USING SPATIAL INTERPOLATION TO DETERMINE IMPACTS OF SNOWFALL ON TRAFFIC CRASHES

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ABSTRACT

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Snowfall affects traffic safety by impacting vehicle performance, driver behavior, and the transportation infrastructure. Depending on intensity, snowfall can reduce visibility, pavement friction performance, vehicle stability and maneuverability. Based on this premise, the objective of this study is to use spatial interpolation to analyze the effects of annual snowfall on interchange and non-interchange freeway crashes during winter periods in the State of Michigan. Using the geostatistical method of Ordinary Kriging, site specific historical snowfall values are estimated based on data obtained from a series of weather stations for the winter months during the years of 2004 through 2014 along Michigan's entire limited access freeway network. Data is spatially matched with historical crash data and roadway inventory data for each freeway segment. Two Negative Binomial regression models are generated to quantify the effects of snowfall on crashes, each of which include annual average daily traffic, segment length, horizontal curvature, and a snowfall variable. The two models vary solely based on the format of the snowfall variable, which is a continuous variable first model and categorized in the second model to further examine the relationship between the effects of snowfall and crashes. The results indicate that annual snowfall has a statistically significant positive effect on winter crashes for all types of crashes analyzed. The snowfall effects are stronger for segments experiencing the largest amount of snowfall, and are more emphasized for non-interchange crashes as opposed to interchange crashes.

This thesis is dedicated to my family.
Thank you for your support throughout all these years.

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KEY TO ABBREVIATIONS

AADT	Annual Average Daily Traffic
BL	Business Loop
BR	Business Route
DOT	Department of Transportation
GIS	Geographic Information Systems
HSM	Highway Safety Manual
MDOT	Michigan Department of Transportation
MGF	Michigan Geographic Framework
MISH	Meteorological Interpolation based on Surface Homogenized Data Basis
MPH	Miles per Hour
MSP	Michigan State Police
NB	Negative Binomial
NFC	National Functional Classification
NOAA	National Oceanic and Atmospheric Administration
PDO	Property Damage Only
PR	Physical Road
PRISM	Parameter Elevation Regressions on Independent Slopes Model
IDW	Inverse Distance Weighting
ITS	Intelligent Transportation Systems
US	United States

INTRODUCTION

Inclement weather can influence crash occurrence in a transportation system. Nearly one-quarter of all crashes in the United States (US) are a result of adverse weather patterns (FWHA, 2016). Severe weather conditions can impact vehicle performance, driver behavior, and infrastructure through reduced visibility, pavement friction performance, vehicle stability and maneuverability (Pisano et al., 2008; Liu, 2013; Leard and Roth, 2015). Anecdotal knowledge suggests that these effects are more pronounced during winter weather. Indeed, existing literature on adverse weather effects on crashes indicates that the “risk of crashes increases if precipitation is snow” (Qiu and Nixon, 2008; Andersson and Chapman, 2011). While several studies have evaluated the effects of snowfall on crashes and in particular on crash severity outcomes, there has been little consideration on the effects of snowfall on additional types of crashes as well as differentiations between the various facility types of the network on which these crashes occur.

Accordingly, an investigation into the effects of snowfall on different crash categories and locational scenarios can provide revealing information that could prove useful to transportation agencies in implementing mechanisms to minimize crashes due to inclement weather conditions. These effects are particularly pertinent in regions like the Great Lake basin of the US where snow events occur frequently during winter months due to lake effect climactic conditions. Although drivers in these regions are presumed accustomed to driving in snowy weather, crash occurrence continues to be high (Andreescu and Frost, 1998). More recently, severe winter events have resulted in dramatic accidents such as the events of January 2015 in southwest Michigan, where extreme whiteout conditions led to a 193 car pile-up along Interstate 94 (I-94) resulting in loss of life, multiple injuries, and significant economic cost (Sell, 2016).

Based on this premise, this study aims to investigate the effects of annual snowfall on freeway crashes during winter periods in the State of Michigan for interchange and non-interchange (i.e. midblock) segment crashes based on spatial analytical methods and appropriate statistical techniques. These two locational circumstances are analyzed separately to account for the unique road, operational, and behavioral elements which defines and distinguishes them. Several winter crash categories are considered during the analysis. These include all winter crashes, crashes involving a truck or bus, crashes not involving a truck or bus, injury crashes (including fatalities), and Property Damage Only (PDO) crashes. The time period of the analysis consists of the winter months of January, February, and December for the 11-year period of 2004 to 2014. The study network consists of the entire freeway network of the State of Michigan, where freeways are defined as National Functional Class (NFC) equal to either Principal Arterial Interstate or Principal Arterial-Other Freeways. Cumulatively this represents approximately 1,955 miles of roadway throughout Michigan.

The selected roadway network provides variability in snowfall along the network with snowfall typically peaking along the western coastline of the state and in the Upper Peninsula due to lake-effect snow impacting the region (Andresen et al., 2012). Additional Michigan historical weather conditions for the 1981 to 2010 winter months of January, February, and December indicate spatial variability in the mean temperature as well, with the northern half of the state experiencing mean temperatures in the 15-25 ^{o}F range and the southern half experiencing temperatures in the 25-30 ^{o}F range (Andresen et al., 2012). Precipitation, while varying in value between the northwest and southeast region of the State, occurs less often during winter months due to characteristic sub-freezing temperatures experienced during this time (Andresen et al., 2012).

CHAPTER 1: LITERATURE REVIEW

1.1 General Snow Effects

Severe winter weather conditions can have direct and indirect effects upon the transportation system. These effects can impact vehicle performance, driver behavior, and the infrastructure through reduced visibility, pavement friction performance, roadway operations (i.e. travel speeds, roadway capacity, delay), vehicle stability and maneuverability, thus increasing the risk of accidents (Pisano et al., 2008; Liu, 2013; Leard and Roth, 2015).

In regions like the Great Lakes basin of the US, snowfall is often the primary weather factor impacting traffic operations and safety. Prior research has investigated the effects of snowfall on crashes utilizing various levels of detail and across several roadway types. It is commonly accepted that overall, snowfall results in an increase in the crash occurrence rate (Qiu and Nixon, 2008). These effects are observed through traditional crash modeling means such as Negative Binomial models specified by the Highway Safety Manual (HSM) (AASHTO, 2010), and through more unconventional means incorporating spatial statistical methods (Khan et al., 2008).

While overall crash risks are expected to increase during snow conditions, effects of snowfall on different vehicle types (i.e. commercial vehicles, non-commercial vehicles) and crash outcomes (i.e. fatal, injury, PDO) may vary. With regards to crash outcomes, the literature appears to be in general agreement that snowfall results in an increase in PDO crashes (Eisenberg, 2004; Eisenberg and Warner, 2005; Blionis, 2013). These findings are not surprising given that, throughout snow conditions, accidents can occur at low speeds due to poor pavement friction performance and decreased vehicle control capabilities.

Comparatively, findings on injury crashes and fatal crashes are less decisive. For example Fridstrom et al. (1995) found a negative relationship between snow and injury crashes in a study on various locations in the Nordic region. By contrast Eisenberg (2004) found that snowfall results in increased numbers of non-fatal crashes. These findings are corroborated by additional studies which found that snowfall exhibits a positive significant impact on injury crashes, albeit at lower levels than PDO crashes (Eisenberg and Warner, 2005; Bilionis, 2013; Liu, 2013). The difference between non-fatal injury and PDO crashes may be attributed to heightened driver alertness and lower vehicle speeds to adjust to the adverse weather conditions (Eisenberg, 2004; Bilionis, 2013). Additionally Brorsson et al. (1988) suggested that lower levels of injuries involving single motor vehicles could be a result of snow walls developed along the roadway which help vehicles decelerate prior to collision. This effect would also translate in decreasing numbers of non-fatal injury crashes with increasing snow depth and consistent sub-zero temperatures.

The impact of snowfall on fatal crashes is similarly inconclusive. For instance Eisenberg and Warner (2005), in a study on the effects of snowfall on US crash rates for 1975-2000, found that snowfall does not result in an increase in fatal crashes. These findings are also supported in Eisenberg (2004) for monthly snowfall values. Comparatively, Perry and Symons (1991) found fatal crash rates to increase for snowy days in the UK. Eisenberg (2004) also found an increase in fatal crashes when assessing daily snowfall effects on crashes in the US. The author however attributes this positive relationship to a lag effect on precipitation (i.e. crashes decrease when it snows every day and increase significantly when the time since the last snowfall increases). This lag effect is illustrated in additional studies (Eisenberg and Warner, 2005; El-Basyouny et al., 2014; Seeherman and Liu, 2015) and indicates that snow events which follow a dry season tend to be more dangerous, a result likely related to drivers being unaccustomed to sudden changes in driving conditions.

Parallel variances can also be found in crashes involving commercial vehicles and non-commercial vehicles whether due to differences in trip characteristics or mechanistic characteristics. For example, drivers perceive severe snow events as dangerous and may avoid unnecessary trips. Commercial vehicle trips however are commonly business related and thus less flexible in route choice (Pisano et al., 2008). Truck performance is also more vulnerable to decreasing visibility as it can affect stopping distance more significantly than smaller and lighter vehicles, among other physical characteristics attributed to weight and truck performance (Pisano et al., 2008).

Effects of snowfall on crashes are additionally shown to exhibit a non-linear relationship with crash occurrences. Eisenberg (2004) found crashes to peak at moderate snowfall levels and decline at higher ranges due to potential reductions in travel as weather severity increases. Additional studies show similar relationships where larger amounts of snowfall do not necessarily translate to higher crash occurrences (Khattak and Knapp, 2001), or they exhibit decreasing marginal impacts with increasing snowfall amounts (Seeherman and Liu, 2015). In circumstances where crashes continue to increase at larger snowfall levels, the data may be displaying effects of underlying events such as higher frequencies of snowstorms and/or storms of greater intensity. These particular weather patterns are shown to result in higher crash frequencies (Khattak and Knapp, 2001).

A secondary noteworthy dimension towards the effects of snowfall on crashes is the facility in which these crashes occur. Two particular facility types can be defined in a freeway setting based on their unique characteristics of geometry, operational behavior and driver behavior: the interchange and non-interchange (i.e. midblock) segment area of the freeway. Existing literature suggests that interchange and non-interchange segments should be treated separately in crash modeling as crash rates in the interchange sphere of influence are much higher than their non-interchange counterpart (Kiattikomol, 2005). Given their distinctive characteristics, the effects of snowfall on interchange versus non-interchange segment crashes may vary as well.

1.2 Weather Data Spatial Interpolation

Since historical snowfall data is a key component of this study, the estimation of historical snowfall amounts along the study network must be reliable and reflect with a degree of accuracy likely conditions experienced by drivers along each point on the network for that particular time period. Presently there is no practical method to explicitly measure such data continuously along an expansive freeway system. To overcome this barrier snowfall data are commonly estimated from weather stations which are randomly distributed throughout the US (Bostan et al., 2012). Each of these stations captures and reports weather conditions on that particular location over pre-established time periods. Because distances between these stations may vary in magnitudes of less than a mile to several miles, values reported by one station do not provide the level of accuracy required to estimate snowfall when applied to specific locations along a freeway. Additionally, weather patterns can be localized in small geographic regions that experience relatively different snowfall amounts among each other or their surroundings due to lake-effect climatic conditions, wind patterns, or terrain. Thus it is naive to average these values across a specific region (Leard and Roth, 2015).

To overcome these shortfalls weather data prediction models must incorporate the density and locations of weather stations to obtain accurate weather values on desired localities (Ashraf et al., 1997). Spatial interpolation is the procedure utilized in incorporating these variables to estimate weather related data at specific locations. Sluiter (2009) states that spatial interpolation methods can be grouped into three categories: deterministic, probabilistic, and other; where deterministic methods produce continuous surfaces based on specific geometric characteristics of existing observations (i.e. nearest neighborhood, triangulation, Inverse Distance Weighting (IDW), splines, linear regression); probabilistic methods produce continuous surfaces based on statistical theory (i.e. Ordinary Kriging, Simple Kriging, Universal Kriging); and other consists of a combination of deterministic and probabilistic methods (i.e. Parameter Elevation Regressions on Independent Slopes Model (PRISM), Meteorological Interpolation based on Surface Homogenized Data Basis (MISH)).

Traditionally deterministic methods have an extended history of use in predicting meteorological data. In recent trends however, probabilistic methods have become a more preferred approach in predicting weather values since they provide statistical reliability, consider the spatial correlation between the observations, and allow for the inclusion of secondary explanatory variables (i.e. elevation) in improving the estimation on unknown locations (Mair and Fares, 2011). While more demanding to implement, several studies have found that probabilistic methods deliver superior estimates than their deterministic counterparts. For example Mair and Fares (2011) found Ordinary Kriging and Simple Kriging with local means outperform Thiesen polygons, IDW, and linear regression in rainfall estimations in a mountainous region in Hawaii. Tabios and Salas (1985) found comparable findings in their review of 30 years of annual precipitation in Region II of North Central US, with Kriging and other optimization interpolation techniques outperforming deterministic approaches (i.e. Thiesen polygons, IDW, Lagrange approach). Ashraf et al. (1997) in their review of two years of daily climate data in three states in the US found that Kriging produces the lowest root mean square interpolation error compared to inverse distance methods. Goovaerts (2000) found probabilistic methods (i.e. Ordinary Kriging, Co-Kriging, Simple Kriging with local means) outperform Thiessen polygons, IDW, and linear regression in rainfall estimations even when elevation data is not incorporated. When elevation is included in the process, results produce more reliable values. Similar findings are reflected in Huang et al. (2015) in their analysis of daily snow depth, with the authors noting that Ordinary Kriging produces the best results when elevation is not correlated with predicted snow depth. In contrast, Mair and Fares (2011) did not find any accuracy improvement in Ordinary Kriging results when secondary data (i.e. elevation) are highly correlated to the predictor, thus indicating that different and more advanced types of Kriging techniques may be more appropriate when secondary variables are considered (i.e. Co-Kriging, Universal Kriging).

Despite the increasing widespread use of the probabilistic family of Kriging, several authors underscore the importance of using proper care throughout the estimation process as these techniques are fundamentally linear optimization processes (Lanciani and Salvati, 2008; Oliver and Webster, 2015). In its most basic form, Kriging can be defined as a linear and optimization spatial interpolation method used in estimating unknown values from existing observations where near sample points receive more weight than the ones further away (Oliver and Webster, 2015; Sluiter, 2016). Weights are modeled through semivariograms which identify the spatial correlation between observations (Oliver and Webster, 2015; Sluiter, 2016). The semivariogram is the basic framework of Kriging which defines how space fits the data. Thus if the fit is erroneous, Kriging predictions will not be accurate. (Ali, 2013; Oliver and Webster, 2015). To avoid biased Kriging outputs, Oliver and Webster (2015) recommend using an adequate number of data points, selecting the proper semivariogram form (i.e. lag interval, bin width), transforming data to achieve a near normal distribution when significant skewness is present, careful examination of outliers to identify erroneous observations, and de-trending data when significant trends are evident, depending on the Kriging method used.

1.3 Crash Modeling

Crash frequency is the primary indicator of safety of a roadway, where crash frequency is defined as the number of crashes occurring in a site over a period of one year (AASHTO, 2010). Crash modeling entails estimating the average expected crash frequency of a particular site given its specific geometric, operational, and local conditions over a pre-defined time period (AASHTO, 2010). Typically, such traffic crashes are assumed to be random occurrences in time and space (AASHTO, 2010; Bilionis, 2013; Zou et al., 2015). Since crashes represent counts of specific events, they have been originally presumed to follow a Poisson distribution where the mean is equal to the variance of the data (Kim et al., 2010; Lord and Mannering, 2010; Bilionis, 2013; Seeherman and Liu, 2015). In these cases crash modeling has been conducted via a Poisson regression model (Lord and Mannering, 2010). The equivalency of the mean and the variance however is not always achieved, as researchers have found that crashes often exhibit extra dimensions of variance or over-dispersion. To account for this inequality where the variance exceeds the mean, crash modeling has been most often conducted by employing a Negative Binomial regression model (AASHTO, 2010; Kim et al., 2010; Lord and Mannering, 2010; Bilionis, 2013; Seeherman and Liu, 2015). The Negative Binomial model is an extension of the Poisson model which accounts for the over-dispersion in the data by including a gamma distributed error term with mean 1 and variance α^2 (Lord and Mannering, 2010). While the Negative Binomial model has consistently been the most often used method for crash modeling, it falls short when the data is under-dispersed or the sample size is too small (Lord and Mannering, 2010). To account for some of these shortfalls additional alternatives to the Negative Binomial model have been used like the Poisson-Lognormal model and Conway-Maxwell-Poisson model (Lord and Mannering, 2010). There are also cases however where there may be time periods or sections of a study site that exhibit a high frequency of no crashes. These could occur when the time period or the dataset utilized is relatively small. In these cases a zero-inflated regression model may be most appropriate to account for the recurring zero variables (Lord and Mannering, 2010; Bilionis, 2013).

CHAPTER 2: OBJECTIVE & STUDY FRAMEWORK

The objective of this study is to investigate the effects of annual snowfall on freeway crashes during winter periods in the State of Michigan. Separate analyses are performed for interchange and non-interchange segment (i.e. midblock) crashes due to their differing geometric, operational, and behavioral characteristics. These two primary crash classifications are based on the annual Michigan State Police (MSP) statewide crash database codebook and can be defined as follows:

- Midblock crashes – Traffic crashes not associated with an interchange or intersection (typically occurring between two interchanges)
- Interchange crashes – Traffic crashes associated with an interchange (typically occurring between ramp termini)

The specific crash categories analyzed include:

- All winter crashes – All crashes occurring on the study network during January, February, and December between 2004 and 2014.
- Truck/bus winter crashes – Crashes involving at least one truck or bus during January, February, and December between 2004 and 2014.
- Non-truck/bus winter crashes – Crashes involving no trucks or buses during January, February, and December between 2004 and 2014.
- Injury winter crashes – Crashes where at least one injury (or fatality) was reported during January, February, and December between 2004 and 2014.
- PDO winter crashes – Crashes involving only property damage during January, February, and December between 2004 and 2014

The inclusion of the listed crash categories as well as their differentiation between interchange and non-interchange (i.e. midblock) crashes can contribute and potentially fill a void in the existing literature with regards to the impacts of snowfall on these crash scenarios.

