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MINETA TRANSPORTATION INSTITUTE

Effect of Weather Events on Travel Time Reliability and Crash Occurrence

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Mineta Transportation Institute

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16. Abstract

The magnitude of the effect of adverse weather conditions on road operational performance varies with the type of weather condition and the road characteristics of the road links and adjacent links. Therefore, the relationship between weather and traffic is always a concern to traffic engineers and planners, and they have extensively explored ways to integrate weather information into transportation systems. Understanding the influence of weather on operational performance and safety helps traffic engineers and planners to proactively plan and manage transportation systems. The main objective of this research is to evaluate the effect of adverse weather conditions on travel time reliability and crash occurrence, by severity, using weather data, road data, travel time data, and crash data for North Carolina. The methodology and results from this research are useful for transportation system managers and planners to manage the traffic and improve safety under different weather conditions. They also help improve the functionality of weather-responsive management strategies like variable signs to indicate the change in reliability and safety under rainfall and low visibility conditions.

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Executive Summary

Different weather conditions disrupt the operational performance of roads in different ways. The reduction in travel demand and road capacity, deterioration in safety performance, and the worsening of travel speed or travel time are among the significant effects of weather events on the operational performance of roads. Understanding the influence of weather on operational performance and safety helps traffic engineers and planners to proactively plan and manage transportation systems. Therefore, the main objective of this research is to evaluate the effect of weather conditions on travel time reliability (TTR) and crash occurrence.

To achieve the aforementioned objective, data integration and data analysis are carried out at two levels. Initially, travel time data and weather-related information for 50 selected road segments in North Carolina were used to evaluate the effect of weather conditions on road traffic TTR. Secondly, the effect of weather conditions on crash occurrence and severity was assessed using data collected from the Highway Safety Information System (HSIS). The weather and travel time data for the same time of day and day of the week were extracted and integrated for analysis at the link level. The effect of other factors (geometric conditions, traffic patterns, and other environmental factors) beyond the scope of this research was minimized by comparing the travel time data for a week before and after rainfall and visibility conditions at which times weather conditions were confirmed to be clear with the travel time during a given rainfall and visibility condition.

TTR indices such as planning time index (PTI) and travel time index (TTI) were explored to quantify the effect of the most common weather conditions such as rainfall and poor visibility on the TTR. The results indicated that different rainfall intensities with poor visibility have a maximum adverse effect on freeway TTR. Heavy rain and poor visibility caused a 5.50% increase in the average travel time (ATT) and a 12.24% increase in PTI on urban freeway road segments. Similarly, a 7.55% increase in TTI was observed under the condition of moderate rain with poor visibility on the urban freeway road segments. In the case of arterial road segments, the increase in PTI was 6.70% and 4.02%, respectively, under the heavy rain with good visibility and heavy rain with poor visibility conditions. Overall, PTI was observed to be a better measure than TTI as it normalizes the 95th-percentile travel time for all the road segments in terms of free-flow travel time.

A survival analysis was conducted to estimate the probability of a road segment reaching an unreliable state under rainfall and visibility conditions. The analysis was performed using data for the freeway and arterial road segments. The probability of a segment being unreliable under a specific PTI value was studied using the survival function. The likelihood of reaching a moderately to highly unreliable condition is 8% to 15% higher on urban freeway road segments in the case of poor visibility condition compared to the normal weather condition. However, the survival analysis for arterial road segments indicated a minimal effect of rainfall and visibility conditions on the TTR.

Overall, the effect of the weather on TTR was lower for urban arterial road segments than for freeway road segments. The maximum effect was observed in the case of heavy rain condition. The data points for the arterial road segment analysis were fewer compared to the freeway road segment analysis. The lower operating speeds and the interrupted traffic conditions on the arterial road segments may have neutralized the variability in travel times during rain and visibility constraints.

The effect of weather conditions on crash occurrence was assessed using logistic regression modeling. The weather conditions considered in the assessment include cloudy, rain, snow, fog, sleet, hail, freezing rain, drizzle, severe crosswinds, and blowing sand. Three separate models were developed for each injury severity level. These included separate models for severe injury (fatal and injury type A), moderate injury (injury type B and injury type C), and PDO (no injury). Independent variables include crash type and contributing factors, crash location characteristics (lighting condition, locality, etc.), driver (gender and age), road characteristics (functional class, speed limit, etc.), seasonal factors, and temporal factors. The results obtained from the logistic regression model for severe injury crashes indicate that variables including road surface condition, lighting condition, speed limit, vehicle type, seasonal factors, locality, and temporal factors influence the occurrence of weather-related severe crashes.

Similarly, those variables, as well as road terrain, have statistically significant effects on the occurrence of weather-related moderate injury crashes at a 95% confidence level. The presence of a work zone increases the likelihood of the occurrence of property damage only (PDO) crashes during adverse weather conditions.

A partial proportional odds model was developed to identify factors contributing to the injury severity of crashes occurring during adverse weather conditions. The results indicate that driving on road with no lighting in weather conditions increases the likelihood of severe injury crash as compared to driving on roads during daylight hours in adverse weather conditions. Variables such as road functional class, presence of an intersection, driver gender, road characteristics, speed limit, crash, vehicle type, seasonal factors, time of the day, and day of the week have a statistically significant positive effect on weather-related crash injury severity at a 95% confidence level.

The findings from the analysis on the effect of weather conditions on TTR and crash occurrence and severity can be utilized to enhance operational performance and promote safety in adverse weather conditions. They will help planners to install solutions aimed at reminding drivers of the need to be vigilant and cautious during adverse weather conditions.

1. Introduction

On average, nearly 5,000 people are killed and more than 418,000 people are injured, in weather-related crashes every year in the United States (USDOT 2018). Further, about 23% of the non-recurring road delay in the United States can be attributed to snow, ice, and fog. Rain, which occurs more frequently than snow and fog, leads to more traffic delay (USDOT 2018). In other words, weather conditions such as precipitation, high-speed winds, fog—and other extreme events such as high-volume snowfall, flooding, hurricanes, and so on—disrupt the operational performance of roads. They reduce road capacity, travel speed, and safety performance. Operational performance measures include travel time and travel time reliability (TTR), and safety is measured as crash occurrence; the magnitude of the effect on these measures varies with the type of weather condition and the road characteristics of the studied road links and adjacent links.

Ensuring higher levels of TTR and safety is critical for efficient transportation system management. Therefore, there is a need to analyze the travel time fluctuations (deviations from normal conditions) and crashes during such events. Besides, understanding the type of weather condition and anticipating its duration, and identifying the most affected segments, is important for proactively planning for, and disseminating information about, the effect on travel patterns over space and time.

A key challenge to achieving this objective is the integration of weather-related information and traffic conditions during the weather conditions. Advancements in data collection technologies make it possible to collect and archive real-world travel time data at the link level. Similarly, databases like the Highway Safety Information System (HSIS) maintain motor vehicle crash data, road inventory, and traffic volume data at the state level in the United States. The HSIS is a valuable source of data for evaluating the effect of weather conditions on crash occurrence and safety.

In the present research, data integration and data analysis are carried out at two levels. Initially, travel time data and weather-related information for 50 selected road segments in North Carolina were used to evaluate the effect of weather condition on road TTR. The meteorological data obtained from the Integrated Surface Database (ISD) were used for analysis. Rainfall and visibility are the only two weather-related variables considered in the TTR assessment. The HSIS provides details on the weather condition when a crash occurred. These details are more comprehensive than the ISD data and include weather-related information such as whether the weather condition involved rain, snow, fog, smog, smoke, sleet, severe crosswinds, and blowing sand. Therefore, the effect of weather condition on crash occurrence and severity was assessed using data collected from HSIS.

1.1 Problem Statement

The weather has a significant effect on vehicle travel on roads. The reduction in travel demand and road capacity, deterioration in safety performance, and the worsening of travel speed or travel time are some of the major effects of weather condition on roads' operational performance. Therefore, the relationship between weather and traffic is always a concern to traffic engineers and planners, and they have extensively explored ways to integrate weather information into transportation systems.

From a road user perspective, weather information remains one of the most important pieces of information road users want to know before making travel decisions, especially whether or not to make a trip. Therefore, clear insight into how weather conditions influence traffic is essential for traffic engineers, planners, and policymakers to implement advisories, alerts, and warnings for the road users. However, the main challenge faced by these professionals when evaluating the effect of weather conditions on traffic conditions is the integration of weather-related information with traffic- or travel-time-related data. Nowadays, the increased availability of travel time data and crash data with spatial attributes makes it possible to integrate weather-related information, travel time, and crash data. Such an integrated data mining framework was not explored in the past to assess the effect of weather condition on travel time and crashes. Further, analyzing the historical pattern of travel times, computing and comparing TTR measures, and analyzing the factors modulating weather-related crashes and their severity will help quantify and promote understanding of the spatiotemporal effects of such events on road traffic.

1.2 Objectives of the Research

The objectives of the research are:

(1) To establish a methodological framework for capturing, processing, and integrating weather-condition-related information and travel time for selected road segments in the state of North Carolina,

(2) To quantify the effect of weather condition on travel time and TTR of the freeway and arterial corridors under consideration, and

(3) To examine the relationship between selected weather conditions and crash occurrence by severity.

1.3 Organization of the Report

The remainder of the report is comprised of seven chapters. Chapter 2 summarizes literature related to weather conditions and their effect on operational performance, travel patterns and road capacity, traffic speed, and road safety. Chapter 3 discusses the study area and approaches to data collection. Chapter 4 presents the comprehensive methodological framework adopted for evaluating the effect of selected weather conditions on TTR and crash occurrence. Chapter 5 quantifies the effect of rainfall and visibility conditions on road traffic TTR. Chapter 6 discusses the likelihood of a weather-related crash occurrence, and that discussion is followed by the identification of potential risk factors associated with the injury severity of crashes during adverse weather conditions. Lastly, Chapter 7 presents the conclusions from this research.

2. Literature Review

Adverse weather conditions disrupt the operational performance of roads in different ways. The reduction in travel demand and road capacity (Agarwal et al. 2005; Maze et al. 2006; Datla and Sharma 2008), deterioration in safety performance, and the worsening of travel speed or travel time (Agarwal et al. 2005; Koetse and Rietveld 2007) are the significant effects of weather conditions on the operational performance of roads.

In this report, the material in the literature review is organized in two different parts: the effect of weather conditions on road operational performance and the effect of weather conditions on crash occurrence and severity.

2.1 Weather and Operational Performance

Ibrahim and Hall (1994) analyzed the effect of rainfall and its intensity on fundamental traffic flow relationships. They found a minimal effect of light rain and a maximum effect of heavy rain on free-flow speed and road capacity. Cools et al. (2009) evaluated the effect of weather conditions on traffic intensities in Belgium. The results from their research indicated an increase in traffic volume during high-temperature conditions and a reduction in traffic volume during snowfall, rainfall, and high wind speed conditions. Call (2011) observed a reduction in traffic volume during snowfall conditions. Similarly, Kwon et al. (2013) illustrated the effect of snow intensity and visibility on free-flow speed and capacity.

The Highway Capacity Manual (HCM) 2000 states that light rain conditions can cause a reduction of 1.9% in free-flow speed; in heavy rain conditions, a 4.8% to 6.4% reduction in free-flow speed is reported. According to Smith et al. (2004), rainfall could cause a 5% to 6.55% reduction in the operating speed regardless of the intensity of rainfall. Maze et al. (2006) found that heavy rain caused a reduction in speed by 6%, while moderate rains caused an average reduction in speed by 4% on urban freeways compared to clear weather conditions. Wang et al. (2006) reported a 3.91-mph reduction in average speed during heavy rains compared to the case of no rain. They also pointed out that the effect of rainfall varies with road characteristics, such as the route class and the number of lanes. Similarly, Unrau and Andre (2006) studied the effect of rainfall on traffic speed by considering the urban expressway in Toronto, Canada, as the study corridor; their results indicate a 10% reduction in speed during the uncongested daytime condition and light rain.

Stern et al. (2003) studied the effect of weather conditions on the average travel time (ATT) by considering selected road segments in Washington, DC. The results from their research indicated a 14% increase in the ATT during rainfall conditions. Camacho et al. (2010) studied the effect of rainfall on free-flow speed by considering selected freeway segments from north-western Spain. Their study results indicated a 3.1-mph and 4.3-mph reduction in free-flow speed under the light rain and heavy rain conditions, respectively. Kang et al. (2008) studied the effect of poor visibility on car-following performance. Car-following performance describes the one-by-one following process of vehicles in the same lane. They observed that the distance headway decreased in the densest fog conditions, while the root mean square error (RMSE) of velocity increased with an increase in fog density (Kang et al. 2008).

Nowadays, TTR is considered to be a critical performance measure to assess the condition of freeway and arterial road segments. It is a measure of service quality (Chen et al. 2003). It can used to quantify the performance of a system from both the planner's and the user's perspective (Wakabayashi and Matsumoto 2012). Some recent research initiatives have illustrated the use of TTR-based measures to quantify the effect of weather conditions on road performance (Chien and Kolluri 2012; Zhao and Chien 2012; Yazici et al. 2013). Chien and Kolluri (2012) assessed TTR under adverse weather conditions using TTR indices such as planning time (PT), buffer index (BI), and planning time index (PTI). Zhao and Chien (2012) used BI to evaluate the effect of adverse weather on TTR.

The buffer index represents the extra time that travelers must add to their average travel time to avoid late arrival (Zhao and Chien 2012). Yazici et al. (2013) studied the effect of different weather types on travel time variability and concluded that the effects vary with the day of the week and time of the day. Also, a higher effect was observed in less congested periods (Chien and Kolluri 2012). Zhang and Chen (2019) evaluated the effect of rain and snow events on both congestion and TTR. The effect of weather on TTR is more severe than the effect of weather on average delay (Zhang and Chen 2019).

The recent version of HCM incorporated measures such as PT, travel time index (TTI) and PTI to assess the reliability of freeway and urban streets (Kittelson and Vandehey 2013). PTI indicates the total time a traveler should allocate to ensure on-time arrival. Wolniak and Mahapatra (2014) stated that PTI could accommodate the effect of adverse weather and other events on the TTR. PT, PTI, and TTI can be computed using equations 1, 2, and 3:

$$PT = 95th\ percentile\ travel\ time \tag{1}$$

$$PTI = \frac{PT}{Free-flow\ travel\ time} \tag{2}$$

$$TTI = \frac{Average\ travel\ time\ (ATT)}{Free-flow\ travel\ time} \tag{3}$$

Van Der Loop et al. (2014) identified the main causes of the unreliability of travel times for Netherlands urban roads. They considered factors like traffic, weather condition, road work, and crashes in the assessment process. Ravi Sekhar and Asakura (2014) modeled travel time variation by considering supply-side and demand-side of transportation system. They observed that rainfall has a significant influence on travel time variations, and the magnitude of influence is high on weekdays.

