crash rate. These plots proved that conclusion to be erroneous. A logical reason for the higher crash rates may be the prolonged exposure of drivers to winter weather conditions. The winter events that tended to have higher crash rates also spanned a long duration. Because of this, the events' impacts on traffic safety are much greater due to their greater duration. Past research has suggested that the time of day impacts traffic volumes. Short-duration storms may allow the public to alter their travel plans and avoid dangerous driving conditions. In contrast, longer-duration storms may not offer travelers the choice of altering their travel plans. Additionally, it may be the case that the longer the storm duration, the higher a driver's tolerance for adverse driving conditions. These factors may have played a role in the crash discrepancy.

Crash Frequency Model

Determining the impacts and interactions of the AVL and weather variables proved to be a continuous task. Each storm event provided a unique set of variables that hindered the ability to quantify and group the dataset. The issue was compounded by the fact that AVL operations often are a byproduct of the winter storm conditions. Furthermore, each Iowa DOT garage operator drew from unique experience in determining the plow operations were executed.

Because of the complex relationships between the variables, a thorough vetting was performed when determining the important factors in the final model. In order to fully depict the relationships, several key ratios were developed. The pertinent AVL variable was divided by the total snowfall from that storm. For example, the number of laps divided by the total snowfall resulted in Laps per Snow, with the units in truck laps per inch of snowfall. The reciprocal of each of these calculations was also performed, the result being Snow per Laps.

Figure 18 and Figure 19 demonstrate the relationships and interpretation of results for these variables.

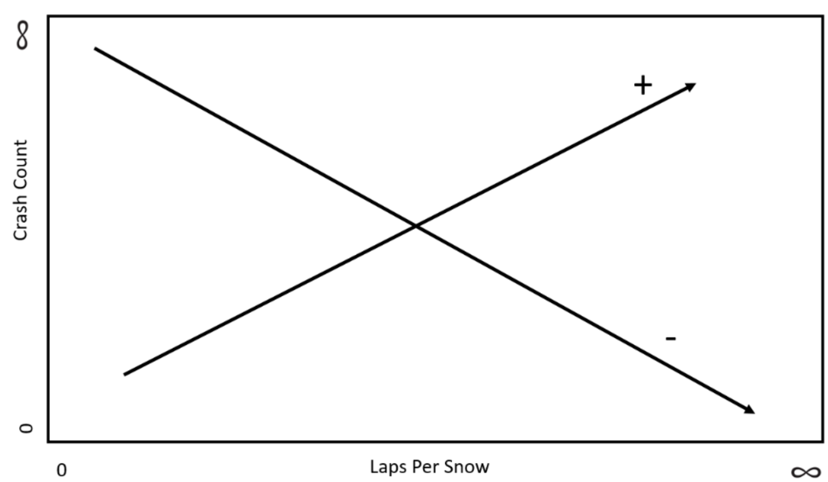


Figure 18. AVL per snowfall relationship versus crash

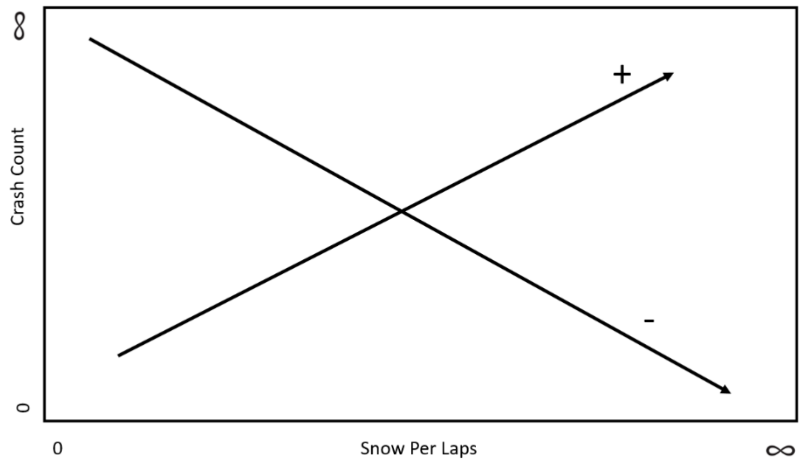


Figure 19. Snowfall per AVL relationship versus crash

Figure 18 depicts the relationship between the AVL parameter normalized by the snowfall parameter. A positive relationship indicates that the more laps driven, compared to the same amount of snowfall, the higher the crash rate. This is because the more laps driven, the larger the dividend of laps per inch of snowfall. Therefore, the data point slides to the right along the positive arrow. In contrast, a negative relationship yields the opposite description. The more laps driven, compared to the same amount of snowfall, the lower the crash rate. The more laps driven also creates a larger dividend of laps per inch of snowfall. However, instead of sliding to the right and up, the point slides down and to the right.

Figure 19 reveals the relationship between the snowfall normalized by the AVL parameter compared to the crash rate. A positive correlation signifies that the same amount of snowfall with more laps produces a lower crash rate. A higher number of laps create a smaller dividend of inches of snowfall per lap. The data point slides to the left along the positive arrow, which move closer to 0 on the y-axis. Conversely, a negative correlation signifies that more laps produces a higher crash rate. The more laps, the smaller the dividend of inches of snowfall per lap. The data point slides along the negative arrow, which leads to infinity on the y-axis.

Snowplow operations are capable of distributing various materials for the sake of route maintenance. The possibilities in the AVL data included solid and liquid material. Apart from these, variables related to the truck distance traveled were provided. The three main variables used for the analysis are the liquid material, solid material, and truck laps. While these variables concern different aspects of plow operations, a correlation matrix was developed to determine the relationships among the variables.

Figure 20 presents the correlations that exist among the AVL variables.

Figure 20. AVL variable correlation matrix

In this example, the snowplow variable was normalized by the total snowfall. The three resulting variables calculated were Solid_Per_Snow, Liquid_Per_Snow, and Laps_Per_Snow. The dark green color in the matrix constitutes a high correlation value. In this particular matrix, all of the three variables were found to be highly correlated. This pattern was illustrated in the various sets of snowplow categories, such as Solid/Liquid Per Lane Mile. Because of this correlation, only one of the variables from each group could be included in the model building.

Figure 12 through Figure 17 highlight the intricate interactions among the data types. Because of these interactions, the initial modeling proved to be an elaborate task. This was compounded by the inability to group similar storms. The solution was to filter the data even further with the purpose of creating similar, and therefore comparable, storms. The new filter specified that all storms needed to have had at least one truck lap. Both Figure 12 and Figure 13 portray a natural cut off at the one-lap mark. This eliminated the low-intensity storms, or the ones that did not result in a heavy Worst Snow variable. This also eliminated the low-snowfall events from the analysis. In regards to the AVL parameters, Figure 15 suggests that using a one-lap cutoff provides similar snowplow and storm characteristic relationships. Many of the high-intensity plowing operations that occurred in the top left and the non-existent plowing operations that occurred in the bottom right of Figure 15 were excluded.

The first attempt to build a crash frequency model implemented a stepwise function in RStudio. Simply put, a stepwise function takes all of the input variables and then determines the model that best follows the trend line. The results of this attempt proved disorderly. Because of the complex interactions between the AVL and weather variables, the outputs simply did not provide reasonable results. In order to build an accurate and reasonable model, a second approach was applied. A strategic list of weather variables was included to represent the weather variables of the winter storms. Subsequently, a single AVL variable was added to the weather variables with the intent of observing the snowplow's interactions with the various weather variables. This approach was applied for each AVL variable. Ultimately, a final model was selected with the intention of representing the interaction between crash frequency and the weather, AVL, and traffic variables.

Table 10 presents the final model.

Table 10. Crash frequency model

Coefficient	Estimate	Std. Error	Z value	P-value	Significance
(Intercept)	-14.530	2.386	-6.092	0.000	***
Ln(Exposure)	1.092	0.159	6.869	0.000	***
Road Condition	0.238	0.136	1.753	0.080	.
Total Precipitation (in.)	0.109	0.076	1.431	0.153	
Wind Speed (knots)	-0.012	0.027	-0.439	0.661	
Visibility (km)	0.054	0.068	0.795	0.427	
City - CedarRapids	-0.577	0.390	-1.478	0.140	
City - CouncilBluffs	0.099	0.399	0.248	0.804	
City - IowaCity	-1.566	0.443	-3.538	0.000	***
City - QuadCity	-0.750	0.463	-1.619	0.106	
City - SiouxCity	-0.890	0.384	-2.316	0.021	*
City -Waterloo	-0.635	0.582	-1.091	0.275	
Solid Per Snow (ton per mi.)	-67.448	0.000	-2.151	0.031	*
AIC			773.820		

As noted in past research, road conditions play a significant role in crash safety (Usman et al. 2010). Road conditions were scaled from 1 to 6, with 6 being the worst, the positive estimate for this variable follows past findings.