The effects of snowfall on winter-season crashes are assessed in terms of the estimated annual winter snowfall occurring along the study network. The relationship between snowfall and crashes is further examined by categorizing annual snowfall in terms of its quartile intervals. The time period of the analysis includes the months of January, February, and December during the 11-year period of 2004 and 2014, where the selected months represent the winter period in Michigan which historically experiences the most snowfall amounts. Accordingly data used in this study correspond exclusively to this time period.

The study network consists of the entire limited access freeway network in the State of Michigan (i.e. NFC equal to Principal Arterial-Interstate or NFC equal to Principal Arterial-Other Freeways). This system contains approximately 1954.9 one directional miles of freeway which are primarily concentrated in the southern half of Michigan and decrease towards the more remote northern parts of the state. The composition of this network contains a mix of Interstate, Interstate Business Loop (BL), US, US Business Route (BR), State, and Connector routes. The dominant speed limit on these routes is 70 mph (60 mph for trucks); with a relatively small group of segments comprising an estimated five percent of the total mileage of the network having posted speed limits of less than 70 mph. The latter occurs only within selected major urban areas of the state.

The study network is additionally comprised of 2,398 discrete freeway segments of lengths varying from 0.034 to 9.35 miles. These segments are based on the 2014 Michigan Department of Transportation (MDOT) sufficiency database and represent the base framework of the study. All data used in this study are binned on these segments prior to any crash analysis. Characteristics of these freeway segments are presented in Table 1, while the freeway network is illustrated in its entirety in Figure 1.

TABLE 1 Characteristics of the Study Network

Route	Total Miles*	Mean Number of Lanes	Typical Speed Limit	Mean Shoulder Width	Mean AADT*	Mean CMV AADT*
Interstate	1241.2	2.6	70 mph	9.5	30,658	3,117
US	564.3	2.1	70 mph	9.0	15,599	1,385
Michigan	119.1	2.6	55/70 mph	8.7	35,742	1,231
Interstate - BL	3.6	2.0	55/70 mph	8.8	16,293	367
US - BR	18.5	1.9	55/65/70 mph	8.0	8,933	699
Connector	8.2	1.9	70 mph	9.1	8,569	421
All Routes	**1954.9**	**2.5**	**70 mph**	**9.3**	**27,137**	**2,476**

Lane width = 12 ft in nearly all segments
**Includes both directions*

FIGURE 1 Michigan Freeway Study Network

CHAPTER 3: DATA COLLECTION

The data used in this study includes traffic crashes, snowfall, directional Annual Average Daily Traffic (AADT) volumes, directional commercial AADT volumes, horizontal curvature, and segment length for each of the 2,398 freeway segments during the 11-year period of 2004 to 2014. With the exception of snowfall which represents the primary explanatory variable of interest, the other four variables are included based on their notable role in predicting crashes and their common use in crash modeling. Specifically AADT or commercial AADT represent the primary exposure variable for the corresponding crash category, length acts as a normalizing explanatory variable due to the varying lengths of the segments, and horizontal curvature is included based on the relationship between road alignment and crash occurrence. These variables are used in prior studies investigating the impact of weather on crashes and are shown to be significant factors in crash occurrence under these conditions (Khattak and Knapp, 2001; Ahmed et al., 2011; Ahmed et al., 2012; Bilionis, 2013). Rainfall was also included in the initial investigation phase of the study, however it exhibited a high degree of correlation with snowfall thus was removed from the analysis to avoid multicollinearity bias.

3.1 Crash, Traffic, and Roadway Data

The crash data is obtained from the annual MSP statewide crash database for the months of January, February, and December for the 11-year period of 2004 to 2014. The crash categories are isolated for both midblock and interchange scenarios based on the coded values provided in the MSP database, and are matched to the corresponding freeway segments as annual winter-season totals based on their Physical Road (PR) identification number and mile point. The PR system is a linear referencing system which distinctively identifies roadway events (i.e. crashes, segments) along Michigan's transportation network. Descriptive statistics for these crashes are provided in Table 2.

TABLE 2 2004-2014 Winter Crash Count Descriptive Statistics of Study Network

	2004-2014 Winter Crash Totals		Winter Crashes per Segment per Year			
Category	**Count**	**Percent**	**Min**	**Max**	**Mean**	**St Dev**
All Crashes	125,665	100%	0	61	4.76	5.13
Non-Truck/Bus	114,824	91%	0	49	4.35	4.76
Truck/Bus	10,841	9%	0	18	0.41	0.84
Injury	24,462	19%	0	17	0.93	1.38
PDO	101,203	81%	0	50	3.83	4.20
Cumulative		***100%***				
All Crashes	49,944	100%	0	43	1.89	3.02
Non-Truck/Bus	45,377	91%	0	39	1.72	2.76
Truck/Bus	4,567	9%	0	15	0.17	0.55
Injury	9,640	19%	0	15	0.37	0.82
PDO	40,304	81%	0	40	1.53	2.50
Midblock		***40%****				
All Crashes	74,141	100%	0	44	2.81	3.88
Non-Truck/Bus	67,977	92%	0	39	2.58	3.62
Truck/Bus	6,164	8%	0	7	0.23	0.59
Injury	14,543	20%	0	15	0.55	1.07
PDO	59,598	80%	0	34	2.26	3.15
Interchange		***59%****				

1% of cumulative crashes are non-traffic coded crashes
**Relative to the cumulative 2004-2014 winter crash population*

Overall, a total of 125,665 crashes occurred on the study network for the 2004-2014 winter-season period. Interchange crashes comprise the majority of the crashes with approximately 59% of the total amount; while approximately 40% represent midblock crashes. The difference or approximately 1% are crashes coded as non-traffic and are not included in this study. With respect to crash types, the distribution is nearly equivalent between the three crash categories (i.e. all winter, midblock, interchange) and ranges in the 91-92% for non-truck/bus crashes vs 8-9% for truck/bus crashes, and 80-81% for PDO crashes vs 20-21% for injury crashes.

With respect to traffic volumes, directional AADT and directional commercial AADT values are obtained from the 2014 MDOT sufficiency database for all freeway segments for each year of the 2004 to 2014 time period. These values represent the average AADT (or commercial AADT) experienced on each of the freeway segment for each year of the study period.

Horizontal curvature is extracted from a comparable database developed by calculating the radii of curved segments from the 2014 Michigan Geographic Framework (MGF) shapefile and adapting it to the 2014 MDOT sufficiency database segments. This database provides horizontal curvature information binned in various design speed of curve formats by assuming a 7% maximum superelevation, which corresponds to the maximum superelevation allowed on Michigan’s freeway network. In this study, this variable is presented as the fraction of the segment with a horizontal curve with a design speed less than 85 mph and is assumed temporally constant.

Lastly, the length of each of the 2,398 freeway segments is calculated based on their geographic length in miles using the ArcGIS for Desktop software. Table 3 presents descriptive statistics for these four variables, while Figure 2 illustrates the overall average AADT distribution throughout the study network.

TABLE 3 2004-2014 AADT, commercial AADT, Length, and Horizontal Curvature Descriptive Statistics of Study Network

	Per Segment per Year			
Category	**Min**	**Max**	**Mean**	**St Dev**
AADT	100	107,000	27,144	21,472
Commercial AADT	25	8,846	2,477	1,771
Segment Length (miles)	0.03	9.35	1.62	1.38
Fraction of Horizontal Curvature with design speed less than 85 mph	0.00	1.00	0.11	0.24

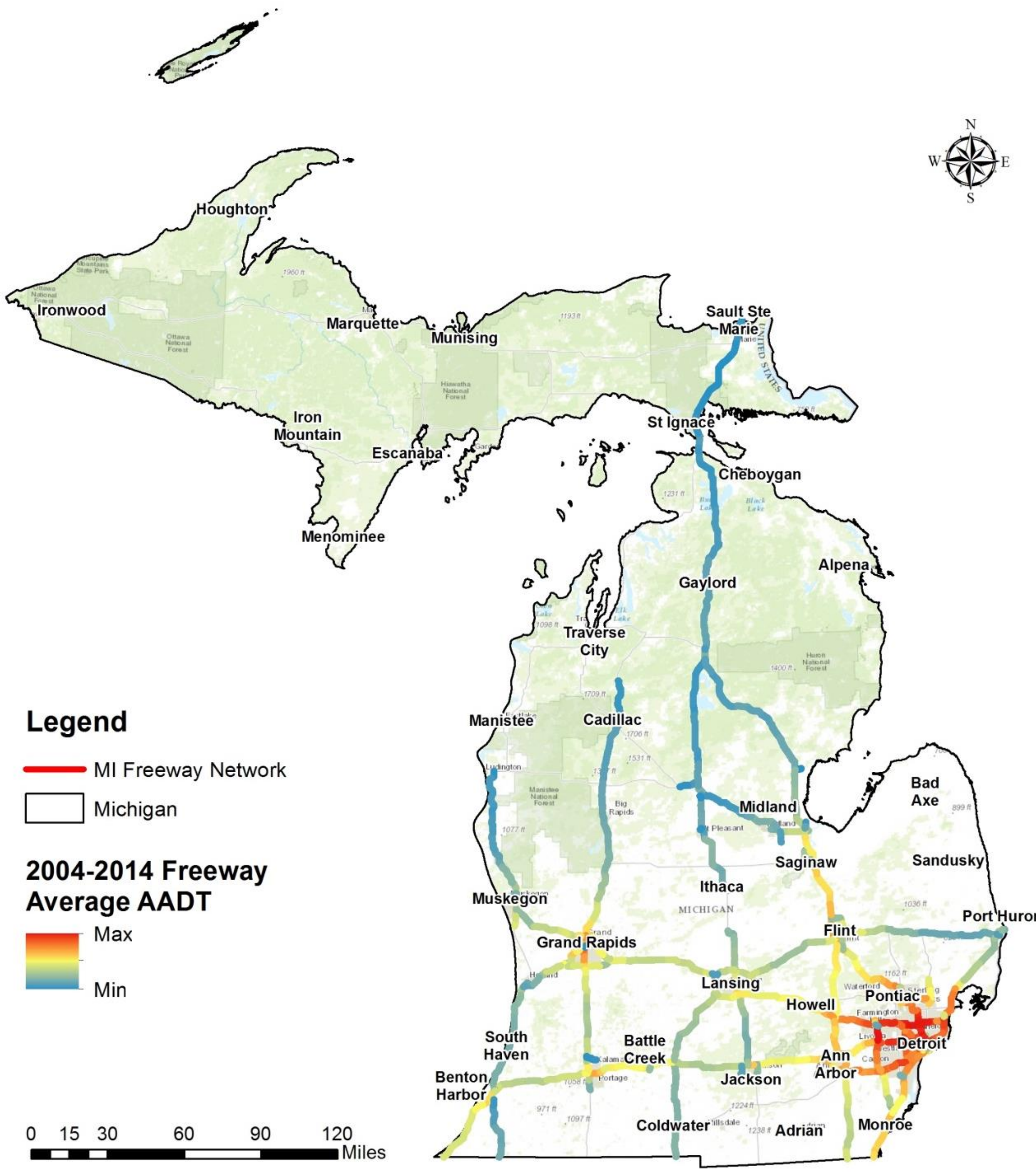


FIGURE 2 2004-2014 Network Average AADT Distribution

The average AADT distribution along the network indicates that the highest traffic volumes are experienced southeast of the state in the Metro Detroit region and tend to dissipate outwards of this area. Significant volumes are also experienced in regions surrounding primary cities such as Grand Rapids, Lansing, Kalamazoo, Flint, and Saginaw. Comparatively, areas experiencing the lowest volumes are located primarily in the northern half of the state given the region's less populous and more rural nature.

3.2 Snowfall Data

To assess historical snowfall conditions along the study network, monthly snowfall data is extracted from the National Oceanic and Atmospheric Administration (NOAA) climate data center for January, February, and December of the 11-year period of 2004 to 2014. The climate data center provides weather data as captured and reported by weather stations across the US for their respective location and time period selected. These stations are randomly located with varying distances between each other ranging from less than a mile to several miles. A similar pattern is observed for weather stations surrounding the study network (Figure 3).

Consequently, the random distribution of the stations necessitates the use of spatial interpolation methods to predict likely historical snowfall values throughout the network with a degree of accuracy. While a multitude of spatial interpolation methods exist, the probabilistic method of Ordinary Kriging is employed due to its consistent and superior performance in estimating precipitation versus deterministic methods such as IDW, nearest neighborhood, splines, and linear regression (Tabios and Salas, 1985; Ashraf et al, 1997; Goovaerts, 2000; Mair and Fares, 2011; Huang et al. 2015), as well as due to its prevalent use in spatial interpolation as it requires a minimal number of assumptions to be satisfied (Oliver and Webster, 2015).

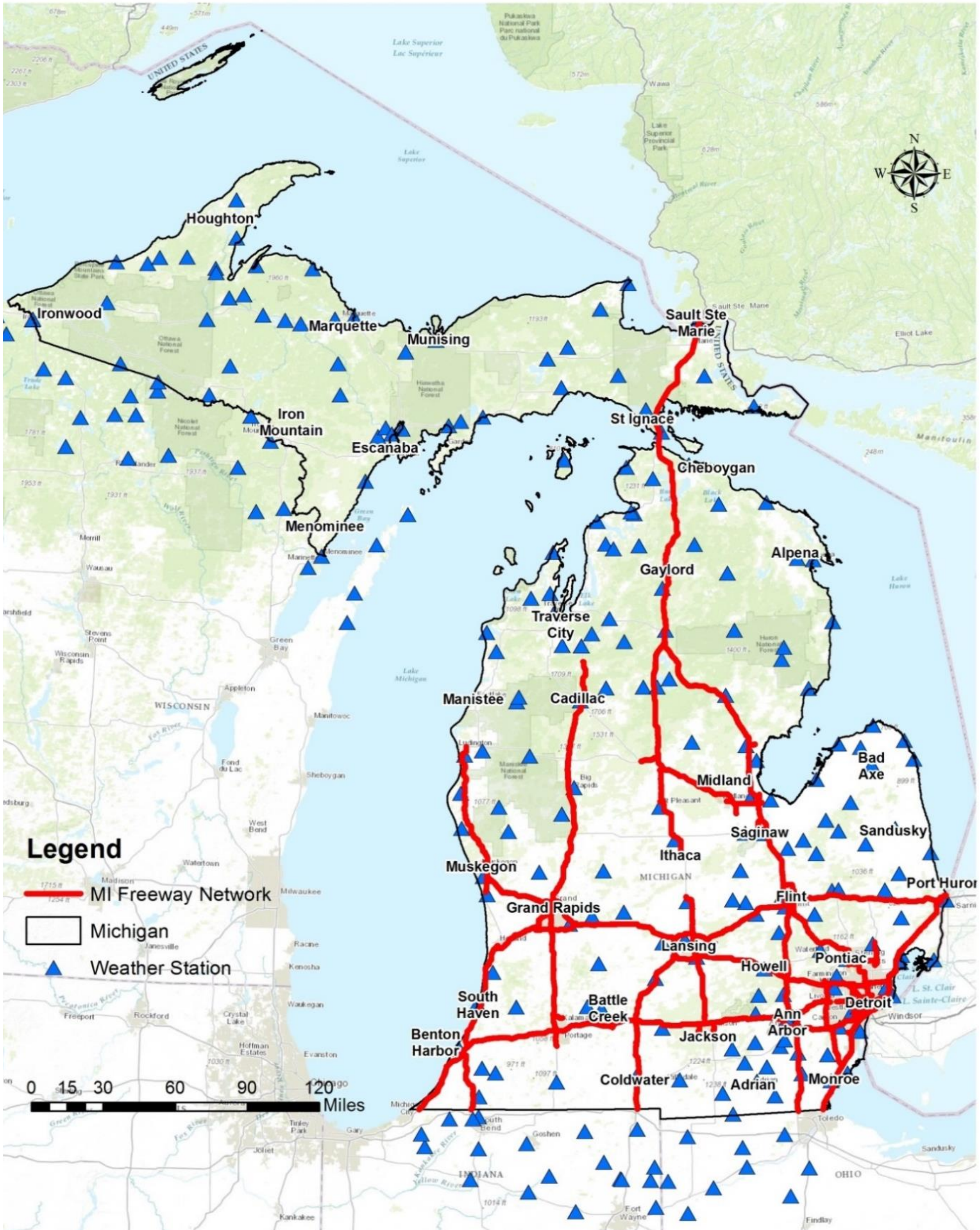


FIGURE 3 Weather Station Locations for a Typical Winter Month, January 2010

3.2.1 Spatial Interpolation Implementation & Optimization

Ordinary Kriging is one form of Kriging used to predict values from known observations, where the mean is assumed unknown, constant, and is estimated from the local neighborhood (Oliver and Webster, 2014). Since Ordinary Kriging is a local neighborhood estimator, nearby values closest to the subject location receive more weight than the ones further away. The weights are identified through a spatial function called a semivariogram which assesses the spatial correlation of the existing observations and the extent of this correlation (Oliver and Webster, 2015). In its most basic form, the semivariogram relates graphically the semivariance of the observations to the distances (lag) between these observations (ArcGIS 9: Using ArcGIS Geostatistical Analyst, 2003). The primary goal then in this process is to identify the best fit for this structure by selecting the optimal semivariogram model, where the fit is sensitive to the sample size of the observations, lag interval and size (i.e. grouping of observations based on distance to help identify spatial correlation patterns), data distribution where a normal distribution is preferred, outliers, and trends in the data (Oliver and Webster, 2015).

While the semivariogram identifies the weights used in the estimation process, the predicted values of any unknown location in the Ordinary Kriging process are defined in the following general form (Huang et al., 2015; Oliver and Webster, 2015):

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \omega_i z(x_i) \tag{1}$$

Where, $\hat{Z}(x_0)$ = predicted monthly snowfall at unknown location x_0

$z(x_i)$= observed monthly snowfall at known location x_i

ω_i = estimated weight for $z(x_i)$, where $\sum_{i=1}^{n} \omega_i = 1$

n = number of weather stations

Typically at least 50 observations points are required to produce accurate predictions (Holdaway, 1996), although 100 to 150 observations may be preferred (Oliver and Webster, 2015).

Ordinary Kriging in this study is implemented via the ArcGIS geostatistical extension. Predictions are made for each individual winter month of the 2004-2014 time period by using all stations reporting snowfall data in Michigan as well as stations located within approximately 50 miles of its borders. This additional extent is deemed appropriate through observational examinations of the region as it provides an adequate number of weather stations to use for interpolation even in the more remote endpoints of the study network. Outliers are also examined and removed where applicable. In this context, outliers are defined as those stations which report monthly snowfall values of 0 inches, are surrounded by at least two nearby stations reporting significant monthly snowfall values, and repeat this pattern for at least one more month in the study time period. Lastly, data is further de-trended where appropriate and normalized if possible to facilitate optimized Ordinary Kriging outputs.

