# MODELLING OF INTERSTATE I-465 CRASH COUNTS DURING SNOW EVENTS

by

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# ABSTRACT

Traffic safety management on interstates is crucial during adverse winter weather. According to the Federal Highway Administration (FHWA), there are over 5,891,000 vehicle crashes each year in the United States. Approximately 21% of these crashes are weather-related. INDOT spends $60 million on winter operations each year to minimize the weather impacts on driver capability, vehicle performance, road infrastructure, and crash risk. Several studies have sought to investigate the relationship of crash counts with weather, speed, traffic and roadway data during snow events, in order to help agencies, identify needs and to distribute the resources effectively and efficiently during winter weather events. The limitation of these studies is that weather variables are often correlated to each other, for example, visibility may be correlated to snow precipitation and air temperature may be correlated to net solar surface radiation. The randomness of crash occurrence also increases difficulty in such studies.

In this study, a random parameter negative binomial model was used for Interstate I-465 in Indianapolis in winter 2018 and 2019. The results show that during snow events in Indiana, air temperature, wind speed, snow precipitation, net solar surface radiation, and visibility significantly impact the number of crashes on I-465. Driving over the speed limit (55 mph), especially on wet pavements are more likely to lose control of vehicles and cause crashes. Travel speed between 45 mph to 55 mph and travel speed between 15 mph to 25 mph are both strong factors. Somewhat surprising was that speeds between 25 mph and 45 mph were not found to be significant. The number of interchanges is also positively related to crash counts due to the high number of conflict points at ramp merging sections. Also, travelling over speed limit is a random parameter with unobserved heterogeneity which is intuitive since speeding could be more dangerous in certain areas with complex road geometry and narrower lanes. Traffic counts have a negative correlation with crash counts, likely due to faster speeds when fewer vehicles are travelling on the loop.

Crash counts increased about 70% during severe storm days on I-465, and visibility and air temperature are highly correlated to crash counts. These key findings can help the agency to deploy warnings when visibility is low, or temperature falls sharply.

# 1. INTRODUCTION

Data from the National Highway Traffic Safety Administration (NHTSA) suggest that weather is predominantly responsible for approximately 21% of vehicle crashes and 5,376 deaths and 418,005 injuries from 2007 to 2016 (FHWA, 2020). This research evaluated several models and proposed a random parameter negative binomial (RP-NB) regression model to estimate the relationship between highway features, weather impacts, and traffic factors with crash counts across I-465 around Indianapolis, Indiana. The primary objective was to investigate which factors significantly contribute to the crash counts during snow events. The secondary objective was to conduct a statistical model to find the contributing factors to crash counts.

Crashes are defined as events that result in property damage, person injury or fatality due to a collision involving a motorized vehicle, bicyclist, pedestrian, or obstacle. The terms “crash”, “collision”, or “accident” typically have the same meaning in transportation literature. “Crash frequency” or “crash counts” are defined as the number of crashes occurring at a certain place, in a chosen time period. Crash counts observed at a highway segment, an intersection, an interchange, or a roundabout are commonly used as a fundamental safety performance measure for roadway safety analysis. A high level of randomness resides in crash count data because crash counts naturally vary over time at different places and under different circumstances. The randomness of an accident occurrence indicates that short-term crash counts alone are not a reliable estimator of long-term crash counts. However, it could identify the major contributing factors to crashes and make highway agencies and the public aware of these situations and develop the appropriate countermeasures. In this study, a two-year period of crashes on I-465 was analyzed to estimate crash counts. It is worth noting that the snow events during the two-year period are adequate to carry out the analysis, but additional years of data are expected to throw more light on the trend.

The total number of crashes that occurred on I-465 in 2018 and 2019 are 859 and 940, respectively. During January to March 2018 and January to March 2019, there were 353 crashes that occurred during snow days.

## 1.1 Study Area

The study area is I-465, a beltway around Indianapolis, Indiana, which is 53-miles in length (85 kilometers) and has 30 interchanges. All interchanges and their location mile markers (MM) are described in Table 1.1. The travel speed limit on I-465 is 55 miles per hour (mph). However, it is observed that vehicles often travel at higher speeds on I-465, especially during rush hours. The beltway spans three counties (Marion, Boone, and Hamilton) in Indiana. It is also one of the most congested highways in Indiana, serving both in-state commuters and out-of-state visitors. I-465 also intersects with other major interstates, like I-65, I-69, I-70, I-74 and I-865, which lead to a mix of trucks, commercial vehicles, and regular cars in the traffic. This study divided the entire beltway/ loop into eight segments when carrying out the analysis. Each segment is highlighted with a different color and is labeled with a number near the segment shown in Figure 1.1. The average length of the segment is about 6.5 miles, and the start and end mile marker of each segment are shown in Table 1.2.

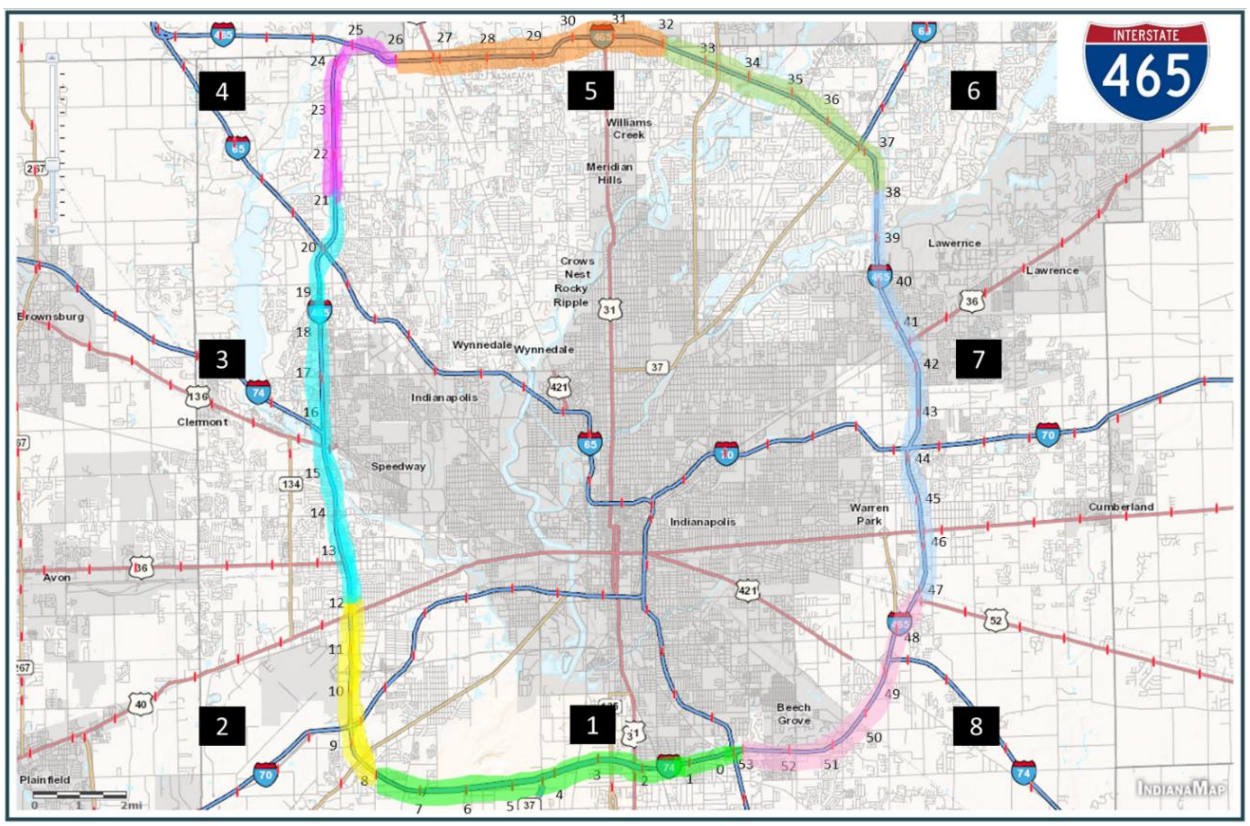



Figure 1.1 Study location I-465 with eight segments

Table 1.1 I-465 interchanges with location mile marker (MM)

| No. | Intersect with | MM |
|---|---|---|
| 2 | U.S. 31 / East St. | 2.2 |
| 4 | S.R. 37 | 4.3 |
| 7 | Mann Road | 7.33 |
| 8 | S.R. 67/Kentucky Avenue | 8.51 |
| 9 | I-70 | 9.32 |
| 11 | Sam Jones Parkway | 10.48 |
| 12 | U.S 40/ Washington St. | 11.77 |
| 13 | U.S 36/ Rockville Road | 12.91 |
| 14 | 10thSt. | 13.95 |
| 16 | I-74/ Crawfordsville Rd. | 15.55-15.77 |
| 17 | 38thSt. | 17.02 |
| 19 | 56thSt. | 19.03 |
| 20 | I-65/ Lafayette Rd. | 19.80 |
| 21 | 71st St. | 20.82-21.45 |
| 23 | 86th Street | 23.15 |

| No. | Intersect with | MM |
|---|---|---|
| 25 | I-865 | 24.26-24.63 |
| 27 | U.S. 421 | 26.42 |
| 31 | U.S. 31/ Meridian St. | 30.27 |
| 33 | U.S. 431/ Keystone Ave. | 32.87 |
| 35 | Allisonville Rd. | 34.94 |
| 37 | I-69/ S.R. 37/ Binford Dr. | 36.50 |
| 40 | 56th Street/Fall Creek/Shadeland Ave. | 38.83 |
| 42 | Pendleton Pike/ S.R. 67/ U.S. 36 | 41.05 |
| 44 | I-70 | 43.43 |
| 46 | U.S. 40/ Washington St. | 45.27 |
| 47 | U.S. 52/Brookville Rd at I-465 | 46.81 |
| 48 | Shadeland Ave at I-465 | 47.27 |
| 49 | I-74/Southeastern Ave. | 48.33 |
| 52 | Emerson | 51.40 |
| 54 | I-65 | 52.79 |

Table 1.2 I-465 segment start and end mile markers with number of interchanges

| I-465 Inner Loop | | |
|---|---|---|
| Start MM | End MM | # of interchanges |
| 0.88 | 7.59 | 3 |
| 7.59 | 12.25 | 4 |
| 12.25 | 20.7 | 6 |
| 20.7 | 25.86 | 3 |
| 25.86 | 32.34 | 2 |
| 32.34 | 38.38 | 3 |
| 38.38 | 47.14 | 5 |
| 47.14 | 0.88 | 4 |

| I-465 Outer Loop | | |
|---|---|---|
| Start MM | End MM | # of interchanges |
| 1.36 | 7.62 | 3 |
| 7.62 | 12.65 | 4 |
| 12.65 | 20.76 | 6 |
| 20.76 | 25.95 | 3 |
| 25.95 | 32.73 | 2 |
| 32.73 | 38.45 | 3 |
| 38.45 | 47.1 | 5 |
| 47.1 | 1.36 | 4 |

## 1.2 Study Period

This study included a two-year period for January to March in 2018 and 2019. The final dataset contained weather variables, speed attributes, traffic counts, roadway information, and crash counts. Each observation was obtained and aggregated into a six-hour period for the analysis and modelling. Many previous studies aggregated data by year and did the modelling on a macro scale (Qiu & Nixon, 2008) (Khattak & Knapp, 2001). However, to get a better understanding on crash counts during winter events for I-465, it was beneficial to investigate the data in a micro way. The hourly data could provide more precision in weather variables. However, the tradeoff was the excessive zeros in the crash counts, since it is unlikely, on each segment, that a crash would happen on an hourly basis. Thus, aggregating time into 6 hours was selected as a reasonable compromise. A sample of observations is shown below, which means on Mar 24th, 2018 12:00 to 18:00, there were 2 crashes in segment 1, and 1 crash in segment 5.

Table 1.3 Sample data for crash counts

| Datetime | Crash counts | Segment |
|---|---|---|
| Mar 24th, 2018 12:00 to 18:00 | 2 | 1 |
| Mar 24th, 2018 12:00 to 18:00 | 1 | 5 |

## 1.3 Study Motivation

INDOT spends more than $60 million annually on winter operations and strives the best to provide a safe and reliable roadway system during adverse weather conditions. Each year, more than 1,000 snowplows are deployed to keep 29,000 miles of interstate, U.S routes, and state roads clean and safe. Up to 2,000 operators, mechanics, and clerks work on alternating 12-hour shifts, 7 days per week as needed. The three major goals of INDOT on winter operation website are to: (1) Keep all roads and bridges open and passable; (2) Operate as efficiently and effectively as possible; (3) Maximize safety and mobility during winter weather conditions (Indiana Department of Transportation, 2018). Even though great efforts were made, severe snow days still increase crash counts by 70% on I-465. FHWA reports have found that snow events may cause interstate speed to reduce by 35% to 42%. Studies also showed consistently that traffic flow on arterial is reduced by 13% in light snow events and 25% to 30% in heavy snow events (Qiu & Nixon, 2008). Researchers have been actively working on crash prediction models in the past two decades, but there are no general applicable standards or models that could be used to deliver a microscopic analysis for the case of I-465. At the same time, knowing contributing factors to crash counts are crucial for the agencies to get prepared and develop weather-responsive traffic management plans. Hence, a model to quantify the critical factors is in urgent need for future winter operation planning and could also aid in delivering key messages to drivers through dynamic message signs.

It is noted that although congestion always leads to low travel speed on highways, low speed does not always imply congestion. Camera images in Figure 1.2 showed congested condition, low speed condition/ uncongested condition with or without snow below.

In Figure 1.2 d, the travel speed is low. However, it is a different situation compared with Figure 1.2 a and b which the roadway was heavy congested, and vehicles can barely move. It is beneficial in future work to either use a "congested" variable or to combine speed bins so that low speed, median speed and high speed could be used as factors to assess their impacts on crash counts (Lord, 2005) (Tarko, 2016).

A summary table of primary factors for these crashes were provided in Table 1.4. It is worth noting that "Speed too fast for weather conditions" and "Road surface condition" combined to 19.6% of the crashes in 2018 January to March and to 25.3% in 2019 January to March. For road surface conditions, the snow/ slush condition totaled 13.8% in 2018 January to March and 21.7% in 2019 January to March (JTRP, 2020). Two pie charts for illustrating the results are shown in Figure 1.3.

Table 1.4 Primary factors for crash on I-465 during winter 2018 and winter 2019

| Primary factors for crash on I-465 | 2018 (Jan to Mar) | 2019 (Jan to Mar) |
|---|---|---|
| Following too closely | 30% | 28.5% |
| Speed too fast for weather conditions | 17.5% | 23.5% |
| Unsafe lane movement | 20.3% | 20.1% |
| Ran off road | 5.5% | 6.2% |
| Overcorrecting/oversteering | 4.7% | 3.3% |
| Animal/ object in roadway | 3.9% | 2.8% |
| Road surface condition | 2.1% | 1.8% |
| Driver | 2.8% | 1.5% |
| Tire failure or defective | 1.3% | 0.8% |
| Other | 12% | 11.5% |

An internal Purdue Research team's "heatmap" was used to monitor and diagnose real-time traffic/ congestion problems on I-465 (Desai et al., 2020). A clear-day and snow-day heatmap comparison is shown in Figure 1.4, where the x-axis is the time of day by hour and the y-axis is the mile marker (location) on I-465. Jan 12$^{th}$, 2019 was a heavy snow day whereas Jan 5$^{th}$, 2019 was a clear day without adverse winter weather conditions. On the heatmap (Figure 1.4 a-d), white circles represent property-damage-only crashes and grey circles represent injury crashes; green areas mean that vehicle travel speeds were over 55 mph, while yellow areas are where congestions (speed smaller than 45 mph but greater than 35 mph) started to occur and red areas are where queueing started since vehicles were travelling under 35 mph.


a. Congestion without snow


b. Congestion with snow


c. No congestion without snow


d. Low speed with snow

Figure 1.2 Congestion, low speed and no congestion on I-465 with or without snow

From Figure 1.4, it is clearly shown that the snow day had more congestion on I-465 especially during the snow time in the morning; at the same time, there were significantly more crashes during the snow day compared to the clear day. Callout i and ii are two camera images showing the roadway and environmental condition at the same location, at the same time of day (9:01 a.m.) for the two days. The images also indicate that the visibility and pavement condition both deteriorate during snow days.

For the same two days as above, Figure 1.5 (clear day) and Figure 1.6 (snow day) show the crash counts, Interstate miles below 45 mph, temperature and precipitation for each hour of day. These figures also indicate more crashes and congestion during the snow day compared to the clear day. The clear day on January 5$^{th}$ has a total of 4 reported crashes and a summary for each direction on I-465 is shown below.

- Inner Loop (0 property-damage-only; 0 injury; 0 fatal)
- Outer Loop (3 property-damage-only; 1 injury; 0 fatal)

For the snow day on January 12$^{th}$, however, the total crash count is 63 with a summary for each direction on I-465 shown below.