In this analysis, the city center factor was included so that any geographic trends could be identified. Of the eight city centers, only six are represented in the model. The seventh city, Ames, was taken as the baseline. The eighth city, Des Moines, did not produce any storm samples that passed all of the required criteria for the final analysis. Consequently, only one city, Iowa City, proved to be significant in terms of the model's outcome. According to the model, Iowa City experiences a lower crash frequency than Ames. The final coefficient in the model presented is Solid Per Snow. Figure 18 presents the methodology to interpret the results for this variable. Because the estimate is negative, the more solid material deployed, the lower the crash frequency. This variable also proved to be statistically significant.

Crash Severity Analysis

The crash severity model encompassed every crash that occurred on Iowa DOT-maintained roadways. Because the data were filtered by weather conditions and roadway conditions, it is possible that some crashes occurred outside the presence of a winter storm event. In total, 1,372 crashes met the criteria threshold and were able to be analyzed. Table 11 contains a description of the data.

Table 11. Crash severity data description

	n	mean	Standard Deviation	min	max
Plow Duration (Hours)	1,370	37.97	15.4	0	102.54
Rural / Urban	1,370	1.39	0.49	1	2
AADT (Vehicles)	1,368	1,668.42	1,704.08	0	11,394.77
Storm Tag (1 - Storm, 0 - Non-Storm)	1,370	0.47	0.5	0	1
Storm Duration (Hours)	650	7.98	5.07	0.58	21
Total Passes (Pass Count)	1,370	4.89	4.11	1	42
Before Passes (Pass Count)	1,370	2.13	2.43	0	29
After Passes (Pass Count)	1,370	2.76	2.59	0	27
Nearest Pass After (Hours)	1,192	0.7	0.56	0	2
Nearest Pass Before (Hours)	974	-0.65	0.52	-1.99	0
Before/After Passes (Ratio)	1,192	0.83	1.06	0	9
Property Damage (Dollars)	1,370	8,115.92	12,451.03	200	250,000
Total Precipitation (Liquid in.)	1,369	0.14	0.35	0	7.14
Wind Speed (Knots)	1,369	5.81	2.89	0	19
Temperature (Degrees)	1,369	19.41	12.09	-16.10	48
Visibility (Miles)	1,369	8.96	5.99	0.4	16.09
Relative Crash Time - Storm (Normalized Percent)	650	0.42	0.28	0	1
Relative Crash Time - AVL (Normalized Percent)	1,368	0.34	0.27	-1.67	1.47
Speed Limit (Miles Per Hour)	1,370	61.5	10.8	20	70

The Plow Duration variable indicates the amount of time that AVL operations were ongoing, while the storm duration was the hours that the winter event lasted. Most storms had longer plow durations than storm durations, with the plow durations almost four times those of the storms. Because blowing snow is a common after effect, plow operations can typically last much longer than the storm itself. This indicates that pavement conditions were deteriorated and had an effect on driver safety. Blowing snow also causes reduced visibility, which contributes to a greater crash risk as well. One distinction between the storm and snowplow durations that needs clarification is the methodology involved. Storm events could not have a gap in precipitation greater than 20 minutes. Snowplow operations had no such distinction. In general, some snowplow operations most likely spanned the duration of several winter storm events.

Approximately 60 percent of all crashes occurred in the rural regions of Iowa. Approximately 52 percent of crashes occurred during a storm. During winter events, traffic volumes decreased. In spite of this reduction, a large number of crashes in this study occurred during a storm.

Meanwhile, half of all crashes occurred outside of a storm's duration. The number of crashes that occurred outside of storm events also signifies that pavement conditions and visibility have a significant effect on safety. Perhaps the traveling public does not recognize that driving conditions are still adverse despite the fairer weather conditions after a storm. Both the Relative Crash Time – Storm and Relative Crash Time – AVL variables indicate that crashes take place earlier in the respective events.

Each crash averages approximately two plow passes beforehand and just under three passes afterwards. The results suggest that most crashes occur on routes that have a moderate to high plow pass frequency. Because the cycle time is two hours, the Total Passes variable would need to be at approximately three to be at the standard cycle time, the first pass being two hours before the event, the second being at the time of the event, and the third being two hours after the event. For the Nearest Pass Before and Nearest Pass After variables, the nearest pass occurs roughly 45 minutes before/after the crash time.

The FHWA reports that approximately 0.4 percent of winter crashes result in a fatality (FHWA 2018). The data observed in this study show that approximately 0.3 percent of all crashes were fatal. By performing a difference of proportions test, it was determined that the proportion of fatal crashes observed nationwide resembles that seen in Iowa.

In total, 1,372 crashes occurred over the winters of 2016–2017 and 2017–2018 (Figure 21). Close to 80 percent of all crashes were classified as property damage only and just over 90 percent of crashes were classified as either property damage only or possible/unknown.

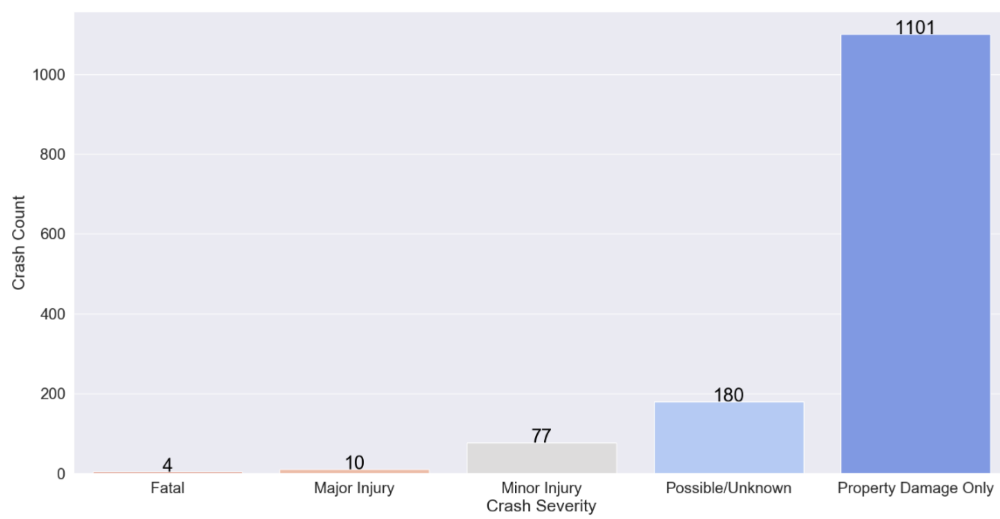


Figure 21. Crash severity table bar plot

All Iowa crash data spanning 2016 to 2018, regardless of weather or season, were compiled in order to compare the difference in crash severity proportions between winter crashes and all crashes.

Table 12 displays the results of the proportions test between the winter crashes and all Iowa crashes.

Table 12. All crashes – winter crashes

Crash Severity	Winter	Proportion	All	Proportion	P-value
Fatal	4	0.003	147	0.006	0.171
Major	10	0.007	437	0.017	0.006
Minor	77	0.056	1908	0.075	0.011
Possible	180	0.131	3760	0.147	0.107
PDO	1101	0.802	19330	0.756	0.000
Sum	1372	1.000	25582	1.000	

The winter crashes had a higher proportion of PDO crashes compared to all crashes. Furthermore, the winter crashes had fewer major and possible/unknown injuries. The general trend suggests that Iowa follows the previously established pattern of crash severity proportions.

Snowplow Pass Time Interval

The complexities of the interactions between winter maintenance operations and crash safety present unique problems. Researchers at Iowa State University attempted to elucidate these interactions by displaying temporal tables (Hans et al. 2018). A similar method was employed for the data in this study (Figure 22, Figure 23, and Figure 24).

