Road Salt Impact Assessment: Safety Study of Lane Departure Crashes in Maine

Final Report
June 2022

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Sponsored By

Transportation Infrastructure Durability Center

Maine Department of Transportation

Transportation Infrastructure Durability Center
AT THE UNIVERSITY OF MAINE

A report from

University of Maine

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Acknowledgements

Funding for this research is provided by the Transportation Infrastructure Durability Center at the University of Maine under grant 69A3551847101 from the U.S. Department of Transportation's University Transportation Centers Program. The authors would like to thank Robert Skehan, Dale Peabody, Brian Burne, and Edward Beckwith from the Maine Department of Transportation for their support throughout the research. The opinions expressed by the authors in this research do not necessarily reflect those of the Maine DOT or TIDC UTC program. Authors also appreciate Dr. Per Grader for his insightful comments.

Technical Report Documentation Page

1. Report No. **4-10**	**2. Government Accession No.**	**3. Recipient Catalog No.**
4 Title and Subtitle Road Salt Impact Assessment (Safety Study of Lane Departure Crashes in Maine)		**5 Report Date** June 2022 **6 Performing Organization Code**
7. Author(s) Jonathan Rubin; Mohammadali Shirazi; Alainie Sawtelle		**8 Performing Organization Report No.**
9 Performing Organization Name and Address University of Maine		**10 Work Unit No. (TRAIS)** **11 Contract or Grant No.**
12 Sponsoring Agency Name and Address Maine DOT, 24 Child St., Augusta, ME 04330 Transportation Infrastructure Durability Center, ASCC, University of Maine, 35 Flagstaff Rd., Orono, Maine		**13 Type of Report and Period Covered** **14 Sponsoring Agency Code**
15 Supplementary Notes		

16 Abstract

The proposed study supports a project sponsored by Maine DOT titled as "Road Salt Impact Assessment." Winter weather and maintenance treatments have significant impact on highway safety and operations. Understanding the safety impact of these factors directly influences decisions on diminishing maintenance funds, and cost-benefit analysis of alternative maintenance strategies. This research will conduct analysis of lane departure crashes in Maine. Models will be developed to explore to what extent seasonal (i.e., winter vs. non-winter) and monthly weather factors impact frequency of lane departure crashes in Maine. The proposed research will also analyze the impact of different roadway, driver, and weather factors on the severity of single-vehicle lane departure crashes on rural roadways in Maine.

17 Key Words Lane Departure Crashes. Crash Frequency, Crash severity, Statistical Modeling, Multinomial Logit.		**18 Distribution Statement** No restrictions. This document is available to the public through	
19 Security Classification (of this report) Unclassified	**20 Security Classification (of this page)** Unclassified	**21 No. of pages** 62	**22 Price** NA

Form DOT F 1700.7 (8-72)

Contents

List of Figures 5
List of Tables 5
Abstract 6
Chapter 1: Introduction 7
Chapter 2: Literature Review 9
2.1 Introduction 9
2.2 Adverse Weather Conditions 9
2.3 Crash Frequency 10
2.4 Crash Severity 12
2.5. Winter Maintenance Strategies 15
2.6 Climate Change and Transportation Safety 17
2.7 Weather Data 18
2.8 Conclusion 18
Chapter 3: Crash Frequency Analysis 20
3.1 Introduction 20
3.2 Data Description 21
3.3 Methodology 26
3.4 Modeling Results 26
3.5 Marginal Effects 31
3.6 Summary and Conclusions 33
Chapter 4: Crash Severity Analysis 36
4.1 Introduction 36
4.2 Description of Data 37
4.3 Methodology 43
4.4 Results and Discussion 43
4.4.1 Interstate Facilities 43
4.4.2 Minor Arterial Facilities 46
4.4.3 Major Collector Facilities 47
4.4.4 Minor Collector Facilities 49
4.5 Summary and Conclusion 51
Chapter 5: Summary and Recommendations 52
5.1 Crash Frequency Analysis Summary 52

5.2 Severity Analysis Conclusion 54
5.3 Recommendations 56
5.3.1 Methodological Recommendations 56
5.3.2 Practical Recommendations 57
References 57

List of Figures

Figure 1: Total monthly lane departure crashes for each facility type. 21
Figure 2: Thiessen polygons and weather station locations 25

List of Tables

Table 1: Summary Statistics of Exposure, Geometry and Crashes. 23
Table 2: Summary Statistics for Monthly Weather Factors 24
Table 3: Modeling Results for Interstates 27
Table 4: Modeling Results for Minor Arterials 28
Table 5: Modeling Results for Major Collectors 29
Table 6: Modeling Results for Minor Collectors 30
Table 7: Results of Marginal Effects Analysis 32
Table 8: Count and Frequency of Variables for the Interstate Facility 39
Table 9: Count and Frequency of Variables for the Minor Arterial Facility 40
Table 10: Count and Frequency of Variables for the Major Collector Facility 41
Table 11: Count and Frequency of Variables for the Minor Collector Facility 42
Table 12: Modeling Results for Interstates. 45
Table 13: Modeling Results for Minor Arterials. 47
Table 14: Modeling Results for Major Collectors. 48
Table 15: Modeling Results for Minor Collectors. 50
Table 16: Frequency Analysis Marginal Effects (Replica of Table 7). 53
Table 17: Crash Severity Odds Ratio Results 55

Abstract

Lane departure crashes account for approximately 34% of all roadway crashes, and over 70% of roadway fatalities in Maine. Despite an 18% decrease in average daily traffic volume during the half of the year with colder weather, the months of November to April comprise over 64% of the yearly lane departure crashes. The majority of roadways and roadway crashes in Maine are in rural regions. Moreover, Maine has aging infrastructure, houses the oldest population in the United States, has diverse terrain and land use, and experiences several extreme weather events. The combination of these factors impacts the frequency and severity of crashes in Maine.

This report first investigates the impact of various weather factors on frequency of monthly crashes in Maine. A Negative binomial model with panel data was used to analyze monthly crashes on Interstates, minor arterials, major collectors, and minor collectors from 2015 to 2019 for winter (November to April) and non-winter (May to October) periods. The data include monthly average daily traffic, geometric characteristics, and monthly weather variables. Second, the impact of roadway, driver and weather factors on the severity of single-vehicle lane departure crashes occurring from 2017 to 2019 on rural roadways in Maine is analyzed using a multinomial logit (MNL) model. Four facility types: Interstates, minor arterials, major collectors, and minor collectors were considered for analysis. Four severity outcomes were considered including, fatal-incapacitating injury crashes (KA), non-incapacitating injury (B), possible injury (C) and property damage only (PDO). The PDO outcome was used as the reference (or base) category in the MNL model.

To better account for weather factors, instead of using police reported weather, daily weather data was obtained from National Oceanic and Atmospheric Administration online resources for a total of 16 weather stations and matched to road segments in the created regions. To analyze the impact of monthly weather factors on frequency of crashes, the weather variables were aggregated to monthly values. To analyze severity of crashes, we considered daily weather variables for the time of crash. The analysis provides safety analysts and practitioners in Maine a comprehensive study of factors that influences the frequency and severity of rural lane departure crashes in Maine at different facilities to improve maintenance strategies, enhance safety using proper safety countermeasures, or increase awareness across the state.

Chapter 1: Introduction

Lane departure crashes (i.e., crashes described as went-off road, head-on, or those that rollover is primary event) account for over 34% of all roadway crashes, and over 70% of all roadway fatalities in Maine. Maine has aging infrastructure and houses the oldest population in the United States (U.S.). Its vast range in terrain as well as several extreme weather events every year also make the state a unique case study to better understand the cause of lane departure crashes. The purpose of this report is to identify factors that affect the frequency and severity of rural lane departure roadway crashes in Maine.

First, the impact of weather factors on crash frequencies is analyzed. The monthly average daily traffic (ADT) and other roadway factors were also included in the model as control variables. A Negative binomial (NB) model (with panel data) was used to analyze frequency of crashes from 2015-2019 during the winter (November to April) and non-winter (May to October) periods. Second, this report investigates the impact of weather, driver and roadway factors on severity of single-vehicle lane departure crashes from 2017-2019 using a multinomial logit (MNL) model. In this report, models were developed for four facility types: Principal arterials-Interstates (referred to as Interstates in this report), minor arterials, major collectors, and minor collectors. It is important to analyze each of these facilities separately due to differences in design standards, traffic volume, winter maintenance priority and many other factors. In particular, winter maintenance priority is divided into six levels in Maine, with the Priority 1 for the highest priority roads such as Interstates, and Priority 6 for the lowest, such as the local roads.

Infrastructure, including roads and bridges in Maine are aging. The use of anti-icing solutions also exacerbates the poor road conditions. In the 2020 American Society of Civil Engineering (ASCE) report, Maine received an overall C- grade (on an A-F grading system) (Bouchard et al., 2020). In addition, Maine roadways received a D grade indicating that roads are in poor or at-risk conditions, compared to C grade describing mediocre condition that require attention. Gaps in funding for necessary upgrades are a contributing factor to aging infrastructure and poor roadway conditions. The report discusses that 8% of the highest priority roadways in the state (Interstates and freeways) continue to rate low with poor conditions and safety. Another alarming statement in the report is that "Maine motorists spend at least an extra $1 Billion per year in vehicle operating costs congestion and crashes" (Bouchard et al., 2020).

After the Second World War, the "baby boomer" phenomenon began in the U.S.. The massive rise in population at the time is reflected in the large proportion of older citizens. Maine is experiencing this impact more than any other states in the U.S., and currently houses the oldest population (Himes & Kilduff, 2019). Since 1990 the median age in Maine has grown from 33.9 to 45.0 in 2020 (Meyer, 2001). The U.S. median age has also grown, but not at such a significant rate, and has gone from 32.9 in 1990 to 38.2 in 2020. In the state of Maine driver age is also continuing to rise. The study period in this report is from 2015-2019, just in the five-year period the percentage of drivers over the age of 65 has grown from 21.9% to 24.8%. The risk of injury increases when older drivers involve in crashes. Older drivers may also experience medical conditions or take medicine that may enhance the risk of crash involvement (Welsh et al., 2006).

Though Maine is the 11th smallest in the U.S., the varying geographic features, land use and location makes this state a unique case study to evaluate the factors contributing to the frequency and severity of cashes. Located in the northeastern corner of the U.S., with the Atlantic

Ocean along its southern region and the Appalachian Mountain Range spanning the middle of the state there are many factors that create regional variations. Due to the variations, the Maine DOT has five maintenance regions. Each maintenance region varies in maintenance practices, funds and resources based on terrain, road priorities and AADT.

Due to its location, the state experiences the 3rd coldest temperatures in the U.S., with an average yearly temperature of 41ºF (*Coldest States 2021*, 2021). Temperature, precipitation and snowfall vary considerably between different regions throughout the state. For example, average temperature varies by 5ºF from coastal to northern Maine with the northern region experiencing colder temperatures. Likewise, the northern region experiences on average more snowfall than the coastal region, varying yearly by more than 40 inches. However, coastal Maine experiences more precipitation than the northern region by more than 10 inches of precipitation on average. Along with regional differences in weather, Maine is also experiencing more unpredictable weather events, with extreme storms occurring year-round. Winter events in Maine often occur during more than six months of the year.

Due to the aging infrastructure, aging population, diverse terrain and extreme weather, Maine is a unique case study with regard to roadway safety. This report analyzes lane departure crashes on rural Maine roads. The outline of this report is as follows: Chapter 2 provides a systemic review of literature related to frequency and severity of lane departure crashes especially regarding weather factors. Chapter 3 documents the models developed to analyze the impact of weather factors on frequency of lane departure crashes. Chapter 4 documents the models developed to analyze the impact of different weather, driver and roadway factors on severity of lane departure crashes. Chapter 5 presents the summary of findings and formulates recommendations for future research.

Chapter 2: Literature Review

2.1 Introduction

The purpose of this research is to analyze severity and frequency of lane-departure crashes in Maine. The current chapter reviews studies related to crash frequency, crash severity, maintenance strategies, and climate change. Due to the projects' goal, the impact of weather variables on frequency and severity is highlighted throughout the chapter along with other important variables including roadway and driver factors.

2.2 Adverse Weather Conditions

Adverse weather conditions affect various aspects of transportation safety and operations. Not only the crash frequency and severity, but also the driver behavior, driver speed and traffic volume. Researchers have tried to quantify how much traffic volume is affected by adverse weather conditions. Maze et al. (2006) conducted an extensive literature review about the impact of weather factors on traffic demand, traffic volume, and safety. The researchers indicated that the traffic volume reduces by about 5% during rain events and by 7%-80% during the snow events. The study also used data from highway crashes provided by the Iowa Department of Transportation (DOT). Findings of this research suggest that the storm duration and intensity play a key role on traffic volume. During high intensity rain events (at least 0.25 in/hr.), the analysis showed a decrease of up to 14% in volume. During high intensity snow events (at least 0.5 in/hr.) the analysis showed a decrease of 22% in traffic volume. Although it is drastic, the difference in volume reduction, depends on the storm duration, accumulation, and intensity (Maze et al., 2006).

Qiu and Nixon (2008) found 1.35-3.45% reduction in traffic volume during the rain events and a 7-56% decrease in traffic volume during the snow events. To compare studies, the researchers weighted each study using factors such as sample size. The traffic volume reduces by 1.35% due to light precipitation, by 2% due to rain, by 15% due to snow and by 29% due to heavy snow. In a review study, Strong et al. (2010) found a range of 3-42% reduction in operational speed during snow events. They also found that the storm type, intensity, and duration impact speed and traffic volume; they also concluded that stronger storms impact both speed and volume more than less severe storms,

Kilpelanien and Summala (2007) prepared and distributed a questionnaire during 16 snow events in southern and mid Finland during the 2001-2002 winter season (Kilpeläinen & Summala, 2007). The 44-questions of the questionnaire were completed at 11 service stations along two-way highways by drivers during snow events. There was a total of 1,437 questionnaire responses with 75% of drivers driving passenger cars, 12.7% driving vans, and 12% driving trucks. The intent of the questionnaire was to understand what kinds of trips were made during snow events, if and where drivers received forecast information, and to understand how drivers altered their behavior while driving based on the perceived roadway conditions. Only 5.8% of drivers reported altering their trips due to the weather, which included changing paths, or leaving earlier. This study however underrepresents the drivers who chose to postpone or cancel their trip due to the weather conditions. When comparing the answers of the current road condition to the ones that the drivers perceived based on the Road Weather Information System (RWIS) values of good, poor or very poor conditions, 4.3% of drivers answered conditions were worse, 73.4% answered the same, and 22.3% of drivers answered that the conditions were better than the RWIS values.

2.3 Crash Frequency

A common theme in transportation safety research is that crash frequency is strongly correlated with traffic volume; the more vehicles on the road, the more likely a crash will occur. As discussed, during adverse weather conditions studies suggest that the traffic volume decreases, however, studies discussed in this section suggests that during the same conditions, the frequency and risk may increase.

Shankar et al. (1995) evaluated the impact of roadway geometric features and weather conditions on frequency of crashes along on a 61km segment highway near Seattle, Washington (Shankar et al., 1995). The analyzed roadway segments involve horizontal and vertical curves that vary in radius, grade, and superelevation. Negative binomial models were used to analyze crash frequency for various crash types due to different weather and roadway conditions. Weather factors included in this study include intensity, frequency and accumulation of rain and snow events. Roadway factors include curvature and grade. Crash types include sideswipe, rear-end and overturning crashes. Rainfall intensity resulted in increasing the frequency of sideswipe, parked vehicle, fixed object, and overturning crashes. However, rainfall intensity resulted in decreasing the rear-end crash frequency. This observation was explained because of lower visibility and more driver awareness. Average daily rainfall resulted in an increase in rear-end crash frequency. The number of rainy days in a month increased fixed object crashes and decreased the number of sideswipe crashes. Snowfall intensity resulted in an increase in crash frequency for rear end, and other same direction crashes, as well as parked vehicle, and fixed object crashes. The number of snow days increased sideswipe, fixed object, and overturning crash frequency. Interesting results concerning weather and geometric interactions include an increase in sideswipes, rear-end, parked vehicle, and other same direction crashes for snowfall and grade interactions. The results for the relationship between snowfall and curve interactions included an increase in rear-end, overturning, and other same direction crash frequency. For rainfall and curve interaction, there is an increase in rear-end and other same direction crashes, and a decrease in fixed object and overturning crash frequency.

Usman and Fu (2010) analyzed crash frequency during snowstorm events in Ontario, Canada (Usman et al., 2010). The study considered four major roadways and used data from three winters. The researchers used the RWIS data, that incudes hourly weather data at various segment sites. The weather and crash data were then used to find the relationship with road surface condition index (RSI) that was used to determine the road conditions at the time of a crash. RSI was broken down into seven different classifications ranging from dry/bare pavement to icy pavement. The information was collected by observation of maintenance personnel and was collected on average 3-4 times during each event. The classifications were used rather than actual maintenance strategies, as the RSI is the direct result of the maintenance that was completed. Other factors that were observed in the study include, exposure, visibility, temperature, and total precipitation.

