INVESTIGATING IMPACT OF WORK ZONES ON CRASH FREQUENCY, SEVERITY AND TRAFFIC

by

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A Dissertation submitted to the

Graduate School-New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

Graduate Program in Civil and Environmental Engineering

written under the direction of

Kaan Ozbay

and approved by

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New Brunswick, New Jersey

May, 2014

ABSTRACT OF THE DISSERTATION

Investigating Impact of Work Zones on Crash Frequency, Severity and Traffic

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Work zone presence is an important concern for drivers in terms of safety and congestion. In recent years, work zone safety has received much attention due to numerous highway renovation projects that have resulted in many work zone crashes. To minimize the effect of work zones on roadway safety risks and traffic conditions, potential factors need to be addressed and countermeasures need to be implemented to ensure that the motorist can drive in a safe manner.

The impact of the work zones can be estimated by using descriptive analysis and different statistical modeling methods. To this end, this study focused on three major areas: the crash frequency at work zones, the crash severity at work zones and the change in traffic conditions at work zones. Statistically robust models were developed by incorporating integrated datasets that could identify significant factors affecting each of these study areas. To better understand this, different from the previous studies, model

results were compared against reference conditions, such as work zone crash frequency and modeling parameters were compared with non-work zone parameters. In addition, different statistical modeling techniques were applied to examine the best model or set of variables to connect crash severity and possible causative factors for binary level and multiple level outcomes. Two crash severity indexes were proposed and used to estimate multilevel crash severity by using both maximum severity and the monetary cost weighted severity. Besides safety issues, different types of lane closures and crashes observed within lane closures were studied to examine if there would be a change in traffic conditions compared with normal time traffic.

Comparisons of each concept provides an idea for agencies about the differences of work zone and non-work zone conditions which is important if indeed there is a specific impact for the work zone cases. Work zone presence was found to have an increasing effect on crash occurrence. Nighttime shifts were found to be safer when compared to daytime work zone periods. Injury crashes for two-lane closure cases were found to have a more marked impact on traffic volume compared with other cases studied in this dissertation. In the conclusions chapter, all of these findings are summarized along with specific recommendations.

Dedication

To dear my parents Fatma-Halil Ozturk,

my dearest wife Ayse Ozturk,

and my lovely sons…

Acknowledgements

I would like to express my deepest appreciation to my advisor Dr. Kaan Ozbay for his guidance, encouragement and support during my Ph.D. studies. I have learned a lot from him about how to think about the relationship between real life and statistical models after long discussions. I would also like to thank my committee members, Dr. Hani Nassif, Dr. Eric Gonzales and Dr. Dilruba Ozmen-Ertekin for their insightful comments which improved the quality of my dissertation. In addition to my committee members, I would like to specifically thank Dr. Bekir Bartin and Dr. Hong Yang for their significant contributions to shaping my study.

My colleagues deserve sincere thanks as well for their help and support. Ender Faruk Morgul was the closest friend to me from the first day of this study. We overcame our degree challenges together step by step. Thanks to my generous friends Sami Demiroluk, Abdullah Kurkcu and Sandeep Mudigonda for their friendly help and technical support both during my study and when collaborating on other projects.

Special thanks go to my wife, Ayse Ozturk who deserves much appreciation for being patient with my studies and baring up to the problems together especially those that occurred at the beginning of our US life. I can’t ignore my parents’ help and endless support both financially and mentally even though I am over 30 years of age.

Preface

This dissertation is based on the following studies.

Projects

1. Ozbay, K., Yang, H., Ozturk , O., Yildirimoglu , M., Demiroluk, S., and Bartin, B. "*Work Zone Safety Analysis*", New Jersey Department of Transportation, New Jersey, 2013.
2. Ozbay, K., Bartin, B., Kurkcu, A., Ozturk, O. "*Highway Repair Consolidation Feasibility*" New Jersey Department of Transportation, New Jersey, (Ongoing)

Papers

1. Ozturk, O., Ozbay, K., Yang, H., and Bartin, B., (2013) "Crash frequency modeling for highway construction zones", *Transportation Research Board 92nd Annual Meeting*, Transportation Research Board of the National Academies, Washington, D.C.
2. Yang, H., Ozbay, K., Ozturk, O., and Yildirimoglu, M., (2013) "Modeling work zone crash frequency by quantifying measurement errors in work zone length", *Accident; Analysis and Prevention*, vol.55 (6), 2013, pp. 192–201.
3. Ozturk, O., Ozbay K., and Yang, H., (2014) "Estimating the impact of work zones on highway safety", *Transportation Research Board 93rd Annual Meeting*, Transportation Research Board of the National Academies, Washington, D.C.
4. Yang, H., Ozturk, O., Ozbay, K., and Xie K., (2014) "Work zone safety analysis and modeling: state-of-the-art review", *Transportation Research Board 93rd Annual Meeting*, Transportation Research Board of the National Academies, Washington, D.C.

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CHAPTER 1. INTRODUCTION

1.1 Background

Numerous renovation and reconstruction projects are funded by the Federal Highway Administration (FHWA) and State Departments of Transportation (DOT) to keep the road network in a good state. Reconstruction, maintenance and utility types of work zones are important concerns for drivers in terms of safety and congestion. Thus, the FHWA and State DOT's are continuously investigating design procedures to improve safety and minimize the traffic impact of work zones.

Safety improvement strategies are also introduced by various forms of legislation. Several operational guidelines are developed by safety organizations for specific cases such as "nighttime lighting guidelines for work zones" which is published by the American Traffic Safety Services Association. Similarly, most State DOTs have their own policy or procedures concerning work zone safety. For example, the Departments of Transportation highlighted a week within April as "National Work Zone Awareness Week" at the beginning of the construction season by reminding road users of the importance of work zone safety via variable message signs. The main objective here is that motorists would become more aware of the potential risks at work zones.

In spite of the above legislative and operational efforts, statistics show that there are still a large number of injury and non-injury work zone crashes (FHWA, 2012). To minimize the effect of work zones on roadway safety risks, potential factors that influence these risks need to be addressed. This can be done by identifying the possible risk factors and implementing countermeasures to ensure that the motorist can drive in a safe manner.

1.2 Motivation

Work zone safety has received much attention in recent years due to numerous highway renovation projects that have resulted in many work zone crashes. On average, road users are likely to encounter an active work zone for every 100 miles of national highway system (Ullman et al., 2004). There were 87,606 nationwide work zone crashes in 2010 and 37,476 injury crashes, resulting in approximately one injury work zone crash every 14 minutes (FHWA, 2012).

Similar statistics are observed at the state level as well. New Jersey is called the corridor state, an apparent consequence of its perceived role and proximity to the strong markets in New York City, Philadelphia and the Boston-Washington Northeast Corridor. NJ experiences the second highest travel delays and total congestion costs in the nation (Schrank et al., 2011). Moreover, its aging infrastructure requires regular maintenance and replacement. According to a recent report, about half of the state-maintained roads in NJ are in a deficient condition (NJDOT, 2012). Furthermore, NJ is the state with the highest capital and bridge disbursement and the maintenance disbursement per mile (Hartgen et al., 2010). Accordingly, a major increase in number of work zone projects and work zone crashes in NJ is expected as well. NJ crash statistics show this increase distinctly for work zone labeled crashes in 2010. The yearly average number of work zone crashes between 2004 and 2009 in NJ was 5,395; however this number increased in

2010 by 26.7 percent to 6,837 crashes equal to 7.8 percent of the nationwide total number of work zone crashes. Figure 1-1 shown below details the increase in work zone crashes by year, in New Jersey.

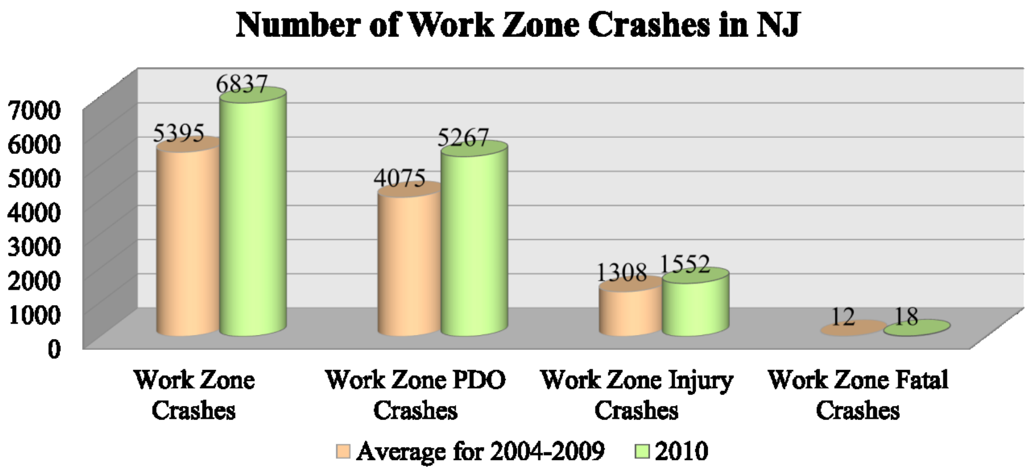


Figure 1-1 Work Zone Crashes in NJ

Temporary traffic control measures have been developed and used in work zones. However, the effectiveness of traffic control methods in work zones has not been clearly identified. To further improve the safety and to identify effective control measures, there is a need to determine the factors that lead to crashes in work zone. Using real crash data and some regression techniques, work zone crash factors and their corresponding countermeasures can be identified. Many possible factors may cause this increase in work zone crashes. Factors that can play a role in the increase in crash frequency and severity can best be identified by using historical crash data. Additionally, these factors need to be compared with non-work zone conditions to assess their difference from regular traffic conditions.

1.3 Research Objectives

The main objective of this dissertation was to estimate the impact of work zone presence on traffic conditions in terms of crash frequency, severity, and road capacity. Statistically accurate models were developed by incorporating enhanced datasets that could identify significant factors effecting crash frequency, severity and resulting road capacity. In the literature, specific variables related to work zones such as speed reduction or lane closure were not widely used in the models. By combining different data sources, such as crash records, project layouts, and traffic data from sensors enhanced models were developed for work zones.

To identify reasons for crash occurrences under work zone conditions, frequency models were developed. Work zone specific parameters such as lane closures and speed reduction were included in the model to examine the interaction between these parameters and crash occurrences in the presence of work zones. Directional annual average daily traffic (AADT) data was adjusted by seasonally and hourly factors to examine the precise effect of traffic exposure to work zone crashes. Overall crash counts and periodic crash counts were used as dependent variables. Crash frequency was investigated for injury and property damage only (PDO) crashes and for day and night time conditions separately to examine the effect of night shift working on safety. Moreover, a temporal analysis of work zone crashes was conducted to test the hypothesis that there would be a change in the frequency of work zone crashes as drivers became more familiar with a specific mid or long-term work zone. This analysis was specifically conducted for nighttime work zone crashes.

Identifying factors affecting work zone crash occurrences is important, however, factors affecting crash severity also need to be studied by considering individual work zone crashes. In the literature, there are several studies on work zone crash severity where a large number of factors are investigated to determine appropriate models for estimating work zone crash severity. In this dissertation, work zone crash severity was modeled by including a combination of most of the previous parameters used for modeling as well by adopting a novel approach for defining a combined severity index as the dependent variable. The severity index was defined by using different definitions including those representing overall severity in a crash or in a vehicle. The most significant factors in terms of crash severity from a very large amount of data were extracted from DOT's crash records. Moreover, several other related datasets were combined to support this effort. Crash severity was modeled based on this severity index by using a logistic regression technique for binary level analysis and an ordered probit technique for examining multilevel crash severity.

The impact of a work zone on roadway traffic has been investigated in previous studies. However, the impact of work zone crashes on roadway traffic conditions has not been investigated in a detailed manner. By merging different data sources such as event data, sensor data and crash data, work zone crash impact on roadway traffic and travel time, one can analyze several scenarios such as injury or property damage only crashes more ably. In detail, different lane closure types were investigated in terms of the vehicle counts, speed and occupancy information obtained from sensor data for the initial setup of work zone and crash occurred within lane closure cases. This relation was modeled in terms of vehicle counts to see the difference between normal time traffic condition and these specific cases.

The main objective of this dissertation was to define the characteristics of work zone crashes in terms of crash frequency and severity as well as capacity reduction. These factors were compared with those from non-work zone conditions to better understand the specific impact of work zones.

The following questions were answered by this dissertation;

1) Does work zone presence increase occurrence of the crashes at a location? Which factors are most correlated with crash frequency? Are night time work zones safer than day time work zones? What is the difference between work zone crashes and non-work zone crashes in terms of factors affecting crash frequency? What is effect of time (driver's familiarity with work zones) on work zone on crash occurrences? In other words, are numbers of work zone crashes reduced in time as a result of increasing driver familiarity?
2) Which factors have the most significant effect on the severity of work zone crashes? Which severity index has better explanatory power? What is the difference between work zone crashes and non-work zone crashes in terms of factors affecting crash severity?
3) How does work zone presence affect traffic conditions? What is the difference between non-work zone and work zone crashes in terms of travel time, volume, speed and occupancy? What are the significant factors for work zones that are different from the factors for the non-work zone conditions?

1.4 Thesis Outline

In this dissertation, work zone safety issues are studied through the modeling of crash frequency, severity and roadway capacity by using the aforementioned data and statistical methods.

Chapter 2 includes a comprehensive review of previous research about work zone safety. The literature review provides the background for understanding safety issues and potential contributing factors. Previous studies describing descriptive analysis and models of work zone crash frequency, severity and roadway capacity are reviewed.

Chapter 3 presents a descriptive analysis of a large sample of work zone crashes in New Jersey and three different models in terms of work zone crash frequency. The negative binomial regression technique was used to model the entire duration and periodical crash counts within the pre-defined work zone sites by fusing the crash database and project files. Potential factors affecting work zone crash occurrence were identified using the modeled results. The difference between the work zone crash occurrence model and the non-work zone crash occurrence model was investigated by using control sites with similar characteristics. Moreover, the initial impact of the work zone set up on crash occurrence was investigated by using a special time indicator.

Chapter 4 provides a detailed descriptive analysis of the crash severity data in New Jersey. This large dataset was created for purposes of modeling crash severity at work zones. The binary logistic regression was used to model crash severity. Results for the binary level severity modeling were provided in terms of different categories. A multilevel crash severity index was proposed for modeling crash severity. This new severity index was defined by using two different weighting strategies which were based on monetary values of severity levels and the maximum severity level of occupants. Crash severity for non-work zone crashes was also modeled using the same approaches. Differences and similarities were investigated between work zone and non-work zone conditions to define potential risk factors.

Chapter 5 examines the relationship between work zone conditions and roadway traffic. To do so, the effects of different lane closure strategies on roadway traffic parameters were investigated. Different sources of datasets were used, such as sensor data and toll count data. The reduction effect of work zone crashes on traffic flow was compared to non-work zone crashes. Various parameters were investigated in terms of their effect on flow reduction at work zone conditions.

Chapter 6 concludes the dissertation and provides the major findings from each section. Future work is discussed in this chapter as well.

CHAPTER 2. LITERATURE REVIEW

2.1 General Overview of Work Zone Studies

Numerous studies on work zones from different points of view have been reviewed. Work zone crash analysis studies can be arranged in several categories. In this chapter, a review of these studies dealing with the descriptive analysis, frequency analysis, and severity analysis of the work zone crashes is presented. Additionally, work zone capacity modeling studies are reviewed to assess the state-of-the art in road capacity estimation in the presence of work zones.

2.2 Descriptive Analysis for Work Zone Crashes

Most previous work zone studies focused on descriptive statistics to examine the relationship between work zone and crash characteristics, such as crash rates, location, severity etc. The descriptive analysis of work zone related studies are summarized below. Table 2-1 provides explanatory information about previous studies.

Descriptive studies are categorized into several topics in order to provide a short discussion about each of these factors based on the review of the literature. Some of these factors are crash rate, crash severity, location of the occurrence, time of occurrence, environmental conditions, crash types, speed limits and traffic control devices were reviewed within the following section.

Table 2-1 The List of Reviewed Work Zone Studies Utilizing Descriptive Statistics

Authors	Study Area	Topic
Nemeth and Migletz (1978)	OH	Work zone crash characteristics
Hargroves and Martin (1980)	VA	Work zone crash characteristics
Rouphail et al. (1988)	IL	Short-term work zones
Hall and Lorenz (1989)	NM	Accident rates
Pigman and Agent (1990)	KY	Work zone crash rates
Ha and Nemeth (1995)	OH	Work zone crash characteristics
Wang et al. (1996)	--	Work zone data issues
Bryden et al (1998)	NY	Traffic control device involved crashes
Daniel et al. (2000)	GA	Work zone fatal crash characteristics
Zhao and Garber (2001)	VA	Work zone crash characteristic
Garber and Zhao (2002)	VA	Work zone crash location
Chambless et al. (2002)	AL, MI, TN	Work zone crash characteristics
Shrock et al. (2004)	TX	Work zone fatal crash characteristics
Arditi et al. (2007)	IL	Crash time
Ullman et al. (2008)	NY, CA, NC, OH, WA	Crash time
Jin et al. (2008)	UT	Work zone crashes by highway type
Dissanayake and Akepati (2009)	IA, KS, MO, NE, WI	Work zone crash Location

2.2.1 Crash Rate

The crash rate analysis within the work zones was tested by analyzing crash rate differences before-during or before-after work zone activities at a specific site. Crash rates are generally estimated based on a normalized formulation (Equation 2-1) that yields a crash rate for millions of vehicle entrances (Khattak et al., 2002).

$$R = \frac{A \times 10^6}{V \times T \times L} \tag{2-1}$$

Where,

A = Average number of crashes at study location,

V = Volume in the study location, ADT or AADT,

T = Time, number of days in the study period,

L= Length of work zone (mile).

Common results for crash rate comparisons within the literature suggest that work zones have an incremental effect on increasing crash rates over a given period. Juergens (1972) reported an increase of 7.0-21.4 percent for 10 work zone sites and Graham et al. (1977) reported an average increase of 7.5 percent for 79 work zone sites (Graham et al., 1977; Paulsen et al., 1978). Rouphail et al. (1988) described an increase for crash rates of an average of 88 percent during the work zone period, and a decrease of an average of 34 percent in the period after their removal based on the before period crash rates. Hall and Lorenz (1989) found that crash rates increased by 26 percent during the construction period. Garber and Woo (1990) reported that the crash rates at work zones on multilane highways in Virginia increased on average by 57 percent and the crashes at work zones on two-lane urban highways in Virginia increased about 168 percent on the average. The research by Pigman and Agent (1990) also showed increasing crash rates on work zones in that 14 out of 19 work zone sites experienced increasing crash rates compared to the before period. Rouphail et al. (1988) and Ha and Nemeth (1995) found out that work zone crashes were less severe than pre-construction term crashes. Rouphail et al. (1988) and Wang et al. (1996) found that rear-end crashes increased significantly during work zone periods. Khattak et al. (2002) found that crash rates were higher in work zones with rates of 23.5 percent for non-injury crashes and 17.5 percent for injury crashes. Interestingly, Jin et al. (2008) observed lower rates especially for severe crashes during construction periods at two case sites. Except for a few studies, crash rates increase during work zone conditions for most work zone crash rate studies.

2.2.2 Crash Severity

The severity index for crashes is mainly categorized in crash records for three levels; property damage only crashes (PDO), injury crashes, and fatal crashes. Injury is separated into five levels for some DOT's crash records as follows; non-injury, complaint of pain, moderate injury, incapacitated, and fatality. Crash severity change belonging to work zones is investigated by many studies. The relationships between severity and work zone crashes have resulted in different findings in previous studies. Schrock et al. (2004) analyzed fatal crashes at Texas, and found that 8 percent of the 77 fatal crashes were directly influenced, and 39 percent were indirectly influenced by work zones. Pigman and Agent (1990) and Garber and Zhao (2002) stated that work zone crashes were more severe than non-work zone accidents. On the other hand, Rouphail et al. (1988) found that work zone crashes were less severe than non-work zone crashes. There were also some other studies those could not establish any relationship between severity and work zone crashes at a significant level (Hall and Lorenz, 1989; Chambless et al., 2002). Because of this unclear connection, this relationship needs to be investigated.

2.2.3 Location of Occurrence

Work zones are generally separated into five different components according to location; (i) Advance Warning Area, (ii) Transition Area, (iii) Buffer Area, (iv) Work Area, and (v) Termination Area (Figure 2-1) Garber and Zhao (2002) analyzed the descriptive characteristics for these different locations. The activity area was found to be most risky and the termination area was the safest area for drivers compared to other components. Nemeth and Migletz (1978) concluded that construction areas are more risky than other areas in terms of crash or injury severity. Pigman and Agent (1990) stated that advanced warning areas are the densest areas in cases of crash occurrences. Location based studies show that analyzing work zone crashes by location provides for more detailed correlations between crashes and work zone characteristics. Jin et al. (2008) stated that upstream activity areas were more prone to have a work zone crash when they compared two work zones in their study.

Pigman and Agent (1990) and Chambless et al. (2002) stated in their studies that Interstate and state highways are more likely to have work zone crashes compared to other types of road systems. However Chambless et al. (2002) claimed that work zone crashes were observed mainly in rural areas, and urban highways were found predominant when compared to rural highways according to Garber and Zhao's study (2002). This is another study that could not find any relationship between highway class and work zone crashes (Jin et al., 2008).

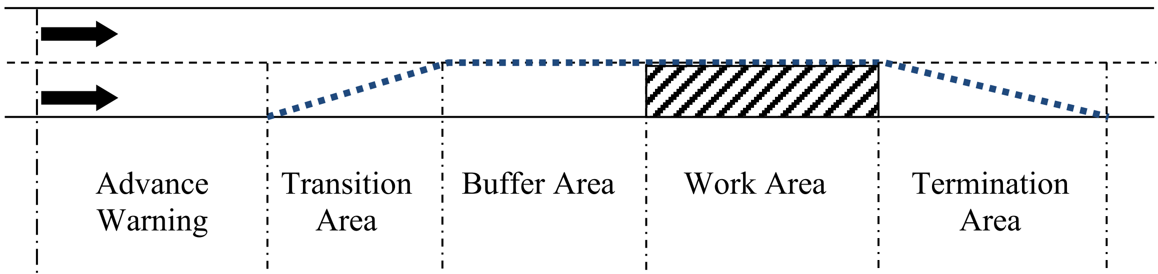


Figure 2-1 Component Segments of the Work Zone

2.2.4 Time of Occurrence

The time distribution of crash occurrences has been investigated by many researchers. This descriptive information is essential for clarifying whether night time or day time is safer for motorists. Arditi et al. (2007) investigated crashes in terms of two groups, "Day" work zone accidents and "Not-Day" work zone accidents. They found that nighttime work zone crashes were five times more dangerous than day time work zone crashes. Bai and Li (2006) found that the daytime off-peak period (10:00 a.m.–4:00 p.m.) is the most dangerous time interval for work zone crashes in terms of fatalities and injuries. Ullman et al. (2008) investigated crash risk changes between nighttime and daytime work zone crashes. They stated in their report's finding that there was no significant difference in terms of crash risk for night time and day time construction. During temporal lane closure conditions the total number of crashes increased for day time observations by 66% and by 61% for the nighttime period.

2.2.5 Environmental Conditions

Light, weather and nature of the road surface can be categorized as environmental conditions. According to the Garber and Zhao (1990) work zone crash characteristics analysis, 65% of the crashes occurred on dry pavements, 55% of them during daylight, and 50% of them during clear weather conditions. Adverse weather condition slightly affected the crash occurrences at work zones. Daniel et al. (2000) stated in their study about Georgia work zones that the fatal crashes percentage (42%) during dark conditions was higher than the non-work zone fatal crashes percentage (32%) during dark conditions. Qi et al. (2005) found that there was a correlation between weather conditions and rear-end work zone crashes occurrences. Dissanayake and Akepati (2009) too found that most of the work zone crashes at five states (Iowa, Kansas, Missouri, Nebraska, Wisconsin) occurred during daylight and under clear weather conditions.

2.2.6 Crash Types

Crash types are identified in most of the state crash reports (i.e. rear-end, side swipe) (NJDOT, 2011). The rear-end crash type is found as the most predominant work zone crash type by many researchers. Hall and Lorenz (1989) concluded that rear-end crashes proportions increased from 9% to 14% during construction. Rouphail et al. (1988) stated that there was a 50 percent increase in rear-end crashes during work zone periods.

Pigman and Agent (1990) found that most the frequent work zone crash types were side-swipes and rear-end. Garber and Zhao (2002) investigated crash types by work zone locations. They concluded that the most frequent crash types for advanced warning and transition area were rear-end and side swipe crashes. However the proportion of these crashes decreased when going through activity and termination areas. Angular and fixed object crash proportion increased at activity and termination areas. Wang et al. (1996) found that the percentage of rear-end crashes within the work zone was significantly higher than the rear-end percentage in non-work zone crashes. There is agreement that the majority of the work zone crash types are rear-end crashes as described by previous researchers. For further investigation, Qi et al. (2005) focused on rear-end crashes at work zones determine the related contributing factors. Meng et al. (2011) found in their studies that the lane closer to work zone is associated with higher rear-end crash risk at work zones.

2.2.7 Speed Limit and Traffic Control Devices

Speed limit is another focal point for researchers who have focused on work zone crashes, since there is an expectation the speed limit is a primary cause of crashes. Chambless et al. (2002) concluded in their study that 48% of work zone crashes occurred at a 45-55 mph speed interval. However, this number was 37% for non-work zone crashes at the same 45-55 mph speed interval. Daniel et al. (2000) found that the majority of fatal work zone crashes occurred on roadways with a speed limit of 55 mph. Dissanayake and Akepati (2009) found similar results in previous studies. They compared five states and most work zone crashes occurred at 51-60 mph posted speed intervals.

Traffic control devices are also another important element of work zone sites. The correlation of these devices was investigated by a number of researchers. Bryden et al. (1998) found that one-third of all work zone accidents involved impacts with work zone traffic control devices and safety features introduced into the roadway environment by construction activity and 37 % of those caused serious injury. On the other hand, Dissanayake and Akepati (2009) stated that most work zone crashes occurred in the absence of any traffic control devices.

2.3 Frequency Modeling of Work Zone Crashes

Crash frequency models have been used for purposes of road safety analysis by many researchers. However, in the literature, there are a few studies directly related to the work zone crash frequency modeling. Crash counts are non-negative integers that are influenced by several factors. To model such crash count data, negative binomial modeling (Poisson-Gamma) is the one of the best alternatives within available statistical methods. Besides this, there are several methods for modeling crash frequencies such as the Poisson model, zero inflated negative binomial and Poisson, truncated regression, generalized additive model, Conway Maxwell Poisson model, and negative multinomial model etc. (Lord and Mannering, 2010). The following studies are focused on modeling work zone crash occurrences by using different factors as model components. Table 2-2 shows a summary of the studies about work zone crash frequency.

Table 2-2 Work zone crash frequency modeling literature summary

Work Zone Crash Frequency Models	Pal & Sinha (1996)	Venugupal & Tarko (2000)	Elias & Herbsman (2000)	Khattak et al. (2002)	Qi et al. (2005)	Srinivasan et al. (2008)
Duration	*	*	*	*	*	
AADT	*	*	*	*	*	*
Length	*	*	*	*		*
No. of Operating Lanes						
Work Zone Speed Limit						
Cost of Project		*				
Lane Closure					*	
Speed Reduction						
Urban Indicator				*	*	
Road System						
Weather	*					*
Crash Rate			*			
Intersection					*	
Ramp		*				
Daytime-Nighttime						
PDO-Injury				*		
Control Device					*	
Type of Work		*			*	
Sample Size (Site)	34	116	-	36	-	1
Model	NB, NLR,P	NB	Monte Carlo	NB	TNB	MNL

NB:Negative Binomial Regression, P:Poisson, NLR:Normal Linear Regression, TNB:Truncated NB, MNL:Multinomial Logit Regression

Pal and Sinha (1996) investigated lane closure strategies safety effects at interstate work zones in Indiana. Normal regression, negative binomial and Poisson regression models were developed by using the following parameters; duration, traffic interactions and crash rates under normal conditions. Normal regression modeling predicted crash counts better than the other two regression models, since the data set was smaller and improved the predictive power of these exponential models.

Khattak et al. (2002) developed a negative binomial model for crash modeling by using the following parameters; daily traffic volume (ADT), length, duration, an urban indicator, an injury indicator, and a work zone indicator. A negative binomial model is considered superior to the Poisson and other statistical models, because it allows for over-dispersion caused by other variables not included in the model. The following formulation used to modeling crash frequency.

$$Y = x_1^{\beta_1} x_2^{\beta_2} x_3^{\beta_3} \exp(\beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6) \tag{2-2}$$

Where,

Y = expected number of crashes in a given duration,

x_1 = average ADT on the work zone segment,

x_2 = the duration of observation (day),

x_3 = the length of the work zone (mile),

x_4 = the dummy variable indicating urban / rural area,

x_5 = the dummy variable indicating injury / non-injury crashes,

x_6 = the dummy variable indicating pre or during work zone period, and

$\beta_{1\text{ to }6}$=coefficients for the parameters.