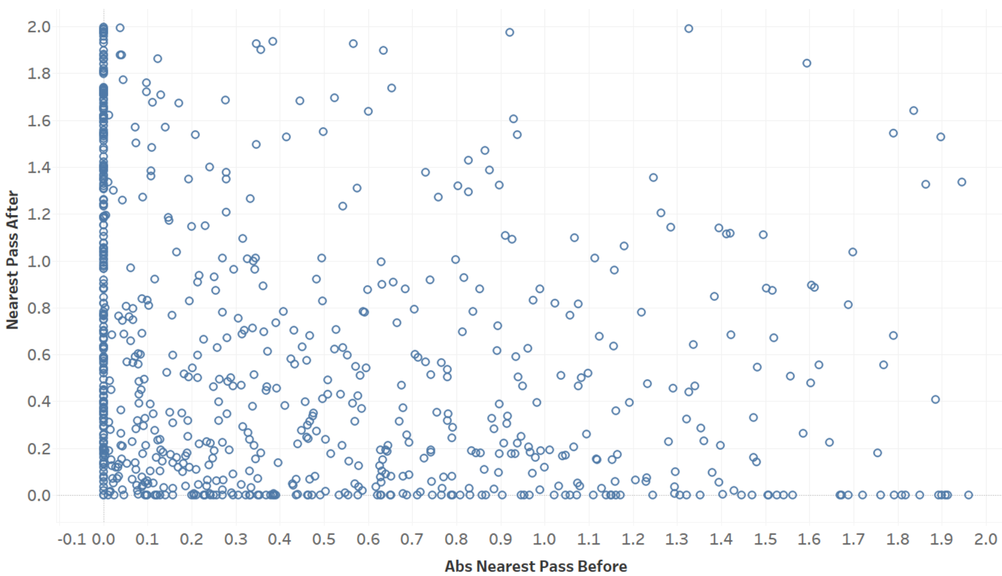


Figure 22. Snowplow pass to crash time classification – Interstate routes

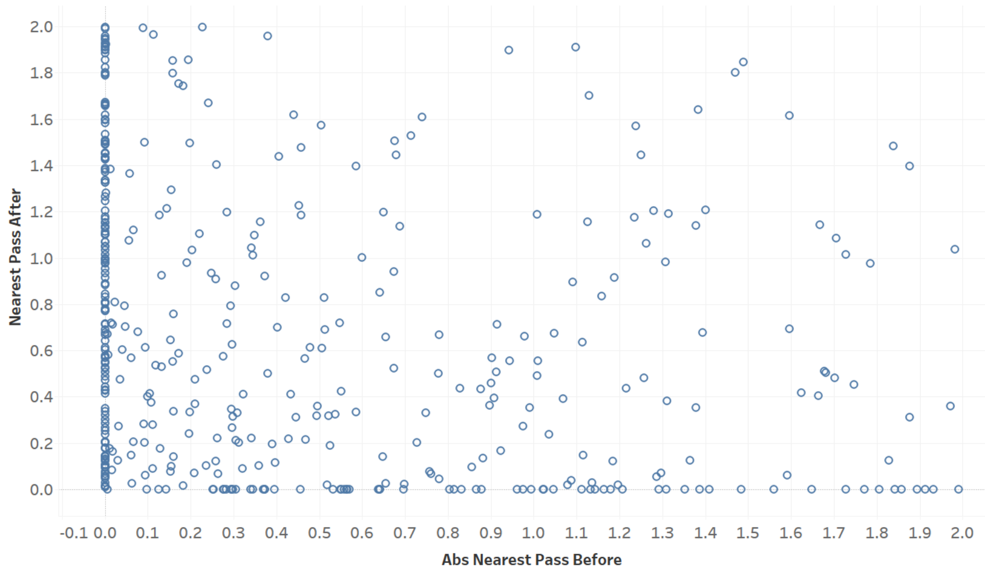


Figure 23. Snowplow pass to crash time classification – US routes

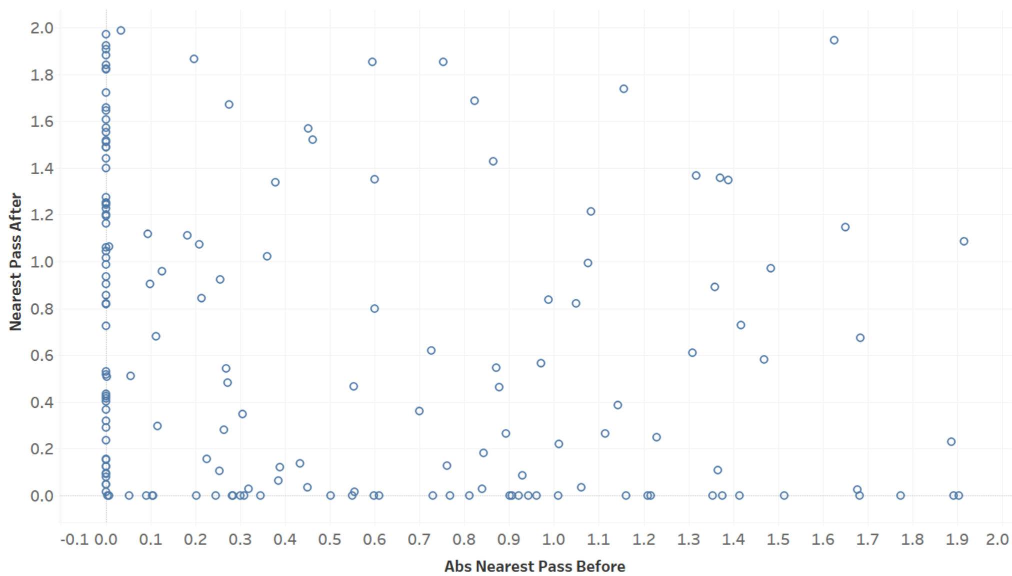


Figure 24. Snowplow pass to crash time classification – Iowa routes

Each graph represents data from both winter seasons combined. Both axis labels represent hours. The y-axis represents the nearest recorded snowplow pass that occurred after the recorded crash time. The further away from 0 the point is, the later in the day the plow pass occurred. Any point that lies directly on top of the y-axis signifies that there was no plow pass before the crash. The further away from 0, the longer it took for the next snowplow pass to occur. The x-axis shows the absolute value of the nearest plow pass that occurred before the recorded crash time. Because this value is displayed as an absolute value, the closer to 0 the value is, the closer to the time of the crash it is. Conversely, the further away from 0 the value is, the earlier in the day the plow pass occurred. Any point that lies directly on top of the x-axis represents a crash that had no plow pass occur after the crash. A point that lies at (1.5, 0.5) specifies that the closest plow pass before the crash occurred 1.5 hours beforehand and the earliest subsequent plow pass occurred 30 minutes after the crash.

Figure 22, which represents Interstate crashes, contains the highest total number of crashes compared to the other routes. Interstates produce more traffic volumes than other road types, especially when considering the presence of winter driving conditions (Datla et al. 2013). Most of the crashes reside in the lower left corner of the plot. This area indicates that a plow pass occurred close to the time of the crash and that the crash location experienced a high plow pass frequency at the time of the crash. These locations may have significant traffic volumes, which constitutes a higher maintenance priority and therefore more snowplow passes. Because Interstates are more frequently traversed roadways, there are often multiple lanes of travel in each direction. Because no distinction could be made as to the lane in which each event occurred, these plow passes may ultimately have had little impact on the crash itself. One significant finding is that a high proportion of crashes did not receive a plow pass before the crash occurred. This signifies that crashes occur early in winter events.

While the pattern in Figure 23, which represents US routes, closely resembles the pattern of Interstate routes, Figure 24 tells a different story. Figure 24 details the crashes that occurred on Iowa routes. It was not surprising that this route type contained the fewest total number of crashes of the three route types. Iowa routes contain lower traffic volumes, especially during severe events, than the other route types. Many crashes still occurred on these routes without the occurrence of a plow pass before the event. However, the spread of crashes is much larger and diverse than those of the previous routes. For example, a greater portion of crashes occurred that were not relatively close to a before or after plow pass. This signifies that these routes are receiving plow passes much less frequently. This may be a result of the lower priority for these routes compared to Interstates and US routes, or it may be the result of having fewer lanes and therefore fewer plow passes.

To further illustrate the interactions between plow pass frequency and crashes, the plow pass times were categorized and displayed in heat maps as well as percentage tables (Figure 25, Figure 26).

Figure 25, Figure 26, and Figure 27 represent all of the crashes from both winters and all of the route types combined.