Usman and Fu (2010) used the Generalized Negative binomial (GNB) model and found that the frequency of crashes increases with lower RSI, reduced visibility, or increase in exposure. The results of the GNB suggest that an increase in 1% of the RSI would result in 2.28% decrease in crashes; this confirms that roadway maintenance is important during snowstorms to reduce the number of crashes. Initially the researchers found that the air temperature and precipitation did not lead to higher frequency in crashes; however, further study in subsequent years showed that indeed lower air temperature and higher precipitation both lead to a higher crash frequency (Usman et al., 2012). This later study used crash, weather, and RSI data from 31 sections of highway over six winter seasons from 2000-2006 in Ontario, Canada. Factors included in this analysis include exposure, month, first hour of storm, air temperature, precipitation intensity, RSI, visibility, exposure, and wind speed. Results from the 2012 study include: crash frequency increases as RSI, visibility, or temperature decreases, or as exposure, precipitation intensity, and wind speed increases. The results show that a 1% increase in RSI would result in a 2% decrease in crash frequency, and a 1% increase in visibility would result in a 0.5% decrease in crash frequency.

Andrey et al. (2003) evaluated crash risk during adverse weather for six mid-sized Canadian cities located in different regions of Canada varying in weather and climate (Andrey et al., 2003). The study used weather and crash data from 1995-1998 and used a matched-pair analysis to determine the crash risk. The analysis used crash data during 6-hr of precipitation events, analyzing snow and rain separately. To match the event data from one week before or after the event was compared to the adverse condition event to determine the risk change. A goal for the study was not only to determine how crash risk changes due to weather variation but also comparing the results between different climate regions. In all cases, precipitation resulted in an average increase in crash and injury risk by 75% and 45% respectively, compared to their matched pair event of normal conditions. The research explored snow and rain precipitation events separately and found that the relative crash risk during snow was 2.54, while the relative crash risk during rain events averaged to 1.65.

Andrey (2010) explored the long-term crash risk due to weather conditions (Andrey, 2010). The study duration was from 1984 to 2002, with weather and crash data from 10 cites, spread through four Canadian Provinces. The study used a similar matched-pair design method previously discussed. In this study, precipitation was separated into three categories: (1) 0.29-2.00mm, (2) 2.01-10.00mm, and (3) greater than 10mm. The study also included time of day as a factor, separating crashes into morning, afternoon, evening, and nighttime crashes. During the 20-year study time, for all weather conditions, the total number of crashes and crash severity decreased in Canada. The overall relative risk of crashes during rainy conditions was found to be 1.73 and during snow events was found to be 1.87. In addition, from the beginning period to the end of the study, the relative crash risk during rain events changed from 1.9 to 1.5. The author explained this observation as possible impact of vehicle and roadway design improvements or changes in maintenance strategies. The study concluded an insignificant change to the overall relative crash risk during snow conditions, described to have "declined in a way that is consistent with the overall safety trend." The relative crash risk during snow conditions stayed as the average of 1.87. For the rainfall intensity, it was found that as intensity increased, the crash risk also increased, but for snowfall crash risk increased for low and medium accumulation storms, or >10cm, and decreased for high intensity storms. The risk of both forms of precipitation resulted in a number greater than 1, which concludes that crash risk increases with precipitation.

Zhao et al. (2019) studied the impact of monthly weather variations on crashes in Connecticut (Zhao et al., 2019). The study used a random parameters Negative binomial regression with first-order autoregressive covariance. The analysis considered crash data from 2011 to 2015 and exposure data using continuous count stations located on freeways. Variables considered in this analysis included monthly weather data including temperature, maximum precipitation, days with thunderstorms or fog, days with more than 0.1 or 0.01 inch of precipitation and average monthly wind speed. Roadway geometric variables considered include rural/urban area, lane width, number of lanes, and more. The researcher found that the precipitation and crash frequency are negatively correlated, the visibility (in the form of heavy fog days) was related to the monthly crash frequencies, and wind speed was found to have a negative correlation with monthly crash frequencies.

Strong et al. (2010) showed that compared to normal conditions, during snow conditions, crash rates increase between 30-250% regardless of the expected decrease in traffic volume. Qiu and Nixon (2008) conclude that the crash rates increase by up to 84% during the snow conditions, and by up to 71% during rainy conditions compared to normal conditions regardless of expected decline in traffic volume. Maze et al. (2006) concluded that severe winter storms can put drivers at 25 times higher risk of getting into a crash, and that drivers during moderately severe storms are 13 times more at risk. Qiu and Nixon (2008) concluded that rain increased crash rates by up to 71%.

Previous studies show that higher temperatures result in increased crash frequencies. Higher temperatures impact driver behavior, vehicle safety, and traffic exposure; it is also correlated with other weather conditions that impact safety (such as snowfall or icy roads). Driver behavior is affected by higher temperatures as it increases the level of fatigue (McDonald, 1984). High temperature is also associated with increase in heart related illnesses such as heart attack or strokes (Wu et al., 2018). These illnesses are also more likely in older people. Maine has the oldest population in the U.S., and a high percentage of older drivers. Wu et al. (2018) discovered higher crash rates during heat waves among older drivers of 55-65 years old. Research studies also found larger numbers of steering or other forms of adjustments in higher temperatures (Mackie & O'Hanlon, n.d.) which could result in lane departure crashes. In terms of vehicle impact, higher temperatures are associated with increased rates of flat or failing tires (Ma et al., 2020; Ratrout & Mahmoud, 2006) which increased risk of crash due to tire blowout. Weather factors are also correlated with higher temperatures, including higher rates of thunderstorms leading to less visibility and more rainfall creating higher rates of hydroplaning during higher temperature periods (S. Zhao et al., 2019). Finally, higher temperatures are also associated with higher travel volume.

2.4 Crash Severity

This section reviews studies that explored the relationship between crash severity and weather variables. Morgan and Mannering (2011) evaluated single-vehicle police reported crashes during 2007-2008 in Indiana (Morgan & Mannering, 2011). They examined dry, wet, and snow/ice surface crashes and from there broke crashes down by driver age, male/female drivers, and crash severity (severe, minor, and no injury). A mixed logit method was used to develop 12 different severity models. Results of this study suggests that not using seat belts, rollover crashes, fixed object crashes, head on crashes, and crashes that result in an occupant being trapped under the vehicle impact injury severity. This study also showed that most driver groups had over a 100% increase in severe injury due to adverse surface conditions caused by weather. For male drivers, men under 45 years old resulted in a higher probability for minor injuries and a lower probability for no-injury when a crash happens on wet surface conditions, and a lower probability for minor injury and a higher probability for no-injury when a crash happens on snow and icy surfaces. Note that these are in comparison to their male counterparts older than 45 years old. For female drivers, women under 45 years old have a lower probability to experience minor-injuries and a higher change of experiencing no-injuries when a crash happens on wet, snowy, or icy surfaces. Note that like the male results, the results are in comparison to the female counterparts older than 45 years old.

Shaheed et al. (2016) used a multivariate model to determine the relationships between the crash severity and weather variables (Shaheed et al., 2016). Crash data in four winter seasons (from 2008-2012) on I-80 Interstate in Iowa were evaluated. Weather factors included in this study involves the precipitation type, intensity and accumulation, visibility, surface temperature, surface condition, and air temperature. Injury severity was broken down into two categories, serious (fatal/incapacitating/non-incapacitating) injury and possible injury. Then, a multilevel multinomial logit model was used. By using this approach, the results include what the predicted result of a crash would be given different conditions. For example, men are 23% less likely to be seriously injured and 37% less likely to be possibly injured during winter weather crashes than women.

The researchers also found that when an occupant in a vehicle, during a winter weather crash, was wearing a seatbelt, they were 53% less likely to sustain possible injury, and 32% less likely to sustain serious injury. For all-weather related crashes, it was found that occupants that are trapped in or under or ejected from a vehicle have a higher chance of being seriously injured. It was found that a lower visibility resulted in less severe crashes. In this study for all normal condition's crashes, those of which have with dry pavement and above freezing temperatures, the chance of getting possibly injured is 70% higher and the chance of getting seriously injured is 39% higher than winter weather conditions. For all normal condition run-off, the road crashes, the probability of sustaining serious injuries is 247% higher and the chance of sustaining possible injuries is 90% higher than those occurring during winter weather conditions. These interesting conclusions result in lower speeds, and higher driver awareness and caution during winter weather events. It was found that there is a 70% higher chance of serious injury than no injury on roadways that are dry and when pavement temperature is above freezing. This is considered clear conditions; clear conditions result to more severe crashes. They also found that when visibility was within six miles and surface condition was not dry (i.e., wet, snowy, etc.), the odds of occupants getting into a severe crash decreased by 45%.

Mills et al. (2019) evaluated risk of injury and non-injury crashes during winter storm events in Ontario, Canada from 2002 to 2016 (Mills et al., 2019). A matched-pair retrospective cohort method was used to analyze the impact of different factors. Factors considered include time of day, precipitation type, intensity, storm duration, and accumulation, date, visibility, and temperature over entire storm events. The storms evaluated were broken down into two categories, those of only snow, and those of mixed precipitation. The storm events that were evaluated provide more "real" weather situations. There are many factors that go into changing weather and differentiating storms. The authors were able to fill in a gap in the research by separating events out by multiple factors including low visibility, low or changing temperature, and precipitation amount. By differentiating storm events into more categories, it is easier to understand what storms are causing the most and severe crashes and therefore have the highest risk of crash or injury. Interesting trends that resulted from this study include, the highest relative risk out of all winter weather events were those with the highest snow counts of greater than or equal to 10cm that resulted in non-injury, where the relative risk was almost 3.5. It was also interesting that the highest risk of injury crashes resulted during mixed winter weather events. The results also showed that snow events have a significantly higher risk of non-injury crashes than crashes resulting in injury. Overall, the study showed that for all winter weather events relative risk for crashes has decreased over time.

Li et al. (2019) studied rural single-vehicle crashes during rain events from 2012-2014 in Texas, Arkansas, Oklahoma and Louisiana (Li et al., 2019). This study analyzed driver injury severity using a mixed logit and latent class modeling approach. Key findings of this study include variables such as grade, curve, impaired driving, multiple lanes and not using a seatbelt increases probability of crashes being severe. The variable of grade was found to increase severe injury during rain events by 50%. The variable that included curves found that there is an increase in crash severity by a range of 20-80% during rain events. The study concluded that the likelihood of being in a severe crash is 38-43% less for younger drivers (below the age of 25), and that male drivers are 6-17% less likely to be in fatal crashes. The authors found severity increases by 265-318% when seatbelts are failed to be worn and that operating under the influence increases the likelihood of severe and fatal crashes by 204-502%. When road conditions were wet the probability of severe crashes decreased by about 40%.

Wu et al. (2016) studied injury severity of drivers involved in single-vehicle crashes in New Mexico during 2010-2011 using nested logit and mixed logit modeling approaches (Wu et al., 2016). Factors included in this study include weather, crash, driver and roadway characteristics. Weather factors included rainfall, snowfall, and wind. Crash characteristics included vehicle type, vehicle rollover or hitting a fixed object. Driver characteristics include variables such as driving under the influence of drugs or alcohol, female drivers and driver age groups. Roadway factors include the number of lanes, curve and traffic control type at crash locations. The analysis considered urban and rural roadways separately. The following are significant results that indicate an increase or decrease in odds of incapacitating injury and fatality on rural roads: when drivers are above the age of 65 years old, there is an increase in odds of 63.8%, driving under the influence increases the odds by 252.3% and snow conditions decrease the odds by 50.4%. The following are significant results in increasing or decreasing the odds of incapacitating injury and fatality on urban roads: when drivers are above the age of 65 there is an increase in odds of 66.2%, driving under the influence increases the odds by 149.6% and snow conditions decrease the odds by 64.5%.

Eisenberg and Warner (2005) studied the effects of weather involved crashes in the contiguous 48 States (Eisenberg & Warner, 2005). The study focused on estimating the effect of rain and snowfall on crashes using a Negative binomial regression analysis. The modeling results show that snow days increased non-fatal injury rates, and property damage only crashes. Another result indicated that during the first snow day of the season, the fatal and injury rates increase, resulting in more severe crashes. This was found to be especially relevant for older drivers. Accounting for all snow days, the results indicate that crash fatality rates decreased by 16%. However, the property damage only crash rates increased by 78% compared to dry weather days. Accounting for all rain days, the fatality rates increased by 6%, the injury crash rates increased by 19% and the property damage only crash rates increased by 15% compared to dry weather days.

Kim et al. (2013) used single vehicle crash data in California to study the driver injury severity (Kim et al., 2013). This research studied the impact of driver, and roadway factors on severity using a mixed logit modeling approach. Findings of this study showed that drivers over 65-years old are 105% more likely to be in a fatal crash compared to 25–64-year-old drivers. Male drivers were found to be 107% more likely of being in a fatal crash compared to female drivers. From the results, it was found that when seatbelts are worn, the chances of crashes resulting in a fatality decrease by 60%. When drivers exceed the posted speed limit it was found that crashes are 105% more likely to result in a fatality. When drivers are under the influence of alcohol, crashes are 73% more likely to result in a fatality.

Zhang et al. (2021) analyzed crash severity outcome of freeway crashes in China (Zhang et al., 2021). The study considered time of day, vehicle type, roadway and weather factors to analyze the crash severity using a multinomial logit modeling approach. Results of this study show that the decrease in minimum visibility by one unit leads to an increase in 0.1% in the probability of non-injury crashes. This indicates that lower visibility decreases the chances of severe crashes, perhaps due to increased caution. It was found that as wind speed increased by one unit there was a 0.9% decrease in severe and fatal crashes, and that a 1% increase in grade increases the probability of severe and fatal crashes by 2.86%.

2.5. Winter Maintenance Strategies

Winter maintenance strategies vary among states, counties and even towns; therefore, it is difficult to measure or compare the safety impacts of different strategies. Environmental and economic costs are measured in different ways and each area that experiences winter weather uses their best judgment, as well as the budget and resources when determining what practices to administer. This section discusses the publications that present findings on different maintenance strategies, or how different regions determine what strategies to enforce.

Norrman et al. (2000) evaluated data from two RWIS stations in Sweden over the course of three winters (Norrman et al., 2000). The data from the stations includes a computer generated "slipperiness" factor of 1-10. The factor is generated every 30 minutes to record the current road condition. The study used all crash data reported by police to derive a relationship between winter road conditions caused by winter road maintenance and crash risk. The study also collected reports from the contractors conducting winter road maintenance. Reports were completed each time maintenance was completed, to determine what maintenance was being done at the time of the crash that was caused by slippery road conditions. This approach was similar to Usman et al. (2010, 2012). Instead of accounting for the actual maintenance strategy, they used a roadway surface condition index which, assumed to be a direct result of maintenance. A total of 246 winter crashes were reported on the road segment observed in the 2000 study, and out of those 50% were a result of slippery roads either by police report, RWIS, or both. The majority of crashes occurred on slippery roads were caused by snow falling on frozen surfaces, or snow and hoarfrost together. It was also found that out of the crashes that occurred during these two classifications, all occurred when 100% of the winter road maintenance was being completed. The authors conclude that maintenance is not enough, and that public awareness is also important to decrease crash risk during snow.

Marquis et al. (2009) discussed that the Maine DOT does not use any form of salt during roadway maintenance when temperatures are below 15ºF (Marquis et al., 2009). The reasoning for this is that salt is not effective in melting ice at low temperatures. Therefore, only plowing and sanding is done during colder storms. During colder storms, winter maintenance takes a significantly longer amount of time because snow is lighter at colder temperatures, and there is an absence of salt that would cause partial melting making snow heavier. This kind of snow is more prone to blow and cause snow drifts. Snow drifts also cause another safety concern from winter weather on roadway safety.

Usman et al. (2010, 2012) use a GNB model to determine how road surface index (RSI) affects crash frequency. It was determined in both studies that changes in RSI result in significant changes in crash frequency. The study conducted by these researchers in 2010 showed that a 1% increase in RSI results in a 2.28% decrease in crashes; the study conducted in 2012 show a 2% decrease in crashes. This means that increasing or updating maintenance strategies to better road surface conditions is important to decrease overall roadway crash frequency and create safer roads during winter events. Usman et al. (2012) discussed how changing the time that it takes to regain bare pavement for roadways after a storm event is completed can help in decreasing the overall crash frequency. The situation evaluated assumed an 8-hour recovery period from the time that the storm stops to the time that the pavement is cleared and dried. It is discussed that by cutting that time in half, from four hours, would result in a reduction of more than 50% of overall crashes.

Dao et al. (2019) developed a two-part questionnaire that was distributed to individual state Department of Transportations to better understand their current winter maintenance practices and how they measure the performance of their practices (Dao et al., 2019). Out of the 50 States, 31 answered the initial questionnaire. The states answered how important different winter weather variables were in determining their maintenance strategies. The states also disclosed what sources they used for their weather forecast information, and how important accurate forecasting has proven to be in determining the extent each weather variable will expectedly impact the area. Notable responses for the initial questionnaire include, road temperature and snowfall being the most important weather variables, from 28 states, or 90% of respondents. Most receive their weather forecasting information from the national weather service, mobile phone applications and private weather consulting companies.