The natural logarithmic values of AADT, length and duration were used for modeling. These parameters were directly related to crash occurrences. A 1% increase in AADT, caused a 1% increase in expected crash counts. Separate models were constructed for both injury and non-injury outcomes in the pre-work zone and during work zone periods. According to the negative binomial regression results, duration had significant effect on both injury and non-injury work zone crash frequencies.

Venugopal and Tarko (2000) proposed two models for crashes as approaches to examining work zones and factors inside the work zones. They used the cost of the project and work zone type as parameters that were not employed in previous studies. Since the cost of the project correlated with other parameters, it was normalized by dividing the production length and duration, therefore this parameter served as an intensity of work activity variable in the model. Traffic volume and length variables turned out to be statistically significant and their parameters were close to 1, indicating the dependence was almost linear. However, the duration parameter took values around 0.6, showing that the number of crashes did not increase linearly with the duration factor, but tended to taper off after some time. Other factors, such as the number of ramps, type of the work and the costs of the project had less marked effects on work zone crashes compared to the other variables.

Elias and Herbsman (2000) developed a crash frequency probability function by using a Monte Carlo simulation. They used a different approach of risk evaluation that was generated from cumulative probability distributions of the study parameters. Engineers can decide upon which are the most some essential parameters for reducing the numbers of work zone crashes. For example, if the risk is too high for the length or duration of the work zone, then they could simulate the model by shortening the duration and length or both until they reach a low level of risk for crash rates. Generally, the modeling results showed that work zone crash frequency rates increase according to ADT, duration, and work zone length.

Qi et al. (2005) analyzed the rear-end accidents in New York State work zones between 1994 and 2001. As the data consisted solely of accidents (information on work zones without accidents is not available), they developed two truncated regression models to identify the relationship between crash frequency and work zone characteristics. They compared two modes for estimating work zone rear-end crash frequency; a truncated regression and a zero inflated truncated regression model. The zero inflated truncated regression method was used to model crash frequency by considering only counts greater than zero. By using three different statistical tests (t-test, Likelihood ratio test and LM test); they selected the zero inflated truncated regression model for their study. They found that the occurrence of rear-end accidents was more likely in work zones with flaggers, alternating one way traffic, and higher AADT.

Srinivasan et al. (2008) attempted to model the location of crashes within work zones as a function of length of work zone segments, traffic volume, and weather. The model was based on the data that was generated from a single work zone in Florida, therefore, the results may vary by work zone. A multinomial logit model was used to construct crash probabilities per lane-mile for different segments. The work zone was divided into five segments; before the advance-warning sign, the advance-warning area, the transition or taper area, the work area and the exit area. Once the model parameters were calculated, crash probabilities for different segments were identified. Among the various weather and traffic volume scenarios, bad weather and high traffic volumes made the advance warning area relatively unsafe, while the exit area was found to be the most unsafe segment during off-peak hours.

Considering potential data deficiency, Yang et al. (2013) developed measurement error models to improve the modeling results. They found that the model performance was greatly improved by addressing the measurement errors for work zone crash frequency.

2.4 Severity Modeling of Work Zone Crashes

Savolainen et al. (2011) revised and analyzed the evolution of crash severity related statistically modeling in their study. They reviewed over 100 studies with models related to crash severity. More than 20 statistical models were included in their study. Several studies focused on modeling connections between work zone crash characteristics and the level of crash severity. The severity of the crashes was investigated in terms of crash level of severity, driver level of severity, occupant level of severity and vehicle level of severity. Generally, crash severity data is used to provide a discrete explanation such as, information on fatalities, injuries and non-injuries. Crash records include many pieces of characteristic information occurring at the different levels mentioned above. Statistical modeling techniques, especially regression techniques applied to model such a relationship are used to examine possible severity contributors for work zone crashes. Fatality, injury or PDO data are used as binary outcomes for the severity model.

Driver effects, vehicle characteristics, crash characteristic, work zone characteristics, environmental and road conditions are the main categories investigated partially by previous studies (Khattak et al., 2003; Khattak and Targa, 2004; Qi et al., 2005; Li and Bai, 2007, 2008, 2009; See et al., 2009; Meng et al., 2010; Akepati and Dissanayake, 2011; Elghamrawy, 2011; Meng and Weng, 2011; Weng and Meng, 2011). Table 2-3 provides a summary of these studies, their methodologies and related parameters. Parameters used in the models depend on objective of the study. For example Khattak and Targa (2004) investigated crash severity data to model truck involved crashes within work zones by using ordered probit techniques. They concluded that multivehicle truck involved crashes within work zone were "*the most injurious and harmful*" when compared to other types of crashes. Advanced regression techniques were applied by the researchers to model crash severity for different analysis levels. As is seen from the table, frequently used methods to model crash severity are logistic regression for fatalities and ordered probit for multilevel injury crashes at work zones.

Tens of factors were investigated in previous studies shown at Table 2-3. The most effective factors which increased crash severity at work zones were found to be the following severity modeling elements; higher posted speed limit at work zone (Khattak et al., 2003; Khattak and Targa, 2004; Li and Bai, 2008, 2009; Akepati and Dissanayake, 2011; Elghamrawy, 2011; Meng and Weng, 2011; Weng and Meng, 2011), driving at nighttime (Khattak and Targa, 2004; Qi et al., 2005; Li and Bai, 2008, 2009; Weng and Meng, 2011), driving under the influence (i.e., alcohol/drug) (Qi et al., 2005), vehicle age (Meng and Weng, 2011; Weng and Meng, 2011), numbers of vehicles and persons involved in crashes (Khattak et al., 2003; Khattak and Targa, 2004; Qi et al., 2005), and truck-involved crashes (Qi et al., 2005; Li and Bai, 2008, 2009; Weng and Meng, 2011).

Besides this, factors found to have a significant effect on decreasing crash severity were using safety equipment (i.e. seat belt, airbag) (Akepati and Dissanayake, 2011; Meng and Weng, 2011; Weng and Meng, 2011), flagger control (Qi et al., 2005; Li and Bai, 2008) and surprisingly, adverse weather (Khattak et al., 2003; Akepati and Dissanayake, 2011; Weng and Meng, 2011).

There is no common thread among previous studies as regards some factors that affect work zone crash severity. While male drivers increase the severity in some studies (Li and Bai, 2008; Li and Bai, 2009), female drivers were found to be the increasing factor for severity in other studies (Weng and Meng, 2011). Another conflictive factor is the light condition; poor light was found to be as incremental factors by Li and Bai (2008,2009), on the other hand, good lighting conditions was found to be a possible causative factor influencing crash severity (Akepati and Dissanayake, 2011; Weng and Meng, 2011). Number of lanes was found to be an augmenting factor for crash severity by Elghamrawy (2011) and Weng and Meng (2011), however, Li and Bai (2008) found an inverse relationship between the number of lanes and crash severity at work zones.

Although there are many studies based on work zone crash severity, the relationship and potential risk factors between work zone crashes and a crash injury index is not clear. Using different approaches to defining severity may help to connect possible risk factors for drivers and occupants.

Table 2-3 Summary of work zone crash injury severity modeling studies

Category	Reference	Khattak & Targa	Qi et al.	Li & Bai	See et al.	Elghamrawy	Khattak et al.	Weng & Meng	Akepati & Dissanayake	Meng et al.	Meng & Weng
	Methodology	OP, OLS	OP	LR	LR	OL	OP, OLS	LR	OP	QRA	LR, GA
	Unit of analysis	Crash Level	Crash Level	Crash Level	Crash Level	Crash Level	Crash/Vehicle Level	Driver Level	Driver Level	Occupant Level	Occupant Level
Timeline	Time of day			X	X	X					
	Day of week			X				X			
Environmental conditions	Light condition	X		X		X	X	X	X	X	X
	Weather condition	X		X	X	X	X	X	X		X
	Road surface condition			X		X		X	X		X
Road conditions	Road class		X	X		X					
	Road alignment			X	X			X			
	Roadway divided by median	X				X	X				
	Median width						X				
	Road surface type			X							
	Number of lanes			X		X		X			X
	Lane width					X					
	Posted speed limit	X		X		X	X	X	X		X
	Area information		X	X	X						
	Road special feature			X		X					
	ADT				X	X					
Road user attributes	Driver age			X			X	X	X		
	Driver gender			X			X	X	X		
	Driver race						X				
	Driver vision obstruction						X				
	Occupant age									X	
	Occupant gender										X
	Driver license state										
	Driving under the influence						X				
	Seat position										X
Vehicle characteristics	Vehicle type						X		X	X	
	Vehicle age							X			X
	Traveling speed						X				X
Work zone information	Type of work zone	X	X			X	X	X			
	Traffic control	X	X	X		X	X	X	X		X
	Workers present								X		
	Work zone activity	X					X				X
	Work zone duration		X								
	Type of work being done	X	X				X		X		
	Work effect on the roadway	X	X		X		X				
Crash Information	Location within work zone	X	X				X		X		
	Number of vehicles involved	X	X	X			X			X	X
	Number of persons involved	X					X				
	Cell phone use										
	Alcohol consumption				X					X	X
	Truck involved in crash		X	X				X			X
	Light vehicle involved in crash										
	Hazardous material involved										
	Crash type	X					X		X	X	
	Contributing circumstances		X	X					X		X
	Vehicle pre-crash actions						X		X		X
	First/most harmful event	X					X	X	X		
	Incident location		X	X	X	X			X		X
	Restraint use							X	X		X
	Airbag deployment							X	X		X

Note: LR = logistic regression; OP = ordered probit model; OL = ordered logit model; OLS = ordinal least squares model; QRA = quantitative risk assessment; GA = genetic algorithm

2.5 Work Zone Capacity Estimation

Capacity is defined in the Highway Capacity Manual (HCM 2000) as

> "*The maximum hourly rate at which persons or vehicles can be reasonably expected to traverse a point or a uniform section of a lane or roadway during a given time period under prevailing roadway, traffic, and control conditions*" (Transportation Research Board, 2000).

There are different approaches in the literature to measure work zone capacity. The majority of these definitions are based on queue discharge and maximum flow rates for congested and uncongested conditions. Bham and Khazraee (2011) classified work zone capacity definition as both conceptual and operational. The conceptual definition of work zone capacity is based on mean queue discharge or breakdown flow rates. For instance, if capacity estimation is used to schedule lane closure, then breakdown flow rates will be the most appropriate definition for avoiding traffic congestion. Mean queue discharge data are mostly used to estimate delays and user costs since they reflect the expected average flow rate once queues form at a given work zone. The operational definition is based on a volume analysis by taking vehicle counts in a given time interval and vehicle counts at selected measurement locations such as at the end of a transition or activity area. Most of the studies covered in this literature review can be categorized as employing a conceptual definition. Dudek and Richard (1982) defined the work zone capacity as the mean queue discharge rate at a freeway bottleneck. Dixon et al. (1996) identified work zone capacity as the 95th percentile value of all 5-minute flow rate observations within queue conditions. According to Jiang (1999), work zone capacity is "*the traffic flow rate just before a sharp speed drop followed by a sustained period of low vehicle speed and fluctuating traffic flow rate*". Al Kaisy et al. (2000) described work zone capacity as a mean queue discharge rate at the end of the work zone transition area. Maze et al. (2000) defined work zone capacity as the average of 10 highest volumes during the before and after queuing conditions. Benekohal et al. (2004) defined work zone capacity as the discharge flow from platooning vehicles within continuous traffic condition.

Several studies were conducted to examine the independent or joint effects of each factor on work zone capacity. According to studies performed by Al-Kaisy and his colleagues, there was a 7 percent reduction in work zone capacity during off-peak versus peak hours and a 16 percent reduction during weekend versus weekdays (Al Kaisy et al., 2000; Al Kaisy and Hall, 2001). Work activity reduced capacity by 6 percent at the work zone sites they studied. Left lane closure caused a 5.7 percent reduction in work zone capacity. Similarly, they found a 5 percent decrease in work zone capacity at darkness versus day time light condition. Regarding the impact of adverse weather conditions, HCM suggested that capacity is reduced during heavy rain by 10-20 percent or higher on freeways. Venugupal and Tarko (2001) found a 10 percent reduction and Al-Kaisy and Hall (2003) found a 4.4-7.8 percent reduction in capacity due to rain conditions at observed work zones. Potentially, adverse weather conditions have a negative effect on work zone capacity. Weng and Meng (2012) expressed work zone capacity as a function of sixteen different factors, which are shown below Figure 2-2.

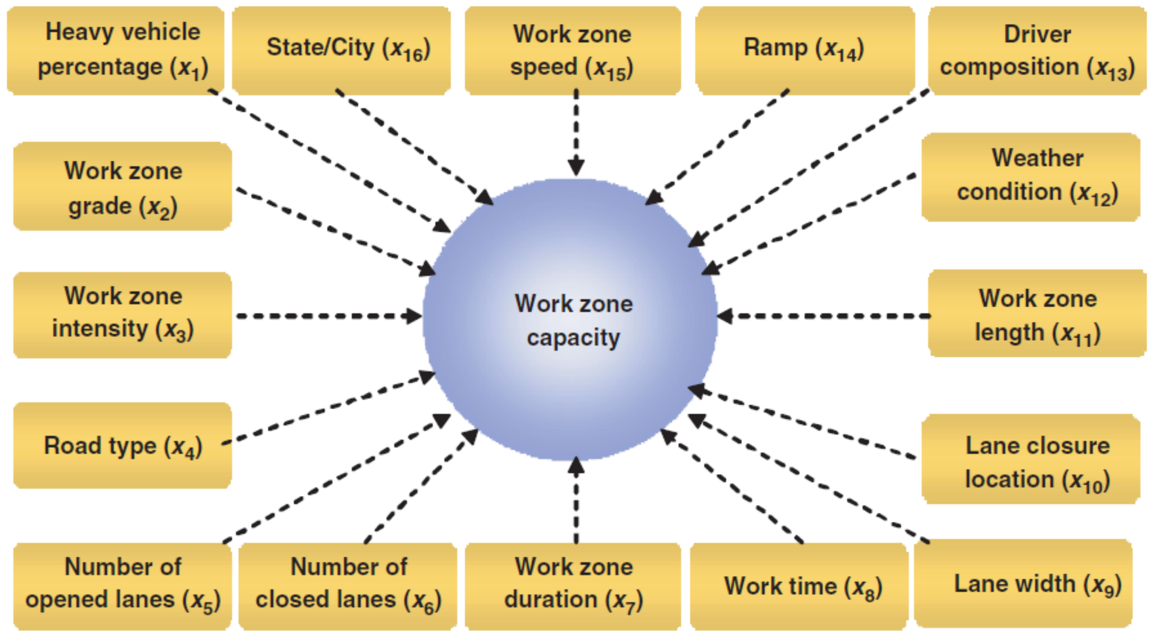


Figure 2-2 Factors Affecting Work Zone Capacity (Weng and Meng, 2012)

2.5.1 Estimation of Work Zone Capacity

The majority of work zone capacity estimation methods is based on modifying the base capacity by several affecting factors mentioned in the previous section. Multiplicative, additive and mixed models were developed based on linear and multivariate linear regression (Al-Kaisy and Hall, 2003; Krammes and Lopez, 1992; Kim et al., 2001). To obtain more precise capacity estimation, different combinations of affecting factors were used. Besides linear models, the Neuro-Fuzzy Logic Model was also used to estimate work zone capacity by incorporating various factors that affect work zone capacity (Adeli and Jiang, 2003). The ensemble tree approach is also one of the recent techniques used to develop work zone capacity estimation models, and was also used in Weng and Meng (2012).

In several studies the estimation of remaining capacity at work zones was based on affecting factors, such as the ratio of heavy vehicles, the number of lanes closed and the intensity of the work zone activity. Table 2-4 summarizes some of the previous studies on work zone capacity and the corresponding capacity estimations.

The capacity estimation model developed by Krammes and Lopez (1992) was adopted by HCM (2000, 2010) for estimating work zone capacity. According to this model, capacity is estimated by multiplication and interaction of reduction factors with base capacity, which is assumed as 1,600 vphpl regardless of any conditions. Several adjustments were made to the base capacity value including adjustments for the intensity of the work activity, the effect of heavy vehicles, and the presence of ramps when applying to specific work zone location. The following equation may be acceptable as a base formulation for work zone capacity estimation purposes.

$$f_{HV} = \frac{1}{1+P_T(E_T-1)} \tag{2-3}$$

$$C_a = [1600 - I - R] * f_{HV} * N \tag{2-4}$$

Where,

f_{HV} = adjustment for heavy vehicles as defined

P_T= proportion of heavy vehicles,

E_T= passenger car equivalent for heavy vehicles,

C_a = adjusted mainline capacity (veh/h),

I = adjustment factor for type, intensity, and the activity location (±160 pc/h/ln),

R = adjustment for ramps,

N = number of lanes open through the short-term work zone.

Table 2-4 Studies on Work Zone Capacity

Study	Year	Location	Road Type	#of Work	Length of Study	Capacity at Work Zone
Krammes and Lopez	1992	Texas	Freeway	33	4 years	1,600 pcphpl
Dixon et al.	1996	North Carolina	Rural, Urban Freeway	24	9 months	1,440 vphpl
Yi Jiang	1999	Indiana	Freeway	4	19 months	1,258-1,689 pcphpl
Maze et al.	2000	Iowa	Rural Freeway	1	19 days	1,400-1,600 pcphpl
Al-Kaisy et al.	2000	Ontario	Freeway	2	3 days	1,750-2,150 pcphpl
Kim et al.	2001	Maryland	Freeway	12	Not reported	1,228-1,790 pcphpl
Schnell et al.	2002	Ohio	Interstate, State	4	Not reported	866-2,982 vphpl
Al-Kaisy, Hall	2003	Ontario	Urban Freeway	6	Different for sites	1,853-2,252 pcphpl
Sarasua et al.	2004	South Carolina	Interstate	23	1 year	1,460 pcphpl
Benekohal et al.	2004	Illinois	Interstate	11	1 day	597-1,294 vphpl
Lee et al.	2008	Wisconsin	Urban Freeways	8	4 months	1,134-2,643 pcphpl
Heaslip et al.	2008	Florida, Massachusetts	Interstate	2	7 and 10 days	1,245-1,992 vphpl
Benekohal et al.	2010	Illinois	Interstate	3	AM, PM	868-1,604 vphpl
Bham and Khazraee	2011	Missouri	Interstate	1	4 days	1,194-1,404 vphpl
Weng and Meng	2012	Maryland, North Carolina,	Rural, Urban Freeway	182	Not Reported	1,180-2,090 vphpl
Edara et al.	2012	Missouri	Urban Interstate	2	2 day	1,149-1,301 vphpl

Note: vphpl = vehicles per hour per lane; pcphpl = passenger car per hour per lane.

Adeli (2004) conducted a study to model work zone capacity using a case-based reasoning model for freeway work zone traffic management that considered work zone layout, traffic demand, work characteristics, traffic control measures, and mobility impacts. An adaptive computational model was created for estimating work zone capacity, queue length, and delay.

Benekohal et al. (2004) presented a methodology for estimating speed and capacity in freeway work zones. The underlying principle of this methodology is that operating factors in work zones, which include work intensity, lane width, lateral clearance, and other factors, cause motorists to reduce their speed. The collected video data included 11 two-to-one work zone lane closures on interstates in Illinois including eight long-term and three short-term sites. Work zone intensity was quantified and correlated with consequent speed reduction using field data for long-term work zones and driver survey data for short-term work zones. Based on these relationships an anticipated work zone operating speed variable was computed using a speed-flow relationship developed from project data. The model was expressed by the following equation:

$$C_{adj} = C_{U_O} * f_{HV} * PF \tag{2-5}$$

Where,

C_{adj} = adjusted capacity,

C_{U_O} = capacity at operating speed U_O,

f_{HV} = heavy – vehicle adjustment factor, and

PF = platooning factor.

Weng and Meng (2012) used an ensemble tree approach to model work zone capacity model. This was described as a set of decision trees that was employed to determine the factors affecting work zone capacity. A sample of 182 sets of data from different states; Maryland, Texas, North Carolina, California, Indiana, Ontario, Toronto, South Carolina and Florida was used to develop the model. They observed stable results with the ensemble tree approach when compared to the decision tree method. The reproduced ensemble tree approach outperformed the existing capacity estimation methods by providing more accurate results.

Besides numerical methods, work zone capacity is also estimated by using field data. HCM 2000 suggested the capacity be defined as the maximum flow rate that was observed under sustainable conditions for 15 min. Benekohal et al. (2004) developed a technique called the "h-n" or "h minus n" method to estimate work zone capacity by using field data. This method was developed in order to overcome data errors attributable to the presence of large gaps between vehicles. The main idea is to better estimate missing capacity data due to the underutilization of the roadway. H denotes the headway in seconds and n denotes the headway threshold for free flow traffic. If the observed headway is longer than 8 seconds then this value is replaced with a reduced value of 4 seconds from the observed headway value. Using this approach, the capacity values estimated by the "h-n" method were larger than those estimated when using the HCM 2000 method.

Karim and Adeli (2003) developed an adaptive computational model for estimating the work zone capacity, queue length and delay. In their model, they proposed various factors that affect work zone capacity such as the number of lanes, number of open lanes, work zone layout, length, lane width, percentage of trucks, grade, speed, work intensity, darkness factor and the proximity of ramps. A radial-basis function neural network (RBFNN) model was developed to learn the mapping from quantifiable and non-quantifiable factors describing the work zone traffic control problem to the associated work zone capacity. Based on the RBFNN model, root mean square error was estimated as 165 vph which is in acceptable range for practical purposes.

Lee et al. (2008) developed a tool to predict delays and queues for short-term lane closures. In order to evaluate and enhance their tool, they collected field data that contained information on traffic flow and queuing patterns during work zone operations on selected urban freeways. The field data showed that roadway capacity varied between 1,134 pcphpl and 2,643 pcphpl depending on the number of lanes closed and the intensity of the work zone activity.

Heaslip et al. (2008) proposed an enhanced methodology for measuring capacity at work zones. They investigated the impact of driver behavior at work zones and found that driver behavior influences flow quality when drivers encounter changing roadway conditions and lane configurations. For this study, the data collected originated from two highways, one in Florida for ten days and the other in Massachusetts for seven days. The observations showed that the average capacity was 1,992 vphpl for Florida site whereas it was 1,245 vphpl for the Massachusetts site (how did they measure these capacities). Later, based on the data from the field observations they calculated the driver behavior factor, which was based on an assessment of tendencies such as driver familiarity, driver adaptability, driver aggressiveness, and driver accommodation tendencies that are unique for different demographic groups.

Bham and Khazree (2011) recorded the video streaming of traffic within the presence of a work zone on the I-44 in Missouri. They used Autoscope to detect and count the number of vehicles traversing the work zone area. Both breakdown flow and maximum sustained flow rates methods were used to estimate work zone capacity. The averages of 15 min maximum sustained flow rates were observed as 1,307 and 1,406 vphpl for westbound and eastbound directions, respectively. The average of 11 breakdown flow rates (range of 1,194-1,404) was estimated as 1,295 vphpl. It was found that the mean discharge queue rate of 1,072 vphpl was significantly smaller than the observed breakdown flow rate.

Edara et al. (2012) estimated work zone capacity for four different short-term work zones in Missouri. Maximum sustained flow, rescaled cumulative flow and the 85th percentile flow techniques were used to estimate work zone capacity. The capacity values estimated by the queue discharge flow methods were found to be more accurate when compared to other methods. These researchers had conducted a nationwide survey using several state DOTs. The estimated capacity values reported by Edara et al. (2012) were close to capacity values estimated by the HCM method for Missouri. The survey results showed that the work zone capacities used by the other state DOTs were higher than the estimated values. Findings from Edara et al. (2012) are shown in Table 2-5, which depicts work zone capacity for different state DOTs.

Table 2-5 Work Zone Capacity Values Adopted by State DOTs

State	2 to 1	3 to 1	3 to 2	2 Two-way one-lane (TWOL)	Two-way one-lane (with median crossover)
Florida	1,800 vph	—	3,600 vph	1,400 vph	—
Wisconsin	1,500 pcphpl	1,500 vph	1,500 pcphpl	—	1,400 pcphpl
Nevada	1,500–1,600 pcphpl	1,500–1,600 pcphpl	1,500–1,600 pcphpl	1,500–1,600 pcphpl	1,500–1,600 pcphpl
Massachusetts	1,500 vph	1,500 vph	3,000 vph	850–1,100 vph	
Hawaii	1,600 pcphpl	1,600 pcphpl	1,600 pcphpl	600-800 pcphpl	
Iowa	1,450 vphpl	—	1,450 vphpl	—	—
New York	1,800 pcphpl	1,600 pcphpl	1,700 pcphpl	—	1,800 pcphpl
New Jersey	1,300–1,400 vphpl	1,200–1,300 pcphpl	3,000–3,200 vphpl	600–750 vphpl	1,200–1,500 vphpl

Note: vph = vehicle per hour; vphpl = vehicles per hour per lane; pcphpl = passenger car per hour per lane.

2.6 Work Zone and Non-Work Zone Comparison

Harb et al. (2008) distinguished between single vehicle and two vehicle crashes at work zones. For the single vehicle crashes, freeway work zones with single vehicle crashes were compared with freeway non-work zones with single vehicle crashes. For two vehicle crash analysis, first a comparison between at-fault drivers and not at-fault drivers (quasi-induced exposure analysis) was conducted, using multiple logistic regression results. Second, similar to single vehicle crashes, roadway characteristics were compared for work zone and non-work zone crashes. Since crashes show different characteristics under different roadway and light conditions, the within-stratum analysis was implemented. The stratification criteria for the developed models were speed limit, number of lanes and time of day (a.m. or p.m.). For each stratum, a separate analysis was performed to classify the work zone factors associated with crashes.

In a matched work zone non-work zone analysis, a subset of work zone crashes was identified using the matching factors; speed limit, number of lanes and time of day. For the estimation of the logistic regression, within stratum differences between the work zone and non-work zone crashes were utilized:

$$\text{logit}(p_j(x_{ij})) = \alpha_j + \beta_1 x_{1ij} + \beta_2 x_{2ij} + \ldots + \beta_k x_{kij} \tag{2-6}$$

Where,

x_{ij} is the vector of traffic characteristics, j is the stratum number and, i is the crash number.

Three separate models were estimated for environmental characteristics in single vehicle crashes, driver characteristics and environmental characteristics in two vehicle crashes. The important contribution of this study was its ability to distinguish between the differences of work zones and non-work zones using the within-stratum analysis. Some of their findings were documented as follows:

- Straight freeway segments were more susceptible to crashes in work zone areas (this may be due to the alertness of drivers on a non-straight segment).
- Poor lighting was associated with an increase in work zone crash frequency.
- Trucks were more likely to be involved in a single-vehicle work zone crash.

CHAPTER 3. FREQUENCY MODELING OF WORK ZONE CRASHES

3.1 Introduction

In recent years, work zone safety has become essential with numerous highway renovation projects and a rising number of work zone crashes. Work zone safety is one of the most important issues for project contractors in terms of economic impact. Road user cost (RUC) estimations are included in the costs of work zone crashes. Incentive and disincentive amounts are estimated based on the RUC value which includes accident costs for construction zones (Zhu et al., 2009). Therefore, crash frequency prediction methods are important for preparing safety policies for any project. Several studies have focused on obtaining an answer as to whether work zones increase crash frequency. As mentioned in the literature review, most of these studies showed that work zones have a significant incremental effect on crash rates.

New Jersey work zone crash statistics shows that there was a significant increase in these in 2010. The prior six year average number of work zone crashes was 5395, however this number increased in 2010 by 26.7 percent. The number of property damage crashes reported for 2010 was 5267 which was 1192 crashes higher than the prior six year average (4075). The average number of injury crashes per year was 1308 for the time period 2004-2009, which increased by 244 crashes to a 1552 in 2010. The number of fatalities increased to 18 in 2010, while the six year average was 12. This data stresses the point that further investigation of work zone crashes is needed to ascertain possible contributing factors. Figure 3-1 shows the yearly change in work zone crash rates for New Jersey.