- Inner Loop (22 property-damage-only; 3 injury; 0 fatal)
- Outer Loop (36 property-damage-only; 2 injury; 0 fatal)

An overview of the monthly ”interstate miles below 45 mph” on I-465 for 2018 and 2019 winter seasons is provided in Figure 1.7 to Figure 1.12. It can be observed that the pattern has been very consistent, being relatively higher during weekdays than during weekends, except for some major snow/ storm days during which more low speed/ congestions occurred. There were about four or five major winter events (storm days) each year during the studied period. It is also noticed that most of the winter events and snow days seemed to have significant impact on I-465. For example, in Figure 1.10, the snow day (January 12$^{th}$, 2019, also shown as winter event 19-2) has a lot more miles which travel speed under 45 mph compared to the previous Saturday which was a clear day (January 5$^{th}$, 2019). However, in Figure 1.7 there was low traffic/ congestion impact on Jan 8$^{th}$, 2018, even though it was a winter event. This means snow is not the only factor causing more crashes. Hence, it is critical to find the other contributing factors for the low speed/ congestion and crashes during such snow days. That way, the agency will have the information needed to allocate resources to increase both the mobility and safety on the road.

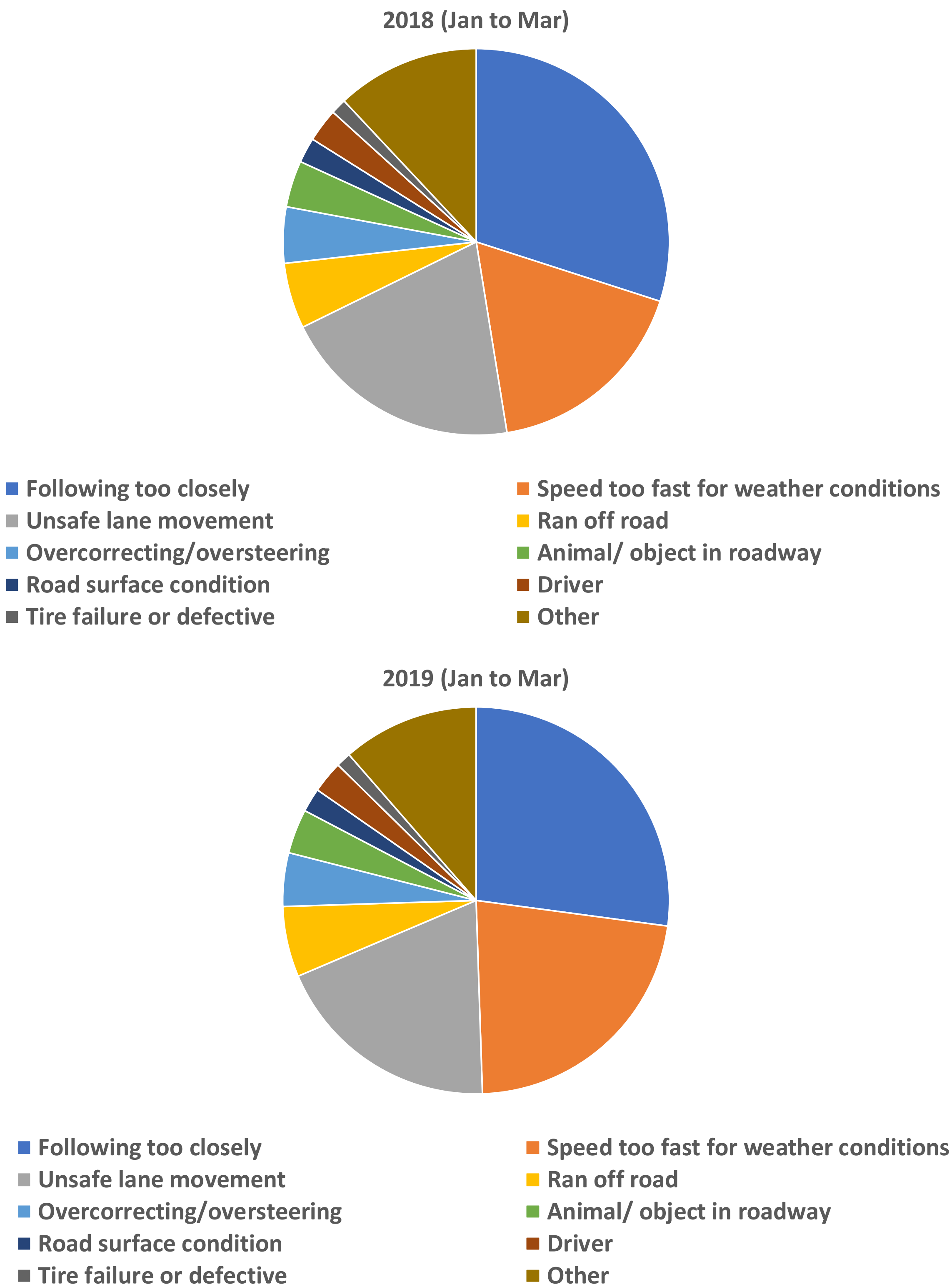
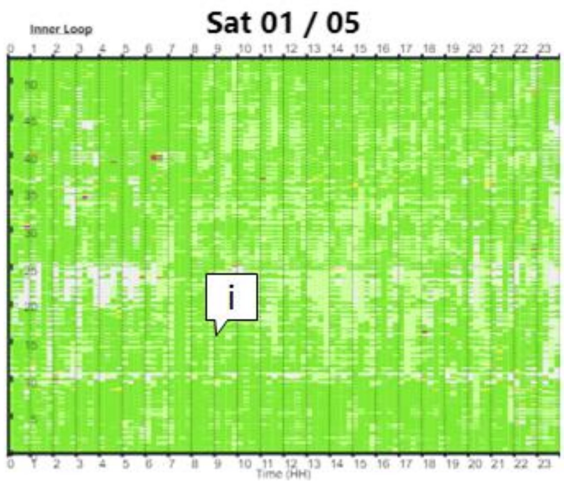
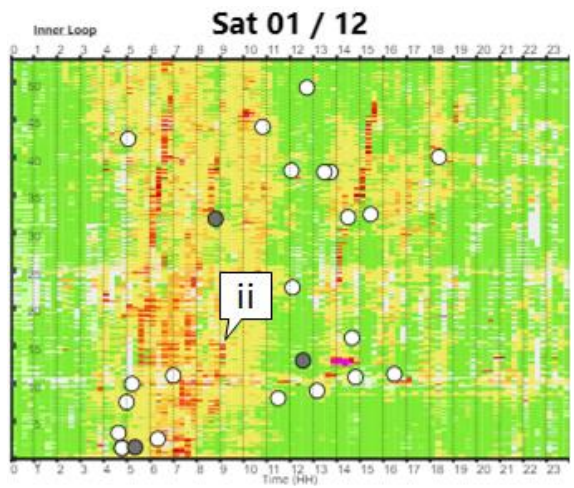


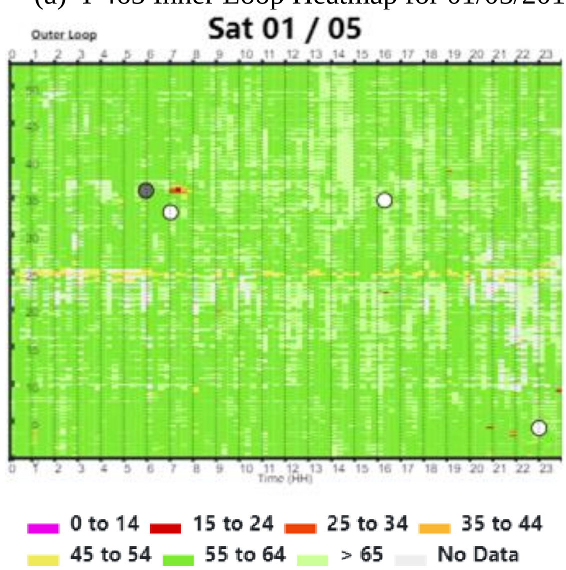

Figure 1.3 Pie charts for primary factors of crashes in winter 2018 and winter 2019 (Source: Purdue JTRP, 2020)



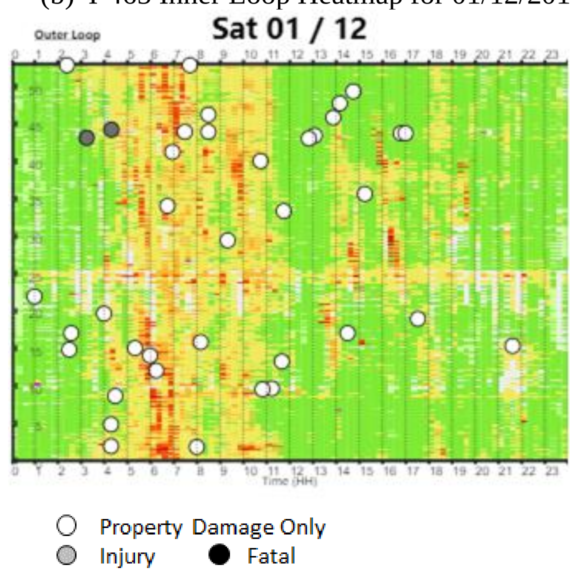

(a) I-465 Inner Loop Heatmap for 01/05/2019




(b) I-465 Inner Loop Heatmap for 01/12/2019




(c) I-465 Outer Loop Heatmap for 01/05/2019




(d) I-465 Outer Loop Heatmap for 01/12/2019


(e) Camera image at MM11.7 for 01/05/19


(f) Camera image at MM11.7 for 01/12/19

Figure 1.4 I-465 Heatmap with crashes and camera image comparisons for clear day (01/05/2019) and snow day (01/12/2019)

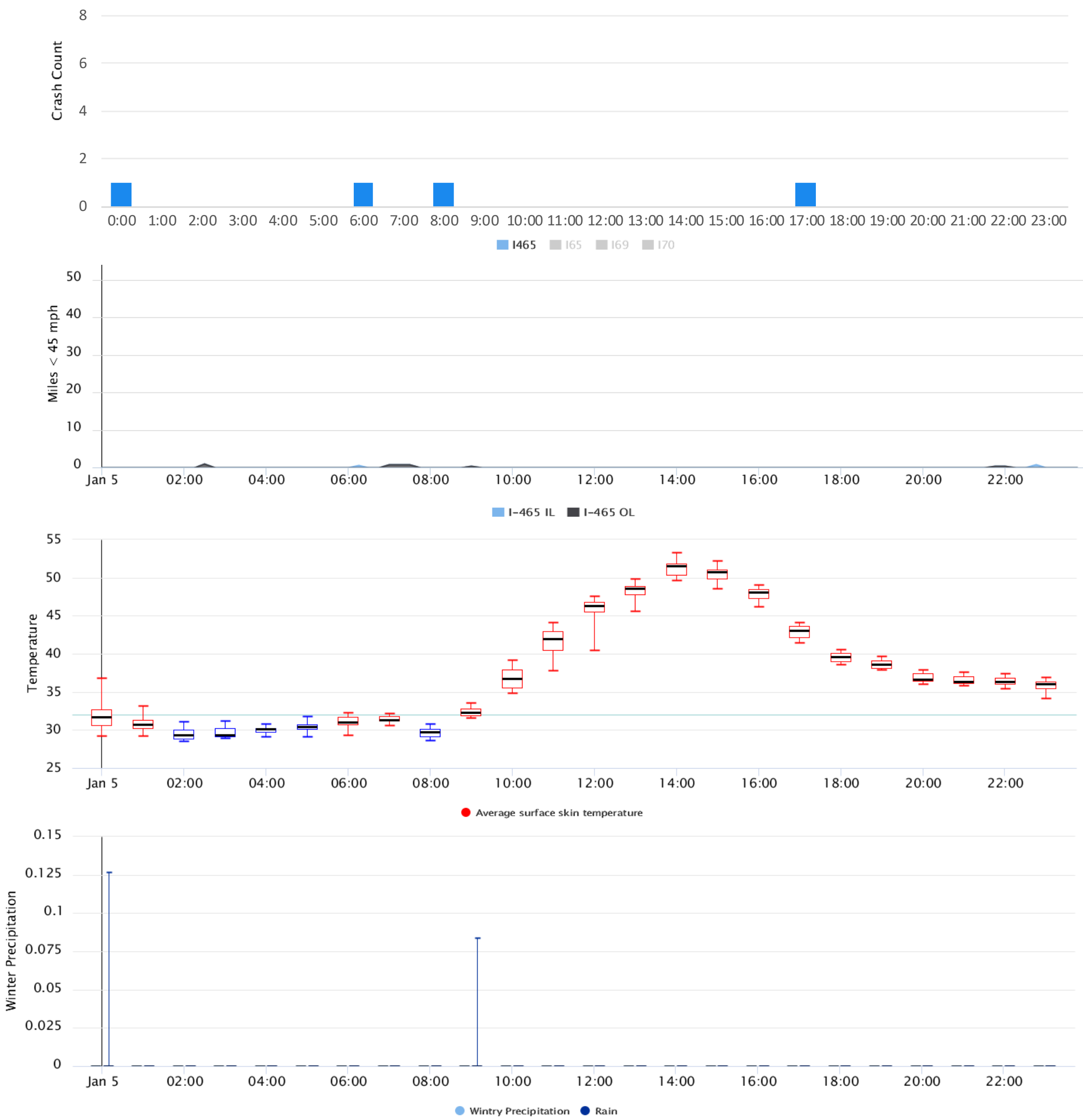



Figure 1.5 Crash counts, interstate miles below 45 mph, temperature and winter precipitation for clear day (01/05/2019)

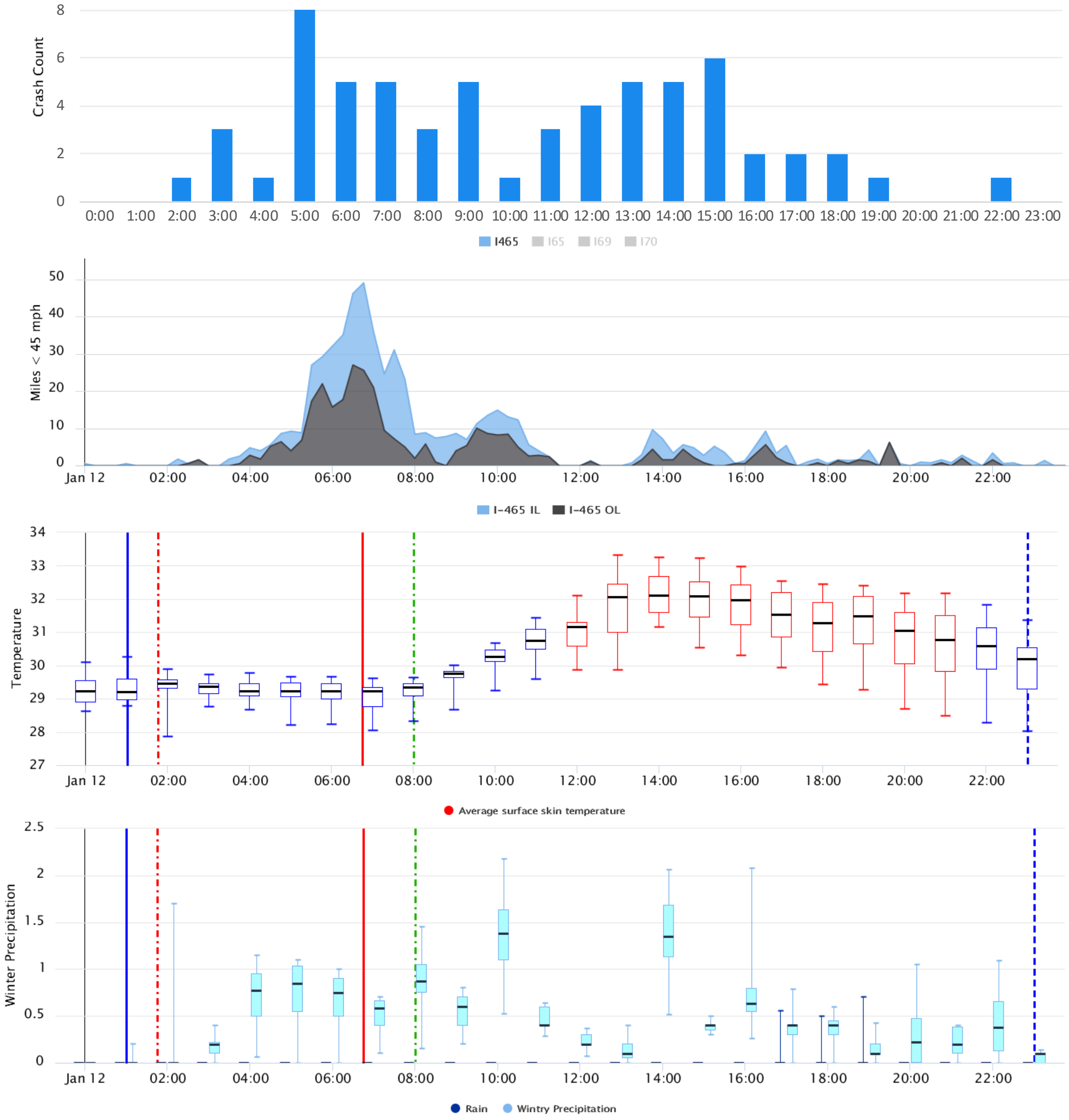



Figure 1.6 Crash counts, interstate miles below 45 mph, temperature and winter precipitation for snow day (01/12/2019)