The weather forecast's accuracy mostly ranged from moderately accurate to elevated accuracy for most weather variables, though freezing rain and snow accumulation were stated as the least accurately reported. Most states reported that to properly plan for weather maintenance they need to know the weather conditions three days in advance (Dao et al., 2019). The follow-up questionnaire included winter severity index (WSI) performance measurement information. Out of the 31 states polled, nine states answered regarding their WSI, including Maine. The most important reason for using WSI for the nine states that responded, was for performance improvement. However, it also is important for expense verification. Most states WSI includes snow amount, freezing rain, snow frequency and blowing/drifting as variables, and most states indicated that snowfall duration, intensity, and accumulation, as well as air temperature were the most important in their WSI calculations. Other performance measures recorded by state DOT's include visual inspection, accounting records, closed circuit televisions/webcams, global positioning systems, equipment hours, and customer satisfaction as well as many others. The benefits most recorded of using WSI included improved decision process relating to snow and ice control and improved communications with staff. WSI is measured on a scale of 1-100 with one being a mild winter and 100 being a very extensive and severe winter. By using WSI states can justify their budgets for winter weather maintenance, as a higher WSI should account for a higher cost in maintenance as the winter was more severe. WSI is not a predicted measurement it is a measurement that is found after the winter season (Dao et al., 2019).

Marquis et al. (2009) discussed how the state of Maine developed a Winter Severity Index System that is used to understand material usage and winter maintenance costs. The WSI is very important for Maine because 20% of the Maine DOT budget for maintenance and operations is spent just on winter weather maintenance. Colson Nouhan from the National Weather Service collaborated with the Maine DOT to develop the WSI. There are different factors used to develop WSI such as snow and rain accumulation, intensity, and storm duration. The entire state of Maine is separated into five maintenance regions, with Region 4, Bangor region, being the largest. The WSI was determined for each of the regions for 26 winters. The more modern winter WSI was compared to the maintenance and material costs for each region for each winter season after 2001. In 1998 most of the state transferred from reactive maintenance to proactive maintenance which included experimenting with anti-icing and salt brines with different liquids including magnesium chloride and liquid calcium, and other strategies. A summary of the current maintenance strategies for four of the regions discussed in the article and summarized as follows: in Region 1 (Southern Maine), the town of Scarborough converted to using only salt, including pre-wetting salts using magnesium chloride. In Region 2 (Central Maine), Augusta uses pre-wetted salts with liquid calcium and still uses sand. In Region 3 (Western Maine), Farmington uses sand, salt and sand/salt mixture, and uses liquid calcium. In Region 4 (Bangor Area), when the paper was published in 2009, they were experimenting with different strategies and still used a sand/salt mix.

It was found that WSI closely followed the same trend as maintenance cost. Meaning a very severe winter also resulted in high cost of maintenance and materials. This was the trend in all regions besides Region 3, the western mountainous region. However, WSI did not follow the same trend as cost when the cost of material skyrocketed or when there was a salt shortage in Maine during the winter of 2007-2008 due to high snow accumulation. It was concluded that WSI is a good indicator of material and labor cost, but that to accurately account for each land area in the state the regions should be separated. This is because weather varies due to different factors including the proximity to the ocean or mountains.

2.6 Climate Change and Transportation Safety

Climate change is a worldwide problem that may fields is being affected from, including transportation of all forms. Weather is changing and storms are becoming more severe. For the northeast United States, including Maine, storms are also more prevalent than ever before. This section discusses the studies related to how climate change has and is going to continue to affect roadway safety.

Andersson and Chapman (2011) investigated the relationships between the temperature and severe crashes (Andersson & Chapman, 2011). The article discusses how climate change has and will continue to impact crashes and roadway maintenance in West Midlands, United Kingdom. The critical air temperature that resulted in the highest crash frequency was found to be between 1-7°C, with the most critical temperature of 5°C, rather than the freezing point of water at 0°C. The authors conclude that this is due to the pavement temperature being lower than the air temperature. The climate change program used Intergovernmental Panel on Climate Change, and derived models that predicted the number of days that the air temperature is going to be less than 0°C and 5°C in 2080, with results of decreasing days by 43% and 21% respectively compared to the number of days in 2005. The results could directly change winter weather maintenance strategies however, the authors present a warning that even though the number of below freezing temperature nights is going to decrease based on the model, no drastic changes should be made based on changing winter maintenance. The article discussed the winter of 2008-2009, when throughout the UK the quantity of rock salt was decreased in storage due to the observed weather data from the past few mild winters. Many areas in the country ran out of salt and it resulted in poor maintenance and lower safety due to cost cutting that occurred based only on a few mild winters.

Andrey (2010) determined long term trends of weather, rain, and snow, on crash risk. The author evaluates crash and weather data from 10 cities throughout Canada over a 20-year period, from 1984-2002 (Andrey, 2010). The weather trends presented in the paper are interesting as they are not consistent. Over time the amount of snow and rain that occurred varied significantly with some years having a major increase or decrease in wither weather condition. This is interesting in the sense that we understand that weather effects crash risk, but it is difficult to predict what the weather conditions over a season are going to be as weather is random and does not act in a way that is easily predicted especially coupled with climate change.

2.7 Weather Data

How weather data is collected, and where it is collected from is an important aspect of crash-weather studies. Most weather data were collected from weather stations, and in most cases those stations are national stations (often located at airports), rather than local stations. In many studies, the location of the weather stations is far from a crash; this creates a significant uncertainty in modeling results. studies recommended changing the location of the stations to address this issue in future studies. For instance, Young and Liesman (2007) found that one of the weather stations, is too far from the crash locations analyzed in their study. Therefore, they suggested to change the location of the weather station to accurately measure variables such as wind speeds to predict overturning truck crashes (Young & Liesman, 2007).

Marquis et al. (2009) noted that in coastal regions of Maine traveling just 20-30 miles in any directions from a weather station, the snow accumulations during the storm events, and the total season accumulation vary by 4-8 inches and 10-20 inches, respectively. The weather information that was collected in Naik et al. (2016) were from national weather stations, and the authors describe that if the data were obtained by a more local station in closer proximity to the crash sites and highways, they would be more reliable. To accurately observe how crashes are influenced by weather factors, it is important to have accurate and reliable data. However, access to reliable weather data is a limitation for most places and discussed throughout most of the studies in literature.

2.8 Conclusions

The literature review showed the various impact of weather factors on transportation. For example, during precipitation events, traffic volume is decreased. Overall, crash risk has decreased during the weather events over time; this is a result of higher exposure, better vehicle and roadway design, advanced technology, and maintenance improvements. Crash risk and frequency were found to be highest during the initial snowstorms of the season. Andrey et al. (2003) found that the relative risk of crashes during the first three snowfalls of the seasons was 4.39 on average.

Andrey et al. (2003) concluded that, during precipitation events, there was a 75% increase in crash risk and a 45% increase in risk of injury. Shaheed et al. (2016) observed a 70% increase in odds of crashes during normal conditions that result in possible injury, and a 39% increase in odds of crashes during normal conditions that resulted in serious injury. This conclusion determines that severity in crashes is higher during normal conditions than those during winter weather. The state of Maine has a strong presence of all four seasons and experiences diverse weather year-round. As climate change continues to change the weather, bringing more severe and diverse storm events, understanding how weather has affected roadway safety in recent years in Maine is an important step to reduce frequency and severity of crashes.

Chapter 3: Crash Frequency Analysis[1]

Chapter 3 documents the crash frequency models developed to analyze the impact of roadway and weather factors on the frequency of lane departure crashes in Maine. This chapter is divided into 6 subsections. Section 3.1 provides a brief Introduction. Section 3.2 documents data used in this study. Section 3.3 documents the methodology used. Section 3.4 documents the results of the Negative binomial models for each facility. Section 3.5 documents the marginal effects analysis for each facility. Section 3.6 provides the summary and conclusions of the crash frequency analysis.

3.1 Introduction

Roadway crashes are caused by various factors. Understanding the cause of crashes is an essential step towards improving safety across roadway networks. Among all crash types, lane departure crashes are the leading cause of crash fatalities in Maine, USA accounting for over 70% of all roadway fatalities. Most of these crashes (64%) occur during the winter period which in Maine spans from November to April. This study explores the impact of different weather variables on frequency of lane departure crashes (i.e., crashes described as went-off road, head-on, or those that rollover is primary event) on rural roads in the state of Maine, in recent years, from 2015 to 2019.

Maine is the most northeast state in the United States (U.S.). The state's location, land use and terrain make this state having unique features that it is not comparable to other U.S. states. The state experiences all four seasons with fluctuating weather year-round. Maine has a diverse geography, from the lengthy coastline surrounded by the Atlantic Ocean to the mountainous terrain from the Appalachian Mountain Range. Due to the significant differences, the weather from east to west, or from north to south varies substantially. The state ranks as the *third coldest in the U.S.*, with an average yearly temperature of 41ºF (*Coldest States 2021*, 2021). Coastal Maine experiences an average yearly temperature of 43.8ºF where northern Maine experiences an average yearly temperature of 38.2ºF (Fernandez et al., 2020). Though it is comparatively small in area, ranking as the 39th largest state in the U.S., the regional differences in weather in Maine vary greatly (*State Area Measurements and Internal Point Coordinates*, 2018). The winter season is long and can occur during at least half of the year (typically from November to April). However, it is not uncommon for below freezing temperatures or winter storm events to persist through May or begin in late October especially in the mountainous or northern regions.

As climate continues to change, Maine is experiencing more severe and diverse storm events. Though overall the warmer air and ocean temperatures are causing less snow accumulation, the trend is not linear. From 2010 to 2019, Maine regions have experienced record low and record high snowfalls. During the 2009-2010 winter season northern Maine experienced 64 inches of snow, where the average snowfall is 110 inches per winter season. During the same winter period the coastal region received 37 inches of snow, where the average is 60 inches per winter season. In terms of record high accumulations, during the 2018-2019 season, northern Maine set record snowfalls, as well as a record of 163 consecutive days with at least one inch of snow on the ground

[1] This chapter in part is from Sawtelle, A., Shirazi, M., Garder, P. E., & Rubin, J. (2022). Exploring the impact of seasonal weather factors on frequency of lane-departure crashes in Maine. Journal of Transportation Safety & Security, 1-22.

in Caribou, Maine (*State of the Climate: National Climate Report for April 2019*, 2019). The total snowfall during the season was more than 165 inches. During the same season coastal Maine experienced 66 inches of snowfall. Overall, the state's location, land use and terrain make it unique when analyzing the weather impacts.

Due to the changing climate, especially during winter months (in Maine from November to April), coupled with the high frequency of lane departure crashes during these months, it is crucial to better understand how different weather variables impact lane departure crashes in Maine. We use a Negative binomial (NB) model with panel data and Generalized Estimating Equations (GEE) to analyze how monthly weather variables impact the frequency of lane departure crashes on rural Maine roads during the winter and non-winter periods from 2015 to 2019. The analysis involves principal arterials-Interstates (referred to as Interstates in this paper), minor arterials, major collectors, and minor collectors. This information provides a better understanding of how different weather factors influence lane departure crashes on different roadway facilities and jurisdictions leading to improved maintenance strategies, countermeasures, safety and awareness.

3.2 Data Description

We collected, combined, and reduced the roadway network (roadway segments) and historical crash data from 2015 to 2019 and created uniform datasets for analysis. We analyzed four facilities: Interstates, minor arterials, major collectors, and minor collectors. Since more than 80% of all roadways in Maine are rural, compared to urban, only rural roadways were considered for this study. To isolate the impact of weather factors on monthly lane departure crashes, winter and non-winter period datasets were created and used in modeling. For each segment, we aggregated crash data in each month and recorded as a monthly crash observation. Therefore, in total, each segment has 60 observations in 5 years. As discussed, over 64% of all lane departure crashes in Maine occur during the winter period. The total observed lane departure crashes by each facility type are visually presented in Figure 1.

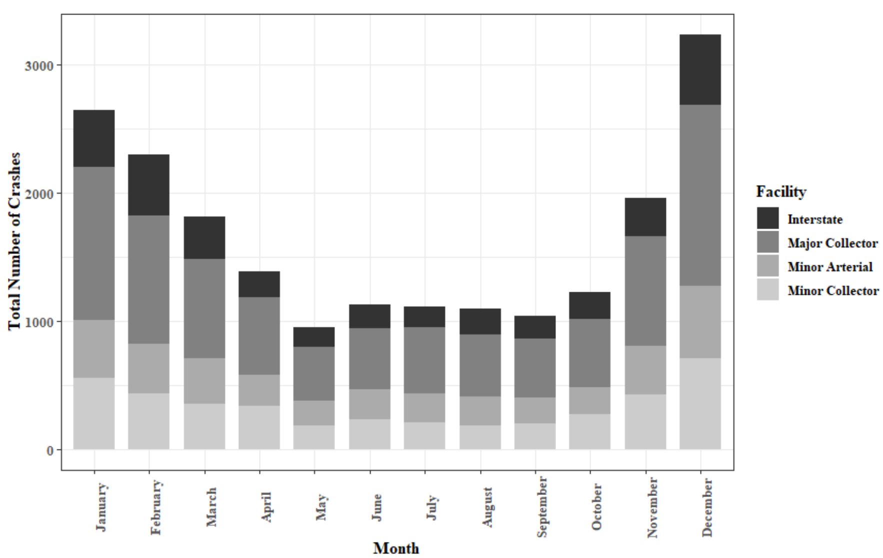

Figure 1: Total monthly lane departure crashes for each facility type.

We considered the monthly average daily traffic (MADT) rather than the annual value in our analysis to account for monthly variations of traffic volume due to events such as seasonal tourism. The summary statistics for crashes, roadway geometry, and MADT for all four facilities are presented in Table 1. All Interstate segments in the study were divided roadways; all other analyzed facilities (minor arterials, major collectors, and minor collectors) were undivided two-lane roadways. The segments used in this analysis include segments with geometric characteristics that remained consistent (or unchanged) over the five-year analysis period.

We obtained weather data from the National Oceanic and Atmospheric Administration (NOAA) through their online resource (*Search | Climate Data Online (CDO) | National Climatic Data Center (NCDC)*, n.d.). As discussed, the state is geographically very diverse that results in very different weather from one place to another. Accurate representation of weather data is necessary to ensure accuracy of the analysis. We compiled daily and monthly weather data from 16 weather stations throughout the state. We used two periods in the analyses. The winter period spans from November to April and the non-winter period from May to October. The summary statistics for weather variables for each period is presented in Table 2. It is worth pointing out that winter variables including snow or freezing temperatures are not applicable during the non-winter period. The maximum precipitation and maximum snowfall indicate the maximum 24-hr (12:00am-11:59pm) accumulation. It is also worth noting that multiple variables related to snowfall were considered in modeling, including but not limited to maximum snowfall, total snowfall, the number of days in a month with snowfall accumulations, and the number of days in a month with more than 1-inch of snowfall [note: this variable considers snow events that can last several days, which is common in Maine].

Table 1: Summary Statistics of Exposure, Geometry and Crashes.