2.2 Weather and Safety

Per the National Highway Traffic Safety Administration (NHTSA), 1,235,000 weather-related crashes occurred in the United States from the year 2007 to the year 2016 (USDOT 2018). The relationship between weather conditions and crashes has been investigated extensively in recent years. The weather variables considered in the past studies include temperature (Keay and Simmonds 2005; Brijs et al. 2008; Malyshkina et al. 2009; El-Basyouny et al. 2012; Antoniou et al. 2013; Gariazzo et al. 2021), rainfall/precipitation (Brijs et al. 2008; Jung et al. 2010; Jung et al. 2014; Ashley et al. 2015; Tamerius et al. 2016; Black et al. 2017; Wang et al. 2017; Zhao et al. 2019; Tobin et al. 2019; Uddin and Huynh 2020), sunlight (Mitra and Washington 2012; Redelmeier and Raza 2017; Das et al. 2022), wind speed (Khattak and Knapp 2001; Young and Liesman 2007; Jung et al. 2010; Wen et al. 2019), low visibility (Abdel-Aty et al. 2012; Hassan and Abdel-Aty 2013; Peng et al. 2017; Li et al. 2018), and snowfall (Eisenberg 2004; El-Basyouny et al. 2012; Heqimi et al. 2018).

Past studies on the effect of weather conditions on crashes typically fall into one of two categories: modeling the crash risk (dependent variable is crash frequency or crash rate) and modeling the crash severity (dependent variable is crash severity). A few studies evaluated both the crash frequency/rate and crash severity in the assessment process.

Notably, most weather-related crashes happen during rainfall and other wet pavement conditions (Ashley et al. 2015; Tamerius et al. 2016; Black et al. 2017; Omranian et al. 2018; Tobin et al. 2019). According to Tobin et al. (2019), 8.6% of the vehicle-related fatalities from 2013 to 2017 in the United States occurred during rainfall conditions. Moreover, the crash risk associated with precipitation varies spatially and temporally (Tamerius et al. 2016). Under rainfall conditions, interstates and major highways have higher crash risk than local roads (Tamerius et al. 2016). Selected past studies evaluating the effect of rainfall/precipitation on crash occurrence and severity are summarized in Table 1.

Table 1. Effect of Rainfall on Crash Occurrence/Severity

Author (year)	Country	Dependent variable	Method	Summary of key findings
Eisenberg (2004)	USA	Crash frequency	Negative binomial regression	Monthly precipitation has a negative association with monthly number of fatal crashes Risk imposed by precipitation increases dramatically as the time since last precipitation increases
Abdel-Aty and Pemmanaboina (2006)	USA	Probability of crash occurrence	Logistic regression	Probability of rainfall has a positive effect on crash occurrence
Brijs et al. (2008)	Netherlands	Crash frequency	Integer autoregressive model	Rainfall intensity and duration have a positive association with the number of crashes
Jung et al. (2010)	USA	Crash severity	Ordinal logistic and sequential logistic regressions	Rainfall intensity, wind speed, roadway terrain, driver's gender, and use of seat belt were found to be the significant factors affecting single-vehicle crash severities
Ahmed et al. (2012)	USA	Probability of crash occurrence	Logistic regression	Precipitation (rainfall and snow) significantly increase the crash risk on mountainous freeways
Yu et al. (2013)	USA	Crash frequency	Bayesian hierarchical models (fixed effect, random effect uncorrelated, and random effect correlated)	Mountainous freeway segments experiencing sudden rain or snow are more dangerous than those experiencing continuous precipitation
Hambly et al. (2013)	Canada	Crash frequency	Estimate the extent to which crash rates are elevated during precipitation relative to dry, seasonal conditions	Moderate to high rainfall (>10 mm) have the greatest adverse effect on crash frequency

Author (year)	Country	Dependent variable	Method	Summary of key findings
El-Basyouny et al. (2014)	Canada	Crash frequency	Full Bayesian multivariate Poisson lognormal models	No significant association between rainfall and crashes Rainfall following a dry weather condition is highly significant and positively related to following too close, stop-sign violation, and ran-off-road crashes
Jung et al. (2014)	USA	Crash frequency and severity	Negative binomial regression Ordered logit and multinomial logit	Average daily rainfall per month was found to decrease the likelihood of crashes The impacts of traffic, pavement, and road geometries interacting with rainfall on crashes were found to be significantly greater than the impact of the rainfall itself.
Tamerius et al. (2016)	USA	Crash risk	Matched pair analysis: relative crash risk	Interstates and major highways tend to have higher crash risk than smaller roads during precipitation conditions
Black et al. (2017)	USA	Crash rate	Matched pair analysis: pair rainfall days with dry days to determine the relative risk of crash	Risk of crashes and injuries increases with increasing daily rainfall totals Urban counties have increased crash risk during rainfall.
Wang et al. (2017)	USA	Fatal crash frequency	Statistical analysis of Fatality Analysis Reporting System (FARS) data	Fatal crashes in rain are three times as likely to involve 10 or more vehicles compared to fatal crashes in good weather
Zhao et al. (2019)	USA	Crash frequency	Random parameters negative binomial models with first-order, autoregressive covariance	Precipitation has a negative association with the crash frequency
Uddin and Huynh (2020)	USA	Probability of crash	Mixed logit models	Factors such as daylight, speed limit 65 mph, and freeways are significant

Author (year)	Country	Dependent variable	Method	Summary of key findings
		occurrence and severity		variables contributing to truck crashes during rainfall conditions
Tobin et al. (2021)	USA	Crash risk	Matched pair analysis of relative crash risk	Crash relative risk is higher during freezing rain, snow, and rain conditions
Aguilar et al. (2021)	USA	Crash frequency	Negative binomial models with random parameters	Higher annual rainfall has a positive association with the passenger car and freight-involved crash frequency

In the literature, findings related to the effect of rainfall on crash occurrence/severity are quite consistent. In most past studies, a positive association between rainfall and crash frequency is observed. A meta-analysis of rainfall-related crash risk in the United Kingdom, Canada, and the United States conducted by Qiu and Nixon (2008) indicated a 31–111% increase in the overall crash rate during rain conditions (they defined rain as total 6-h precipitation amount above 0.4 mm) compared to non-adverse weather conditions.

A few studies have also indicated a negative association between crash occurrence and rainfall (Eisenberg 2004; Zhao et al. 2019). This may be a result of lower speeds or longer headway maintained by riders in these conditions; it could also be attributed to a potential reduction in traffic demand in rainy conditions.

Past studies evaluating the effect of weather conditions such as temperature, snowfall, visibility, sunlight, and wind speed on crash occurrence/severity are summarized in Table 2.

Table 2. Effect of other Weather Conditions on Crash Occurrence/Severity

Author (year)	Weather conditions other than rainfall	Dependent variable	Method	Summary of key findings
Khattak et al. (2001)	Snowfall and wind speed	Crash frequency	Poisson regression	Snow event duration, snowfall intensity, and average wind speed during snow events are important contributing factors to crash frequency
Young and Liesman (2007)	Wind speed	Over-turning-truck crash likelihood	Binary logit model	Wind speed and the difference between measured wind gust speed and average wind speed were found to have a significant influence on overturning-truck crashes
Brijs et al. (2008)	Temperature, wind speed, and sunshine	Crash frequency	Integer autoregressive model	Crash frequency decreased with an increase in absolute temperature and number of hours of sunshine
Malyshkina et al. (2009)	Temperature, snowfall, and visibility	Crash frequency	Markov switching negative binomial model	Severe crashes and minor crashes increased in adverse weather conditions
Abdel-Aty et al. (2011)	Visibility	Crash severity	Multilevel ordered logistic model	Crashes due to low visibility tend to result in more severe injuries and involve more vehicles
Abdel-Aty et al. (2012)	Visibility	Probability of crash occurrence	Bayesian matched case-control logistic regression models	Average speed observed at the nearest downstream station 5–10 min prior to the crash time, coupled with the coefficient of variation in speed observed at the nearest upstream station at the same time, was found to have a significant effect on visibility-related crash risk
El-Basyouny et al. (2012)	Temperature, snowfall, and wind speed	Crash frequency	Full Bayesian multivariate Poisson lognormal models	All types of crashes decreased with an increase in the mean temperature All types of crashes increased with an increase in total daily snow Heavy snowfall decreases the visibility and makes the road surface slippery, leading to a higher number of crashes

Author (year)	Weather conditions other than rainfall	Dependent variable	Method	Summary of key findings
Hassan and Abdel-Aty 2013	Visibility	Probability of crash occurrence	Random forest; matched case-control logistic regression	Traffic flow variables influencing visibility-related crashes are slightly different from those variables influencing clear-visibility crashes
Antoniou et al. (2013)	Temperature	Crash frequency	Generalized linear model with negative binomial distribution; generalized linear model with Poisson and quasi-Poisson distribution	Lower temperature reduces the number crashes due to reduced mobility
Ahmed et al. (2014)	Visibility	Probability of crash occurrence	Logistic regression	Lower-visibility conditions increase the likelihood of crash occurrence
Li et al. (2018)	Visibility	Crash severity	Finite mixture random parameters model	Variables such as rural location, wet pavement, speed limit of 60 mph or higher, no statutory limit, dark lighting, Sunday, curve, rollover, light truck, old driver, and drug/alcohol impairment have a significant influence on low-visibility-related single-vehicle crashes
Heqimi et al. (2018)	Snowfall	Crash frequency	Negative binomial regression	Annual snowfall has a statistically significant positive effect on winter crashes
Gariazzo et al. 2021	Temperature	Crash frequency	Poisson generalized linear regression model	Road crashes are positively associated with hot temperatures

2.3 Limitations of Past Research

2.3.1 The Effect of Weather Conditions on Road Operational Performance

Many past studies have quantified the effect of rainfall and visibility on the operational performance of a road using traffic speed or from a congestion perspective. A limited number of road segments have been used for the analysis in past studies. Further, road characteristics such as functional class and speed limit are neglected in many of the past studies. The effects of rainfall and different visibility ranges over time need to be carefully accounted for in the travel time reliability (TTR) quantification process.

Many researchers in the past have illustrated varying travel time patterns for a segment by day of the week and time of the day. The present research accounts for the temporal element of the travel times and weather conditions by considering travel times for a relatively large number of road segments for one week before and after rainfall and visibility conditions (same day of the week and time of the day). Also, this research proposes a methodological framework to integrate the travel time data and weather data to compare TTR indices under the normal weather condition with those obtained under different intensities of rainfall and visibility impairment (same day of the week and time of the day). Such an integrated data mining framework to assess the effect of weather condition on reliability (TTR) has not been applied in the past.

Most past studies have considered the average values to examine the effect of rainfall and visibility on a road, but that approach may not give a clear picture of what is happening on a road segment (a link). TTR indices such as PTI and TTI can better capture the effect using reliability thresholds; these measures have already been proposed in the past (Wolniak and Mahapatra 2014). Therefore, comparing PTI and TTI thresholds under varying weather conditions can be considered a significant research development. Further, when performing a system-level analysis, normalizing the TTR measure is very important to enable general conclusions about the effect of weather conditions on the TTR. The PTI is considered to be a better TTR index as it normalizes the 95th-percentile travel time for all the road segments in terms of free-flow travel time.

2.3.2 The Effect of Weather Conditions on Crash Occurrence/Severity

The literature shows several studies analyzing the effect of weather events on crash occurrence/crash frequency. However, a general trend can be found that adverse weather and other factors like road characteristics, driver characteristics, vehicle characteristics, seasonal factors, temporal factors, and spatial factors can easily elevate the severity of weather-related crashes. For example, differences in location type (urban/rural) have been shown to affect weather-related crash severity, with rural areas prone to more fatal crashes in comparison to urban areas. As many agencies consider reducing crash severity as the basis of their vision zero plans or the safe system approach, it is important to study and identify crash risk factors associated with the injury severity of weather-related crashes.

This study contributes to the existing literature that analyzes weather-related crash occurrence/severity by conducting a comprehensive review of the past studies on crash statistics, the effect of weather, and the association of crash severity with various explanatory variables. In particular, the list of contributing factors and methods used for crash severity prediction was compiled. An in-depth analysis was also conducted to identify crash risk factors associated with crash occurrence and injury severity for weather-related crashes. This research also differs from past studies by considering many weather conditions (e.g., rain, snow, fog, sleet, hail, freezing rain, drizzle, severe crosswinds, and blowing sand) and other variables such as contributing factors to the crash, road surface conditions, functional class of road, location type, light conditions, road characteristics, driver characteristics, crash type, vehicle type, seasonal factors, temporal factors, and spatial factors in the assessment process.

3. Study Area and Data

This chapter provides an overview of the study area and data used in this research.

3.1 Data Collection

The state of North Carolina is the study area of this research. Travel time data, weather data, road data, and crash data were considered in the assessment process.

3.1.1 Weather Data

The weather and travel time data used in this research were for the years 2017 and 2018. In this research, meteorological data obtained from the Federal Climate Complex Data Documentation for Integrated Surface Data (ISD) were used for analysis. The ISD database from the National Oceanic and Atmospheric Administration (NOAA) and the National Center for Environmental Information (NCEI) contains hourly surface observations for over 20,000 locations across the world (Smith et al. 2011). The database includes various weather indicators such as visibility, rainfall, dew point temperature, and wind speed. In the present research, 10 weather stations in North Carolina were considered in the road segment identification process.

3.1.2 Road Data

The road network data were obtained in a geospatial format (shapefile) from the North Carolina Department of Transportation (NCDOT). The NCDOT's road inventory database provides a digital file that describes a subset of characteristics of the state road network. The state road system consists of interstates, US and NC routes, secondary roads, ramps, and all non-state roads maintained in North Carolina. This database includes speed limit, number of lanes, functional class, etc.

3.1.3 Travel Time Data

The raw travel time data were collected from the Regional Integrated Transportation Information System (RITIS) website, with support from NCDOT, at five-minute intervals. The database contains data corresponding to the date, time of the day, average speed, travel time, and reference speed. Data corresponding to each segment were coded with a nine-digit identification code, referred to as the Traffic Message Channel (TMC) code.

3.1.4 Crash Data

The crash data for North Carolina for the years 2015–2017 were obtained from the Highway Safety Information System (HSIS). The raw crash data were obtained in three subfiles; crash,vehicle, and road. Crashes are typically represented using the case number allotted, while the vehicle subfile contains records of the multiple vehicles involved in the associated case number. Hence, the raw files were combined prior to other data cleaning and filtering processes.