To further optimize the models and resulting prediction accuracy, output errors are inspected and minimized via the cross-validation process. The cross-validation process is a leave-one-out algorithm which withholds an observation point, makes a prediction about that point, and compares and validates the two values by outputting various error measurements. This procedure is then looped for the remaining observations (Ali, 2013; Laaha et al, 2013; Laaha et al., 2014; Oliver and Webster, 2015). The error output contains the following measurement errors which assist in optimizing and selecting the ideal prediction model (ArcGIS 9: Using ArcGIS Geostatistical Analyst, 2003):

$$Mean\ Error = \frac{\sum_{i=1}^{n}\left(\hat{Z}(x_i) - z(x_i)\right)}{n} \quad (2)$$

$$\textit{Root-Mean-Square Error} = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{Z}(x_i) - z(x_i)\right)^2}{n}} \tag{3}$$

$$\textit{Average Standard Error} = \sqrt{\frac{\sum_{i=1}^{n} \hat{\sigma}(x_i)^2}{n}} \tag{4}$$

$$\textit{Mean Standardized Error} = \frac{\sum_{i=1}^{n}\left(\hat{Z}(x_i) - z(x_i)\right)/\hat{\sigma}(x_i)}{n} \tag{5}$$

$$\textit{Root-Mean-Square Standardized Error} = \sqrt{\frac{\sum_{i=1}^{n}\left[\left(\hat{Z}(x_i) - z(x_i)\right)/\hat{\sigma}(x_i)\right]^2}{n}} \tag{6}$$

Where, $\hat{Z}(x_i)$ = predicted monthly snowfall at location x_i

$z(x_i)$ = observed monthly snowfall at location x_i

$\hat{\sigma}(x_i)$ = predicted standard error at location x_i (measure of uncertainty between the true and predicted value at location x_i, represented by the squared root of the prediction variance at location x_i)

n = number of weather stations

Target prediction errors needed to obtain ideal prediction values are listed in Table 4 (ArcGIS 9: Using ArcGIS Geostatistical Analyst, 2003; Oliver and Webster, 2015). These values are used as reference throughout the Ordinary Kriging optimization process for each monthly output case.

TABLE 4 Ordinary Kriging Target Prediction Errors

Mean Error	Root-Mean-Square Error	Average Standard Error	Mean Standardized Error	Root-Mean-Square Standardized Error
very small (0)	very small (0), within range of Average Standard Error	very small (0), within range of Root-Mean-Square Error	very small (0)	1

The number of weather stations used in each monthly output in the Ordinary Kriging process along with the five corresponding prediction errors are listed in Table 5.

TABLE 5 Weather Stations and Prediction Errors for Ordinary Kriging Outputs

			Error				
Year	**Month**	**No. of Stations**	**Mean**	**RMS**	**Mean Std**	**RMS Std**	**Avg Std**
2004	January	211	-0.020	9.139	-0.003	1.211	7.327
	February	212	0.056	5.248	0.007	1.177	4.420
	December	214	0.018	7.239	-0.004	1.146	6.209
2005	January	209	-0.084	5.983	-0.012	0.989	6.013
	February	209	0.017	1.058	0.017	1.101	0.959
	December	218	0.007	7.327	0.003	1.148	6.234
2006	January	212	0.158	3.889	0.005	0.995	5.548
	February	215	-0.109	7.218	-0.020	1.243	5.723
	December	229	-0.028	4.761	-0.008	1.158	3.944
2007	January	227	-0.016	7.138	-0.004	1.240	5.599
	February	227	-0.015	7.063	-0.001	1.177	5.764
	December	224	0.009	6.474	0.004	1.198	5.340
2008	January	225	-0.058	8.586	-0.006	1.185	7.126
	February	225	-0.058	6.845	-0.007	1.174	5.744
	December	241	0.069	10.801	0.004	1.084	9.754
2009	January	239	-0.051	8.601	-0.003	1.116	7.415
	February	246	0.020	6.322	0.003	1.197	5.153
	December	249	-0.053	8.734	-0.004	1.144	7.508
2010	January	253	-0.045	6.845	-0.004	1.063	6.377
	February	255	-0.051	6.359	-0.005	1.098	6.263
	December	246	0.009	7.658	-0.003	1.087	6.985
2011	January	265	0.019	11.375	0.003	1.130	10.068
	February	261	-0.107	8.289	-0.012	1.005	8.247
	December	268	-0.001	3.676	0.000	1.027	3.566
2012	January	264	0.016	8.932	0.002	1.119	7.955
	February	269	-0.056	5.082	-0.010	1.029	4.943
	December	275	-0.011	4.777	-0.001	1.053	4.548
2013	January	261	-0.052	8.111	-0.004	1.121	7.204
	February	260	0.016	10.470	0.002	1.045	10.048
	December	262	-0.124	10.812	-0.010	1.063	10.162
2014	January	254	-0.030	14.446	0.000	1.016	14.277
	February	255	-0.058	7.876	-0.007	0.981	8.060
	December	259	0.042	4.587	0.010	1.180	3.827
Average		**241**	**-0.017**	**7.325**	**-0.002**	**1.112**	**6.615**

In all cases the minimum number of stations reporting data is greater than 200, thus meeting the observation sample recommended to produce accurate predictions. Similarly, while fluctuations exist among the individual monthly Ordinary Kriging outputs, obtained average prediction errors are within range of the target values for all five error measurements. These fluctuations are largest in instances where weather stations in proximity of one another report values of significant differences (i.e. 40 inch snowfall on Station 1 vs 5 inch snowfall on Station 2) and cannot be identified as outliers.

3.2.2 Spatial Interpolation Output

The output of each monthly Ordinary Kriging model consists of a continuous raster surface covering the entire study network, the cells of which correspond to predicted monthly snowfall values in inches. Following each raster output, predicted values are than assigned to the endpoints of each roadway freeway segment and averaged for that segment in Geographical Information Systems (GIS) space. To ensure uniformity and integrity throughout the monthly snowfall segment assignment, any segment greater than 0.25 miles is split in 0.25 mile intervals. Predicted values for these segments are than assigned to the endpoints of the 0.25 mile breaks and averaged to obtain the final predicted monthly snowfall along that segment. Figure 4 illustrates a typical Ordinary Kriging output for monthly snowfall; Figure 5 illustrates the developed GIS algorithm for segment snowfall assignment, while Table 6 presents the mean predicted snowfall in inches for each 2004-2014 winter month for all freeway segments (i.e. network).

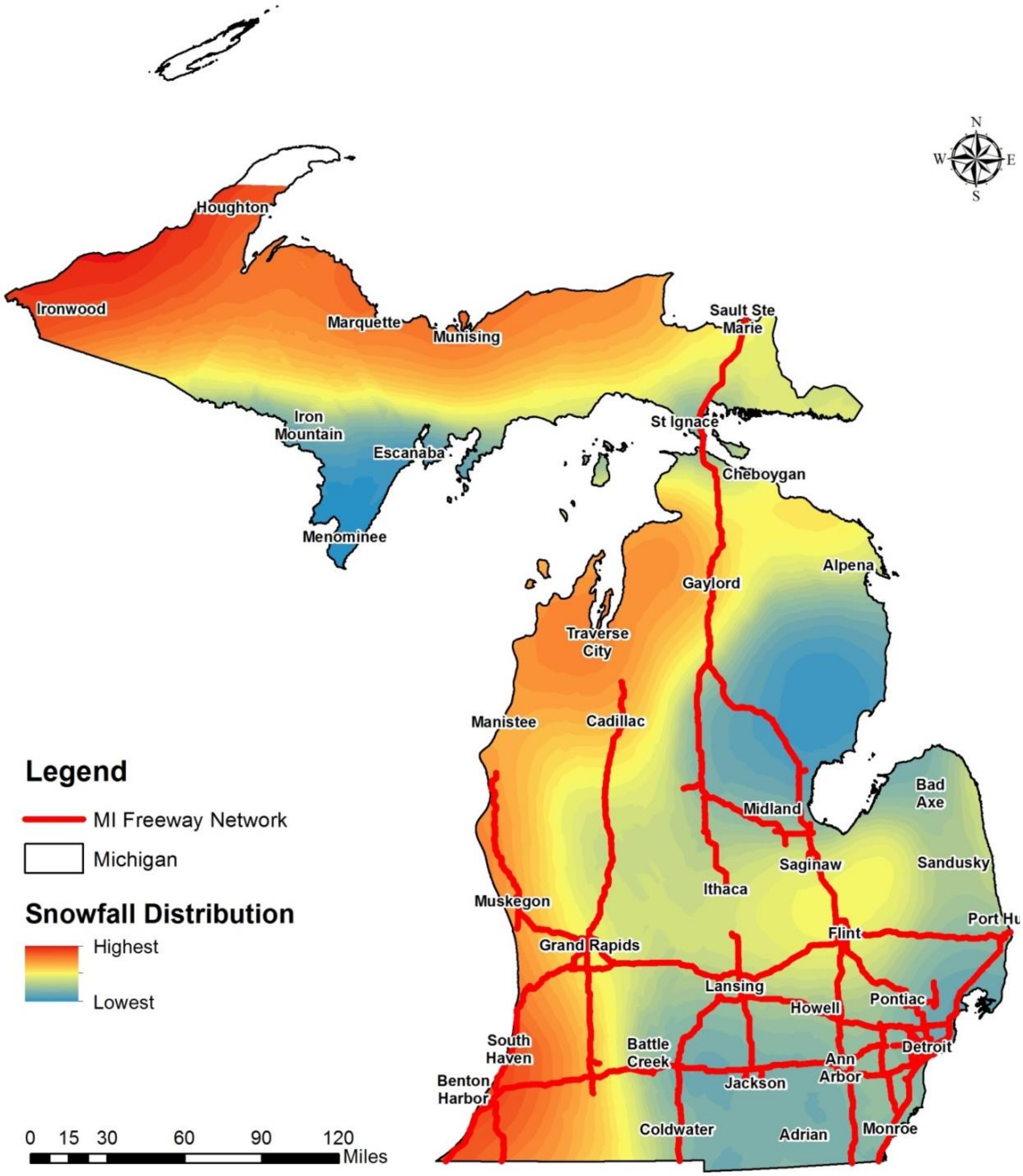


FIGURE 4 Typical Ordinary Kriging Output for Snowfall, January 2010

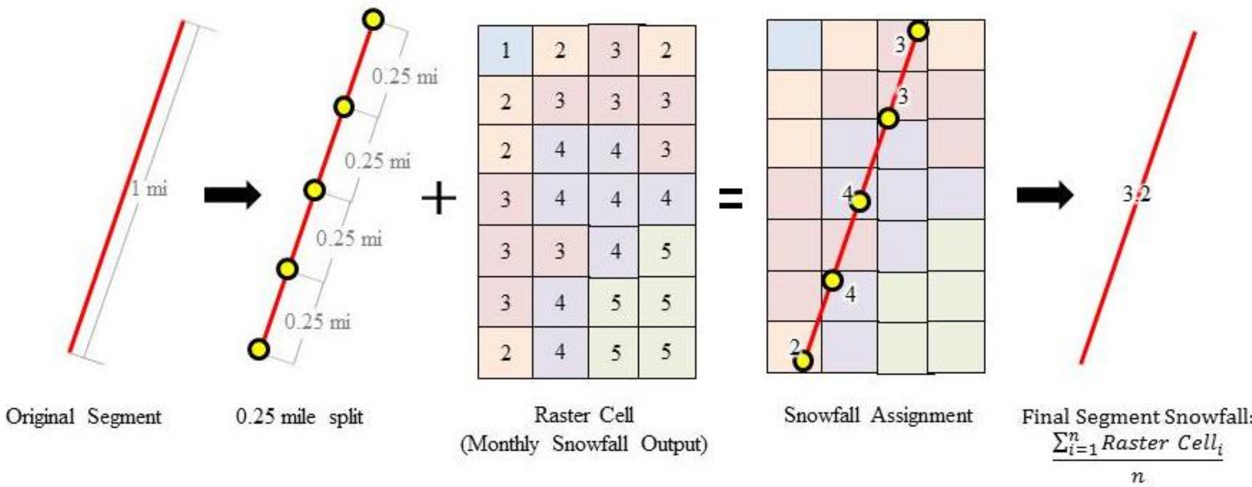


FIGURE 5 Segment Snowfall Assignment Algorithm

TABLE 6 Network Mean Predicted Snowfall (inches) for Winter Months 2004-2014

	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**Avg**
January	26.3	22.2	6.8	12.0	19.6	23.4	9.8	16.3	12.0	8.3	25.3	16.5
February	6.7	0.0	8.6	14.3	23.9	9.3	18.8	21.8	7.8	17.4	16.8	13.2
December	12.8	20.2	5.9	16.2	32.6	13.0	10.3	3.3	6.4	14.3	1.0	12.4
Monthly Avg	**15.3**	**14.1**	**7.1**	**14.1**	**25.4**	**15.3**	**13.0**	**13.8**	**8.7**	**13.3**	**14.4**	**14.0**
Annual Total	**45.8**	**42.4**	**21.3**	**42.4**	**76.1**	**45.8**	**38.9**	**41.5**	**26.1**	**40.0**	**43.1**	**42.1**

Lastly, snowfall values are converted into annual totals for use with the crash model. Figure 6 below presents the average 2004-2014 annual winter snowfall distribution along the network. The snowfall distribution indicates that historically the western part of mainland Michigan and the Upper Peninsula experience more snowfall than the rest of the network. Snowfall tends to decline moving towards the eastern portion of the network in mainland Michigan. This variation could be explained by the Great Lakes lake-effect and is consistent with other documented historical snowfall trends for this region (Andresen et al., 2012).

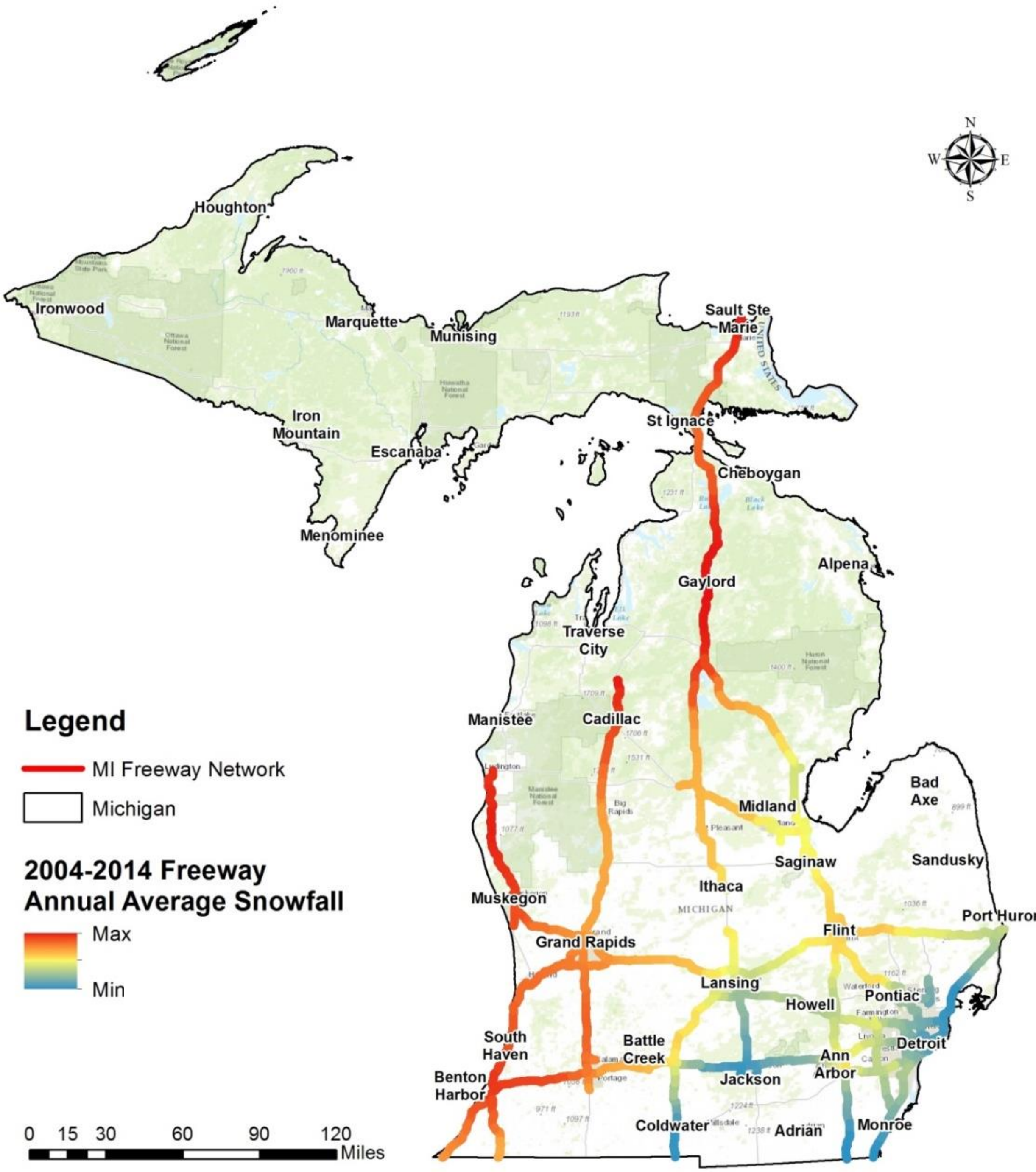


FIGURE 6 Network Average Annual Snowfall during January, February, and December 2004-2014

CHAPTER 4: STATISTICAL ANALYSIS

4.1 Statistical Methods

A series of regression models are conducted to investigate snow effects on crash types and crash outcomes for midblock and interchange crashes along the network. Since all of the crash categories in the dataset reflect a Poisson distribution with over-dispersion (i.e. variance > mean), the Negative Binomial regression model is employed for each case. The basic form of this model can be expressed as:

$$\lambda_i = EXP(\beta X_i + \varepsilon_i) \tag{7}$$

Where, λ_i = expected number of crashes of segment i

X_i = explanatory variables

β = regression coefficient

ε_i = gamma distributed error term with mean 1 and variance α^2 (α = dispersion paramater

Two Negative Binomial models are developed to assess the effects of snowfall on crashes. The first model (i.e. Model 1) aims to assess the overall effects of snowfall on crashes and represents the primary crash model in this study. The second model (i.e. Model 2) aims to complement the first model by further investigating the relationship between snowfall and crashes. In this context, Model 1 represents the more preferred approach in evaluating these effects, with the two models differing solely based on the format of the snowfall variable.