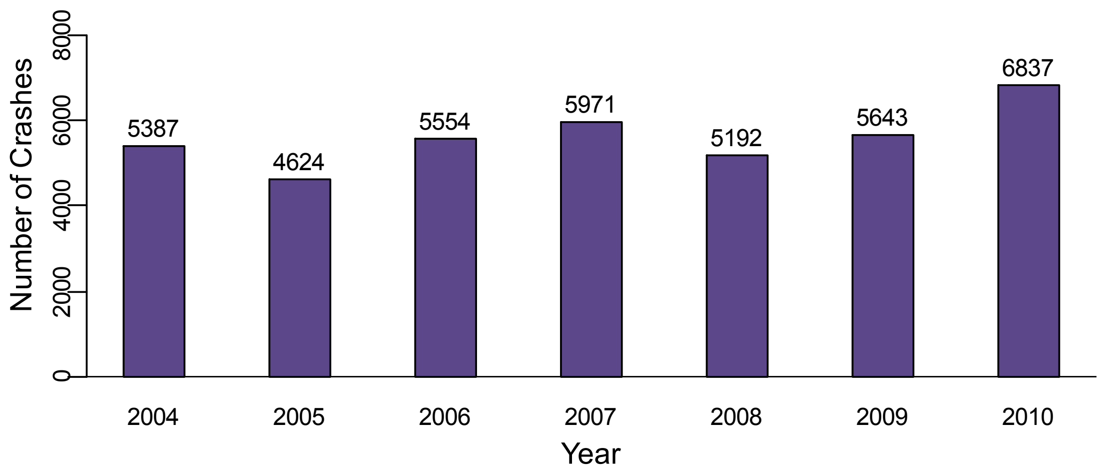


Figure 3-1 Yearly Distribution of Work Zone Crashes in New Jersey

In this chapter, crash frequency at work zone areas was investigated to predict numbers of injuries and extent of property damage only in work zone crashes by using available parameters. There are a few studies which are directly related to work zone crash frequency modeling. Generally a negative binomial regression approach is preferred for modeling work zone crash frequency rates by using parameters such as AADT, duration, length and urban indicator, plus work zone type to determine contributing factors related to work zone accidents (Abdel-aty and Radwan, 2000; Mitra and Washington, 2007). Work zone crash frequency models were developed based on daytime and nighttime crash counts. Variables used in previous studies are mostly similar to the general crash frequency modeling approach. This study aimed to characterize work zone crashes with general crash frequency modeling parameters and work zone related parameters such as speed reduction and lane reduction. These parameters were used within severity models before but were not included for purposes of crash frequency modeling. The New Jersey crash database (2004-2010), plus 34 different project drawings and the NJ straight line diagrams were combined to create the main database for modeling. These models were also separated into injury and non-injury crashes. In the duration based model, total crash numbers are taken into account for work zone duration, and in the period based models, three monthly crash counts are used to set the models. Poisson and negative binomial regressions are the major methods used for modeling such crash count data. Because of the dispersion of data, the negative binomial regression (Poisson Gamma) method was chosen for the modeling component.

The structure of the chapter is arranged as follows; first are the descriptive statistics for New Jersey crash frequency between 2004 and 2010, followed by the methodology for the work zone crash frequency modeling, the case study and its data preparation, and the interpretation of the model's results. Moreover, work zone crash frequency modeling parameters were compared to non-work zone crash parameters to distinguish work zone characteristic parameters. Specifically, time and space impact on the crash occurrence by project development were investigated to examine driver familiarity effects on crash frequency.

3.2 Descriptive Statistics for Crash Frequency

The New Jersey work zone crash frequency data and related parameters were described in the following order; time of occurrence, spatial, seasonal and light condition information of the work zone crashes for the years 2004 to 2010. Instead of using only exact project locations, all work zone crashes defined as "work zone crash" were included for the descriptive analysis. According to the New Jersey Crash Database between 2004 and 2010, the following descriptive statistics were analyzed.

3.2.1 Crash Frequency by Temporal Information

Annual work zone accidents between 2004 and 2010 are shown at Figure 3-1**.** The average yearly work zone crash number for the given period was 5,601. The lowest number of work zone crashes was observed in 2005. The largest number of work zone crashes was observed in 2010. Compared to the average yearly number of work zone crashes, the frequency increased more than 20 percent in 2010.

The monthly distribution of work zone crashes over the studied seven year period is shown in Figure 3-2. The total number of work zone crashes during the winter season was lower than for the other seasons. The minimum numbers were observed for January and February; the maximum numbers were observed for August and October. More work zone crashes occurred during the summer and fall seasons, which were the expected time intervals for the construction process.

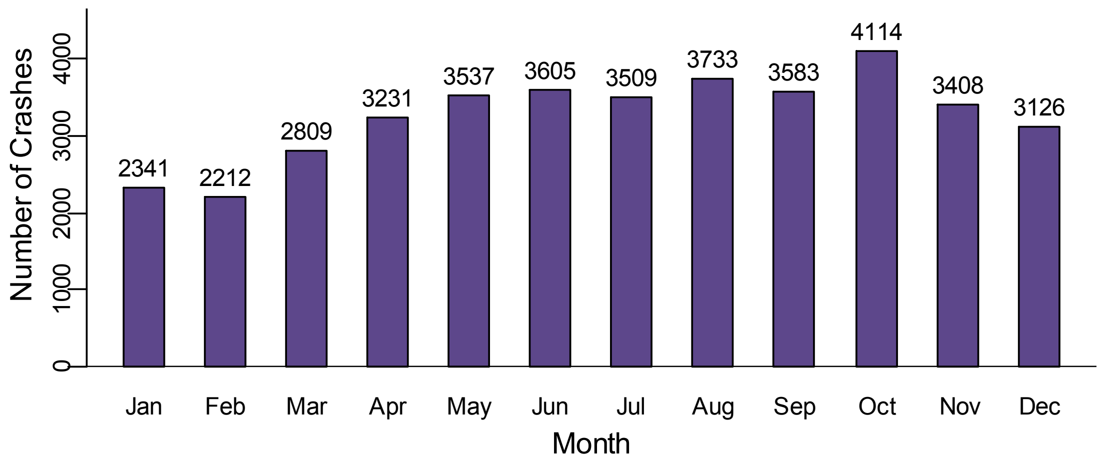


Figure 3-2 Monthly Distribution of Work Zone Crashes in New Jersey

Figure 3-3 shows the total number of accidents per day of the week. The number of weekday work zone crashes is significantly higher than weekend work zone crashes. Friday had the greatest number of work zone accidents during the seven-year period.

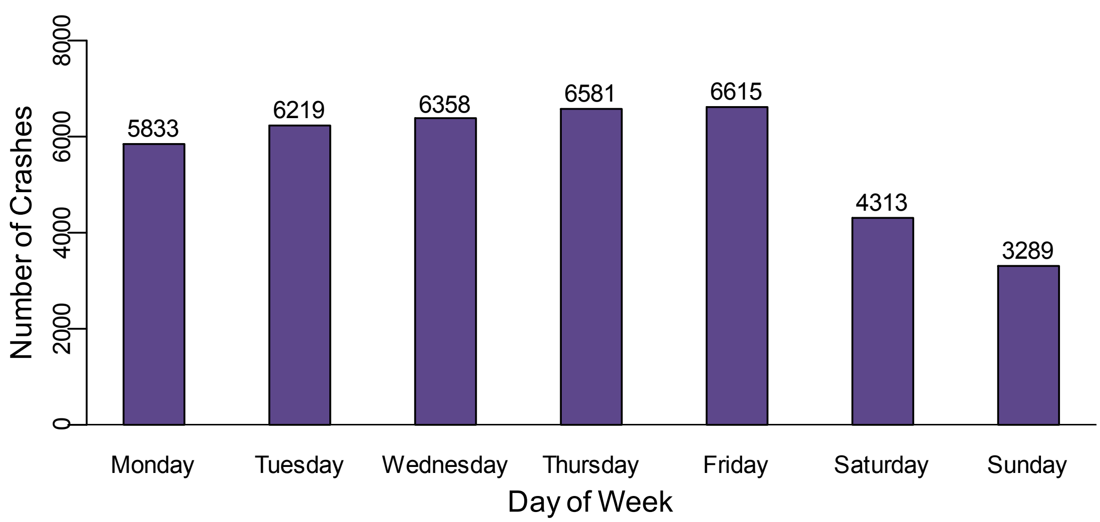


Figure 3-3 Daily Distribution of Work Zone Crashes in New Jersey

The hourly distribution of all observed work zone crashes is shown in Figure 3-4. According to the table, 9.3 percent of work zone crashes appeared between the hours of 12:00 A.M. and 7:00 A.M., 16.4 percent between the hours of 7:00 A.M. and 10:00 A.M., 39 percent between the hours of 10:00 A.M. and 16:00 P.M., 18.8 percent between the hours of 16:00 P.M. and 19:00 P.M., and 15.8 percent between the hours of 19:00 P.M. and 11.59 P.M.. Daytime and off-peak hours were most likely to be related to more work zone crashes because of the strongest presence of construction during this part of the day. Peak values for the hourly distribution ranged between 15:00 and 15:59, with 2,762 total number of work zone crashes.

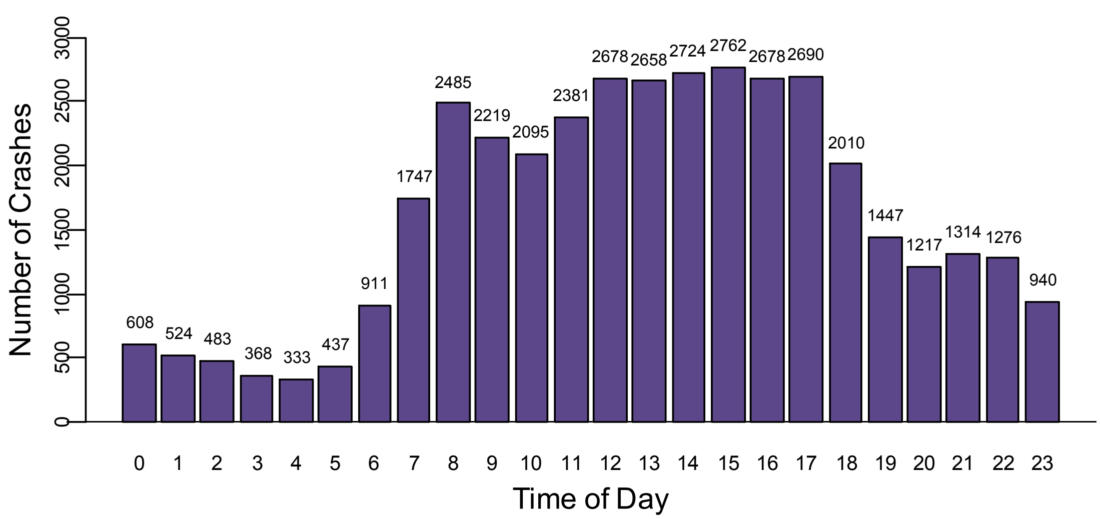


Figure 3-4 Hourly Distribution of Work Zone Crashes

3.2.2 Crash Frequency by Crash Types

Consistent with the literature findings, rear-end crashes were the predominant crash type for the work zone crashes. Rear-end crashes were the most frequent work zone crash type, representing 44 percent of the total work zone crashes. Side swipe and fixed-object crashes were also significant types. Crash types were investigated according to the total number of vehicles involved in the work zone accident. Figure 3-5 shows the distribution of all crash types by the number of crashes.

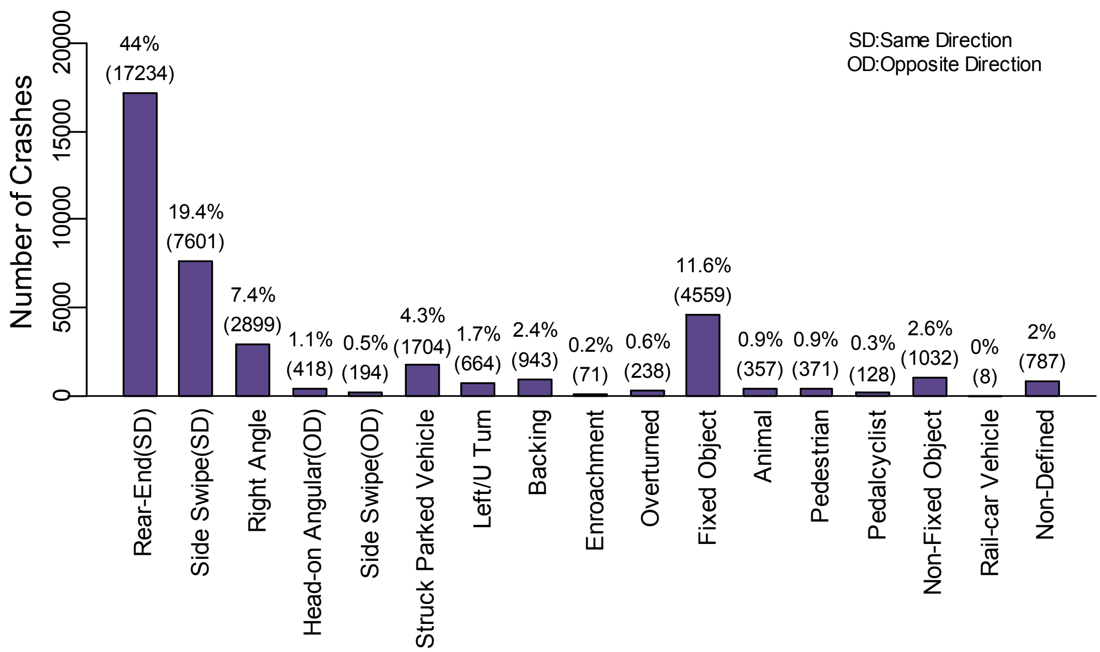


Figure 3-5 Work Zone Crashes by Crash Types

Figure 3-6 shows the relationship between work zone crash types and the number of vehicles involved in an accident. As is apparent, the distribution of crash types for single-vehicle work zone crashes is completely different from the work zone crashes in which two or more vehicles were involved. Significant crash types for single-vehicle accidents are collision with fixed and non-fixed objects. More pedestrian and animal accidents were observed in single-vehicle accidents. Accordingly, by increasing the number of vehicles involved in work zone crashes, the rear-end crash percentage increased among other crash types. The side-swipe crash type proportion decreased when three or more vehicles were involved in the work zone accident.

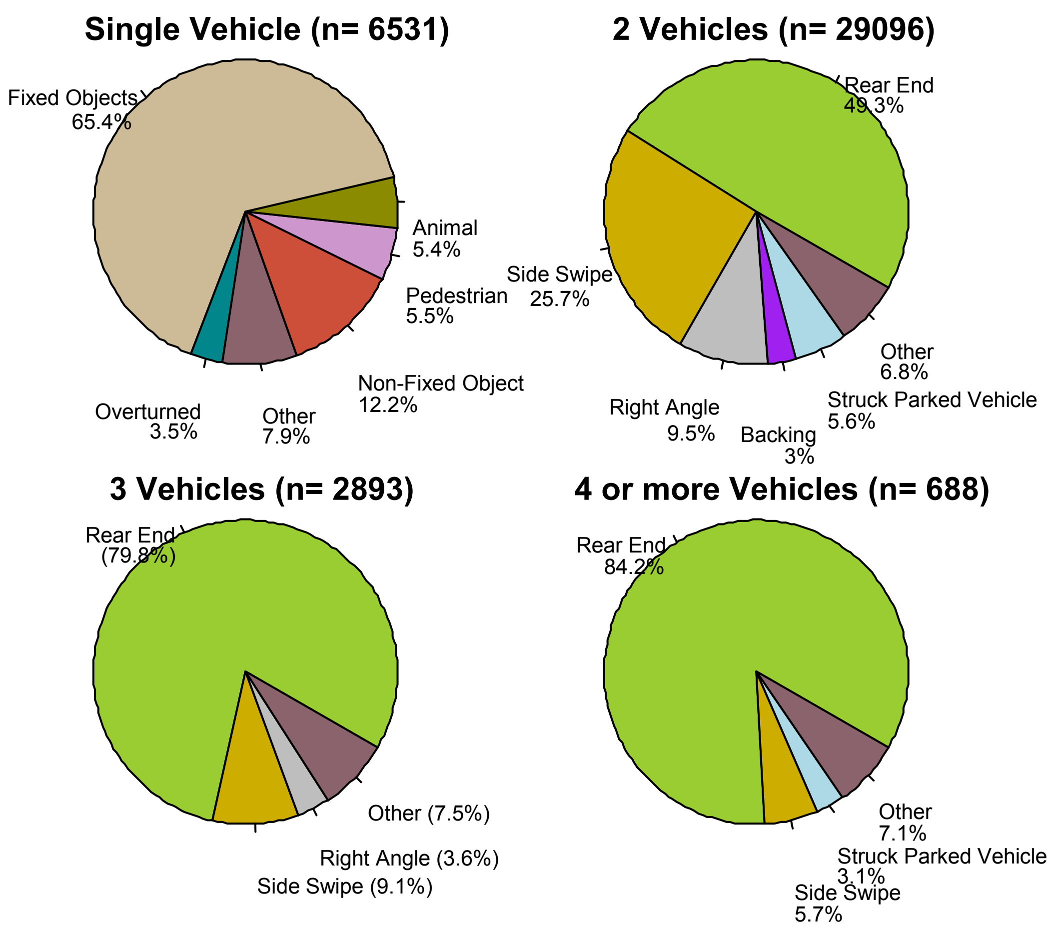


Figure 3-6 Crash Types by Total Number of Vehicle Involved

3.2.3 Crash Frequency by Road Characteristics

Spatial information about the work zone accidents is described in this section according to the road system, posted speed, road character in a work zone accident. The number of accidents and percentage values for each category are shown in the following figures. As shown in Figure 3-7, state highways and interstate highways were involved in 67.2 percent of all work zone crashes in New Jersey.

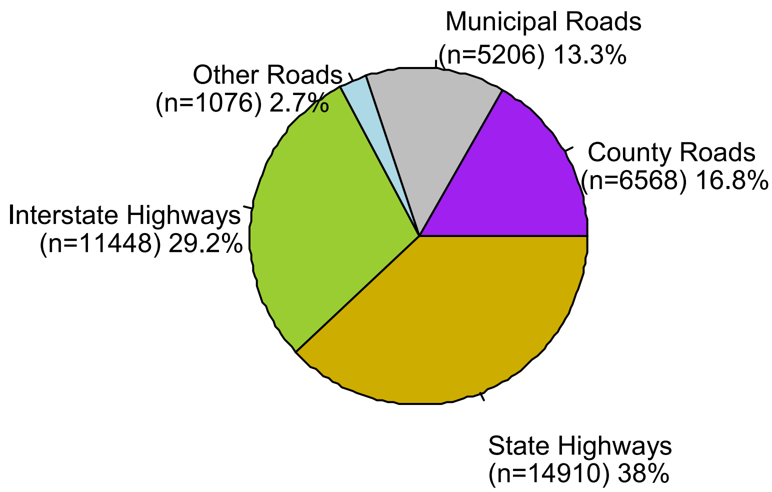


Figure 3-7 Work Zone Crashes by Road Class

There was no clear information about posted speed—that is, whether this was a reduced work zone speed or not. If the speed limit from the crash records matched the road system information (New Jersey Straight Line Diagrams), it may be concluded however, that the posted speed was correct. From Figure 3-7, the number of work zone crashes on the interstate highways (11,448) was almost twice the number of work zone crashes having a posted speed greater than or equal to 55 mph (6,787). If we consider that the minimum limit is 45 mph for state highways and 55 mph for interstate highways, the percentage of posted speeds over-45 mph should be 67.2 percent based on road system ratios (Figure 3-7). However, the percentage of posted speeds over-45 mph was

51 percent in the dataset. Thus, it can be concluded that the majority of the posted speed information reflected the presence of a reduced work zone speed (Figure 3-8).

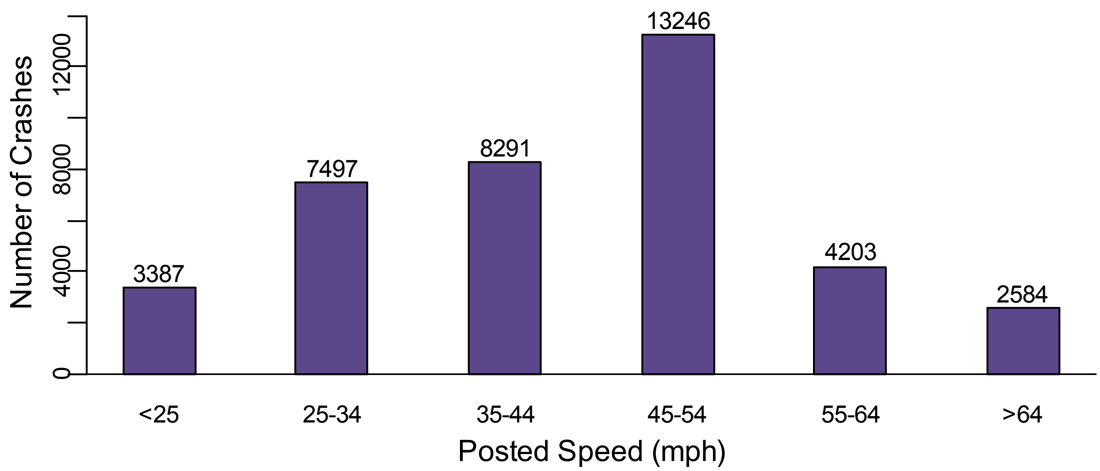


Figure 3-8 Total Number of Work Zone Crashes by Posted Speed Limit

The road character distribution for the work zone crashes is shown in Figure 3-9. Most of the work zone crashes occurred on straight and level roads. These percentages were related to the distribution of the road character for New Jersey. Road character may affect a drivers' ability to recognize a work zone visually.

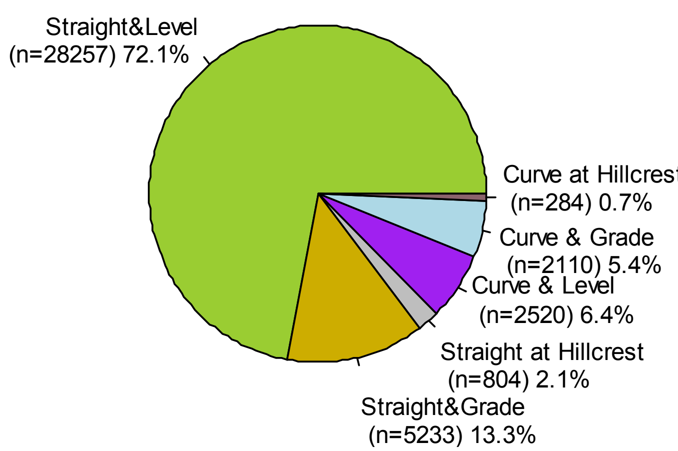


Figure 3-9 Road Character Distribution for Work Zone Crashes

3.2.4 Crash Frequency by Environmental Conditions

From the Figure 3-10, it can be seen that 71.4% of the work zone crashes happened in a daylight condition. “Street lights on” percentage represents the likely number of active work zone condition crashes that occurred during the night time. We can also say that “dark” as a light condition represents the percentage of crashes inside the work zone area, but where there was no active work. The traffic volume was also effective in influencing the distribution of the work zone crashes according to the light condition. As Figure 3-4 showed, most accidents happened during the day time, which supports the distribution chart of the light condition.

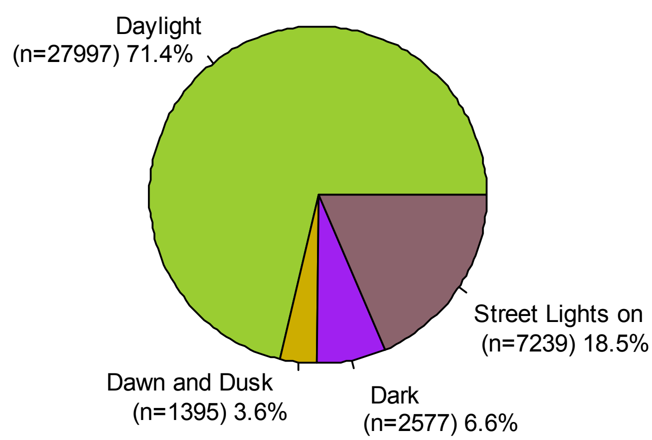


Figure 3-10 Light Conditions for Work Zone Crashes

Road surface condition distribution for the work zone accidents are represented below Figure 3-11. As shown, most work zone crashes happened on a dry road surface condition.

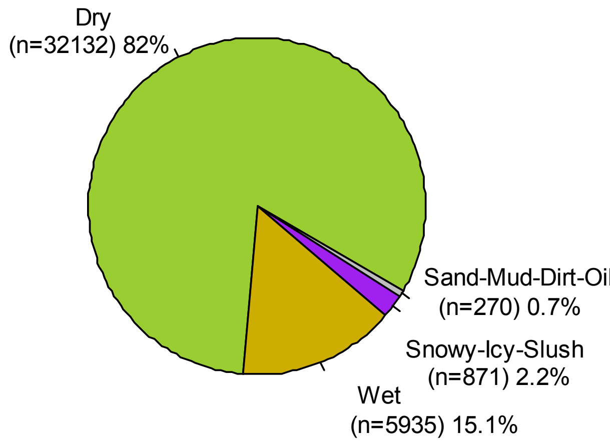


Figure 3-11 Road Surface Condition for Work Zone Crashes

Weather conditions for work zone crashes are represented by four categories; Clear, rainy, overcast, and adverse. Adverse weather conditions are defined as a combination of following; snow, blowing snow, severe crosswinds, fog, smog, smoke, sleet, hail, freezing rain, blowing sand, dirt. Crash types were investigated for these weather conditions categories. Figure 3-12 shows major crash types for each weather category. "Other" is an insignificant representation of crash types for specific weather condition. Interestingly, the "rear - end" crashes ratio decreased during good weather conditions (45.9 %) to bad weather conditions (27 %) relatively and the "fixed - object" crashes ratio increased from clear weather condition (9.9 %) to adverse weather condition (30.4%). Side swipe, right angle and struck parked vehicle types of crashes ratio were almost similar for all weather condition.

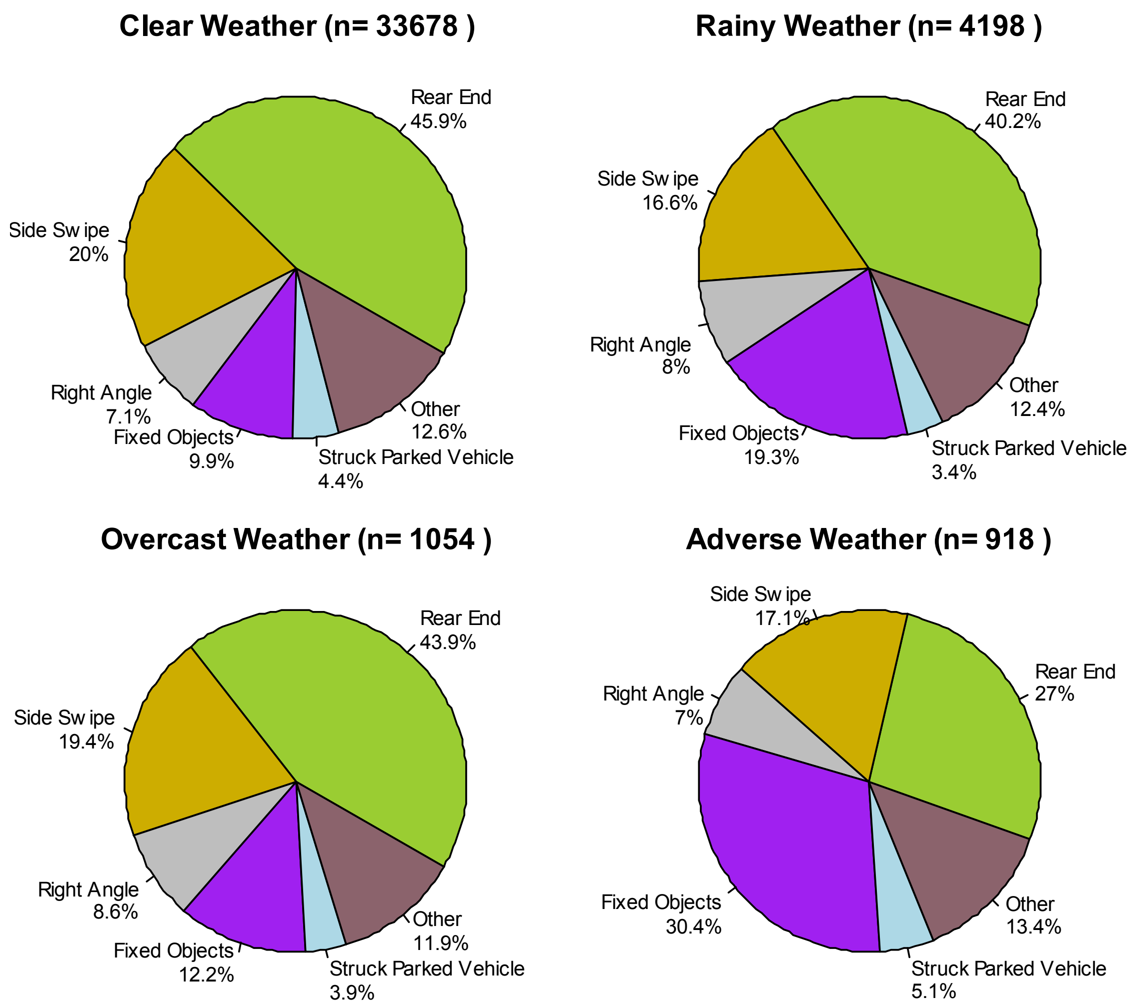


Figure 3-12 Crash Types for Different Weather Conditions

3.2.5 Crash Distribution within Different Work Zone Components

Work zones were separated into five locations: advanced warning, transition, buffer, work, and termination areas. This information was available for some verified work zones used in this study (project files provided by NJDOT). The crash distribution was investigated for these sub-locations and shown as a pie chart in Figure 3-13. As observed by previous studies, work zone accidents are predominantly located within the activity area (Nemeth and Migletz, 1978; Garber and Zoo, 2002).