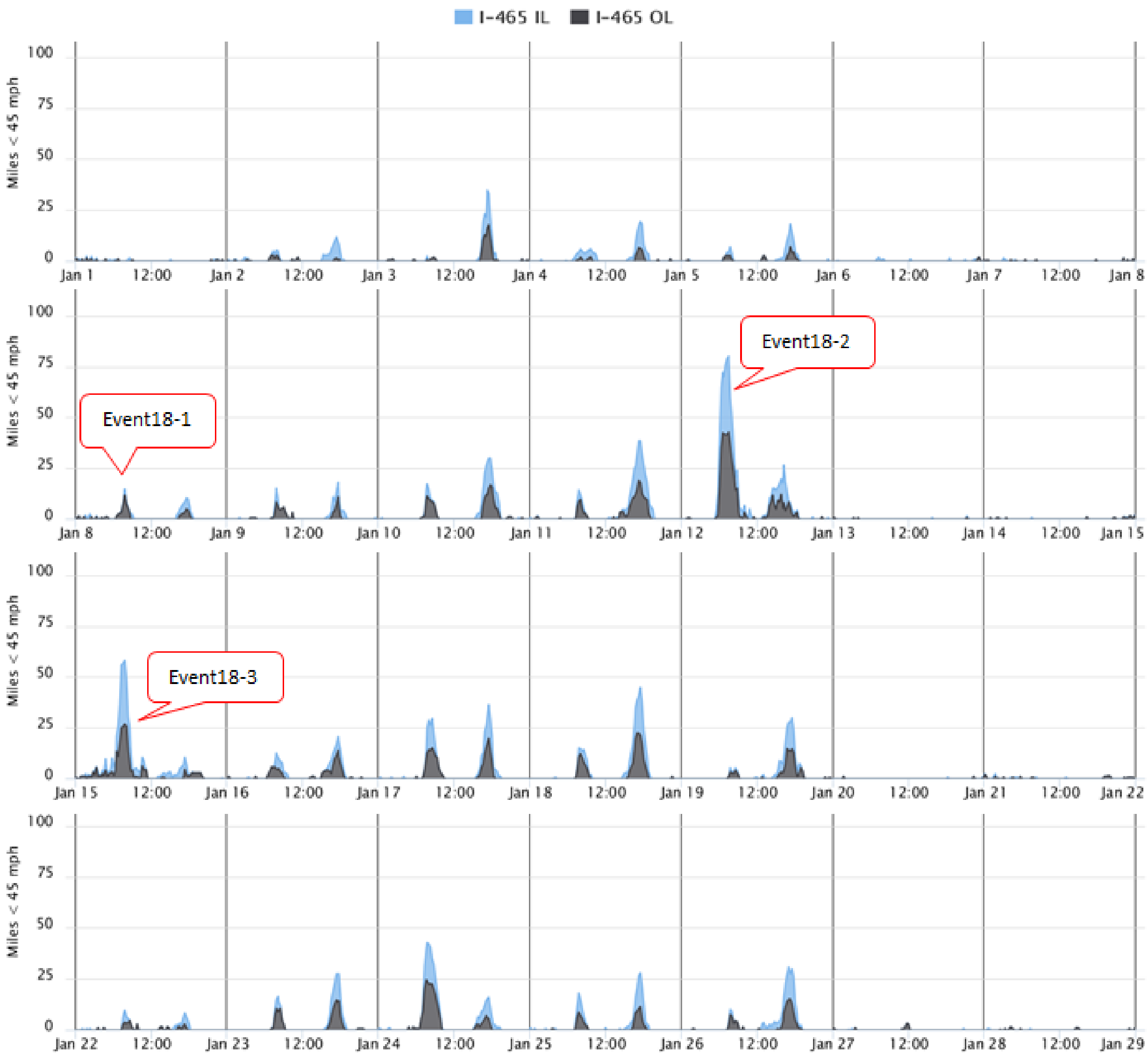



Figure 1.7 I-465 2018 January weekly interstate miles below 45 mph (Monday to Sunday) for both directions (inner loop and outer loop)

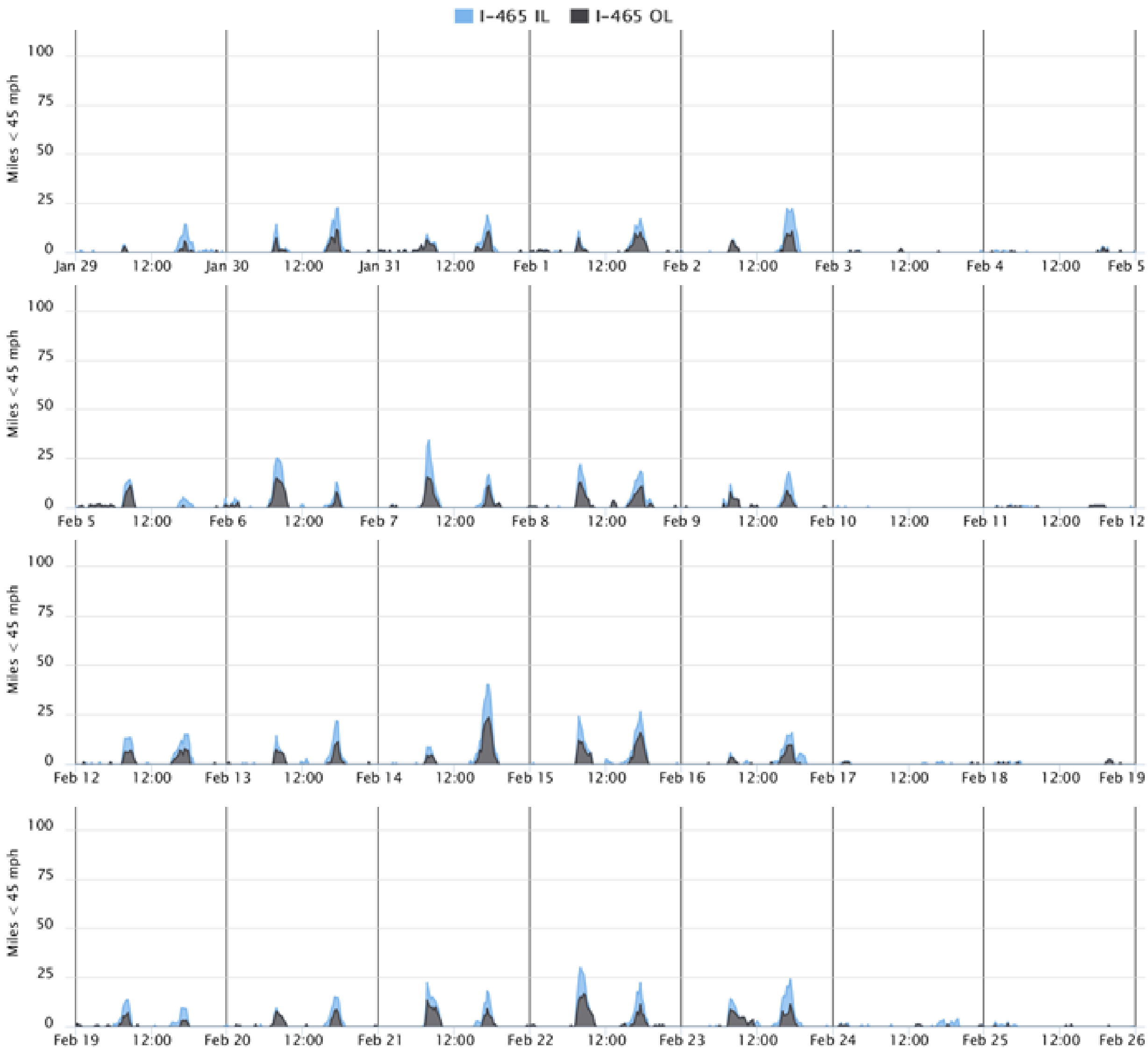



Figure 1.8 I-465 2018 February weekly interstate miles below 45 mph (Monday to Sunday) for both directions (inner loop and outer loop)

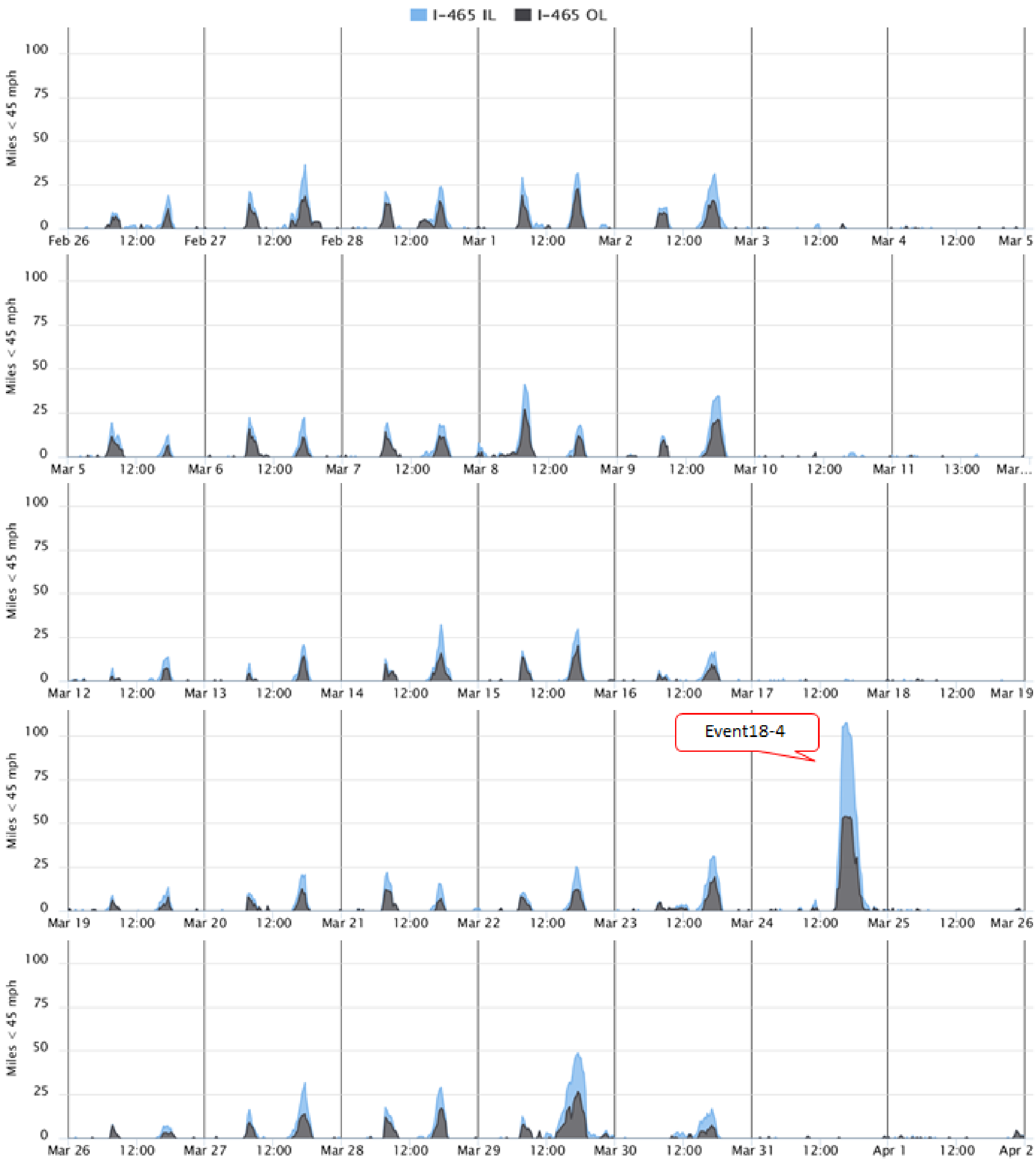



Figure 1.9 I-465 2018 March weekly interstate miles below 45 mph (Monday to Sunday) for both directions (inner loop and outer loop)

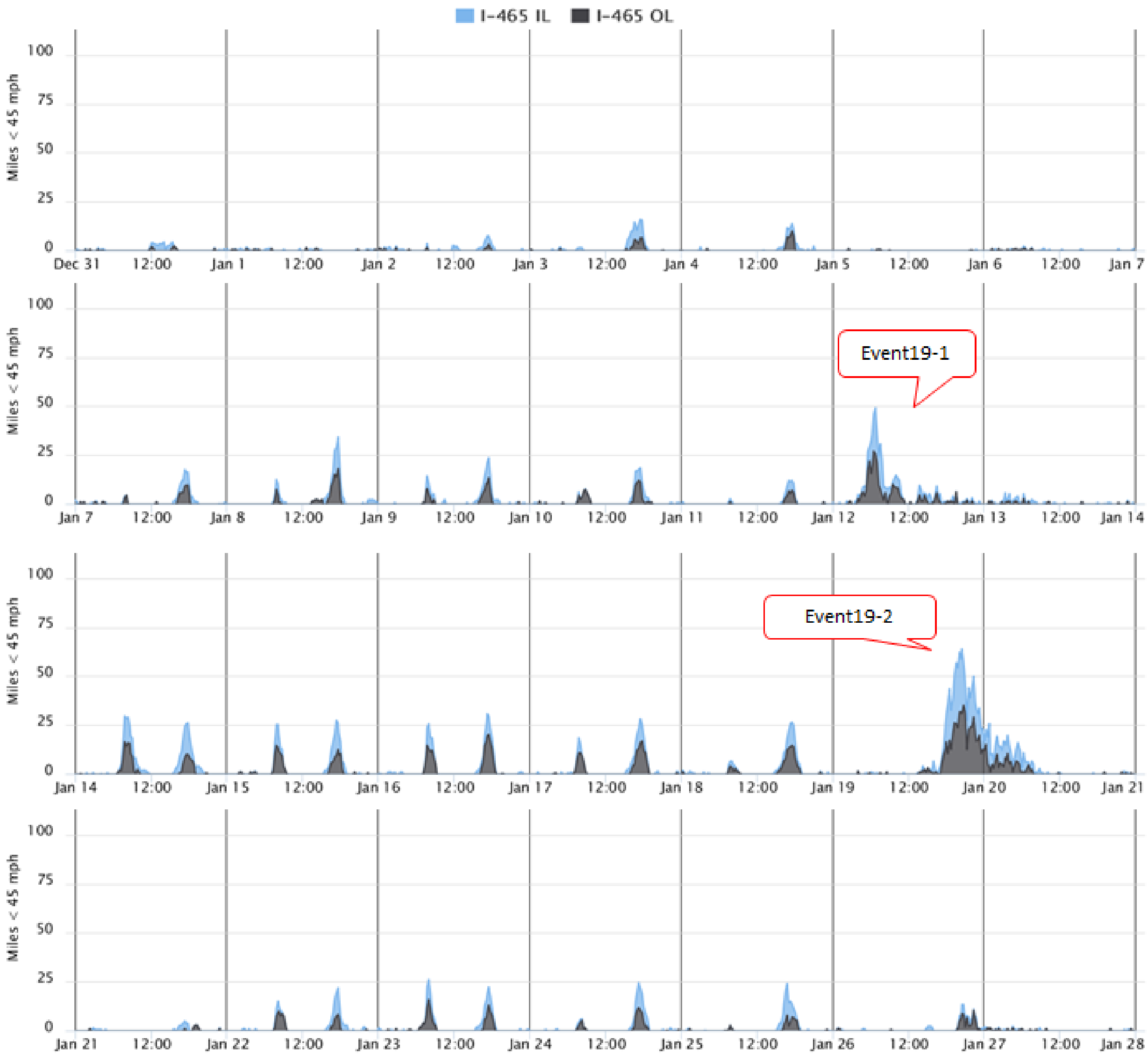



Figure 1.10 I-465 2019 January weekly interstate miles below 45 mph (Monday to Sunday) for both directions (inner loop and outer loop)