Variables	Interstates				Minor Arterials				Major Collectors				Minor Collectors			
	Mean	S.D.	Max.	Min	Mean	S.D.	Max.	Min	Mean	S.D.	Max.	Min	Mean	S.D.	Max.	Min
Total Crashes (5-years)	2.63	4.08	44.00	0.00	0.50	1.02	13.00	0.00	0.33	0.80	22.00	0.00	0.24	0.64	11.00	0.00
Segment Length (mile)	0.49	0.60	4.88	0.01	0.12	0.15	2.253	0.01	0.12	0.15	2.442	0.01	0.12	0.14	3.91	0.01
Lane Width (feet)	12.04	0.72	24.00	9.33	11.25	1.19	22.00	8.00	10.41	1.30	30.00	8.00	10.13	1.20	25.00	8.00
Number of Lanes	2.14	0.35	3.00	2.00	2.00	0.00	2.00	2.00	2.00	0.00	2.00	2.00	2.00	0.00	2.00	2.00
Speed Limit (mph)	68.31	6.74	75.00	25.00	45.17	9.71	55.00	25.00	43.18	8.06	55.00	20.00	41.81	5.85	50.00	20.00
Median (Present=1, not present=0)	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Left Shoulder Width (feet)	7.18	3.43	40.00	1.00	5.65	2.33	26.00	0.00	3.93	2.08	20.00	0.00	2.96	1.54	16.00	0.00
Right Shoulder Width (feet)	7.16	3.25	40.00	4.00	5.78	2.40	26.00	0.00	3.98	2.14	24.00	0.00	2.97	1.54	18.00	0.00
Travel Lane (Paved=1, not paved==0)	1.00	0.00	1.00	1.00	0.99	0.03	1.00	0.00	0.99	0.03	1.00	0.00	0.99	0.04	1.00	0.00
Left Shoulder (paved=1, not paved=0)	1.00	0.00	1.00	1.00	0.87	0.34	1.00	0.00	0.42	0.49	1.00	0.00	0.07	0.26	1.00	0.00
Right Shoulder (paved=1, not paved=0)	1.00	0.00	1.00	1.00	0.87	0.34	1.00	0.00	0.43	0.49	1.00	0.00	0.07	0.25	1.00	0.00
Curve Present (present=1, not present=0)	0.30	0.46	1.00	0.00	0.47	0.50	1.00	0.00	0.51	0.50	1.00	0.00	0.53	0.50	1.00	0.00
AADT (5 years)	12,668	9,536	41,190	230	5,164	3,241	20,983	357	2,125	1,809	16,950	32	1,134	972	16,447	29
January MADT	10,134	7,477	33,467	178	4,630	2,941	20,039	341	1,840	1,607	16,187	26	998	889	13,363	24
February MADT	9,929	7,160	33,261	185	4,557	2,905	19,881	338	1,821	1,589	16,060	26	982	882	13,281	23
March MADT	10,622	7,747	35,526	188	4,832	3,082	20,983	357	1,930	1,686	16,950	28	1,043	933	14,186	25
April MADT	11,764	8,629	38,224	210	5,181	3,340	22,284	379	2,085	1,816	18,001	30	1,120	993	15,263	27
May MADT	13,117	9,803	43,250	234	5,705	3,690	23,921	407	2,326	2,011	19,323	34	1,242	1,081	17,269	30
June MADT	14,222	10,837	46,442	250	5,987	3,908	24,235	412	2,461	2,133	19,577	36	1,305	1,118	18,544	33
July MADT	15,852	12,501	51,076	270	6,356	4,192	25,232	421	2,654	2,301	20,001	40	1,399	1,181	20,394	36
August MADT	16,004	12,541	51,282	276	6,292	4,133	24,570	418	2,638	2,279	19,832	40	1,393	1,174	20,477	36
September MADT	13,942	10,511	46,298	242	5,924	3,848	24,047	409	2,430	2,105	19,425	36	1,290	1,109	18,486	33
October MADT	13,055	9,603	43,250	232	5,624	3,617	23,344	397	2,285	1,978	18,857	34	1,219	1,062	17,269	30
November MADT	12,318	8,960	40,366	229	5,291	3,358	22,662	386	2,137	1,846	18,306	31	1,152	1,018	16,118	28
December MADT	11,376	8,444	36,659	200	4,958	3,132	21,277	362	1,979	1,718	17,187	28	1,068	950	14,638	26

Table 2: Summary Statistics for Monthly Weather Factors

Variables	Winter Period						Non-Winter Period					
	Nov.	Dec.	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.
	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)	Mean (std.)
Max. Temperature (^{o} F)	44.15 (4.35)	33.69 (4.75)	29.23 (3.77)	30.88 (6.66)	37.74 (3.31)	51.07 (2.42)	64.72 (4.29)	71.87 (2.23)	79.41 (2.23)	78.73 (1.76)	72.40 (2.56)	64.72 (4.29)
Average Temperature (^{o} F)	35.58 (3.72)	25.16 (5.37)	19.76 (4.74)	20.34 (7.34)	28.04 (4.13)	41.09 (2.39)	53.82 (2.83)	61.25 (1.59)	68.61 (1.89)	67.86 (2.07)	61.33 (2.48)	53.82 (2.83)
Min. Temperature (^{o} F)	27.05 (3.49)	16.64 (6.20)	10.28 (5.91)	28.04 (8.21)	18.36 (5.35)	31.11 (2.96)	42.91 (2.25)	50.62 (1.94)	57.82 (2.22)	57.00 (2.97)	50.26 (3.04)	42.91 (2.25)
Days with Max Temp ≤ 32^o F	3.13 (3.32)	13.65 (5.57)	18.21 (5.40)	15.43 (6.54	8.15 (3.90)	0.74 (0.91)	NA[1]	NA	NA	NA	NA	NA
Max Precipitation (inch)	1.18 (0.41)	1.41 (0.58)	1.63 (0.62)	1.02 (0.44)	0.99 (0.41)	1.28 (0.51)	0.87 (0.49)	1.28 (0.50)	0.90 (0.44)	1.22 (0.49)	1.31 (1.12)	0.87 (0.49)
Total Monthly Precipitation (inch)	4.26 (2.04)	4.61 (1.24)	4.27 (1.34)	3.48 (1.28)	2.80 (1.00)	4.20 (1.38)	3.15 (1.83)	4.47 (1.55)	2.76 (1.11)	3.50 (1.33)	3.07 (1.69)	3.15 (1.83)
Days with Precipitation ≥ 0.1 inch	11.99 (3.31)	12.64 (3.14)	10.81 (2.70)	11.85 (2.13)	10.15 (2.37)	14.19 (3.40)	12.35 (4.20)	13.34 (2.64)	10.55 (2.36)	10.59 (2.28)	9.00 (2.21)	12.35 (4.20)
Days with Precipitation ≥ 1.0 inch	7.81 (3.20)	8.54 (2.42)	7.13 (2.35)	7.81 (1.96)	6.28 (2.19)	8.95 (2.61)	7.66 (3.39)	8.06 (2.25)	6.14 (1.84)	6.53 (1.97)	4.86 (1.54)	7.66 (3.39)
Max. Snowfall (inch)	2.18 (2.60)	6.83 (3.92)	8.67 (4.96)	9.37 (4.24)	8.46 (5.58)	3.06 (1.99)	NA	NA	NA	NA	NA	NA
Total Monthly Snowfall (inch)	5.24 (7.42)	16.98 (9.79)	21.81 (12.52)	26.65 (12.14)	15.97 (10.58)	4.61 (3.28)	NA	NA	NA	NA	NA	NA
Days with Snowfall ≥ 1.0 inch	1.66 (2.13)	4.36 (2.00)	5.33 (2.52)	6.31 (2.13)	3.29 (1.67)	1.50 (1.06)	NA	NA	NA	NA	NA	NA

[1] Not Applicable

The 16 weather stations used this study are scattered throughout the state, with one located in each of the 16 Maine counties. As noted in the literature review, most studies experienced limitations due to weather station locations or missing data. This was also a problem in this study. More weather stations could produce more accurate data for each roadway segment. With lack of data, assigning the weather-station data to each roadway segment becomes significantly important. We created Theisen Polygons to minimize the spatial differences in matching the monthly weather variables to the road segments. Thiessen polygons are polygons that are created around individual data points that ensures only one data point (in this case weather station) is located in each polygon. The area within the polygon is assumed to have the weather observations of the associated station. Using ArcGIS Pro, each segment that falls inside of each polygon was assigned the corresponding weather station (*ArcGIS Pro (Version 2.5)*, 2020). Figure 2 shows the polygons used in this study.

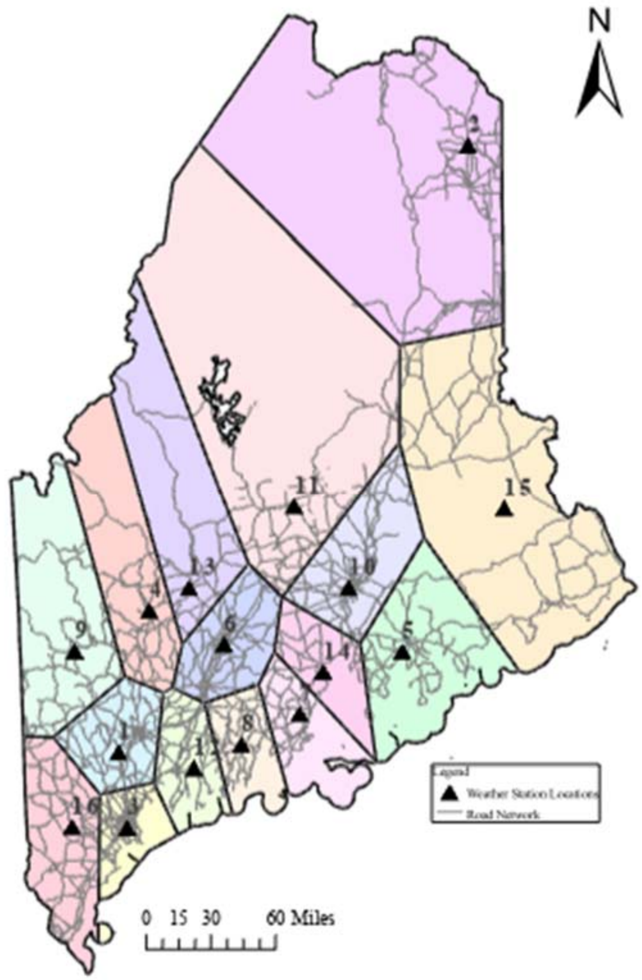

Figure 2: Thiessen polygons and weather station locations

3.3 Methodology

In our study, the geometric characteristics of the segments remain constant from month to month while weather factors and MADT change. This will result in a panel (longitudinal) dataset. Panel data are data that include repeated observations or measurements across time for the same cross-sectional units (Hilbe & Robinson, 2013; Shirazi et al., 2021). In crash data modeling, panel data models are used to account for repeated crash observations across time at each location or site (Lord & Mannering, 2010; Mannering et al., 2016; Shirazi et al., 2021). Generalized Estimating Equations (GEE) and random effect models are two common methods to analyze panel data (Lord & Mannering, 2010; Mannering & Bhat, 2014). In this study, a Negative Binomial model was estimated using the Generalized Estimating Equations (GEE) approach to estimate the coefficients of the panel data (Geedipally et al., 2020; Hutchings et al., 2003; Mohammadi et al., 2014; Qi et al., 2007; Wang & Abdel-Aty, 2006). For each facility type, a model was developed to analyze how monthly weather variables impact the frequency of lane departure crashes on rural Maine roads during the winter and non-winter periods from 2015 to 2019.

The following equation indicates the general form of Negative binomial model (Hilbe, 2011):

$$f(y_i; \mu_i, \alpha) = \frac{\Gamma\left((1/\alpha) + y_i\right)}{\Gamma(1/\alpha)\Gamma(y_i + 1)} \left(\frac{1}{1 + \alpha\mu_i}\right)^{\frac{1}{\alpha}} \left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i} \qquad (1)$$

where y_i is crash observation at site "i", μ_i is the mean response variable at site "i" and α is the over dispersion parameter. We assumed a log-linear function between the mean response variables and covariates (x_{ik}) as follows:

$$f\log(\mu_i) = \beta_0 + \sum_{k=1}^{m} \beta_k x_{ik} \qquad (2)$$

where βs show the regression coefficients. Once the NB models were developed, the marginal effects at the mean were calculated for each variable. The analysis used the estimated coefficients and the average value of all variables, to predict the effect that 1% change of the respective variable would have on the average total monthly crashes.

3.4 Modeling Results

A total of eight NB models were estimated. We considered segment length as an offset. The developed models covered two seasonal periods and four rural facility types (i.e., Interstates, minor arterials, major collectors, and minor collectors) Two seasonal groups of months were modeled separately to estimate the effects of the weather variables in different periods (i.e., winter vs. non-winter). The use of seasonal groups rather than one total model helped in limiting the amount of heterogeneity in the model and creating more accurate results for each seasonal period. The impact of winter weather variables would be depreciated if seasonal periods were not separated as snow and below freezing temperatures are not present during the non-winter period.

Since some geometric characteristic variables for some facility types are constant across the dataset, they were not included in the model. For example, the median was excluded from the model for all Interstate segments, as Interstates are always divided; the median was excluded for other facility types because they are almost always undivided. Travel lane pavement type was also excluded from the models, due to over 99% of all pavements being flexible pavement (e.g.: asphalt) and only less than 1% being gravel or rigid. The number of lanes was excluded for minor arterials, major collectors, and minor collectors given that almost all roads are two lanes (therefore we excluded roads that were not two lanes). For Interstate models, left and right shoulder type was the same for all segments (due to design requirement, they are all paved) and were excluded from the Interstate models.

Each model included traffic volume, geometric characteristics, and weather variables. The modeling results are presented in Tables 3-6. The tables also include Quasi-Likelihood under the Independence Model Information Criterion (QIC), Root Mean Square Error (RMSE), Mean Square Prediction Error (MSPE) and Mean Absolute Error (MAE) to analyze goodness of fit (GOF). The empty cells on the tables show the insignificant or non-applicable variables.

Table 3: Modeling Results for Interstates

Variables	Winter Period[1]		Non-Winter Period[1]	
	Estimate	S.D.	Estimate	S.D.
Intercept	-10.320	1.280	-12.435	2.037
Ln (MADT)	0.676	0.057	0.642	0.084
Number of Lanes	-0.184	0.113	-	-
Speed Limit	0.061	0.011	0.090	0.018
Left Shoulder Width	-0.181	0.047	-0.230	0.054
Right Shoulder Width	-0.184	0.047	-0.220	0.054
Curve Present	-0.212	0.079	-0.168[3]	0.099
Max. Precipitation	-[2]	-	0.089	0.035
Days with Precipitation ≥1.0 (in)	0.022	0.009	0.027	0.012
Days with Snowfall ≥ 1.0 (in)	0.119	0.008	-	-
Dispersion Parameter (α)	1.134	0.147	0.849	0.271
QIC	16,444		9,204	
RSME	2.723		3.471	
MSPE	7.415		12.049	
MAE	2.624		3.382	

[1]Winter period is from November-April and non-winter period is from May-October.
[2]The empty cells show that variable is not statistically significant to the respective model or not applicable.
[3]Variable statistically significant at 90% otherwise significant at 95%.

Table 4: Modeling Results for Minor Arterials

Variables	Winter Period[1]		Non-Winter Period[1]	
	Estimate	S.D.	Estimate	S.D.
Intercept	-9.721	0.434	-11.262	0.592
Ln (MADT)	0.526	0.045	0.606	0.055
Lane Width	-[2]	-	0.067	0.030
Speed Limit	0.036	0.003	0.028	0.004
Left Shoulder Width	-0.071	0.012	-	-
Right Shoulder Width	-	-	-0.070	0.015
Right Shoulder Type	-	-	0.213	0.112
Curve Present	0.135	0.053	0.234	0.065
Days with Precipitation ≥1.0 (in)	0.025	0.008	-	-
Days with Snowfall ≥ 1.0 (in)	0.061	0.008	-	-
Dispersion Parameter (α)	1.661	0.355	1.029	0.569
QIC	26,162		15,890	
RSME	3.684		4.237	
MSPE	13.569		17.954	
MAE	3.656		4.212	

[1]Winter period is from November-April and non-winter period is from May-October.

[2]The empty cells show that variable is not statistically significant to the respective model or not applicable)

Table 5: Modeling Results for Major Collectors

Variables	Winter Period[1]		Non-Winter Period[1]	
	Estimate	S.D.	Estimate	S.D.
Intercept	-12.214	0.230	-11.269	0.283
Ln (MADT)	0.854	0.024	0.723	0.029
Speed Limit	0.038	0.002	0.030	0.003
Left Shoulder Width	-0.033	0.016	-[2]	-
Right Shoulder Width	-0.046	0.016	-0.083	0.011
Left Shoulder Type	-0.247	0.081	-	-
Right Shoulder Type	-0.164	0.082	-0.119	0.045
Curve Present	0.181	0.033	0.261	0.042
Total Precipitation (in.)	-	-	0.016	0.010
Max. Precipitation (in.)	0.136	0.025	-	-
Days with Precipitation ≥1.0 (in)	0.015	0.005	-	-
Days with Snowfall ≥ 1.0 (in)	0.078	0.005	-	-
Dispersion Parameter (α)	1.953	0.246	1.030	0.469
QIC	66,275		37,548	
RSME	4.266		4.793	
MSPE	18.198		22.970	
MAE	4.206		4.754	

[1][1]Winter period is from November-April and non-winter period is from May-October.
[2]The empty cells show that the variable is not statistically significant to the respective model or not applicable.

Table 6: Modeling Results for Minor Collectors

Variables	Winter Period[1]		Non-Winter Period[1]	
	Estimate	S.D.	Estimate	S.D.
Intercept	-13.000	0.348	-10.200	0.392
Ln (MADT)	0.878	0.032	0.621	0.040
Lane Width	0.044	0.021	-	-
Speed Limit	0.036	0.005	0.020	0.006
Left Shoulder Width	-0.030	0.015	-	-
Right Shoulder Width	-[2]	-	-0.036[3]	0.020
Left Shoulder Type	-0.359	0.153	-0.367	0.139
Right Shoulder Type	-0.488	0.156	-	-
Curve Present	0.153	0.047	0.364	0.063
Max. Precipitation	0.192	0.034	-	-
Days with Precipitation ≥1.0 (in)	0.040	0.008	-	-
Days with Snowfall ≥ 1.0	0.076	0.007	-	-
Dispersion Parameter (α)	1.791	0.422	2.595	1.184
QIC	34,252		17,912	
RSME	4.540		5.088	
MSPE	20.613		25.885	
MAE	4.473		5.059	

[1]Winter period is from November-April and non-winter period is from May-October.
[2]The empty cells show that the variable is not statistically significant to the respective model or not applicable.
[3]Variable statistically significant at 90% otherwise significant at 95%.

Traffic volume was modeled as a natural log of the monthly average daily traffic (MADT). As expected, MADT is positively correlated with the monthly crashes; as MADT increases, the number of crashes increases as well. This is the case for all four facilities and for both winter and non-winter periods. When comparing the two seasonal periods, MADT impact Interstate crashes similarly for both periods; for major and minor collectors, MADT impacts the number of crashes more during winter periods, likely because these facilities are not high priority for winter maintenance comparing to Interstates.