4. Methodology

The methodological framework consists of two different phases. In the first phase, the effect of rainfall and visibility conditions on road traffic time reliability (TTR) is estimated by processing, integrating, and analyzing weather information and travel time data. In the second phase, the likelihood of crash occurrence during different weather conditions is assessed, and potential risk factors contributing to crash severity are identified.

4.1 Effect of Weather Conditions on Travel Time Reliability

The methodological framework adopted for this phase includes the following steps:

- Selection of weather stations in North Carolina
- Identification of road segments
- Data processing
- Integration of weather and travel time data
- Distribution-based quantification of the weather effect on the TTR

4.1.1 Selection of Weather Stations in North Carolina

In this research, 70 weather stations in the state of North Carolina were initially considered in the study segment identification process. The final database includes data from 10 spatially distributed weather stations in North Carolina.

4.1.2 Identification of Road Segments

It is assumed that rainfall and visibility data obtained from a weather station would be consistent for the segments within a 1-mile vicinity of the weather station. ArcGIS software was used to identify road segments within a 1-mile buffer of each selected weather station (Figure 1). Geo-referencing of the road segments was performed using four coordinates collected from the RITIS website. A segment was selected if at least 50% of the total length of the segment is inside the 1-mile buffer around the weather station. The road network data were obtained in a geospatial format (shapefile) from the NCDOT. The spatial join feature in the ArcGIS was employed to join the road characteristics into the segment-level data.

The length of some road segments is less than 0.05 mile. Considering these short segments may result in some bias. Therefore, segments with length less than 0.05 mile were not considered for the analysis. The final database includes 46 separately identified road segments within the vicinity of the 10 weather stations in North Carolina. The study area is shown in Figure 1.

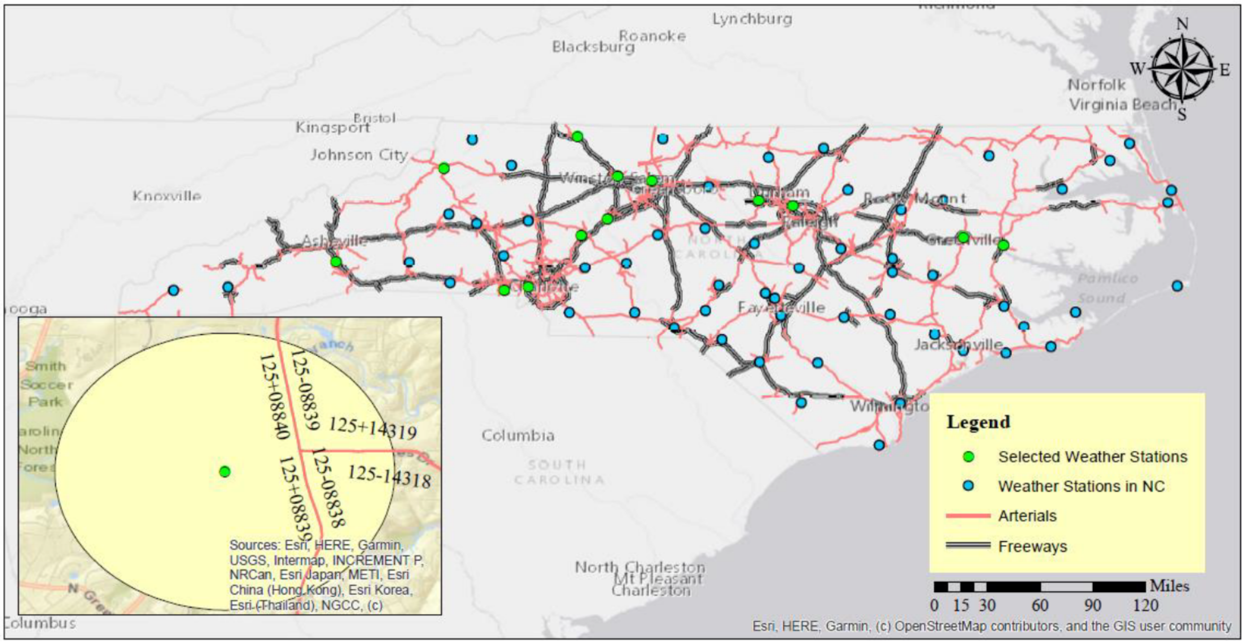


Figure 1. Study Area

4.1.3 Data Processing

Initially, Data related to weather and travel time were processed separately for 2017 and 2018. The data from one week before and after the adverse weather condition was used to minimize the effect of other factors (seasonal variations, lighting conditions, changes in traffic patterns due to road construction activities or other events). Also, the data did not include weekends and federal holidays to minimize the effect of special events and holiday travel patterns.

Based on the time of observation and duration for which rainfall measurements were taken, weather-related data was processed. The data were processed using Microsoft SQL Server to remove the missing values and values which did not pass the quality checks mentioned in the ISD data documentation (NOAA 2018). For example, rainfall data coded as 'erroneous' or 'suspect' were removed. In addition, rainfall with snowfall conditions were also excluded from the database. The average value of visibility was estimated using all the reported visibility values within that hour. The processed database contains the weather station ID, rainfall intensity, visibility, date, and time of the day. Further, identified segments with road characteristics were added into the database by relating the weather station ID. The weather data processing methods and algorithms developed by Duddu et al. (2017), Pulugurtha et al. (2019), and Duddu et al. (2020) were modified and used to accomplish this task.

Since rainfall and visibility observations were obtained hourly, travel time data at five-minute intervals were aggregated every one hour. For example, a weather observation at 11:00 AM would be paired with TTR indices based on travel time observations from 10:01 AM to 11:00 AM.

4.1.4 Integration of Travel Time and Weather Data

The overall process followed in the weather, travel time, and road characteristics data integration is summarized in Figure 2.

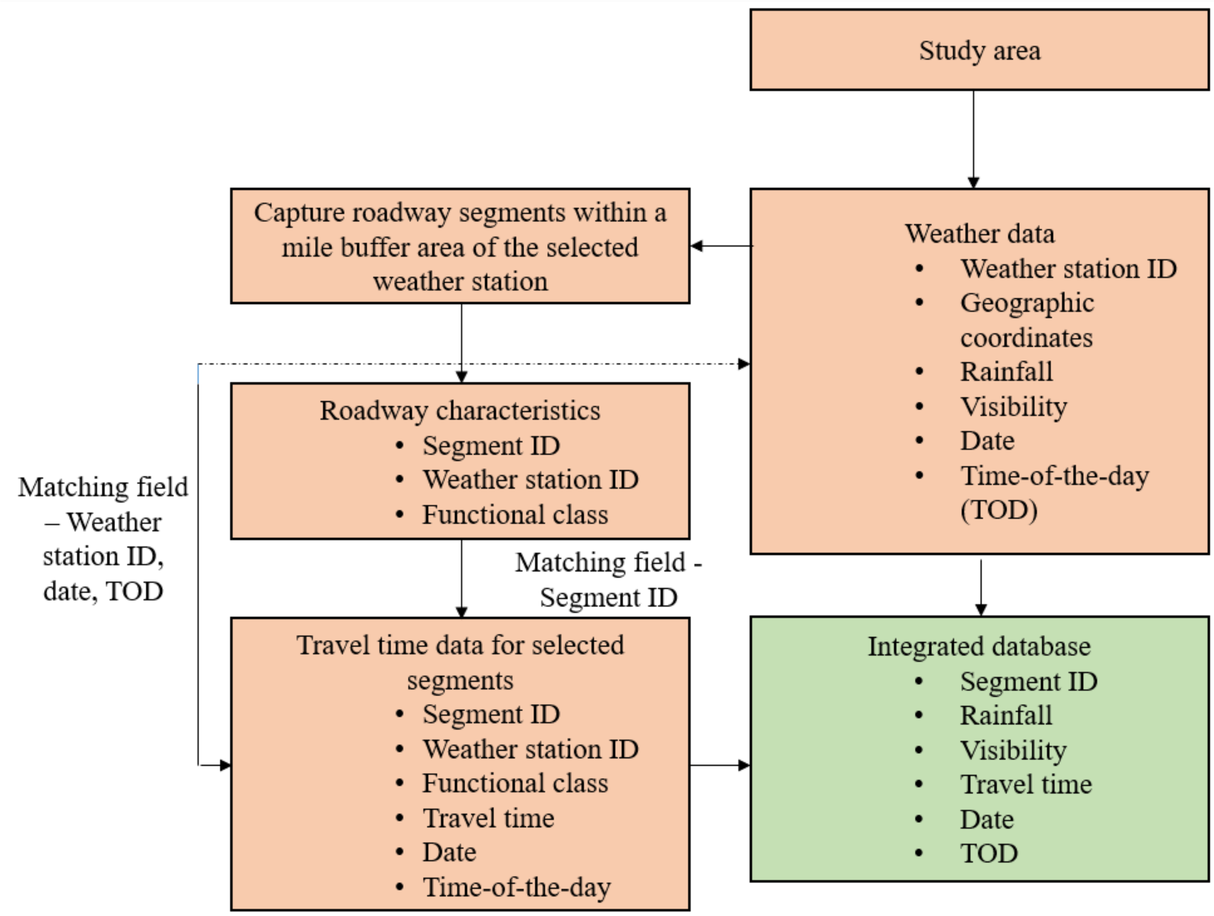


Figure 2. Travel Time and Weather Data Integration Process

The weather database was joined with the travel time database using the common fields in both the databases such as road segment ID, date, and time of the day. The fields in the new database are segment ID, road characteristics, rainfall, visibility, date, time of the day, and travel time. Further, travel time data corresponding to one week before and travel time corresponding to one week after were added into the database. The measurements for one week before and after were recorded at the same time each day, exactly one week apart. If normal weather conditions were not observed one week before and after, data for two or three weeks before and after were considered for the analysis. Plausibly, comparing travel time data for the same time of the day and day of the week during normal weather conditions will minimize the variability in travel patterns. Also, it will reduce the effect of other factors beyond the scope of this research. Overall, a total of 28,247 rainfall and/or visibility conditions were segregated from the initial database and considered for the analysis. The categorized weather conditions and selected variables for the analysis are summarized in Table 3.

Table 3. Selected Weather Conditions and Data Density

Type of road	Weather condition	Variables	Intensity levels	Sample Size (%)
Freeways	Rain (mm/hr)	Light	Trace–2.5	13,886 (81.0%)
		Moderate	2.5–7.6	2,736 (15.9%)
		Heavy	>7.6	523 (3.1%)
	Visibility (m)	Good	>10000	8,327 (48.5%)
		Moderate	4000–10000	5,919 (34.5%)
		Poor	<4000	2,899 (17.0%)
Arterials	Rain (mm/hr)	Light	Trace–2.5	9,308 (83.8%)
		Moderate	2.5–7.6	1,542 (13.8%)
		Heavy	>7.6	252 (2.4%)
	Visibility (m)	Good	>10000	5,101 (45.9%)
		Moderate	4000–10000	4,295 (38.6%)
		Poor	<4000	1,706 (15.5%)

Note: Rain classification per Table 8-1 of the Federal Meteorological Handbook, No. 1and visibility classification per Cho and Kim (2005).

4.1.5 Distribution-Based Quantification of Weather's Effect on Travel Time Reliability (TTR)

The steps followed to evaluate the effect of rainfall and visibility conditions on road traffic TTR are summarized in Figure 3.

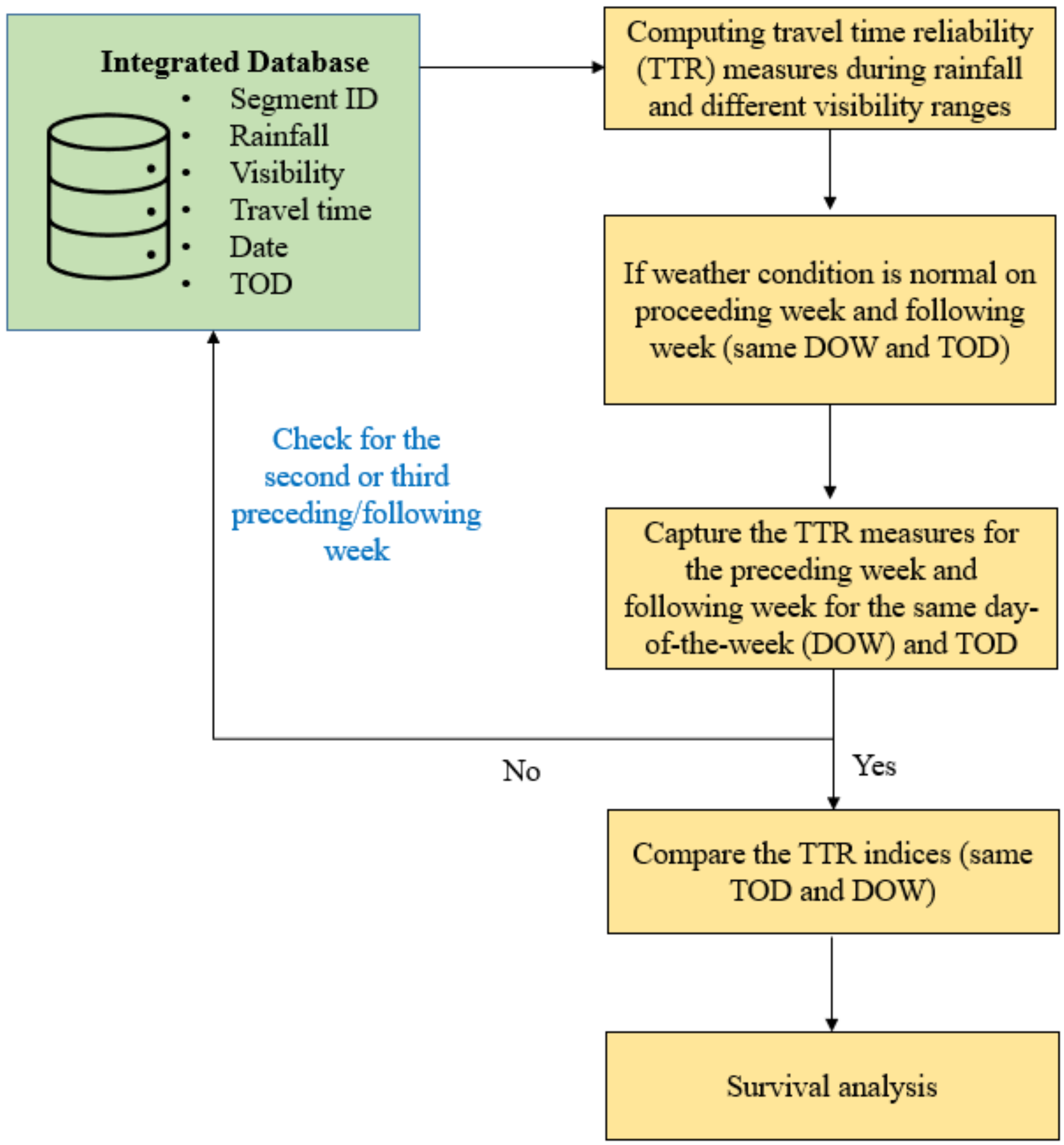


Figure 3. Methodological Framework to Quantify the Weather Effects on TTR

The travel time variability patterns may help in determining the peak and off-peak hours of the day. The ATT, PTI, and TTI, as well as the 95th percentile travel time (PT), were computed for each road segment, for 1-hour intervals, by aggregating data by day of the week and time of the day. The historical free-flow travel time (off-peak free-flow travel time) was used to compute the PTI and TTI to capture the effect of rainfall and visibility conditions on the TTR of the road segment.