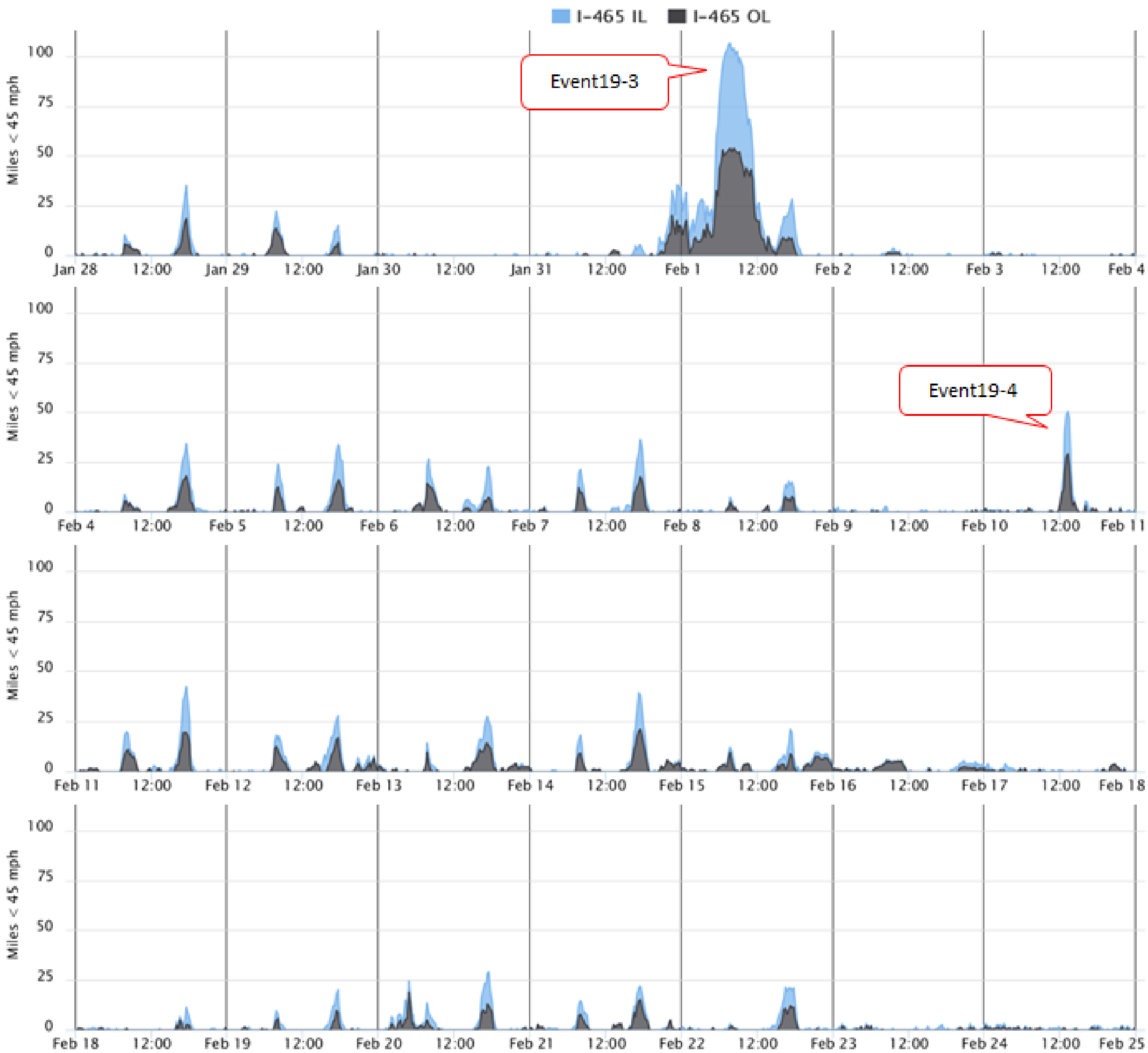



Figure 1.11 I-465 2019 February weekly interstate miles below 45 mph (Monday to Sunday) for both directions (inner loop and outer loop)


Figure 1.12 I-465 2019 March weekly interstate miles below 45 mph (Monday to Sunday) for both directions (inner loop and outer loop)

# 2. LITERATURE REVIEW

There are two attributes from the literature review section. First is to help identify the potential predominant factors to crashes. Second is to figure out the models utilized in the crash count modelling and provide fundamentals for the model selection in this study. The aim of the literature review is to better understand the problem and assess some best practices to develop a suitable model for adverse weather conditions and ultimately provide insights to lower the crash counts and increase efficiency in safety management.

## 2.1 Predominant Factors related to Crashes

Among the risk factors, driver's age and gender, speed zone, traffic control type, time of day, crash type and seatbelt usage are significantly related to highway crashes (Chen et al., 2012) (Sinha et al., 2007). Winter weathers and work zones also play critical roles in crash analysis. Identifying the predominant factors are especially important for roadway safety planning. The chapter examines potential key factors that could raise risks for crashes, as discussed in previous research papers on highway safety.

### 2.1.1 Human Factors

Human factors account for several crashes due to erroneous driving behavior and incorrect decisions. Several studies suggested that driver age and physical condition are strongly correlated with collision. Elderly drivers (Hakamies-Blomqvist, 1993), young drivers (Dissanayake & Lu, 2002), drivers with invalid license (Willis, 2000), and drivers without seatbelts (Cohen & Einav, 2003) are more likely to be involved in a collision. The safety-related studies revealed that the driver's age and crash risk relationship is bell-shaped under similar amount of exposure (Mayhew et al., 2006). When taking severity of the crash into consideration, elderly drivers are the most vulnerable (Hanrahan et al., 2009). Due to elderly drivers' reduced psychological and physical driving abilities, such as "inattention, perceptual lapses, misjudgment and illness", behaviors as failure to yield the right-of-way, disobeying traffic controls, or involvement in other traffic offenses were more frequently observed (Mayhew et al., 2006). Alcohol is also a non-negligible factor which resulted in 35% of fatal crashes in the U.S., this means about one in three traffic deaths involves a drunk driver. Alcohol-related crashes in the United States cost the public more than $44 billion in 2016, plus unforeseeable quality-of-life losses (Centers for Disease Control and Prevention, 2017).

### 2.1.2 Vehicle Design/ Safety Features

New vehicle design concepts and safety features, such as, lane-keeping assist, traction control, automatic emergency braking, blind spot warning and adaptive cruise control, were introduced in the past decades to increase the safety on the road and protect the vulnerable roadway users like pedestrians and motorcyclists. The National Highway Traffic Safety Administration (NHTSA) promotes these driver assistance technologies and states “if used properly, the technology will save lives”. On the other hand, vehicles with outdated design or with no safety features could be under higher risk of causing crashes (USDOT, 2016).

### 2.1.3 Roadway

Roadway characteristics are also critical components for safety analysis studies (Labi, 2006). For example, many studies suggested replacing an intersection with a roundabout to reduce crash counts and crash severity because a roundabout typically has only eight conflicting points whereas a four-way intersection has thirty-two conflicting points. Thus, roundabouts could reduce injury crashes by 30%-50% and fatal crashes by 50%-70% (Elvik, 2003). Moreover, number of lanes and lane width are also significant since many crashes happen when the driver is trying to change or merge into different lanes (Karim, 2015). Similarly, number of interchanges and exits are also important since plenty of crashes occur on ramps or exit areas.

### 2.1.4 Weather

Various environmental factors and weather parameters were studied, such as pavement temperature, air temperature, atmospheric visibility, wind speed and direction, as well as snow intensity, duration, and coverage (Xiao et al., 2006). A study conducted on the interstate highway system in Iowa used detailed crash counts, weather, traffic exposure, and roadway geometry data.

The results showed that higher wind speed (gusts) led to more injurious crashes, whereas higher snowfall intensity tended to result in less injurious crashes (Khattak & Knapp, 2001). Although the previous results varied, conclusions for such studies were mutually consistent (Xiao et al., 2006)(Eisenberg & Warner, 2005)(Brown & Baass, 1997). All emphasized the safety benefits offered by winter maintenance roadway de-icing activities. Researchers studied the economic impacts of winter road maintenance on roadway users and found a significant decrease in crash rates after de-icing maintenance activity when compared with crash rates prior to de-icing(U.S. National Research Council, 1993). Another study was conducted in Quebec, Canada, of crash rates during winter months as compared with crash rates during summer months. The research indicated that winter months had higher minor and material damage accident rates but lower severe and fatal crash rates. They acknowledged, however, that these results could change if winter road maintenance activities were modified (Brown & Baass, 1997). Snow-event based study claimed that weather conditions such as rain, snow, sleet, fog, and ice are accountable for reducing road surface friction, impairing driver visibility, obstructing roadway and thus, engendering traffic collisions (Xiao et al., 2006).

***Snow and Rain precipitation***

Snow has a greater effect on crash counts than rain. It can increase the crash rate by 84% and the injury rate by 75%, while rain can increase the crash rate by 71% and the injury rate by 49%. As precipitation intensity increases, the crash risk also increases (Qiu & Nixon, 2008). Roadway friction condition could be reduced significantly during such events and would therefore require longer stopping distances.

***Visibility***

Low Visibility caused by wind-blown snow, heavy rain, fog, and smoke can significantly decrease drivers' performance and judgement, and increase the crash risk. Low visibility could also decrease the overall system's travel speed and cause congestion. Each year, over 38,700 vehicle crashes occur in low visibility conditions. Over 600 people are killed and more than 16,300 people are injured in these crashes annually (FHWA, 2018).

***Temperature***

A sudden air temperature drop causing freezing rain or snow could be very challenging for highway treatment. Studies showed that temperature extremes have a direct influence on traffic volume or amount of mobility (Chrzan & Smal, 2015). Although the results about temperature varied, its negative influence on the number of accidents seemed to dominate (Hermans et al., 2006). However, temperature around freezing point could lead to different complex scenarios which could lead to different outcomes.

***Solar flux***

Solar radiation and sunshine duration both had a significant negative impact on road safety (Hermans et al., 2006). The more solar radiation during winter season means the snow are melting down and road surface condition getting back to normal so the probability of crash decreases.

### 2.1.5 Temporal

Time of the day or day of the week could also impact crash counts since people's travel pattern and travel behavior change during different times. For example, the peak hours always have more commute traffic and may lead to more crashes. Nighttime may have poor visibility compared to daytime. Studies reported that weekend trip length and travel duration are usually longer than weekday trips which could leave impacts on crash counts as well (Theses & Agarwal, 2004).

### 2.1.6 Traffic

Annual average daily traffic (AADT) was widely adopted when considering factors influencing crash counts (Labi, 2011) (Tarko & Songchitruksa, 2005). The studies' results varied due to the studied location (urban or rural), the methodology used to aggregate data, and the type of accidents being investigated. Positive linear relationships between traffic volume and total accidents were a common finding, as were the U-shaped functions, where accident occurrence was greatest at extreme low and extreme high levels of traffic volume (Martin, 2002). Shefer proposed that, when considering only fatal accidents, the opposite would be observed; fatalities were predicted to be greatest at median levels of traffic volume and lowest when congestion was extreme low or high (Shefer, 1994).

Additionally, researchers identified that winter storms were responsible for a traffic volume reduction of 7% to 56% on the major rural highways in the U.S. based on the snowfall intensity (National Research Council (U.S.). Transportation Research Board., 1993). Similarly, Knapp estimated an average of 16% to 47% reductions in traffic volume on the interstate highways in

Iowa during severe winter storms (at least 4-hour duration of snowfall with 0.51cm/hour) (Knapp & Smithson, 2000).

### 2.1.7 Spatial

Different study location would obviously have a different impact on crash counts. The demographics information like population density, household income and land use patterns would significantly impact the traffic count and travel behavior. For example, population has been widely employed as an indicator for crash exposure in previous macroscopic safety studies (Karlaftis & Tarko, 1998). Also, different type of road (urban, rural, freeway, or arterial) could lead to different number of crashes (Chen et al., 2019).

## 2.2 Crash Count Models

The fact that a crash could happen under any circumstances makes it extremely hard to model. However, it is critical for practitioners and engineers to understand the major contributing factors to crashes so that proactive activities/ decisions could be made to minimize crashes. Lord and Mannering did a review and assessment of methodological alternatives for crash modelling and suggested that different models needed to be considered based on the nature of the dataset (Lord & Mannering, 2010). Below are some of the suggested models that may fit the dataset of this study.

### 2.2.1 Poisson and Negative Binomial models

Poisson and negative binomial models are the most used models for crash count analysis (Anastasopoulos et al., 2010). Such models are suitable for predicting random, discrete and non-negative crash counts. Poisson regression is helpful for exploring the relationship between crashes and contributing factors when the mean and variance of the crash frequencies are equal. According to Lord and Mannering, both negative binomial (NB) regression and zero-inflated negative binomial (ZINB) regression can be effective when overdispersion is high. When experimental variance of the data is greater than the anticipated variance or mean, the condition is considered overdispersion (Lord et al., 2005).

Noland employed negative binomial count data models to demonstrate the associations between spatially disaggregate land use type data with traffic fatalities in England (Noland & Quddus, 2004). Studies also used negative binomial models to detect the relationship between crash injuries and major influential factors (Mitra, 2009)(Quddus, 2008)(Chen et al., 2017). Extensive studies have also been conducted on analyzing the relationship between adverse weather and crash incidences (Khattak & Knapp, 2001) (Qiu & Nixon, 2008).

### 2.2.2 Zero-Inflated Poisson and Zero-Inflated Negative Binomial Models

Zero-inflated Poisson (ZIP) and Zero-inflated negative binomial (ZINB) models are getting popular in the past decades for modelling crash counts. Since a crash is an event with high randomness, and based on different aggregation methods, the crash counts could have excessive zeros in the dataset. Both ZIP and ZINB work in a two-step process. The first one being generating excess zero count derived from a binary model and second one being generating non-negative counts for crashes including zero crashes, which are estimated from the Poisson or negative binomial distribution. Although zero-inflated models can provide more reliable models by eliminating the noise effect of excessive zeros, there has been debate on the validation of these models(Lord et al., 2005) (Anastasopoulos et al., 2010).

### 2.2.3 Random Parameter Models

Random parameter models are the ones with parameters varying across observations. This type of model is practically suitable for modelling crash counts because they can address the unobserved heterogeneity issue in the dataset. Considering such unobserved heterogeneity across the spatial zones will provide better insight into the influences of the contributing factors on crash counts (Ukkusuri et al., 2011)(Chen et al., 2019),.

### 2.2.4 Panel Data Models

Panel data models are useful for data with both spatial and temporal dimensions while accounting for heterogeneity across individual observations. Road crash data often involves crosssectional and time-series information, panel data count models have been adopted frequently to isolate the time or location impacts on the crash counts.

# 3. DATA PROCESSING

## 3.1 Weather Data

This study uses data from North American Land Data Assimilation System (NLDAS) for the weather attributes. The data are available in 1-hour intervals and each weather station covers an area of twelve-kilometer by twelve-kilometer grid. Weather related data were collected from the eight weather stations closest to I-465 shown in Figure 3.1 below. Each station's weather data were then assigned to the nearest segment shown in Figure 1.1 (Downing et al., 2020).

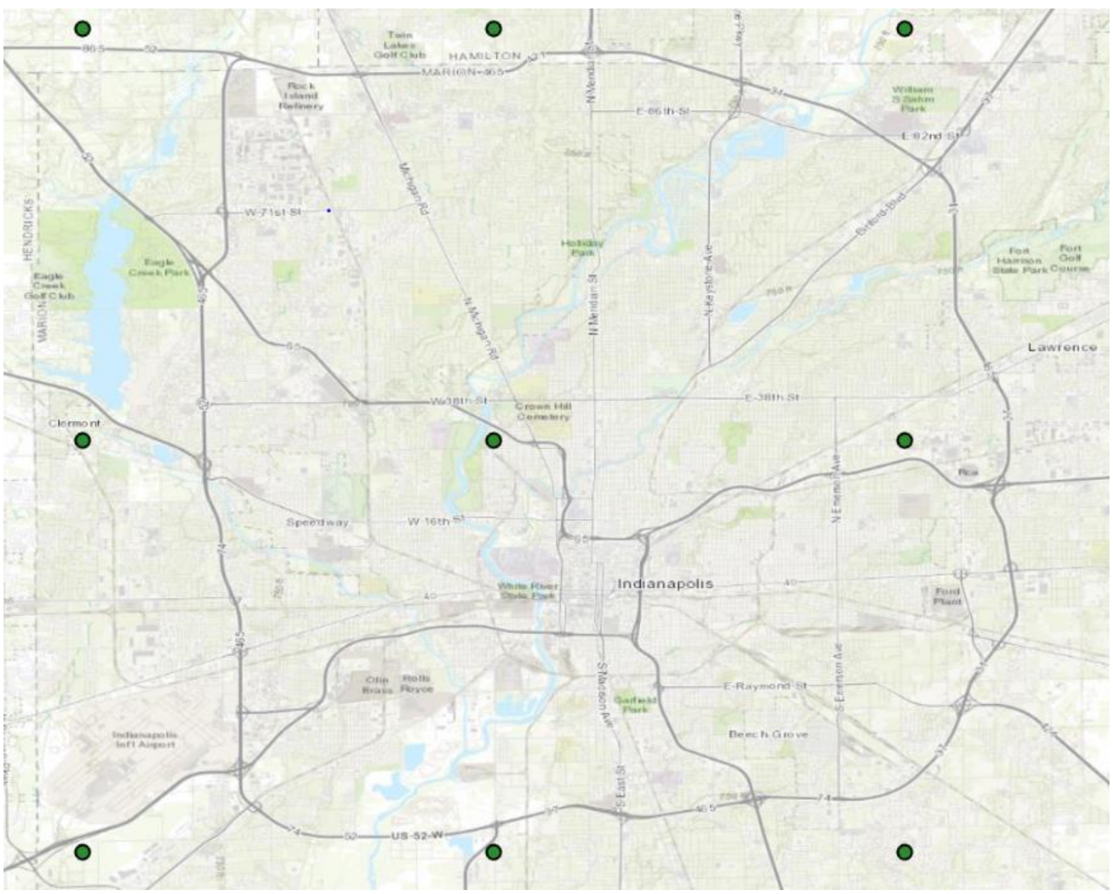



Figure 3.1 Weather stations near I-465

## 3.2 Speed Data

Probe vehicle data collected and provided by INRIX Analytics was used for speed data (Day et al., 2016). The data were collected by dividing the roadway into small segments (“xdid”, which is a serial number for each location). Each segment is in a range of 0.3 to 1.5 miles. For speed variables, if the name of the variable is “Mean_below_15” then it means the average travelling speed on the segment is greater than 0 mph and lower than 15 mph; if it is “Mean_below_25” then the average travelling speed is greater than 15 mph and lower than 25 mph. The rest of the speed variables also correspond to different speed bins in the same manner. The data was provided in fifteen-minute intervals, and for each “xdid”, the duration (minutes) of travel speed under certain miles per hour was recorded. For example, if the raw data showed 5 for speed below 15 mph at location “xdid 1”, then there were 5 minutes out of the 15-minute interval when the overall speed at this particular location was under 15 mph. By aggregating the data into one-hour intervals to achieve consistency with weather data, this study first checked how many “xdids” were in each of the segment and found the mean speed variables at all the “xdids” in that segment. Then, the researchers of this study repeated the same process and aggregated the data into six-hour intervals. It was realized that by doing this the resolution of the data might suffer. However, the congestion trend would not change much. If there was severe congestion during the six-hour period, then the mean time for congestion would be high.