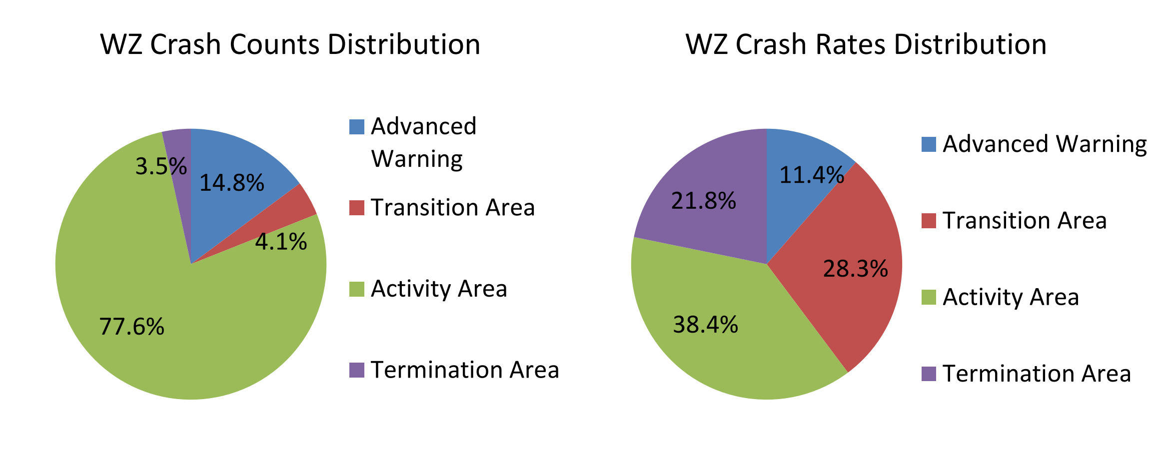
The crash counts and crash rates were estimated for each specific work zone component. Considering crash counts, the risk priority was defined in the following order:

1. Activity area (77.6 %)
2. Advanced warning area (14.8 %)
3. Transition area (4.1 %)
4. Termination area (3.5 %)

The segment length for the transition and termination areas was small compared to the activity area and advanced warning area. Hence, a crash count comparison was biased for these areas according to the risk priority. When crash rates were estimated for these specific locations, the risk priority order required changing. Crash rates were defined by Equation 2-1 based on a million vehicle entrances per mile.

Crash rate distribution shows that transition and termination areas are also risky places in terms of crash occurrence probability. New risk priority levels can be written in the following order:

1. Activity area, 38.4 %
2. Advanced warning area, 11.4 %
3. Transition area, 28.3 %
4. Termination area, 21.8 %.



(a) (b)

Figure 3-13 Work Zone Components (a) Crash Counts, and (b) Crash Rates

3.3 Methodology

The crash counts represent non-negative integers that are contributed to by several factors. To model such crash count data, a Poisson regression is used frequently among other statistical methods (Miaou et al., 1992; Lord et al., 2005). Beside this, there are several methods for modeling crash frequencies, such as the negative binomial (Poisson-Gamma) model, the zero inflated negative binomial and Poisson, truncated regression, the generalized additive model, the Conway Maxwell Poisson model, and the negative multinomial model etc. (Lord and Mannering, 2010). Based on previous studies and data dispersion value, the crash frequency data for the work zones was modeled by using a negative binomial method, where the dependent variable was the three monthly crash counts observed within the work zones.

Let Y_i represents the number of crashes at work zone i for an exact length and duration, accidents occurrence for work zone i is independent and probability density can be Poisson. (Green, 1997; Khattak et al., 2002);

$$\mathrm{P(Y_i = y_i) = Poisson[\lambda_i(y_i)] = exp[-\lambda_i]\lambda_i^{y_i}/y_i} \tag{3-1}$$

In the formulation, y_i is realized number of crashes and λ_i is expected crash frequency for work zone i. λ_i represents explanatory variables such as duration, length and AADT. Y_i' s mean and variance values are equal to λ_i which can be defined by Equation 3-2, where β is the estimated coefficient and x_i is the value of explanatory variables. Over dispersion is included by the error term ε_i, which represents a random effect due to omitted explanatory variables and unmeasured heterogeneity.

$$\lambda_i = exp(\beta x_i + \varepsilon_i) \tag{3-2}$$

In the negative binomial model, $\exp(\varepsilon_i)$ is assumed as gamma distributed with mean 1 and variance α^2(Cameron and Trivedi, 1998; Khattak et al., 2002). Natural form of overdispersion is;

$$Var[y_i] = E[y_i]\{1 + \alpha(E[y_i]\} \tag{3-3}$$

Dispersion rate is;

$$\mathrm{E(Y_i) = \lambda_i}; \qquad \frac{Var(\mathrm{y_i})}{\lambda_i} = 1 + \alpha\lambda_i \tag{3-4}$$

The negative binomial model differentiates from the Poisson model by the parameter α, which is necessary for deciding over dispersion. If α is significantly different from zero, the negative binomial model is appropriate to use such a count data, else a Poisson model should be used.

Safety performance function (SPF) for predicting the number of work zone crashes in an interval of given length and duration can be built as follows;

$$\ln(\lambda_i) = \alpha_1 \ln(L_i) + \alpha_2 \ln(V_i) + \alpha_3 \ln(D_i) + \sum_{j=1}^{m} \beta_j X_{ji}, \quad i = 1, \dots, n \tag{3-5}$$

Where λ_i is the predicted number of accidents in an interval of given length; L_i is the work zone length; $V_i$is the traffic volume during the period of study; X_j represents other explanatory variables; α and β are model parameters. L_i represents the work zone length for the whole period of construction and Di represents the duration of the work zone.

3.4 Case Study I

As mentioned in the beginning of this chapter, crashes frequency data were modeled by using a negative binomial regression technique that included work zone specific parameters for New Jersey work zone crashes. Sixty work zone sites were defined by temporal spatial analysis of work zone labeled crashes. These work zones were verified by project drawings obtained through NJDOT. Data sources, modeling structure and discussions for the case study are included in this section.

3.4.1 Data Sources

Spatial - temporal plots of work zone labeled crashes in the database were analyzed for major roadways of New Jersey. Visually defined work zones were verified by using project drawings in terms of project milepost intervals and timestamps. The New Jersey crash database between 2004 and 2010, 34 work zone project drawings and New Jersey straight line diagrams were combined to form the main database for modeling the work zone crash frequencies. After directional separation of each work zone and the filtering of unclear data, 60 work zones were available for frequency modeling. The verified list of work zones is located below in Table 3-1 according to specific project information. Adjusted length for each work zone was decided upon by temporal - spatial analysis. Work zone crashes around project borders were captured and new mileposts for the border were defined by this adjustment.

Table 3-1Verified Work Zone List by Project Plan

Road	Work Zone	Direction	Date Start	End	Project Mile Start	End	Number of Crash	Adjusted Length
US1	1	North	9/1/2006	9/30/2009	32.2	34.6	423	3.3
	2	South	7/1/2006	10/31/2009	32.2	34.6	217	2.8
	3	North	4/1/2006	12/31/2010	58.5	60.5	196	2.8
	4	South	4/1/2006	12/31/2010	58.5	60.5	181	2.8
	5	North	3/1/2006	12/31/2008	61.1	63.0	81	1.9
	6	South	3/1/2006	11/30/2008	61.1	63.0	93	1.8
	7	North	2/1/2006	1/31/2008	35.8	36.9	87	1.0
	8	South	2/1/2006	10/31/2007	35.8	36.9	89	1.0
	9	North	5/1/2006	2/29/2008	38.0	39.8	58	2.3
	10	South	6/1/2006	8/31/2008	38.0	39.8	93	2.0
	11	North	7/1/2004	5/31/2007	43.6	44.5	62	2.2
	12	South	7/1/2004	5/31/2007	43.6	44.5	54	2.2
I78	13	East	6/1/2007	1/31/2008	29.7	30.5	14	1.2
	14	West	8/1/2007	3/31/2008	29.7	30.5	35	1.1
	15	East	7/1/2006	12/31/2006	50.6	52.8	64	3.3

	16	West	7/1/2006	11/30/2006	50.6	52.8	80	4.1
	17	East	1/1/2004	8/31/2007	4.5	7.4	154	3.2
	18	West	2/1/2004	11/30/2007	4.5	7.4	102	3.0
NJ18	19	North	8/1/2005	10/31/2009	40.6	42.8	299	2.3
	20	South	8/1/2005	8/31/2009	40.6	42.8	292	2.1
US46	21	East	11/1/2004	5/31/2008	57.2	57.9	87	0.6
	22	West	10/1/2004	7/31/2008	57.2	57.9	103	0.9
	23	East	1/1/2005	1/31/2008	55.3	56.8	65	2.4
	24	West	8/1/2005	1/31/2009	55.3	56.8	166	2.2
	25	East	3/1/2005	5/31/2008	60.5	61.2	35	1.0
	26	West	7/1/2005	6/30/2008	60.5	61.2	22	1.2
	27	East	1/1/2005	9/30/2007	54.4	54.9	18	0.5
I287	28	North	8/1/2007	5/31/2010	0.1	5.9	299	6.2
	29	South	8/1/2007	12/31/2010	0.1	5.9	291	6.4
I280	30	East	10/1/2007	12/31/2007	3.4	4.8	8	1.7
	31	West	9/1/2007	3/31/2008	3.4	4.8	32	1.6
	32	East	11/1/2006	11/30/2008	11.8	12.5	29	0.9
	33	West	10/1/2006	11/30/2008	11.8	12.5	79	1.0
	34	East	7/1/2006	12/31/2008	14.4	14.6	74	2.0
	35	West	6/1/2006	9/30/2008	14.4	14.6	75	2.3
I295	36	North	6/1/2007	10/31/2008	14.3	24.5	106	11.4
	37	South	6/1/2007	10/31/2008	14.3	24.5	86	10.7
	38	North	1/1/2004	12/31/2004	32.1	41.0	267	11.1
	39	South	1/1/2004	12/31/2004	32.1	41.0	309	11.4
I80	40	East	1/1/2004	9/30/2005	67.0	67.8	143	3.7
	41	West	1/1/2004	11/30/2005	67.0	67.8	150	4.4
US9	42	North	7/1/2004	12/31/2006	114.4	115.3	76	2.0
	43	South	7/1/2004	7/31/2006	114.4	115.3	45	1.6
	44	North	9/1/2004	7/31/2006	111.0	111.6	32	0.8
	45	South	10/1/2004	7/31/2006	111.0	111.6	32	1.0
	46	North	11/1/2004	7/31/2006	112.3	112.9	51	1.7
	47	South	3/1/2005	7/31/2006	112.3	112.9	58	1.4
	48	South	3/1/2004	1/31/2006	132.0	132.8	14	0.7
NJ35	49	North	5/1/2007	8/31/2008	14.4	14.9	30	1.0
	50	South	12/1/2006	12/31/2008	14.4	14.9	29	1.4
	51	North	7/1/2006	8/31/2007	23.3	23.6	14	0.3
	52	South	6/1/2006	8/31/2007	23.3	23.6	23	0.6
	53	North	4/1/2006	4/30/2008	56.3	56.8	50	0.7
	54	South	2/1/2006	4/30/2008	56.3	56.8	76	1.0
	55	North	1/1/2004	10/31/2005	50.9	52.3	23	1.7
	56	South	1/1/2004	12/31/2005	50.9	52.3	31	1.8
	57	North	2/1/2004	1/31/2005	21.2	21.9	25	1.2
	58	South	1/1/2004	2/28/2005	21.2	21.9	13	0.8
NJ23	59	North	10/1/2005	11/30/2007	4.8	5.8	30	1.0
	60	South	2/1/2006	12/31/2008	4.8	5.8	47	1.8

Analyzing and merging of the data was processed by using the R package program. The R package program is able to merge a large dataset. Crash counts were clustered by 3 monthly periods for each work zone and separated into four crash categories: daytime PDO, daytime injury, nighttime PDO and nighttime injury crashes (Table 3-2). Fatal crashes were included in injury crashes since the number of fatal crashes was small when compared to other two severity types. Categories and sample sizes are shown below in the table;

Table 3-2 Number of Work Zone Crashes for Each Category (60 work zone sites)

Category	PDO	Injury	Total
Daytime Crashes	2915	862	3777
Nighttime Crashes	1192	413	1605
Total Crashes	4107	1275	5382

AADT is one of the most significant parameter for crash frequency models since it reflects the exposure of the traffic. Hence, accuracy of the AADT values is essential for modeling. Khattak et al. (2002) stated that directional AADT should be used for modeling to determine crash distribution more accurately. In this study, directional AADT values were selected from the NJ Straight Line Diagrams for given mileposts and within estimated time posts. All AADT values were adjusted seasonally by using NJDOT adjustment factors, and were also adjusted for nighttime and daytime traffic by using hourly adjustment factors. Bourne et al. (2010) reported an example of normalization issues for results that daytime work zone crashes are often overrepresented among all crashes. Nighttime traffic was approximately estimated as a quarter of the total daily traffic. Therefore, biased relationship between the AADT and crash counts was avoided by using reduced AADT for nighttime conditions. Temporal spatial plots of work zones at I-80 and related project files are shown below as an example of data processing approaches (Figure 3-14, Figure 3-15 and Figure 3-16).

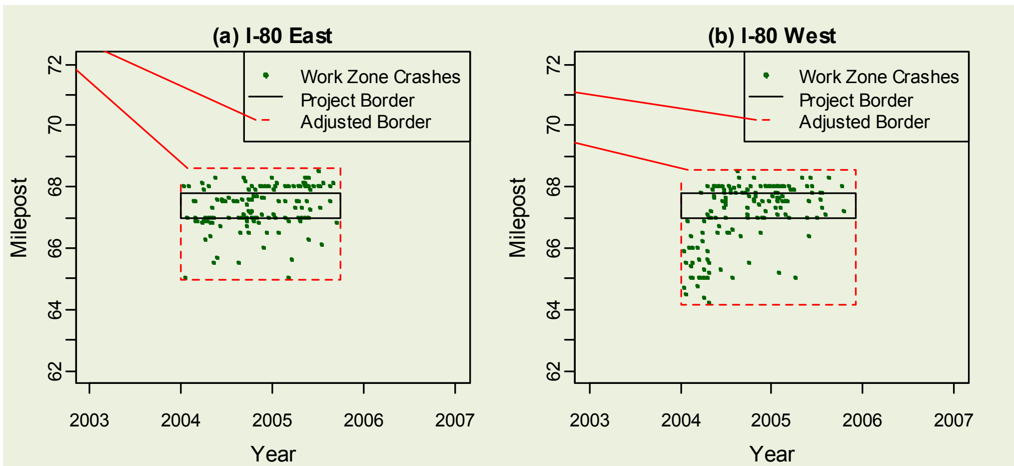


Figure 3-14 Temporal Spatial Plotting of Construction Zone Crashes at I-80

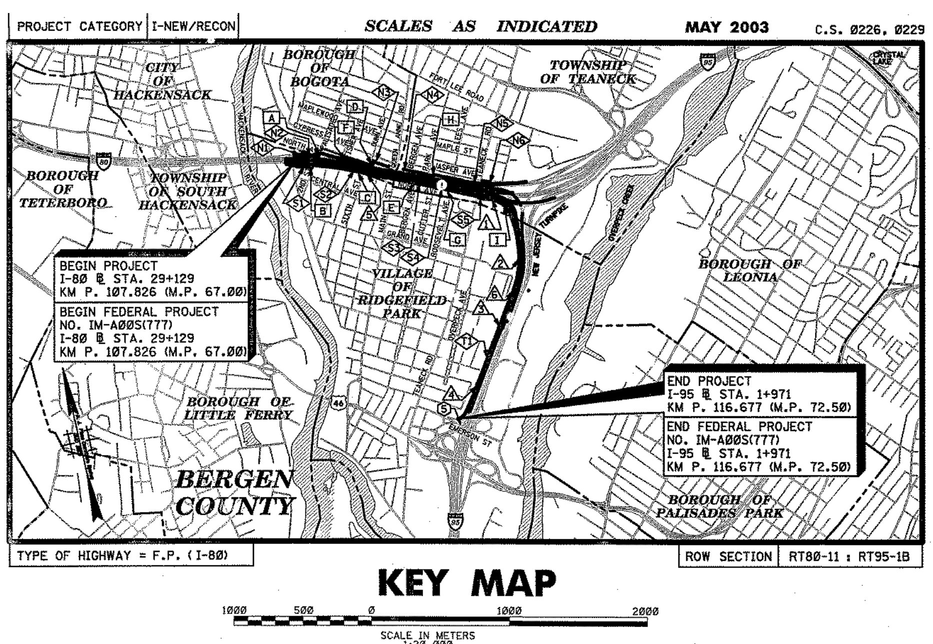


Figure 3-15 Sample Project File For Work Zone on I-80 (Courtesy of NJDOT)

ALLOWABLE LANE CLOSURE SCHEDULE

I-80 EASTBOUND AND WESTBOUND LOCAL LANES, INCLUDING I-95 SB LOCAL:

ALL LANES MAINTAINED (EACH DIRECTION)	6:00 AM TO 9:00 AM AND
MONDAY THROUGH FRIDAY	3:00 PM TO 8:00 PM
	9:00 AM TO 9:00 PM
SATURDAY	10:00 AM TO 9:00 PM
SUNDAY	
TWO LANES MAINTAINED (EACH DIRECTION)	9:00 AM TO 3:00 PM AND
MONDAY THROUGH THURSDAY	8:00 PM TO 6:00 AM (NEXT DAY
	9:00 AM TO 3:00 PM
FRIDAY	9:00 PM TO 10:00 AM SUNDAY
SATURDAY	9:00 PM TO 6:00 AM (MONDAY)
SUNDAY	
ONE LANE MAINTAINED (EACH DIRECTION)	10:00 PM TO 5:30 AM (NEXT DAY)
MONDAY THROUGH THURSDAY	10:00 PM TO 8:30 AM (SATURDAY)
FRIDAY	11:00 PM TO 5:30 AM (SUNDAY)
SATURDAY	10:00 PM TO 5:30 AM (MONDAY)
SUNDAY	

Figure 3-16 Sample Work Zone Project File, Operation Hours on I-80 (NJDOT)

Work zone length, milepost, number of operating lanes and lane closure information were obtained through project drawings. Work zone lengths were also checked by spatial-temporal analysis of the work zone crashes. Length values were adjusted by capturing work zone related crashes within the time post and milepost. NJDOT crash records provide seven different light conditions, however, for the sake of simplicity; these were categorized in two levels: daytime and nighttime. The duration of the projects was included into the general model as the number of days. Work zone speed limits were gathered from NJ crash records according to the distribution of posted speed values within the work zones. Numbers of operated lanes information were obtained through project lane closure plans and decided upon by examining the most representative values during daytime and nighttime. Work zone speed reduction and lane drop parameters were generated by estimating differences between the work zone and normal conditions. Road types were categorized in two levels: interstate and state highways. Number of lanes, number of ramps and intersection for each work zones were obtained from NJ straight line diagrams. 120 (total counts) of data were used for the General model, 950 (3 month period counts) data points were used separately for the PDO and injury crashes analyses. The statistical summary of the 60 work zone sites is shown below in Table 3-3. Crash counts for each component were plotted with intersection and ramp information. Intersection and ramp milepost information was gathered from the New Jersey straight-line diagrams. Figure 3-17 shows a sample for two same-directional work zones.

Table 3-3 Summary Statistics for Work Zones

Variable	Mean	Std.Dev.	Min	Max	(N=60)
Project length	1.85	2.33	0.12	10.20	
AADT/lane	11094	4194	3272	17910	
Ramp	3.35	3.45	0.00	15.00	
Intersection	5.18	7.43	0.00	33.00	
WZ speed	43.17	6.83	25.00	55.00	
Speed reduction	7.83	6.27	0.00	20.00	
Lane	2.62	0.65	2.00	4.00	
Duration	759	395	90	1643	

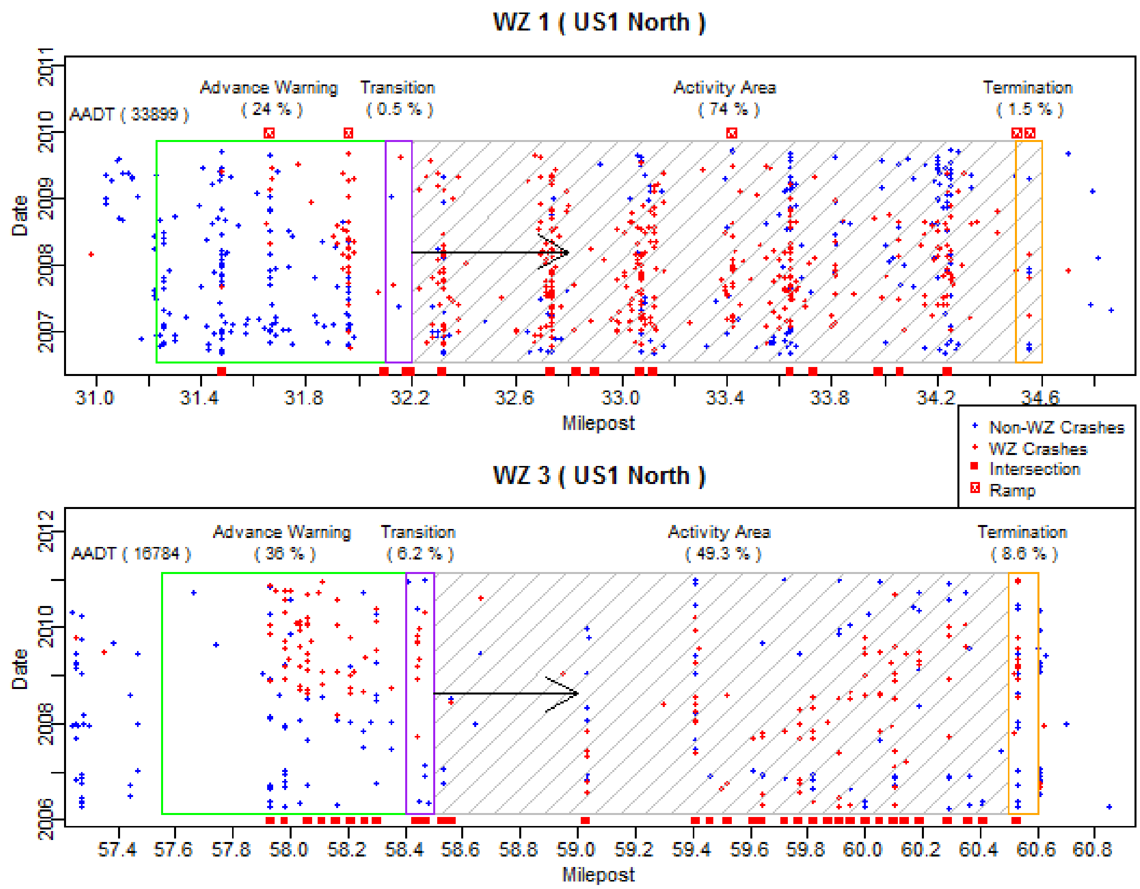


Figure 3-17 Intersection and Ramp vs. Crash Relationship within the Work Zone

3.4.2 Frequency Modeling Structure

Three statistical models were developed in order to analyze crash occurrences key contributing factors. The general model was used to investigate the duration effect of work zone projects by using the total counts for the construction period. Property damage and injury crash models were also developed by using three monthly crash counts as the dependent variable.

Since work zones represent temporary conditions on the roadway and each work zone has its own construction schedule, it was not possible to aggregate the crashes over a longer period. Thus, the shortest appropriate duration to describe work zone crashes was selected as a three month period.

Considering the crash information available from the NJDOT crash database, work zone project files, straight line diagrams, and the following variables were selected for crash frequency modeling as explained in Table 3-4; length, light conditions, annual average daily traffic (AADT), posted speed, speed reduction, number of operated lanes, number of lane closure, road type, number of ramps and intersection within the work zone. The Negative binomial models for total duration counts and three monthly crash counts took the following form:

$$\begin{aligned} \text{crash\_count} = \exp(&\beta_0 + \ln(\text{length})^{\beta_1} + \beta_2\text{night} + \ln(\text{aadt})^{\beta_3} + \beta_4\text{wzspeed} + \\ &\beta_5\text{operatedlane} + \beta_6\text{lanedrop} + \beta_7\text{speedreduction} + \\ &\beta_8\text{roadtype} + \beta_9\text{ramp} + \beta_{10}\text{intersection} + \ln(\text{duration})^{\beta_{11}}) \end{aligned} \tag{3-6}$$

$$\begin{aligned} \text{crash\_count (3 months)} = \exp(&\beta_0 + \ln(\text{length})^{\beta_1} + \beta_2\text{night} + \ln(\text{aadt})^{\beta_3} \\ &\beta_4\text{wzspeed} + \beta_5\text{operatedlane} + \beta_6\text{lanedrop} + \beta_7\text{speedreduction} \\ &\beta_8\text{roadtype} + \beta_9\text{ramp} + \beta_{10}\text{intersection}) \end{aligned} \tag{3-7}$$

The proposed frequency model for the work zone crashes included work zone specific parameters such as speed reduction and number of lane drop. These parameters have never been specified in the literature for frequency modeling of work zone crashes.

Table 3-4 Variables Considered in the Negative Binomial (NB) Model

Category	Variable	Type	Description
Length	length	continuous	length of the work zone (mile)
Light Conditions	night	indicator	daytime = 0, nighttime = 1
AADT	aadt	continuous	adjusted ADT per lane (by direction, seasonal factor, time factor)
WZ Speed	wzspeed	continuous	reduced posted speed limit (mph)
Operated Lane	operatedlane	indicator	number of operating lanes
Lane Drop	lanedrop	continuous	number of closed lanes
Speed Reduction	speedreduction	continuous	reduction in posted speed limit (mph)
Road System	roadsystem	indicator	interstate = 0, state = 1
Ramp Number	ramp	continuous	number of ramps at work zone
Intersection	intersection	Continuous	number of intersections at work zone
Duration	duration	continuous	duration of the work zone (days)

3.4.3 Frequency Modeling Results and Discussions

The estimated parameters from the modeling results are shown in Table 3-5, Table 3-6 and Table 3-7 were used to determine the relationship between the independent variables and the frequency of work zone crashes. The interpretation of the results explained the model parameters at the 95% level of significance.

Interpretation of the NB Model for Total Number of Crashes

- Duration of the work zone was the most significant parameter related to total number of crashes for the general model.
- Length of the work zone was found to be the significant factor for crash occurrences.

- The frequency of work zone crashes was higher for daytime traffic than for nighttime traffic; nighttime produces fewer crashes by considering adjusted AADT values.
- As expected, crash frequency increased by an increment of AADT values. Because AADT represented daily traffic patterns for each lane, the number of operating lanes was significant for reflecting exposure to traffic.
- Speed reduction affects work zone crash occurrence positively. An increase in the variance of speed change results in more crashes.
- Work zone speed limit was not significant at the 0.05 level, but it was still within the acceptable range for the model.
- Road type, the number of lane drops, intersection and ramp numbers were not significant for this model.
- The alpha number was not close to zero, which means that overdispersion occurred. In other words, the NB regression was more appropriate for this dataset than the Poisson regression.

According to the general work zone crash frequency modeling result, duration was found to be the most efficient parameter in explaining occurrence of crashes. Similar results were found in previous studies for duration of work zones (Khattak et al., 2002) (Venugopal and Tarko, 2000). Work zone length and AADT of the construction site were also found to be significant for the general model. A 1% increase in duration, AADT, and length variables caused an increment in crash frequency by 0.71%, 0.51% and 0.48% respectively. When compared to previous studies, length and AADT coefficients seemed to be lower; however almost twice as many parameters were used in this model and that may reduce the impact of the coefficients. The AADT parameter represents traffic volume per lane, thus number of operating lanes reflects traffic exposure with the joint effect of AADT. Each additional operating lane increases the crash counts by 89.6%. Speed reduction is another efficient parameter for the general model. An increase in variance for the speed limit between the pre-construction and during the construction phases increases crash occurrence probability. A 1 mph reduction in posted speed limit caused a 2.6% increase in total crash counts.