4.1.1 Model 1 – Natural Log of Snowfall

The first model aims to assess the overall effects of snow on crashes using the natural log of snowfall amounts. Explanatory variables include annual winter snowfall, AADT or commercial AADT (where commercial AADT is applicable for truck/bus crashes only as it is a more representative exposure variable for these types of vehicles), length, and horizontal curvature. The variables of snowfall, AADT or commercial AADT, and length are included in the model in natural log form, while horizontal curvature is expressed as a fraction. Thus Model 1 can be stated as:

$$\lambda_i = EXP(\beta_{1\text{-}0} + \beta_{1\text{-}1} HCurve_i) Length^{\beta_{1\text{-}2}}{}_i AADT^{\beta_{1\text{-}3}}{}_i Snow^{\beta_{1\text{-}4}}{}_i \tag{8}$$

Where, λ_i = expected number of crashes of segment *i* per year

$HCurve_i$ = fraction of segment *i* with horizontal curve w/ design speed < 85 mph

$Length_i$ = length of segment *i* in miles

$AADT_i$ = annual average daily traffic of segment *i* for year OR commercial annual average daily traffic of segment *i* for year (applicable for truck/bus crashes only)

$Snow_i$ = annual winter snowfall of segment *i* in inches

$\beta_{1\text{-}0}, \beta_{1\text{-}1}, \beta_{1\text{-}2}, \beta_{1\text{-}3}, \beta_{1\text{-}4}$ = model 1 regression coefficients

The inclusion of the snowfall variable in natural log form further facilitates the interpretation of the regression coefficients, where the latter represents the percent change in crashes associated with a one-percent change in the snowfall variable.

4.1.2 Model 2 – Categorized Snowfall

The second model aims to investigate more closely the relationship between snowfall and crashes. This is achieved by breaking down annual snowfall amounts into three categories, or dummy variables, based on its four quartiles, where:

- 1^{st} and 2^{nd} annual snowfall quartile: 5.2 in $\leq$ X < 37.4 in
- 3^{rd} annual snowfall quartile: 37.4 in $\leq$ X < 50.2 in
- 4^{th} annual snowfall quartile: 50.2 in $\leq$ X < 157.1 in

AADT or commercial AADT, and length are retained in the model in natural log form, horizontal curvature is retained as a fraction, while snowfall is expressed as a binary (0/1) variable for each of the three categories. The equation for Model 2 then becomes:

$$\lambda_i = EXP(\beta_{2\text{-}0} + \beta_{2\text{-}1} HCurve_i + \beta_{2\text{-}4_a} S3_i + \beta_{2\text{-}4_b} S4_i) Length_i^{\beta_{2\text{-}2}} AADT_i^{\beta_{2\text{-}3}} \tag{9}$$

Where, λ_i = expected number of crashes of segment *i* per year

$HCurve_i$ = fraction of segment *i* with horizontal curve w/ design speed < 85 mph

$Length_i$ = length of segment *i* in miles

$AADT_i$ = annual average daily traffic of segment *i* for year OR commercial annual average daily traffic of segment *i* for year (applicable for truck/bus crashes only)

$S3_i, S4_i$ = categorical variable (0/1) of segment i experiencing annual snowfall amounts in inches which fall in the 3rd or 4th quartile range. Reference category is the bottom two quartiles.

$\beta_{2\text{-}0}, \beta_{2\text{-}1}, \beta_{2\text{-}2}, \beta_{2\text{-}3}, \beta_{2\text{-}4_a}, \beta_{2\text{-}4_b}$ = model 2 regression coefficients

The interpretation of the categorical snowfall variable coefficients in this case can be facilitated by taking their exponent, subtracting one, and multiplying by 100, where the obtained value than represents the percent change in crashes relative to the reference point (i.e. 1st and 2nd annual snowfall quartiles).

4.2 Model 1 – Natural Log of Snowfall

4.2.1 Midblock Crashes

The Model 1 results for midblock crashes are provided in Table 7. These results indicate that the effects of snowfall on winter crashes differ in magnitude between crash types and crash severity outcomes. Each obtained equation along with the variables of length, AADT or commercial AADT, horizontal curvature, and snow are statistically significant at the 0.01

significance level. Furthermore, all variable coefficients are positive indicating increasing crash occurrence with increasing values of the explanatory variables.

TABLE 7 Model 1 (Natural Log of Snowfall) - Midblock Crashes NB Regression Results

Variable	B	Std Error	Lower CI	Upper CI	Wald Chi-Square	df	p-value
All Winter Crashes							
Intercept	-8.429	0.146	-8.715	-8.143	3329.615	1	<0.001
Ln Length	1.210	0.012	1.187	1.234	10012.338	1	<0.001
Ln AADT	0.667	0.011	0.645	0.689	3533.089	1	<0.001
Horiz. Curve < 85 mph	0.497	0.037	0.425	0.569	181.405	1	<0.001
Ln Snow	0.501	0.017	0.468	0.534	876.531	1	<0.001
Negative Binomial	0.781	0.015	0.753	0.811	na	na	na
Non-Truck/Bus Crashes							
Intercept	-8.464	0.149	-8.755	-8.173	3240.817	1	<0.001
Ln Length	1.213	0.012	1.189	1.237	9637.573	1	<0.001
Ln AADT	0.661	0.011	0.639	0.683	3384.573	1	<0.001
Horiz. Curve < 85 mph	0.533	0.038	0.459	0.606	201.408	1	<0.001
Ln Snow	0.498	0.017	0.464	0.532	827.817	1	<0.001
Negative Binomial	0.771	0.015	0.742	0.802	na	na	na
Truck/Bus Crashes							
Intercept	-13.235	0.276	-13.776	-12.694	2298.446	1	<0.001
Ln Length	1.220	0.028	1.166	1.274	1962.894	1	<0.001
Ln Commercial AADT	1.119	0.027	1.067	1.171	1776.413	1	<0.001
Horiz. Curve < 85 mph	0.563	0.092	0.382	0.744	37.180	1	<0.001
Ln Snow	0.596	0.037	0.525	0.668	266.987	1	<0.001
Negative Binomial	0.864	0.061	0.752	0.992	na	na	na
Injury Crashes							
Intercept	-10.943	0.245	-11.423	-10.462	1991.654	1	<0.001
Ln Length	1.245	0.021	1.204	1.285	3639.899	1	<0.001
Ln AADT	0.765	0.019	0.729	0.802	1679.932	1	<0.001
Horiz. Curve < 85 mph	0.580	0.061	0.461	0.700	91.174	1	<0.001
Ln Snow	0.463	0.028	0.409	0.518	276.768	1	<0.001
Negative Binomial	0.788	0.036	0.720	0.863	na	na	na
PDO Crashes							
Intercept	-8.604	0.153	-8.903	-8.305	3174.904	1	<0.001
Ln Length	1.213	0.013	1.188	1.238	9129.151	1	<0.001
Ln AADT	0.655	0.012	0.632	0.678	3138.357	1	<0.001
Horiz. Curve < 85 mph	0.467	0.039	0.391	0.543	145.291	1	<0.001
Ln Snow	0.522	0.018	0.488	0.557	869.662	1	<0.001
Negative Binomial	0.753	0.016	0.723	0.785	na	na	na

na = not applicable; CI = Confidence Interval; df = degrees of freedom

Overall, winter crashes increase by 0.5% for each one-percent increase in annual snowfall. Snow effects are most pronounced for those winter crashes involving a truck or bus, which show the most elastic relationship where each one-percent increase in snowfall results in a 0.6% percent increase in truck/bus crashes. Conversely, the effect of snow on crashes not involving a truck or bus experiences a lower elastic relationship with an increase in approximately 0.5% for each additional one-percent increase in snowfall. Among crash severity outcomes, injury crashes show a less pronounced effect than PDO crashes. While injury crashes increase by 0.46% for each additional one-percent increase in snowfall, PDO crashes increase by 0.52% for each additional one-percent increase in snowfall.

4.2.2 Interchange Crashes

The Model 1 results for interchange crashes are provided in Table 8. Similar to the Model 1 midblock crash results, these findings illustrate that snowfall has an impact on and varies among the crash categories analyzed, albeit less emphasized in magnitude as opposed to midblock crashes. In all cases the attained equations along with the variables of length, AADT or commercial AADT, horizontal curvature, and snow are significant at the 0.01 significance level. Akin to the Model 1 midblock crash results, all variable coefficients are positive indicating increasing crash occurrence with increasing values of the explanatory variables.

Overall, winter interchange crashes increase by 0.4% for each one-percent increase in annual snowfall. Unlike the midblock crash results, crashes involving a truck or buss are less susceptible to snow with a 0.26% increase in crashes for each one-percent increase in annual snowfall. Comparatively, the effects of snow on non-truck/bus crashes increase by 0.4% for each one-percent increase in annual snowfall. Among crash severity outcomes, results are relatively similar to midblock crashes where injury crashes are less susceptible to snow as opposed to PDO crashes, and experience a 0.37% increase for each one-percent increase in snowfall; while PDO crashes experience a 0.41% increase for each one-percent increase in snowfall.

TABLE 8 Model 1 (Natural Log of Snowfall) - Interchange Crashes NB Regression Results

Variable	B	Std Error	Lower CI	Upper CI	Wald Chi-Square	df	p-value
All Winter Crashes							
Intercept	-11.984	0.125	-12.229	-11.738	9165.422	1	<0.001
Ln Length	0.388	0.010	0.369	0.407	1621.871	1	<0.001
Ln AADT	1.124	0.010	1.105	1.143	13379.684	1	<0.001
Horiz. Curve < 85 mph	0.481	0.028	0.427	0.535	305.285	1	<0.001
Ln Snow	0.396	0.014	0.368	0.424	759.827	1	<0.001
Negative Binomial	0.631	0.011	0.610	0.652	na	na	na
Non-Truck/Bus Crashes							
Intercept	-12.050	0.128	-12.301	-11.798	8822.444	1	<0.001
Ln Length	0.388	0.010	0.369	0.408	1552.878	1	<0.001
Ln AADT	1.123	0.010	1.103	1.142	12749.754	1	<0.001
Horiz. Curve < 85 mph	0.517	0.028	0.462	0.572	340.363	1	<0.001
Ln Snow	0.393	0.015	0.364	0.422	708.554	1	<0.001
Negative Binomial	0.640	0.011	0.619	0.663	na	na	na
Truck/Bus Crashes							
Intercept	-12.076	0.243	-12.553	-11.600	2464.885	1	<0.001
Ln Length	0.220	0.021	0.179	0.261	110.795	1	<0.001
Ln Commercial AADT	1.224	0.025	1.175	1.272	2444.429	1	<0.001
Horiz. Curve < 85 mph	0.485	0.061	0.366	0.604	63.473	1	<0.001
Ln Snow	0.255	0.031	0.195	0.315	69.650	1	<0.001
Negative Binomial	0.866	0.052	0.770	0.974	na	na	na
Injury Crashes							
Intercept	-15.402	0.216	-15.824	-14.979	5096.870	1	<0.001
Ln Length	0.404	0.016	0.373	0.434	667.505	1	<0.001
Ln AADT	1.305	0.017	1.272	1.338	6011.224	1	<0.001
Horiz. Curve < 85 mph	0.499	0.040	0.421	0.577	156.899	1	<0.001
Ln Snow	0.368	0.023	0.322	0.413	252.326	1	<0.001
Negative Binomial	0.587	0.024	0.543	0.636	na	na	na
PDO Crashes							
Intercept	-11.935	0.130	-12.190	-11.680	8430.201	1	<0.001
Ln Length	0.385	0.010	0.366	0.405	1499.181	1	<0.001
Ln AADT	1.096	0.010	1.076	1.115	11805.188	1	<0.001
Horiz. Curve < 85 mph	0.440	0.028	0.384	0.495	241.655	1	<0.001
Ln Snow	0.408	0.015	0.378	0.437	748.062	1	<0.001
Negative Binomial	0.609	0.011	0.587	0.632	na	na	na

na = not applicable; CI = Confidence Interval; df = degrees of freedom

4.2.3 Model 1 Results Discussion

The Model 1 results on the effects of snowfall on all of the crash categories are summarized in terms of their elasticity in Table 9.

TABLE 9 Model 1 Snowfall Elasticities by Crash Category

	Midblock		Interchange	
Crash Category	**Percent Increase in Annual Crashes Associated with 1-pct. Increase in Annual Snowfall**	**p-value**	**Percent Increase in Annual Crashes Associated with 1-pct. Increase in Annual Snowfall**	**p-value**
All Crashes	0.501	<0.001	0.396	<0.001
Non-Truck/Bus	0.498	<0.001	0.393	<0.001
Truck/Bus	0.596	<0.001	0.255	<0.001
Injury	0.463	<0.001	0.368	<0.001
PDO	0.522	<0.001	0.408	<0.001

These results, in particular for midblock crashes, are generally in line with prior studies on the effects of snowfall on crashes (Qiu and Nixon, 2008), and are particularly intuitive for crashes involving trucks or buses. For instance, non-commercial trips are flexible in departure times, route changes, or route cancelation during severe snow events; while trips taken by truck or buses are generally business oriented thus less flexible on time and route choice. Truck performance is also more susceptible to decreasing visibility during adverse snow weather due to greater stopping distances required for larger and heavier vehicles (Pisano et al., 2008).

Existing literature also supports results for injury and PDO crashes with snowfall having a larger influence on PDO crashes and less, albeit positive, on injury crashes (Eisenberg, 2004; Eisenberg and Warner, 2005; Bilionis, 2013; Liu, 2013). These effects can be attributed to heightened driver alertness and lower speeds exhibited during snow events thus reducing the likelihood of high speed collisions and resulting injuries. Snow walls developed along the roadway can also be a cause for lower injury crash frequencies, and would be mostly applicable on segments experiencing the highest amounts of snowfall supplemented by continuous sub-freezing temperatures.

In comparison, the effects of snowfall on interchange crashes, while not as emphasized in magnitude as midblock crashes, are not particularly surprising and appear to be in concert with Kiattikomol (2005) findings that interchange and non-interchange segments should be treated separately in crash modeling. While snowfall has a positive significant impact on all crash categories analyzed, its magnitude is likely suppressed due to the various effects in play in an interchange setting such as over-emphasized roadway geometry, sudden deceleration and acceleration of vehicles, and additional traffic flow patterns and driver behavior characteristics unique to these locations. These factors are not captured in this model but are potentially reflected in the lower magnitude and variability of the snowfall coefficient.

4.3 Model 2 – Categorized Snowfall

4.3.1 Midblock Crashes

The Model 2 results for midblock crashes are provided in Table 10. These results indicate that the impact of snowfall on winter crashes varies among the different snowfall intervals. In all cases the attained equations along with the variable of length, AADT or commercial AADT, horizontal curvature, and the snowfall intervals in the 3rd and 4th quartile ranges are significant at the 0.01 significance level.

TABLE 10 Model 2 (Categorized Snowfall) - Midblock Crashes NB Regression Results

Variable	B	Std Error	Lower CI	Upper CI	Wald Chi-Square	df	p-value	Exp (B)
All Winter Crashes								
Intercept	-6.671	0.117	-6.900	-6.442	3251.847	1	<0.001	na
Ln Length	1.215	0.012	1.191	1.239	9997.124	1	<0.001	na
Ln AADT	0.655	0.011	0.633	0.678	3363.958	1	<0.001	na
Horiz. Curve < 85 mph	0.499	0.037	0.427	0.572	181.420	1	<0.001	1.648

TABLE 10 (cont'd)

Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.171	0.019	0.134	0.208	80.850	1	<0.001	1.186
Snow - 4th Quartile	0.527	0.020	0.489	0.566	715.332	1	<0.001	1.694
Negative Binomial	0.797	0.015	0.768	0.827	na	na	na	na
Non-Truck/Bus Crashes								
Intercept	-6.698	0.119	-6.931	-6.465	3183.369	1	<0.001	na
Ln Length	1.218	0.012	1.193	1.242	9614.877	1	<0.001	na
Ln AADT	0.649	0.011	0.626	0.671	3207.715	1	<0.001	na
Horiz. Curve < 85 mph	0.534	0.038	0.460	0.608	200.237	1	<0.001	1.705
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.167	0.019	0.129	0.205	74.951	1	<0.001	1.182
Snow - 4th Quartile	0.514	0.020	0.475	0.554	657.344	1	<0.001	1.672
Negative Binomial	0.789	0.015	0.759	0.820	na	na	na	na
Truck/Bus Crashes								
Intercept	-11.13	0.220	-11.563	-10.700	2555.502	1	<0.001	na
Ln Length	1.225	0.028	1.171	1.279	1966.418	1	<0.001	na
Ln Commercial AADT	1.098	0.026	1.046	1.150	1721.704	1	<0.001	na
Horiz. Curve < 85 mph	0.553	0.093	0.372	0.735	35.676	1	<0.001	1.739
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.264	0.042	0.181	0.348	38.701	1	<0.001	1.303
Snow - 4th Quartile	0.618	0.041	0.538	0.698	228.126	1	<0.001	1.856
Negative Binomial	0.898	0.062	0.784	1.028	na	na	na	na
Injury Crashes								
Intercept	-9.307	0.197	-9.693	-8.920	2225.145	1	<0.001	na
Ln Length	1.249	0.021	1.208	1.289	3638.146	1	<0.001	na
Ln AADT	0.754	0.019	0.717	0.790	1613.762	1	<0.001	na
Horiz. Curve < 85 mph	0.581	0.061	0.462	0.701	91.000	1	<0.001	1.789
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.165	0.030	0.105	0.224	29.526	1	<0.001	1.179
Snow - 4th Quartile	0.481	0.031	0.420	0.543	233.479	1	<0.001	1.618
Negative Binomial	0.805	0.037	0.736	0.881	na	na	na	na
PDO Crashes								
Intercept	-6.761	0.122	-7.001	-6.521	3057.707	1	<0.001	na
Ln Length	1.218	0.013	1.193	1.243	9105.181	1	<0.001	na
Ln AADT	0.643	0.012	0.619	0.666	2970.205	1	<0.001	na
Horiz. Curve < 85 mph	0.469	0.039	0.393	0.546	145.287	1	<0.001	1.599
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.178	0.020	0.139	0.216	80.828	1	<0.001	1.194
Snow - 4th Quartile	0.540	0.020	0.500	0.580	702.204	1	<0.001	1.717
Negative Binomial	0.772	0.016	0.741	0.804	na	na	na	na

na = not applicable; CI = Confidence Interval; df = degrees of freedom

Overall, snowfall effects show monotonic increases when moving to higher quartiles or segments experiencing increasing annual snowfall amounts. And while the incremental differences in the regression coefficients between each of the snowfall quartiles are relatively consistent across all crash categories, annual snowfall amounts in the 4th quartile are associated with the greatest percent increase in crashes relative to the reference point (1st and 2nd quartile). Similar to the Model 1 midblock crash results, crashes involving a truck or bus are the most susceptible to increasing snowfall amounts. Translated in practical terms, while the 3rd snowfall quartile displays 30% greater crashes compared to the reference point, the 4th quartile range displays 86% greater crashes compared to the reference point. Comparatively, non-truck/bus crashes display approximately 18% and 67% greater crashes for the 3rd and 4th quartile intervals relative to the reference point. Similar effects are observed for injury and PDO crashes, where akin to Model 1 results, PDO crashes are more susceptible to higher snowfall amounts as opposed to injury crashes.