## 3.3 Traffic Data

Traffic data, were provided by INDOT’s Traffic Management Center This involved an hourly traffic counts near each interchange, for all thirty interchanges on I-465 (INDOT, 2020). For further analysis, a new hourly traffic count was calculated by taking the average of the data between interchanges on each of the eight segments, after which a six-hour aggregation was calculated by taking the sum of each six hours. For example, a typical Monday and Saturday hourly traffic count were shown in Figure 3.2 and  Figure 3.3, respectively. It was observed in the dataset that, the traffic count for weekends from 1:00 p.m. to 7:00 p.m. were recorded as the same count. However, the trend for a six-hour aggregation was not affected significantly. As of the time of this study, 2019 traffic count data were not available. According to INDOT, the AADT generally had the same trend from 2018 to 2019, thus the traffic count for 2019 was assumed to be the same for

2018. It is noted that location 6 and 7 have the highest traffic volume; location 2,3,5,8 have medium traffic; and location 1 and 4 have the lowest traffic.

## 3.4 Crash Data

The crash data used for this analysis was extracted from Automated Reporting Information Exchange System (ARIES) used by the Indiana State Police to record all crash incidents occurring on roadways in the state of Indiana(Tarko et al., 2016). Crash data were generated through first responder crash reports and collected within ARIES. Crash data are available whenever the police officers enter them into the system. For some severe crashes, it may take longer time to investigate and process the reports. This dataset includes crash details such as vehicle information, road conditions, crash severity, weather conditions, location, date, and time. Due to the confidential nature of this dataset and the parties involved, this study does not use any personal or identifying information from the crash database.

The total number of crashes occurred on I-465 are 859 and 940 in 2018, and 2019, respectively. This study focuses mostly on snow days, and the total crashes during the defined snow days in two years, is 353.

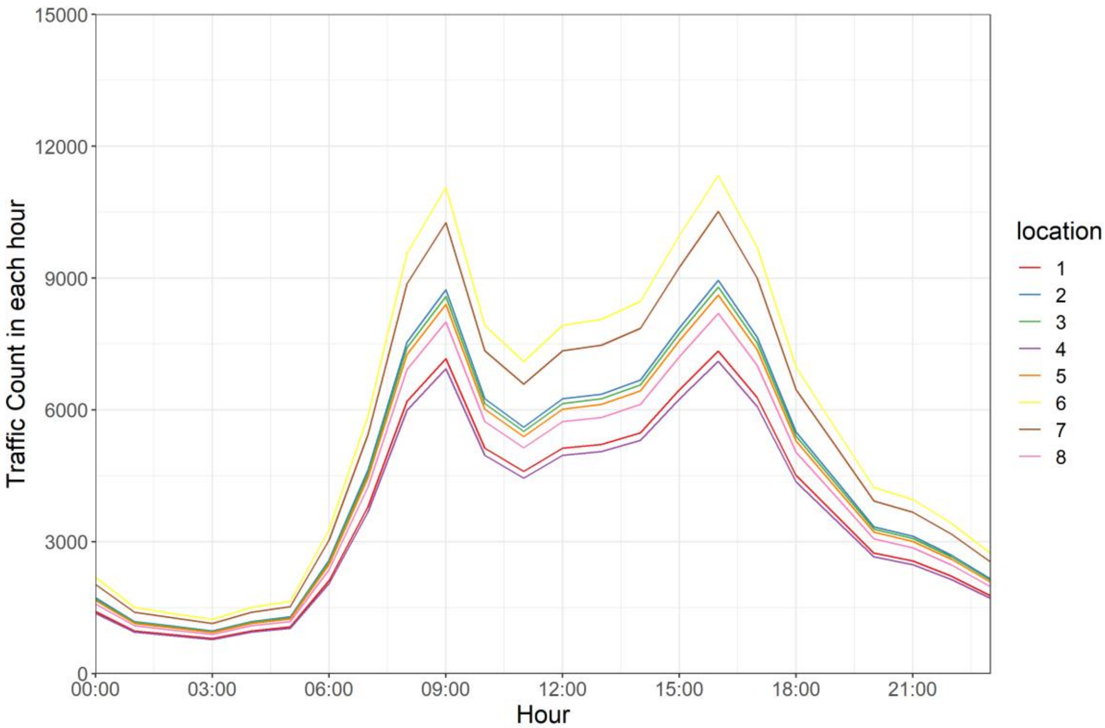



Figure 3.2 I-465 Typical Monday average hourly traffic count in each location (segment)

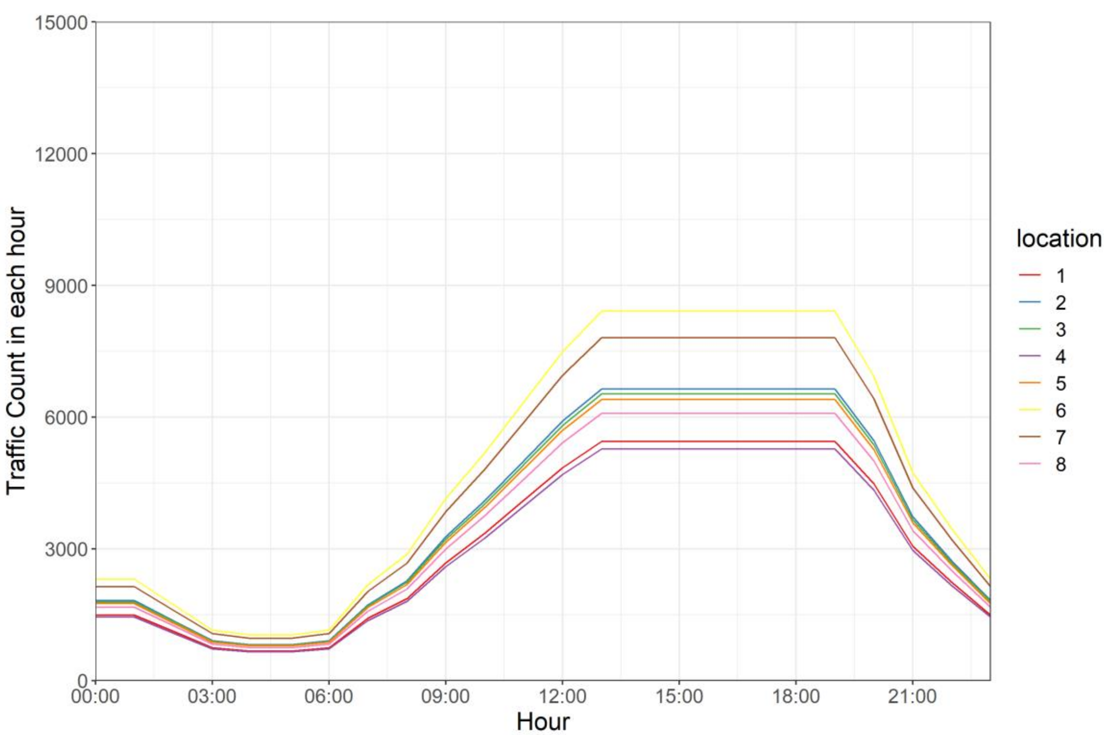



Figure 3.3 I-465 Typical Saturday average hourly traffic count in each location (segment)

# 4. ANALYSIS

To understand the relationship between the contributing factors and crash counts, with the extracted data from police reports and state highway-asset-management database, the analyses of traffic safety estimate the likelihood of a traffic crash. The number of crashes occurring on a defined spatial entity over a specific time period (for example, the number of crashes occurred at segment one of I-465 during Jan 3rd 0:00 a.m. to 6:00 a.m.) would be considered as the dependent variable, while most of the factors available and affecting the likelihood of a traffic crash are analyzed and examined. Although data on certain factors were not available for inclusion in this study, the major factors that are relevant to the traffic crashes have been incorporated and the model functional form was selected carefully in order to yield promising results. This section explains how the final data were selected, what variables were used, and which model provided the best fit.

## 4.1 Data Selection

After processing all the data, the snow days only dataset was filtered out and used in modelling. Doing this helped to reduce the excessive zeros in the crash counts. Snow days were defined as the days when the mean snow precipitation is greater than 0. Daily crash counts with congestion-mile hours plots for both 2018 and 2019 are shown in Figure 4.1 and Figure 4.2 below. Congestion-mile hours is a concept introduced in 2015 Indiana Mobility Report (Day et al., 2016), and the threshold for congestion was defined to be speed below 45 miles per hour. It is obvious for storm dates that both the number of crashes and congestion mile hours are high. However, for snow days with light precipitation, the correlation is not that evident. It is more reasonable to choose the snow days only dataset over the full dataset and the storm days only dataset (where mean snow precipitation > 0.1 millimeter), just to include sufficient and non-misleading information for predicting the crash counts. Figure 4.3 shows the dates selected for the modelling; days highlighted in red were winter event days (storm) and days highlighted in blue were the days with relatively light precipitation (snow).

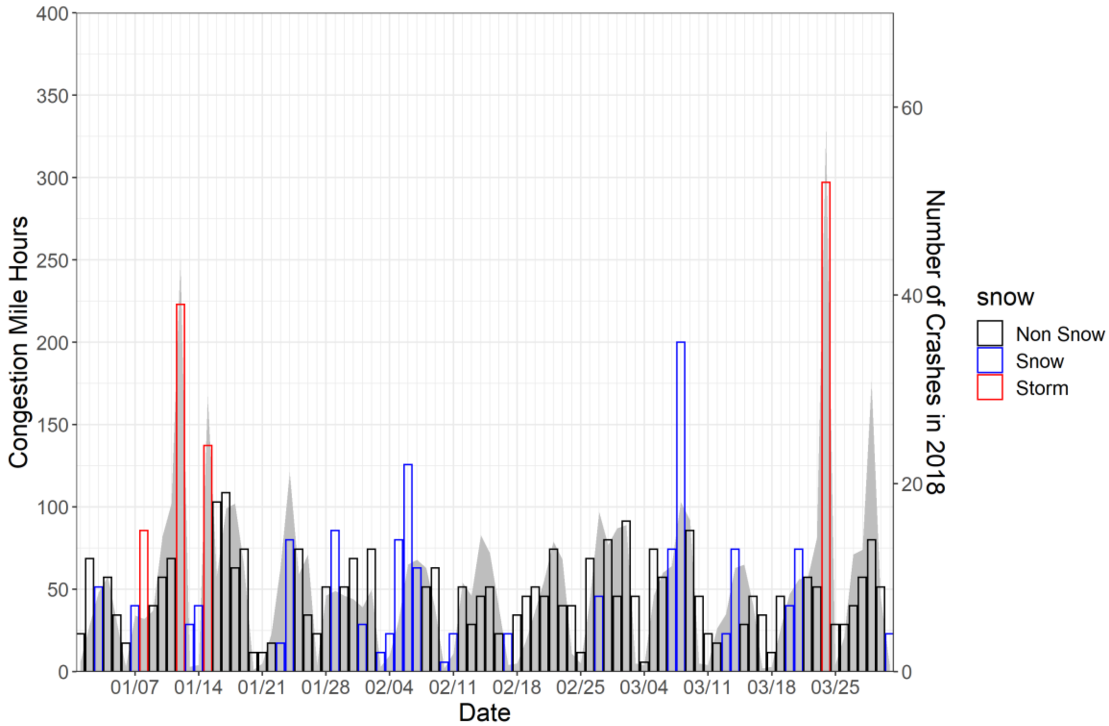



Figure 4.1 Daily congestion-mile hours vs. crash counts in 2018 with snow condition

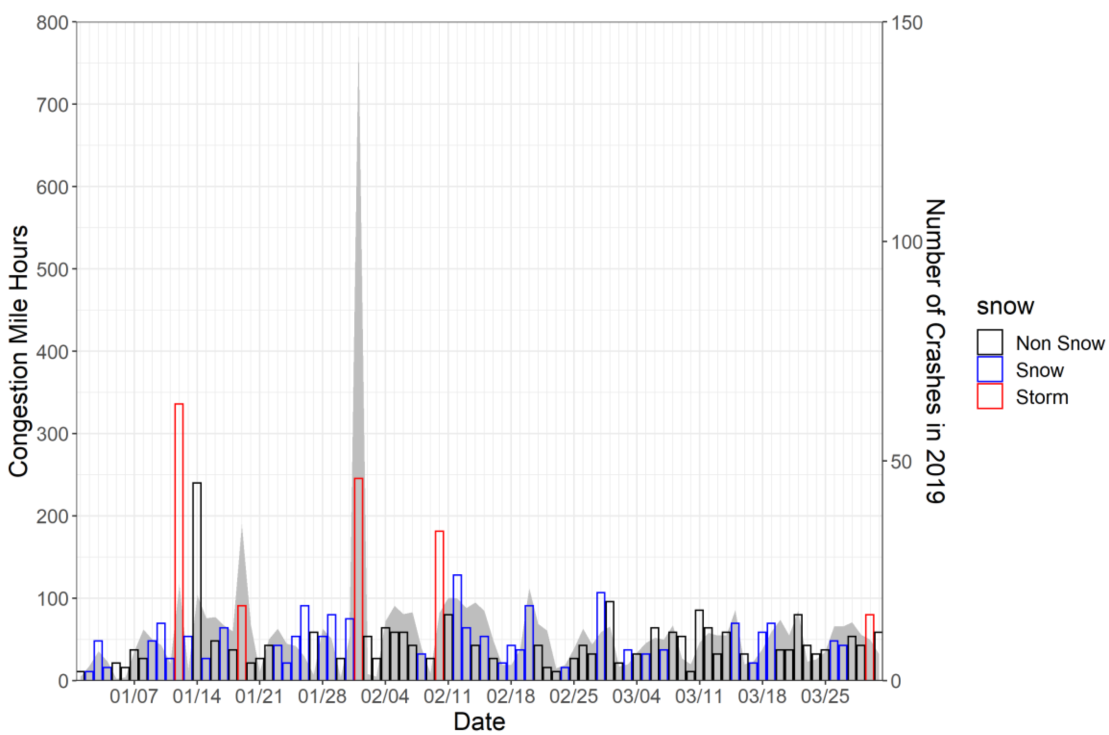



Figure 4.2 Daily congestion-mile hours vs. crash counts in 2019 with snow condition