For all facilities, during both winter and non-winter periods, posted speed limit is positively correlated with monthly crashes; as the posted speed limit increases, the number of monthly lane departure crashes increases. The width of the left and right shoulders (whenever significant) showed a negative correlation with monthly crashes for all facilities for both seasonal periods. In Maine snow is plowed throughout the winter and left on the shoulder, accumulating with each storm (unless located in a hazardous location such as on bridges). This may explain why the impact of shoulder width on crashes is larger during the non-winter period compared to the winter periods. The results show that the paved shoulder can reduce number of crashes during winter session. The type of shoulder pavement is not significant in the non-winter period. For Interstates, the modeling results show counterintuitive results for the curve present variable. Note that this variable only considers the presence of the curve on the segment, and not the in-depth characteristics or dimensions of the curve. Therefore, the counterintuitive sign can be due to the high design standards for majority of curves on Interstates (most curves are smooth). In addition, drivers are more cautious when negotiating a curve on Interstates. For all other facilities, the presence of curves is positively correlated with monthly crashes.

All 11 weather variables described in Table 2 were considered in modeling. Many of these variables however are correlated with each other (e.g., snow and freezing temperatures). We chose the best variables for modeling after careful investigations of their correlations, and accounting for test of significance and GOFs. For winter period models, the temperature variable was correlated with other weather variables; yet it did not increase the goodness of fit, significance, or precision of coefficients as much as other weather variables. Hence, for winter period, we did not include this variable in the model. For non-winter periods, temperature factors were considered though found to be insignificant in the models.

Snow is one of the most important weather variables that impact roadway safety in Maine. Hence, finding the best variable to account for snowfall was important. After exploring many alternatives, we used the following variables for consideration: maximum monthly snowfall, total monthly snowfall, and the number of days in a month that received at least 1 inch of snow. We found that the number of days in a month that received at least 1 inch of snowfall provides the best statistical fit. The modeling results show that this variable has a positive correlation with winter month crashes for all four roadway types. We also considered multiple precipitation variables in modeling. For winter period, we found that days with precipitation greater 1 inch variable has a positive correlation with lane departure crashes for all facility types. This variable is also significant for Interstates during the non-winter period. For major and minor collectors, the maximum precipitation variable is also significant and has a positive correlation with number of lane departure crashes during the winter period. This variable is significant for Interstates during non-winter period as well. The total monthly precipitation variable was found significant for major collectors during the non-winter period.

3.5 Marginal Effects

Once the models were developed, the estimated coefficients can be used to analyze the marginal effect of each variable for each model. The results of the marginal effect analysis are presented in Table 7. Marginal effects show by how much the mean number of monthly crashes would be expected to change if the variable is changed by 1% compared to the mean value (Hilbe, 2011). Marginal effects are calculated based on the estimates from the models. Therefore, only variables that are significant in models (as shown in Tables 3-6) are included in the marginal effect analysis.

Table 7: Results of Marginal Effects Analysis

Variables	Winter Period				Non-Winter Period			
	Interstate	Minor Arterial	Major Collector	Minor Collector	Interstate	Minor Arterial	Major Collector	Minor Collector
MADT	2.89%	0.44%	0.38%	0.30%	1.25%	0.25%	0.19%	0.12%
Lane Width	Not Sig[1]	Not Sig	Not Sig	0.02%	Not Sig	0.03%	Not Sig	Not Sig
Number of Lanes	-0.79%	NA	NA	NA	Not Sig	NA	NA	NA
Speed Limit	0.26%	0.03%	0.02%	0.01%	0.18%	0.01%	0.01%	0.01%
Left Shoulder Width	-0.77%	-0.06%	-0.02%	-0.01%	-0.45%	Not Sig	Not Sig	Not Sig
Right Shoulder Width	-0.79%	Not Sig	-0.02%	Not Sig	-0.43%	-0.03%	-0.02%	-0.01%
Left Shoulder Type	NA[2]	Not Sig	-0.11%	-0.12%	NA	Not Sig	Not Sig	-0.07%
Right Shoulder Type	NA	Not Sig	-0.07%	-0.17%	NA	0.09%	-0.03%	Not Sig
Curve Present	-0.91%	0.11%	0.08%	0.05%	-0.33%	0.10%	0.07%	0.07%
Max. Precipitation	Not Sig	Not Sig	0.06%	0.07%	0.17%	Not Sig	Not Sig	Not Sig
Total Monthly Precipitation	Not Sig	Not Sig	Not Sig	Not Sig	Not Sig	Not Sig	0.004%	Not Sig
Days with Precipitation >= 1.0 (in)	0.09%	0.02%	0.01%	0.01%	0.05%	Not Sig	Not Sig	Not Sig
Days with Snowfall >= 1.0 (in)	0.51%	0.05%	0.04%	0.03%	NA	NA	NA	NA

[1] The variable is not statistically significant to the respective model.
[2] Not Applicable.

The marginal effects of MADT variables are larger during the winter periods comparing to non-winter period. For Interstates, 1% increase in the natural log of MADT from its average value would cause an expected increase of 2.89% in average number of monthly crashes during the winter period whereas this number is 1.25% during the non-winter period. For minor arterials, major collectors, and minor collectors, 1% increase in the mean of natural log of MADT respectively would result in an expected increase of 0.44% 0.38% and 0.30% in average monthly crashes during the winter period, and increase of 0.25%, 0.19%, and 0.12% during the non-winter period.

Regarding the geometric characteristics, a few notable results should be discussed. For winter period models, lane width is significant only for minor collectors. The marginal effect analysis shows that 1% increase in mean of lane width would result in 0.02% increase in average monthly crashes. During the non-winter period, lane width is significant only for minor arterials. The marginal effect shows that 1% increase in lane width would result in 0.03% increase in average monthly crashes of minor arterials during non-winter period. The positive correlation between lane width and monthly crashes may be counterintuitive, however the increase could be due to increase of traffic speed on wider roadways on these facilities. For Interstates, the marginal effect analysis showed that 1% increase in the number of lanes from the mean would result in 0.79% decrease in average monthly winter period crashes. The posted speed limit is a significant variable for all facilities. However, as expected, the marginal effect analysis shows that the impact of posted speed limit is higher during the winter period compared to the non-winter period. For Interstates, 1% increase in posted speed limit would result in 0.26% and 0.18% increase in average monthly crashes during the winter and non-winter periods, respectively. The width of the left and right shoulders is negatively correlated with crashes. For Interstates, as the mean of the right or left shoulder width increases by 1%, the average monthly crashes are expected to decrease by around 0.78% during the winter period and around 0.44% during the non-winter period.

Weather variables affect crashes during the winter period more than the non-winter period. As discussed, only precipitation and snowfall variables were used in the winter-period models, due to the correlations with temperature. For all facilities, the number of days in a month with more than 1 inch of precipitation, and the number of days with more than 1 inch of snowfall were significant. For both variables, the highest impact is observed on Interstates. The analysis showed that as the number of days with more than 1 inch of precipitation increases by 1% from the mean, the expected monthly crashes increase by 0.09% on Interstates, 0.02% on minor arterials, 0.01% on major collectors and 0.01% on minor collectors. The analysis also showed that as the number of days with more than 1 inch of snowfall increases by 1% from the mean, the expected monthly crashes increase by 0.51% on Interstates, 0.05% on minor arterials, 0.04% on major and 0.03% on minor collectors. In addition, as the maximum precipitation increases from the mean by 1%, the expected monthly crashes increase by approximately 0.06% and 0.07% during the winter period for major and minor collectors respectively.

For the non-winter period, the precipitation variables are significant only for Interstates and major collectors. For non-winter period, on Interstates, as the maximum daily precipitation increases from the mean by 1%, the average of monthly crashes increases by 0.17%. In addition, on Interstates, as the number of days in a month with more than 1 inch of precipitation increases by 1%, the average monthly crashes increased by 0.05% for Interstates. For non-winter period, on major collectors as the total monthly precipitation increases from the mean by 1%, the average of monthly crashes increases by 0.004%.

3.6 Summary and Conclusions

Lane departure crashes are the leading cause of roadway fatalities in Maine. The majority of these crashes happen during the winter period (November through April). This study analyzed the impact of weather variables on lane departure crashes on rural Maine roads for four facility types: Interstates, minor arterials, major collectors, and minor collectors. To appropriately estimate the impact of weather variables, we developed two separate models for two seasonal periods. We used monthly aggregated segment crashes along with monthly AADT, geometric characteristics, and weather factors in the model. The modeling results and marginal effects analysis indicate a significant difference between the coefficients of the models developed for winter and non-winter periods. We found that, during the winter period, the number of days that experienced at least 1 inch of snow or precipitation significantly impact the crash frequency. The marginal effect analysis shows that as the number of days with more than 1 inch of precipitation increases by 1% from the mean, the expected monthly crashes increase by 0.09% on Interstates, 0.02% on minor arterials, 0.01% on major collectors and 0.01% on minor collectors. The marginal effect analysis also shows that as the number of days with more than 1 inch of snowfall increases by 1% from the mean, mean of crashes increase by 0.51% on Interstates, 0.05% on minor arterials, 0.04% on major collectors and 0.03% on minor collectors. During the non-winter period, Interstate crashes are positively correlated with two variable, maximum precipitation and days with precipitation greater than 1 inch. During the non-winter period, major collector crashes are positively correlated with total monthly precipitation.

The primary goal of this analysis was to determine the impact of various weather factors on lane departure crashes. For all four facilities, the number of days in a month with more than 1-inch of precipitation or snowfall showed to positively associated with the frequency of crashes. Various countermeasures should be considered to help decrease crashes on these days, including use of signage, news reporting, and education to ensure awareness of the danger to drivers on these days. In rainfalls, the risk of hydroplaning, and in snowfalls, the risk of slippery conditions and driver error increases which could result in higher crash frequencies.

The state may consider reducing the adverse impact of these factors by imposing higher tire condition standards. Precipitation also alters visibility of drivers. Therefore, it is recommended to also ensure decreased driving speeds on high precipitation days with proper messaging. During the non-winter period, both Interstates and major collectors showed increased crash frequency on days with maximum rainfall. Similar countermeasures as those stated earlier such as increased signage or enforcement to decrease speed should be considered. Finally, more safety education and awareness are recommended during the storm events.

In terms of geometric features that positively effect crashes, curve presence proved to increase crash frequency on minor arterials, major collectors, and minor collectors. Countermeasures that should be considered for these locations include increasing the message signs to make drivers aware of the upcoming curves, speed reduction at these locations, as well as development in the infrastructure or roadway facility. Lane departure countermeasures to reduce lane departure crashes include the installation of rumble strips as well as the barriers and guardrails. This analysis only considered the presence of a curve as a variable in the models; however, more research is recommended to include more information about the curves such as radius, friction, or superelevation in the model to determine hotspots. Finally, higher speed limits were associated with higher crash frequencies. It is recommended to reevaluate the speed limits in high crash locations to potentially reduce lane departure crashes at these locations.

The GEE approach was used in this study to account for panel data. According to Hilbe (2011), The GEE approach increases the flexibility in the model to enhance its ability to consider panel clusters. Our focus in this analysis was mainly from the practical perspective to better understand the impact of weather factors using the marginal effect analysis, therefore the GEE method was considered to estimate the model coefficients and account for panel data. Other methods including Random-Effect NB (Lord and Mannering, 2010; Mannering and Bhat, 2014), Random Parameters NB (RPNB) (Mannering et al., 2016), semiparametric NB (Shirazi et al., 2016) and NB-Lindley (Geedipally et al, 2012; Shirazi, et al., 2017; Shaon et al., 2018; Rusli et al., 2018; Khodadadi et al., 2022a; Khodadadi et al., 2022b) are recommended in future analysis. In particular, it would be interesting to model and compare the impact of weather factors in different regions in Maine using Grouped RPNB model.

It is also worth noting that our analysis considered two time periods, the winter period, from November to April, and the non-winter period from May to October. By separating these two periods, we indirectly accounted for the greater darkness during the winter period. It is, however, recommended to study the impact of time of day (or darkness) in frequency of lane departure crashes in the future research.

Chapter 4: Crash Severity Analysis

The current chapter documents the crash severity analysis that was completed to analyze the impact of roadway and weather factors on the severity of lane departure crashes in Maine. First, in Section 4.1 a brief Introduction is provided. In Section 4.2 data used in this study is described in detail. Next, in Section 4.3 the methodology used in the analysis is described. Section 3.4 provides the multinomial logit modeling and odds ratio results and discussion. Section 4.5 provides a summary and conclusion of the severity analysis.

4.1 Introduction

Compared to other New England states, Maine has the highest roadway fatality rate (Bouchard et al., 2020). Lane departure (including run-off-road and head-on crashes) account for *more than 70% of* the total roadway fatalities in Maine. Maine has aging infrastructures, the oldest population in the U.S., and experiences significant number of extreme weather events during a long winter season (often spanning from November to April). Maine is a unique case study to better understand the impact of aging infrastructure, older population, and extreme weather conditions on severity of lane departure crashes.

The state manages 37% of Maine's total 23,000 roadway miles (Bouchard et al., 2020). In terms of infrastructures, the ASCE 2020 Annual Infrastructure Report Card gave Maine a C- grade. The report also gave roadways in Maine a D grade. The Annual Report suggests that the Maine highway system managed by the state has an annual gap in necessary funds of $135 million to make necessary roadway upgrades on aging infrastructure, proper maintenance and renovations or improving safety.

Maine also houses the oldest population in the U.S. (Himes & Kilduff, 2019). The population has been showing an aging trend since the 1990 census, where the median age was 33.9 years-old, and the U.S. median was 32.9 years-old (Meyer, 2001). The current median age in Maine is 45.0, and the median age in the U.S. is 38.2. It is also worth noting that with the aging population in Maine, the number of licensed drivers with an age of 65 or older also continued to grow. In 2010, the older population accounted for 17.8% of the total licensed drivers; however, this number has grown to 24.8% in 2019. Younger drivers (with an age of 16-29) accounted for 20.2% of all Maine licensed drivers in 2010. In 2019, this percentage had reduced to 16.9%.

The state also experiences lengthy winter seasons and around six months of winter precipitation, freezing temperatures, and several extreme storm events. In fact, the state is *the third coldest state in the U.S.* (*Coldest States 2021*, 2021). The total precipitation and snowfall accumulation totals vary by location in the state. From 2017 to 2019 (duration used in this study period), coastal Maine received an average of 51.6 inches of precipitation and 101.9 inches of snowfall. During this same period, northern Maine received an average of 41.9 inches of precipitation and 138 inches of snowfall. Despite its relatively small size, due to the vast differences in terrain from the coastline to the western mountain region, the weather conditions and temperatures vary substantially throughout the state.

In Maine, winter storm maintenance is classified by six priority levels (*Roads Report*, 2016) based on the facility type and vehicle miles traveled (VMT). All roadways, regardless of priority level, are plowed and different anti-icing strategies are conducted periodically throughout storm events. However, Interstates and the key principal arterials are considered as Priority 1 (highest priority) roadways. For this priority, the roadway is cleared within three daylight hours after a storm event. Other arterial facilities (e.g., the majority of minor arterials) are Priority 2. Priority 2 roadways take up to eight daylight hours to be cleared. Major collectors are Priority 3 or 4 (based on the volume they carry). Priorities 3 and 4 take up to 24 and 30 hours respectively to be cleared. Minor collectors are Priority 5. The clearance time for this priority level is up to 30 hours. The local roads are Priority 6. For roads in this priority level, municipalities are mainly responsible for management and maintenance.

Limited research has been done to explore contributing factors on lane departure crashes considering the combination of driver, roadway, and daily weather (rather than weather cited in crash reports). It is hypothesized that the combination of discussed factors contributes to the severity of lane departure crashes, and the higher proportion of fatalities in Maine compared to other New England states. This study uses the Multinomial Logistic Regression model to understand the impact of various roadway, driver, and weather factors on the severity of single-vehicle lane departure crashes that occurred in the three-year period from 2017 to 2019. Given the difference in roadway conditions as well as maintenance strategies, the analysis is divided based on four different facility types. These facilities are (1) Interstate, (2) minor arterials, (3) major collectors, and (4) minor collectors. The results of this study provide a better understanding of contributing factors (e.g.: roadway, driver, and weather) on severity of lane departure crashes on different roadway facilities leading to improved management, maintenance, and safety.

4.2 Description of Data

We collected crash data and contributing factors recorded in Maine and created a uniform dataset for each facility type. As discussed, four rural roadway facility types were considered for the analysis: Interstates, minor arterials, major collectors, and minor collectors. A total of 11,409 single-vehicle lane departure crashes were reported from 2017 to 2019 in Maine. The total crashes for Interstates, minor arterials, major collectors, and minor collectors are 2,190, 1,994, 4,940, and 2,285 respectively. It is important that these facilities are analyzed separately due to the design, safety conditions and differences in maintenance strategies (as described above). Four injury severity categories were considered for analysis. Fatal-incapacitating injury crashes (KA), non-incapacitating injury (B), possible injury (C) and property damage only (PDO).