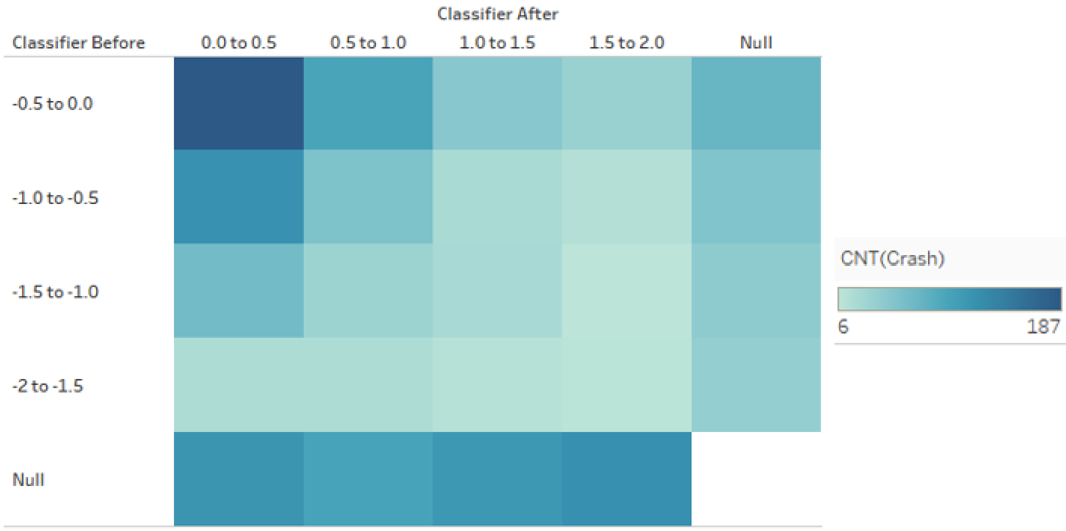


Figure 25. Snowplow pass time interval heat map

	Nearest PassAfter					
Nearest PassBefore	0.0 to 0.5	0.5 to 1.0	1.0 to 1.5	1.5 to 2.0	Null	Grand Total
-0.5 to 0.0	13.63%	6.85%	3.35%	2.33%	5.25%	31.41%
-1.0 to -0.5	8.53%	3.94%	1.46%	0.95%	3.72%	18.59%
-1.5 to -1.0	4.59%	2.19%	1.53%	0.44%	2.99%	11.73%
-2 to -1.5	1.24%	1.24%	0.80%	0.51%	2.62%	6.41%
Null	8.24%	7.00%	7.94%	8.67%		31.85%
Grand Total	36.22%	21.21%	15.09%	12.90%	14.58%	100.00%

Figure 26. Snowplow pass time interval percentages

	Nearest PassAfter					
Nearest PassBefore	0.0 to 0.5	0.5 to 1.0	1.0 to 1.5	1.5 to 2.0	Null	Grand Total
-0.5 to 0.0	187	94	46	32	72	431
-1.0 to -0.5	117	54	20	13	51	255
-1.5 to -1.0	63	30	21	6	41	161
-2 to -1.5	17	17	11	7	36	88
Null	113	96	109	119		437
Grand Total	497	291	207	177	200	1,372

Figure 27. Snowplow pass time interval count values

Five time bins were created for each axis. Each bin contains 30 minutes of time until the two-hour limit was reached. The fifth bin represents null values, or crashes for which no snowplow pass occurred either before or after the crash. In Figure 25, Figure 26, and Figure 27, the nearest pass before is represented as a negative value. The time of the crash is represented by the time 0, and the further away from 0, or the more negative the number, the earlier in the day the crash occurred.

In Figure 25, the darker the color, the more crashes that occurred in that cell. The majority of crashes fall within the top left corner, which corresponds to the bottom left corner of the previous tables. Furthermore, the heat map categorization allows for a breakdown of percentages. Figure 26 displays each cell as a percentage of all crashes. Along with the values in the cells is a total for the row and column for each major category. One-third of all crashes took place before a snowplow had passed. This is compared to just 14 percent of crashes where no snowplow pass took place after the crash.

These representations of the data suggest that the most dangerous scenario is when a plow has recently passed and is about to pass as well. In other words, the highest density of crashes occurs in very close temporal proximity to plow passes. This conclusion is contrary to conventional wisdom, which holds that a higher plow pass frequency is unlikely to lead to more crashes.

A more thorough inspection was required in order to determine potential explanations as to why most crashes fall within the nearest plow pass quadrant. The data from the “0” Before Passes and the “-0.5 to 0.0” row were extracted for further analysis. This dataset was compared to the dataset of observed crashes for the crash severity analysis. After the creation and examination of histograms and proportions, two variables provided more in-depth knowledge. The first was plow pass frequency. The Total Passes, Before Passes, and After Passes variables were compared between the two datasets. A two-tailed difference of proportions test was performed for each of the categories. It was found that the crashes in the extracted data experienced a higher plow pass frequency than the other crashes. The second variable was the route type. By means of a t-test of means, it was determined that the extracted data have a higher portion of Interstate crashes. Interstates tend to have more plow passes, by virtue of their greater number of lanes and higher priority, than other roadways. Therefore, the pass frequency and Interstate variables go hand in hand.

The previous graphs represent the snowplow conditions at the time of each crash. Because crashes are rare events, the snowplow conditions presented are only snapshots of the overall winter storm. The predominant snowplow conditions of the storm in its entirety are unknown. In other words, plow pass proximity may vary across the span of the maintenance operations and the winter storm event. In order to compare the effect of plow pass proximity on crashes, an understanding of the conditions at the same location during non-crash time periods is necessary. In other words, how representative is the plow pass frequency around the crash events compared to the plow pass frequency conditions throughout the storm. By comparing the observed plow pass frequency to the storm-wide frequency, any trends or differences in the data could be easily identified. It was discussed in the Methodology chapter that a list of plow operation events was compiled. These events were overlapped for each respective crash event. The following process was developed to establish the continuous conditions of the plow operations:

1. Start at time 0 of the snowplow operations event
2. Filter snowplow passes within two hours before and after the crash
3. Add count to snowplow pass time interval category
4. Add 30 minutes to time 0
5. Repeat steps 2 through 4 until snowplow operations event concludes
6. Repeat for each crash event

By following this method, a representation of snowplow proximity throughout the storm was possible. Because the categories are divided into 30-minute segments, aggregating the plow conditions by this interval offered continuous coverage throughout the event.

Figure 28, Figure 29, and Figure 30 represent the final compilation of the storm-wide conditions for all crashes. The formats of these tables resemble those of their complementary tables (Figure 25, Figure 26, and Figure 27).

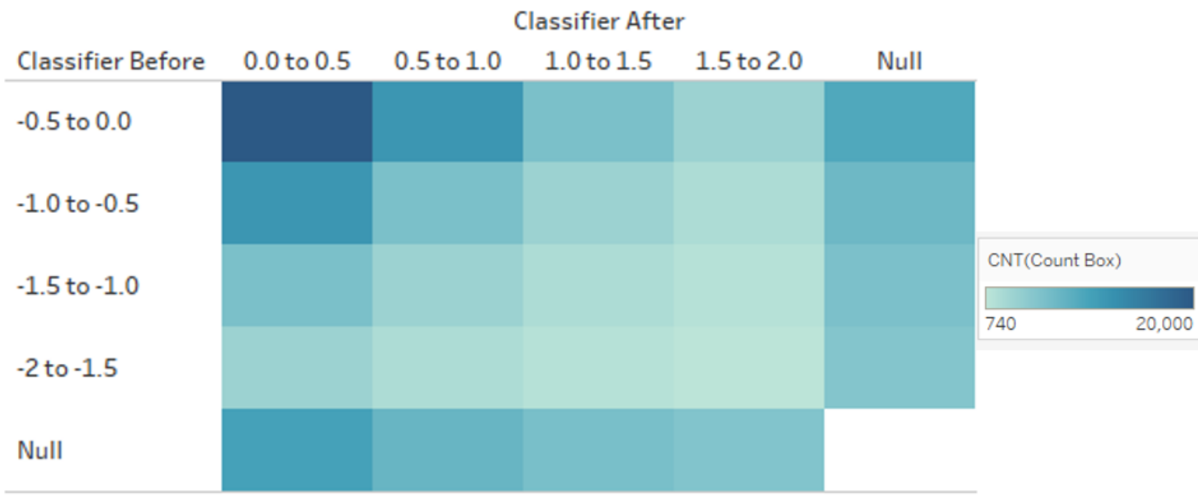


Figure 28. Snowplow pass time interval heat map – storm-wide

	Classifier After					
Classifier Before	0.0 to 0.5	0.5 to 1.0	1.0 to 1.5	1.5 to 2.0	Null	Grand Total
-0.5 to 0.0	16.01%	8.17%	4.18%	2.27%	6.55%	37.18%
-1.0 to -0.5	8.16%	4.18%	2.27%	1.32%	4.95%	20.88%
-1.5 to -1.0	4.17%	2.27%	1.32%	0.85%	4.13%	12.74%
-2 to -1.5	2.27%	1.32%	0.85%	0.51%	3.68%	8.61%
Null	7.19%	5.30%	4.31%	3.79%		20.59%
Grand Total	37.80%	21.23%	12.92%	8.73%	19.31%	100.00%