The TTI is considered an indicator of congestion. It indicates how much longer the road segment travel times are when there is congestion compared with the normal traffic. The PTI indicates the total travel time required for a traveler to ensure the on-time arrival at their destination. While looking into the TTR, PTI gives useful indications. For example, a PTI value of 1.5 indicates that total trip time under free-flow conditions should be increased by 50% to ensure on-time arrival during congested conditions. When performing a system-level analysis, normalizing the TTR measure is very important to enable general conclusions about the effect of weather conditions on the TTR. The PTI is considered to be a better TTR index as it normalizes the 95th-percentile travel time for all the road segments in terms of free-flow travel time.

Martchouk and Mannering (2009) used the survival function to assess the probability of a trip lasting any specified length of time. The same concept illustrated by Martchouk and Mannering (2009) was employed in this research to evaluate the probability of unreliability for the road segment under any specified value of a selected reliability measure.

We compared empirical survival function plots based on real-world TTR measures to theoretical survival function plots using various distribution fits. A Kolmogorov-Smirnov (KS) test was used to identify the best theoretical distribution (for example, log normal, Weibull, Burr, etc.). The survival function S(t), which indicates the probability that the TTR is more than a specified value, is estimated using Equation 4.

$$S(t) = Pr(TTR > \mathrm{t}) = 1 - F(t) \tag{4}$$

where t is the TTR threshold, TTR is the travel time reliability, and F(t) is the cumulative distribution function.

The probability of a segment being unreliable under normal weather condition and under different rainfall and visibility conditions was tested using the survival analysis. In other words, the likelihood of unreliability in normal and adverse weather conditions is evaluated in this phase of the analysis.

4.2 Effect of Weather Conditions on Crash Occurrence and Crash Severity

The methodological framework adopted for this phase includes the following steps:

- Data processing and filtering
- Modeling the effect of weather on crash occurrence
- Modeling the effect of weather on crash severity

4.2.1 Data Processing and Filtering

The initial processing of crash data involved combining subfiles and removing records with null values. The crash data from the three subfiles (crash, vehicle, and road) are combined using the crash case number and location information (milepost). Crashes are typically represented using the case number allotted, while the vehicle sub-file contains records of the multiple vehicles involved in the associated case number. Hence, the raw files were combined prior to other data cleaning and filtering processes. The combined crash dataset (joining sub-files) contains a unique case number allocated to each crash, with vehicle information provided in separate rows.

Following the data cleaning, variables capturing the crash, location, road, driver, and surrounding area characteristics were chosen for the analysis. In addition, the weather conditions were captured from the weather characteristics in the database. The following categories of weather conditions were considered in this analysis: cloudy, rain, snow, fog/smog, sleet/hail/freezing rain/drizzle, severe crosswinds, or blowing sand.

Injury severity was given a typology of five levels as defined in the HSIS database. They are fatal crash, injury type A, injury type B, injury type class C, and no injury (property damage only, PDO). For the purposes of the present investigation, the crash severity was re-categorized into three levels: severe injury (fatal and injury type A), moderate injury (injury type B and injury type C), and PDO (no injury).

4.2.2 Modeling the Effect of Weather Conditions on Crash Occurrence

Past studies have supported the application of logistic regression for examining the factors associated with the crashes (Sze and Wong 2007). The logistic regression model with a binary dependent variable is used to evaluate the effect of different weather conditions on crash occurrence. Independent variables include crash type and contributing factors, crash location characteristics (lighting condition, locality, etc.), driver (gender and age), road characteristics (functional class, speed limit, etc.), seasonal factors, and temporal factors. Three separate models were developed for each injury severity level. They include separate models for severe injury (fatal and injury type A), moderate injury (injury type B and injury type C), and PDO (no injury). Developing separate models for each injury type will help identify underlying patterns and risk factors associated with the crash occurrence.

Equation (5) represents the general form of logistic regression, where β0 is the model constant and β1, …, βk are unknown parameters corresponding to the independent variables X1, …, Xk. The odds ratio represents the odds of the category to the reference category considered. Reference category is typically used to represent ideal conditions (for example, clear weather conditions - with respect to the weather conditions). The reference categories were chosen and modeled based on the frequency distribution and a detailed inspection of variables. Finally, odds ratio illustrates the likelihood of the event occurring for the response variable category with respect to their reference category (Williams 2006). The maximized log-likelihood expression obtained from Equation (6) is used to compute the odds ratio, shown as Equation (7).

$$\mathrm{Ln}(Y_i) = \mathrm{logit}\,[\pi(x)] = \ln\left(\frac{\pi(x_i)}{I-\pi(x_i)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_k X_k \quad (5)$$

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i} + (1 - \pi(x_i))^{1-y_i} \quad (6)$$

$$\text{Odds Ratio} = e^{\beta_k} \quad (7)$$

Initially, the model with all the independent variables was checked, followed by a stepwise backward elimination of variables whose categories were not found to be significant at a 90% confidence level. On the other hand, an independent variable is included in the model if at least one category is significant at a 90% confidence level.

4.2.3 Modeling the Effect of Weather Conditions on Crash Severity

Risk factors associated with the degree of injury severity in weather-related crashes assist researchers and practitioners in identifying underlying patterns and proposing relevant countermeasures. We categorized crash severity as an ordered response variable ranking injury severity. Hence, discrete choice modeling was adopted for the analysis.

Identifying the effect of the independent variables on injury severity is a main aim in the analysis. Modeling approaches such as the ordered probit/logit assume that independent variables have the same influence on various levels of the dependent variable (injury severity), which may not be true (Savolainen et al. 2011; Eluru and Yasmin 2018). On the other hand, multinomial modeling ignores the ordinal nature of the dependent variable (in this case, injury severity) (Savolainen et al. 2011; Eluru and Yasmin 2018). Hence, a proportional odds model was opted for to overcome the assumptions and limitations of other approaches.

The proportionality odds assumption states that the influence of an independent variable is similar for all dependent variable categories. To assess the applicability of that approach to the developed dataset, the proportional odds test was performed. The null hypothesis states that all the independent variables have equal slopes across the dependent variable categories. The obtained p-value was less than 0.05, resulting in the rejection of the stated null hypothesis. Hence, the nonproportional odds test was conducted to examine, for each variable, whether it has an equal or unequal slope. Based on the obtained p-values, unequal slopes were allocated for the variables, prompting a rejection of the null hypothesis (that all the independent variables have unequal slopes). The partial proportional odds model was then developed using an equal or unequal slope option for each independent variable. The model uses a reference category through which the results are interpreted. In the present research, the reference categories were chosen and modeled based on the frequency distribution and a detailed inspection of variables. The PDO (or no injury) severity is considered as the reference category for the dependent variable in this research. For each independent variable, the reference category is compared with the results of other categories of the same independent variable. For example, passenger car is the reference category in the case of vehicle type variable and other categories include pickup, light truck, van, bus, motor scooter, etc.

Equation (8) represents a partial proportional odds model with ordinal dependent variable Yi as the injury severity level of crash i (with i 1) and Xj as independent variables (Williams 2006). The model has (i-1) intercepts with j slopes. The model prediction is called the expected logit. The expected logit for each variable of interest are used to calculate cumulative probabilities using Equation (9) (Williams 2006).

$$\mathrm{Ln}(Y_i) = \mathrm{logit}\,[\pi(x)] = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + (\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_j X_j) \tag{8}$$

$$P(Y \geq i) = \frac{e^{\beta_0 + (\beta_1 X_1 + \cdots + \beta_j X_j)}}{1 + e^{\beta_0 + (\beta_1 X_1 + \cdots + \beta_j X_j)}} = \frac{e^{\ln(Y_i)}}{1 + e^{\ln(Y_i)}} \tag{9}$$

where the function (x) indicates the probability of a resulting outcome, β_0 is the constant, and β_1, …, β_j are the coefficients, which are the unknown parameters corresponding to independent variables X_1, …, Xj (Williams 2006).

Similar to the binary logistic regression model, a stepwise backward elimination was performed for the partial proportional odds model in such a way that the independent variables are included if at least one category is significant (at a 90% confidence level).

5. Effect of Weather Conditions on Travel Time Reliability

The previous chapter outlined the methodological approach used to investigate the effect of weather condition on road segment. This chapter presents the results of the analysis of the effect of weather condition on road segments' TTR. The analysis was carried out separately for the freeway segments and urban arterial road segments.

5.1 Effect of Rainfall and Visibility on Urban Freeway Segment

Table 4 shows the percentage of differences in TTR indices for the freeway road segments (functional class 1 and 2) for selected categories of rainfall and visibility compared to the normal weather condition. Eighteen freeway segments were considered in the analysis. The speed limit for the selected segments is 60 mph or 65 mph. Hence, all freeway segments are considered together for the analysis.

Table 4. TTR Indices for Freeways in Different Weather Conditions

Weather condition	**Intensity**	**Change in the TTR**			
		ATT	**PT**	**PTI**	**TTI**
Rain	Light	+1.50%	+1.25%	+2.22%	+3.06%
	Moderate	+2.50%	+1.25%	+0.06%	+0.90%
	Heavy	+2.08%	+1.96%	+4.90%	+4.91%
Rain and visibility	Light rain with moderate visibility	+6.75%	+7.92%	+11.11%	+8.16%
	Light rain with poor visibility	+9.32%	+8.78%	+8.70%	+8.59%
	Moderate rain with moderate visibility	-0.27%	-4.30%	-4.22%%	+0.96%
	Moderate rain with poor visibility	+7.66%	+13.08%	+8.60%	+7.55%
	Heavy rain with moderate visibility	+1.29%	+2.25%	+0.43%	+0.40%
	Heavy rain with poor visibility	+5.50%	+8.54%	+12.24%	+8.69%

From Table 4, notice that the poor visibility along with rainfall intensity has the maximum adverse effect on the TTR. Heavy rain and poor visibility were associated with a 5.50% increase in the ATT and a 12.24% increase in PTI on urban freeway road segments. Similarly, the moderate rain with poor visibility condition resulted in a 9.32% increase in ATT. The light rain with poor visibility condition also resulted in noticeable (7.55% to 13.08%) increases in various TTR indices. The effect of heavy rain on the TTR in moderate- and good-visibility conditions was found to be minimal. Most of the cases with heavy rain resulted in poor visibility.

Past studies have reported different outcomes related to rainfall and visibility effects accounting for the network, traffic, and socio-economic characteristics of the study area. They showed that the effect of light rain on travel time or operating speed is minimal (Maze et al. 2006; Datla and Sharma 2008; Smith et al. 2004; Tsapakis et al. 2013). According to the findings from present research, light rain can cause a 1.25% to 3.06% increase in the TTR without any decreased visibility. However, the effect will be higher under conditions with adverse (moderate or poor) visibility.

PTI-based analysis was carried out to find the percentage of reliable conditions and unreliable conditions during different rainfall intensities and associated visibility ranges. The estimated PTI values were compared for rainfall/visibility and normal weather conditions. A PTI value less than 1.5 is considered as reliable, a PTI value between 1.5 and 2.5 is considered as moderately to highly unreliable, and a PTI value greater than 2.5 is extremely unreliable (Wolniak and Mahapatra 2014). Light rain with poor visibility caused the maximum number of unreliable events; ~4% of the total samples were extremely unreliable during the light rain with poor visibility condition. In the case of moderate rain and poor visibility, ~25% of the total samples were moderately to highly unreliable.

As noted previously, the reliability of the segments is lower during the poor visibility condition. To understand the probability of a road segment being unreliable (based on PTI thresholds) under different intensities of rainfall and visibility, survival functions were developed. The parametric approach was adopted as smaller sample sizes associated with some of the selected cases like heavy rain and poor visibility reduced the accuracy of the non-parametric estimates. Similarly, the distributions were not continuous in many cases. Past studies indicated that lognormal distribution is generally suitable for modeling the travel time data.

To identify the best distribution, the goodness-of-fit for some of the theoretical distributions was plotted and tested using the Kolmogorov-Smirnov (KS) test. This was done for lognormal distribution, Weibull distribution, Gamma distribution, Burr distribution, and three-parameter lognormal distribution.

From the KS test results, a three-parameter lognormal distribution was found to be the best survival function to model PTI. This is in line with the work of Zhang et al. (2016), who pointed out the applicability of three-parameter lognormal distribution in travel time modeling. Figure 4 illustrates the comparison of theoretical survival functions (three-parameter lognormal distribution) with the empirical survival function (using the real-world-data-based PTI values).

From Figure 4, the empirical survival function approximates the three-parameter lognormal distribution quite well.