The contributing factors were classified in four major subcategories. First, the driver factors. This subcategory includes variables such as driver age and sex as well as behavioral factors such as speeding, operating under the influence (OUI) and seatbelt usage. Over 15 driver variables were considered, and eventually seven variables were included in the analysis. The second subcategory included crash variables, such as time of day, crash type, day of the week or vehicle type. In total 20 variables in this category were considered and eventually four variables were included in the analysis. The third subcategory included roadway characteristics, such as curve presence, posted speed limit, lane width and more. Over 12 variables were considered, and eventually three variables were included in the analysis. The fourth subcategory included weather variables, a total of seven weather variables were considered and eventually four variables were selected in the analysis.

The weather data was extracted from the National Oceanic and Atmospheric Administration (NOAA) for the day of crash from 16 weather stations (*State of the Climate:*

National Climate Report for April 2019, 2019). As noted in previous studies the number of weather stations are limited (S. Zhao et al., 2019). To allocate the weather variables to each crash record, we created Thiessen Polygons around the 16 weather stations using ArcGIS Pro (*ArcGIS Pro (Version 2.5)*, 2020) . Thiessen Polygons are polygons created around a point (in this case a weather station) so that each point within the polygon is closest to the respective weather station. Therefore, we assumed that the weather station inside each polygon represents the weather in that area. The map of the polygons is presented in Figure 2 in Chapter 3.

As noted above, many variables or combination of variables were considered, but not included in the final analysis (due to exploring correlation, significant test, and statistical fit). These variables include but are not limited to shoulder width, shoulder pavement type, lighting condition, the presence of rumble strips, freezing temperatures, wind and more. The categorical variables were also created based on extensive preliminary analyses. For example, for the driver age variable, we found that designating "young" to drivers under the age of 30, "middle" to drivers from 30 and 64, and older to drivers of 65-years or above is the best representation of age category for this study. As another example, the variable "time of day" was divided into peak and off-peak time after extensive investigations. The peak time is between 6:00 AM-10:00 AM and 3:00PM-7:00PM Monday-Friday; the off-peak is otherwise. The speed limit variable differentiates between roadways with posted speed limits above 70mph on Interstates, and above 45mph on all other facilities. The time between dawn and dusk was considered as the nighttime variable. The seasonal period variable represents the winter period from November to April and the non-winter period from May to October. In this study, the surface conditions are considered as not dry if an officer noted the surface as wet, snow, slush, etc. and dry otherwise. This variable is not the same as weather variables as the surface condition may or may not necessarily be dry after storms. The variable snow day was used to describe if the area a crash occurred experienced at least one inch of snow accumulation on the day of the crash. The variable precipitation describes if there was any precipitation accumulation on the day the crash occurred. Tables 8-11 show the summary of data used for the analysis for Interstates, minor arterials, major collectors, and minor collectors respectively.

Table 8: Count and Frequency of Variables for the Interstate Facility

Variables		PDO		C		B		KA	
		Count	Ratio	Count	Ratio	Count	Ratio	Count	Ratio
Driver Age	Young	679	31.0%	138	6.3%	103	4.7%	23	1.1%
	Middle	735	33.6%	153	7.0%	148	6.8%	41	1.9%
	Older	100	4.6%	28	1.3%	27	1.2%	15	0.7%
Male Driver Indicator	Male	1,024	46.8%	183	8.4%	176	8.0%	58	2.6%
	Not Male	490	22.4%	136	6.2%	102	4.7%	21	1.0%
Driver License	Suspended	27	1.2%	10	0.5%	12	0.5%	7	0.3%
	Active	1,487	67.9%	309	14.1%	266	12.1%	72	3.3%
Sobriety	OUI	43	2.0`%	8	0.4%	17	0.8%	15	0.7%
	Not OUI	1,471	67.2%	311	14.2%	261	11.9%	64	2.9%
Distractions	Distracted	74	3.4%	24	1.1%	17	0.8%	8	0.4%
	Not Distracted	1,440	65.8%	295	13.5%	261	11.9%	71	3.2%
Driver Speed	Speeding	13	0.6%	3	0.1%	4	0.2%	3	0.1%
	Not Speeding	1,501	68.5%	316	14.4%	274	12.5%	76	3.5%
Seatbelt	Not Wearing	18	0.8%	21	1.0%	30	1.4%	22	1.0%
	Wearing	1,496	68.3%	298	13.6%	248	11.3%	57	2.6%
Crash Type	Rollover	23	1.1%	8	0.4%	15	0.7%	3	0.1%
	Not Rollover	1,491	68.1%	331	15.1%	263	12.0%	76	3.5%
Time of Day	Peak	648	29.6%	163	7.4%	109	5.0%	34	1.6%
	Not Peak	866	39.5%	156	7.1%	169	7.7%	45	2.1%
Night-time	Night	696	31.8%	127	5.80%	117	5.3%	33	1.5%
	Not Night	818	37.4%	192	8.77%	161	7.4%	46	2.1%
Speed Limit	> 70mph	1,509	68.9%	319	14.6%	278	12.7%	78	3.6%
	< 70mph	5	0.2%	0	0.0%	0	0.0%	1	0.0%
Curve	Present	323	14.7%	72	3.3%	63	2.9%	12	0.5%
	Not Present	1,191	54.4%	247	11.3%	215	9.8%	67	3.1%
Grade	Not Level	346	15.8%	97	4.4%	69	3.2%	18	0.8%
	Level	1,168	53.3%	222	10.1%	209	9.5%	61	2.8%
Season	Winter	1,103	50.4%	211	9.6%	166	7.6%	29	1.3%
	Not Winter	411	18.8%	108	4.9%	112	5.1%	50	2.3%
Surface Condition	Not Dry	1,084	49.5%	212	9.7%	163	7.4%	23	1.1%
	Dry	430	19.6%	107	4.9%	115	5.3%	56	2.6%
Snow	> 1 inch	182	8.3%	40	1.8%	20	0.9%	1	0.0%
	< 1 inch	1,332	60.8%	279	12.7%	258	11.8%	78	3.6%
Temperature	> 60ºF	1,166	53.2%	229	10.5%	188	8.6%	43	2.0%
	≤ 60ºF	348	15.9%	90	4.1%	90	4.1%	36	1.6%
Precipitation	Present	488	22.3%	105	4.8%	82	3.7%	18	0.8%
	Not Present	1,026	46.8%	214	9.8%	196	8.9%	61	2.8%

Table 9: Count and Frequency of Variables for the Minor Arterial Facility

Variables		PDO		C		B		KA	
		Count	Ratio	Count	Ratio	Count	Ratio	Count	Ratio
Driver Age	Young	524	26.3%	164	8.2%	77	3.9%	24	1.2%
	Middle	652	32.7%	209	10.5%	88	4.4%	43	2.2%
	Older	124	6.2%	42	2.1%	38	1.9%	9	0.5%
Male Driver Indicator	Male	851	42.7%	250	12.5%	124	6.2%	53	2.7%
	Not Male	449	22.5%	165	8.3%	79	4.0%	23	1.2%
Driver License	Suspended	38	1.9%	20	1.0%	15	0.8%	8	0.4%
	Active	1,262	63.3%	395	19.8%	188	9.4%	68	3.4%
Sobriety	OUI	98	4.9%	55	2.8%	24	1.2%	20	1.0%
	Not OUI	1,202	60.3%	360	18.1%	179	9.0%	56	2.8%
Distractions	Distracted	130	6.5%	45	2.3%	24	1.2%	7	0.4%
	Not Distracted	1,170	58.7%	370	18.6%	179	9.0%	69	3.5%
Driver Speed	Speeding	20	1.0%	6	0.3%	1	0.1%	6	0.3%
	Not Speeding	1,280	64.2%	409	20.5%	202	10.1%	70	3.5%
Seatbelt	Not Wearing	49	2.5%	48	2.4%	35	1.8%	42	2.1%
	Wearing	1,251	62.7%	367	18.4%	168	8.4%	34	1.7%
Crash Type	Rollover	32	1.6%	19	1.0%	10	0.5%	5	0.3%
	Not Rollover	1,268	63.6%	396	19.9%	193	9.7%	71	3.6%
Time of Day	Peak	580	29.1%	162	8.1%	90	4.5%	36	1.8%
	Not Peak	720	36.1%	253	12.7%	113	5.7%	40	2.0%
Night-time	Night	581	29.14%	179	8.98%	84	4.21%	35	1.76%
	Not Night	719	36.06%	236	11.84%	119	5.97%	41	2.06%
Speed Limit	> 45mph	1,099	55.1%	365	18.3%	165	8.3%	64	3.2%
	< 45mph	201	10.1%	50	2.5%	38	1.9%	12	0.6%
Curve	Present	608	30.5%	192	9.6%	110	5.5%	39	2.0%
	Not Present	693	34.8%	223	11.2%	93	4.7%	37	1.9%
Grade	Not Level	469	23.5%	141	7.1%	76	3.8%	19	1.0%
	Level	831	41.7%	274	13.7%	127	6.4%	57	2.9%
Season	Winter	953	47.8%	232	11.6%	94	4.7%	26	1.3%
	Not Winter	347	17.4%	183	9.2%	109	5.5%	50	2.5%
Surface Condition	Not Dry	773	38.8%	184	9.2%	72	3.6%	15	0.8%
	Dry	527	26.4%	231	11.6%	131	6.6%	61	3.1%
Snow	> 1 inch	131	6.6%	14	0.7%	6	0.3%	2	0.1%
	< 1 inch	1,169	58.6%	401	20.1%	197	9.9%	74	3.7%
Temperature	> 60ºF	1,018	51.1%	264	13.2%	116	5.8%	30	1.5%
	≤ 60ºF	282	14.1%	151	7.6%	87	4.4%	46	2.3%
Precipitation	Present	348	17.5%	88	4.4%	41	2.1%	13	0.7%
	Not Present	952	47.7%	327	16.4%	162	8.1%	63	3.2%

Table 10: Count and Frequency of Variables for the Major Collector Facility

Variables		PDO		C		B		KA	
		Count	Ratio	Count	Ratio	Count	Ratio	Count	Ratio
Driver Age	Young	1,469	29.7%	436	8.8%	237	4.8%	78	1.6%
	Middle	1,448	29.3%	461	9.3%	247	5.0%	108	2.2%
	Older	241	4.9%	131	2.7%	51	1.0%	33	0.7%
Male Driver Indicator	Male	1,994	40.4%	572	11.6%	361	7.3%	151	3.1%
	Not Male	1,164	23.6%	456	9.2%	174	3.5%	68	1.4%
Driver License	Suspended	108	2.2%	46	0.9%	36	0.7%	20	0.4%
	Active	3,050	61.7%	982	19.9%	499	10.1%	199	4.0%
Sobriety	OUI	210	4.3%	117	2.4%	95	1.9%	62	1.3%
	Not OUI	2,948	59.7%	911	18.4%	440	8.9%	157	3.2%
Distractions	Distracted	244	4.9%	116	2.3%	58	1.2%	16	0.3%
	Not Distracted	2,914	59.0%	912	18.5%	477	9.7%	203	4.1%
Driver Speed	Speeding	56	1.1%	31	0.6%	20	0.4%	32	0.6%
	Not Speeding	3,102	62.8%	997	20.2%	515	10.4%	187	3.8%
Seatbelt	Not Wearing	132	2.7%	117	2.4%	107	2.2%	123	2.5%
	Wearing	3,026	61.3%	911	18.4%	428	8.7%	96	1.9%
Crash Type	Rollover	78	1.6%	55	1.1%	32	0.6%	14	0.3%
	Not Rollover	3,080	62.3%	973	19.7%	503	10.2%	205	4.1%
Time of Day	Peak	1,454	29.4%	427	8.6%	197	4.0%	79	1.6%
	Not Peak	1,704	34.5%	601	12.2%	338	6.8%	140	2.8%
Night-time	Night	1378	27.89%	447	9.05%	248	5.02%	84	1.70%
	Not Night	1780	36.03%	581	11.76%	287	5.81%	135	2.73%
Speed Limit	> 45mph	2,486	50.3%	834	16.9%	429	8.7%	189	3.8%
	< 45mph	672	13.6%	194	3.9%	106	2.1%	30	0.6%
Curve	Present	1,635	33.1%	520	10.5%	306	6.2%	132	2.7%
	Not Present	1,523	30.8%	508	10.3%	229	4.6%	87	1.8%
Grade	Not Level	1,315	26.6%	418	8.5%	226	4.6%	86	1.7%
	Level	1,843	37.3%	610	12.3%	309	6.3%	133	2.7%
Season	Winter	2,339	47.3%	594	12.0%	293	5.9%	77	1.6%
	Not Winter	819	16.6%	424	8.6%	242	4.9%	142	2.9%
Surface Condition	Not Dry	2,067	41.8%	532	10.8%	221	4.5%	64	1.3%
	Dry	1,091	22.1%	496	10.0%	314	6.4%	155	3.1%
Snow	> 1 inch	332	6.7%	63	1.3%	16	0.3%	2	0.0%
	< 1 inch	2,826	57.2%	965	19.5%	519	10.5%	217	4.4%
Temperature	> 60ºF	2,485	50.3%	675	13.7%	338	6.8%	90	1.8%
	≤ 60ºF	673	13.6%	353	7.1%	197	4.0%	129	2.6%
Precipitation	Present	2,339	47.3%	594	12.0%	293	5.9%	77	1.6%
	Not Present	819	16.6%	424	8.6%	242	4.9%	142	2.9%

Table 11: Count and Frequency of Variables for the Minor Collector Facility

Variables		PDO		C		B		KA	
		Count	Ratio	Count	Ratio	Count	Ratio	Count	Ratio
Driver Age	Young	762	33.3%	210	9.2%	109	4.8%	35	1.5%
	Middle	662	29.0%	188	8.2%	102	4.5%	42	1.8%
	Older	111	4.9%	32	1.4%	21	0.9%	11	0.5%
Male Driver Indicator	Male	949	41.5%	208	9.1%	141	6.2%	57	2.5%
	Not Male	586	25.6%	222	9.7%	91	4.0%	31	1.4%
Driver License	Suspended	48	2.1%	22	1.0%	11	0.5%	8	0.4%
	Active	1,487	65.1%	408	17.9%	221	9.7%	80	3.5%
Sobriety	OUI	84	3.7%	41	1.8%	45	2.0%	21	0.9%
	Not OUI	1,451	63.5%	389	17.0%	187	8.2%	67	2.9%
Distractions	Distracted	121	5.3%	40	1.8%	29	1.3%	7	0.3%
	Not Distracted	1,414	61.9%	390	17.1%	203	8.9%	81	3.5%
Driver Speed	Speeding	41	1.8%	25	1.1%	21	0.9%	11	0.5%
	Not Speeding	1,494	65.4%	405	17.7%	211	9.2%	77	3.4%
Seatbelt	Not Wearing	52	2.3%	59	2.6%	43	1.9%	37	1.6%
	Wearing	1,483	64.9%	371	16.2%	189	8.3%	51	2.2%
Crash Type	Rollover	45	2.0%	24	1.1%	12	0.5%	6	0.3%
	Not Rollover	1,490	65.2%	406	17.8%	220	9.6%	82	3.6%
Time of Day	Peak	705	30.9%	198	8.7%	103	4.5%	34	1.5%
	Not Peak	830	36.3%	232	10.2%	129	5.6%	54	2.4%
Nighttime	Night	631	27.61%	183	8.01%	88	3.85%	35	1.53%
	Not Night	904	39.56%	247	10.81%	144	6.30%	53	2.32%
Speed Limit	> 45mph	1,069	46.8%	313	13.7%	174	7.6%	72	3.2%
	< 45mph	466	20.4%	117	5.1%	58	2.5%	16	0.7%
Curve	Present	870	38.1%	248	10.9%	128	5.6%	64	2.8%
	Not Present	665	29.1%	182	8.0%	104	4.6%	24	1.1%
Grade	Not Level	673	29.5%	209	9.1%	98	4.3%	37	1.6%
	Level	862	37.7%	221	9.7%	134	5.9%	51	2.2%
Season	Winter	1,161	50.8%	291	12.7%	127	5.6%	35	1.5%
	Not Winter	374	16.4%	139	6.1%	105	4.6%	53	2.3%
Surface Condition	Not Dry	1,049	45.9%	239	10.5%	108	4.7%	27	1.2%
	Dry	486	21.3%	191	8.4%	124	5.4%	61	2.7%
Snow	> 1 inch	174	7.6%	23	1.0%	21	0.9%	1	0.0%
	< 1 inch	1,361	59.6%	407	17.8%	211	9.2%	87	3.8%
Temperature	> 60ºF	1,244	54.4%	315	13.8%	143	6.3%	41	1.8%
	≤ 60ºF	291	12.7%	115	5.0%	89	3.9%	47	2.1%
Precipitation	Present	407	17.8%	81	3.5%	52	2.3%	12	0.5%
	Not Present	1,128	49.4%	349	15.3%	180	7.9%	76	3.3%

4.3 Methodology

Crash severity is identified as one of the following five categories, property damage only (PDO), possible injury (C-Injury), non-incapacitating injury (B-Injury), incapacitating injury (A-Injury) and fatal (K) crash. For the analysis, we combined K and A crash outcomes. To model crash severity, we used a Multinomial Logistics (MNL) model (Geedipally et al., 2019; Hilbe, 2011; Shankar & Mannering, 1996; Shirazi et al., 2017; Washington et al., 2003; X. Zhao et al., 2021).