Figure 29. Snowplow pass time interval percentages – snowplow operation-wide

	Classifier After					
Classifier Before	0.0 to 0.5	0.5 to 1.0	1.0 to 1.5	1.5 to 2.0	Null	Grand Total
-0.5 to 0.0	23,408	11,949	6,120	3,319	9,575	54,371
-1.0 to -0.5	11,940	6,109	3,313	1,930	7,245	30,537
-1.5 to -1.0	6,105	3,314	1,930	1,239	6,046	18,634
-2 to -1.5	3,313	1,930	1,238	740	5,376	12,597
Null	10,521	7,751	6,300	5,540		30,112
Grand Total	55,287	31,053	18,901	12,768	28,242	146,251

Figure 30. Snowplow pass time interval counts – snowplow operation-wide

The snowplow operation-wide conditions suggest that a majority of crashes also occur in the recent plow pass interval quadrants, as in the previous analysis. In order to determine the precise differences, a difference of proportions test was performed on each corresponding cell. For example, the cells at the intersection of column "0.0 to 0.5" and row "-0.5 to 0.0" for the crash data and storm data were compared. This process was followed for each individual cell. The results are displayed in Table 13.

Table 13. Difference of proportions test – plow pass intervals

Classifier Before \ After	0.0 to 0.5	0.5 to 1.0	1.0 to 1.5	1.5 to 2.0	Null	Grand Total
0.0 to 0.5	0.017	0.076	0.125	0.876	0.053	0.000
0.5 to 1.0	0.624	0.657	0.045	0.229	0.035	0.037
1.0 to 1.5	0.442	0.844	0.496	0.098	0.034	0.266
1.5 to 2.0	0.011	0.795	0.857	0.982	0.039	0.004
Null	0.137	0.005	0.000	0.000	NaN	0.000
Grand Total	0.230	0.984	0.017	0.000	0.000	NaN

This table represents the p-values from the proportions test. A value of less than 0.05 indicates that a statistically significant difference in the proportions was observed. The general trend observed earlier (Table 12) was that the "0.0 to 0.5" and the "0.5 to 1.0" Classifier Before rows for the observed data had fewer crashes than the storm proportions estimated. Roughly 31 percent of crashes are in the "0.0 to 0.5" Classifier Before row, while the storm-wide analysis estimated that scenario to be almost 38 percent. In contrast, the storm-wide analysis estimated that roughly 20 percent of crashes occur without the presence of a snowplow pass beforehand. In actuality, that same scenario represented almost one-third of all crashes. This suggests that the closer the plow pass occurs to the time of the crash, the greater the safety benefit gained. Conversely, the lack of a plow pass beforehand significantly increases the crash risk.

Snowplow Pass Frequency

Another temporal table representation presented in previous work was a snowplow pass frequency table (Hans et al. 2018). The methodology is that a four-hour window is placed around each crash. The total snowplow passes are then counted and categorized as either before or after passes.

Figure 31 represents the heat map of aggregated data for snowplow pass frequency. The y-axis represents the number of passes before the crash, while the x-axis represents the number of passes after the crash. The darker the color, the higher the crash density for that category.

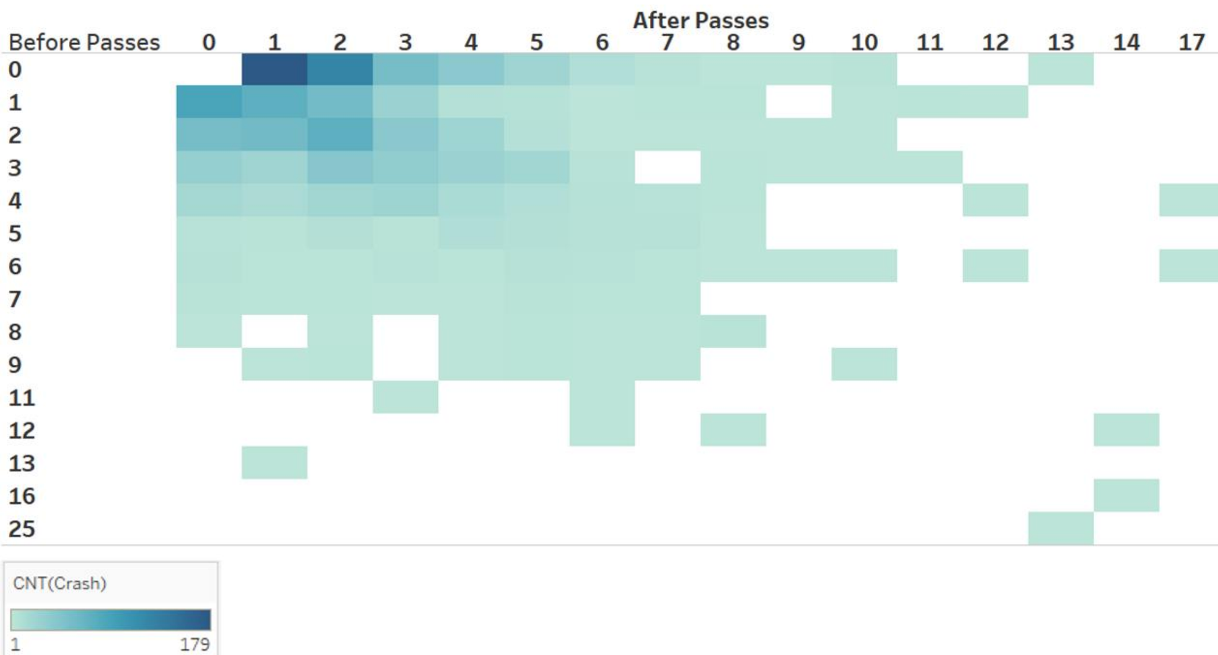


Figure 31. Snowplow pass frequency heat map

Figure 32 represents the same data, except in percentage form.

	After Passes																
Before Passes	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	17	Grand Total
0		13.05%	9.11%	3.94%	2.77%	1.60%	0.66%	0.29%	0.07%	0.07%	0.22%			0.07%			31.85%
1	6.34%	5.32%	4.15%	1.82%	0.51%	0.44%	0.07%	0.15%	0.15%		0.07%	0.15%	0.07%				19.24%
2	3.94%	4.23%	5.32%	2.84%	1.68%	0.51%	0.07%	0.07%	0.07%	0.07%	0.07%						18.88%
3	2.11%	1.60%	3.06%	2.41%	1.82%	1.46%	0.29%		0.15%	0.07%	0.07%	0.07%					13.12%
4	1.24%	0.95%	1.46%	1.75%	1.02%	0.66%	0.44%	0.29%	0.15%				0.07%			0.07%	8.09%
5	0.29%	0.22%	0.58%	0.22%	0.73%	0.58%	0.36%	0.36%	0.07%								3.43%
6	0.36%	0.15%	0.15%	0.29%	0.15%	0.36%	0.29%	0.15%	0.07%	0.07%	0.07%		0.07%			0.07%	2.26%
7	0.22%	0.15%	0.15%	0.07%	0.07%	0.22%	0.15%	0.15%									1.17%
8	0.07%		0.07%		0.07%	0.15%	0.07%	0.07%	0.22%								0.73%
9		0.07%	0.15%		0.07%	0.15%	0.07%	0.07%			0.07%						0.66%
11				0.07%			0.07%										0.15%
12							0.07%		0.07%						0.07%		0.22%
13		0.07%															0.07%
16															0.07%		0.07%
25														0.07%			0.07%
Grand Total	14.58%	25.80%	24.20%	13.41%	8.89%	6.12%	2.62%	1.60%	1.02%	0.29%	0.58%	0.22%	0.22%	0.15%	0.15%	0.15%	100.00%

Figure 32. Snowplow pass frequency percentages

The evidence from these figures suggests that crashes take place early in winter events. The majority of crashes fall within the top left quadrant of Figure 31. This area represents crashes that occur before maintenance operations begin. Furthermore, nearly half of all crashes take place before a second snowplow pass has occurred. A possible interpretation of these results is that these could be short storms that do not necessitate heavy maintenance operations from Iowa DOT personnel. The higher the plow pass frequency, the lower the total crash count. This could be a result of plowing operations providing a greater safety benefit. The alternative is that very high plow pass frequencies are not common.