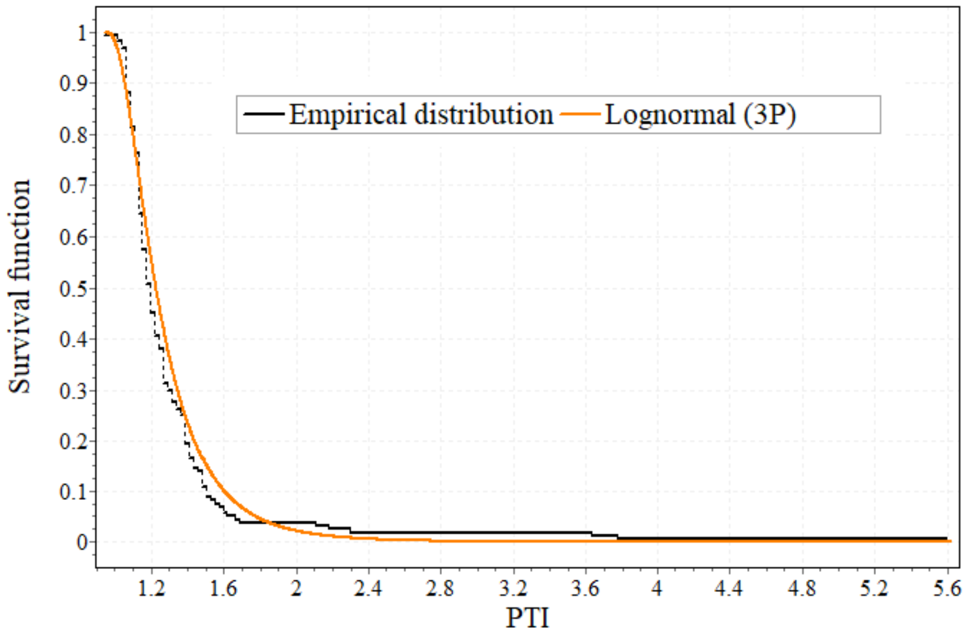


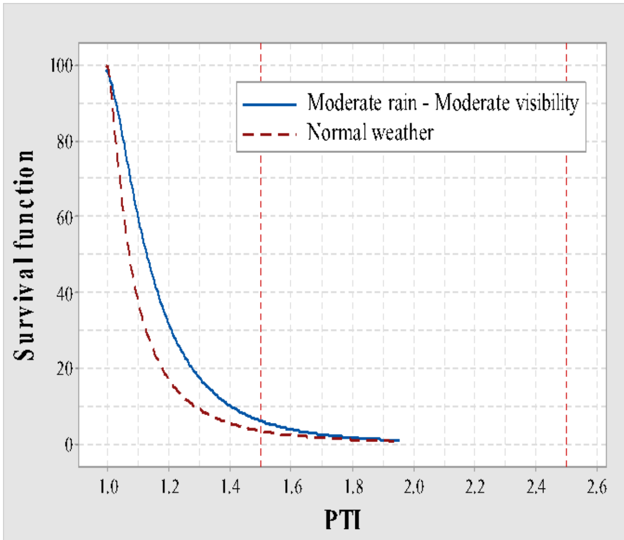
Figure 4. Comparison of Three-Parameter Lognormal Distribution with Empirical Distribution

The density function for the three-parameter lognormal distribution is shown in Equation 10:

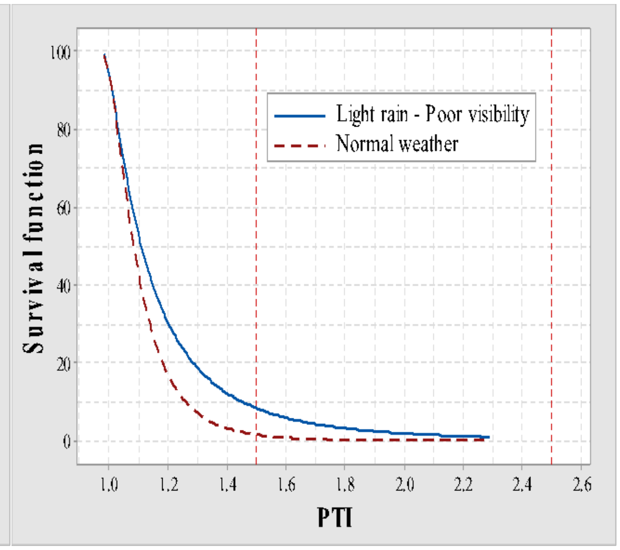
$$f(x) = \frac{1}{(\chi-\gamma)\sqrt{2\pi\sigma}}.\exp\left(-\frac{1}{2}.\left(\frac{\ln(\chi-\gamma)-\mu}{\sigma}\right)^2\right) \tag{10}$$

where μ, σ, and γ are the parameters (location, scale, and threshold, respectively) of the lognormal distribution.

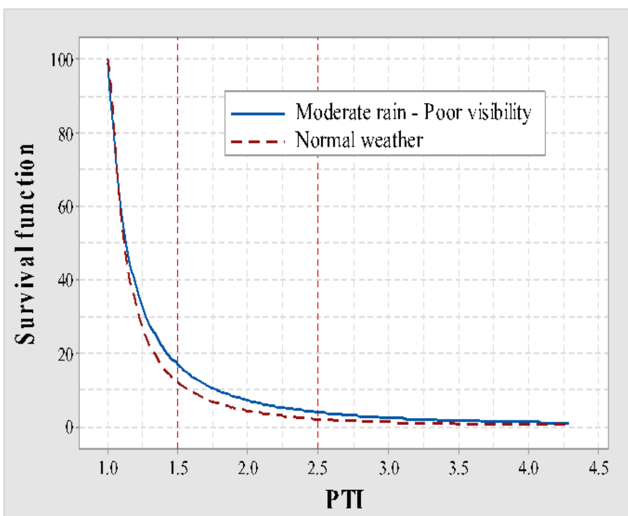
The survival function plots developed using three-parameter lognormal distribution for the freeway segments are shown in Figure 5.



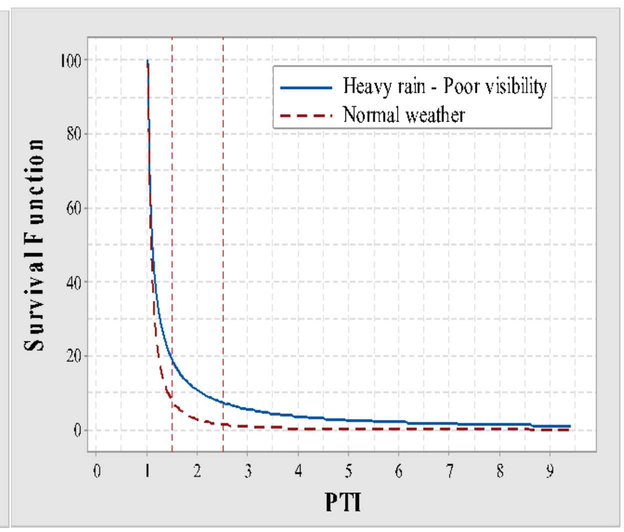
a. Moderate rain with moderate visibility



b. Light rain with poor visibility



c. Moderate rain with poor visibility



d. Heavy rain with poor visibility

Figure 5. PTI-based Survival Function Plots for Freeways Under Different Weather Conditions

Under rainfall and poor visibility conditions, the survival function shifts to the right (increasing PTI values), increasing the probability of the segment being unreliable. In other words, the probability of becoming unreliable is less in the case of normal weather conditions. From Figure 5(d), note that the maximum difference between the curves is between a PTI of 1.15 to 2.2, which corresponds to the moderately to highly unreliable traffic condition in the road segments. For example, the probability of reaching a moderately to highly unreliable state (PTI>1.5) is almost 10% higher in the case of heavy rain with poor visibility condition than for the normal weather condition. Overall, the effect of rainfall and reduced visibility on the TTR is found to be less during the free-flow state and the highly congested state. A PTI value less than 1.5 indicate no congestion on the road segment, and PTI values greater than 2.8 indicate high congestion (Gore and Pulugurtha 2021). The shift is minimal in both cases.

A summary of the survival statistics is provided in Table 5. The probability of observing unreliable conditions is higher in the case of the heavy rain with poor visibility condition and the heavy rain with moderate visibility condition.

Table 5. Survival Analysis Summary for Freeway Segments

Weather condition	Intensity	Reliable		Moderately to highly unreliable		Extremely unreliable	
		Adverse	Normal	Adverse	Normal	Adverse	Normal
Rain	Light rain	84.50%	86.28%	15.55%	13.72%	0.51%	0.39%
	Moderate rain	87.02%	90.01%	12.97%	9.99%	0.27%	0.21%
	Heavy rain	85.84%	94.87%	14.16%	5.13%	3.30%	<0.01%
Rain and visibility	Light rain with moderate visibility	78.36%	85.69%	22.64%	14.31%	2.03%	0.38%
	Light rain with poor visibility	71.17%	79.72%	28.83%	20.28%	3.90%	1.56%
	Moderate rain with moderate visibility	88.77%	85.32%	11.23%	14.68%	0.15%	0.43%
	Moderate rain with poor visibility	75.61%	83.09%	24.39%	16.91%	2.45%	0.86%
	Heavy rain with moderate visibility	91.81%	94.28%	8.19%	5.72%	<0.01%	<0.01%
	Heavy rain with poor visibility	84.45%	98.84%	15.44%	1.16%	0.41%	<0.01%

5.2 Effect of Rainfall and Visibility on Urban Arterial Road Segments

This analysis also considered road segments of functional class 3 and 4 (principal arterial and minor arterial). A total of 28 urban arterial segments were evaluated to quantify the effect of rainfall and visibility on TTR indices. For these segments, Table 6 shows the percentage differences in TTR indices for selected intensities of rainfall and visibility conditions compared to the normal weather condition.

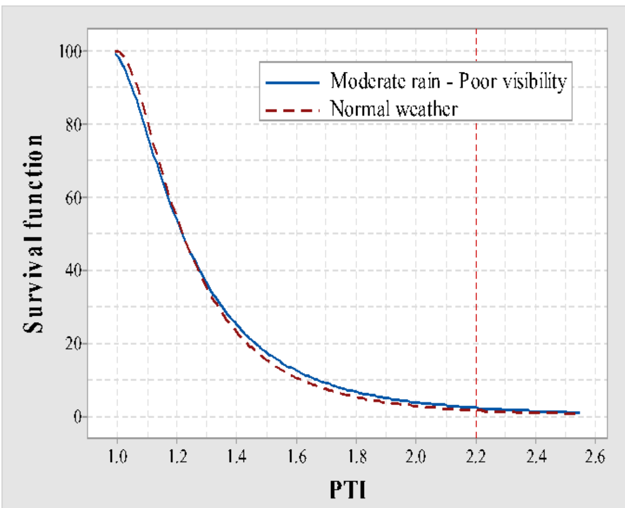
Table 6. TTR Indices for Urban Arterials in Different Weather Conditions

Weather condition	Intensity	Change in the TTR			
		ATT	PT	PTI	TTI
Rain	Light	+0.04%	-0.30%	-0.12%	+1.01%
	Moderate	+2.70%	-3.21%	-2.91%	4.31%
	Heavy	+1.10%	+8.88%	+6.70%	+7.91%
Rain and visibility	Light rain with moderate visibility	+1.21%	-1.68%	-1.53%	+1.50%
	Light rain with poor visibility	+5.79%	+3.78%	+2.98%	+6.17%
	Moderate rain with moderate visibility	-1.90%	-4.86%	-5.75%	-0.06%
	Moderate rain with poor visibility	+6.70%	+6.52%	+1.14%	0.24%
	Heavy rain with moderate visibility	+4.58%	+3.51%	+0.06%	+2.72%
	Heavy rain with poor visibility	+3.20%	+3.63%	+4.02%	+1.22%

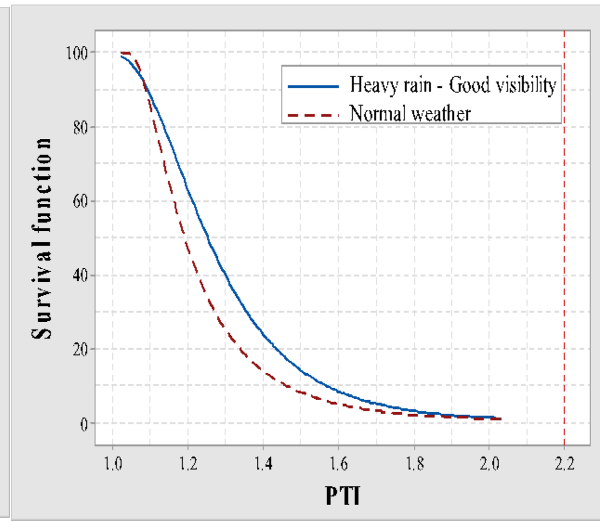
From Table 6, note that the heavy rain condition corresponds to the highest change in the TTR. Under the heavy rain condition without any decreased visibility, PTI increased by 6.70%. Similarly, PTI increased by 2.98% in the case of light rain with poor visibility, and PTI increased by 4.02% in the case of heavy rain with poor visibility. A 1.22% to 7.91% increase in TTI was observed for the heavy rain condition. However, the light and moderate rain conditions did not have much of an effect on TTR indices. Overall, the change in TTR indices was found to be lower on arterial road segments than on freeway road segments.

Survival functions plots were developed to evaluate the probability of an arterial road segment being unreliable under rainfall and different visibility conditions (Figure 6). In most cases, the survival function plots are similar for the normal weather condition and adverse weather condition.

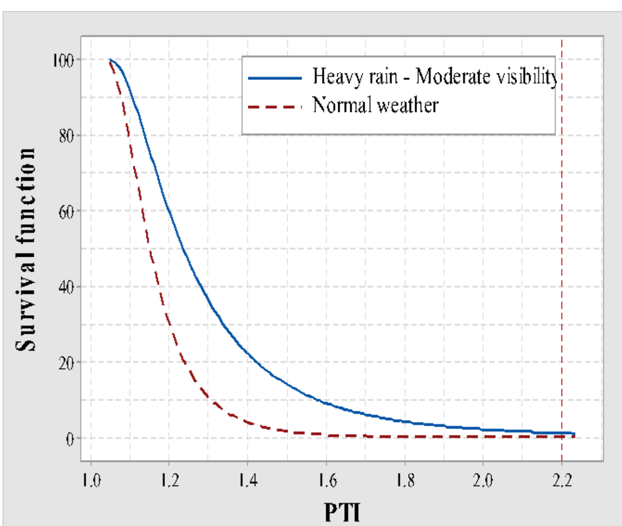
The PTI thresholds for urban arterial segments were assessed based on the TTI reliability rating guidelines suggested by Cambridge Systematics et al. (2014). A PTI value less than 2.2 is considered reliable, a PTI value between 2.2 and 3.5 is considered moderately to highly unreliable, and a PTI value greater than 3.5 is considered extremely unreliable.