Similar to some of the previous studies (see, (Geedipally et al., 2019)), the MNL model was found to be a more appropriate model compared to the mixed logit for the data in hand. When using the MNL model, one category is designated as the reference category, and all other categories are compared to the reference; in this study, the PDO severity outcome was considered as the reference category. The probability of the i-th observation experiencing the j-th output injury is defined as follows:

$$p_{ij} = \frac{e^{U_{ij}}}{1 + \sum_j e^{U_{ij}}} \tag{5}$$

where, p_{ij} is the probability of the occurrence of crash severity "j" for observation "i", and U_{ij} is the deterministic part of the crash type likelihood. A linear function is used to link the crash severity with the various contributing factors as follows:

$$U_{ij} = \beta_{0j} + \sum_k \beta_{kj} X_{ik} \tag{6}$$

Where β_{0j} is the constant term for j-th category, X_{ik} is the k-th variable for the i-th observation and β_{kj} is the coefficient for the k-th variable j-th crash type. The coefficients are estimated using the maximum likelihood approach. To interpret the, we also estimated the Odds Ratio (OR) (Holdridge et al., 2005; Rahman et al., 2021) and reported in results section.

4.4 Results and Discussion

A multinomial logit model was estimated for each facility type. As noted before, the PDO severity outcome was used as the reference (or base) category in each model. Therefore, the modeling results and the corresponding odds ratios discussed in this section are compared to crashes the PDO crash outcome. Tables 12-15 show the modeling results (e.g., the estimated coefficient of significant variables), and the corresponding odds ratios (OR) for Interstate, minor arterials, major collectors, and minor collectors respectively. The tables also include the Akaike Information Criterion (AIC), Log-Likelihood, and McFadden's R^2 to analyze the goodness of fit (GOF).

4.4.1 Interstate Facilities

Table 12 shows the modeling results for rural Interstate roadways in Maine. As discussed, the driver age variable was classified into three groups (young, middle, and older). The young-driver category, indicating drivers with an age of 29 or less, was used as the reference (or base) group. The results show a positive correlation between the age of middle and older drivers and the Level B and Level KA severity outcomes. Given a crash, the odds of Level B and Level KA severity outcomes compared to PDO increases by 39% and 83% respectively, for middle aged drivers compared to young drivers. For older drivers, the results show that the odds of Level B and Level

KA severity outcomes compared to PDO increases by 72% and more than 327%, compared to young divers. The modeling results show that the odds a crash leading to a Level C or Level B severity outcome compared to PDO is respectively 38% and 30% smaller for male drivers. The results indicate that the odds of Level B and Level KA severity outcomes compared to PDO is 105% and 172% higher for drivers with suspended driver license; these results are expected due to the risky behavior of these drivers. Speeding (driving above speed limit) often contributes to more severe crashes. The modeling results show that vehicle speeding increases the odds of Level KA severity outcome by 2.8-times. The modeling results indicate that the odds of Level C severity outcome increases by 58% compared to PDO when the driver is distracted.

The modeling results shows a significant association between the severity of crashes and use of seatbelt. Given a crash, the odds of Level C severity outcome increases by over 5.2 times, Level B outcome by over 9.8 times, and Level KA outcome by over 26.3 times when seat belt is not used, compared to the crash resulting in PDO. The odds of Level B and Level KA severity outcomes increases by 3.4 and 2.2 times compared to PDO when the vehicle rolls over. The modeling results show that crashes that occur during the peak hours have higher odds of resulting in Level C severity outcomes (about 33% more). Combination of nighttime and operating under the influence was a significant variable for Level KA severity outcome. The odds of a crash resulting in a Level KA severity outcome is more than 2.5 times higher when a driver is operating under the influence at the nighttime (between dawn and dusk). For the Interstate facilities, the odds of a crash resulting in Level C injury outcome increases by 60% when the speed limit is greater than 70mph. These results are expected since higher vehicle speeds often result in more severe crashes. The odds of resulting in Level C injury outcome increases by 68% compared to PDO when the roadway is not level, likely due to reduced visibility.

Table 12: Modeling Results for Interstates.

Variables		Estimate (S.D.) C	Estimate (S.D.) B	Estimate (S.D.) KA	Odds Ratio C	Odds Ratio B	Odds Ratio KA
Intercept		-1.476 (0.288)	-1.099 (0.284)	-2.272 (0.451)	-	-	-
Driver Age	Middle	-[2]	0.326 (0.145)	0.604 (0.291)	-	1.386	1.829
	Older	-	0.544 (0.253)	1.452 (0.389)	-	1.723	4.271
Male Driver Indicator	Male	-0.481 (0.130)	-0.345 (0.142)	-	0.618	0.708	-
Driver License	Suspended	-	0.721 (0.376)[1]	1.001 (0.527)[1]	-	2.056	2.722
Driver Speed	Speeding	-	-	1.336 (0.721)[1]	-	-	3.803
Distractions	Distracted	0.455 (0.258)[1]	-	-	1.577	-	-
Seatbelt	Not Wearing	1.834 (0.336)	2.379 (0.314)	3.308 (0.383)	6.257	10.789	27.331
Crash Type	Rollover	-	1.472 (0.348)	1.167 (0.684)[1]	-	4.356	3.212
Time of Day	Peak	0.285 (0.128)	-	-	1.330	-	-
Nighttime and OUI	Yes	-	-	1.277 (0.453)	-	-	3.585
Speed limit	$\geq$ 70mph	0.471 (0.150)	-	-	1.601	-	-
Grade	Not Level	0.516 (0.141)	-	-	1.676	-	-
Season	Winter	-	-0.686 (0.247)	-1.711 (0.373)	-	0.504	0.181
Surface Condition	Not Dry	-	-0.313 (0.156)	-1.199 (0.295)	-	0.731	0.302
Temperature	> 60°F	-	-	-0.910 (0.365)	-	-	0.402
AIC		3,804					
Log-Likelihood		-1,854.08					
McFadden's R^2		0.077					

[1]Variable statistically significant at 90% otherwise significant at 95%.
[2]The empty cells show that the variable is not statistically significant to the respective model or not applicable.

Given a crash, the odds of Level B and Level KA severity outcomes respectively decreases by 50% and 82% compared to the PDO during the winter period (November-April). These results are expected as in winter, Interstate's experience over 2.5 times more PDO crashes. Despite the significant increase in PDO crashes, the number of severe crashes remain more or less the same. In other words, although the inclement weather causes more PDO crashes, it does not increase the severity of crashes, due to presumably more cautious driving behavior under bad weather conditions. Given a crash, the odds of Level B and Level KA severity outcomes decreases by 27% and 70% respectively compared to PDO when the surface is not dry. Again, this observation is likely due to the cautious driving behavior. The odds of Level KA severity outcome (compared to PDO outcome) also decreases by 60% for days with temperature of 60ºF or above.

4.4.2 Minor Arterial Facilities

Table 13 shows the modeling results for rural minor arterial roadways. The modeling results show that, given a crash, the odds of Level B and Level KA severity outcomes compared to PDO is respectively 1.4- and 1.5-times higher for older drivers comparing to young drivers. Given a crash, the odds of Level C and Level B crash outcomes is about 30% smaller for male drivers compared to female drivers. As discussed, drivers with suspended licenses are expected to be involved in more severe crashes due to their risky behavior. This observation was reflected in modeling results for minor arterials as well. The odds of Level C, Level B and Level KA severity outcomes respectively increases by 64%, 170% and 287% compared to PDO for drivers with suspended license. The modeling results also show that the odds of Level C severity outcome increases by 42% when the driver is under the influence.

Not wearing a seatbelt has the largest impact on severity of crashes for minor arterials as well. Failing to wear a seatbelt increases the odds of Level C, Level B or Level KA severity outcomes by 1.9-, 3.8-, and 23.1-times compared to PDO respectively. Crash severity increases when a rollover crash occurs. Given a crash, vehicle rollover increases the odds of Level C, Level B, and Level KA severity outcomes by 1.4-, 1.7-, and 2.7-times compared to PDO. For road segments with a posted speed limit of greater than 45mph the odds of a crash resulting in Level C severity outcome increases by 46%. When a crash occurs on a curved segment, the odds of Level B severity outcome compared to PDO increases by 29%.

For minor arterials, the PDO crashes increases during the winter period by about 2.7-times; however, severe crashes (KA, B, and C outcomes) do not increase in proportion to PDOs. This observation was reflected in modeling results as well. During the winter period, the odds of Level C, Level B and Level KA severity outcomes respectively decreases by 45%, 54% and 65% in comparison to the PDO severity outcome. On roadways with surface conditions that are described as "not dry", the odds of Level B and Level KA severity outcome decreases by 31% and 63% respectively compared to the PDO severity outcome. For minor arterials, the odds of Level C and Level B severity outcomes decreases by 27% and 50% (compared to PDO crashes) during the days with at least one inch of snowfall. These results are expected as during the snow days, often, more PDO (due to inclement weather) but less severe (due to cautious driving behavior) crashes are expected.

Table 13: Modeling Results for Minor Arterials.

Variables		Estimate (S.D.) C	Estimate (S.D.) B	Estimate (S.D.) KA	Odds Ratio C	Odds Ratio B	Odds Ratio KA
Intercept		-0.923 (0.220)	-1.310 (0.273)	-3.232 (0.483)	-	-	-
Driver Age	Older	-[2]	0.875 (0.235)	0.918 (0.440)	-	2.398	2.504
Male Driver Indicator	Male	-0.344 (0.120)	-0.360 (0.163)	-	0.709	0.698	-
Driver License	Suspended	0.493 (0.290)[1]	0.994 (0.332)	1.354 (0.478)	1.637	2.702	3.871
Sobriety	OUI	0.351 (0.192)	-	-	1.420	-	-
Seatbelt	Not Wearing	1.066 (0.221)	1.561 (0.250)	3.183 (0.296)	2.905	4.764	24.107
Crash Type	Rollover	0.870 (0.307)	0.988 (0.394)	1.316 (0.568)	2.388	2.685	3.728
Speed Limit	$\geq$ 45mph	0.376 (0.175)	-	-	1.456	-	-
Curve	Present	-	0.255 (0.158)[1]	-	-	1.291	-
Season	Winter	-0.591 (0.138)	-0.784 (0.182)	-1.039 (0.298)	0.554	0.456	0.354
Surface Condition	Not Dry	-	-0.373 (0.190)	-0.996 (0.357)	-	0.689	0.369
Snow	$\geq$ 1 inch of snow	-0.310 (0.187)[1]	-0.679 (0.316)	-	0.733	0.507	-
AIC		3,565					
Log-Likelihood		-1,743.62					
McFadden's R^2		0.092					

[1]Variable statistically significant at 90% otherwise significant at 95%.
[2]The empty cells show that the variable is not statistically significant to the respective model or not applicable.

4.4.3 Major Collector Facilities

Table 14 shows the modeling results for rural major collector roadways. For middle-aged drivers, the modeling results show increased odds of 45% in Level KA severity outcomes compared to younger drivers. Likewise, for older drivers, the odds of Level C, Level B and Level KA crash outcomes increases by 90%, 39% and 243% respectively compared to young drivers. The results show that, given a crash, the odds of Level C and Level KA severity outcomes is respectively 38% and 30% smaller for male drivers compared to female drivers. When drivers are under the influence of drugs or alcohol, it is expected that they involve in more severe crashes due to more reckless or aggressive driving behavior. The estimated model shows the same expectation. When operating under the influence, the odds of Level C, Level B and Level KA severity outcomes increases by

45%, 74% and 134% compared to PDO. In addition, the odds of crashes result in Level C and Level KA severity outcomes compared to PDO increases by 100% and 419% respectively when it is both nighttime, and the driver is speeding.

Table 14: Modeling Results for Major Collectors.

Variables		Estimate (S.D.)			Odds Ratio		
		C	B	KA	C	B	KA
Intercept		-0.694 (0.177)	-1.678 (0.228)	-4.202 (0.400)	-	-	-
Driver Age	Middle	-[2]	-	0.370 (0.171)	-	-	1.448
	Older	0.645 (0.126)	0.328 (0.175)[1]	1.231 (0.250)	1.905	1.387	3.426
Male Driver Indicator	Male	-0.472 (0.076)	-	-0.345 (0.170)	0.624	-	0.708
Sobriety	OUI	0.374 (0.131)	0.556 (0.147)	0.852 (0.203)	1.454	1.744	2.344
Nighttime and speeding	Yes	0.690 (0.322)	-	1.647 (0.404)	1.993	-	5.189
Seatbelt	Not Wearing	1.023 (0.138)	1.518 (0.147)	3.123 (0.178)	2.782	4.563	22.715
Crash Type	Rollover	0.875 (0.185)	1.044 (0.223)	1.330 (0.332)	2.398	2.840	3.779
Time of Day	Peak	-	-0.196 (0.102)[1]	-	-	0.822	-
Speed Limit	≥ 45mph	0.204 (0.094)	0.207 (0.122)[1]	0.816 (0.222)	1.226	1.230	2.261
Curve	Present	-	0.205 (0.098)	0.313 (0.159)	-	1.228	1.368
Season	Winter	-0.565 (0.134)	-0.401 (0.168)	-0.594 (0.282)	0.568	0.670	0.552
Surface Condition	Not Dry	-	-0.490 (0.123)	-	-	0.613	-
Snow	≥ 1 inch of snow	-0.230 (0.116)	-0.865 (0.183)	-1.520 (0.483)	0.795	0.421	0.219
Temperature	> 60°F	-	-	0.584 (0.274)	-	-	1.793
Precipitation	Yes	-	0.187 (0.107)[1]	-	-	1.205	-
AIC		8,956					
Log-Likelihood		-4,430.03					
McFadden's R^2		0.096					

[1]Variable statistically significant at 90% otherwise significant at 95%.
[2]The empty cells show that the variable is not statistically significant to the respective model or not applicable.

Like Interstates and minor arterials, there is a significant association between injury/fatality outcomes (KA, B, and C outcomes) and not wearing a seatbelt. When a seatbelt is not used, the odds of Level C, Level B and Level KA severity outcomes compared to PDO increases by 1.8-, 3.6-, and 21.7-times. The vehicle rollover increases the odds of Level C, Level B and Level KA severity outcomes by 1.4-, 1.8-, and 2.8-times respectively (compared to the PDO outcome). The odds of Level B severity outcome decreases by 18% compared to PDO during the peak hour, likely because of congestion and speed reduction during peak hours. The odds of a crash leading to Level C, Level B, and Level KA crash severity outcomes increases by 23%, 23% and 126% respectively on roads with speed limit of 45mph or above. This observation is expected, as the vehicle speed is a major contributing factor to severity of crashes. When crashes occur on curved segments, the odds of Level B or Level KA severity outcomes compared to PDO increases by 23% and 37% respectively.

During the winter period, major collectors experience 2.9-times more PDO crashes than the non-winter period. However, the severe crash outcomes do not increases in proportion to the PDOs. The odds of Level C, Level B and Level KA severity outcomes decreases by 43%, 33% and 45% respectively during the winter period in comparison with the PDO outcome. The odds of Level B severity outcome decreases by 39% when the surface is not dry in comparison with the PDO severity outcome. The severity of crashes decreases on days with at least one inch of snow accumulation as well. During inclement weather, especially winter conditions, drivers slow down due to slippery conditions and lower visibility; therefore, the negative correlation with severe crashes is expected. During snow days with more than one inch of snow, the odds of Level C, Level B and Level KA severity outcomes decreases by 20%, 58% and 78% respectively. On days that the maximum temperature is above 60ºF, the odds of crashes resulting in Level KA severity outcome increases by about 79%. These results are different from the Interstates results, perhaps due to narrow lanes and smaller shoulders, more congestion on major collectors, as well as increase in speeding behaviors during warmer weathers. Precipitation increases the odds of level B-level crash severities by 20% compared to days without precipitation.

4.4.4 Minor Collector Facilities

Table 15 shows the modeling results for rural minor collector roadways. The results show increased odds of 58% in Level KA severity outcomes for middle-aged drivers compared to young drivers. The odds of level B and level KA crash severity compared to PDO is respectively 68% and 266% higher for older drivers compared to the younger drivers. The results show that, given a crash, the odds of Level C and Level B severity outcomes increases by 48% and 22% respectively for male drivers compared to female drivers. The "speeding" variable was found to be significant for Level C, Level B and Level KA severity outcomes for minor arterials. These results are expected as speeding may result in losing the control of the vehicle; higher speeds also result in more severe impact. The modeling results show that the odds of Level C, Level B and Level KA severity outcomes increases by 58%, 123% and 148% respectively when drivers are speeding (drive above speed limit).

Table 15: Modeling Results for Minor Collectors.