A more thorough inspection was required in order to determine potential explanations as to why most crashes fall within the low plow pass frequency quadrant. The data from the 0 Before Passes and the 1 After Passes cell were extracted for the purpose of further examination. The extracted data were contrasted with the observed data, as was performed for the previous analysis. In this analysis, the major contributing variables were the route type, crash severity, nearest plow pass, and relative crash time to AVL operations. It was discovered that a higher proportion of crashes occurred along US and Iowa routes for the extracted data compared to the crash data. Correspondingly, the crash data contained a higher proportion of Interstate crashes than the extracted data. When comparing the mean crash severity scale between the datasets, it was found that the extracted dataset contained more severe crashes than the observed dataset.

The mean values of the third variable, the nearest plow pass, were compared for both datasets as well. It was found that the crashes in the extracted dataset, or the 0 Before Passes and 1 After Passes dataset, saw plow passes come much later after the crash than the crashes in the observed dataset. A comparison of the datasets for the fourth and final variable, the relative crash time to AVL operations, suggested that the crashes from the extracted dataset occurred much earlier than the observed crashes.

The higher-severity crashes can be linked to the plow pass frequency as well as the route type. Because the US and Iowa routes receive less winter maintenance attention, the crash risk on these routes can be expected to be higher than on Interstate routes. Furthermore, because no plow passes were recorded before the crashes on these routes, it can be assumed that the road conditions tended to be more deteriorated and therefore less safe. The late plow pass time may have several explanations. First, because the routes are non-Interstate, the snowplows may simply not be prioritizing these locations. Because of this, the snowplows are not prepping these roadways before a storm as thoroughly as other roadways. The evidence did suggest that these crashes occur much earlier during the storm event than other crashes. This may mean that travelers underestimate the severity of the winter event at the beginning of the storm or the worsening crash safety levels.

As with the plow proximity data, a storm-wide analysis was conducted to determine the plow frequency conditions during non-crash times. Correspondingly, the same process was applied, with the exception being that a total pass count was taken in lieu of the nearest pass.

Figure 33 and Figure 34 represent the storm-wide conditions for snowplow pass frequency.

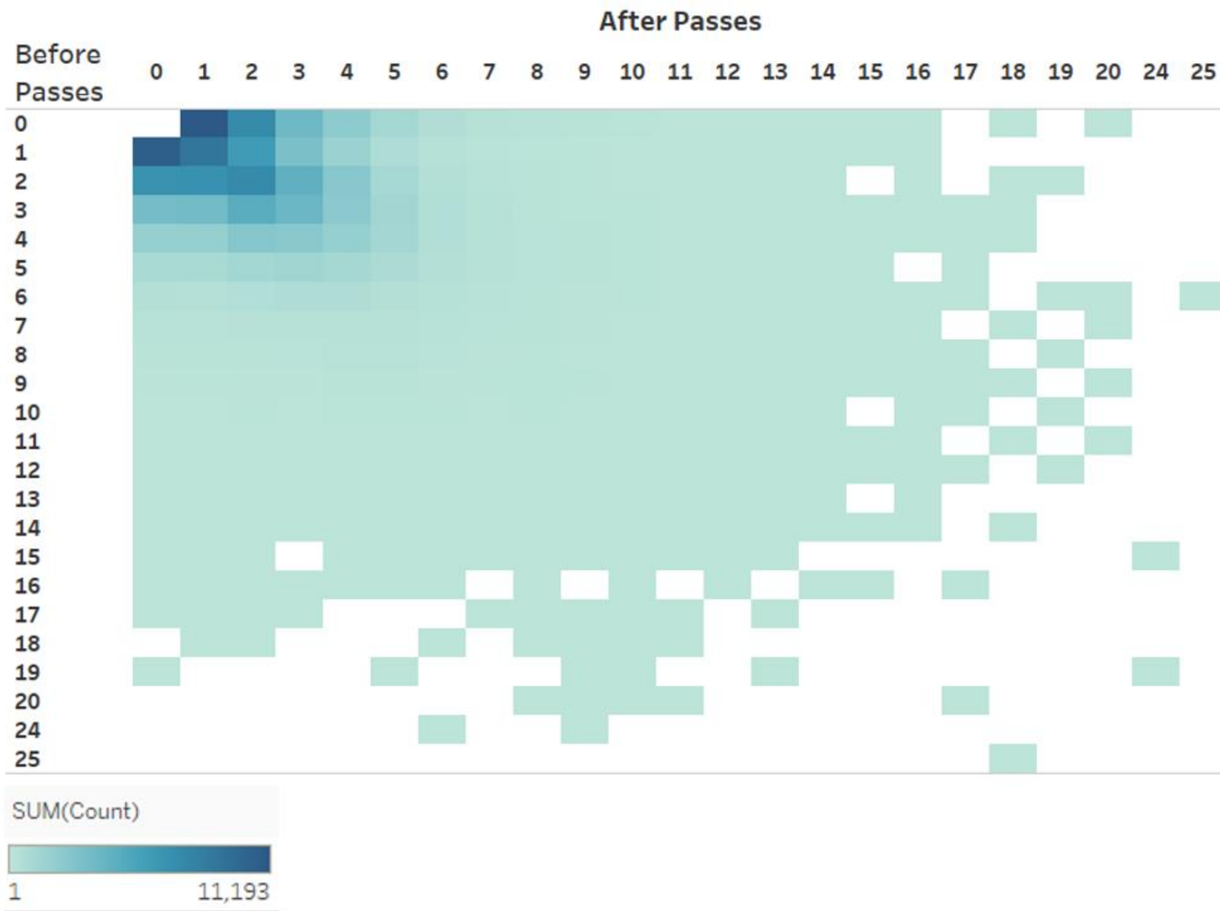


Figure 33. Snowplow pass frequency heat map – storm-wide

	After Passes																							
Before Passes	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**24**	**25**	**Grand Total**
0		8.09%	5.37%	2.70%	1.57%	0.76%	0.41%	0.24%	0.14%	0.08%	0.05%	0.03%	0.02%	0.01%	0.01%	0.01%	0.01%		0.00%		0.00%			19.50%
1	7.78%	6.49%	4.39%	2.27%	1.09%	0.46%	0.22%	0.11%	0.06%	0.04%	0.02%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%							22.96%
2	4.93%	4.96%	5.36%	3.21%	1.82%	0.72%	0.35%	0.18%	0.09%	0.05%	0.03%	0.02%	0.01%	0.00%	0.00%		0.00%		0.00%	0.00%				21.74%
3	2.47%	2.58%	3.42%	2.80%	1.68%	0.85%	0.37%	0.20%	0.09%	0.06%	0.04%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%					14.61%
4	1.30%	1.32%	1.85%	1.75%	1.31%	0.81%	0.38%	0.20%	0.12%	0.07%	0.04%	0.01%	0.02%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%					9.21%
5	0.61%	0.61%	0.82%	0.92%	0.76%	0.55%	0.32%	0.18%	0.11%	0.07%	0.04%	0.02%	0.02%	0.00%	0.01%	0.00%		0.00%						5.04%
6	0.32%	0.27%	0.38%	0.45%	0.43%	0.32%	0.23%	0.14%	0.09%	0.06%	0.04%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%		0.00%	0.00%		0.00%	2.77%
7	0.17%	0.14%	0.19%	0.22%	0.21%	0.19%	0.17%	0.11%	0.07%	0.06%	0.03%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%		0.00%		0.00%			1.59%
8	0.08%	0.08%	0.09%	0.12%	0.13%	0.13%	0.10%	0.06%	0.05%	0.03%	0.03%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%		0.00%				0.95%
9	0.07%	0.05%	0.06%	0.07%	0.07%	0.09%	0.06%	0.05%	0.05%	0.03%	0.02%	0.02%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%		0.00%			0.66%
10	0.03%	0.02%	0.03%	0.03%	0.04%	0.04%	0.04%	0.03%	0.03%	0.03%	0.02%	0.02%	0.00%	0.00%	0.00%		0.00%	0.00%		0.00%				0.38%
11	0.01%	0.01%	0.02%	0.02%	0.02%	0.03%	0.02%	0.02%	0.02%	0.01%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%		0.00%		0.00%			0.22%
12	0.01%	0.00%	0.02%	0.01%	0.01%	0.02%	0.02%	0.01%	0.01%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%				0.15%
13	0.01%	0.00%	0.01%	0.00%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.00%	0.01%	0.00%		0.00%							0.10%
14	0.01%	0.00%	0.00%	0.01%	0.00%	0.00%	0.01%	0.01%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%					0.06%
15	0.00%	0.00%	0.00%		0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%								0.00%		0.02%
16	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%		0.00%		0.00%		0.00%		0.00%	0.00%		0.00%						0.02%
17	0.00%	0.00%	0.00%	0.00%				0.00%	0.00%	0.00%	0.00%	0.00%		0.00%										0.01%
18		0.00%	0.00%				0.00%		0.00%	0.00%	0.00%	0.00%												0.01%
19	0.00%					0.00%				0.00%	0.00%			0.00%								0.00%		0.01%
20									0.00%	0.00%	0.00%	0.00%						0.00%						0.00%
24							0.00%			0.00%														0.00%
25																			0.00%					0.00%
Grand Total	17.80%	24.63%	22.03%	14.57%	9.16%	4.99%	2.71%	1.56%	0.96%	0.63%	0.38%	0.21%	0.15%	0.08%	0.06%	0.02%	0.02%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%	100.00%