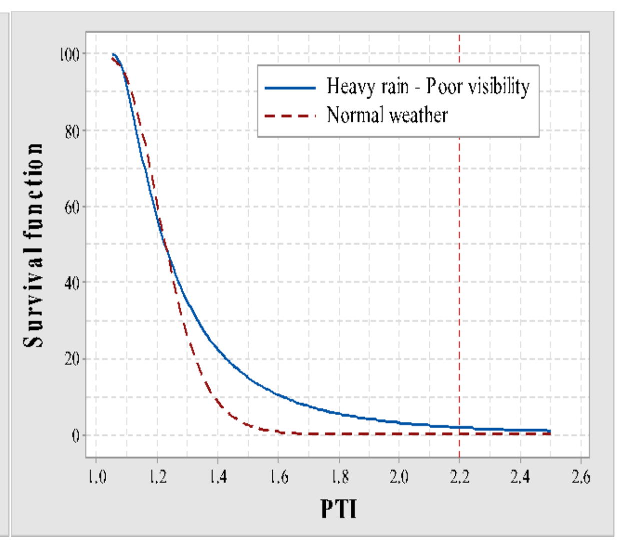
a. Moderate rain with poor visibility



b. Heavy rain with good visibility



c. Heavy rain with moderate visibility



d. Heavy rain with poor visibility

Figure 6. PTI-based Survival Function Plots for Arterial Roads under Different Weather Conditions

A summary of survival statistics for the urban arterial road segments is provided in Table 7. The effect of rainfall and visibility on the TTR was found to be minimal on the arterial road segments, which can be attributed to the traffic and operating characteristics of the arterial roads. In general, the operating speeds are lower on urban arterials when compared to freeways. Also, the presence of signalized intersections and other entry/exit points, as well as frequently used stops, may nullify the overall effect of weather conditions on urban arterial streets. The possible reduction in travel demand under raining conditions can also account for such a steady trend in the TTR.

Table 7. Survival Analysis Summary for Urban Arterials

Weather condition	Intensity	Reliable		Moderately to highly unreliable		Extremely unreliable	
		Adverse	Normal	Adverse	Normal	Adverse	Normal
Rain	Light rain	72.10%	70.20%	27.90%	29.80%	8.08%	6.80%
	Moderate rain	79.95%	77.68%	20.05%	22.32%	4.55%	4.92%
	Heavy rain	78.51%	88.67%	21.49%	11.37%	3.51%	1.82%
Rain and visibility	Light rain with moderate visibility	69.30%	66.53%	30.70%	33.47%	9.67%	9.23%
	Light rain with poor visibility	66.71%	67.72%	33.29%	32.28%	10.94%	9.37%
	Moderate rain with moderate visibility	76.29%	72.61%	23.71%	27.39%	5.92%	6.56%
	Moderate rain with poor visibility	71.60%	70.69%	28.40%	29.31%	8.88%	7.82%
	Heavy rain with moderate visibility	80.63%	80.10%	19.37%	19.90%	4.37%	2.95%
	Heavy rain with poor visibility	75.15%	78.10%	24.85%	21.91%	5.79%	4.50%

6. Effect of Weather Conditions on Crash Occurrence

A total of 935,005 crash-vehicle records from 2015 to 2017 in North Carolina were considered for the analysis after removing the outliers and null records. These records were further segregated based on the injury severity of the crash, after which a binary logistic regression analysis was conducted.

6.1 Descriptive Analysis

Table 8 summarizes the frequency distribution of the data categorized based on crash injury severity. For the binary variables, "0" represents the crash in normal weather, and "1" represents extreme weather (cloudy, rain, snow, fog/smog/smoke, sleet/hail/freezing rain/drizzle, severe crosswinds, or blowing sand/dirt/snow).

A subset of the complete dataset (with all injury severity levels) with adverse weather conditions was used for modeling injury severity using a partial proportional odds model. This subset dataset, which includes information on the weather-related crashes, comprises a total of 238,252 crash-vehicle records. Table 9 summarizes the frequency distribution of the crashes that occurred during different weather conditions.

Table 8. Frequency Distribution of Crash Data for Binary Logistic Regression

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Weather condition	0	Normal weather conditions	10,918	78.72	210,305	74.58	475,530	74.40
	1	Weather conditions (cloudy, rain, snow, fog/smog/smoke, sleet/hail/freezing rain/drizzle, severe crosswinds, or blowing sand/dirt/snow)	2,952	21.28	71,688	25.42	163,612	25.60
Contributing factor of the crash	1	No contributing factors	5,611	40.45	132,116	46.85	319,450	49.98
	2	Disregarding signs or signals	523	3.77	9,247	3.28	10,307	1.61
	3	Exceeded safe speed/speed limit or fail to reduce speed	1,914	13.80	54,231	19.23	124,028	19.41
	4	Improper turn or right turn on red	75	0.54	3,199	1.13	8,722	1.36

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
	5	Crossed centerline, improper lane change, or use of an improper lane	1,076	7.76	9,106	3.23	27,528	4.31
	6	Overcorrected, oversteered, improper passing, or improper backing	491	3.54	6,102	2.16	10,824	1.69
	7	Failing to yield to the right-of-way, or driver inattention	1,503	10.84	40,054	14.20	81,676	12.78
	8	Operating too closely, aggressive driving, or alcohol use	2,211	15.94	16,550	5.87	24,906	3.90
	9	Visibility obstruction, or defective equipment	74	0.53	1,690	0.60	4,611	0.72
	10	Other/unable to determine	392	2.83	9,698	3.44	27,090	4.24
	1	Dry	12,040	86.81	234,132	83.03	527,194	82.48

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Road surface condition	2	Wet, presence of water (standing/moving)	1,711	12.34	44,345	15.73	100,185	15.67
	3	Ice, snow, slush	101	0.73	3,358	1.19	11,479	1.80
	4	Sand, mud, dirt, gravel, fuel, or oil	18	0.13	158	0.06	284	0.04
Functional class of road	1	Principal arterial – interstate, freeways and expressways	1,756	12.66	44,864	15.91	129,191	20.21
	2	Principal arterial – other	3,220	23.22	92,424	32.78	200,271	31.33
	3	Minor arterial	3,210	23.14	74,786	26.52	159,694	24.99
	4	Major collector	3,650	26.32	45,900	16.28	93,015	14.55
	5	Local	2,034	14.66	24,019	8.52	56,971	8.91
Location type	0	Non-intersection	11,682	84.22	225,933	80.12	543,900	85.10
	1	Intersection	2,188	15.78	56,060	19.88	95,242	14.90
	1	Daylight	8,617	62.13	210,299	74.58	478,229	74.82

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Light condition	2	Dusk, and dawn	550	3.97	10,660	3.78	23,792	3.72
	3	Dark lighted roadway/unknown lighting	1,096	7.90	27,798	9.86	55,771	8.73
	4	Roadway not lighted	3,607	26.01	33,236	11.79	81,350	12.73
Road characteristic	1	Straight-leveled road	8,268	59.61	208,204	73.83	492,194	77.01
	2	Straight-grade/hillcrest/bottom	2,186	15.76	44,729	15.86	95,576	14.95
	3	Curve-leveled/grade/hillcrest	3,409	24.58	28,848	10.23	50,776	7.94
	4	Not stated/unknown	7	0.05	212	0.08	596	0.09
Driver gender	1	Male	9,417	67.89	151,487	53.72	354,819	55.51
	2	Female	4,453	32.11	130,506	46.28	284,323	44.49
Driver age	1	15–19 years	1,074	7.74	26,335	9.34	59,643	9.33
	2	19–69 years	11,782	84.95	238,526	84.59	543,020	84.96

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
	3	70 years	1,014	7.31	17,132	6.08	36,479	5.71
Speed limit class	1	20 mph	41	0.30	1,844	0.65	6,979	1.09
	2	20–30 mph* (30 mph included)	111	0.80	4,196	1.49	12,515	1.96
	3	30–40 mph	1,460	10.53	63,018	22.35	146,219	22.88
	4	40–50 mph	4,222	30.44	113,687	40.32	243,990	38.17
	5	50–60 mph	6,847	49.37	78,069	27.68	164,546	25.74
	6	>60 mph	1,189	8.57	21,179	7.51	64,893	10.15
Crash type	1	Ran off-road	483	3.48	7,472	2.65	12,693	1.99
	2	Jackknife, overturn/rollover	721	5.20	5,101	1.81	3,548	0.56
	3	Pedestrian/pedal cyclist	771	5.56	2,139	0.76	277	0.04
	4	Animal or movable object	130	0.94	3,272	1.16	51,722	8.09

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
	5	Parked vehicle or fixed object	2,857	20.60	27,121	9.62	51,883	8.12
	6	Rear-end collision	1,999	14.41	120,938	42.89	272,474	42.63
	7	Left-/right-turn crashes	1,957	14.11	40,099	14.22	66,133	10.35
	8	Head-on collision	1,772	12.78	5,374	1.91	2,406	0.38
	9	Sideswipe or angle collision	2,848	20.53	65,766	23.32	159,286	24.92
	10	Other	332	2.39	4,711	1.67	18,720	2.93
Work zone area	0	No	13,554	97.72	273,270	96.91	619,599	96.94
	1	Yes	316	2.28	8,723	3.09	19,543	3.06
Vehicle type	1	Passenger car/taxi	6,071	43.77	156,095	55.35	352,534	55.16
	2	Pickup, light truck, sports utility, or van	5,424	39.11	110,343	39.13	257,200	40.24
	3	Commercial bus, school bus, activity bus, other bus	50	0.36	893	0.32	2,388	0.37

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
	4	Single unit truck, truck/trailer, truck/tractor, tractor doubles, semitrailer, farm equipment, or other heavy trucks	814	5.87	7,422	2.63	22,757	3.56
	5	Motor scooter, moped, pedal cycle, or motorcycle	1,464	10.56	6,465	2.29	1,387	0.22
	6	Other	47	0.34	775	0.27	2,876	0.45
Seasonal factors	1	Spring	2,663	19.20	62,084	22.02	147,774	23.12
	2	Summer	3,607	26.01	72,671	25.77	156,067	24.42
	3	Autumn	3,691	26.61	71,544	25.37	152,967	23.93
	4	Winter	3,909	28.18	75,694	26.84	182,334	28.53
Road terrain	1	Flat	3,593	25.90	53,673	19.03	118,349	18.52
	2	Rolling	9,158	66.03	210,927	74.80	475,799	74.44
	3	Mountainous	1,119	8.07	17,393	6.17	44,994	7.04

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Time of the day	1	12:00 AM – 03:00 AM	850	6.13	7,794	2.76	15,357	2.40
	2	03:00 AM – 06:00 AM	743	5.36	6,488	2.30	15,118	2.37
	3	06:00 AM – 09:00 AM	1,517	10.94	38,082	13.50	94,136	14.73
	4	09:00 AM – 12:00 PM	1,684	12.14	36,774	13.04	83,236	13.02
	5	12:00 PM – 03:00 PM	2,206	15.90	54,867	19.46	121,328	18.98
	6	03:00 PM – 06:00 PM	2,958	21.33	76,485	27.12	172,967	27.06
	7	06:00 PM – 09:00 PM	2,380	17.16	42,708	15.15	97,298	15.22
	8	09:00 PM – 12:00 PM	1,532	11.05	18,795	6.67	39,702	6.21
Day of the week	1	Sunday	1,854	13.37	27,125	9.62	53,268	8.33
	2	Monday	1,821	13.13	41,088	14.57	96,203	15.05

Variable	Categories	Description	Severe injury		Moderate injury		No injury	
			Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
	3	Tuesday	1,897	13.68	42,838	15.19	100,534	15.73
	4	Wednesday	1,964	14.16	42,777	15.17	99,707	15.60
	5	Thursday	1,906	13.74	42,439	15.05	100,475	15.72
	6	Friday	2,222	16.02	50,441	17.89	116,935	18.30
	7	Saturday	2,206	15.90	35,285	12.51	72,020	11.27
Locality	1	Agricultural	7,380	53.21	79,949	28.35	176,207	27.57
	2	Residential	2,930	21.12	54,476	19.32	107,156	16.77
	3	Commercial	3,441	24.81	143,630	50.93	347,260	54.33
	4	Institutional	68	0.49	2,186	0.78	4,970	0.78
	5	Industrial	51	0.37	1,752	0.62	3,549	0.56

Table 9. Frequency Distribution of Weather-Related Crash Data for Partial Proportional Odds Model

Variable	Categories	Description	Frequency	Percentage
Crash injury severity	1	Fatal + type A injury (Severe injury)	2,952	1.24
	2	Type B + type C injury (Moderate injury)	71,688	30.09
	3	PDO (No injury)	163,612	68.67
Contributing factor of the crash	1	No contributing factors	108,397	45.50
	2	Disregarding signs or signals	4,714	1.98
	3	Exceeded safe speed/speed limit or fail to reduce speed	59,501	24.97
	4	Improper turn or right turn on red	2,726	1.14
	5	Crossed centerline, improper lane change, or use of an improper lane	8,459	3.55
	6	Overcorrected, oversteered, improper passing, or improper backing	4,599	1.93
	7	Failing to yield to the right-of-way, or driver inattention	28,284	11.87
	8	Operating too closely, aggressive driving, or alcohol use	10,775	4.52
	9	Visibility obstruction, or defective equipment	1,762	0.74
	10	Other/unable to determine	9,035	3.79
Road surface condition	1	Dry	89,032	37.37
	2	Wet, presence of water (standing/moving)	137,076	57.53
	3	Ice, snow, slush	12,037	5.05
	4	Sand, mud, dirt, gravel, fuel, or oil	107	0.04
Functional class of road	1	Principal arterial – interstate, freeways, and expressways	48,021	20.16
	2	Principal arterial – other	73,729	30.95
	3	Minor arterial	58,915	24.73
	4	Major collector	36,898	15.49
	5	Local	20,689	8.68
Location type	0	Non-intersection	198,679	83.39
	1	Intersection	39,573	16.61
Light condition	1	Daylight	171,369	71.93
	2	Dusk, and dawn	11,544	4.85
	3	Dark-lighted roadway/unknown lighting	22,596	9.48
	4	Roadway not lighted	32,743	13.74
Road characteristic	1	Straight-leveled road	170,529	71.58
	2	Straight-grade/hillcrest/bottom	40,598	17.04
	3	Curve-leveled/grade/hillcrest	26,885	11.28
	4	Not stated/unknown	240	0.10