4.3.2 Interchange Crashes

Lastly, the Model 2 results for interchange crashes are presented in Table 11. Similar to the Model 2 midblock crash findings, these results indicate that the effects of snowfall on winter crashes vary among the different snowfall intervals for this particular crash scenario. Furthermore, all attained equations along with all of the explanatory variables are statistically significant at the 0.01 significance level.

TABLE 11 Model 2 (Categorized Snowfall) - Interchange Crashes NB Regression Results

Variable	B	Std Error	Lower CI	Upper CI	Wald Chi-Square	df	p-value	Exp (B)
All Winter Crashes								
Intercept	-10.47	0.101	-10.672	-10.275	10672.373	1	<0.001	na
Ln Length	0.389	0.010	0.370	0.408	1619.511	1	<0.001	na

TABLE 11 (cont'd)

Ln AADT	1.103	0.010	1.084	1.122	12779.120	1	<0.001	na
Horiz. Curve < 85 mph	0.482	0.028	0.428	0.537	302.460	1	<0.001	1.620
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.184	0.016	0.153	0.215	134.706	1	<0.001	1.202
Snow - 4th Quartile	0.385	0.018	0.350	0.419	479.367	1	<0.001	1.469
Negative Binomial	0.644	0.011	0.623	0.666	na	na	na	na
Non-Truck/Bus Crashes								
Intercept	-10.54	0.104	-10.741	-10.334	10305.667	1	<0.001	na
Ln Length	0.390	0.010	0.370	0.409	1549.626	1	<0.001	na
Ln AADT	1.101	0.010	1.081	1.120	12158.944	1	<0.001	na
Horiz. Curve < 85 mph	0.518	0.028	0.463	0.574	336.442	1	<0.001	1.679
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.181	0.016	0.149	0.213	124.614	1	<0.001	1.198
Snow - 4th Quartile	0.373	0.018	0.338	0.409	429.839	1	<0.001	1.453
Negative Binomial	0.655	0.011	0.633	0.678	na	na	na	na
Truck/Bus Crashes								
Intercept	-11.11	0.201	-11.502	-10.713	3039.152	1	<0.001	na
Ln Length	0.227	0.021	0.186	0.268	117.659	1	<0.001	na
Ln Commercial AADT	1.204	0.025	1.156	1.252	2393.418	1	<0.001	na
Horiz. Curve < 85 mph	0.467	0.061	0.348	0.587	58.615	1	<0.001	1.596
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.227	0.034	0.160	0.295	43.830	1	<0.001	1.255
Snow - 4th Quartile	0.214	0.038	0.140	0.288	31.903	1	<0.001	1.239
Negative Binomial	0.874	0.052	0.778	0.982	na	na	na	na
Injury Crashes								
Intercept	-14.06	0.179	-14.410	-13.709	6168.780	1	<0.001	na
Ln Length	0.406	0.016	0.375	0.437	673.368	1	<0.001	na
Ln AADT	1.291	0.017	1.257	1.324	5819.473	1	<0.001	na
Horiz. Curve < 85 mph	0.499	0.040	0.421	0.577	156.377	1	<0.001	1.647
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.160	0.024	0.113	0.206	44.412	1	<0.001	1.173
Snow - 4th Quartile	0.390	0.029	0.333	0.446	184.053	1	<0.001	1.476
Negative Binomial	0.593	0.024	0.548	0.642	na	na	na	na
PDO Crashes								
Intercept	-10.38	0.105	-10.587	-10.174	9700.057	1	<0.001	na
Ln Length	0.387	0.010	0.367	0.407	1495.482	1	<0.001	na
Ln AADT	1.074	0.010	1.054	1.094	11236.257	1	<0.001	na
Horiz. Curve < 85 mph	0.441	0.028	0.385	0.497	239.595	1	<0.001	1.554
Snow - 1st & 2nd Quartile	base	na	na	na	na	na	na	na
Snow - 3rd Quartile	0.188	0.016	0.156	0.220	132.440	1	<0.001	1.207
Snow - 4th Quartile	0.393	0.018	0.358	0.429	470.284	1	<0.001	1.482
Negative Binomial	0.624	0.012	0.602	0.648	na	na	na	na

na = not applicable; CI = Confidence Interval; df = degrees of freedom

Overall, the Model 2 results for interchange crashes reflect combined findings for the Model 1 interchange and Model 2 midblock crashes. Akin to Model 1 interchange crash results, the snowfall coefficients in this model are lower in magnitude for each snowfall category. Analogous to Model 2 midblock crashes, effects generally display monotonic increases when moving to higher quartiles, with the incremental differences between each of the snowfall categories being reasonably consistent across the various types of crashes considered in the model. With the exception of crashes involving a truck or bus, which show similar crash increases for the 3rd and 4th quartile range, annual snowfall amounts in the 4th quartile are generally associated with the greatest percent increase in crashes relative to the reference point.

4.3.3 Model 2 Results Discussion

The Model 2 results on the effects of snowfall on all of the crash categories are summarized in terms of their elasticity in Table 12.

TABLE 12 Model 2 Snowfall Elasticities by Crash Category

		Midblock		**Interchange**	
Crash Category	**Snowfall Interval in Inches**	**Percent Increase in Annual Crashes Associated with Increase in Annual Snowfall Over Base Category**	**p-value**	**Percent Increase in Annual Crashes Associated with Increase in Annual Snowfall Over Base Category**	**p-value**
All Crashes	37.4 - 50.2	18.6	<0.001	20.2	<0.001
	50.2 - 157.1	69.4	<0.001	46.9	<0.001
Non-Truck/Bus	37.4 - 50.2	18.2	<0.001	19.8	<0.001
	50.2 - 157.1	67.2	<0.001	45.3	<0.001
Truck/Bus	37.4 - 50.2	30.3	<0.001	25.5	<0.001
	50.2 - 157.1	85.6	<0.001	23.9	<0.001
Injury	37.4 - 50.2	17.9	<0.001	17.3	<0.001
	50.2 - 157.1	61.8	<0.001	47.6	<0.001
PDO	37.4 - 50.2	19.4	<0.001	20.7	<0.001
	50.2 - 157.1	71.7	<0.001	48.2	<0.001

Base Category for Annual Snowfall = 5.2 inches – 37.4 inches (Quartiles 1 and 2)
Quartile 3 = 37.4 inches – 50.2 inches; Quartile 4 = 50.2 inches – 157.1 inches

Overall, these findings are surprising as prior studies have suggested that the effects of snowfall on crashes peak at mid ranges and decline or have a lower marginal effect at the higher snowfall levels (Khattak and Knapp, 2001; Eisenberg, 2004; Seeherman and Liu, 2015). One possible explanation for these differences is that the annual snowfall data represents an aggregation of weather patterns and is displaying the effects of underlying events such as higher frequencies of snowstorms and/or storms of greater intensity. This would certainly be plausible given that in nearly all cases the effects of snowfall are highest for those segments experiencing the largest amount of snow.

4.4 Midblock Snowfall Crash Curves

In order to present a secondary avenue for the examination of snowfall effects on crashes and introduce practical implications, Model 1 midblock Negative Binomial crash findings are translated in graphical form for each of the crash types analyzed. To establish the graphical relationship, crashes are predicted as a function of AADT or commercial AADT, length, horizontal curvature, and snowfall, all of which are found significant in the statistical models at the 0.01 significance level. For each graph, predicted crashes are presented as crashes per mile by fixing length to 1 (Y-axis) and plotting it against the AADT or commercial AADT network data range (X-axis), where similar to the Negative Binomial models commercial AADT is only applicable for crashes involving a truck or bus. Crash curves are established for six snowfall 20 inch intervals reflecting values in the network annual snowfall data range. Two graphs are produced for each crash type, one for tangent segments (i.e. fraction of segment with horizontal curve with design speed < 85 mph = 0) and one for curved segments using the mean value of the horizontal curvature network data as baseline (i.e. fraction of segment with horizontal curve with design speed < 85 mph = 0.1). Additional baseline values applicable to these graphical relationships include: Speed Limit = 70 mph / 60 mph, Average Number of Lanes = 2.5, Average Lane Width = 12 ft, Average Shoulder Width = 9.3 ft. Lastly, since interchange crashes are subject to additional factors unique to their design which are not fully captured by the presented models, they are not given the same graphical treatment as midblock crashes.

Figure 7 presents an overlay of selected crash curves for all winter midblock crashes for both tangent and curved segments to allow for the direct comparison of the two curvature scenarios, while Figure 8 through 12 illustrate the developed crash curves for each midblock crash type analyzed.

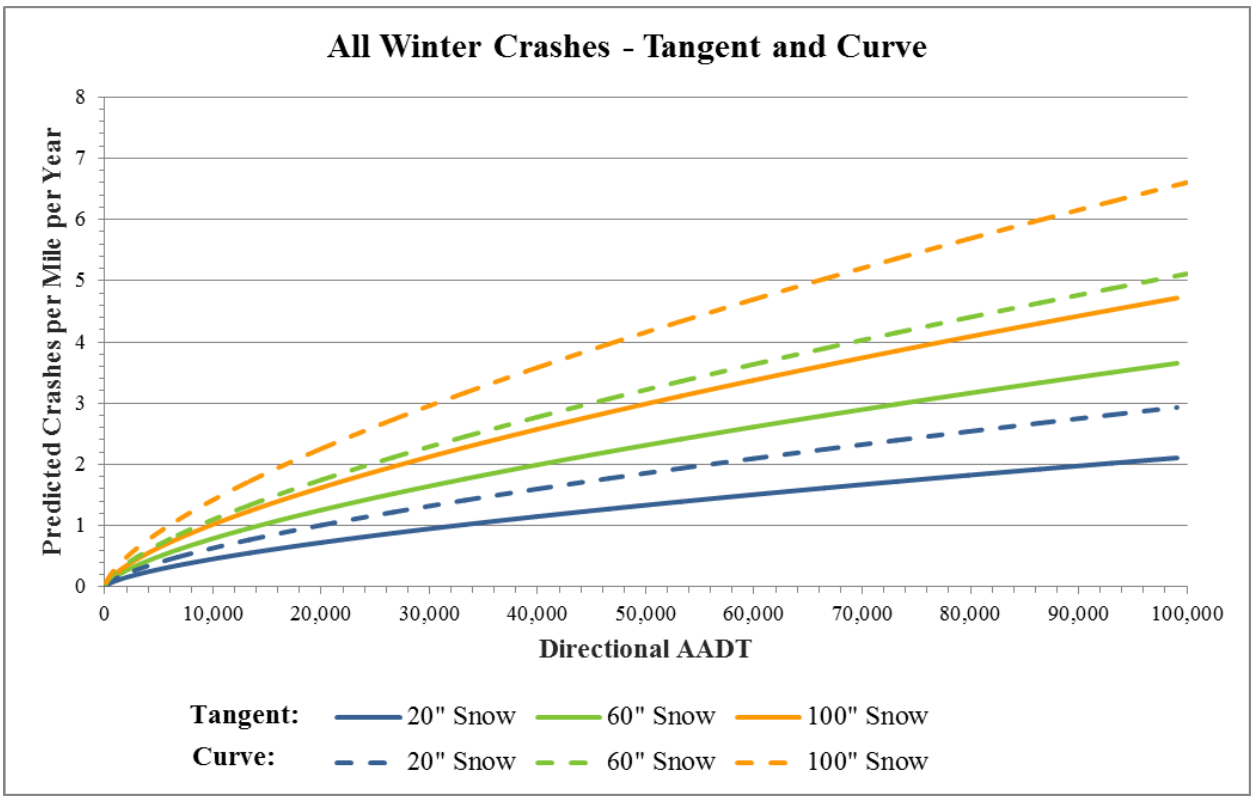
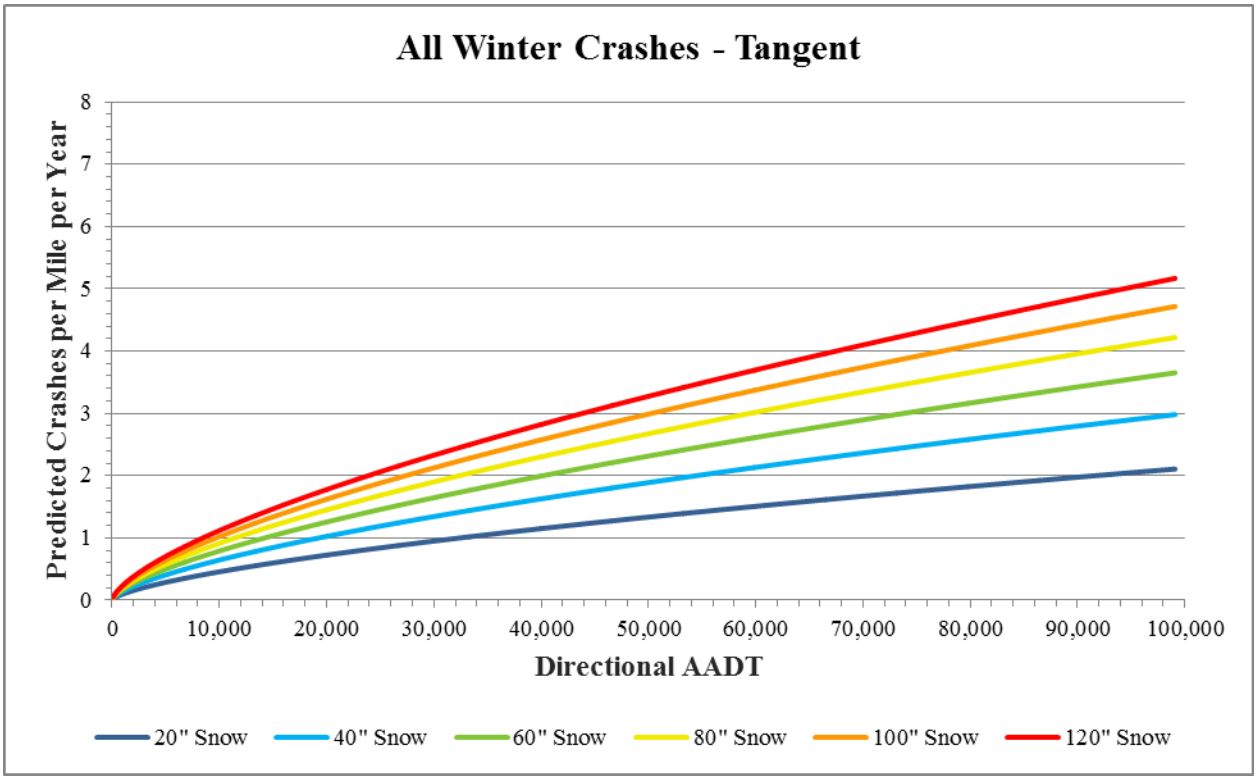


FIGURE 7 Effect of Annual Snowfall on Winter Midblock Crashes Combined for Tangent and Curved Segments