Figure 34. Snowplow pass frequency percentages – storm-wide

Approximately 90 percent of all possible time intervals fell within five before and five after passes. Moreover, over 60 percent of time intervals fell within three before and three after passes. Accordingly, most of the plow event durations in Figure 33 fall within regions with low to moderate plow pass frequencies. One limitation of this analysis is that there is no distinction made as to the number of lanes.

Table 14 represents the p-values from the proportions test for the plow pass frequency data.

Table 14. Difference of proportions test – plow pass frequency

Before \ After Passes	0	1	2	3	4	5	6	7	8	9	10+	Grand Total
0		2.45E-11	1.13E-09	0.004914	0.000420	0.000376	0.157097	0.685067	0.505930	0.937936	0.132656	2.11E-30
1	0.047621	0.079255	0.676843	0.266943	0.039887	0.896161	0.244455	0.724425	0.168558	2.35E-05	0.001126	
2	0.090952	0.210726	0.945940	0.436573	0.694995	0.359406	0.082552	0.354727	0.848965	0.726392	0.944551	0.010405323
3	0.395459	0.023128	0.463194	0.372201	0.681264	0.014000	0.616141	0.520027	0.817860	0.417650	0.120411	
4	0.844489	0.233561	0.280097	0.994653	0.346025	0.514347	0.740074	0.479254	0.790770	0.432297	0.155020	
5	0.127917	0.063676	0.336151	0.006764	0.887968	0.884592	0.792876	0.112779	0.675100	0.289511	0.006461	
6	0.781352	0.388292	0.155381	0.393635	0.109865	0.789038	0.617874	0.979714	0.842561	0.855903	0.079714	0.251739509
7	0.647049	0.945187	0.698924	0.246002	0.273992	0.824833	0.819480	0.655731	0.352733	0.211158		
8	0.937936	0.817530	0.538358	0.891543	0.736765	0.865176	0.010307	0.341890	0.401437			
9		0.704906	0.206402	0.993641	0.461601	0.865176	0.778239	0.910157	0.969215			
10+	0.296009	0.626230	0.283192	0.998457	0.281125	0.241752	0.505462	0.285279	0.848965	0.355517	0.747763	0.14339867
Grand Total	0.001866	0.317437	0.053395	0.224654	0.734552	0.055615	0.838732	0.903060	0.811312	0.115815	0.057930	

As in the previous analysis, a value of less than 0.05 conveys that a statistically significant difference in the proportions was observed. Many observed crashes occurred with a relatively low plow pass frequency. While the storm-wide conditions appeared to exhibit a similar trend, the test of proportions detailed several significant differences. First, the storm-wide conditions analysis estimates that just under 20 percent of crashes would occur with 0 snowplow passes beforehand. By comparison, approximately one-third of all crashes in the observed dataset had 0 plow passes beforehand. The second main difference is in the proportion of crashes that occur with several snowplow passes beforehand. The 2 Before Passes row for the storm-wide conditions data estimates that just under 22 percent of crashes would fall in this category. In reality, the observed crash ratio for that same scenario occurred in just under 19 percent of crashes. The results suggest that the more plow passes that occur before the crash, the safer the conditions will be. However, a lack of snowplow passes represents a greater safety risk than projected. These results similar to the findings from the plow pass intervals analysis.

Crash Severity Model

The first step in creating the crash severity model was to evaluate the interactions of all the variables. The most commonly used method to determine the interactions is a correlation matrix. This matrix allows researchers to easily determine which variables are redundant and which variables may prove the most significant in the final model. In this study, determining the correlations among the variables allowed the best variables for producing a simple and effective crash severity model to be determined.

Figure 35 shows the correlation matrix for the AVL variables.

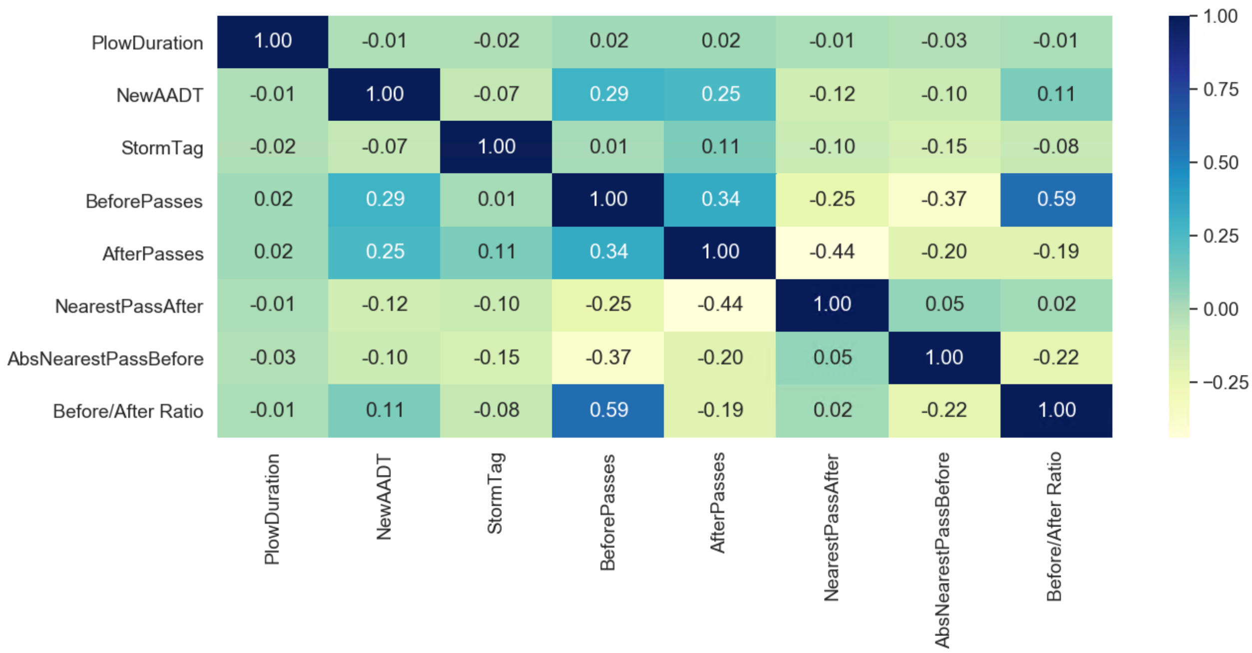


Figure 35. Snowplow correlation matrix – crash severity

Each row, or the y-axis, represents a specific snowplow parameter. The same variables are arrayed along the x-axis as well. Each row's variables intersects with every other column's variables to form the cells of the matrix. Therefore, each cell represents one variable from the y- and x-axis, respectively. The darker or bluer colors represent a higher correlation among the variables. The center of each cell displays the correlation value as well. The further away from zero the value is, the greater the correlation that exists. The dark blue cells running diagonally through the matrix represent the intersection of identical variables from the y- and x-axes. Furthermore, each cell mirrored across from the diagonal line represents the same data.