Table 3-5 Estimated Parameters of The General Crash Frequency Model (N=120)

Variable	Coefficient	Std. Err.	Z	P>|z|	Significant
ln(length)	0.477	0.133	3.580	0.000	***
night	-0.080	0.227	-0.350	0.725	
ln(aadt)	0.512	0.158	3.230	0.001	***
wzspeed	-0.023	0.014	-1.600	0.110	
operatedlane	0.642	0.141	4.540	0.000	***
lanedrop	0.158	0.129	1.230	0.220	
speedreduction	0.025	0.013	2.000	0.045	*
roadsystem	0.203	0.193	1.050	0.292	
ramp	0.011	0.028	0.410	0.680	
intersection	0.014	0.010	1.380	0.167	
ln(duration)	0.710	0.084	8.500	0.000	***
intercept	-6.731	1.097	-6.140	0.000	***
alpha	0.190	0.030			
chibar2 =	614.89	Prob>=chibar2 = 0.000			

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Interpretation of the NB Model for Property Damage Crashes

- AADT per-lane values were significantly related to non-injury CF. The number of lanes with AADT showed exposure to traffic, which were effective parameters for PDO crash occurrences.
- Length of the work zone was strongly associated with the number of crashes. A longer work zone resulted in more accidents.
- Daytime traffic was closely related to property damage work zone crashes; in other words, night conditions in work zones decreased the frequency of PDO crashes.
- Speed reduction was also a significant parameter for the frequency of non-injury crashes. The larger variance in speed limits caused more PDO crashes.
- The number of lane drops increasingly affected PDO crash occurrences.
- Interstate highways tend to have fewer property damage crashes than state highways.
- The number of ramps and intersections increases non-injury CF.
- Work zone speed limit was not significant for the PDO model.
- The alpha value showed overdispersion occurred, because the values differ from 0. The NB model was found appropriate for modeling PDO crashes.
- The intercept value was significant for the PDO CF model.

Table 3-6 Estimated Parameters of PDO Crash Frequency Model (N=950)

Variable	Coefficient	Std. Err.	z	P>|z|	Significant
ln(length)	0.476	0.118	4.04	0.000	***
night	-0.314	0.152	-2.07	0.039	*
ln(aadt)	0.446	0.110	4.06	0.000	***
wzspeed	-0.011	0.009	-1.22	0.223	
operatedlane	0.581	0.099	5.87	0.000	***
lanedrop	0.253	0.084	3.00	0.003	**
speedreduction	0.036	0.010	3.46	0.001	***
roadsystem	0.473	0.138	3.42	0.001	***
ramp	0.042	0.020	2.15	0.032	*
intersection	0.013	0.007	1.84	0.066	.
intercept	-4.648	0.876	-5.30	0.000	***
alpha	0.501	0.040			
chibar2 =	896.1	Prob>=chibar2 = 0.000			

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Three monthly work zone PDO crash counts were modeled by the Negative Binomial regression technique. The PDO crash frequency model result, shown at Table 3-6, depicts the finding that AADT has a significant incremental effect on PDO crashes. A 1% increment in AADT causes a 0.45% increase in total number of work zone PDO crashes. Additional operating lanes causes a 78.8% increase in total PDO crashes since AADT represents traffic volume per lane. Similarly, a lengths' marginal effect of 1% increase causes 0.48% more PDO crashes. As distinct from normal crash modeling parameters, lane drop and speed reduction were also effective for the number of PDO crashes. One more lane drop caused 28.8% and 1 mph speed reduction caused a 3.7% increase in PDO crashes, while other parameters were kept constant. Since reduced AADT was used for the nighttime condition, this interpretation was not biased due to the lower volume of traffic during the nighttime. Considering the AADT adjustment, the night condition decreased overall crash counts by 26.9% when compared to daytime condition. If the work zone occurred on state highways, 60.4% more PDO accidents were expected according to the modeling results. One more ramp within the work zone section caused 4.3% more PDO crashes for the construction site. A proportional increase in PDO crashes was found to be higher than the number of injury crashes.

Interpretation of NB Model for Injury Accidents

- The number of operated lanes and AADT, which reflects traffic density per lane, was the most effective parameter in predicting injury CF.
- Length of the work zone was strongly associated with the number of injury crashes during the work zone period.
- Injury CF was lower at nighttime than in the daytime.
- Lane drop was also an effective parameter for injury crash occurrence within work zones.
- Speed reduction had a slight effect on injury crashes.
- Interstate highways tended to have fewer injury crashes than state highways.
- The number of intersections, number of ramps, and work zone speed limit parameters were not significant (at the level of 95 percent significance) for the injury crash model.
- The intercept value was significant for the model.

Table 3-7 Estimated Parameters of Injury Crash Frequency Model (N=950)

Variable	Coefficient	Std. Err.	z	P>|z|	Significant
ln(length)	0.642	0.153	4.20	0.000	***
night	-0.381	0.189	-2.02	0.043	*
ln(aadt)	0.325	0.137	2.36	0.018	*
wzspeed	-0.016	0.011	-1.46	0.143	
operatedlane	0.590	0.126	4.69	0.000	***
lanedrop	0.393	0.102	3.84	0.000	***
speedreduction	0.024	0.014	1.81	0.071	.
roadsystem	0.959	0.184	5.21	0.000	***
ramp	0.023	0.024	0.96	0.337	
intersection	-0.001	0.009	-0.16	0.873	
intercept	-4.752	1.138	-4.18	0.000	***
alpha	0.489	0.061			
chibar2 =	172.1	Prob>=chibar2 = 0.000			

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

The third model was developed to predict 3 monthly injury crash counts within work zones. According to the modeling results at the 95 % level of significance, the length of the work zone was one of the most effective variables for explaining the injury crashes when compared to the PDO crashes. A 1% increment in length caused a 0.64% increase in injury crash counts. AADT and number of operating lanes were both significant and represented exposure to traffic. Nighttime injury crash occurrence probability rates at work zones were 31.8% less numerous than daytime occurrences. Ullman et al. (2008) stated in their study that nighttime does not cause a significantly greater risk for crash severity than daytime for motorists encountering work zone conditions. Interestingly, work zones at state highways were more likely to have very highly increased injury rates by about 160.9 percent. Lane drop is another efficient factor for increasing injury crash frequency rates at work zones. One more lane drop caused 48.1% more injuries at construction sites.

3.5 Temporal Analysis of Work Zone Crashes and Driver Familiarity

Plotting crash counts by sequential periods provides an idea about the unfamiliarity effects of work zones. The temporal distribution of crashes was further investigated in terms of change in rear-end crash types and night time versus daytime crash count rates.

The main hypothesis was that drivers who may not be familiar with a given mid or long term work zone at the beginning of these projects, then learn based on their day-to-day encounters with the same work zone conditions and adapt their behaviors accordingly. Thus, more crashes may occur at the beginning of the work zone project periods. This hypothesis may be especially relevant when tested for rear-end crashes, the most frequent work zone crash type. Again nighttime shift maximizes the unfamiliarity for drivers. Thus the nighttime crash percentage for the initial period of the work zone projects was compared with the overall occurrence rates of nighttime crashes for the entire duration of the work zone projects.

One way to test this hypothesis was to add the time indicator to the negative binomial crash frequency model. Since the "learning" in the initial period may vary by type or by duration of the work zone projects, a sensitivity analysis was performed to better understand the effect of the initial time period on the dependent measure. As can be seen from the Figure 3-18, there was a significant change for crash occurrence for the initial period of the work zone projects. Crash frequency was stabilized to non-work crash occurrence level after about two year.

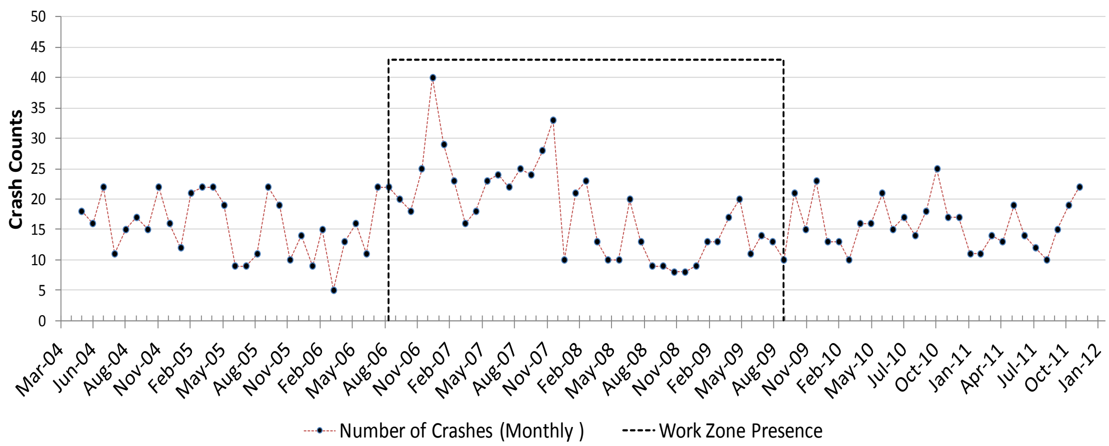


Figure 3-18 Number of Monthly Crashes for Work Zone Project on US 1 North, NJ

3.5.1 Modeling of Initial Impact on Work Zone Crash Frequency

The initial impact of work zones was investigated by using the same modeling structure employed for assessing work zone crash frequency. To clearly examine work zone impact at the beginning of the project, the initial impact data was included within the model as a dummy variable. Three different statistical models were developed; the total crash, PDO crash and injury crash frequency models. The definition of initial impact was selected to represent the first three months period of the each project.

By using the same dataset from the work zone crash frequency modeling section, the following parameters were included within the frequency models; initial impact, length, light conditions, annual average daily traffic (AADT), posted speed, numbers of operated lanes, road type, numbers of ramps and intersections within the work zone. The structure for the crash frequency was developed by using the Negative binomial model. Equation 3-8 represents the modeling structure for the work zone crash frequency modeling for estimating "initial impact".

$$\begin{aligned} \text{crash\_count} = \exp(&\beta_0 + \beta_1 \text{initialimpact} + \ln(\text{length})^{\beta_2} + \ln(\text{aadt})^{\beta_3} + \\ &+ \beta_4 \text{night} + \beta_5 \text{intersection} + \beta_6 \text{ramp} + \beta_7 \text{wzspeed} + \\ &\beta_8 \text{roadtype} + \beta_9 \text{operatedlane}) \end{aligned} \tag{3-8}$$

3.5.2 Modeling Results for Initial Impact of Work Zone Crash Frequency

The estimated results from the three different statistical models are provided within Table 3-8. The interpretation of the modeling results was considered at the 95 percent level of significance confidence interval. According to Table 3-8, all parameters were significant except, road system for total and PDO crash models, ramp for PDO and injury models, and dummy night factors for the injury models. Alpha values showed that the negative binomial was appropriate to use in this case as count data.

Table 3-8 Modeling Results for Initial Impact of Work Zones

Crash Frequency / Variables	Total Crash Count		PDO Crash Count		Injury Crash Count	
	Coef.	**P>|z|**	**Coef.**	**P>|z|**	**Coef.**	**P>|z|**
initial	**0.204**	**0.000**	**0.178**	**0.002**	**0.257**	**0.001**
ln(aadt)	0.659	0.000	0.669	0.000	0.661	0.000
ln(length)	0.496	0.000	0.522	0.000	0.509	0.000
night	-0.142	0.039	-0.196	0.008	0.052	0.585
intersection	0.015	0.000	0.015	0.000	0.013	0.001
ramp	0.018	0.039	0.011	0.211	0.020	0.080
psl	-0.021	0.000	-0.016	0.001	-0.030	0.000
roadsystem	-0.042	0.561	-0.102	0.179	0.207	0.044
lanestd2	0.200	0.000	0.174	0.000	0.250	0.000
intercept	-4.076	0.000	-4.540	0.000	-5.502	0.000
alpha	0.212		0.212		0.225	

From the modeling results, work zone initial impact data for first three month period of the project was shown to include an initial period with a 22.7 percent higher frequency rate in terms of total crashes when compared to other periods. Similarly, a 19.4 percent higher frequency rate was observed for PDO crashes and a 29.3 percent higher rate for injury crashes was found to be associated with the initial impact of the work zones on highways. Different from the previous crash frequency model, injury crashes were more numerous when compared to PDO crashes. Other parameters had similar impacts in terms of crash frequency. Therefore, it can be concluded that there was no interaction between the initial impact and the other variables. If we look specifically at the data, a 1 percent increase in traffic caused a 0.66 percent increase in crashes, and a 1 percent increase in project length caused a 0.51 percent increase for each model.

3.6 Comparison of Crash Frequency between Work Zone and Non-Work Zone Conditions

3.6.1 Comparison of Descriptive Characteristics for Work and Non-Work Zone Crashes

To avoid bias for any seasonal effect and change in traffic conditions, pre-work zone and during work zone crash rates were estimated for one year before and one year after the beginning of the project conditions, respectively. If the work zone duration was less than one year, the same seasonal periods were considered as had occurred before the conditions. Based on a before-during analysis, the total number of crashes, daytime crash and daytime PDO crashes were increased for 34 out of the 45 work zone sites (75.6 %). Nighttime crash counts increased for 28 out of the 45 work zone sites (62.2%), daytime and nighttime injury crashes increased for 26 out of the 45 work zone sites (57.8%). Table 3-9 shows the before-during comparative results for the crash frequency and crash rates. Average crash frequency increased by 18.7 percent and crash rates increased by 24.4 percent for work zone conditions when compared to non-work zone conditions. Daytime crashes increased more than night time crashes, and PDO crashes increased more than injury crashes. Nighttime injury crashes increased more compared to daytime injury crashes.

Table 3-9 Before - During Comparison of Crash Rates at Work Zone Sites (N=45)

	Monthly Average Crash Number			Monthly Average Crash Rate		
	Non-WZ	WZ	% Δ	Non-WZ	WZ	% Δ
Count	6.6	7.9	18.7%	144.2	179.3	24.4%
Day	4.6	5.6	20.7%	101.6	130.6	28.5%
Night	2.0	2.3	14.0%	41.8	47.4	13.6%
WZDayInjury	1.2	1.4	15.5%	28.5	34.7	21.6%
WZNightInjury	0.6	0.7	18.1%	13.3	16.3	23.2%
WZDayPDO	3.4	4.2	22.6%	73.0	95.9	31.2%
WZNightPDO	1.4	1.6	12.2%	29.3	32.4	10.6%
Min Average	1.3	1.4		25.2	35.8	
Max Average	17.4	24.8		529.4	657.8	
Std. Dev.	4.6	5.3		103.2	141.9	

A descriptive comparison of factors between work zone and non-work zone crashes is shown in Table 3-10. Consistent with previous descriptive studies, rear-end crashes were found to be the dominant crash type in work zones. The rear-end crash ratios among all crash types was 8.6 percent more for work zone conditions when compared to non-work zone conditions. Hall and Lorenz (1990) found rear-end crashes increased from 9 to 14 percent at highway construction zones in New Mexico Rouphail et al. (1988) found more than a 50 percent increase for rear-end crashes at freeway work zones in Illinois. Since the comparison was only performed for the same sites on the highways, the changes in crash types reflects the work zone impact on the crash type distribution. If all crashes in New Jersey between 2001 and 2011 are compared for work zone and non-work zone conditions, the change in rear-end crash type was 17.6 percent. This difference may be caused by the distribution of the crashes throughout the overall road system where more than 50 percent of all the crashes occur on municipal and county roads. Approximately 70 percent of the work zone crashes occurred on highways in New Jersey, between 2004-2010.

Crash severity was found to decrease during work zone conditions. As is seen from data in Table 3-10, injury and fatality ratios under the work zone condition were 2.2 and 0.1 percent lower than those of non-work zone crashes, in terms of percent, respectively. This is consistent with findings by Rouphail et al. (1988). However, some studies concluded that there is no significant difference between work zone and non-work zone crash severity.

For work zone crashes clear weather condition were observed to constitute 83 percent of all weather conditions, which is 6.6 percent more than that of non-work zone condition. This is expected because work zones are usually deployed in better weather conditions. Accordingly, work zones have 4.4 percent fewer crashes during rainy conditions. Garber and Zhao (2002) found that 50 percent of work zone crashes occurred in clear weather conditions. Dissanayake and Akepati (2009) found most work zone crashes occurred during daytime and under clear weather conditions. There was no significant difference between day- night time as well as peak-off peak crash ratios for work zone conditions. The ratio for single crashes was 8 percent lower and the crash ratio for two vehicles involved was 6.9 percent higher for work zone conditions than non-work zones. The number of crashes associated with "driver inattention" and "following too closely" was slightly higher and the number of crashes with "unsafe speeds" was lower for work zone conditions. A reduced speed limit or awareness may have reduced the number of crashes due to the unsafe speed at work zone sites.

Table 3-10 Crashes Characteristics in WZ and Non-WZ Conditions

Type	Description	Non-Work Zone		Work Zone		Difference
		Number	%	Number	%	
Crash Type	Rear End	20,449	48.7%	5,012	57.3%	+8.6%
	Side Swipe	9,193	21.9%	2,066	23.6%	+1.7%
	Fixed Object	6,824	16.2%	886	10.1%	-6.1%
	Non-fixed Object	1,041	2.5%	223	2.6%	+0.1%
	Right Angle	1,221	2.9%	152	1.7%	-1.2%
	Other	3,289	7.8%	410	4.7%	-3.1%
Severity	Fatality	128	0.3%	20	0.2%	-0.1%
	Injury	11,090	26.4%	2,121	24.2%	-2.2%
	Property Damage	30,799	73.3%	6,608	75.5%	+2.2%
Day-Night	Day	12,820	69.5%	2,623	70.0%	-0.5%
	Night	29,197	30.5%	6,126	30.0%	+0.5%
Peak - Off Peak	Off-Peak	25,621	61.0%	5,372	61.4%	+0.4%
	Peak	16,396	39.0%	3,377	38.6%	-0.4%
Speed (mph)	0-34	1,158	3.0%	308	3.7%	+0.7%
	35-44	4,925	12.7%	1,383	16.6%	+3.8%
	45-54	12,002	31.0%	5,108	61.2%	+30.1%
	55-64	8,779	22.7%	1,016	12.2%	-10.5%
	65 <	11,812	30.5%	537	6.4%	-24.1%
Total Vehicle Involved	1	8,768	20.8%	1,126	12.9%	-8.0%
	2	25,920	68.7%	6,619	75.6%	+6.9%
	3	3,465	8.2%	777	8.9%	+0.6%
	4 and up	958	2.3%	238	2.7%	+0.4%
Weather	Clear	32,081	76.4%	7,259	83.0%	+6.6%
	Rain	7,066	16.8%	1,103	12.6%	-4.2%
	Snow	1,444	3.4%	155	1.8%	-1.7%
	Overcast	931	2.2%	186	2.1%	-0.1%
	Other	499	1.2%	46	0.5%	-0.7%
Contributing Factors*	None	35,910	44.6%	8,250	46.7%	2.1%
	Driver inattention	19,468	24.2%	4,690	26.5%	2.3%
	Following too closely	4,950	6.1%	1,260	7.1%	1.0%
	Improper lane change	3,254	4.0%	713	4.0%	0.0%
	Unsafe speed	3,513	4.4%	409	2.3%	-2.1%
	Other	13,494	16.7%	2,354	13.3%	-3.4%

**Records from all involved vehicles.*

3.6.2 Modeling Structure for Both Conditions

To examine the effect of work zone parameters on crash frequency the same model structure was used for both work zone and non-work zone conditions. Specific parameters such as numbers of lane drops or speed reduction were not included in the model in order to obtain better and unbiased results. The difference between the coefficients for both models showed the effect of each parameter within the work zone conditions. Table 3-11 shows the parameters for the crash frequency modeling data for work zone and non-work zone conditions.

Table 3-11 Variables Considered in the Negative Binomial (NB) Model

Category	Variable	Type	Description
AADT	aadt	continuous	adjusted ADT (seasonal factor, time factor)
Length	length	continuous	length of the work zone (mile)
Light Conditions	night	indicator	daytime = 0, nighttime = 1
Intersection	intersection	Continuous	number of intersections at work zone
Ramp Number	ramp	continuous	number of ramps at work zone
Posted Speed	psl	continuous	reduced posted speed limit (mph)
Road System	roadsystem	indicator	interstate = 0, state = 1
Number of Lane	operatedlane	indicator	number of operating lanes

Crash frequency was modeled for both conditions by using three monthly crash counts as a dependent variable. Equation (3-9) shows modeling structure for the crash frequency.

$$\begin{aligned} \text{crash\_count} = \exp(&\beta_0 + \ln(\text{length})^{\beta_1} + \beta_2\text{night} + \ln(\text{aadt})^{\beta_3} + \beta_4\text{psl} + \\ &\beta_5\text{operatedlane} + \beta_8\text{roadtype} + \beta_9\text{ramp} + \beta_{10}\text{intersection}) \end{aligned} \quad (3\text{-}9)$$

3.6.3 Comparison of Modeling Results

Crash frequencies for the number of total crashes, PDO crashes and injury crashes was modeled by using Equation 3-9. Sample sizes were 1764 for the non-work zone and 1248 for the work zone and three monthly crash counts for day and night time conditions were analyzed separately.

Total Crashes Comparison

Table 3-12 shows results for WZ and Non-WZ crash frequency models. Both models have sufficient alpha numbers for supporting the negative binomial model selection process. All parameters had a significant p values within 95 percent, except for the road system at work zone model.

Table 3-12 Crash Frequency Modeling Results for WZ and Non-WZ Conditions

Total Crashes	**Non-WZ (N=1764)**			**Work Zone (N=1248)**		
Variable	**Coefficient**	**Std. Err.**	**P>|z|**	**Coefficient**	**Std. Err.**	**P>|z|**
ln(aadt)	0.941	0.046	0	0.660	0.056	0
ln(length)	0.745	0.034	0	0.493	0.038	0
night	0.228	0.057	0	-0.141	0.069	0.041
intersection	0.022	0.003	0	0.015	0.003	0
ramp	-0.021	0.008	0.005	0.018	0.009	0.046
psl	-0.040	0.003	0	-0.021	0.005	0
roadsystem	-0.192	0.056	0.001	-0.048	0.073	0.511
lanestd2	0.166	0.037	0	0.194	0.045	0
intercept	-5.718	0.389	0	-4.057	0.413	0
alpha	0.188	0.011		0.216	0.013	

The differences between the coefficients show the different effects of each parameter on work zone conditions. If we estimate the odd ratios of each parameter then the unique effect of the parameters will appear for both conditions. Since naturel logarithmic values were used for the AADT and length parameters, these parameters were compared based on the effect of percent change, such as a 1 percent increase causing an X amount of increase in the total number of crashes. Table 3-13 shows the odds ratio details for the total number of crashes at work zone and non-work zone conditions.

Table 3-13 Crash Frequency Odd-Ratio Comparison for Modeling Parameters

Variable	**Explanation**	**Non-WZ**	**WZ**	**Difference (WZ and Non-WZ)**
ln(aadt)	1% Increase	1.009	1.007	0.25%
ln(length)	1% Increase	1.007	1.005	0.28%
night	Night	1.26	0.87	38.71%
intersection	1 more intersection	1.02	1.02	0.67%
ramp	1 more ramp	0.98	1.02	-3.90%
psl	1mph increase	0.96	0.98	-1.79%
roadsystem	If state	0.83	0.95	-12.78%
lanestd2	1 more lane	1.18	1.21	-3.37%

Based on the odds ratio comparison of the modeling results for work zone and non-work zone conditions,

- A 1 percent increase in traffic effects non-work zones 0.25 percent more than work zones,

- A 1 percent increase in project length effects non-work zones 0.28 percent more than work zones,
- Nighttime conditions for non-work zones produce 38.71 percent more crashes compared to work zone conditions,
- Intersections have similar effects for both conditions,
- 1 more ramp increased the work zone crash frequency by 3.9 percent compared to non-work zone conditions,
- Posted speed had a higher impact on work zones when compared to non-work zone conditions,
- State roads pose 12.78 percent more risk for work zone conditions when compared to non-work zone conditions.
- One-more lane caused a 3.37 percent increase in work zone crash frequency.

PDO Crashes Comparison

Based on the crash frequency modeling results for both work zone and non-work zone conditions, all parameters were found to be significant at the level of 95 percent confidence interval, except for the number of ramps and road systems for the work zone conditions. Table 3-14 provides the crash frequency modeling results for both conditions by using 3 monthly crash counts. Table 3-15 provides a comparison of the odds ratio of the variables for both conditions which had a significant effect on crash frequency. Based on these values, the AADT and project length had similar effects on crash frequency as the total crash frequency modeling results. Interestingly, the difference between impacts of nighttime on crash frequency is higher for PDO crashes. PDO crashes were 41.98

percent less likely to occur at night at work zones when compared to non-work zone conditions. Other parameters had a similar effect on crash frequency for the work and non-work zone conditions.

Table 3-14 PDO Crash Frequency Modeling Results for WZ and Non-WZ Conditions

PDO Crashes	**Non-WZ (N=1764)**			**Work Zone (N=1248)**		
Variable	**Coefficient**	**Std. Err.**	**P>|z|**	**Coefficient**	**Std. Err.**	**P>|z|**
ln(aadt)	0.975	0.052	0	0.671	0.060	0
ln(length)	0.734	0.038	0	0.519	0.040	0
night	0.218	0.063	0.001	-0.194	0.074	0.008
intersection	0.021	0.003	0	0.015	0.003	0
ramp	-0.022	0.008	0.008	0.011	0.009	0.231
psl	-0.038	0.004	0	-0.016	0.005	0.002
roadsystem	-0.276	0.061	0	-0.108	0.076	0.156
lanestd2	0.132	0.041	0.001	0.169	0.047	0
intercept	-6.306	0.440	0	-4.526	0.448	0
alpha	0.209	0.012		0.215	0.015	

Table 3-15 PDO Crash Frequency Odd-Ratio Comparison for Modeling Parameters

Variable	**Explanation**	**Non-WZ**	**WZ**	**Difference (WZ and Non-WZ)**
ln(aadt)	1% Increase	1.010	1.007	0.21%
ln(length)	1% Increase	1.007	1.005	0.31%
night	Night=1	1.244	0.824	41.98%
intersection	1 more intersection	1.022	1.015	0.65%
ramp	1 more ramp	0.978	1.011	-3.30%
psl	1mph increase	0.963	0.984	-2.10%
roadsystem	State=1	0.759	0.897	-13.84%
lanestd2	1 more lane	1.141	1.184	-4.26%

Injury Crashes Comparison

Results from the crash frequency models for both conditions when using three monthly injury crash counts are given in Table 3-16. Similarly, all parameters within the models were found to be significant except for the road system for non-work zone crashes, and nighttime for work zone crashes.

Table 3-16 Injury Crash Frequency Modeling Results for WZ and Non-WZ Conditions

Injury	**Non-WZ (N=1764)**			**Work Zone (N=1248)**		
Variable	**Coefficient**	**Std. Err.**	**P>|z|**	**Coefficient**	**Std. Err.**	**P>|z|**
ln(aadt)	0.873	0.059	0	0.660	0.077	0
ln(length)	0.750	0.045	0	0.507	0.054	0
night	0.288	0.073	0	0.050	0.096	0.601
intersection	0.025	0.004	0	0.013	0.004	0.001
ramp	-0.017	0.009	0.068	0.020	0.012	0.083
psl	-0.037	0.004	0	-0.029	0.007	0
roadsystem	0.057	0.074	0.442	0.208	0.104	0.045
lanestd2	0.226	0.046	0	0.246	0.062	0
intercept	-6.811	0.525	0	-5.463	0.596	0
alpha	0.136	0.016		0.230	0.025	

The odds ratios for the modeling results are provided in Table 3-17. Based on these estimations, traffic and project length had a similar effect to total crash and PDO crash count models. Different from the previous results, the number of ramps had a higher impact on injury crash frequency at work zone locations when compared to non-work zone conditions. Besides, work zones at state roads had a 17.35 percent higher risk when compared to non-work zone condition on state roads.

Table 3-17 Injury Crash Frequency Odd-Ratio Comparison for Modeling Parameters

Variable	Explanation	Non-WZ	WZ	Difference (WZ and Non-WZ)
ln(aadt)	1% Increase	1.009	1.007	0.21%
ln(length)	1% Increase	1.007	1.005	0.24%
night	Night	1.334	1.051	28.26%
intersection	1 more intersection	1.025	1.013	1.16%
ramp	1 more ramp	0.983	1.020	-3.68%
psl	1mph increase	0.963	0.971	-0.78%
roadsystem	If state	1.058	1.232	-17.35%
lanestd2	1 more lane	1.253	1.278	-2.53%

3.7 Summary

This chapter illustrates the relationship between work zone presence and crash occurrence through a detailed descriptive analysis and crash frequency models. The negative binomial modeling was utilized to analysis crash frequency. Crash frequency was investigated in three sections:

- Work zone crash frequency for PDO and injury crashes,
- Modeling work zone crash frequency by using initial impact, and
- Comparison of the work zone and non-work zone crash frequencies

According to the results from the descriptive analysis, it was found that the average number of crashes and crash rates increased by 18.8 and 24.4 percent respectively compared to pre-work zone conditions. From the modeling results, a proportional increase in PDO crashes was found to be higher than the injury crashes. Lane closure was found to have an increasing effect on work zone crash frequency.