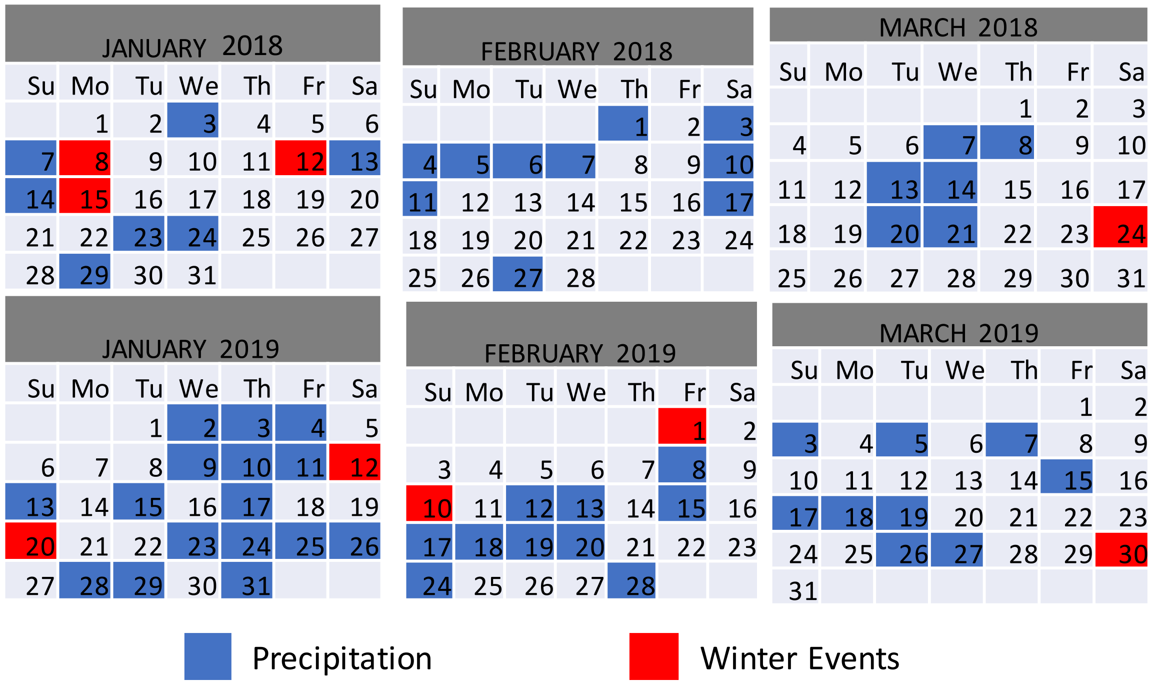



Figure 4.3 Dates selected for modelling with either precipitation or winter events

## 4.2 Model Selection

Poisson model is commonly used as the starting point to model crash counts. In the Poisson regression model, considering the number of crashes occurring per six hours in 2018 and 2019 at various segments on I-465, the probability of segment $i$ having $y_i$ crashes in every six hours (where $y_i$ is a non-negative integer) is given by (Equation 1):

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!} \tag{1}$$

Where: $P(y_i)$ is the probability of segment $i$ having $y_i$ accidents per six hours, and $\lambda_i$ is the Poisson parameter for segment $i$, which is equal to segment $i$'s expected number of crashes per six hours, $E[y_i]$. Poisson regression models are estimated by specifying the Poisson parameter $\lambda_i$ as a function of explanatory variables. In this study, explanatory variables include weather attributes, speed variables, traffic counts, number of interchanges and so on. The most common relationship between explanatory variables and the Poisson parameter is the log-linear model (Equation 2):

$$\lambda_i = EXP(\beta X_i) \tag{2}$$

where $X_i$ is a column vector of explanatory variables and $\beta$ is a row vector of estimated parameters. In this formulation, the expected number of events per period is given by $E[y_i] = \lambda_i$.

From the results, we get the value $\alpha$, the dispersion parameter, meaning the variance is greater than mean and indicating the data is overdispersed. Overdispersion can arise for a variety of reasons, depending on the phenomenon under investigation (Karlaftis & Tarko, 1998). The primary reason in many studies was that variables influencing the Poisson rate across observations had been omitted from the regression. The use of a negative-binomial model would be more appropriate compared to Poisson model for addressing the overdisperson issue. The negative binomial model can be derived from the Poisson model with $\lambda_i$ as follows (Equation 3):

$$\lambda_i = EXP(\beta X_i + \varepsilon_i) \tag{3}$$

Where: $EXP(\varepsilon_i)$ is a Gamma-distributed disturbance.

As with the Poisson regression model, the signs of the estimated parameters in the negative binomial model are as expected and are significant. In addition, the overdispersion parameter is statistically significant, confirming that the variance is larger than the mean. The restricted log-likelihood test suggests that the fitted model is superior to one with only the constant term.

Zero-inflated negative binomial model is also utilized to address the problem of excessive zeros in the crash counts. There are two steps to perform zero-inflated negative binomial model: (1) follow the binary logit model; (2) follow the traditional negative binomial methodology. For the binary logit model, one meaning for zero crash count is, according to certain criteria or under certain exposure, the event will almost never happen. An extreme example to illustrate this could be, if no vehicle travelled on segment one then the crash count should always be zero. Such scenarios can be called “zero count state”. The second meaning for zero crash count is just simply going through the data and finding that the number of crashes occurred during a time period at certain location could be one, two or zero. These scenarios are referred as the result of “normal count state”.

Previous studies suggest that for a highway 1-kilometer section, with conditions of straight roadway with wide lanes, low traffic volumes, and no roadside objects, the likelihood of a vehicle accident occurrence may be extremely small, but still present because an extreme human error could cause an accident. These sections are in a zero-accident state or a low risk zone because the likelihood of a crash is so small (the expectation of a reported accident may occur only once in a

100-year period). Thus, the zero count state may refer to situations where the likelihood of an event occurrence is extremely rare in comparison to the normal-count state where event occurrence is inevitable and follows some known count process (Lambert, 1992).

It is common not to know whether the observation is in the zero state or not - so the statistical analysis process must uncover the separation of the two states as part of the model estimation process. Models that account for this dual-state system are referred to as zero-inflated models (Lambert, 1992)(Greene, 2011). For model comparison purposes, the criteria for the exposure parameters were chosen as speed below twenty-five and snow. In reality, however, this model's concept is hard to be using the current dataset. The binary process of defining a zero-state is almost impossible since no strong evidence can conclude the crash count to be none at any of the segment during a six-hour period. Even though the result of this model gave us a lower AIC number which was preferred, it is more conservative in theory to use the negative binomial model to analyze the data.

The modeling approaches chosen so far, all treated parameters as constant across observations. However, the effect of some individual explanatory variables is not always the same for each observation. (Chen et al., 2017) For such cases, the fixed-parameter assumption could lead to biased results. For example, based on the different design or geometry of different segment of the roadway, speeding could be more dangerous on a complex and narrow road segment compared with a straight and wide road segment. This could be further interpreted in that travelling 70 mph may be not relevant to crash counts on segment one but may significantly impact crash counts on segment two. Thus, a random parameter negative binomial model was chosen to complete the modelling process.

To add random parameters in count-data models, estimated parameters are written as (Equation 4):

$$\beta_n = \beta + \omega_n \tag{4}$$

where $\omega_n$ is a randomly distributed term (e.g., a normally distributed term with mean zero and variance $\sigma^2$). With this equation, the parameter becomes (Equation 5):

$$\lambda_n | \omega_n = EXP(\beta_n X_n + \varepsilon_n) \tag{5}$$

in the negative binomial with the corresponding probabilities for negative binomial now being $P(y_i | \omega_i)$.

The random parameter negative binomial model was estimated using simulation-based maximum likelihood with 200 Halton draws. The number of Halton draws was selected because it has been proven to produce consistent and accurate parameter estimates (Mannering & Bhat, 2014). Halton draws were used for the simulation instead of random draws, because it has been shown that fewer Halton draws are required to attain convergence compared to random draws. Also, the efficiency of Halton draws is generally more significant than random draws. In order to select the random parameter density functional forms, the following distributions were investigated: uniform, lognormal and normal distributions, where the normal distributions were found to yield the best statistical fit for all the parameters amongst the three. Nonetheless, future studies could be conducted to further investigate and compare the different distributions for random parameter model in crash count analysis.

## 4.3 Variable Selection

A list of variables considered for this study is shown in Table 4.1 below. Multiple combinations of variables were used to find the best representative variables to be used in the model. By checking both the AIC numbers (preferring lower ones) and p-values (removing the ones that were not statistically significant), a combination of variables in Table 4.2 was selected for the final model.

Correlation is the state where two variables are highly correlated and contain similar information about the variance within the given dataset. A correlation matrix was generated to detect the collinearity among variables, and variables with large absolute values were not used. To address the multicollinearity issue, the Variance Inflation Factor (VIF) was used to measure the collinearity among predictor variables within a multiple regression. In general, the VIF was wanted to be at least smaller than 5 and ideally less than 2.5. Table 4.2 shows the result of VIFs of the selected variables and all seem acceptable even though the speed factor were a bit high due to its natural correlation to traffic counts and other speed bins.

Table 4.1 All Variable Names with Descriptions

| Variables | Names | Descriptions | Units |
|---|---|---|---|
| X1 | Min_air_Temp | Minimum air temperature | K |
| X2 | Mean_air_Temp | Mean air temperature | K |
| X3 | Max_air_Temp | Max air temperature | K |
| X4 | Min_rain | Minimum rain precipitation | mm |
| X5 | Mean_rain | Mean rain precipitation | mm |
| X6 | Max_rain | Maximum rain precipitation | mm |
| X7 | rain_time | Rain Duration | hr |
| X8 | Min_snow | Minimum snow precipitation | mm |
| X9 | Mean_snow | Mean snow precipitation | mm |
| X10 | Max_snow | Maximum snow precipitation | mm |
| X11 | snow_time | Snow Duration | hr |
| X12 | Min_wind_speed | Minimum wind speed (gust) | m/s |
| X13 | Mean_wind_speed | Mean wind speed (gust) | m/s |
| X14 | Max_wind_speed | Maximum wind speed (gust) | m/s |
| X15 | Min_visibility | Minimum horizontal visibility | m |
| X16 | Mean_visibility | Mean horizontal visibility | m |
| X17 | Max_visibility | Maximum horizontal visibility | m |
| X18 | Min_snow_depth | Minimum snow depth | m |
| X19 | Mean_snow_depth | Mean snow depth | m |
| X20 | Max_snow_depth | Max snow depth | m |
| X21 | Min_net_surface_solar_radiation | Minimum solar influx | W/m^2 |
| X22 | Mean_net_surface_solar_radiation | Mean solar influx | W/m^2 |
| X23 | Max_net_surface_solar_radiation | Max solar influx | W/m^2 |
| X24 | Wday | Day of week (0 to 7) | - |
| X25 | Startmm | Segment start mile marker | - |
| X26 | Endmm | Segment end mile marker | - |
| X27 | Mean_below_fifteen | Duration of speed below 15 mph per hour | min |
| X28 | Mean_below_twentyfive | Duration of speed below 25 mph per hour | min |
| X29 | Mean_below_thirtyfive | Duration of speed below 35 mph per hour | min |
| X30 | Mean_below_fourtyfive | Duration of speed below 45 mph per hour | min |
| X31 | Mean_below_fiftyfive | Duration of speed below 55 mph per hour | min |
| X32 | Mean_below_sixtyfive | Duration of speed below 65 mph per hour | min |
| X33 | Mean_over_sixtyfive | Duration of speed over 65 mph per hour | min |
| X34 | Crash counts | Number of crashes | - |
| X35 | Length | Length of the segment | miles |
| X36 | Weekday | Weekday (1), Weekend (0) | - |
| X37 | Interchange | Number of interchanges | - |
| X38 | Location | Segment number (0 to 8) | - |
| X39 | Six-Hours Traffic | Six hourly traffic counts | cars/six hrs |
| X40 | Interchange | Inner and Outer loop combined X37 | - |
| X41 | Location | Inner and Outer loop combined X38 | - |

Table 4.2 Selected Variables for modelling and their collinearity

| Variables | Name | Tolerance | VIF |
|---|---|---|---|
| X2 | Air Temperature (K) | 0.75 | 1.34 |
| X9 | Snow (mm) | 0.48 | 2.09 |
| X13 | Wind Speed (m/s) | 0.81 | 1.23 |
| X16 | Visibility (m) | 0.40 | 2.47 |
| X22 | Net Surface Solar Radiation (W/m^2) | 0.59 | 1.70 |
| X28 | Speed Below Twenty-five | 0.57 | 1.75 |
| X29 | Speed Below Thirty-five | 0.36 | 2.74 |
| X31 | Speed Below Fifty-five | 0.24 | 4.21 |
| X32 | Speed Below Sixty-five | 0.26 | 3.78 |
| X39 | Six-Hours Traffic | 0.57 | 1.75 |
| X40 | Number of Interchanges | 0.99 | 1.01 |

A summary table of descriptive statistics of estimated variables is shown in Table 4.3. This table represents all the selected variables used in the model are provided with minimum, mean, standard deviation and maximum values. For example, the air temperatures used for the model are within a range of 260.06 Kelvin to 277.08 Kelvin with an average of 270.68 Kelvin which is below freezing point (273.15 Kelvin). This is reasonable because the snow days only dataset was chosen, and the air temperature was supposed to be relatively low. It is noted the snow (X9) is measured in the melted water equivalent, and an average of 0.2 millimeter means that the hourly wintry precipitation is approximately 0.1 inch throughout the snow days in 2018 and 2019. The maximum as 2 millimeters means hourly wintry precipitation peaked at 1 inch at certain location of I-465.

Table 4.3 Descriptive Statistics of Estimated Variables

| Variables | Name | Minimum | Mean | Standard Deviation | Maximum |
|---|---|---|---|---|---|
| X2 | Air Temperature (K) | 260.06 | 270.68 | 3.39 | 277.08 |
| X9 | Snow (mm) | 0 | 0.2 | 0.28 | 2.01 |
| X13 | Wind Speed (m/s) | 0.77 | 10.37 | 4.17 | 19.76 |
| X16 | Visibility (m) | 832.68 | 15581.3 | 7797.96 | 24100 |
| X22 | Net Surface Solar Radiation (W/m^2) | 0 | 33.71 | 56.47 | 268.09 |
| X28 | Speed Below Twenty-five | 0 | 0.27 | 0.76 | 6.82 |
| X29 | Speed Below Thirty-five | 0 | 0.97 | 2.34 | 18.02 |
| X31 | Speed Below Fifty-five | 0 | 7.34 | 9.55 | 49.33 |
| X32 | Speed Below Sixty-five | 1.74 | 40.78 | 13 | 58.82 |
| X39 | Six-Hours Traffic | 5061.33 | 24353.7 | 13332.69 | 58514 |
| X40 | Number of Interchanges | 2 | 3.68 | 1.18 | 6 |

## 4.4 Signs of Coefficients

From the model results in Table 4.4, it is observed that the snow precipitation (X9) is highly correlated to crash counts. Intuitively, the more it snowed, the more crashes happened. Wind speed (X13) was found to have a negative effect on crash counts, due to the risk compensation effect (Labi, 2016) (Mannering, 2009): people drive more cautiously on windy, snowy days. Especially for truck drivers, wind could have a significant impact on overturned truck crashes, so if more attention was raised during such situations, crash counts would drop. At the same time, low visibility (X16) would leave drivers less time to react to incidents, especially when lane markings are covered by snow. The net surface solar radiation (X22) is negatively related to crash counts. A higher solar influx accelerates the snow/ ice removal and provides a better road surface condition, thus reduces the probability of a crash. However, it is realized that there exists time lag effect associated with solar radiation variable, which could be addressed in future studies.

All the speed related factors (X28, X29, X31, X32) had a positive impact on crash count. This is also very intuitive since the more congestion on the road, the higher possibility of rear end crash to occur. Studies in Colorado showed a consistent result and stated that, larger differences between the legal speed limit and the traffic speed contribute to an increase of crash frequency (F. Chen et al., 2016) (Yu et al., 2013). Additionally, if drivers are travelling under 55 mph, it means they are transferring from normal driving conditions to just slowing down. This could result in a high chance of a crash because of a failure to slow down or stop. Travel speed between 55 mph to 65 mph (X32) also has a positive impact on crash counts since the speed limit on I-465 is 55 mph and travelling over the speed limit could result in a higher number of crashes.

The traffic count has a negative relationship with crash counts because the capacity of I-465 is always generally fixed. This means the more traffic on the road, the less likely speeding is to occur and, ultimately, the less likely a crash is to occur. Air temperature (X2) has a positive relationship with crash counts since the dataset only contains the snow day observations. On a typical snow day, if the air temperature rises above freezing point, then the snow/ ice starts to melt. This could lead to a slipperier and messier roadway condition causing more crashes to occur.

Finally, the highway environment is always crucial in predicting crash counts. The number of interchanges (X40) are positively related to crash counts since a large portion of highway crashes happen on the ramp and exit areas.

### 4.5 Random Parameter and Elasticity

Ninety-nine percent of the data shows that during snow days, an increase in air temperature will increase the probability of crash; 98% of the data shows that travel speed over 65 mph will increase the crash counts; and 96% of the data shows that increasing the number of interchanges will increase the possibility of crash occurrence. Clearly, these factors vary on different segments on I-465.