The most highly correlated data were the Before Passes with the Before/After Ratio. This follows intuition, as the total before passes constitute a portion of the Before/After Ratio variable. Oddly enough, the total after passes did not demonstrate a correlation with the Before/After Ratio variable. The reason is most likely that crashes happen early in winter events. This implies that the before passes carry a significantly larger weight than the after passes because they have a more direct impact on crashes.

Because not all crashes occurred during a storm event, the weather variables did not prove important for those crashes that lay outside a storm event. With the inclusion of weather variables, the model becomes skewed and misrepresents the effect of weather on crash safety. For this reason, the weather variables were not included in this section of the analysis.

An ordered logit model was employed in order to create the crash severity model. The model was estimated using the RStudio software. RStudio includes a stepwise function that computes the most accurate model possible given the data variables. Table 15 reveals the final crash severity model.

Table 15. Crash severity model

Coefficient	Estimate	Std. Error	z-value	p-value	Significant
Seasonal AADT (vehicles)	1.25E-04	5.09E-05	2.458	0.014	*
Nearest Pass After (hrs)	3.27E-01	1.72E-01	1.902	0.0572	.
Relative Crash Time to AVL (normalized scale)	-8.51E-01	4.01E-01	-2.123	0.0337	*
Iowa Route	7.87E-01	3.11E-01	2.532	0.0113	*
US Route	3.79E-01	2.29E-01	1.657	0.0976	.

The Seasonal AADT represents the seasonally adjusted AADT for the crash location. The Nearest Pass After represents the most recent plow pass that occurred after the crash event. The Relative Crash Time to AVL represents the crash time relative to the beginning of the AVL operations. The Iowa Route and US Route coefficients originate from the Iowa DOT maintenance route road classification. There is an additional route type, Interstates, that is not displayed in the model. The reasoning is that Interstate routes were taken as the baseline for the model. Therefore, the values for the Iowa Route and US Route coefficients are relative to the Interstate route (Charpentier 2013).

Marginal effects were computed to show the effect that each variable has on the crash severity type, as shown in Table 16.

Table 16. Marginal effects of the crash severity model

Coefficient	PDO	Possible Injury	Minor Injury	Fatal/Major Injury
Seasonal AADT (vehicles)	0	0	0	0
Nearest Pass After (hrs)	-0.048	0.032	0.014	0.003
Relative Crash Time to AVL (normalized scale)	0.126	-0.082	-0.036	-0.008
Iowa Route	-0.141	0.086	0.044	0.01
US Route	-0.059	0.038	0.017	0.004

According to this table, Seasonal AADT has a consistent effect across the crash types. The closer the nearest after pass is from the crash, the less severe the crash, and vice versa. This could imply that the further the plow pass from the crash, the lower the plow pass frequency. With a low pass frequency, roadway conditions worsen. The further along in the AVL operations, the less severe the crash tends to be. Early in plow operations, the winter storm may be in full effect, which impedes driver safety. Furthermore, the more time that passes, the barer the roadway surface becomes. It appears that US routes and Iowa routes pose a greater crash severity risk than Interstate routes. Interstate routes are well traveled and therefore well plowed. With a higher plow frequency, the roadway condition will return to bare conditions much faster.

CONCLUSIONS

Much research has attempted to determine the impacts of weather events on mobility. As more knowledge has been gained, attention has turned to quantifying the impacts of winter maintenance operations on safety. This project studied the relationships between weather, safety, and maintenance operations.

Because inclement weather has demonstrated such a profound impact on safety and mobility, attempts to mitigate this problem have been numerous. In recent years, the Iowa DOT has collected data pertaining to weather, crashes, and maintenance operations. Furthermore, the data collected have been highly granular. Because of the amount of detail in the data, a thorough examination of the interactions between all three issues has become possible. In order to demonstrate the interactions between safety, weather, and maintenance operations, visualization tools were implemented to capture as many of the interactions as possible. Additionally, a crash frequency model and a crash severity model were developed to quantify the safety benefits of maintenance operations.

It was found that a roughly fifty-fifty split of winter weather-related crashes occurred during a winter storm and after a winter storm. Because a large portion of crashes occur outside of a winter event, several factors may be at work. First, road conditions proved to be a major factor in crashes. When winter storms end, plow operations often continue for long stretches of time in order to clear the pavement surface. Because of this extended exposure of traffic to adverse pavement conditions, crash counts trend higher. The second factor is the erroneous perception of safety by travelers. Many associate unsafe driving conditions with present precipitation. When the storm event ends, many people may gain a false perception of the crash risk. This leads travelers to drive at higher speeds and proceed less cautiously than needed. In either case, the road conditions play an integral role in crash safety.

Another trend in the crash data analyzed revealed that crashes resulting from winter events tend to be less severe than other crashes. Compared to all observed crashes in the same timeframe, the 2016–2018 winter crashes had a greater proportion of PDO crashes and a lower proportion of major injury and possible injury crashes. The prevailing theory on this phenomenon is that travel speeds are lower during winter events, thus decreasing the potential for severe crashes.

With respect to the snowplow data, the initial findings suggested that snowplow parameters were directly correlated to the duration of the winter event. When long storm events occur, the distance in miles traveled by snowplows is inherently greater, and more material is spread. Additionally, the longer-duration storms tended to have more intense weather conditions at various points in the storm. Meanwhile, as the duration of a storm increases, the opportunity for a higher crash count exists. Because of this relationship, the natural tendency is to correlate higher crash counts and crash frequencies with higher AVL parameter values. While counterintuitive, the data suggest such a conclusion.

Because of the depth of data available, a deeper analysis was conducted and deeper relationships were discovered. An analysis of various ratios produced a clearer picture of the relationship between snowplow parameters and crash safety. When controlling for weather variables, the total solid material spread by the plows normalized by the total snowfall produced a promising interaction: the more solid material spread, the greater the safety benefit.

Many winter crashes were found to be temporally located near a snowplow pass either before or after the plow pass. Many of these crashes occurred along Interstate routes. These routes generally consist of several lanes and are plowed at a higher frequency than other routes. Because these routes are plowed at a high frequency, most of the crashes on these routes inherently occur in close proximity to a plow pass. While Interstates had a high proportion of crashes that occurred near a plow pass, Iowa routes experienced a different trend. These crashes tended to occur when plow passes were temporally further away from the time of the crash. Because snowplow passes can provide a safety benefit, it was expected that these routes would be less safe than Interstate routes. The crash severity model also provided evidence for this point. The US and Iowa routes proved to have a higher propensity for severe crashes than the Interstate routes according to the crash severity model.

When determining the difference of proportions between observed crashes and storm-wide conditions, several key interactions were noted. Almost one-third of all crashes occurred before a snowplow pass was recorded. The proportion of crashes that occurred without a snowplow pass beforehand was significantly higher than the theoretical proportion derived from the storm-wide conditions analysis. Conversely, the proportion of observed crashes that occurred with several snowplow passes before the crash was significantly lower than that predicted by the storm-wide conditions analysis. These relationships offer evidence that the greater the number of snowplow passes that occur early in the storm, the fewer the crashes.

Several limitations restricted the analysis. A major factor in determining the interactions among the variables examined in this study is the ability to quantify similar groups. Because the quantification of winter storms proved difficult, a more thorough investigation was not possible. In addition, the limited number of RWIS sensors restricted the scope of the study. The crash severity model was not able to control for the effects of the road conditions. Another limitation was the quality of data. A number of crashes along the I-80/I-35 corridor could not be attached to a specific route and direction and therefore could not be included in the crash severity model. Additionally, non-precipitation based winter weather events were not analyzed in the crash frequency model. For example, blowing snow can cause hazardous driving conditions across Iowa. Because of time and resource constraints, these events could not be incorporated into that part of the study.

In regards to the plow pass frequency analysis, attempting to normalize the variables by the number of lanes may provide greater insight. Many of the high-frequency pass locations occurred along Interstate routes, which always have multiple lanes. Exploring this relationship between plow pass frequency and number of lanes may provide more insight into how each plow pass impacts safety. In the storm-wide analysis, crashes that occurred after the end of the storm were not included in the analysis. Because the ratio of storm to non-storm crashes was approximately 50-50, an underrepresentation of crashes may be occurring. By extending the time filter after the storm, a more complete picture of the data may appear.

Ultimately, this project provided a greater understanding of key relationships among weather, snowplow operations, and safety. These key findings can help better inform decision makers about how maintenance operations impact safety.

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