In addition to comparison of the frequency modeling, initial impact of the work zone on crash frequency investigated. For the first period, work zone crash frequency was found to be 22.7 percent higher for first three months period. Initial impact factor was found to be higher for injury crashes compared to PDO crashes.

When compared to work zone conditions, non-work zone crash frequencies were increased more due to exposure parameters such as AADT and segment length. One of the major findings from this section is that nighttime has a decreasing effect for both PDO and injury work zone crash frequency compared to non-work zone crashes. Nighttime effect on work zone crash frequency is 38 percent higher than the nighttime effect on non-work zone crash frequency. In another saying work zone presence during nighttime was found to be safer compared to daytime. State highways are less likely to have risk for the motorist for both work zone and non-work zone conditions; however, work zone at state highway have 12.8 percent higher risk compared to non-work zone one. The number of intersections and ramps were found to be positively correlated with crash frequency and to have slightly higher impact on work zone crash frequency along the studied segments.

CHAPTER 4 SEVERITY MODELING OF WORK ZONE CRASHES

4.1 Introduction

Safety improvements for road users are one of the most important factors for transportation systems. Billions of dollars are invested in projects to reduce the many risks for road users. In recent years, by increasing the number of renovations or reconstruction projects on roadways, work zone safety has become one of the critical arguments for project planning decisions. Work zone crashes are now considered to be an essential part of the project cost. Some of the states apply incentives / disincentives in terms of road user costs which are mainly based on time and crash costs (Zhu et al., 2009). Hence, it is essential to figure out possible causes for crash severity.

In this chapter, crash severity for work zone crashes is investigated in terms of severity by using various modeling technique including possible factors for crash severity. Numerous parameters thought to be related to crash severity are available in the crash records for different levels. Most studies used crash based analysis for work zone crash severity. Different statistical regression techniques were applied to examine the best model or set of variables to connect crash severity and possible causative factors. Crash severity was investigated for binary level and multiple level outcomes. A stepwise regression technique was used to avoid including insignificant parameters. The new crash severity indexes were proposed to estimate multilevel crash severity by using both maximum severity and the total monetary costs of the severity within a crash.

Work zone crashes between 2004 and 2010 years were focused by using data available through the NJDOT website (NJDOT, 2011). Datasets from different categories were merged by using the R package program. Descriptive statistics for these crashes are also included in this chapter. The methodology for modeling severity is mentioned statistically after the descriptive elements are presented. Binary and multiple level crash severity models were developed for both work zone and non-work zone crashes. The significant results from these models were compared to find out characteristic factors on the work zone crash severity. Comparison results are included in detail for each model at the end of this chapter.

4.2 Descriptive Statistics for Crash Severity

Classification is an essential process for forging relationships in terms of different severity levels and work zone crashes. Severity of crashes is classified as PDO, injury and fatality by adopting the New Jersey crash records format. Between 2004 and 2010, a total of 39208 work zone labeled crashes were reported in New Jersey. Table 4-1 shows the number of crashes per year in terms of different severity categories. In terms of total numbers, 75.8% of the work zone crashes were PDO, 24.0% of the work zone crashes were injury and 0.8% of the work zone crashes were fatal crashes. As can be seen from the numbers in 2010, an unusual increment was observed for work zone crashes for each category

Table 4-1 New Jersey Work Zone Crash Severity Statistics (2004-2010)

Crash Severity	2004	2005	2006	2007	2008	2009	2010	Total
PDO	4024	3450	4102	4619	3957	4294	5267	29713
Personal Injury	1354	1158	1438	1341	1223	1336	1552	9402
Fatal	9	16	14	11	12	13	18	93

According to the statistics, the fatality proportion appeared to be lower, but approximately one in every 4 accidents was the result by injuries at work zones. It was anticipated that by focusing on these work zone crashes, the relationship between crash severity and severity contributing factors would be explained. The following descriptive analyses provide the summary statistics linking the severity factor and possible contributing factors.

4.2.1 Severity Distribution by Time

The four different time periods were defined based on peak and off-peak hours. The severity versus time period data is shown as a pie chart below Figure 4-1. Based on the proportions observed, night time crashes seemed more severe than daytime crashes. Injury and fatal crashes ratio during off-peak night (20:00-06:00) were significantly higher than other periods. The AM peak (06:00-10:00) was the safer time period based on the statistical results. The most frequent work zone crashes occurred during daytime off peak periods (10:00-16:00) which was matched with possible construction times. The time periods and severity relationship was tested by using the chi-squared method. The test results (χ^2 = 95.768, df=6) showed that severity and time periods were related significantly at the 95% level of confidence.

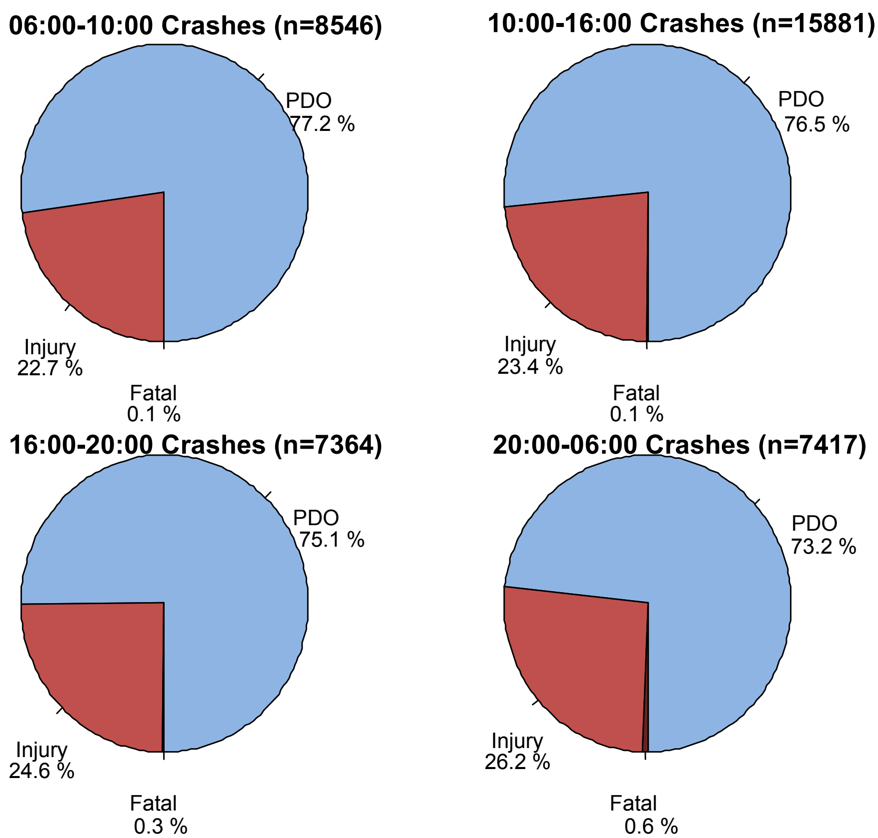


Figure 4-1 Severity Distributions by Time of the Day

4.2.2 Severity Distribution by Environmental Conditions

Light, weather and road surface conditions of work zone crashes were investigated as environmental conditions in terms of severity.

Figure 4-2 shows the work zone crashes distributions for different light conditions. The original database included 7 different light conditions such as daylight, dusk, dawn etc. For the sake of simplicity, light conditions were categorized as daylight and poor light conditions. According to the statistics, poor light conditions were more risky for drivers.

Injury and fatality proportions were higher for poor light conditions. Chi-squared test results (χ^2=88.609, df = 2) indicated that light conditions and severity were correlated significantly.

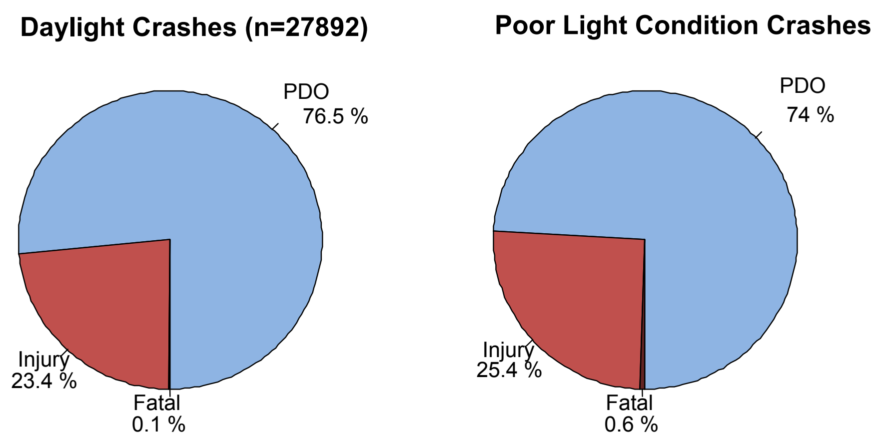


Figure 4-2 Crash Severity Distributions under Different Light Conditions

Similar relationships were observed between road surface conditions and severity. As is seen below in

Table 4-2, there is no significant change in ratios for different road surface conditions. The Pearson chi-squared test result (χ^2=23.72, df = 16) showed that the *P* value (0.094) was greater than 0.05, therefore the null hypothesis that an association existed between the road surface conditions and work zone crash severity was rejected.

Weather conditions were categorized into 4 groups as shown below in Figure 4-3; clear, overcast, rainy and adverse weather conditions. The majority of the work zone crashes occurred during clear weather conditions (84.2%). Injury and fatalities slightly increased for overcast and rainy weather conditions. The Pearson chi-squared test result

(χ^2=15.72, df = 6) showed there was a significant (P < 0.05) association between the weather conditions and work zone crash severity variable.

Table 4-2 Road Surface Conditions versus Severity

Severity	Surface Condition								
	Dry	Wet	Snowy	Icy	Slush	Water (Standing/Moving)	Sand, mud, dirt	Oil	Other
PDO	24,301	4,397	369	279	49	40	97	6	68
%	82.1	14.9	1.3	0.9	0.2	0.1	0.3	0.0	0.2
Injury	7,695	1,458	78	71	17	9	23	4	22
%	82.1	15.6	0.8	0.8	0.2	0.1	0.3	0.0	0.2
Fatality	77	11	1	1	0	0	0	0	1
%	84.6	12.1	1.1	1.1	0.0	0.0	0.0	0.0	1.1

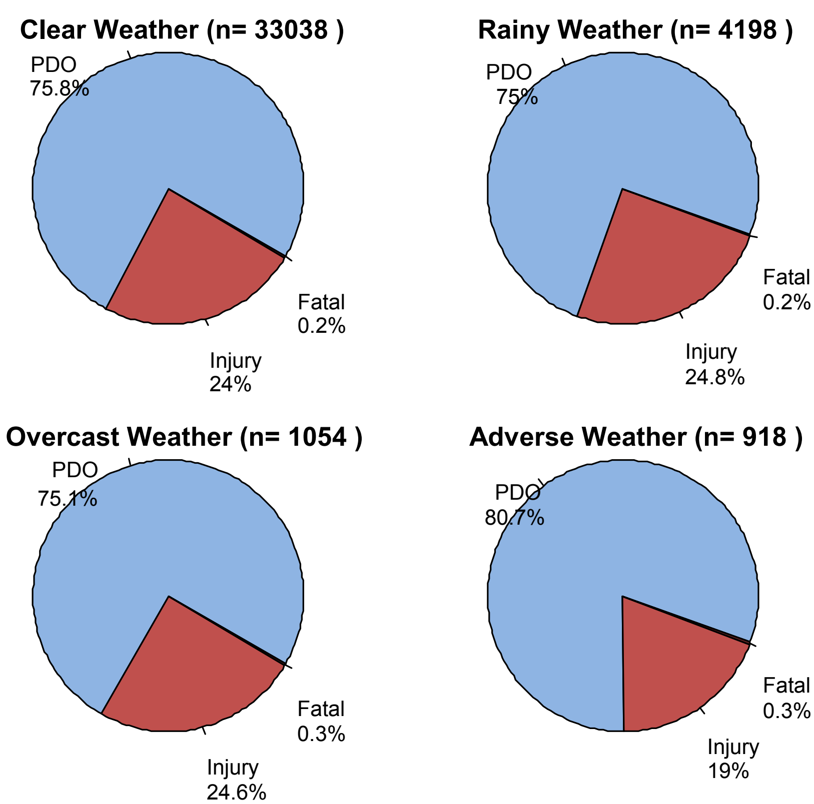


Figure 4-3 Crash Severity Distributions under Different Weather Conditions

4.2.3 Severity Distributions by Work Zone Types

Work zone types were included in the New Jersey crash records as temporary traffic control zones. As seen below in Table 4-3, the majority of the work zone crashes occurred at construction (91.98 %) work zones. The Pearson chi-squared test results indicated that (χ^2=5.8243, df = 4, P=0.213) there was no significant relationship between work zone types and crash severity. According to the statistics, injury crash proportions within maintenance work zones were slightly higher than other types of work zones. Similarly, fatal crash proportions within utility work zones were higher than other work zone types.

Table 4-3 Crash Severity Distributions at Different Work Zone Types

Severity	Work Zone Type			
	Construction	**Maintenance**	**Utility**	**Total**
PDO	20,444	857	938	22,239
% in PDO	91.93	3.85	4.22	100
% in Type	76.13	74.91	78.23	76.17
Injury	6,347	286	257	6,890
% in Injury	92.12	4.15	3.73	100
% in Type	23.64	25	21.43	23.6
Fatality	63	1	4	68
% in Fatality	92.65	1.47	5.88	100
% in Type	0.23	0.09	0.33	0.23
Total	26,854	1,144	1,199	29,197
	91.98	3.92	4.11	100
	100	100	100	100

4.2.4 Severity Distribution by Road Characteristics

Road systems were defined in the crash reports as interstate, state, municipal systems etc. These categories were merged into four characteristic categories based upon similarity; interstate highways, state highways, county roads and municipal and other roads. The Majority (67.2%) of the work zone accidents occurred at interstate and state highways. Four categories had similar severity proportions except for state highways that had significantly higher injury rates and interstate highways had a higher fatality rate. The Pearson chi-squared test result (χ^2=223.095, df = 6) showed there was a significant relationship between work zone crash severity data and road systems at the 95% level of significance. Figure 4-4 shows the severity distributions for the different types of road systems.

Median types were defined in the crash record file as barrier medians, curbed medians, grass and painted medians and no medians. These types were merged into two groups; the median group and the no median group.

Figure 4-5 indicates that 62 percent of the work zone crashes occurred on roads with medians, compared to about 38 percent of work zone crashes occurred on roads without median. The Pearson's Chi-squared test (χ^2=21.399, df = 2) shows that there is a relationship between the crash severity and roadway division type. Roadways by having median are slightly carrying higher risk for road users. Injury and fatality rates for roadways having no median are smaller than median designed roadways.

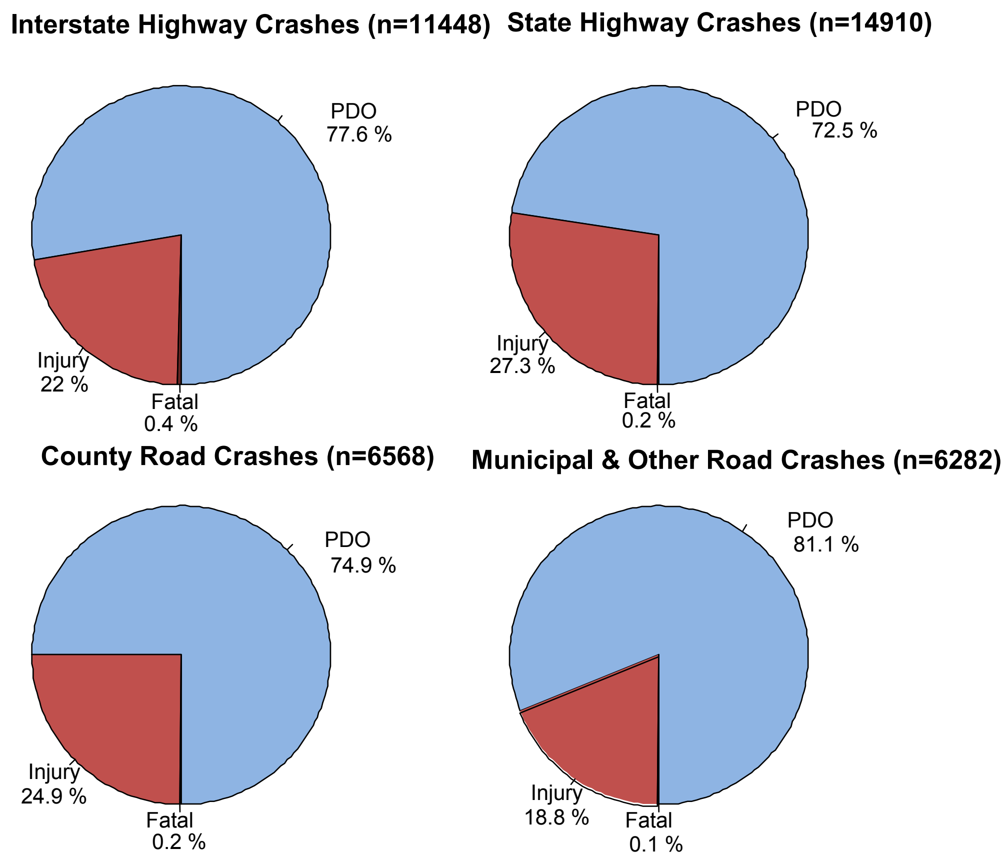


Figure 4-4 Crash Severity Distributions for Different Types of Roadways

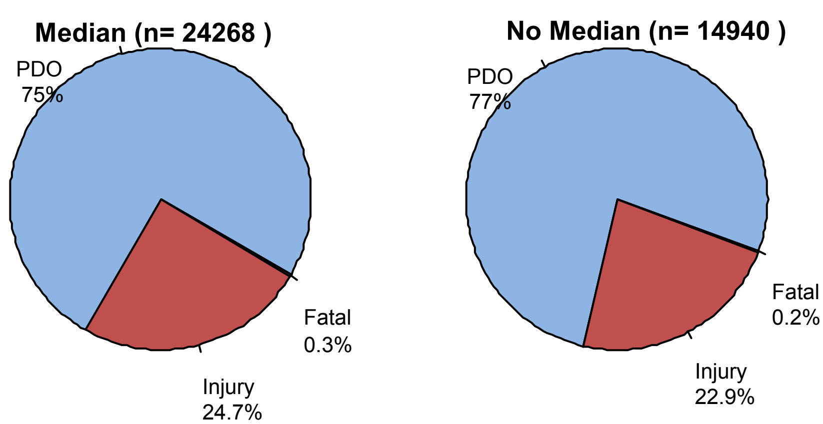


Figure 4-5 Crash Severity Distributions by Road Medians

Speed limit is one of the major concerns for the safety of roadways. In this present study, speed limit distributions for each severity category were investigated. Posted speed limits were grouped into 6 different range categories as shown below in

Figure 4-6. The majority of the work zone crashes occurred at a speed limit range of 45-54 mph. By increasing the posted speed limit, the injury and fatality proportions were also increased for that range. Fatality crash percentages increased significantly for speeds above 65 mph. The Pearson's Chi-squared test (χ^2=106.348, df = 10) showed there was a strong correlation between the speed limit and work zone crash severity.

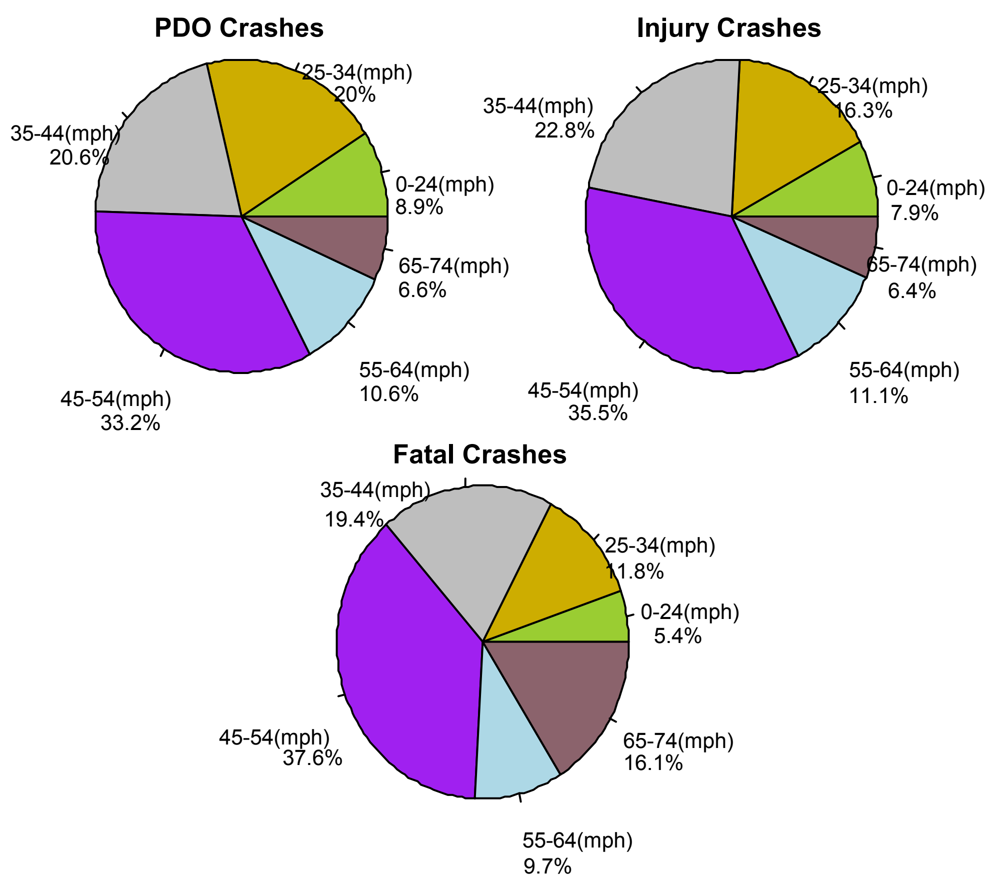


Figure 4-6 Crash Severity Distributions by Posted Speed Limits

4.2.5 Severity Distribution by Number of Vehicles Involved

The crash dataset reports "the numbers of involved vehicles" in a crash. In the present study, the relationship between crash severity and the number of involved vehicles relationship was investigated. Table 4-4 shows this relationship clearly. When excluding single vehicle crashes, an increasing number of vehicles caused increases in crash severity. Injury and fatality crash percentages were higher for 3 and 4 or more vehicles involved in crashes when compared to fewer vehicle work zone crashes. When single crashes were examined, almost 50 percent of the fatal crashes (N=46) occurred within this category. In terms of proportions, the highest ratio for fatal crashes was 0.87 percent for an involvement of 4 or more vehicles. The PDO crash proportion was the highest for two vehicle involved crashes (77.59%). The Pearson's Chi-squared test result showed that (χ^2=1383.398, df = 6) there was an association between the number of vehicle involved and crash severity within the 95 % level of significance.

Table 4-4 Crash Severity Distributions by Number of Vehicles Involved

Severity	Number of Vehicles Involved				
	1	2	3	4 or more	Total
PDO	4,774	23,053	1,600	286	29,713
% in PDO	16.07	77.59	5.38	0.96	100
% in Type	73.1	79.23	55.31	41.57	75.78
Injury	1,711	6,011	1,284	396	9,402
% in Injury	18.2	63.93	13.66	4.21	100
% in Type	26.2	20.66	44.38	57.56	23.98
Fatality	46	32	9	6	93
% in Fatality	49.46	34.41	9.68	6.45	100
% in Type	0.7	0.11	0.31	0.87	0.24
Total	6,531	29,096	2,893	688	39,208
% in Type	16.66	74.21	7.38	1.75	100

4.2.6 Severity Distribution by Number of Occupants Involved

Each occupant has a separate record with the same case number for each work zone crash. The numbers of occupants involved in a work zone crash was defined as the maximum occupant id for the same case number, and 100640 occupants were involved in 39208 work zone crashes. As the average occupant number for the investigated work zone crashes was 2.57, it was obvious, an increase in occupant involvement in the crash caused an increase in the injury and fatality proportions. Figure 4-7 shows the severity distributions in terms of numbers of occupants involved in work zone crashes. The fatality ratio increased significantly with 3 and 4 or more occupants involved in crashes. The injury ratio also increased from 22.7 percent to 26.2 percent from single occupant through 4 or more occupants involved in crashes. The Chi-squared test result (χ^2 =818.329, df = 6) showed a 95 percent level of significance correlation between the number of occupants involved and work zone crash severity.

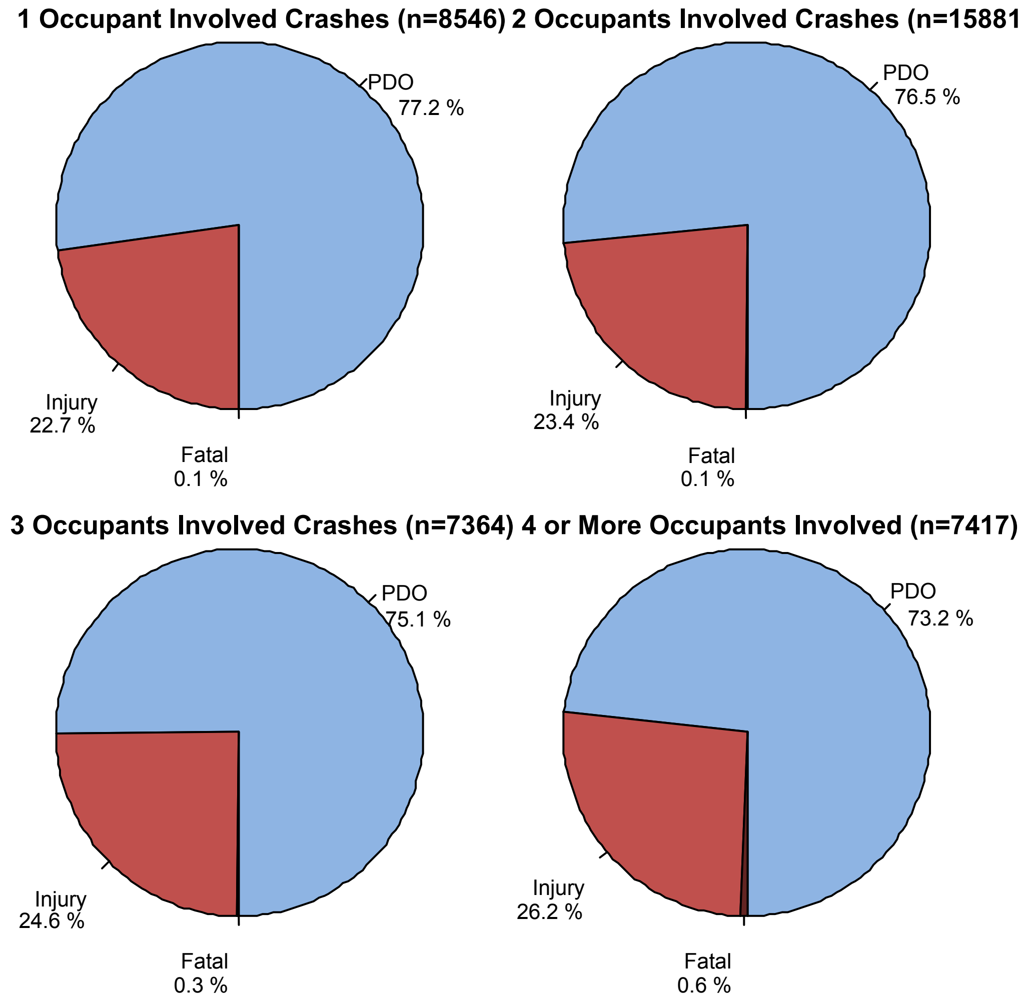


Figure 4-7 Crash Severity Distributions by Number of Occupants Involved

4.2.7 Severity Distribution by Truck Involvement

Truck involvement in a work zone accident is defined by a vehicle type column within the vehicle database. Figure 4-8 shows the distribution of severity for truck-involved crashes and truck not involved crashes, and that 18 percent of work zone crashes involved trucks. Surprisingly, truck involved crashes were less likely to be severe when compared to non-truck involved crashes. Injury and fatality proportions were significantly smaller for truck-involved crashes. The Pearson chi-squared test (χ^2 =366.943, df=2) result showed there was an association between truck involvement and crash severity within the work zones.