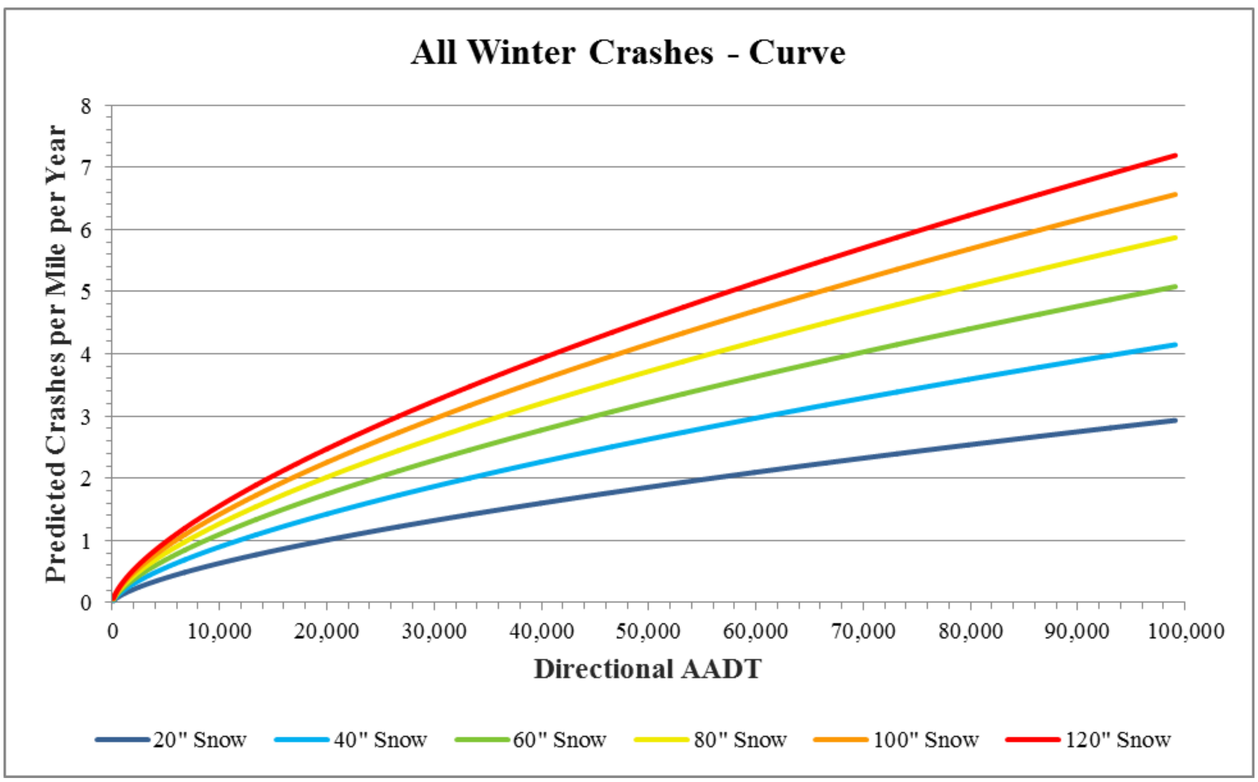
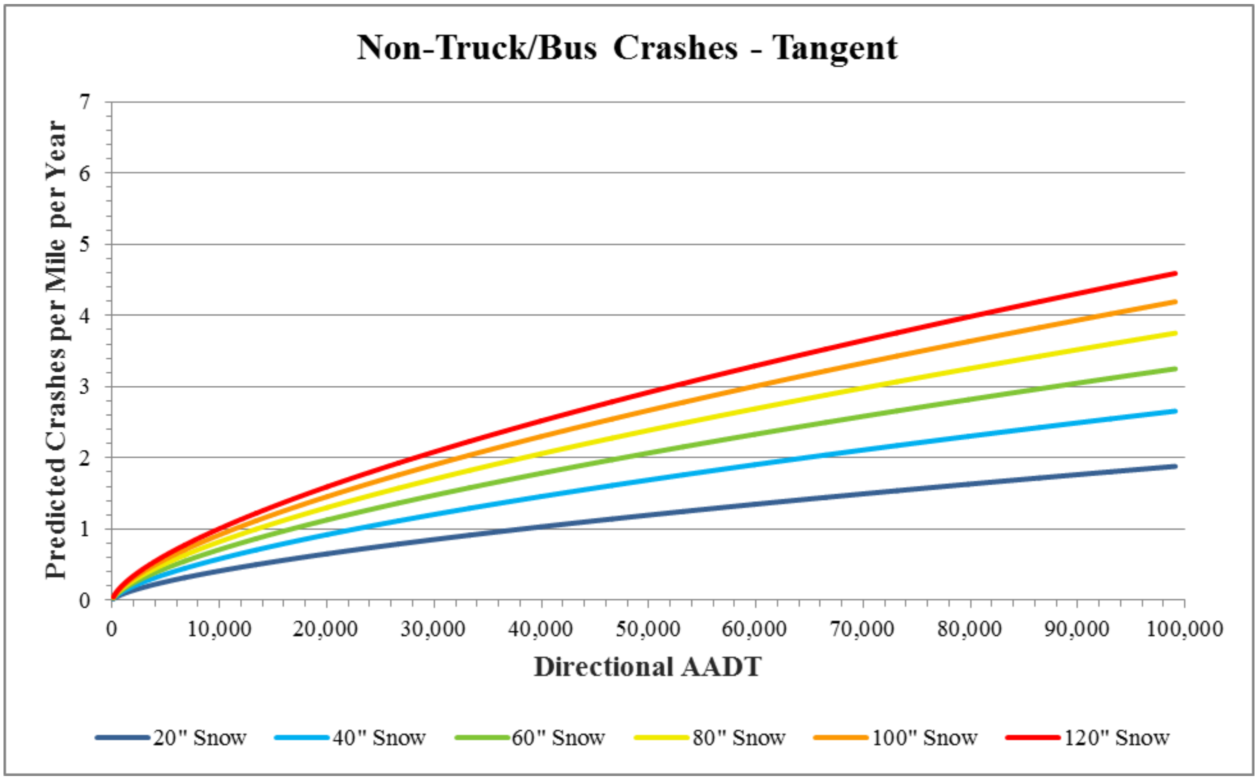


FIGURE 8 Effect of Annual Snowfall on Winter Midblock Crashes for Tangent and Curved Segments



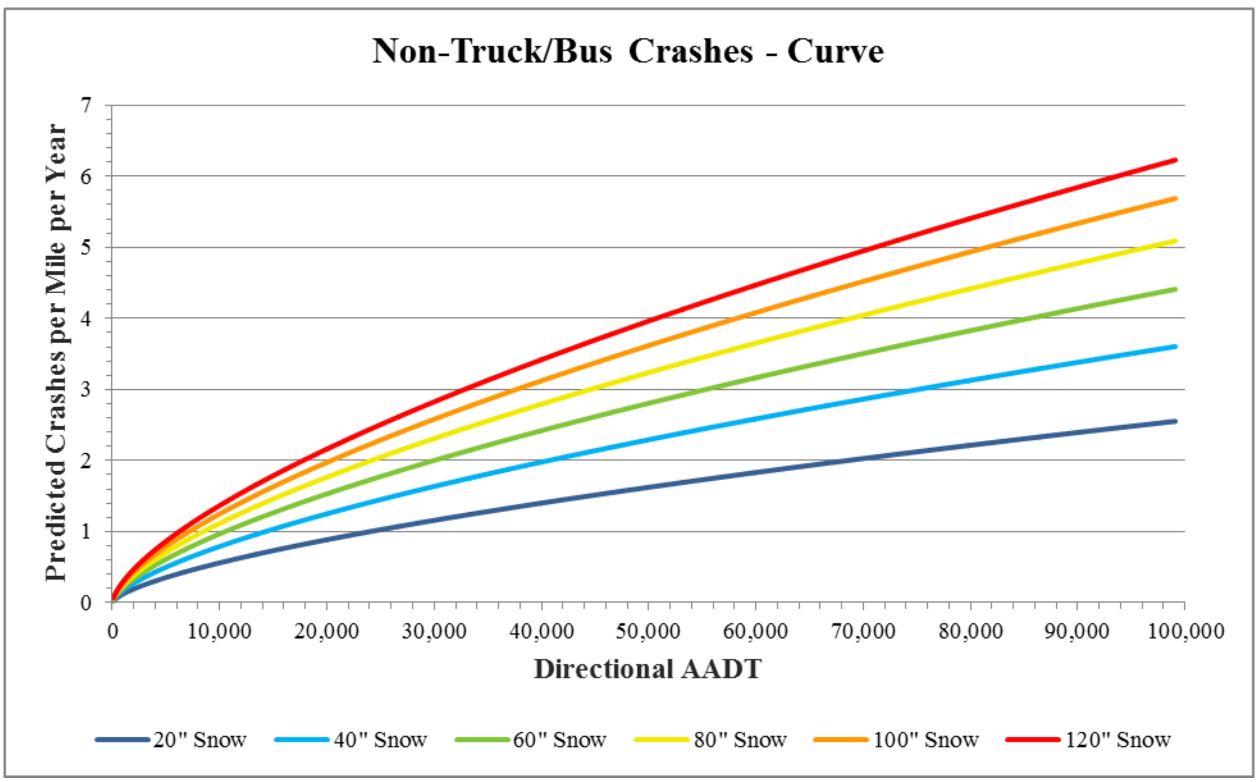
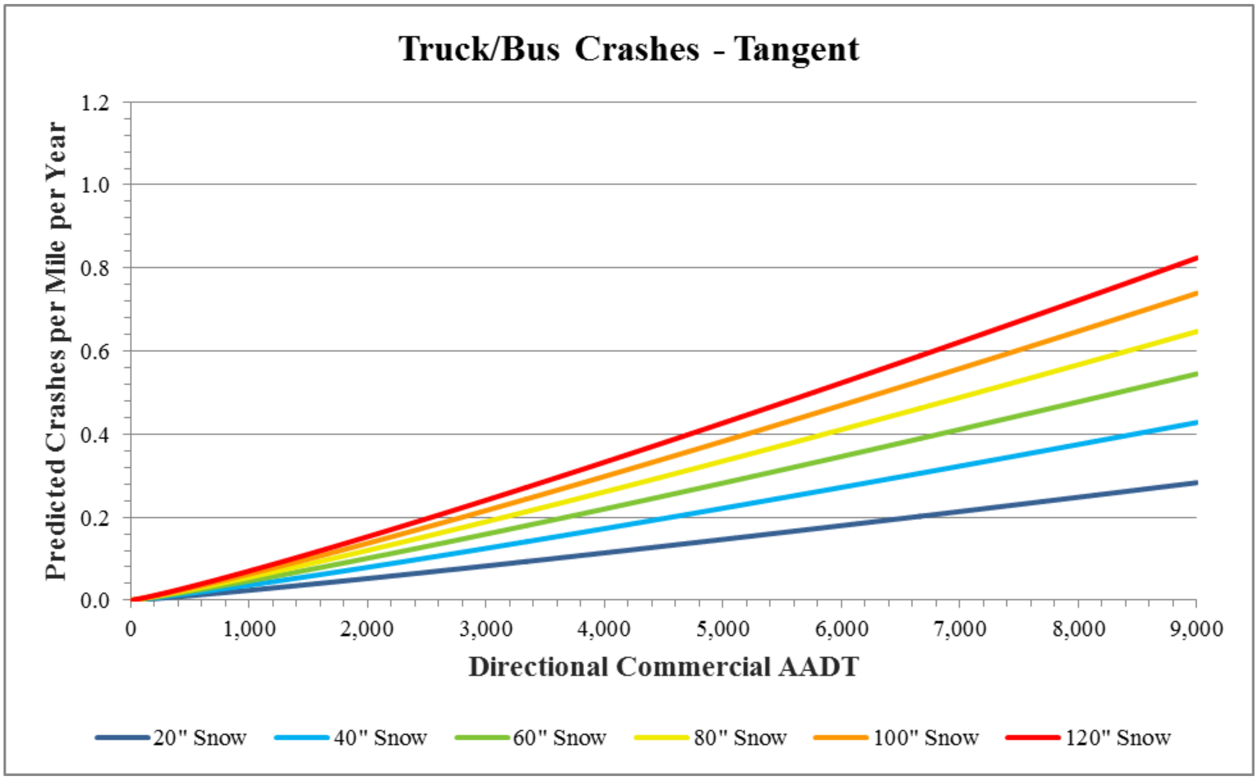


FIGURE 9 Effect of Annual Snowfall on Non-Truck/Bus Winter Midblock Crashes for Tangent and Curved Segments



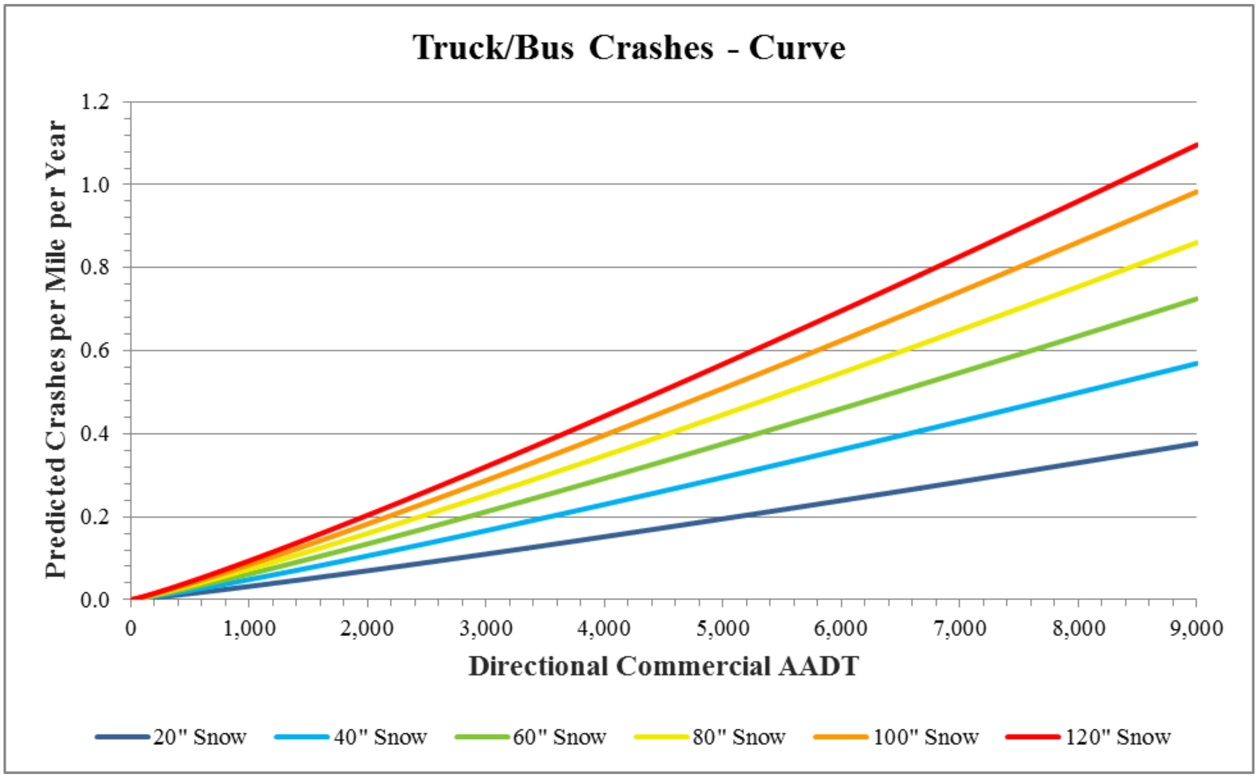
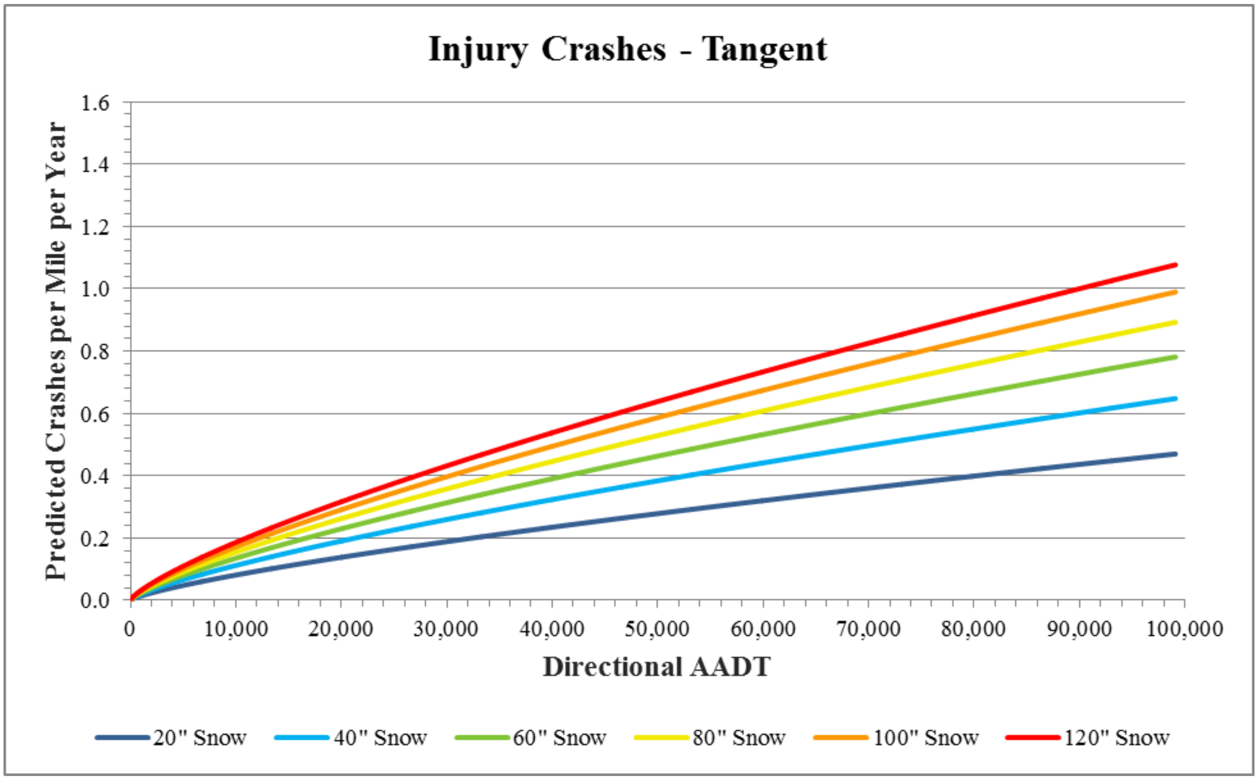


FIGURE 10 Effect of Annual Snowfall on Truck/Bus Winter Midblock Crashes for Tangent and Curved Segments