Elasticity is commonly used to determine the relative importance of a variable in terms of its influence on a dependent variable (Chen et al., 2017) (Chen et al., 2019). In this case, the dependent variable is the crash counts. Elasticity is generally interpreted as the percent change in the dependent variable induced by a 1% change in the independent variable. Elasticity values only make valid sense for continuous variables and not for indicator or discrete variables. Elasticities are an appropriate way to evaluate the relative impact of each variable in the model. The results are shown in Table 4.5 below. An example interpretation is, for travel speed between 55 mph and 65 mph (high-speed bin), the elasticity of 1.37 means an increase in the crash counts by 1.37% when the high-speed bin increases by 1%. Similarly, it is observed during snow events that, as air temperature increases by 1%, the crash counts could result in an 15.72% increase.

Table 4.4 Estimation Results of Random Parameter Negative Binomial Model

| Description | Parameter Estimate | Std. Error | P-value | Significance Level |
|---|---|---|---|---|
| *Constant* | -19.07 | 6.17 | 0.002 | *** |
| *Non-Random Parameter* | | | | |
| Snow (mm) | 0.81 | 0.24 | 0.0006 | *** |
| Wind Speed (m/s) | -0.058 | 0.016 | 0.0002 | *** |
| Visibility (m) | -3.90E-05 | 1.10E-05 | 0.0005 | *** |
| Net Surface Solar Radiation | -0.0031 | 0.0019 | 0.0927 | * |
| Speed Below Twenty-five | 0.21 | 0.072 | 0.0038 | *** |
| Speed Below Thirty-five | 0.081 | 0.033 | 0.0133 | ** |
| Speed Below Fifty-five | 0.058 | 0.013 | 0 | *** |
| Traffic Count | -8.70E-06 | 5.00E-06 | 0.0808 | * |
| *Random Parameter* | | | | |
| Air Temperature (K) | 0.058 (0.0023) | 0.022 (0.00021) | 0.0098 (0.0000) | *** (***) |
| Speed Below Sixty-five | 0.033 (0.015) | 0.0099 (0.0015) | 0.0007 (0.0000) | *** (***) |
| Number of Interchanges | 0.24 (0.042) | 0.047 (0.013) | 0.0000 (0.0014) | *** (***) |
| Log Likelihood (restricted): -852.48 | | Log Likelihood (unrestricted): -700.21 | | |
| $X^2$: 304.55 | | $\rho^2$: 0.18 | | |
| AIC: 1432 | | | | |

Table 4.5 Elasticity for the random parameter negative binomial model

| Variable Name | Description | Elasticity |
|---|---|---|
| X2 | Air Temperature (K) | 15.72 |
| X9 | Snow (mm) | 0.16 |
| X13 | Wind Speed (m/s) | -0.61 |
| X16 | Visibility (m) | -0.61 |
| X22 | Net Surface Solar Radiation (W/m^2) | -0.11 |
| X28 | Speed Below Twenty-five | 0.056 |
| X29 | Speed Below Thirty-five | 0.079 |
| X31 | Speed Below Fifty-five | 0.43 |
| X32 | Speed Below Sixty-five | 1.37 |
| X39 | Six-Hours Traffic | -0.21 |
| X40 | Number of Interchanges | 0.86 |

## 4.6 Discussion

Most of the results are consistent with literatures mentioned before. More plots for discussion are provided in this section. Visibility vs. crash counts during snow days is shown in Figure 4.4. It can be seen in the blue box that low visibility increases the chance of crash as well as the number of crashes. A possible reason for this could be that, situations like snow, fog or haze happened when visibility was under 10,000 meters. In Figure 4.5, negative correlation can be seen between visibility and total number of crashes. This finding could lead agencies to closely monitor the weather condition especially when visibility drops below 7,000 meters during snow events. Roadway assistance warnings delivered at these situations can alert the roadway users to drive more cautiously. In Figure 4.6, two cases were presented to show the significance of low visibility in causing more crashes. Callout A and B showed the same location's camera image during winter storm on Jan 12$^{th}$, 2019, when the air temperature was about 272 Kelvin during both time periods. The number of crashes during callout A's time period (0:00 a.m. - 6:00 a.m.) was four and the average visibility at this location was about 1,000 meters, whereas callout B (6:00 p.m. - 24:00 p.m. in the same day) had zero crash and a much higher visibility (6,000 meters). The other case showed in callout C and D also confirms the result of lower visibility causing higher crash counts.

Air temperature vs. crash counts during snow days is shown in Figure 4.7. Clearly, the crash counts increase when air temperature is near freezing point, where icy road conditions and low pavement friction can occur. Drivers could make judgment mistakes around air temperature at 30-

32 Fahrenheit. In Figure 4.8, one of the key findings is that the crash counts' peak is at air temperature around 30 Fahrenheit instead of the freezing point (32 Fahrenheit). This information will be very helpful for agencies to set up thresholds in monitoring the weather and making snow/ice removal treatment plans. Figure 4.9 and Figure 4.10 present a case where air temperature could be the significant contributing factor for the increasing number of crashes. In Figure 4.9, from the ten-day overview, it can be seen that number of crashes (callout a) are highly related to the wintry precipitation (callout b). With a more detailed look in Figure 4.10, it can be found that after the snow event, the number of crashes increased twice (callout c and e) when there was an obvious change in temperature (callout d and f). Even if the increase of crash counts in callout e could also be related to the increase of traffic count during daytime, however, it is observed in Figure 4.9 that, in the previous Saturday the traffic was not very heavy during morning hours. Hence, sudden change in temperature plays critical role in the increasing number of crashes for that day on I-465.

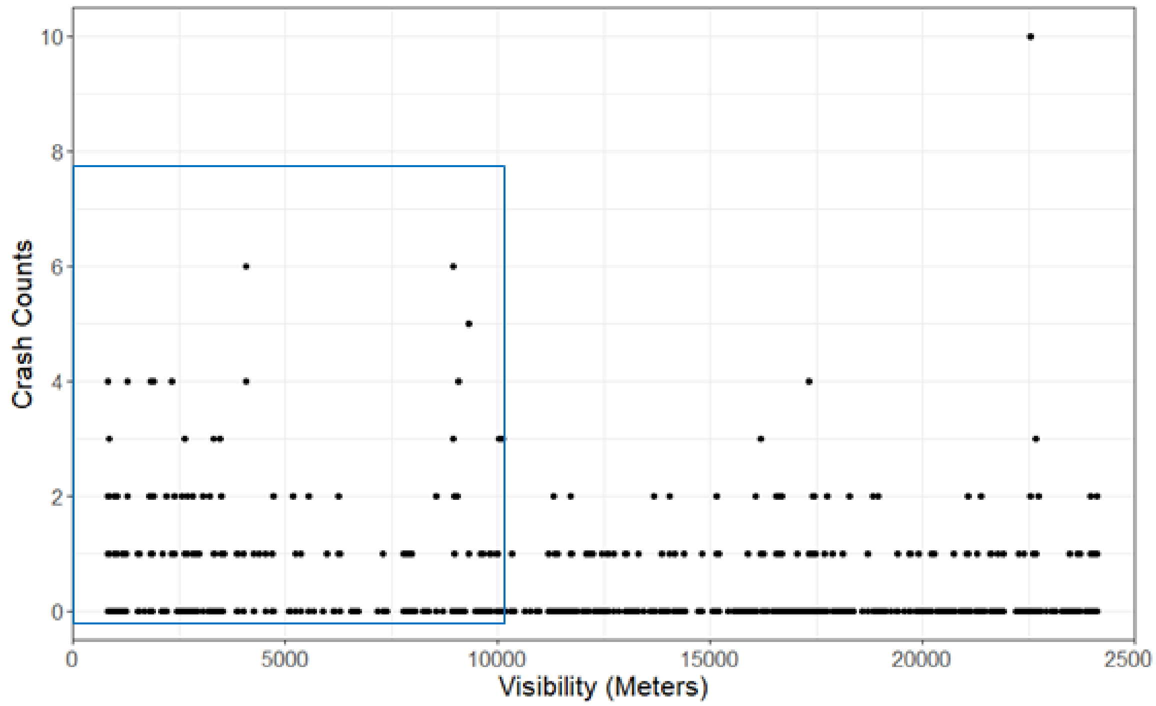



Figure 4.4 Visibility vs. crash counts during snow days

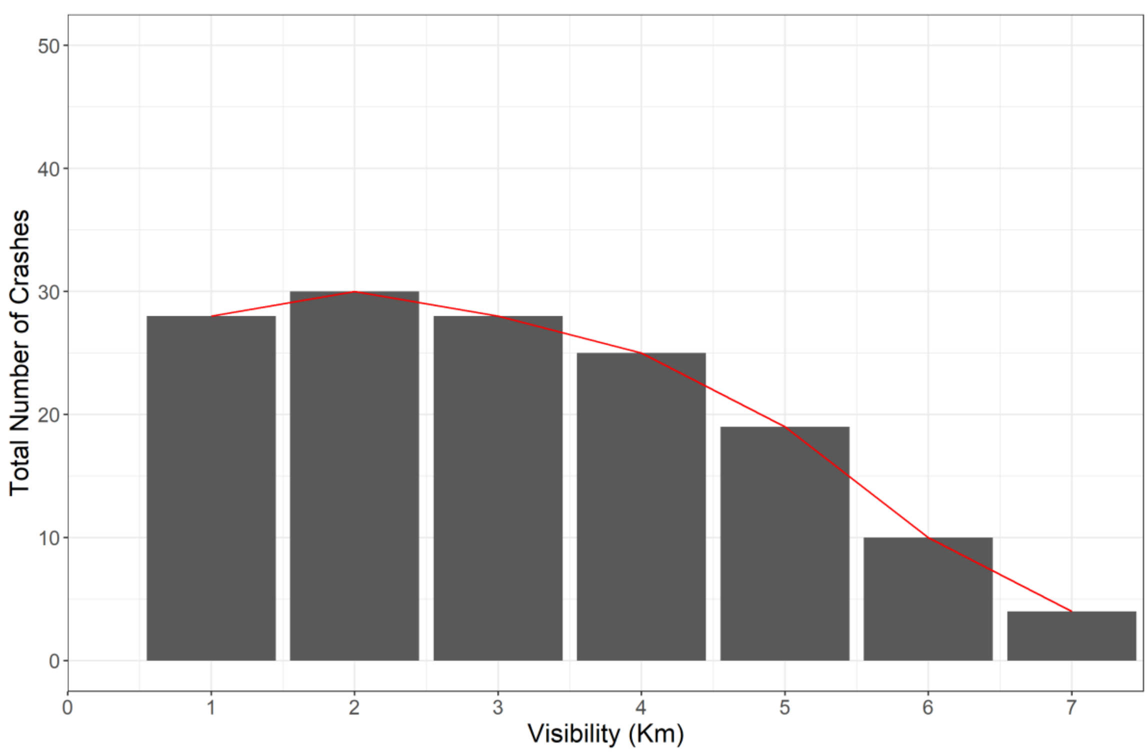
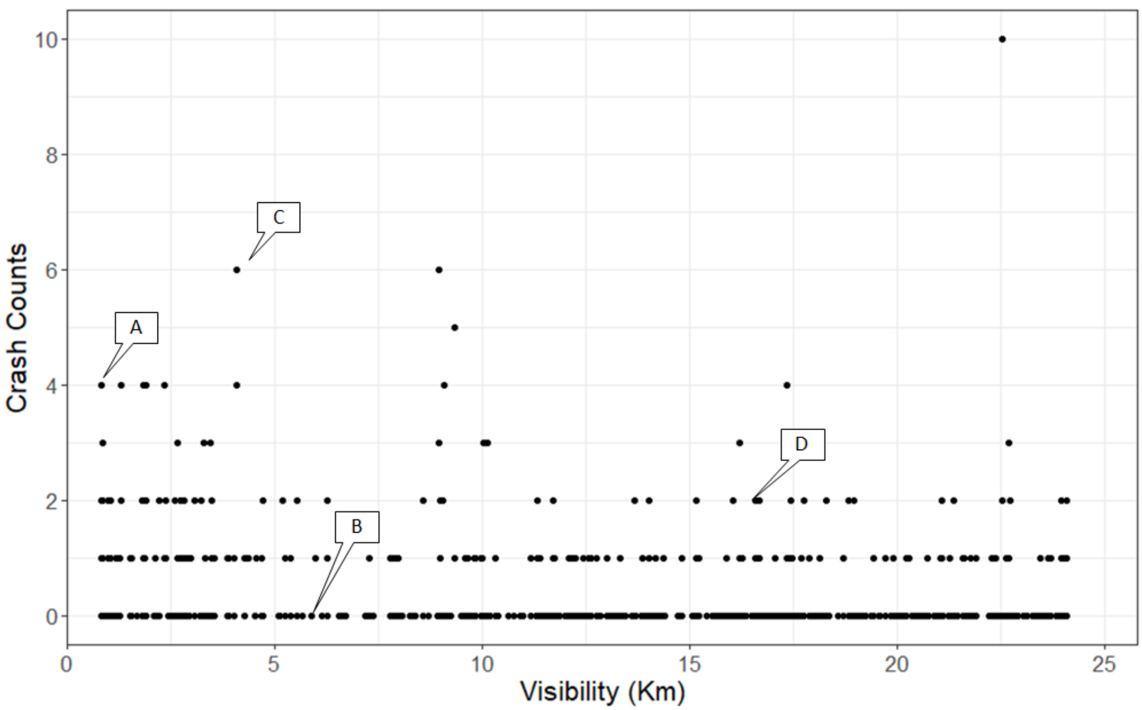



Figure 4.5 Negative correlation between visibility and total number of crashes




(a) Examples of low visibility with high crash counts and high visibility with low crash counts