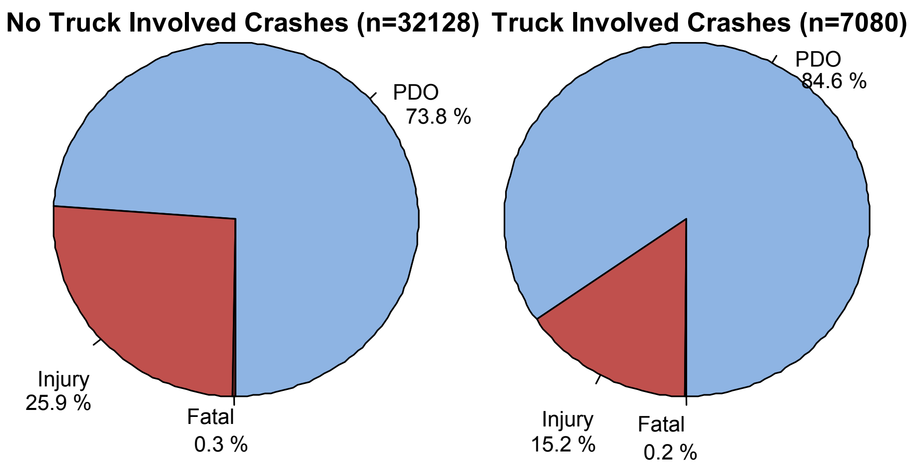


Figure 4-8 Severity Distributions of Truck Involved Crashes

4.2.8 Severity Distribution by Alcohol Use

Also included in the crash data base was information on alcohol involvement. Work zone crashes were thus investigated for alcohol involvement. Approximately 2.5 % of the work zone crashes were labeled as alcohol involved crashes. Figure 4-9 indicates the severity distribution in terms of alcohol involvement. As can be seen, there is an obvious difference in crash severity between alcohol involved and no alcohol involved crashes. Injury rates increased almost two fold and fatality rates increased three fold for alcohol involved crashes when compared to no alcohol involved crashes. There was a significant relationship between work zone crash severity and alcohol involvement proven by the Pearson's Chi-squared test result within the 95% level of significance (χ^2= 183.424, df=2).

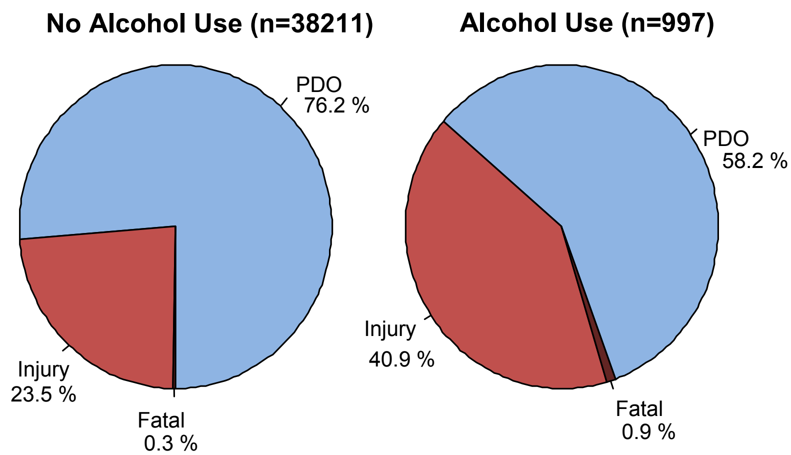


Figure 4-9 Severity Distributions of Alcohol Use Involved Crashes

4.2.9 Severity Distribution by Crash Types

The characteristic work zone crash types were defined by previous studies as rear-end crashes (Duncan et al., 1998; Meng and Weng, 2011; Khattak, 2001). Crash types were recorded as 17 different types. New Jersey work zone crashes severity distribution was investigated in terms of crash types. Table 4-5 shows the number of crashes for each crash type and crash severity. From Table 4-5 leading crash types for work zones can be interpreted as rear-end, side swipe, fixed object and right angle crashes. Rear-end crashes are more likely to be severe based on severity proportions. The injury percentage was 29.8 while the overall injury percentage was 24.0. Interestingly, the fixed object type was the leading type among the number of fatal crashes, and 26 of the 93 fatal crashes occurred as a fixed object crash. Approximately 85 percent of pedestrian and pedal-cyclist crashes resulted in an injury, and represented the highest injury rates among all crash types. If rail-car crash types are ignored because of the small number of these, pedestrian crash types had the highest proportion of fatalities, and 16 of the 93 fatality crashes within the work zones occurred as pedestrian crashes. Side swipes, backing up, and animal related types of crashes were the safest types among all crash types in terms of severity distribution. The Pearson chi-squared test result showed (χ^2 = 3695.471, df=32) a significant association between crash types and severity for the work zones.

Table 4-5 Work Zone Crash Severity Statistics by Crash Types (2004-2010)

Crash Type	**Total Number**	**Property Damage**		**Personal Injury**		**Fatal**	
		Number	Percent	Number	Percent	Number	Percent
Rear End	17234	12088	70.14%	5136	29.80%	10	0.06%
Side Swipe	7601	6843	90.03%	754	9.92%	4	0.05%
Right Angle	2899	2017	69.58%	875	30.18%	7	0.24%
Opposite (Head on, Angular)	418	220	52.63%	193	46.17%	5	1.20%
Opposite (Side Swipe)	194	150	77.32%	44	22.68%	0	0.00%
Struck Parked Vehicle	1704	1531	89.85%	168	9.86%	5	0.29%
Left Turn/ U Turn	664	438	65.96%	224	33.73%	2	0.30%
backing	943	890	94.38%	52	5.51%	1	0.11%
Encroachment	71	59	83.10%	12	16.90%	0	0.00%
Overturned	238	71	29.83%	161	67.65%	6	2.52%
Fixed Object	4559	3470	76.11%	1063	23.32%	26	0.57%
Animal	357	332	93.00%	25	7.00%	0	0.00%
Pedestrian	371	33	8.89%	322	86.79%	16	4.31%
Pedal-cyclist	128	19	14.84%	107	83.59%	2	1.56%
Non-fixed Object	1032	934	90.50%	94	9.11%	4	0.39%
Railcar-Vehicle	8	6	75.00%	1	12.50%	1	12.50%
Unknown	787	612	77.76%	171	21.73%	4	0.51%

4.3 Methodology

In this section, the factors that contributed to the severity of the work zone and non-work zone crashes were investigated by modeling this using stepwise logistic regression for the base severity analysis and by using binary levels crash severity outcomes. For multilevel crash severity outcomes, Ye and Lord (2013) defined three commonly used models, multinomial regression, ordered probit and mixed logit. Among these models, ordered the probit model is theoretically superior to most other models for analyzing this kind of dataset (Kockelman and Kweon, 2002).

4.3.1 Binary Level Work Zone Crash Severity Analysis

Work zone crashes were defined as either injury or non-injury crashes in terms of severity. Therefore crash severity could be represented as a dichotomous outcome (injury vs. non-injury) of a work zone crash.

Let $y = 1$ for the severity index injury and $y = 0$ for the non-injury crash. Binomial logistic regression is capable of modeling severity as a binary dependent variable to test the effects of different independent variables on the probability of crash severity. Thus, let $\pi(x)$ denote the probability of a injury work zone crash and $1 - \pi(x)$ is the probability of a non-injury work zone crash. From the model, the influence of the factors can be interpreted by the log odds of the dichotomous outcome and risk factors. This relationship can be formulated as outline in Equation 4-1:

$$\text{logit}[\pi(x)] = \log\left[\frac{\pi(x)}{1-\pi(x)}\right] = \alpha + X'\beta \tag{4-1}$$

According to Equation 4-1, the probability of injury work zone crash occurrence can be written by using the logistic distribution shown in Equation 4-2:

$$P(y = 1|X) = \pi(x) = \frac{exp(\alpha + X'\beta)}{1 + exp(\alpha + X'\beta)} \quad (4\text{-}2)$$

Where,

$\pi(x)$ = the conditional probability of the form $P(y = 1|X)$,

X = explanatory variables (risk factors),

α = intercept.

Parameters used for the logistic regression model were decided upon by using the Maximum-likelihood method. The validation of the overall model was tested by using a chi-square test. The independent risk factors for crash severity were determined by using the Wald chi-square statistics. The interaction between factor X and crash severity were analyzed using the odds ratio (OR), as outlined by the following Equation 4-3:

$$OR = \exp(\beta_j) \quad (4\text{-}3)$$

By using OR, the independent effect of a unit increase in each factor (for 95 percent level of significance) can be interpreted when the other factors are fixed.

4.3.2 Multi-level Work Zone Crash Severity Analysis

The crash severity index can be defined into descending or ascending categorical levels. For such a case, multinomial logit, ordered probit and mixed logit models are the most common methods for analyzing crash severity. The severity index was defined to represent five different levels for work zone crashes. The occupant's physical condition parameter obtained from the crash report was used.

The ordered probit model is superior to the most other crash severity models regarding data's ordinal attributes (Kockelman and Kweon, 2002). Ordered probit regression was chosen as a technique for modeling the work zone crash severity. Since there were large numbers of parameters, for the sake of simplicity, the stepwise technique was used to filter the significant parameters related to the severity index.

Let y_n denote the observed maximum injury severity level for the work zone crashes, and μ_i (i=1,2,3,4) denote threshold points as following;

$y_n = 0$ (no injury)	if	$y_i < \mu_1$
$y_n = 1$ (complaint of pain)	if	$\mu_1 \leq y_i < \mu_2$
$y_n = 2$ (moderate injury)	if	$\mu_2 \leq y_i < \mu_3$
$y_n = 3$ (incapacitated)	If	$\mu_3 \leq y_i < \mu_4$
$y_n = 4$ (killed)	if	$\mu_4 \leq y_i$

$$y_n = \beta' X_n + \varepsilon_n \tag{4-4}$$

Where;

$\mathrm{y_n}$ = maximum observed crash severity index in a crash

β' = Coefficient of factors to be estimated

ε = error term

According to these equations, the probability of work zone crash severity index for each level can be described as following;

$$P(0) = \Pr(y_n = 0) = \Pr(\ y_n^* \leq \ \mu_1) = \Pr(\beta' X_n + \varepsilon_n \leq \mu_1) =$$

$$\Pr(\ \varepsilon_n \ \leq \mu_1 - \beta' X_n) = \Phi(\mu_1 - \beta' X_n) \qquad (4\text{-}5)$$

$$P(1) = \Pr(y_n = 1) = \Pr(\mu_1 \ \leq y_n^* \leq \ \mu_2) = \Phi(\mu_2 - \beta' X_n) - \ \Phi(\mu_1 - \beta' X_n) \qquad (4\text{-}6)$$

$$P(2) = \Pr(y_n = 2) = \Pr(\mu_2 \ \leq y_n^* \leq \ \mu_3) = \Phi(\mu_3 - \beta' X_n) - \ \Phi(\mu_2 - \beta' X_n) \qquad (4\text{-}7)$$

$$P(3) = \Pr(y_n = 3) = \Pr(\mu_3 \ \leq y_n^* \leq \ \mu_4) = \Phi(\mu_4 - \beta' X_n) - \ \Phi(\mu_3 - \beta' X_n) \qquad (4\text{-}8)$$

$$P(4) = \Pr(y_n = 4) = \Pr(\mu_4 \ \leq y_n^*) = 1 - \Phi(\mu_4 - \beta' X_n) \qquad (4\text{-}9)$$

Φ is the standart normal distribution and sum of all level probabilites is 1.

4.4 Case Study II

4.4.1 Data

Instead of using work zone crashes in the specific locations, individual work zone crashes were used to analyze severity in the presence of work zones, in New Jersey. Crash data between 2006 and 2010 were obtained from the New Jersey Department of Transportation (NJDOT) website. Crash records were available in the form of five different types of tables;

- Accident table,
- Driver table,
- Vehicle table,
- Occupant table, and
- Pedestrian table

Crashes were identified in the accident table with a unique case number. The accident table included one record for each crash regardless of the number of vehicles involved in a crash. In other words, the number of records in the accident table showed the number of accidents that occurred. Driver, vehicle and occupant tables have unique records for each unit including related information. These tables were merged by using a unique case number. Figure 4-10 shows the merging process for the crash database. Related information regarding a crash can be formed as a unique record. Two categories of crash severity were included in the crash tables. The first category is included in the accident table as severity, which was separated into three types; (1) Property damage only (PDO), (2) Injury, and (3) Fatality. The second category is included in the occupant table that shows the occupant's physical condition as described by four levels; (1) Killed, (2) Incapacitated, (3) Moderate injury, (4) Complaint of pain. When merging these pieces of information and eliminating the improper data, the crash severity index could be categorized into five levels by adding non-injury to the occupant's physical condition.

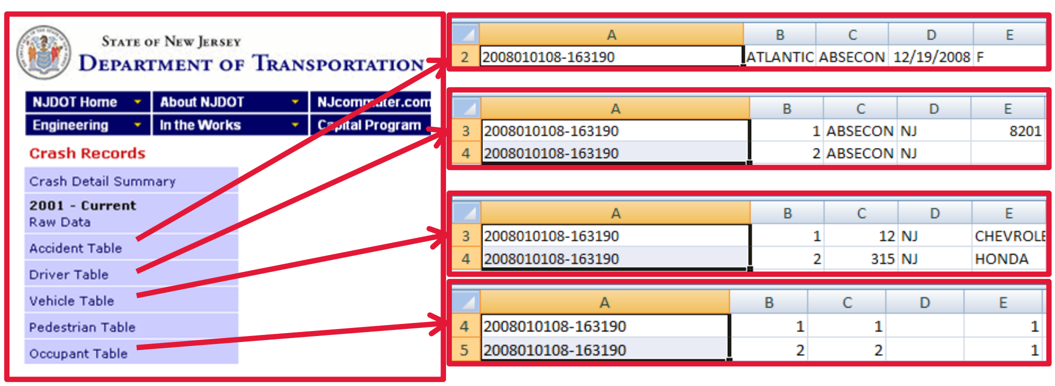


Figure 4-10 Crash Record Tables Merging Process

The crash records are defined in the crash database in terms of five types of temporary traffic control zones; (1) None, (2) Construction Zones, (3) Maintenance Zones, (4) Utility Zones, and (5) Incident Zones. Work zone crashes were filtered by using a temporary traffic control zone parameter and by selecting construction, maintenance and utility zones.

By removing missing values, which constituted about 8.9 percent of the data, 26602 work zone crashes were selected for analysis. Two different severity indexes were used for two different analyses. For the binary level analysis, the crash severity index was defined as non-injury and injury crashes. Fatal crashes were assumed to be injury crashes for purposes of binary level analysis. For multilevel analysis, five different levels were used to define the severity index. The maximum level of severity among the people involved in a crash was defined as the severity index of the crash. In total, there were 26602 work zone crashes between 2006 and 2010, 20180 non-injury and 6422 injury records that were used to model the severity index at the binary-level.

4.4.2 Binary Level Crash Severity Analysis for Work Zone Crashes

A binary logistic regression approach was applied to model crash severity by using the work zone dataset. Coefficients for the factors analyzed are presented in Table 4-6. The chi-squared test was performed to test the model fit. To process this, the deviance between the null model (prediction with only intercept) and the full model (model with independent variables) was estimated based on degrees of freedom (number of independent variables). For the model, the chi-squared test was χ^2 =1983.222 with 46 degrees of freedom, with a p value of less than 0.001. This indicates that overall, the independent factors had an influence on crash risk at the 95 percent level of significance.

The Wald chi-squared test was performed to check the significance of each variable included in the model. Among the variables used for the crash severity model, 26 of the 46 variables were found to be statistically significant at the 95 percent level. The estimated coefficients, Wald chi-squared statistics, standard error, and *p* values for each variable are listed in Table 4-6. To interpret the estimated coefficients, the odd-ratios (OR) were extracted. The OR values provide estimates of the individual effect of each variable on the crash severity.

For the crash severity analysis, the analysis was focused on fault drivers. To do so the driver's at fault records were defined by using the following assumptions;

- *Driver at fault* was defined as the driver being under the influence (DUI) or one who had apparent contributing circumstances.
- For single-vehicle crashes, the driver of the vehicle is automatically considered the driver at fault.
- For multiple-vehicle crashes, if only one driver is involved in the crash who has a driver error, that person is considered the driver at fault.
- For multiple-vehicle crashes, if multiple drivers are involved in the crash, drivers who do not have any error ("none" in the driver error column) are excluded from the dataset. If more than one driver is left in the dataset for a particular crash after the above step, a random selection is made among them.

According to Table 4-6, following findings were identified:

Time and Environmental Characteristics

The OR value of 1.147 for time of day means that nighttime work zone crashes are 14.7 percent more likely to have severe crashes when compared to day time crashes. This result is consistent with the descriptive statistics. Approximately 27 percent of the crashes between 20:00 and 6:00 A.M. were resulted injury and fatality; on the other hand, about 23 percent of the day time crashes resulted with injury or fatality. Nighttime shift may increase risk for drivers as a result of visibility, lighting glare and driver alertness (Qi et al., 2005; Li and Bai, 2009; Elghamrawy, 2011). Similarly with some studies, weather conditions, road surface conditions and the day of week were found to be not significant for the work zone crash severity (Li and Bai, 2008; Li and Bai, 2009).

Driver and Vehicle Characteristics

Driver age was not found to be significant for the injury risk of work zone crashes. Li and Bai (2008) found out that age has a significant impact on crash severity. They also stated that male drivers have a 70 percent higher risk when compared to female drivers in fatal work zone crashes. From the model results, surprisingly, female drivers at fault were found more likely to be involved in an injury crash (OR:1.209). DUI drivers were also more likely to be involved in an injury work zone crashes when compared to normal physical condition drivers, which is consistent with the previous study (Wang, 2009). Familiarity of the driver was found to be a higher risk factor for crash severity. In other words, drivers from out of state were less likely to be involved in a severe crash than the drivers from the state (OR:0.924).

Light duty vehicles such as motorcycles have higher rates of injury risk when involved in a work zone crash when compared to other vehicles (OR: 1.627). A possible cause of this is that these drivers are less protected than other users. Findings are consistent with the Khattak et al. (2003) analysis concerning multivehicle collisions. Old vehicles have a slightly higher risk when compared to newer vehicles, which may signify a contribution of old technology as far as safety equipment goes within the vehicle. Interestingly, out-of-state drivers were less likely to cause severe crashes (OR: 0.924), which can be explained by people driving more carefully on roads with which they are unfamiliar. Inconsistent with a previous study, crashes involving trucks were found to decrease the likelihood of severe crashes (Li and Bai, 2008). Such findings are not the same as we commonly anticipate. Wang (2009) suggested that the reason for this may be attributed to people driving carefully when a truck is nearby.

Crash Characteristics

Rear-end crashes were used as the base crash type. Most of the crash types such as right-angle, or head on crashes cause severe injuries when compared to rear-end crashes. The overturned crash type had the most significant coefficient of crash severity with a maximum odds ratio value of 13.72. This means that an overturned crash type has 13.7 times more risk than rear-end crashes.

Contributing factors were investigated in terms of unsafe speed, inattention, and following too closely. These factors were found to increase crash severity. The odds ratio for unsafe speed was 1.616, which means that the driver applying an unsafe speed has a 61 percent higher risk than normal drivers. Inattentive driving or following too close may increase the injury risk of work zone crashes by about 20 percent. Compared to vehicles going straight ahead, vehicles making turns, interacting with others, or moving slowly lead to less severe crashes.

Table 4-6 Model Estimation for Crash-Level Severity Analysis for Work Zone Crashes (N = 26602)

Variable	Symbol	Description	Estimate	Std. Error	Wald χ2	OR	Significance
Constant	Intercept	Constant in model	−3.078	0.088	1215.3	–	***
Time of day	Time	= 0 if daytime (06:00–20:00); = 1 otherwise	0.137	0.047	8.6	**1.147**	**
Light condition	Light	= 0 if good condition (daylight); = 1 if poor condition (dawn, dusk, dark)	−0.069	0.043	2.6	**0.933**	–
Surface condition	Surf_Cond	= 0 if good condition (dry); = 1 if poor condition (wet, water, sand, snowy, icy, slush, oil)	−0.059	0.041	2.0	**0.943**	–
Driver gender	Drv_gender	= 0 if male; = 1 if female	0.190	0.032	36.0	**1.209**	***
Driver license state	License	= 0 if New Jersey issued; = 1 if other state issued	−0.079	0.041	3.7	**0.924**	.
Driver under the influence	DUI	= 0 if apparently normal; = 1 if under the influence (alcohol, drug, medication, fell asleep etc.)	0.788	0.071	124.3	**2.198**	***
Vehicle type	Light_veh	= 1 if light vehicle (motorcycle, scooter, and so on); = 0 otherwise	0.487	0.210	5.4	**1.627**	*
Vehicle age	Veh_age	Number of years since vehicle was built	0.011	0.003	16.3	**1.012**	***
Road class	Rd_classhigh	= 1 if interstate, state/interstate authority; = 0 otherwise	−0.093	0.059	2.5	**0.911**	–
	Rd_classmedium	= 1 if state highway; = 0 otherwise	0.200	0.044	20.4	**1.221**	***
Road divided by median	Barriermedian	= 1 if barrier median; = 0 otherwise	0.066	0.038	3.0	**1.068**	.
Posted speed limit	Speedhigh	= 1 if speed limit is ≥61 mph; = 0 otherwise	0.206	0.072	8.2	**1.229**	**
	Speedmedium	= 1 if speed limit is 41–60 mph; = 0 otherwise	0.067	0.040	2.8	**1.069**	.
Work zone type	Maintenance	= 1 if maintenance zone; = 0 otherwise	0.159	0.077	4.2	**1.172**	*
Traffic control type	Humancontrol	= 1 if human control (police, flagman, and so on); = 0 otherwise	0.387	0.096	16.3	**1.473**	***
	Signalsign	= 1 if signal, sign, flashing, and so on; = 0 otherwise	0.334	0.053	40.2	**1.396**	***
	Lanemark	= 1 if lane markings; = 0 otherwise	0.159	0.050	9.9	**1.172**	**
	Channelization	= 1 if channelization; = 0 otherwise	0.096	0.067	2.0	**1.101**	–
Number of vehicles involved	Veh_num	Total number of vehicles involved in crash	0.446	0.034	174.3	**1.562**	***
Number of persons involved	Person_num	Total number of occupants involved in crash	0.156	0.012	161.9	**1.169**	***
Truck involved in crash	Truck_involved	= 1 if yes; = 0 no	−0.398	0.045	76.9	**0.672**	***
Light vehicle involved in crash	Lightvehinvolved	= 1 if yes; = 0 no	0.524	0.163	10.3	**1.688**	**
Crash type	C_angle	= 1 if with angle (right angle, left turn or U turn); = 0 otherwise	0.620	0.061	103.4	**1.859**	***
	C_opposite	= 1 if opposite direction (head on, angular, side swipe); = 0 otherwise	0.787	0.113	48.7	**2.196**	***
	C_overturn	= 1 if overturned; = 0 otherwise	2.619	0.180	212.2	**13.716**	***
	C_fixedobj	= 1 if fixed objected; = 0 otherwise	0.638	0.060	114.0	**1.892**	***
Contributing circumstances	Unsafespeed	= 1 if unsafe speed; = 0 otherwise	0.480	0.071	46.2	**1.616**	***
	Inattention	= 1 if driver inattention; = 0 otherwise	0.208	0.035	34.5	**1.231**	***
	Close	= 1 if following too closely; = 0 otherwise	0.199	0.051	15.3	**1.220**	***
Vehicle precrash action	Maketurn	= 1 if making turn; = 0 otherwise	−0.493	0.064	60.2	**0.611**	***
	Slowmove	= 1 if low-speed manipulation (slow moving, parking, backing, and so on); = 0 otherwise	−0.108	0.038	8.2	**0.898**	**
	Interaction	= 1 if driving interaction (changing lanes, merging, passing, and so on); = 0 otherwise	−0.534	0.048	121.6	**0.586**	***

Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

4.4.3 Binary Level Crash Severity Analysis for Non-Work Zone Crashes

A non-work zone dataset was created by using crash records between 2006 and 2010 which is the same period the work zone dataset used. A large number of non-work zone crash records are available each year. To reduce the model sample size, 10.000 sample records were gathered for each year and a related merged dataset was created. Based on a filter process, 41,806 records were used to model the binary level crash severity for non-work crashes. The severity for non-work zone crashes was modeled by using logistic regression for the binary level of severity of the dependent variables. The same parameters were used to model severity to compare results with work zone crash severity. Assumptions used for work zone crash severity were applied for the non-work zone crash severity model.

The deviance between the null and full models was estimated by using the chi-squared test. For the model, the chi-squared test was χ^2 =3162.738 with 44 degrees of freedom and with a p value of less than 0.001. This shows that the overall independent factors had an effect on crash risk at the 95 percent level of significance. Similarly, the Wald chi-squared test was applied to check significance of each variable for the non-work zone crash severity model. For the model, 31 of the 44 variables were found to be statistically significant. The estimated coefficients, Wald chi-squared statistics, standard error, and p values for each variable are listed in Table 4-7. The OR values provide an estimate of the individual effect of each variable on crash severity. To interpret the estimated coefficients the ORs were extracted and listed in Table 4-7.

According to Table 4-7, the following findings were observed:

Time and Environmental Characteristics

There is no significant relationship between the time variable of non-work zone crashes and crash severity. However, some of the previous studies reflect that driving at night can cause high rates of injury crashes (Rice et al., 2003).

Driver and Vehicle Characteristics

Female drivers are likely to have a 15.1 percent greater risk of being involved in a severe crash in non-work zone conditions. The risk for female drivers at work zone conditions was higher than those for non-work zone drivers. Kweon and Kockelman (2003) found that women have a greater risk than men for every driven mile. DUI drivers had a 112.7 percent higher risk of being involved in a severe crash at non-work zone conditions. This is consistent with the finding of Traynor (2005) that the drinking at fault drivers produces more serious injuries than sober drivers. Unfamiliar drivers have an 11 percent lower risk when compared to the state-licensed drivers. Donaldson et al. (2006) stated that there was a correlation between location of fatal crashes and driver's residence.

Vehicle size is also an important factor for determining crash severity. Light vehicles such as motorcycle had a 55.1 percent higher risk when compared to heavy vehicles. Besides this, light vehicles involved crashes were 1.66 times more likely to result in injury crashes. The possible reason behind this can be the low safety level of these vehicles. Hague et al. (2009) stated that the ratio of fatalities and injuries for motorcyclists is higher than it is for other motor vehicles, at rates of 13 and 7 times higher in Singapore, respectively. On the other hand, heavy vehicles such as trucks and buses are 17.9 percent safer when compared to other cars at non-work zone conditions.

Truck involved crashes are 23.3 percent less likely to result in injury crashes. Similar to previous studies (Goldenbeld et al., 2013), the number of vehicles and number of person involved in a crash increased the crash severity by 6 and 20.3 percent, respectively. Vehicle age was also found to be significant for non-work zone crashes. Although it had a small effect, older vehicles had a 1.1 percent higher risk for each year difference when compared to newer vehicles. Unfamiliar drivers had an 11.0 percent lower risk of being involved in a severe non-work zone crash when compared to state licensed drivers.

Crash Characteristics

Similarly with the work zone crash severity analysis, rear-end crashes were taken as the base crash type. The most significant crash type observed was the ”overturn” type which was 4.9 times more dangerous than rear-end crashes. The opposite side crash type was second in terms of the effect on severity of the non-work zone crashes. Angle and fixed object types also had incremental effects on crash severity, however, non-fixed object crashes were found to be less severe when compared to rear-end crashes at non-work zone conditions.

When considering all contributing factors for non-work zone crashes, the only severity increasing parameter from the model results was found for “Unsafe Speed”. This type of crash was 19.4 percent more likely to result in a severe crash. Other factors such as “inattention” and “improper lane change” which contribute to crashes were found to have a decreasing effect on crash severity. Pre-crash actions for non-work zone conditions such as “making a turn”, “slow move” and “interaction”, were found to be less severe when compared to “going straight” actions.