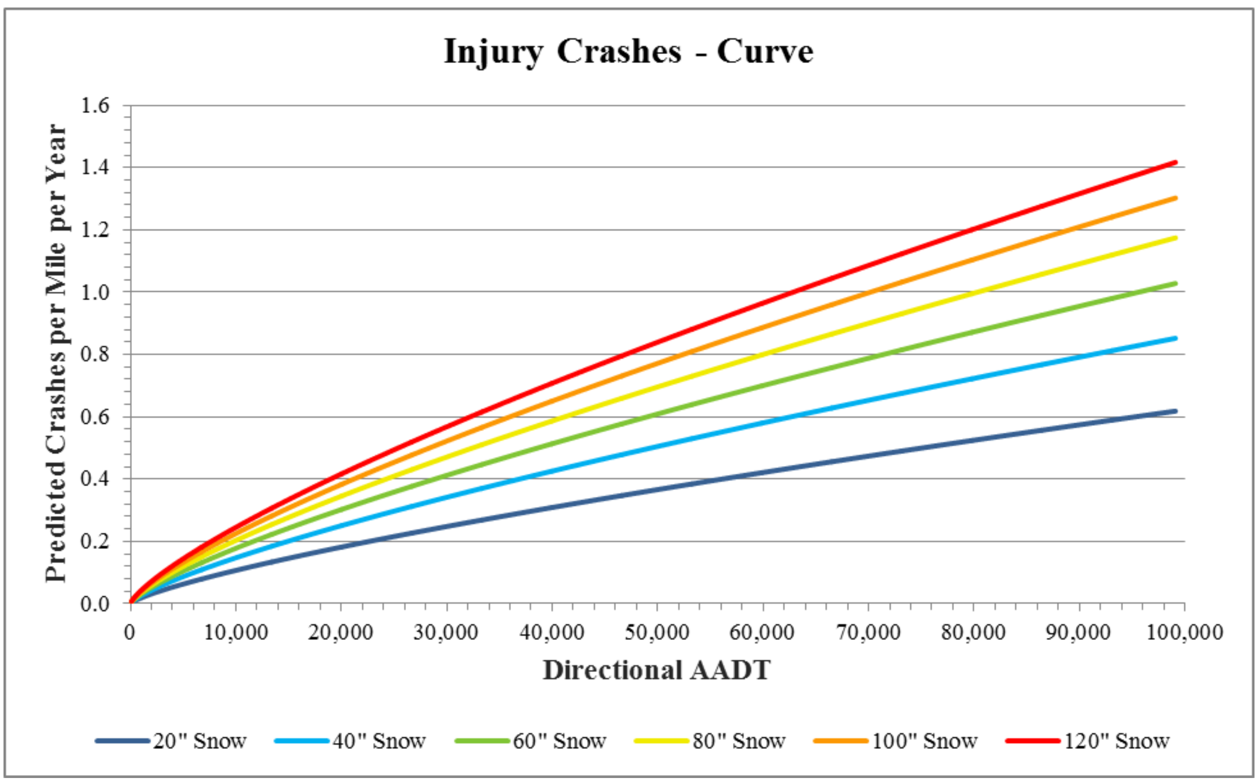
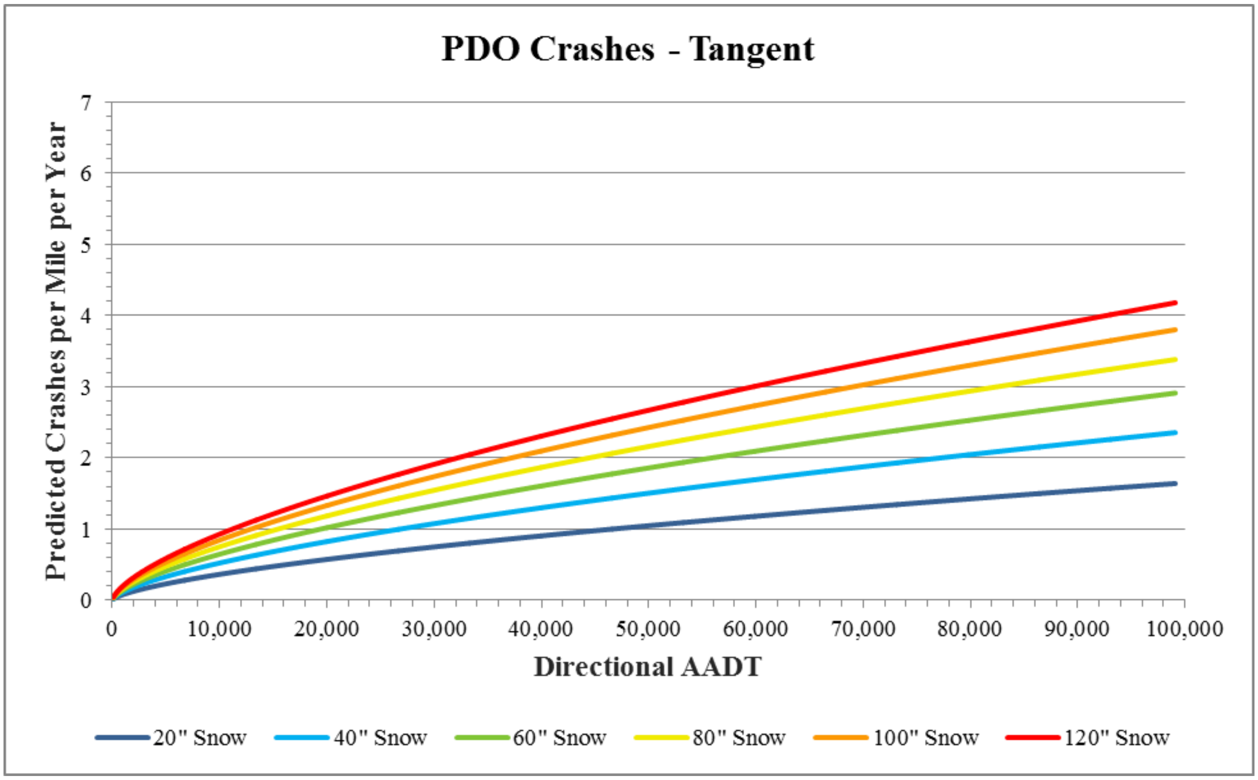


FIGURE 11 Effect of Annual Snowfall on Injury Winter Midblock Crashes for Tangent and Curved Segments



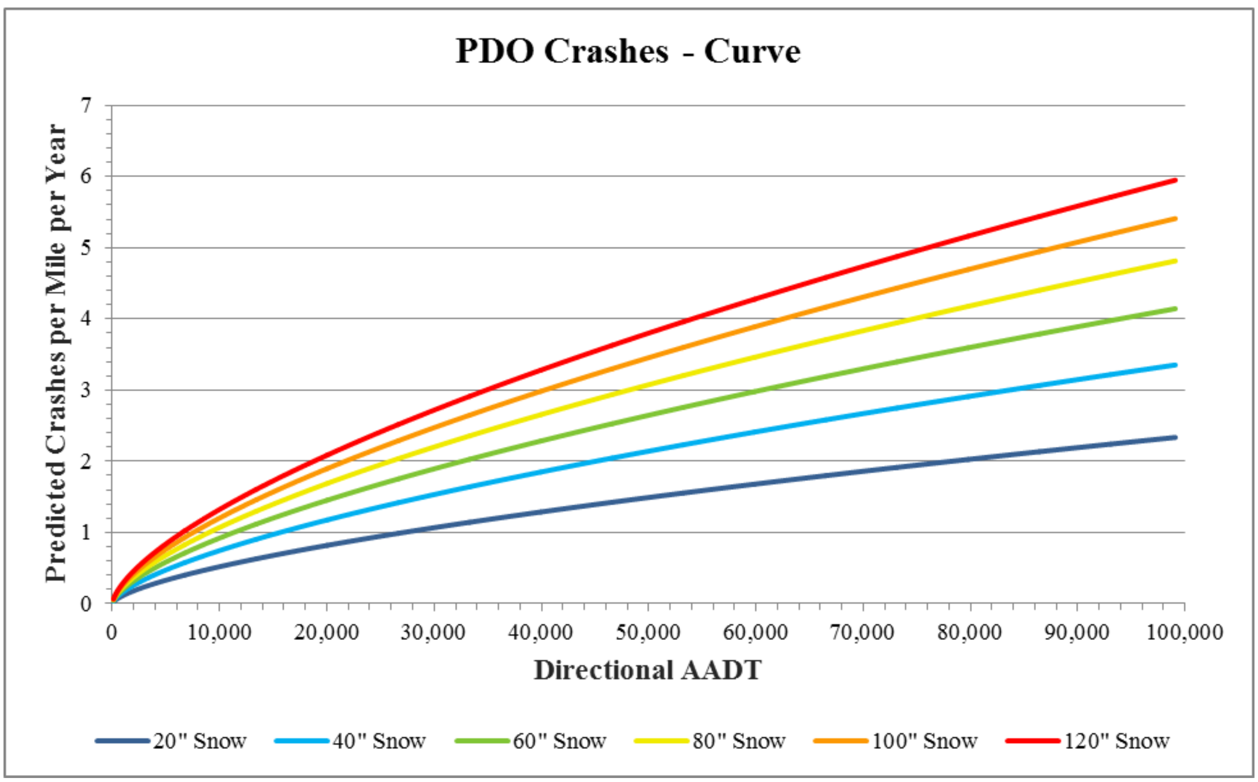


FIGURE 12 Effect of Annual Snowfall on PDO Winter Midblock Crashes for Tangent and Curved Segments

Similar to the negative binomial results, predicted crashes for each crash type increase with increasing values of AADT or commercial AADT, and snowfall. Crash occurrence is furthermore larger in the presence of horizontal curvature. These results are overall consistent for each crash category, with the crash curves for each snowfall interval illustrating similar graphical patterns among them. Crashes involving a truck or bus represent the only exception to the latter where commercial AADT has a larger impact on these types of crashes with a parameter coefficient greater than one, thus leading to an exponential growth pattern for the provided crash curves.

CHAPTER 5: SPATIAL PATTERN ANALYSIS

5.1 Crashes & Kernel Density Function

While statistical analysis demonstrates that annual snowfall has a statistically significant positive effect on all crash types and locational scenarios analyzed, an examination of the spatial dispersion pattern of these crashes can provide practical insights which may assist agencies in identifying potential candidate segment areas for countermeasure implementation. Spatial patterns for freeway crashes in this study are examined using the kernel density function. This method is used at length in identifying crash patterns or “hot spots” in crash analysis (Xie and Yan, 2008; Anderson, 2009; Blazquez and Celis, 2012).

Kernel density is a spatial pattern identifier which calculates the density of data points in a circular region. The circular area over which density is determined is called the kernel (Rushton and Tiwari, 2009). Within the kernel, density peaks at the location of the data point and becomes zero at the kernel boundary. When kernel density is applied over counts (i.e. individual crashes in XY spaces), the total sum value under the kernel is 1. When counts are assigned a secondary value (i.e. snowfall amount), the kernel assumes this value within its perimeter (How Kernel Density works, 2016). Additionally, kernels are drawn for each cell in the geographic extent of the dataset thus resulting in a smooth raster output also known as spatial filtering which helps to identify potential patterns (Rushton and Tiwari, 2009; How Kernel Density works, 2016). This process can be utilized for both points (i.e. crashes) and lines (i.e. segments) in GIS space. A simplified visual representation of the kernel density process is presented in Figure 13.

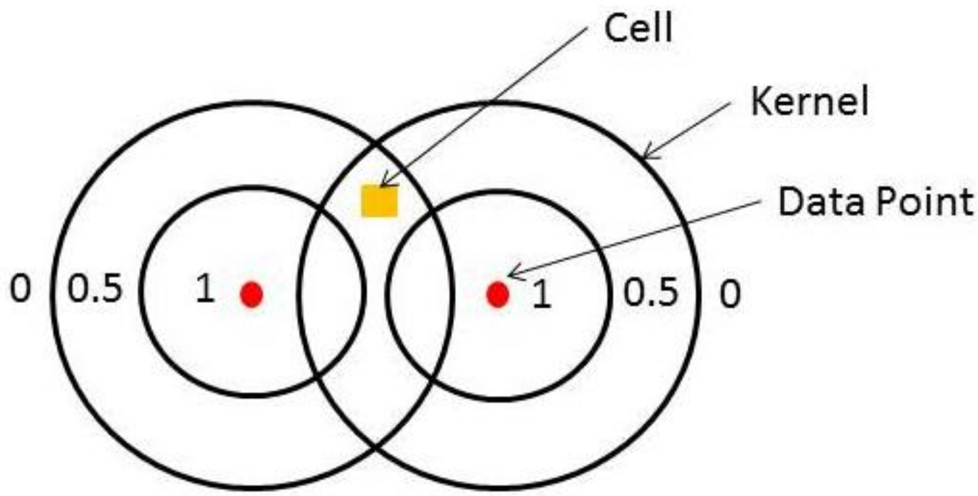


FIGURE 13 Simplified Visual Representation of Kernel Density Process

Kernel density on crash analysis is typically applied to the count distribution of crashes to identify potential patterns. This process however is not applicable for this particular study since crashes along the subject freeway network are overly concentrated in the Metro Detroit region due to elevated AADT volumes and a relatively high concentration of interchanges, thus producing unusable patterns. To overcome this challenge, crashes are applied to the freeway segments in crash rate form for midblock scenarios. Crash rate in this case is defined as:

$$Crash\ Rate_i = \frac{C_i * 100{,}000{,}000}{V_i * 365 * N * L_i} \tag{10}$$

Where, $Crash\ Rate_i$ = 2004-2014 winter midblock crash rate for segment *i*

C_i = 2004-2014 winter midblock crashes for segment *i*

V_i = 2004-2014 average AADT for segment *i*

N = number of years of data

L_i = length in miles for segment *i*

The applied transformation eliminates the problem of high crash densities in high AADT regions since crashes are presented as a function of AADT and length. These two variables are also included as explanatory variables in the Negative Binomial models and are found significant at the 0.01 significance level for all crash types analyzed. The additional omission of interchange crashes further facilitates the pattern identification process since only midblock crashes are considered. These are correspondingly shown to be more susceptible to snowfall effects for all crash categories. Not surprisingly the relationship between average annual snowfall and winter midblock crash rates for the network has a linear correlation with a Pearson coefficient of 0.327 (p-value <0.001) (Figure 14). The linear relationship indicates that spatial identification of segments most prone to snowfall is feasible under this structure.

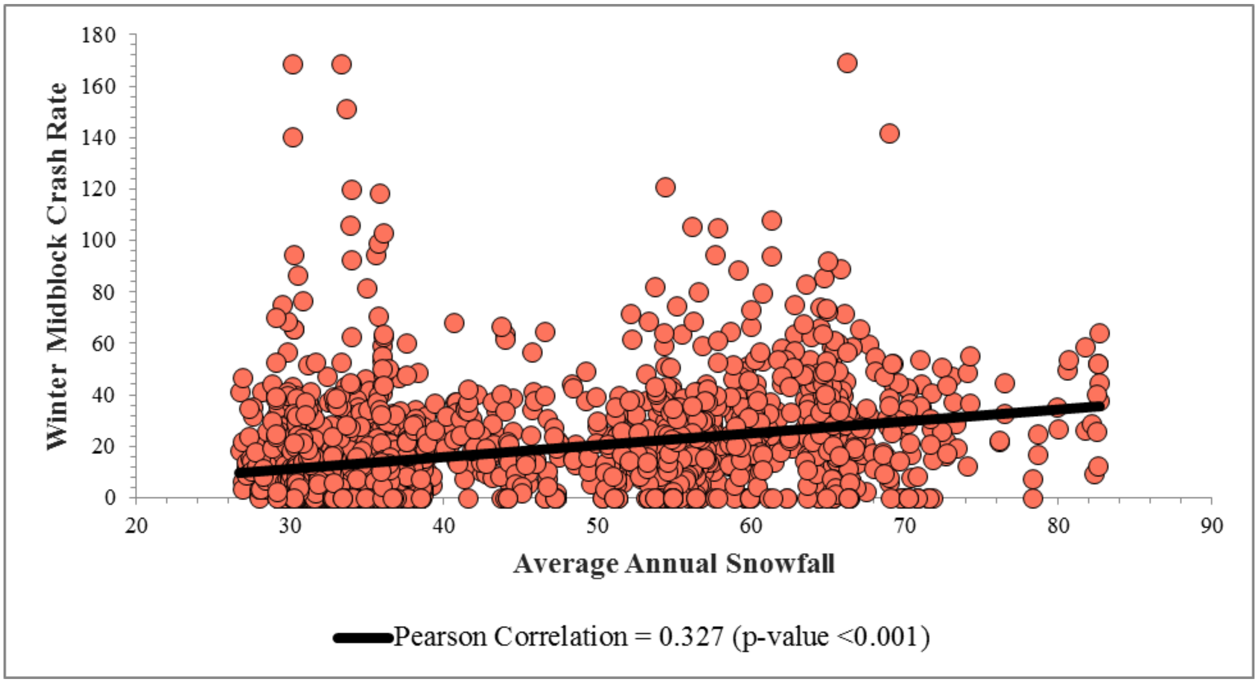


FIGURE 14 2004-2014 Network Winter Midblock Crash Rate & Average Annual Snowfall

Following the crash rate transformation, the kernel density function is performed on all winter midblock crash rates for two case studies, Interstate 75 (I-75) and Interstate 94 (I-94). These two freeway corridors are selected based on their lateral and longitudinal spread over the state of Michigan, thus providing a relatively complete coverage of snowfall distribution for both north-south and east-eest directions. To provide comparable metrics, the kernel density function is also applied to the AADT volumes and annual snowfall amounts averaged for the 11 year period of 2004-2014 for each freeway segment corresponding to the two corridors. Kernel outputs are then stacked against each other to facilitate the identification of crash rate patterns. The two case studies are presented below.

5.2 Case Study 1 – Interstate 75

Case study 1 is represented by I-75. This freeway corridor runs from the Ohio border to the south up to the Canadian border to the north. It is the longest freeway in Michigan and covers a distance of approximately 397 miles per direction. The lateral spread provides an ideal distribution in assessing crash patterns between the northern and southern parts of the state. Similar to the network, I-75 exhibits a linear relationship between average annual snowfall and winter midblock crash rates with a Pearson coefficient of 0.423 (p-value <0.001) (Figure 15). The spatial distribution of this relationship is presented below in Figure 16. This image compares in sequential order the AADT, snowfall, and winter midblock crash rate kernel density distribution along the entire interstate.