(b) Camera images with different visibilities at the same locations

Figure 4.6 Low visibility high crash counts

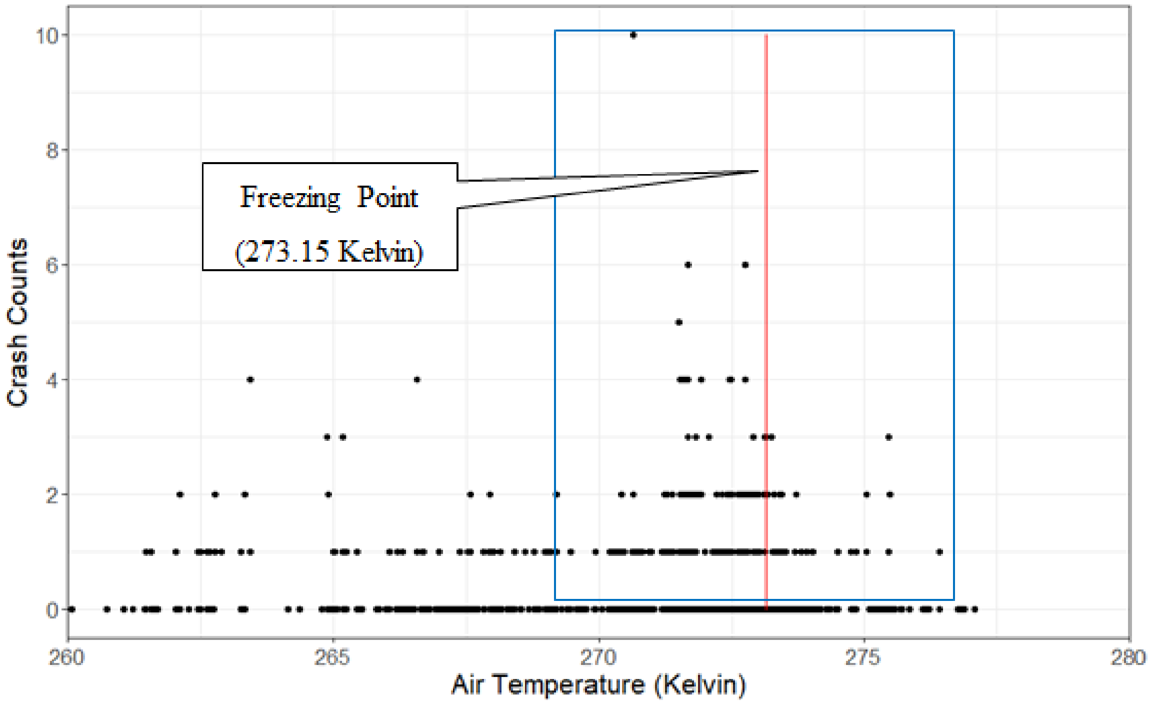



Figure 4.7 Air temperature vs. crash counts during snow days

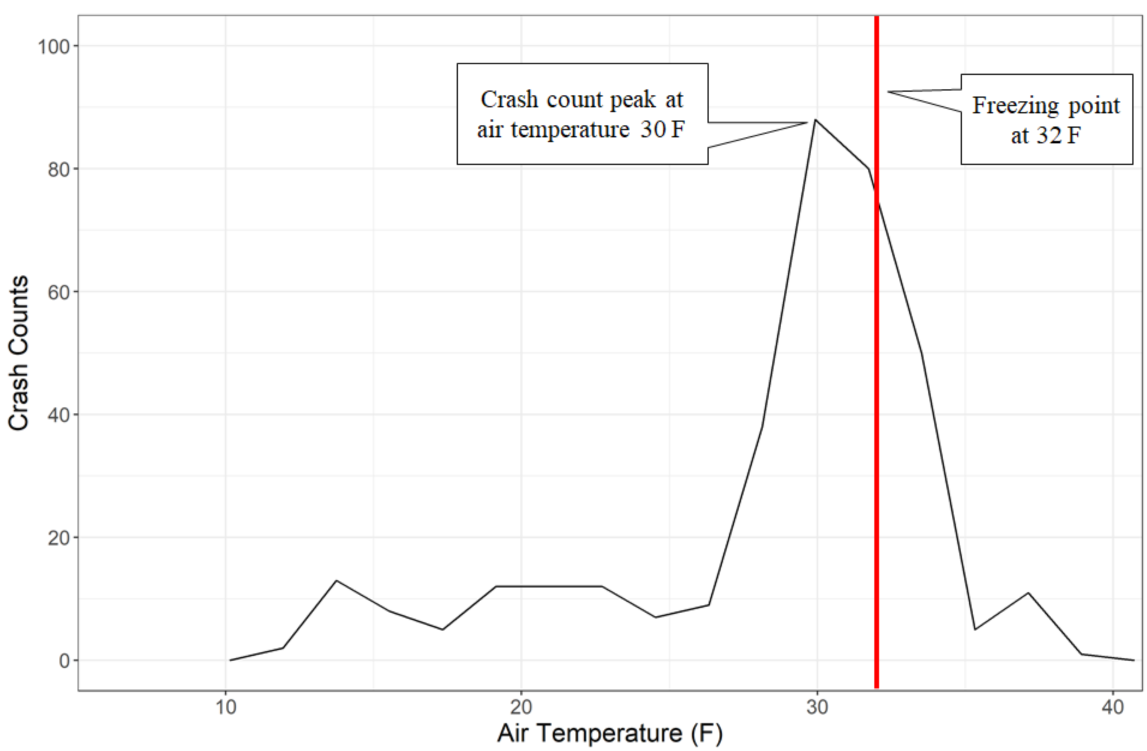



Figure 4.8 Relationship between air temperature (F) with crash counts

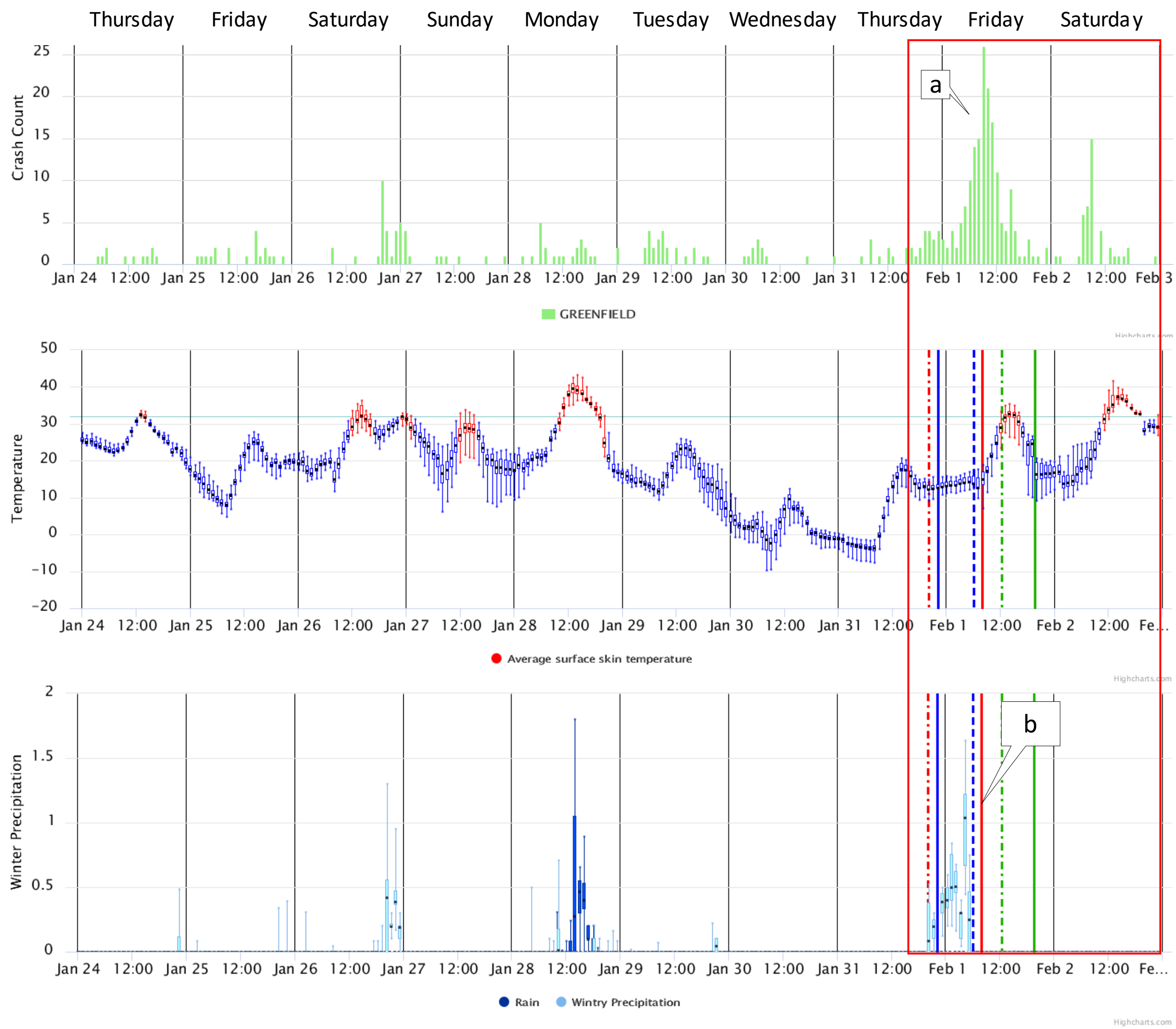



Figure 4.9 Indianapolis Greenfield District crash counts, temperature and winter precipitation for a ten-day view (01/24/2019 to 02/02/2019)

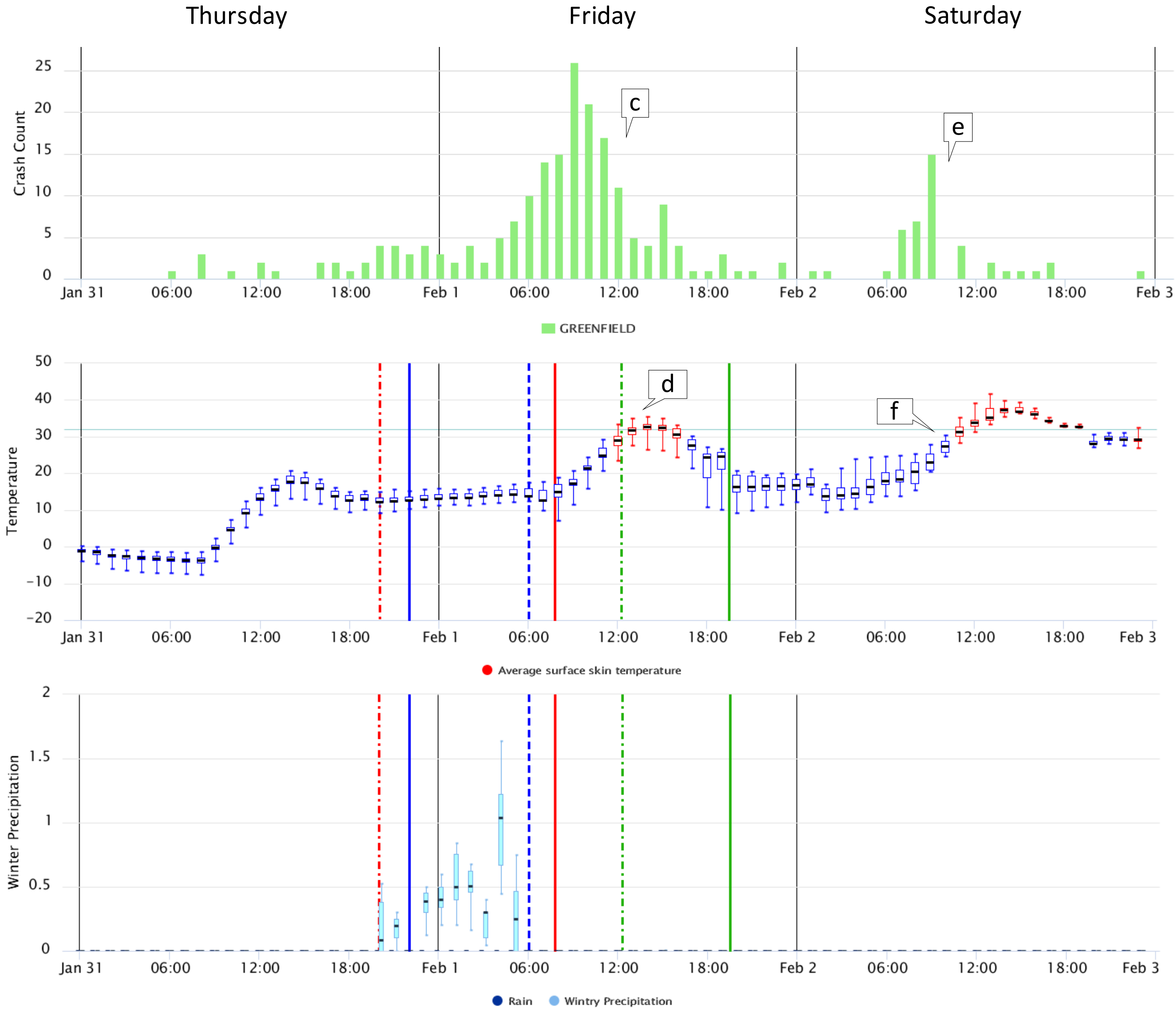



Figure 4.10 Indianapolis Greenfield District crash counts, temperature and winter precipitation for a three-day view (01/31/2019 to 02/02/2019)

# 5. CONCLUDING REMARKS

## 5.1 Conclusion

This paper developed a random parameter negative binomial model to find the contributing factors to crashes on I-465 around Indianapolis. Most of the variables used in the model showed statistical significance and were consistent with results from similar studies. Some of the results also have practical meanings and can be used for improving current winter operation. One of the key findings is that the critical air temperature is slightly below the freezing point, most likely due to some stored thermal energy in the pavement and residual salt. Visibility, solar influx and wind speed all show negative impact on crash counts. It is notable that lower visibility has great impact on number of crashes during snow days. It is unclear if that is because reduced visibility is correlated with increased snow fall rate, or with reduction in reaction times.

Both highly congested areas and high-speed areas are the high crash risk zones for snow days. Severe storm days could result in higher number of crashes, so de-icing treatments are very critical. Although the R-square value was relatively low, it was not surprising given the nominal/ binary properties of the dependent variable and the stochastic nature of crash involvement (Af Wåhlberg, 2003). This model result could be used as a basis framework to develop tools for traffic safety management. Some of the important weather (temperature and visibility) or speed variance information could also be delivered to highway users via intelligent signage systems, so that they are well informed to avoid some dangerous situations.

## 5.2 Study Limitations

One of the limitations is weather conditions could corelated to each other. For example, visibility can be correlated to snow precipitation and air temperature can be correlated to net surface solar radiation. Another limitation is that lower speed variables does not always implies congestion. Congested, uncongested and transition conditions all have different impact on crashes. It would be helpful for future studies to include a "congested" variable in the model. If more years of data available, then different aggregation methods should be tested (by each mile or by each hour). Some random non-snow days' data should be included in order to get an unbiased model result. Endogeneity issues often caused by omitting variables or the explanatory variables selected for the model were impacted by the dependent variable. The limitation of this study is that different speed flow could be impacted by the crash counts. Multiple crashes or a severe crash could cause significant delay and queueing in traffic thus the travelling speed of the system would be relatively low. Future studies could address this issue by including traffic density in the variables.

## 5.3 Future Work

Several future developments could be done based on this study. Firstly, Purdue JTRP researchers have started to investigate wind speed factor which showed statistical significance to crash counts in this study. More validated cases would be helpful to find the threshold of wind speed or direction that causes more crashes. Since lower visibility is found to have more impact on crash counts, future studies can divide visibility into different intervals for further analysis. More precise visibility data from HRRR database could be applied instead of the current weather database. The HRRR weather station is in 1-mile spatial fidelity so the resolution will be increased significantly.

Secondly, more variables can be gathered, and more data can be collected to refine the model. For example, earlier winter months like November and December as well as variables like pavement temperature, pavement friction, lane width, lane marking, demographics information, etc., can be taken into consideration for the refinement. Also, more indicator variables could be used to find the high-risk locations/ time. Segment length with frequency of interchanges were recommended to be added and could potentially refine the model. Also, some of the non-significant variables may worth to add in the model if it can be verified that they would have impact on the dependent variable.

Thirdly, since this dataset came solely from I-465, which is within urban area. A comparison analysis between the current urban result and a rural segment of a highway (e.g., I-65) can help cross-check the variables’ impact differences.

Finally, real-time monitoring tools can be developed with pop-up warnings once conditions get worse than a certain threshold. This can serve both the traffic management center for distributing resources as well as the public for obtaining real-time roadway assistance messages.

# APPENDIX A. DESCRIPTIVE STATISTICS FOR ALL VARIABLES

| Variable | Name | Minimum | Mean | Deviation | Maximum |
|---|---|---|---|---|---|
| x1 | Min_air_Temp | 257.90 | 269.65 | 3.59 | 276.24 |
| x2 | Mean_air_Temp | 260.06 | 270.68 | 3.39 | 277.08 |
| x3 | Max_air_Temp | 261.86 | 271.92 | 3.59 | 283.03 |
| x4 | Min_rain | 0.00 | 0.00 | 0.01 | 0.18 |
| x5 | Mean_rain | 0.00 | 0.03 | 0.14 | 1.34 |
| x6 | Max_rain | 0.00 | 0.14 | 0.54 | 4.46 |
| x7 | rain_time | 0.00 | 0.25 | 0.65 | 4.00 |
| x8 | Min_snow | 0.00 | 0.06 | 0.16 | 1.36 |
| x9 | Mean_snow | 0.00 | 0.20 | 0.28 | 2.01 |
| x10 | Max_snow | 0.00 | 0.57 | 0.65 | 4.50 |
| x11 | snow_time | 0.00 | 2.34 | 1.69 | 6.00 |
| x12 | Min_wind_speed | 0.20 | 8.98 | 4.12 | 19.00 |
| x13 | Mean_wind_speed | 0.77 | 10.37 | 4.17 | 19.76 |
| x14 | Max_wind_speed | 1.62 | 11.67 | 4.32 | 21.56 |
| x15 | Min_visibility | 59.74 | 9878.65 | 9636.63 | 24100.00 |
| x16 | Mean_visibility | 832.68 | 15581.26 | 7797.96 | 24100.00 |
| x17 | Max_visibility | 900.00 | 20798.28 | 7033.64 | 24100.00 |
| x18 | Min_snow_depth | 0.00 | 0.03 | 0.03 | 0.14 |
| x19 | Mean_snow_depth | 0.00 | 0.03 | 0.04 | 0.14 |
| x20 | Max_snow_depth | 0.00 | 0.04 | 0.04 | 0.14 |
| x21 | Min_net_surface_solar_radiation | -0.05 | 5.00 | 15.40 | 115.89 |
| x22 | Mean_net_surface_solar_radiation | 0.00 | 33.71 | 56.47 | 268.09 |
| x23 | Max_net_surface_solar_radiation | 0.00 | 80.43 | 124.19 | 522.05 |
| x24 | Wday | 1.00 | NA | NA | 7.00 |
| x25 | Startmm | 0.88 | NA | NA | 47.14 |
| x26 | Endmm | 0.88 | NA | NA | 47.14 |
| x27 | Mean_below_fifteen | 0.00 | 0.11 | 0.51 | 7.91 |
| x28 | Mean_below_twentyfive | 0.00 | 0.27 | 0.76 | 6.82 |
| x29 | Mean_below_thirtyfive | 0.00 | 0.97 | 2.34 | 18.02 |
| x30 | Mean_below_fourtyfive | 0.00 | 1.39 | 2.59 | 16.71 |
| x31 | Mean_below_fiftyfive | 0.00 | 7.34 | 9.55 | 49.33 |
| x32 | Mean_below_sixtyfive | 1.74 | 40.78 | 13.00 | 58.82 |
| x33 | Mean_over_sixtyfive | 0.00 | 5.34 | 5.12 | 32.45 |
| x35 | Length | 4.66 | NA | NA | 8.76 |
| x36 | Weekday (If yes, 1, otherwise 0) | 0.00 | NA | NA | 1.00 |
| x39 | Six-Hours Traffic | 5061.33 | 24353.74 | 13332.69 | 58514.00 |
| x40 | Interchange | 2.00 | 3.68 | 1.18 | 6.00 |
| x41 | Location | 1.00 | NA | NA | 8.00 |

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