Variable	Categories	Description	Frequency	Percentage
Driver gender	1	Male	132,369	55.56
	2	Female	105,883	44.44
Driver age	1	15–19 years	24,057	10.10
	2	19–69 years	201,992	84.78
	3	70 years	12,203	5.12
Speed limit class	1	20 mph	1,902	0.80
	2	20–30 mph* (30 mph included)	4,123	1.73
	3	30–40 mph	51,552	21.64
	4	40–50 mph	91,627	38.46
	5	50–60 mph	64,066	26.89
	6	>60 mph	24,982	10.49
Crash type	1	Ran off-road	8,227	3.45
	2	Jackknife, overturn/rollover	2,591	1.09
	3	Pedestrian/pedal cyclist	723	0.30
	4	Animal or movable object	10,040	4.21
	5	Parked vehicle or fixed object	31,971	13.42
	6	Rear-end collision	97,476	40.91
	7	Left/right turn crashes	24,929	10.46
	8	Head-on collision	2,713	1.14
	9	Sideswipe or angle collision	53,729	22.55
	10	Other	5,853	2.46
Work zone area	0	No	232,137	97.43
	1	Yes	6,115	2.57
Vehicle type	1	Passenger car/taxi	132,166	55.47
	2	Pickup, light truck, sports utility, or van	95,432	40.06
	3	Commercial bus, school bus, activity bus, other bus	861	0.36
	4	Single unit truck, truck/trailer, truck/tractor, tractor doubles, semitrailer, farm equipment, or other heavy trucks	7,596	3.19
	5	Motor scooter, moped, pedal cycle, or motorcycle	1,240	0.52
	6	Other	957	0.40
Seasonal factors	1	Spring	63,166	26.51
	2	Summer	56,420	23.68
	3	Autumn	49,767	20.89
	4	Winter	68,899	28.92
Road terrain	1	Flat	43,914	18.43
	2	Rolling	175,906	73.83
	3	Mountainous	18,432	7.74

Variable	Categories	Description	Frequency	Percentage
Time of the day	1	12:00 AM – 03:00 AM	6,232	2.62
	2	03:00 AM – 06:00 AM	6,438	2.70
	3	06:00 AM – 09:00 AM	41,300	17.33
	4	09:00 AM – 12:00 PM	31,914	13.40
	5	12:00 PM – 03:00 PM	43,471	18.25
	6	03:00 PM – 06:00 PM	60,352	25.33
	7	06:00 PM – 09:00 PM	34,067	14.30
	8	09:00 PM – 12:00 PM	14,478	6.08
Day of the week	1	Sunday	20,018	8.40
	2	Monday	42,080	17.66
	3	Tuesday	41,405	17.38
	4	Wednesday	35,470	14.89
	5	Thursday	33,086	13.89
	6	Friday	41,653	17.48
	7	Saturday	24,540	10.30
Locality	1	Agricultural	70,680	29.67
	2	Residential	41,886	17.58
	3	Commercial	122,176	51.28
	4	Institutional	2,012	0.84
	5	Industrial	1,498	0.63

In total, 1.24% of the crashes observed during the study period (2,952) resulted in severe injuries (Table 9). Literature documents that the number of observations should be five to ten times the number of independent variables for adopting methods such as those used in this research (Peduzzi et al. 1996). Therefore, the sample size was considered reasonable for analysis and modeling even using severe injury crash data.

6.2 Maximum Likelihood and Odds Ratio Estimates: Weather-Related Crash Occurrence Model

Table 10 shows the maximum likelihood and odds ratio estimates for the binary logistic regression modeling of weather-related crash occurrence. The results for the models developed using each level of injury severity are shown in Table 10. The estimates which are significant at a 90% and 95% confidence level are indicated with an asterisk (*) and double asterisk (**), respectively, following the number.

The odds ratio is defined as the likelihood of the event occurring for the response variable category with respect to their reference category (Williams 2006). The reference category is mentioned in the parenthesis in the first column (labelled "Variable").

Table 10 Maximum Likelihood and Odds Ratio Estimates: Weather-Related Crash Occurrence Model (by Injury Severity Level)

Variable (Reference category)	Categories	Severe injury		Moderate injury		No injury	
		Estimate	Odds Ratio	Estimate	Odds Ratio	Estimate	Odds Ratio
Intercept		-2.05**	-	-1.91**	-	-1.89**	-
Contributing factor of the crash (No contributing factors)	Disregarding signs or signals	-0.10	0.90	-0.02	0.98	-0.08**	0.92**
	Exceeded safe speed/speed limit or fail to reduce speed	0.02	1.02	0.04**	1.04**	0.02	1.02
	Improper turn or right turn on red	-0.23	0.80	-0.06	0.95	-0.02	0.98
	Crossed centerline, improper lane change, or use of an improper lane	0.01	1.01	0.04	1.04	-0.01	0.99
	Overcorrected, oversteered, improper passing, or improper backing	-0.37**	0.69**	-0.04	0.96	-0.20**	0.82**
	Failing to yield to the right-of-way, or driver inattention	0.07	1.07	0.00	1.00	0.00	1.00
	Operating too closely, aggressive driving, or alcohol use	-0.01	0.99	-0.08**	0.92**	-0.06**	0.94**
	Visibility obstruction, or defective equipment	-0.20	0.82	-0.02	0.99	-0.01	0.99
	Other/unable to determine	0.36**	1.43**	0.01	1.01	0.01	1.01
Road surface condition (Dry)	Wet, presence of water (standing/moving)	4.68**	108.13**	4.82**	123.96**	4.81**	122.86**
	Ice, snow, slush	3.61**	36.93**	3.44**	31.10**	3.38**	29.33**
	Sand, mud, dirt, gravel, fuel, or oil	0.91	2.48	0.82**	2.28**	0.88**	2.41**

Variable (Reference category)	Categories	Severe injury		Moderate injury		No injury	
		Estimate	Odds Ratio	Estimate	Odds Ratio	Estimate	Odds Ratio
Functional class of road (Principal arterial – interstate, freeways, and expressways)	Principal arterial – other	-	-	0.07**	1.07**	0.13**	1.13**
	Minor arterial	-	-	0.00	1.00	0.12**	1.13**
	Major collector	-	-	0.00	1.00	0.07**	1.07**
	Local	-	-	-0.04	0.96	0.00	1.00
Location type (Non-intersection)	Intersection	-	-	0.13**	1.14**	0.15**	1.16**
Light condition (Daylight)	Dusk, and dawn	0.50**	1.64**	0.30**	1.35**	0.25**	1.28**
	Dark lighted roadway/unknown lighting	0.05	1.05	-0.18**	0.84**	-0.12**	0.89**
	Roadway not lighted	0.08	1.08	0.17**	1.19**	0.16**	1.18**
Driver gender (Male)	Female	-	-	0.03**	1.03**	-	-
Road characteristic (Straight-leveled road)	Straight-grade/hillcrest/bottom	0.22**	1.25**	0.18**	1.20**	0.26**	1.30**
	Curve-leveled/grade/hillcrest	0.29**	1.33**	0.16**	1.18**	0.16**	1.18**
	Not stated/unknown	-0.13	0.88	0.22	1.25	0.48**	1.62**
Driver age (19–69 years)	15–19 years	-	-	-0.01	0.99	-	-
	70 years	-	-	-0.05*	0.95*	-	-
Speed limit class (>60 mph)	20 mph	-1.29*	0.27*	-0.14*	0.87*	-0.26**	0.77**
	20–30 mph* (30 mph included)	-0.50	0.61	-0.02	0.98	-0.09**	0.92**
	30–40 mph	-0.20	0.82	-0.03	0.98	-0.12**	0.89**
	40–50 mph	-0.24**	0.79**	-0.01	0.99	-0.06**	0.95**
	50–60 mph	-0.06	0.94	-0.04	0.96	-0.09**	0.92**
Work zone area (No work zone)	Work zone area	-	-	-0.09**	0.92**	0.05*	1.05*
Crash type	Ran off-road	-0.26	0.77	-0.17**	0.84**	-0.05	0.95
	Jackknife, overturn/rollover	0.14	1.15	-0.18**	0.84**	-0.16**	0.85**

Variable (Reference category)	Categories	Severe injury		Moderate injury		No injury	
		Estimate	Odds Ratio	Estimate	Odds Ratio	Estimate	Odds Ratio
(Parked vehicle or fixed object)	Pedestrian/pedal cyclist	0.31**	1.36**	-0.13*	0.88*	-0.45**	0.64**
	Animal or movable object	-0.14	0.87	-0.07	0.93	-0.25**	0.78**
	Rear-end collision	0.10	1.11	-0.18**	0.83**	-0.26**	0.77**
	Left-/right-turn crashes	0.15	1.16	-0.13**	0.88**	-0.23**	0.80**
	Head-on collision	0.09	1.10	-0.23**	0.79**	-0.35**	0.70**
	Sideswipe or angle collision	0.02	1.02	-0.19**	0.83**	-0.22**	0.80**
	Other	-0.30	0.74	-0.03	0.97	-0.18**	0.83**
Vehicle type (Passenger car)	Pickup, light truck, sports utility, or van	0.05	1.06	0.03**	1.03**	0.02**	1.02**
	Commercial bus, school bus, activity bus, other bus	0.46	1.59	0.18*	1.20*	0.06	1.06
	Single unit truck, truck/trailer, truck/tractor, tractor doubles, semitrailer, farm equipment or other heavy trucks	0.24**	1.27**	0.01	1.01	0.03	1.03
	Motor scooter, moped, pedal cycle, or motorcycle	-0.28**	0.75**	-0.34**	0.71**	-0.36**	0.70**
	Other	-0.30	0.74	0.22*	1.24*	0.19**	1.21**
Seasonal factors (Spring)	Summer	0.25**	1.29**	0.10**	1.10**	0.07**	1.08**
	Autumn	0.22**	1.25**	0.05**	1.05**	0.05**	1.06**
	Winter	0.04	1.04	-0.08**	0.93**	-0.10**	0.90**
Time of the day (09:00 AM – 12:00 PM)	12:00 AM – 03:00 AM	-0.12	0.89	-0.48**	0.62**	-0.54**	0.58**
	03:00 AM – 06:00 AM	-0.32*	0.73*	-0.33**	0.72**	-0.36**	0.70**
	06:00 AM – 09:00 AM	0.01	1.01	-0.01	0.99	-0.02	0.98
	12:00 PM – 03:00 PM	0.02	1.03	0.02	1.02	-0.01	0.99
	03:00 PM – 06:00 PM	-0.29**	0.75**	-0.18**	0.83**	-0.19**	0.83**

Variable (Reference category)	Categories	Severe injury		Moderate injury		No injury	
		Estimate	Odds Ratio	Estimate	Odds Ratio	Estimate	Odds Ratio
	06:00 PM – 09:00 PM	-0.38**	0.68**	-0.50**	0.61**	-0.54**	0.58**
	09:00 PM – 12:00 PM	-0.47**	0.63**	-0.63**	0.53**	-0.64**	0.53**
Day of the week (Wednesday)	Sunday	-0.01	0.99	-0.10**	0.91**	-0.08**	0.93**
	Monday	0.10	1.11	0.19**	1.21**	0.22**	1.25**
	Tuesday	-0.26**	0.77**	0.10**	1.10**	0.17**	1.18**
	Thursday	-0.11	0.89	0.03	1.04	0.07**	1.07**
	Friday	-0.20*	0.82*	0.05**	1.05**	0.03**	1.04**
	Saturday	-0.19*	0.83*	-0.05*	0.95*	-0.06**	0.95**
Road terrain (Flat)	Rolling	-	-	0.00	1.00	0.01	1.01
	Mountainous	-	-	0.26**	1.30**	0.17**	1.18**
Locality (Residential)	Agricultural	-0.15*	0.86*	-0.01	0.99	0.01	1.01
	Commercial	0.18**	1.20**	0.06**	1.06**	0.07**	1.07**
	Institutional	-0.34	0.71	0.27**	1.31**	0.16**	1.17**
	Industrial	-0.21	0.81	0.10	1.10	0.29**	1.34**

Note:

** Significant at a 95% confidence level

* Significant at a 90% confidence level

- Not included in the final model

The odds ratio represents, as a percentage, the likelihood of crash occurrence with respect to the reference category. For example, an odds ratio of 0.36 indicates that the outcome is 64% less likely to occur compared to the reference category. Similarly, an odds ratio of 2.71 indicates that the outcome is 171% more likely to occur compared to the reference category. A detailed discussion on weather-related crash occurrence model, by severity, is given in the following sections.

6.2.1 Risk Factors Associated with Weather-Related Severe Injury Crashes

From Table 10, it can be observed that certain contributing factors—type of crash, road surface condition, lighting condition, speed limit, vehicle type, seasonal factors, locality type, and temporal factors—influence the occurrence of weather-related severe injury crashes.

Crashes occurring on wet road conditions (i.e., segments with the presence of snow/water) are more likely to result in severe injury compared to those occurring on dry road surface conditions. In addition, crashes occurring on a segment with a grade or curvature are respectively 25% and 33% more likely to result in severe injury crashes than those occurring on a straight level road during adverse weather conditions.

Compared to a passenger car, trucks (including trailers, semitrailer, farm equipment, or other heavy trucks) are 27% more likely to be involved in a severe injury crash during adverse weather conditions. This may be due to these vehicles' size, weight, and maneuverability characteristics. Contrarily, motor scooters, mopeds, pedal cycles, or motorcycles are 25% less likely than passenger cars to be involved in fatal + type A injury crashes during adverse weather conditions.

Seasonal factors also showed a significant influence on the severe injury crash occurrence during adverse weather conditions. Weather-related crashes occurring in the summer and autumn months are 29% and 25% more likely to result in a severe injury compared to those occurring in spring. These results are attributed to the common weather conditions such as heavy rains and foggy conditions during those seasons.

The model results indicate that area characteristics (i.e., locality) significantly influence the occurrence of weather-related severe injury crashes. Weather-related crashes occurring in commercial localities are 20% more likely to result in a severe injury crash compared to those occurring in residential areas. These results are attributed to the area and corresponding traffic characteristics: commercial areas are expected to have significant traffic activity, whereas the roads near agricultural areas have relatively lower volumes.

6.2.2 Risk Factors Associated with Weather-Related Moderate Injury Crashes

The model results showed the significance of several independent variables at a 95% confidence level. Certain driver factors—exceeded safe speed/speed limit or failure to reduce speed—positively influence the occurrence of weather-related moderate injury crash. In addition, road grade/curvature, mountainous terrain roads, and the presence of materials such as water, ice, snow, sand, etc. positively influence the occurrence of moderate injury crashes during adverse weather conditions. These results could be attributed to unsafe driving conditions, especially during harsh weather conditions.

Road and surrounding area characteristics such as functional class, locality, and location significantly influence the moderate injury crash occurrence during adverse weather conditions. In addition, weather-related crashes occurring in commercial and institutional localities are respectively 6% and 31% more likely to result in a moderate injury than those occurring in residential localities. The results mentioned above are in accord and are attributed to the high traffic volumes and activity at the corresponding roads/locations.

Vehicle type and temporal and seasonal factors showed a significant influence on the occurrence of weather-related moderate injury crashes. Compared to passenger cars, pickups, light trucks, SUVs, and buses are more likely to be involved in moderate injury crashes during adverse weather conditions. The summer and autumn months are positively associated with the weather-related moderate injury crashes, which could be attributed to the adverse weather conditions (such as heavy rains and foggy conditions) during those seasons. Weather-related crashes occurring on

Wednesdays are 9% and 5% less likely, respectively, to result in a moderate injury compared to those occurring on Sundays and Saturdays.