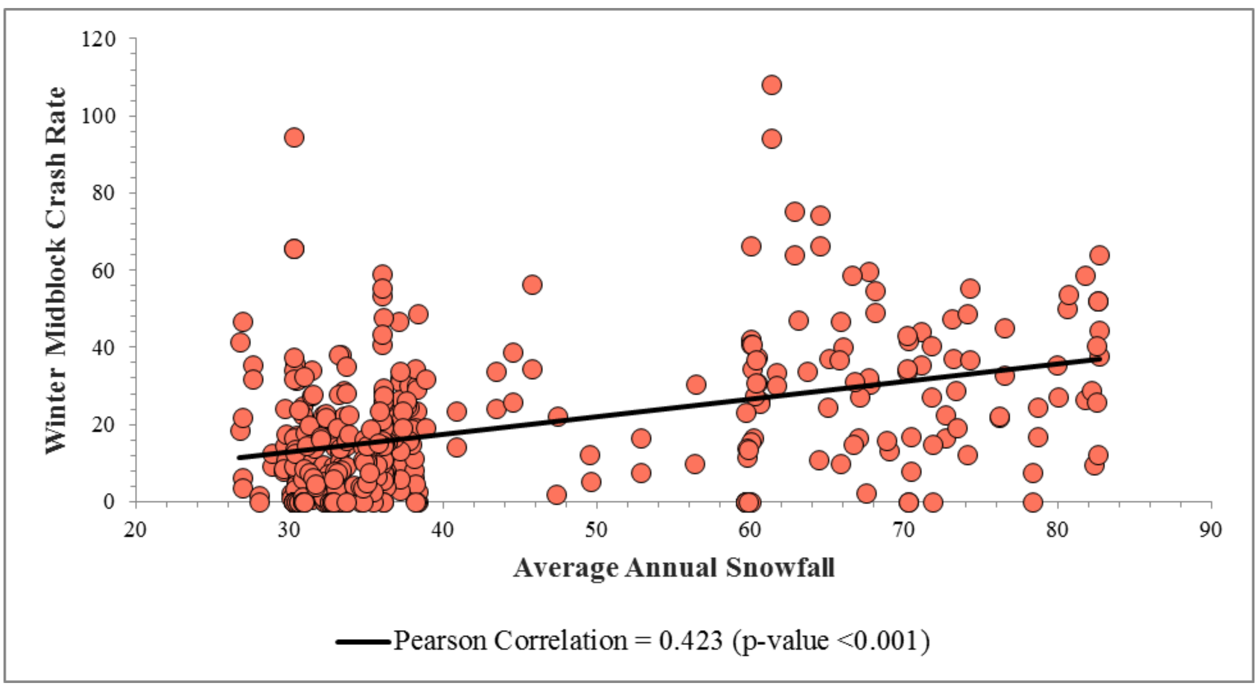


FIGURE 15 2004-2014 I-75 Winter Midblock Crash Rate & Average Annual Snowfall

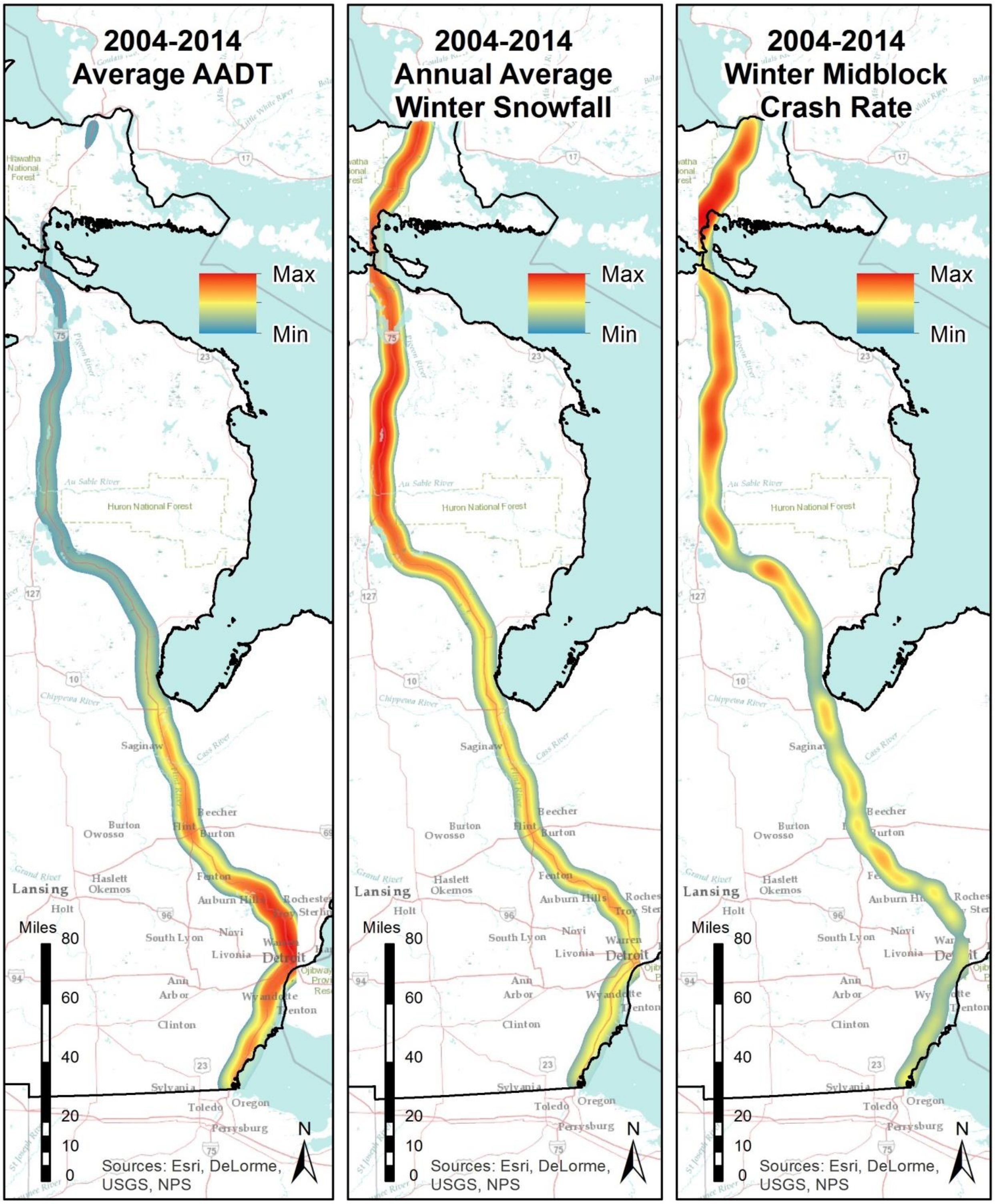


FIGURE 16 I-75 Kernel Density Distribution

The kernel density output indicates very clear and noticeable crash rate patterns for I-75. While the segments with the highest AADT volumes are concentrated in the Metro Detroit area, average annual snowfalls and winter midblock crash rates for this region are relatively low. Conversely the northern section of I-75 between the city of Gaylord and the Canadian border has the lowest AADT volumes, highest average annual snowfall, and highest winter midblock crash rate concentration. The density for the three variables peaks in these corresponding directions for the freeway segments located between the Mackinac Bridge and the Canadian border. This particular distribution indicates that crash rates in this region are more susceptible to snowfall, potentially due to a higher frequency of snowstorms and/or storms of greater intensity experienced during winter periods.

Accordingly countermeasures installed in these segments can have the most impact on winter crash rates. Examples of potential countermeasures may include environmental sensor stations installed near the most susceptible segments to improve winter maintenance, or linking environmental sensors to ITS devices like flashing weather alert signs or variable message signs to alert drivers of adverse weather conditions when passing specific locations along the corridor. On a macro level scale, the attained crash rate patterns can be used to assist agencies in countermeasure implementation segment prioritization.

5.3 Case Study 2 – Interstate 94

While case study 1 presents a lateral cross-section of the state, case study 2 or I-94 presents a longitudinal one. This freeway corridor runs from the Canadian border to the east down to the Indiana border to the west for approximately 276 miles in length per direction. Similar to the I-75 corridor, I-94 provides an ideal longitudinal distribution in assessing crash patterns between the eastern and western portions of the state. Comparably to both the network and the I-75 corridor, I-94 exhibits a linear relationship between average annual snowfall and winter midblock crash rates with a Pearson coefficients of 0.397 (p-value <0.001) (Figure 17).

The spatial distribution of this relationship is presented below in Figure 18. This image lists in sequential order the AADT, snowfall, and winter midblock crash rate kernel density distribution along the entire interstate.

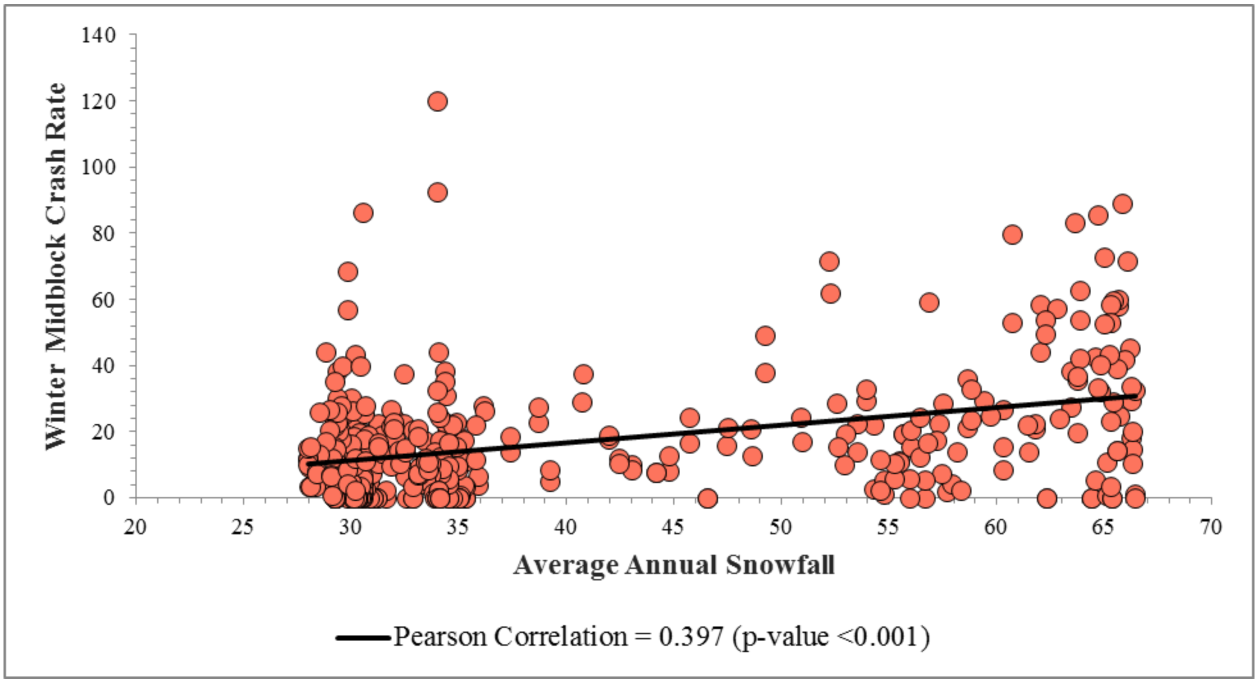


FIGURE 17 2004-2014 I-94 Winter Midblock Crash Rate & Average Annual Snowfall

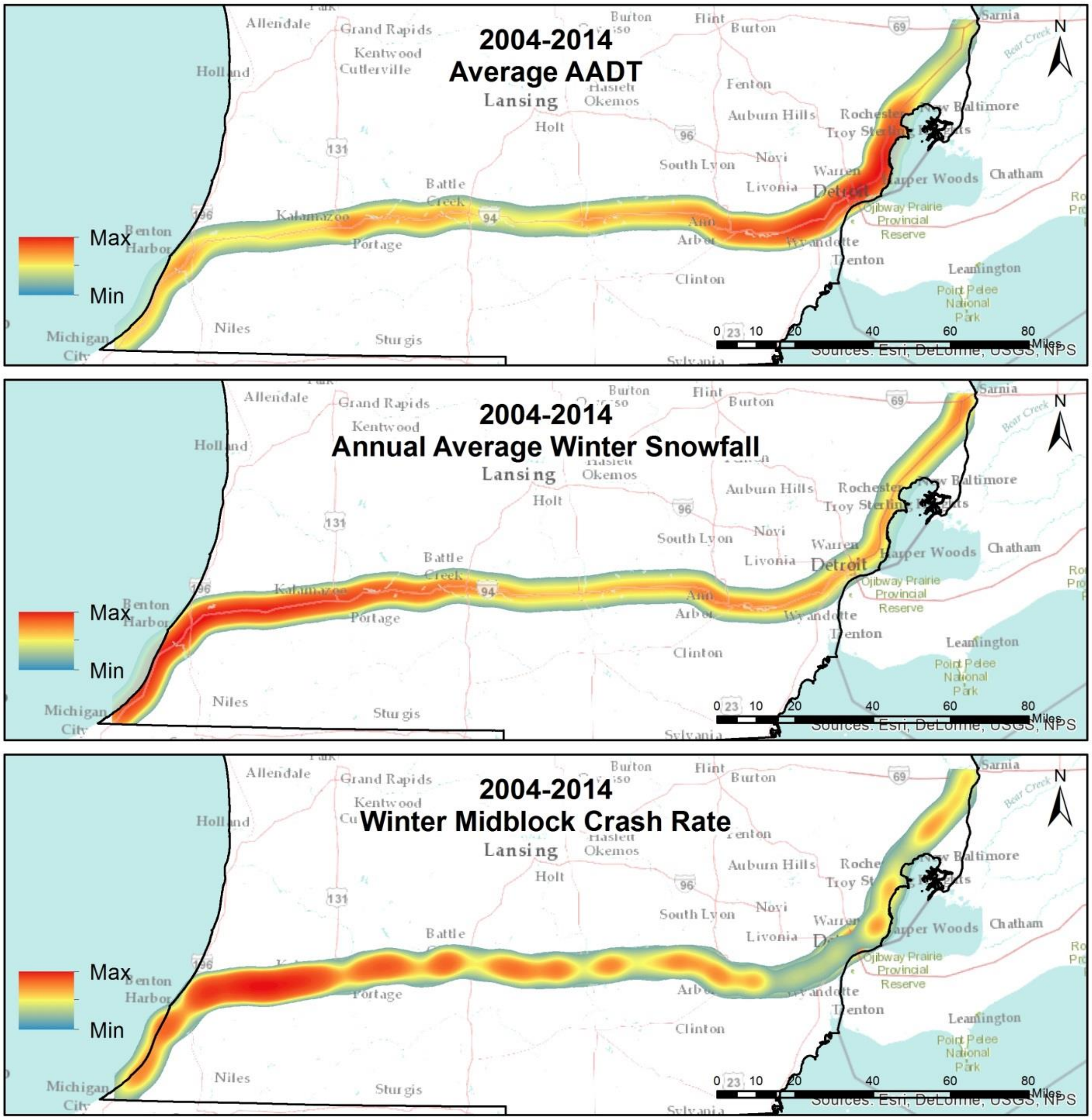


FIGURE 18 I-94 Kernel Density Distribution

Similar to the I-75 case study, the kernel density function for the I-94 corridor presents clear and interpretable patterns. Comparable to I-75, the Metro Detroit region is characterized by the concentration of the highest AADT volumes, and relatively lower average annual snowfall amounts and winter midblock crash rates. Whereas the western section of the corridor in proximity of the coastline (i.e. Van Buren and Berrien County) displays relatively lower AADT volumes, and the highest average annual snowfall amounts and winter midblock crash rate concentration for the corridor. Akin to the northern parts of I-75, this freeway section can benefit from winter weather related countermeasures such as winter weather maintenance sensors and/or ITS signs to alert drivers of adverse winter weather conditions.

CHAPTER 6: CONCLUSIONS

This study investigated the effects of annual snowfall on freeway crashes during winter periods in the State of Michigan. Two principal Negative Binomial regression models are established to assess these effects. Explanatory variables for Model 1 include AADT or commercial AADT, segment length, horizontal curvature, and snowfall. Explanatory variables for Model 2 include all four initial variables from Model 1 and three categorical snowfall intervals based on its quartile distribution. Crash categories considered in the analysis include total winter, truck/bus, non-truck/bus, fatal and injury, and PDO crashes. Separate analyses are additionally performed for each model for interchange versus non-interchange segment crashes to account for their unique physical, operational and behavioral characteristics. This inclusion of the listed crash categories as well as their differentiation between interchange and non-interchange crashes provides an additional perspective not previously covered in the existing literature with regards to the impacts of snowfall on crashes.

The Negative Binomial regression results indicate that annual snowfall has a statistically significant positive correlation with winter crashes for all of the crash categories analyzed. The snowfall effects are stronger for non-interchange segment crashes (i.e. midblock) as opposed to interchange segment crashes. Among crash categories, crashes involving a truck or bus experience the most elastic relationship with snowfall for midblock scenarios. Among crash outcomes, PDO crashes are shown to be more strongly affected by snow conditions as opposed to injury and fatal crashes. The effects of snowfall on crashes are further exacerbated along those segments experiencing the largest amount of annual snowfall (i.e. top 25^{th} percentile of annual snowfall totals). The models further indicate that the risk of crash occurrence increases with increasing AADT or commercial AADT values and along segments characterized by the presence of horizontal curvature.

Overall these findings suggest that drivers are at elevated risks of crash occurrence on freeways experiencing greater annual snowfall totals. The risk is dependent on vehicle type, and is highest for PDO crashes as opposed to injury or fatal crashes. These outcomes can be attributed to differing trip and mechanistic characteristics between commercial and non-commercial vehicles, and heightened driver alertness and lower speeds exhibited during severe snow events (Eisenberg, 2004; Pisano et al., 2008; Bilionis, 2013). Although the risk of crash occurrence is exacerbated along non-interchange segment areas, interchange crashes continue to occur at a higher rate thus indicating that there are other factors at play in such settings not captured by the models. Similarly, while crash risks are highest for the segments experiencing the greatest amounts of snowfall, the findings are inconsistent with prior studies (Khattak and Knapp, 2001; Eisenberg, 2004; Seeherman and Liu, 2015) which have suggested that the effects of snowfall on crashes peak at mid ranges and decline or have a lower marginal effect at the higher snowfall levels, thus likely reflecting underlying events such as higher frequencies of snowstorms and/or storms of greater intensity.

Nonetheless, the areas which experience the highest midblock winter crash rates correspond to those segments experiencing the highest amount of snowfall totals. For both case studies investigated (i. e. I-75 and I-94), the implemented kernel density function displays robust patterns in its identification of the most susceptible freeway segments. These patterns, which can be replicate on other freeways with similar geographic and geometric characteristics, provide practical insights which can assist agencies in countermeasure implementation. Examples of potential countermeasures include environmental sensor stations installed near the most susceptible segments to improve winter maintenance, and linking such sensors to ITS devices to alert drivers of adverse weather conditions when passing particular locations along a freeway corridor.

In conclusion, while these findings are applicable to the freeway network in the State of Michigan, the methodology can be replicated and applied on other regions experiencing significant snowfall. These methods are particularly applicable for annual, monthly, and weekly weather data, as long as such data are available from weather stations located in proximity to the highway in question. Caution should be used when applying these methods to daily, and/or hourly weather as the number of weather stations reporting information at this level of detail is generally low, thus leading to inaccurate results. Likewise, while the Ordinary Kriging method performs satisfactory on regions with a relatively flat terrain (i.e. Michigan), elevation data should be incorporated into the spatial interpolation procedures when predicting weather data on regions characterized by a relatively rugged and in particular mountainous terrain. The inclusion of additional explanatory variables such as vertical curvature and other freeway geometric and operational characteristics could further strengthen the regression models.

Lastly, analysis on a micro-scale (i. e. daily snowfall) could help provide additional detail regarding the winter weather crash causal factors. To minimize data bias due to a limited weather station sample, only corridors surrounded by a sufficient number of weather stations should be considered. Potential variables for such microscopic forms of analysis can include an examination of daily snowfall totals in combination with the number of days with snowfall occurring along a segment. These two variables when combined together reflect more closely the frequency and intensity of snowstorms occurring on a particular roadway section. The additional inclusion of weather related factors such as average temperature and wind speeds on those days experiencing snowfall could help further explain some of the conditions that drivers may be experiencing on the road. Additional non-weather related variables that can strengthen these microscopic models can include applicable geometric and operational roadway characteristics, as well roadside terrain characteristics which represent the natural and man-mad barriers located along the subject segments. The latter may be pertinent in explaining scenarios where snowfall supplemented with high speed winds affects the driver's visibility distance.

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