Variables		Estimate (S.D.)			Odds Ratio		
		C	B	KA	C	B	KA
Intercept		-1.026 (0.190)	-1.720 (0.247)	-3.917 (0.458)	-	-	-
Driver Age	Middle	-[2]	-	0.458 (0.256)[1]	-	-	1.581
	Older	-	0.517 (0.268)[1]	1.298 (0.397)	-	1.677	3.661
Male Driver Indicator	Male	-0.655 (0.114)	-0.251 (0.151)[1]	-	0.520	0.778	-
Drive Speed	Speeding	0.455 (0.277)[1]	0.802 (0.300)	0.907 (0.409)	1.576	2.231	2.476
Seatbelt	Not Wearing	1.423 (0.206)	1.618 (0.230)	2.659 (0.276)	4.149	5.043	14.276
Crash Type	Rollover	0.576 (0.270)	-	-	1.779	-	-
Nighttime and OUI	Yes	-	0.971 (0.259)	0.962 (0.360)	-	2.641	2.616
Speed Limit	$\geq$ 45mph	-	0.380 (0.170)	0.930 (0.301)	-	1.462	2.534
Curve	Present	-	-	0.634 (0.262)	-	-	1.884
Grade	Not Level	0.243 (0.114)	-	-	1.275	-	-
Season	Winter	-	-0.573 (0.182)	-0.663 (0.272)	-	0.564	0.516
Surface Condition	Not Dry	-0.490 (0.142)	-0.393 (0.188)	-0.623 (0.292)	0.675	0.613	0.536
Snow	$\geq$ 1inch of snow	-0.400 (0.161)	-	-1.245 (0.621)	0.671	-	0.288
AIC		4,012					
Log-Likelihood		-1,964.144					
McFadden's R^2		0.085					

[1]Variable statistically significant at 90% otherwise significant at 95%.
[2]The empty cells show that the variable is not statistically significant to the respective model or not applicable.

Like previous facilities, not wearing a seat belt is the most influential factor in severity of crashes. The odds of a crash leading to Level C, Level B and Level KA severity outcomes increases by 3.1-, 4- and 13.3-times compared to PDO when the seatbelt is not used. The odds of Level C severity outcome increases by 78% compared to PDO when the vehicle rolls over. The modeling results show that, given a crash, the odds of Level B and Level KA severity outcomes increases by 162% compared to PDO when it is nighttime, and the driver operates under the influence. The results show that the odds of Level B and Level KA severity outcomes increases by 46% and 153% respectively when the speed limit is 45mph or greater. The odds of a crash leading to a Level KA severity outcome increases by 88% on curved segments. Likewise, the odds a crash leading to a Level C severity outcome increases by 28% when the roadway segment is not level During the winter period, minor collectors experience 3.1-times more PDO crashes than the non-winter season. However, the number of severe crashes remains more or less the same. For minor collectors, the modeling results indicate that during the winter period, the odds of Level B and Level KA severity outcomes decreases by 44% and 48% respectively in comparison to the PDO outcome. Likewise, the odds of level C, level B and level KA severity outcomes is decreased by 34%, 38% and 46% respectively when the surface is not dry (likely due to more cautious behavior of drivers). On snow days with at least one inch of snow, the odds of level C and level KA severity outcomes decreases by 33% and 71% respectively in comparison to the PDO outcome.

4.5 Summary and Conclusion

In Maine, lane departure crashes are the leading cause of crash fatalities. A majority of these crashes occur on rural roadways. Maine is a unique state, with aging infrastructures and population, a challenging climate, and diverse terrain. This study used Multinomial Logit Regression model to estimate severity outcome models for four facility types (Interstates, minor arterials, major collectors, and minor collectors), to analyze the impact of roadway, driver, and weather factors on severity of crashes. Older drivers (aging 65 and older) variable was significance for all analyzed facilities. Crashes that involved older drivers showed increased odds of Level KA severity outcome by 327%, 150%, 243% and 266% on Interstate, minor arterials major collectors and minor collectors respectively compared to younger drivers. Failure to use a seatbelt was the most influential variable causing severe crashes. When the seatbelt is not used, the odds of Level KA severity outcome increases by 26.3-, 23.1-, 21.7- and 13.3-times higher compared to PDO on Interstate, minor arterials, major collectors and minor collectors respectively. As discussed during the winter period, there are significantly more PDO crashes for each facility type (due to inclement weather). However, the severity of crashes does not necessarily increase in proportion to PDOs. During the winter period, the results show that the odds of crashes resulting in Level KA severity outcome decreases by 82%, 65%, 45%, and 48% for Interstate, minor arterial, major collectors, and minor collector facilities respectively in comparison to the PDO outcome. We also mapped the crash data to daily weather data obtained from weather stations to use various weather variables in the model. The modeling results show that crashes that occur on snow days have decreased odds of resulting in Level KA severity outcome by 78% and 71% on major and minor collectors respectively. When the surface is not dry, the odds of Level KA severity outcome decreases by 70%, 63% and 46% on Interstates, minor arterials, and minor collectors respectively in comparison to the PDO outcome. Inclement weather or bad surface conditions result in more PDO but less severe crash outcomes since drivers are more cautious, use lower speeds and are more aware in these conditions.

Chapter 5: Summary and Recommendations

The current section provides a summary of the two topics analyzed throughout this report and overall project recommendations. This chapter is divided into three sections, as follows: First, the summary of the crash frequency analysis is described. Second, the summary of the crash severity analysis is described. And finally, recommendations are provided regarding the methodology and practice.

5.1 Crash Frequency Analysis Summary

In Chapter 3, we analyzed rural lane departure crash frequencies in Maine from 2015 to 2019. Models were developed for four facility types (Interstates, minor arterials, major collectors, minor collectors). To account for weather and maintenance strategies, the winter (November to April) and non-winter (May to October) periods were modeled separately. The monthly average daily traffic (MADT) and geometric characteristics of roadway segments were included in the models as control variables. Once the NB models were developed, the marginal effects were calculated to measure the impact of a 1% change of the respective variable on the mean average of the total monthly crashes. The following discussion describes the results from the marginal effects analysis in Chapter 3. Table 16 is added to this section to show the marginal effects analysis results and is a replica of Table 7 in Chapter 3.

Table 16: Frequency Analysis Marginal Effects (Replica of Table 7).

Variables	Winter Period				Non-Winter Period			
	Interstate	Minor Arterial	Major Collector	Minor Collector	Interstate	Minor Arterial	Major Collector	Minor Collector
MADT	2.89%	0.44%	0.38%	0.30%	1.25%	0.25%	0.19%	0.12%
Lane Width	Not Sig[1]	Not Sig	Not Sig	0.02%	Not Sig	0.03%	Not Sig	Not Sig
Number of Lanes	-0.79%	NA	NA	NA	Not Sig	NA	NA	NA
Speed Limit	0.26%	0.03%	0.02%	0.01%	0.18%	0.01%	0.01%	0.01%
Left Shoulder Width	-0.77%	-0.06%	-0.02%	-0.01%	-0.45%	Not Sig	Not Sig	Not Sig
Right Shoulder Width	-0.79%	Not Sig	-0.02%	Not Sig	-0.43%	-0.03%	-0.02%	-0.01%
Left Shoulder Type	NA[2]	Not Sig	-0.11%	-0.12%	NA	Not Sig	Not Sig	-0.07%
Right Shoulder Type	NA	Not Sig	-0.07%	-0.17%	NA	0.09%	-0.03%	Not Sig
Curve Present	-0.91%	0.11%	0.08%	0.05%	-0.33%	0.10%	0.07%	0.07%
Max. Precipitation	Not Sig	Not Sig	0.06%	0.07%	0.17%	Not Sig	Not Sig	Not Sig
Total Monthly Precipitation	Not Sig	Not Sig	Not Sig	Not Sig	Not Sig	Not Sig	0.01%	Not Sig
Days with Precipitation >= 1.0 (in)	0.09%	0.02%	0.01%	0.01%	0.05%	Not Sig	Not Sig	Not Sig
Days with Snowfall >= 1.0	0.51%	0.05%	0.04%	0.03%	NA	NA	NA	NA

[1] The variable is not statistically significant to the respective model.
[2] Not Applicable.

In terms of weather variable effects, the marginal effect analysis shows that the variable denoting the total precipitation was significant for major collectors. During the non-winter period, as the total precipitation increases by 1% from the mean, the expected monthly crashes increases by about 0.01%. During the winter period, as maximum precipitation increases by 1% from the mean, the expected monthly crashes increase by 0.06% on major collectors, and by 0.07% on minor collectors. During the non-winter period, as maximum precipitation increases by 1% from the mean, the expected monthly crashes increase by 0.17% on Interstates. During the winter period as the number of days with more than one inch of precipitation increases by 1% from the mean, the expected monthly crashes increase by 0.09%, 0.02%, 0.01% and 0.04% on Interstates, minor arterials, major collectors and minor collectors, respectively. During the non-winter period, as the number of days with more than one inch of precipitation increases by 1% from the mean, the expected number of monthly crashes increase by 0.05% on Interstates. During the winter period, as the number of days with more than one inch of snowfall increases by 1% from the mean, the expected monthly crashes increase by 0.51%, 0.05%, 0.04% and 0.03% on Interstates, minor arterials, major collectors and minor collectors, respectively.

In terms of the control factors considered, including MADT and geometric features, multiple variables were significant. During the winter period, as MADT increases by 1% from the mean, the expected monthly crashes increase by 2.89%, 0.44%, 0.38% and 0.30% on Interstates, minor arterials, major collectors and minor collectors, respectively. During the non-winter period, as MADT increases by 1% from the mean, the expected monthly crashes increase by 1.25%, 0.25%, 0.19% and 0.12% on Interstates, minor arterials, major collectors and minor collectors, respectively. During the winter period, as posted speed limit increases by 1% from the mean, the expected monthly crashes increase by 0.26%, 0.03%, 0.02% and 0.01% on Interstates, minor arterials, major collectors and minor collectors, respectively. During the non-winter period, as posted speed limit increases by 1% from the mean, the expected monthly crashes increase by 0.18%, 0.01%, 0.01% and 0.01% on Interstates, minor arterials, major collectors and minor collectors, respectively. All facilities besides Interstates had a positive correlation between crashes and curve presents. Interstates have higher design standards (wider and longer requirements, due to speed and AADT) than any other facility which could be a reason for the different effect on crashes. During the winter period, as curve presence increases by 1% from the mean the expected monthly crashes increases by 0.11%, 0.08% and 0.05% on minor arterials, major collectors and minor collectors respectively whereas on Interstates, crashes decrease by 0.91% on curves. During the winter period, as curve presence increases by 1% from the mean the expected monthly crashes increases by 0.10%, 0.07% and 0.07% on minor arterials, major collectors and minor collectors respectively, whereas on Interstates, crashes decrease by 0.33% on curves.

5.2 Severity Analysis Conclusion

Crash severity was analyzed in Chapter 4. This analysis considered rural single-vehicle lane departure crashes that occurred in Maine during the 2017-2019 period. We developed models for four facility types: Interstates, minor arterials, major collectors, minor collectors and the impact of roadway, weather and crash factors on crash severity was analyzed. Once the models were developed, the Odds Ratio for each significant variable (compared to the base category) was calculated. In this analysis, all values were compared to the PDO severity outcome. The following discussion summarizes the Odds Ratio results presented in Chapter 4. Table 17 provides the change in Odds Ratio.

Table 17: Cheng in Crash Severity Odds Ratio

Variables		Interstate			Minor Arterial			Major Collector			Minor Collector		
		C	B	KA	C	B	KA	C	B	KA	C	B	KA
Driver Age	Middle	-	+39%	+83%	-	-	-	-	-	+45%	-	-	+58%
	Older	-	+72%	+327%	-	+140%	+150%	+91%	+39%	+243%	-	+68%	+266%
Male Driver Indicator	Male	-38%	-29%	-	-29%	-30%	-	-38%	-	-29%	-48%	-22%	-
Driver License	Suspended	-	+106%	+172%	+64%	+170%	+287%	-	-	-	-	-	-
Driver Speed	Speeding	-	-	+280%	-	-	-	-	-	-	+58%	+123%	+148%
Sobriety	OUI	-	-	-	+42%	-	-	+45%	+74%	+134%	-	-	-
Distractions	Distracted	+58%	-	-	-	-	-	-	-	-	-	-	-
Seatbelt	Not Wearing	5.3 times	9.8 times	26.3 times	1.9 times	3.8 times	23.1 times	1,8 times	3.6 times	21.8 times	3.1 times	4.0 times	13.3 times
Crash Type	Rollover	-	+336%	+221%	+139%	+169%	+273%	+140%	+184%	+278%	+80%	-	-
Time of Day	Peak	+33%	-	-	-	-	-	-	-18%	-	-	-	-
Nighttime and OUI	Yes	-	-	+259%	-	-	-	-	-	-	-	+164%	+161%
Nighttime and speeding	Yes	-	-	-	-	-	-	+99%	-	+419%	-	-	-
Speed limit	≥ 70mph	+60%	-	-	-	-	-	-	-	-	-	-	-
Speed Limit	≥ 45mph	-	-	-	+46%	-	-	+23%	+23%	+126%	-	+46%	+153%
Curve	Present	-	-	-	-	+29%	-	-	+23%	+37%	-	-	+88%
Grade	Not Level	+68%	-	-	-	-	-	-	-	-	+28%	-	-
Season	Winter	-	-50%	-82%	-45%	-54%	-65%	-43%	-33%	-45%	-	-44%	-48%
Surface Condition	Not Dry	-	-27%	-70%	-	-31%	-63%	-	-39%	-	-33%	-39%	-46%
Temperature	> 60ºF	-	-	-60%	-	-	-	-	-	+79%	-	-	-
Snow	≥ 1 inch of snow	-	-	-	-27%	-49%	-	-21%	-58%	-78%	-33%	-	-71%
Precipitation	Yes	-	-	-	-	-	-	-	+21%	-	-	-	-

In terms of crash and roadway variables, the odds of Level KA severity outcomes is higher by 126% and 153% compared to PDO on major and minor collectors respectively, on roads with speeds of 45mph or greater. The results indicate that the odds of Level KA severity outcome compared to PDO is 37% and 88% higher for major collectors and minor collectors respectively, on curved segments. The odds of Level KA severity outcomes for middle-aged drivers compared to younger drivers are 82%, 45% and 58% higher on Interstates, major collectors and minor collectors, respectively. The odds of Level KA severity outcomes for older drivers increase by 327%, 150%, 243% and 266% on Interstates, minor arterials, major collectors and minor collectors respectively, compared to younger drivers. The results indicate that the odds of Level KA severity outcome compared to PDO is 172% and 287% higher on Interstates and minor arterials respectively when drivers are driving with a suspended license. When drivers were under the influence of drugs or alcohol, the odds of Level B or Level KA severity outcome compared to PDO is 74% and 134% higher respectively on major collectors. When drivers exceeded the posted speed limit, the odds of Level KA severity outcome compared to PDO is 280% and 148% higher on Interstates and minor collectors respectively. When seatbelts are failed to be worn, the odds of Level KA severity outcome compared to PDO increased by 26.3-times, 24.1-times, 21.7-times and 13.3-times on Interstates, minor arterials, major collectors respectively. The results of a rollover indicate that the odds of Level KA severity outcome compared to PDO is 221%, 273% and 278% higher on Interstates, minor arterials and major collectors respectively.

The final category of variables evaluated a suite of weather variables. The results indicated that the odds of Level KA severity outcome decrease by 70%, 63% and 46% compared to PDO on Interstates, minor arterials and minor collectors respectively, on pavement that was not dry. When the day of a crash experienced at least one inch of snowfall the odds of Level KA severity outcome compared to the PDO crashes decrease by 78% and 71% on major collectors and minor collectors, respectively. As discussed, Maine's winter season may last up to six months. In this analysis the winter season spans from November to April. The results indicated that the odds of Level KA severity outcome decrease by 82%, 65%, 45% and 48% on Interstates, minor arterials, major collectors and minor collectors respectively compared to PDO.

5.3 Recommendations

The following recommendations are provided for future work on the subject evaluated in this report. The recommendations were categorized as methodological and practical recommendations.

5.3.1 Methodological Recommendations

As discussed, to analyze the crash frequency, we used a Negative binomial model, using aggregated segment monthly panel data with GEE equations. Other more advanced methods are recommended to be considered for future work. Other methods including Random-Effect NB (Lord & Mannering, 2010; Mannering & Bhat, 2014) Random Parameters NB (RPNB) (Mannering et al., 2016), semiparametric NB (Shirazi et al., 2016) and NB-Lindley (Geedipally et al., 2012; Khodadadi et al., 2022a; Khodadadi et al., 2022b; Rusli et al., 2018; Shaon et al., 2018; Shirazi et al., 2017; Islam et al., 2022) are recommended in future analysis.

To analyze crash severity, we used a Multinomial Logit model. When analyzing the three-year data set, we also considered a mixed logit model; however, due to limited data and variables the Multinomial Logit model produced better modeling results. With more data, a mixed logit model could also be considered for future investigations. In addition, it is also recommended to use Machine Learning methods to analyze severity of crashes, especially to understand the impact of daily weather factors on lane departure crashes.

5.3.2 Practical Recommendations

A limitation of this research was acquiring accurate data for weather factors. As discussed, using the sparse network of weather stations had limitations (limited locations). For future research, it is recommended to consider data from Road Weather Information Systems (RWIS), which could provide more accurate, and reliable weather data for analysis, especially with regard to important variables such as visibility and wind data. The impact of rumble strips on lane departure crashes should also be investigated. It is also recommended that Maine DOT consider coding and updating crash and roadway data more frequently to better capture various variations. Since most roads I Maine are rural, in this project, only rural facilities were considered in the analyses. However, it is recommended that the future research also include urban areas, allowing a complete assessment of roads in Maine to improve roadway safety throughout the entire network.

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