6.2.3 Risk Factors Associated with Weather-Related No Injury Crashes

Property damage only (PDO) crashes are more frequent in the dataset than the severe and moderate injury crashes. The results from Table 10 indicate that numerous factors significantly influence the occurrence of PDO crashes during adverse weather conditions. Specifically, road surface condition, functional class, location characteristics, light conditions, road characteristics, presence of work zone, and temporal characteristics showed a significant association with the occurrence of no injury crashes during adverse weather conditions.

The model results indicate that crashes occurring on wet road conditions (i.e., segments with the presence of snow/water) are more likely to result in a no injury crash compared to those occurring on dry road surface conditions. Similarly, lighting conditions and road grade/curvature positively influence the no injury crash occurrence during adverse weather conditions. The presence of a work zone has shown a positive influence on the occurrence of no injury crashes during adverse weather conditions.

Similarly, to the results from moderate injury crashes during adverse weather conditions, the results also showed the positive influence of: driving on mountainous terrain; driving a pickup, light truck, sports utility vehicle, or van; and the presence of intersections on weather-related no injury crash occurrence.

6.3 Maximum Likelihood and Odds Ratio Estimates: Crash Injury Severity Analysis

Table 11 shows the results from the partial proportional odds model using the estimates and corresponding odds ratio for each variable category. Separate estimates are provided for severe injury and moderate injury, with unequal slope parameters. Similarly, a single merged cell is used for severe and moderate injury, with equal slope parameters for each category.

Table 11. Maximum Likelihood and Odds Ratio Estimates: Extreme Weather Crash Injury Severity Model

Variable (Reference category)	Categories	Estimate		Odds Ratio	
		Severe injury	Moderate injury	Severe injury	Moderate injury
Intercept		-4.87**	-1.15**	-	-
Contributing factor of the crash (No contributing factors)	Disregarding signs or signals	0.54**		1.72**	
	Exceeded safe speed/speed limit or fail to reduce speed	-0.05**		0.95**	
	Improper turn or right turn on red	-0.37**		0.69**	
	Crossed centerline, improper lane change, or use of an improper lane	-0.30**		0.74**	
	Overcorrected, oversteered, improper passing, or improper backing	-0.02		0.98	
	Failing to yield to the right-of-way, or driver inattention	-0.02		0.98	
	Operating too closely, aggressive driving, or alcohol use	0.24**		1.27**	
	Visibility obstruction, or defective equipment	-0.14**		0.87**	
	Other/unable to determine	-0.20**		0.82**	
Road surface condition (Dry)	Wet, presence of water (standing/moving)	-0.05**		0.95**	
	Ice, snow, slush	-0.56**		0.57**	
	Sand, mud, dirt, gravel, fuel, or oil	-0.15		0.86	
Functional class of road (Principal arterial – interstate, freeways and expressways)	Principal arterial – other	0.21**		1.24**	
	Minor arterial	0.20**		1.23**	
	Major collector	0.24**		1.27**	
	Local	0.10**		1.10**	
Location type (Non-intersection)	Intersection	0.17**		1.19**	
Light condition (Daylight)	Dusk, and dawn	0.39**	0.13**	1.48**	1.14**
	Dark lighted roadway/unknown lighting	0.01	0.09**	1.01	1.09**
	Roadway not lighted	0.78**	0.03	2.17**	1.03
Driver gender (Male)	Female	0.14**		1.15**	
	Straight-grade/hillcrest/bottom	0.07**		1.07**	

Variable (Reference category)	Categories	Estimate		Odds Ratio	
		Severe injury	Moderate injury	Severe injury	Moderate injury
Road characteristic (Straight-leveled road)	Curve-leveled/grade/hillcrest	0.22**		1.25**	
	Not stated/unknown	-0.24		0.79	
Driver age (19–69 years)	15–19 years	-0.10**		0.90**	
	70 years	0.07**		1.07**	
Speed limit class (>60 mph)	20 mph	-0.53**		0.59**	
	20–30 mph* (30 mph included)	-0.38**		0.68**	
	30–40 mph	-0.14**		0.87**	
	40–50 mph	-0.01		0.99	
	50–60 mph	0.20**		1.22**	
Crash type (Parked vehicle or fixed object)	Ran off-road	0.23**		1.26**	
	Jackknife, overturn/rollover	0.66**		1.93**	
	Pedestrian/pedal cyclist	3.51**		33.52**	
	Animal or movable object	-1.83**		0.16**	
	Rear-end collision	0.16**		1.18**	
	Left-/right-turn crashes	0.44**		1.55**	
	Head-on collision	2.24**		9.38**	
	Sideswipe or angle collision	0.17**		1.19**	
	Other	-0.24**		0.79**	
Vehicle type (Passenger car)	Pickup, light truck, sports utility or van	-0.01		0.99	
	Commercial bus, school bus, activity bus, other bus	-0.04		0.96	
	Single unit truck, truck/trailer, truck/tractor, tractor doubles, semitrailer, farm equipment or other heavy trucks	-0.10**		0.90**	
	Motor scooter, moped, pedal cycle or motorcycle	2.49**		12.10**	
	Other	-0.20**		0.82**	
Seasonal factors (Spring)	Summer	0.08**		1.08**	
	Autumn	0.06**		1.07**	
	Winter	0.01		1.02	
Time of the day	12:00 AM – 03:00 AM	0.28**		1.32**	
	03:00 AM – 06:00 AM	0.15**		1.17**	
	06:00 AM – 09:00 AM	-0.04**		0.96**	

Variable (Reference category)	Categories	Estimate		Odds Ratio	
		Severe injury	Moderate injury	Severe injury	Moderate injury
(09:00 AM – 12:00 PM)	12:00 PM – 03:00 PM	0.03**		1.04**	
	03:00 PM – 06:00 PM	-0.01		0.99	
	06:00 PM – 09:00 PM	0.00		1.00	
	09:00 PM – 12:00 PM	0.09**		1.09**	
Day of the week (Wednesday)	Sunday	0.12**		1.12**	
	Monday	0.02		1.02	
	Tuesday	-0.03		0.98	
	Thursday	-0.04**		0.96**	
	Friday	0.00		1.00	
	Saturday	0.09**		1.10**	
Road terrain (Flat)	Rolling	-0.29**	0.01	0.75**	1.01
	Mountainous	-0.31**	-0.15**	0.73**	0.86**
Locality (Residential)	Agricultural	0.03*		1.03*	
	Commercial	-0.18**		0.83**	
	Institutional	-0.09*		0.92*	
	Industrial	0.04		1.04	

Note:

** Significant at a 95% confidence level

* Significant at a 90% confidence level

Table 11 shows that several factors positively influence the occurrence of moderate injury (type B + type C injury) crashes during adverse weather conditions. These factors include driver behaviors (disregarding signs or signals, operating too closely, aggressive driving, or alcohol use), functional class of the road (principal arterial, minor arterial, major collector, and local), presence of an intersection, driver gender, road characteristics (curve-leveled/grade/hillcrest), speed limit (50–60 mph), crash type (ran off-road, jackknife, pedestrian or pedal cyclist, rear-end collision, left-/right-turn crashes, head-on collision, sideswipe or angle collision), vehicle type (motor scooter, moped, pedal cycle, or motorcycle), seasonal factors (summer and autumn), time of the day (12:00 AM–03:00 AM, 03:00 AM–06:00 AM, 06:00 PM–09:00 PM, 09:00 PM–12:00 PM), and day of the week (Sunday and Saturday). Driving on roads with no lights in adverse weather conditions increases the likelihood of severe injury crash as compared to driving on roads in daylight hours during adverse weather conditions. Driver behavior variables such as disregarding signs or signals and operating vehicle too closely, aggressive driving, or alcohol use elevate the risk of occurrence of moderate injury crash during adverse weather conditions.

Compared to driving on roads with a speed limit of >60 mph, driving on roads with speed limits ≤20 mph, 20–30 mph, and 30–40 mph is 41%, 32%, and 13%, respectively, less likely to result in a moderate injury crash during adverse weather conditions. This could be due to a decrease in the time available to make a complete stop, higher speeds upon impact, and difficulty controlling the vehicle when driving on high-speed roads in adverse weather conditions. Similarly, compared to crashes on interstate segments, weather-related crashes on arterial roads and local roads are more likely to result in moderate injury and less likely to result in severe injury.

Female drivers are less likely to be severely injured than male drivers in a weather-related crash, and they are 85% less likely to be involved in severe injury crashes.

Compared to straight-leveled roads, the presence of curvature and grade showed a significant positive influence on the likelihood of moderate injury crashes during adverse weather conditions. This finding could be mainly attributed to the varying maneuverability conditions for road users.

The results associated with the locality characteristics indicate that, during adverse weather conditions, crashes occurring in agricultural and industrial areas have a higher likelihood of moderate injury than crashes occurring in residential areas.

In addition, time of the day and seasonal factors were also found to significantly influence moderate injury crashes during adverse weather conditions. Compared to spring, summer and autumn showed a higher likelihood of severe and moderate injury crashes during adverse weather conditions. With respect to day of the week, the model results indicate that Sunday and Saturday have a statistically significant positive association with crash injury severity. In other words, weather-related crashes occurring on the weekends have an increased possibility of moderate injuries compared to a typical Wednesday. In the case of time of the day variable, likelihood of a moderate injury crash during the 12:00 AM–03:00 AM, 03:00 AM–06:00 AM, 06:00 PM–09:00 PM, and 09:00 PM–12:00 PM intervals is higher compared to 09:00 AM–12:00 PM.

Aside from the surrounding environment, driver behavior and driver characteristics also influence the crash injury severity. Crashes due to operating too closely, aggressive driving, or alcohol use have a statistically significant effect on injury severity during adverse weather conditions.

Compared to a parked vehicle/fixed object crash, other crash types—such as jackknife, overturn/rollover, left-/right-turn, head-on collision, and sideswipe or angle collisions—have a higher likelihood of resulting in severe and moderate injury. Driving a motor scooter, moped, pedal cycle, or motorcycle during adverse weather conditions is more likely to result in an injury crash when compared to driving a passenger car in the same conditions.

7. Conclusions

Ensuring higher TTR and safety levels is critical for efficient transportation system management. This research has analyzed the fluctuations (deviations from the trends observed during normal conditions) in travel time and crashes during various weather conditions. A key challenge to achieving this objective was integrating weather-related information and traffic conditions during the weather condition from disparate data sources.

In this research, the data integration and analysis were carried out at two levels. Firstly, travel time and weather-related data for 50 selected road segments in North Carolina were used to evaluate the effect of weather conditions on road traffic TTR. Secondly, the effect of weather conditions on crash occurrence and severity was assessed using data collected from HSIS.

This research extracted the weather and travel time data for the same time of the day and day of the week and integrated the data for analysis. The effect of other factors beyond the scope of this research (e.g., geometric conditions, traffic patterns, and other environmental factors) was minimized by comparing the travel time data for a week before and after adverse rainfall and visibility conditions with the travel time during rainfall and visibility conditions.

The results indicate that different rainfall intensities with poor visibility have a large adverse effect on freeway TTR. Heavy rain and poor visibility caused a 5.50% increase in the ATT and a 12.24% increase in PTI on urban freeway road segments. Similarly, a 7.55% increase in TTI was observed under the moderate rain with poor visibility condition on the urban freeway road segments. In the case of arterial road segments, the increase in PTI was 6.70% and 4.02%, respectively, under the heavy rain with good visibility and heavy rain with poor visibility conditions. Overall, PTI was observed to be a better measure than TTI as it normalizes the 95th-percentile travel time for all the road segments in terms of free-flow travel time rather than average travel time.

In general, survival function analysis using PTI values is useful in estimating the probability that a road will reach an unreliable state under rainfall and visibility conditions. The analysis was performed using data for the freeway and arterial road segments. The likelihood of reaching a moderately to highly unreliable condition is 8% to 15% higher on urban freeway road segments in the case of poor visibility conditions compared to normal weather conditions. However, the survival analysis for arterial road segments indicated a minimal effect of rainfall and visibility conditions on the TTR.

The effect of the weather on TTR was lower in the case of urban arterial road segments when compared to freeway road segments. The maximum effect was observed in the case of the heavy rain condition. The data points for the arterial road segment analysis were fewer compared to the freeway road segment analysis. Adding more data related to weather and travel time for the arterial roads may give more useful insights into the effect of rainfall and visibility on arterial road operational performance.

The results from the travel-time-based analysis are useful for transportation system managers and planners to manage the traffic under different weather conditions. The findings can also help improve the functionality of weather-responsive management strategies such as variable signs to indicate changes in reliability under rainfall and low-visibility conditions. Communicating the travel time information during various weather conditions can also reduce the crash risks associated with weather conditions.

The crash occurrence and severity assessment outcomes from this research can guide the exploration of potential strategies for enhancing highway safety under adverse weather conditions. The effect of weather conditions on crash occurrence was assessed using the logistic regression approach. In this research, a partial proportionality odds model was developed to identify crash risk factors associated with the weather-related crash injury severity.

The important findings from the weather-related crash occurrence/severity analysis are:

- Driving on dark lighted roads or during dusk hours in adverse weather conditions increases the likelihood of severe injury crash as compared to driving on roads in adverse weather conditions during daylight hours.
- Driving on high-speed roads in adverse weather conditions increases the likelihood of moderate injury crash as compared to driving on low speed roads in adverse weather conditions. Congruent with speed limits, all levels of road classification, with interstate as a base variable, are observed to be positively associated with injury severity during adverse weather conditions.
- The presence of curvature and grade showed a significant positive influence on the likelihood of moderate injury crashes during adverse weather conditions compared to straight level roads.
- Driving a motor scooter, moped, pedal cycle, or motorcycle during adverse weather conditions is more likely to result in a moderate injury compared to driving a passenger car during adverse weather conditions.
- Female drivers are more prone to injury when compared to male drivers during adverse weather conditions.
- Weather-related crashes occurring on weekends (Saturdays and Sundays) are more likely to result in a moderate injury compared to weather-related crashes occurring on weekdays.

Weather-related crashes that occur in the nighttime (09:00 PM to 06:00 AM) are more likely to result in a moderate injury compared to the crashes occurring at other times of the day.

The findings from the analysis, which explores the effect of weather conditions on crash occurrence and severity, could be utilized to enhance highway safety in adverse weather conditions. Potential strategies for enhancing highway safety during adverse weather conditions are: installing more warning signals on selected roads to remind drivers of the need to be vigilant and cautious during adverse weather conditions, using a weather monitoring and warning system that includes pavement surface information, and improving the light conditions on highways.

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