Table 4-7 Model Estimation for Crash-Level Severity Analysis for Non-Work Zone Crashes (n = 41,806)

Variable	Symbol	Description	Estimate	Std. Error	Wald χ2	OR	Significance
Constant	Intercept	Constant in model	-1.978	0.103	365.3	0.138	***
Driver Age	Driver_age	Continuous	0.001	0.001	3.1	1.001	.
Driver gender	Drv_gender	= 0 if male; = 1 if female	0.140	0.024	33	1.151	***
Driver license state	License	= 0 if New Jersey issued; = 1 if other state issued	-0.117	0.038	9.6	0.890	**
Driver under the influence	DUI	= 0 if apparently normal; = 1 if under the influence (alcohol, drug, medication, fell asleep etc.)	0.755	0.052	207.4	2.127	***
Vehicle type	Light_veh	= 1 if light vehicle (motorcycle, scooter, and so on); = 0 otherwise	0.439	0.171	6.6	1.551	*
	Heavy_veh	=1 if heavy vehicle(truck, bus)	-0.197	0.093	4.5	0.821	*
Vehicle age	Veh_age	Number of years since vehicle was built	0.011	0.002	25.5	1.011	***
Road class	Rd_classhigh	= 1 if interstate, state/interstate authority; = 0 otherwise	-0.187	0.064	8.6	0.829	**
	Rd_classmedium	= 1 if state highway; = 0 otherwise	0.121	0.034	12.8	1.129	***
Road character	RoadCharacter	= 1 if curve; = 0 otherwise	0.096	0.040	5.8	1.101	*
Road divided by median	Curbmedian	= 1 if curb median; = 0 otherwise	0.061	0.032	3.5	1.062	.
Posted speed limit	Speedmedium	= 1 if speed limit is 41–60 mph; = 0 otherwise	0.132	0.034	15.5	1.141	***
Traffic control type	Humancontrol	= 1 if human control (police, flagman, and so on); = 0 otherwise	0.617	0.176	12.3	1.853	***
	Signalsign	= 1 if signal, sign, flashing, and so on; = 0 otherwise	0.416	0.035	144.9	1.517	***
	Lanemark	= 1 if lane markings; = 0 otherwise	0.227	0.034	45	1.255	***
Number of vehicles involved	Veh_num	Total number of vehicles involved in crash	0.058	0.030	3.8	1.060	.
Number of persons involved	Person_num	Total number of occupants involved in crash	0.185	0.010	324.9	1.203	***
Cell phone use	Cellphoneuse	=1 if cell phone use: = 0 otherwise	0.311	0.110	7.9	1.365	**
Truck involved in crash	Truck_involved	= 1 if yes; = 0 no	-0.261	0.072	13.3	0.770	***
Light vehicle involved in crash	Lightvehinvolved	= 1 if yes; = 0 no	0.978	0.133	54.3	2.660	***
Crash type	C_angle	= 1 if with angle (right angle, left turn or U turn); = 0 otherwise	0.481	0.038	157.1	1.618	***
	C_opposite	= 1 if opposite direction (head on, angular, side swipe); = 0 otherwise	0.674	0.068	98.2	1.961	***
	C_overturn	= 1 if overturned; = 0 otherwise	1.779	0.133	177.8	5.926	***
	C_fixedobj	= 1 if fixed object; = 0 otherwise	0.397	0.052	58.5	1.488	***
	C_nonfixedobj	=1 if nonfixed object; = 0 otherwise	-0.221	0.042	27.2	0.801	***
Contributing circumstances	Unsafespeed	= 1 if unsafe speed; = 0 otherwise	0.177	0.061	8.4	1.194	**
	Inattention	= 1 if driver inattention; = 0 otherwise	-0.117	0.041	8	0.890	**
	Improper	=1 if improper lane change: = 0 otherwise	-0.248	0.047	27.2	0.781	***
	Close	= 1 if following too closely; = 0 otherwise	-0.104	0.059	3.1	0.901	.
	Other	= 1 if other circumstances (vehicle, road, pedestrian factors); = 0 otherwise	-0.271	0.053	26	0.763	***
Vehicle precrash action	Maketurn	= 1 if making turn; = 0 otherwise	-0.250	0.037	45.6	0.779	***
	Slowmove	= 1 if low-speed manipulation (slow moving, parking, backing, and so on); = 0 otherwise	-0.510	0.033	242.6	0.601	***
	Interaction	= 1 if driving interaction (changing lanes, merging, passing, and so on); = 0 otherwise	-0.505	0.044	131.7	0.604	***
	Otheraction	= 1 if other action (pedestrian action); = 0 otherwise	0.612	0.201	9.3	1.844	**

Significance codes: 0 ‘*’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1**

4.4.4 Comparison of Binary Level Severity Models for Work and Non-Work Zone Crashes

Modeling the variables alone as outlined above may be biased in terms of results. This is because there is a need to understand the natural effect of each parameter on work zone crash frequency in order to critique the model parameters from the work zone crash severity model. Thus, the binary level results of both work zone and non-work zone conditions were compared to the individual effects of each parameter on crash severity for work zone conditions. If a variable was not significant in either the work zone or non-work zone crash severity model, it was eliminated from the comparison of both conditions. The odds ratio values of the variable coefficients were utilized to estimate variable differences. Table 4-8 shows details of the comparison for work zone and non-work zone conditions.

Table 4-8 Comparison of Significant Variables for WZ and Non-WZ Severity Models

Variable	Symbol	Odds Ratio		Difference of Unique Impact
		Work Zone	Non-Work Zone	
Driver gender	Drv_gender	1.209	1.151	5.8%
Driver license state	License	0.924	0.890	3.4%
Driver under the influence	DUI	2.198	2.127	7.1%
Vehicle type	Light_veh	1.627	1.551	7.6%
Vehicle age	Veh_age	1.012	1.011	0.1%
Road class	Rd_classhigh	0.911	0.829	8.2%
	Rd_classmedium	1.221	1.129	9.2%
Posted speed limit	Speedmedium	1.069	1.141	-7.2%
Traffic control type	Humancontrol	1.473	1.853	-38.0%
	Signalsign	1.396	1.517	-12.1%
	Lanemark	1.172	1.255	-8.3%
Number of vehicles involved	Veh_num	1.562	1.060	50.2%
Number of persons involved	Person_num	1.169	1.203	-3.4%
Truck involved in crash	Truck_involved	0.672	0.770	-9.8%
Light vehicle involved in crash	Lightvehinvolved	1.688	2.660	-97.2%
Crash type	C_angle	1.859	1.618	24.1%
	C_opposite	2.196	1.961	23.5%
	C_overturn	13.716	5.926	779.0%
	C_fixedobj	1.892	1.488	40.4%
Contributing circumstances	Unsafespeed	1.616	1.194	42.2%
	Inattention	1.231	0.890	34.1%
	Close	1.22	0.901	31.9%
Vehicle precrash action	Maketurn	0.611	0.779	-16.8%
	Slowmove	0.898	0.601	29.7%
	Interaction	0.586	0.604	-1.8%

From the binary level results of work zone and non-work zone conditions, the largest difference in terms of crash characteristics was observed for the overturn crash types.

- The difference between work zone and non-work zone binary crash severity modeling OR values for overturn crashes was 7.79. This means that “overturn” type of work zone crashes were more likely to be resulted with an injury crashes than non-work zone same type of crashes. The unique impact of fixed object crashes at work zones was 40.4 percent higher, angle crashes 24.1 percent higher, and opposite direction crashes 23.5 percent higher than non-work zone crashes.

- One more vehicle involved in a work zone crash created 50.2 percent more risk of injury result when compared to non-work zones.
- Work zones on the higher class roads such as interstate and state highways had a 8.2 and 9.2 percent higher risk of being involved in a severe crash when compared to non-work zone conditions.
- The work zone crash caused by "unsafe speed" was 42.2 percent more likely to be more severe compared to non-work zone crash caused by unsafe speed. Similarly, as a contributing factor, "inattention" and "following too closely" had a higher impact on the severity of work zone crashes with an increase of 34.1 and 31.9 percent, respectively.
- "Slow moving" and "making a turn" as pre-crash actions reduced the crash severity for both work and non-work zone crashes. "Slow moving" actions caused 29.7 percent less severe crashes and "making a turn" actions caused 16.8 percent more severe crashes at non-work zone conditions.

The difference in terms of the effect of driver and vehicle characteristics as regards severity was not effective as a crash characteristic. Based on a comparison of the results, the following were found:

- Female drivers had a 5.8 percent higher risk of being involved in severe crashes than male drivers at work zones compared to non-work zone conditions.

- Out of state drivers were 3.4 percent more likely to be involved in a severe work zone crash.
- Light vehicles were 97.2 percent and trucks 9.8 percent less likely to be involved severe crashes at work zones compared to non-work zone conditions.
- DUI had a 7.1 percent more effect on crash severity at work zones when compared to non-work zones.

4.4.5 Multi-level Crash Severity Analysis for Work Zone Crashes

The binary level of crash severity provided no information about the level of severity. Instead of using binary level for the severity parameter, a multi-level severity parameter extracted from the crash dataset (killed, incapacitated, moderate injury, complaint of pain and no injury) was used for modeling crash severity. Thus, the relationship between the model parameters and severity level of crash could be investigated precisely. As mentioned in the methodology, the ordered probit regression was utilized to model crash severity for the work zone conditions. Two different models were developed for the multilevel crash severity predictions as follows:

1) By using the maximum crash severity data found among the occupants and driver involved in a crash and naming this as “the crash severity”.
2) Weighting these data by using the monetary cost (Table 4-9) of each level of severity and normalizing this cost based on the complaint level severity monetary cost (Campbell and Knapp, 2005).

Table 4-9 Monetary Values of Crash Severity Types

	Non-injury	Complaint	Moderate	Incapacitated	Killed
Monetary Value	$1,900	**$20,200**	$42,500	$165,000	$3,340,000
Weight Coefficient	0	1	2.1	8.2	165.3

4.4.5.1 Multi-level Severity Analysis for Work Zone Crashes by Using Maximum Severity

The maximum crash severity variable for the occupants involved in a work zone crash was used as a dependent variable for ordered probit regression. Other independent variables were organized in a similar way to those employed in the binary level work zone crash severity analysis. Five levels of crash severity were defined as follows:

1. no injury = 0
2. complaint of pain = 1
3. moderate injury = 2
4. incapacitated = 3
5. killed = 4

Using the maximum severity variable in the ordered probit regression modeling would provide a better estimation about the effect of the each variable. To enhance the understanding of the impact of each factor, the marginal effects of each variable were estimated for each severity threshold by using STATA software package.

The severity of the crash was defined based on the maximum severity of injury of the involved occupants as follow;

$$Severity_{crash} = Max(Occupant\ Severity)_i \qquad \text{(i: Occupant ID)} \qquad (4\text{-}10)$$

As defined in section 4.3.2, work zone crash severity was modeled by using an ordered probit method and multilevel severity data as the dependent variable. The same variables were used for the multilevel crash severity analysis (Table 4-6). 22,651 work zone crashes were filtered to obtain a final dataset.

Multilevel Work Zone Crash Severity Modeling Results (Maximum Severity)

To model crash severity, 52 variables were used and 8 of these variables were omitted as base categories, and 29 of the 44 variables were found to be significant. For the model, the chi-squared test result was χ^2 =1836.17 with 44 degrees of freedom and with a *p* value of less than 0.001.

Table 4-10 shows the results for the multilevel crash severity modeling analysis for the work zones. Besides this, the Wald chi-squared test was applied to check the significance of each variable for the multilevel work zone crash severity model. Only significant variables are included in the Table 4-10.Based on the modeling results, some of the variables were found to have a higher impact than others in terms of their coefficient values such as the overturned type of crash, a crash caused by a DUI driver etc. To interpret the ordered probit model results, marginal effect, the unique impact of each variable was estimated for each severity threshold. Table 4-11 shows the marginal effects on crash severity. The base level was no injury, so the marginal effects show the differences based on no injury. Findings can be interpreted roughly from Table 4-10 Variables which have an increasing effect on crash multilevel non-work zone crash severity from the most efficient to less efficient in order were the following:

Table 4-10 Multilevel Work Zone Crash Severity Modeling Results (Maximum Severity)

Variable	Symbol	Estimate	Std. Error	Wald χ2	Significance
Time of day	Time	0.079	0.027	8.3	**
Surface condition	Surf_Cond	-0.066	0.038	3.0	.
Driver gender	Drv_gender	0.102	0.019	27.6	***
Driver under the influence	DUI	0.550	0.043	166.9	***
Vehicle type	Light_veh	0.348	0.125	7.7	**
Vehicle age	Veh_age	0.007	0.002	18.1	***
Road class	Rd_classmedium	0.114	0.029	1.8	***
Road character	RoadCharacter	0.046	0.028	2.7	.
Road divided by median	Barriermedian	0.058	0.029	4.0	*
Posted speed limit	Speedhigh	0.144	0.041	12.3	***
	Speedmedium	0.061	0.025	6.0	*
Traffic control type	Humancontrol	0.164	0.060	7.4	**
	Signalsign	0.194	0.034	33.4	***
	Lanemark	0.091	0.032	8.1	**
Number of vehicles involved	Veh_num	0.212	0.019	124.8	***
Number of persons involved	Person_num	0.088	0.007	140.3	***
Truck involved in crash	Truck_involved	-0.202	0.038	28.3	***
Light vehicle involved in crash	Lightvehinvolved	0.386	0.097	15.9	***
Crash type	C_angle	0.414	0.040	105.3	***
	C_opposite	0.591	0.072	67.7	***
	C_overturn	1.522	0.093	268.4	***
	C_fixedobj	0.444	0.036	148.5	***
	C_nonfixedobj	0.112	0.035	10.0	**
Contributing circumstances	Unsafespeed	0.291	0.049	35.8	***
	Inattention	0.124	0.031	15.5	***
	Close	0.117	0.037	9.8	**
Vehicle precrash action	Maketurn	-0.264	0.040	43.4	***
	Slowmove	-0.048	0.023	4.3	*
	Interaction	-0.274	0.030	81.2	***

Significance codes: 0 ‘*’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1**

Time and environmental characteristics:

- Traffic control type: signal sign, human control and lane mark,
- Posted speed limit if higher than 60 mph,

- State roads,
- Nighttime has higher impact on multilevel work zone crash severity,
- Barrier median,
- Posted speed limit if between 40 mph and 60 mph,
- Curved roads,

Driver and vehicle characteristics:

- DUI
- Driving light vehicle or light vehicle involved in a crash
- Female drivers
- Vehicle age

Crash characteristics:

- Crash types: Overturn, opposite, fixed-object, angle and non-fixed object crash types had a greater effect on crash severity compared to rear-end crashes (from the most efficient to less efficient in order).
- Contributing circumstances: Unsafe speed, inattention, following too closely,
- Number of vehicles involved,
- Numbers of occupants involved had an increasing effect on multilevel work zone crash severity.

Significant variables are included in Table 4-11. The “dy/dx” values show the percent effect of each on different levels of severity when other variables were kept constant. Due to the sample size being smaller for more severe crashes, the ratio of the marginal effect of each variable to the summation of the absolute marginal effects was estimated to provide an idea about the unique impact of each variable on the exact level of crash severity. Thus, the "Ratio %" factor was added to the results table to provide a comparison for each variable based on impact percentages. To estimate this, the absolute value of each marginal effect was divided by the sum of the absolute marginal effects (Equation 4-11).

$$R_{ij} = \frac{(dy/dx)_{ij}}{\sum_1^i abs((dy/dx)_{ij})} \tag{4-11}$$

Where,

i: variables

j: severity thresholds {complaint, moderate, incapacitated, killed}

dy/dx: marginal effect of each variable.

If we look at the marginal effects of variables for each level of severity;

Level (1) – Complaint of Pain:

The overturn crash type had the highest marginal effect on the "Complaint of Pain" crash severity. If the crash was caused by an "overturn" this increased the Level-1 crash severity by 22.6 percent when compared to non-injury crashes. Similarly, the "opposite type" of work zone crashes had a 14.2 percent greater impact on this level of severity. The third biggest marginal effect for this category was found with DUI and this had an effect of increasing severity by 13.3 percent more when compared with non-injury work zone crashes. Besides this, if a light vehicle was involved in a crash, this was 9.43 percent more likely to result in a Level-1 crash compared to non-injury crashes. If the contributing factor was defined as "Unsafe Speed" than this crash had a 7.1 percent higher risk of resulting in this level of severity. Other results can be interpreted from Table 4-11 using the same approach.

Level (2) – Moderate Injury:

Here, the “overturned crash type” again had the highest impact among the measured variables. If the work zone crash was an overturned type, it was 23.5 percent more likely to result in a “moderate injury” crash. The ratio among all marginal effects for this category showed that the overturn crash marginal effect was 36 percent of the absolute sum of all “dy/dx” values for this severity category. The “opposite crash” type and DUI followed with marginal effects of 5.8 and 5.1, respectively.

Level (3) – Incapacitated:

The ratio increased for “overturn crashes” up to 54.2 percent for the “incapacitated” level of severity. Different from the other results, fixed object work zone crashes constituted a 4.1 percent of the total marginal effects for this category.

Level (4) – Killed:

The “overturn” crash type was a significant factor explaining the “killed” level of severity. If somebody was involved in an overturn crash, the chance of surviving from the crash was 95.3 percent. The opposite crash type, DUI, and light vehicle types involved in a crash were some other variables which had a significant impact on the “killed” level of work zone crash severity.

Table 4-11 Marginal Effects of Each Variable for Different Levels of Work Zone Crash Severity (Maximum Severity)

Variable	Symbol	Complaint (1)		Moderate (2)		Incapacitated (3)		Killed (4)	
		dy/dx	Ratio	dy/dx	Ratio	dy/dx	Ratio	dy/dx	Ratio
Time of day	Time	1.87	1.20	0.50	0.77	0.04	0.49	0.02	0.31
Surface condition	Surf_Cond	-1.54	-0.99	-0.39	-0.59	-0.03	-0.36	-0.02	-0.23
Driver gender	Drv_gender	2.41	1.55	0.64	0.98	0.05	0.62	0.03	0.39
Driver under the influence	DUI	13.33	8.54	5.13	7.84	0.53	6.33	0.33	4.79
Vehicle type	Light_veh	8.52	5.46	2.85	4.36	0.27	3.19	0.15	2.26
Vehicle age	Veh_age	0.18	0.11	0.05	0.07	0.00	0.04	0.00	0.03
Road class	Rd_classmediu	2.69	1.72	0.71	1.09	0.06	0.69	0.03	0.44
Road character	RoadCharacter	1.10	0.70	0.29	0.45	0.02	0.28	0.01	0.18
Road divided by median	Barriermedian	1.36	0.87	0.35	0.54	0.03	0.33	0.01	0.21
Posted speed limit	Speedhigh	3.46	2.22	0.98	1.49	0.08	0.98	0.04	0.64
	Speedmedium	1.43	0.91	0.37	0.57	0.03	0.35	0.02	0.22
Traffic control type	Humancontrol	3.96	2.54	1.15	1.75	0.10	1.17	0.05	0.77
	Signalsign	4.64	2.97	1.31	2.00	0.11	1.30	0.06	0.86
	Lanemark	2.13	1.36	0.55	0.84	0.04	0.52	0.02	0.33
Number of vehicles involved	Veh_num	4.99	3.20	1.30	1.98	0.10	1.23	0.05	0.78
Number of persons involved	Person_num	2.07	1.33	0.54	0.82	0.04	0.51	0.02	0.32
Truck involved in crash	Truck_involved	-4.60	-2.95	-1.10	-1.69	-0.08	-1.00	-0.04	-0.61
Light vehicle involved in	Lightvehinvolve	9.43	6.04	3.24	4.95	0.31	3.69	0.18	2.64
Crash type	C_angle	10.09	6.47	3.42	5.24	0.33	3.88	0.19	2.77
	C_opposite	14.24	9.13	5.79	8.86	0.63	7.40	0.39	5.75
	C_overturn	22.55	14.46	23.54	35.98	4.58	54.22	4.65	67.81
	C_fixedobj	10.80	6.93	3.64	5.57	0.35	4.12	0.20	2.94
	C_nonfixedobj	2.67	1.71	0.74	1.13	0.06	0.73	0.03	0.47
Contributing circumstances	Unsafespeed	7.09	4.55	2.23	3.42	0.20	2.40	0.11	1.65
	Inattention	2.92	1.87	0.77	1.18	0.06	0.74	0.03	0.47
	Close	2.79	1.79	0.77	1.18	0.06	0.76	0.03	0.49
Vehicle precrash action	Maketurn	-5.87	-3.76	-1.33	-2.03	-0.10	-1.15	-0.05	-0.69
	Slowmove	-1.12	-0.72	-0.29	-0.44	-0.02	-0.27	-0.01	-0.17
	Interaction	-6.16	-3.95	-1.44	-2.20	-0.11	-1.27	-0.05	-0.78

4.4.5.2 Multi-level Monetary Weighted Severity Analysis for Work Zone Crashes

The maximum severity model did not consider lower or equal types of severity in a crash. To overcome this problem, the severity level for each crash was defined based on a summation of the monetary weighted values of the occupants involved in a crash. The estimated summations were separated into 5 different levels. Table 4-9 provides the weights for each level of severity. No injury (0), complaint (1), moderate (2.1), incapacitated (8.2) and killed (165.3) Thresholds were defined for sake of simplicity as follows:

1. no injury = 0
2. Level 1 (complaints) = 1
3. Level 2 (moderate) = 2
4. Level 3 (incapacitated)= >2 & <8
5. Level 4 (killed) > 7

By using ordered probit regression, the monetary based severity was modeled for work zone crashes. The estimated coefficient for each variable from the model results provided an idea about the relationship between the variables and the crash severity. However, the interpretation of the ordered probit results is usually evaluated based on marginal effects of each variable for each threshold. Crash severity was thus defined based on the following equation:

$$Severity_{crash} = \sum_i (Monetary\ Value\ of\ Occupant\ Severity)_i \qquad (4\text{-}12)$$

(i: Occupant ID)

The same dataset (N=22,651) was used for the maximum severity model and monetary weighted severity modeling. Severity levels defined for each crash were used as the dependent variable. “No injury” crashes are the base level and results reflected the difference relative to the base level.

Multilevel Work Zone Crash Severity Modeling Results (Monetary Weighted)

Similar to the maximum crash severity model, 52 variables were used for modeling crash severity for work zones. Due to the collinearity of 8 of these variables, 8 were omitted, and 31 of the 44 variables were found to be significant at a 90 percent level of significance. For the model, the chi-squared test result was χ^2=2616.54 with 44 degrees of freedom and with a *p* value of less than 0.001. Moreover, the Wald chi-squared test was applied to check significance of each variable for the multilevel work zone crash severity model. Model estimation results, plus the Wald chi-squared test and other sources of information are provided in the Table 4-12. Based on the Wald chi-squared test results, the most significant relationship between crash severity and the monetary weighted severity was found for number of persons involved in a crash. The “overturn crash” type and number of vehicles involved in a crash was second and third, respectively. From the monetary severity based ordered probit regression model results, the “overturn” and “opposite” crash types were found to have the highest impact on crash severity for work zone crashes. Similar to the previous model, DUI was more likely to be result in a severe work zone crash. The simple interpretation from the monetary weighted modeling results shown in Table 4-12 for work zone crashes is as follows:

Table 4-12 Multilevel Work Zone Crash Severity Modeling Results (Monetary Weighted)

Variable	Symbol	Estimate	Std. Error	Wald χ2	Significance
Time of day	Time	0.082	0.028	8.8	**
Surface condition	Surf_Cond	-0.074	0.039	3.7	.
Driver gender	Drv_gender	0.122	0.020	38.6	***
Driver under the influence	DUI	0.568	0.043	177	***
Vehicle type	Light_veh	0.296	0.127	5.4	**
Vehicle age	Veh_age	0.008	0.002	19.2	***
Road class	Rd_classmedium	0.127	0.029	19.1	***
Road character	RoadCharacter	0.064	0.028	5.2	*
Road divided by median	Barriermedian	0.057	0.029	6	*
	Curbmedian	0.071	0.029	3.9	*
Posted speed limit	Speedhigh	0.171	0.041	17.2	***
	Speedmedium	0.074	0.025	8.7	**
Traffic control type	Humancontrol	0.109	0.064	2.9	.
	Signalsign	0.180	0.034	27.8	***
	Lanemark	0.084	0.032	6.7	**
Number of vehicles involved	Veh_num	0.309	0.019	252.8	***
Number of persons involved	Person_num	0.127	0.007	297.2	***
Truck involved in crash	Truck_involved	-0.180	0.038	22.3	***
Light vehicle involved in crash	Lightvehinvolved	0.317	0.098	10.5	***
Crash type	C_angle	0.473	0.040	136.6	***
	C_opposite	0.643	0.071	81.4	***
	C_overturn	1.516	0.092	269.5	***
	C_fixedobj	0.510	0.037	190.4	***
	C_nonfixedobj	-0.241	0.040	35.8	***
Contributing circumstances	Unsafespeed	0.365	0.049	55.2	***
	Inattention	0.169	0.032	27.3	***
	Improper	0.107	0.041	6.9	**
	Close	0.123	0.038	10.4	***
	Other_circ	0.122	0.042	8.5	**
Vehicle precrash action	Maketurn	-0.345	0.042	68.1	***
	Interaction	-0.295	0.031	93.1	***

Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Time and environmental characteristics:

- Traffic control type: signal sign, human control and lane mark,
- Posted speed limit if higher than 60 mph,
- State roads,
- Nighttime has higher impact on multilevel work zone crash severity,
- Curb median, barrier median,
- Posted speed limit of between 40 mph and 60 mph,
- Curved roads,

Driver and vehicle characteristics:

- DUI
- Driving a light vehicle or light vehicle involved in a crash
- Female drivers
- Vehicle age

Crash characteristics:

- Crash types: Overturn, opposite, fixed-object, and angle crash types had a greater effect on crash severity compared to rear-end crashes (from the most efficient to less efficient in order).
- Contributing circumstances: Unsafe speed, inattention, following too closely, other circumstances and improper lane change,
- Numbers of vehicle involved,

- Number of occupants involved, had an increasing effect on multilevel work zone crash severity.

For precise interpretation, the marginal effects were estimated for each variable and the level of severity. Table 4-13 shows the marginal effects for each variable based on 4 different levels of severities compared to non-injury crashes. Different from the previous models, the marginal effects were not as polarized as the maximum severity model results. From Table 4-13, the marginal effects were distributed among the variables normalized when compared to results of the maximum severity model in Table 4-11.

According to the marginal effects for each monetary weighted severity level;

Level (1) –Complaint of Pain:

For the "overturn" crash type there was an 11 percent higher risk compared to non-injury crashes. This impact was found to be almost half of the impact for "overturn" crashes for level-1 severity. The marginal impact for the "opposite" type of work zone crash was found to be 9.5 percent and for DUI it was 8.58 percent. If the work zone crash was caused by "unsafe speed", this was 5.7 percent more likely to result in a level-1 crash. Different from the previous model, the marginal effects were distributed among other parameters. Similarly, each variable and its impact can be interpreted based on the marginal effects by examining Table 4-13.

Level (2) – Moderate Injury:

All crash types except the "non-fixed object" crash type had an increasing effect on the moderate level of injury. Besides crash types, the DUI and "unsafe speed" contributed crashes were more likely to result in a “moderate injury” level of severity at work zones. If a driver was DUI, then this crash was 6.3 percent more likely to result in a moderate injury.

Level (3) – Incapacitated:

The “overturn crashes” marginal effect of 19 percent for the “incapacitated” severity level was the highest value reached among all severity levels. The marginal effects for DUI, “fixed object” and “opposite” types of crashes were 3.8, 3.1 and 4.7 percent, respectively. One more vehicle involved in a crash caused a 1.3 percent increase in the probability of incurring an “incapacitated “level of severity.

Level (4) – Killed:

Similar to the other levels, the “overturn” crash type had the most significant marginal effect for the “killed” level of severity. If the crash type was overturn, this crash type was 7.8 percent more likely to result in a fatality. In the same way, opposite crashes had 1 percent and DUI had 0.7 percent marginal effects on the killed level of severity. Since the sample size was small when compared to the other levels, the effect of the variables for work zones is potentially better understood when comparing this to the marginal effects for non-work zone crash severity.

Table 4-13 Marginal Effects of Each Variable for Different Levels of Severity (Monetary Weighted)

Variable	Symbol	Level (1)		Level (2)		Level (3)		Level (4)	
		dy/dx (%)	Ratio (%)	dy/dx (%)	Ratio (%)	dy/dx (%)	Ratio (%)	dy/dx (%)	Ratio (%)
Time of day	Time	1.31	1.18	0.73	0.93	0.36	0.68	0.05	0.38
Surface condition	Surf_Cond	-1.17	-1.05	-0.62	-0.79	-0.29	-0.56	-0.04	-0.30
Driver gender	Drv_gender	1.93	1.74	1.07	1.36	0.52	1.00	0.07	0.56
Driver under the influence	DUI	8.68	7.82	6.26	7.99	3.84	7.39	0.73	5.52
Vehicle type	Light_veh	4.71	4.24	2.96	3.78	1.61	3.10	0.26	1.98
Vehicle age	Veh_age	0.12	0.11	0.07	0.09	0.03	0.06	0.00	0.03
Road class	Rd_classmedium	2.02	1.83	1.12	1.42	0.55	1.05	0.08	0.58
Road character	RoadCharacter	1.02	0.92	0.56	0.72	0.28	0.53	0.04	0.30
Road divided by median	Barriermedian	0.90	0.81	0.50	0.63	0.24	0.47	0.03	0.26
	Curbmedian	1.13	1.02	0.61	0.78	0.29	0.57	0.04	0.31
Posted speed limit	Speedhigh	2.73	2.46	1.59	2.03	0.81	1.56	0.12	0.91
	Speedmedium	1.17	1.05	0.63	0.81	0.30	0.58	0.04	0.32
Traffic control type	Humancontrol	1.74	1.57	0.99	1.27	0.50	0.96	0.07	0.55
	Signalsign	2.88	2.59	1.64	2.10	0.83	1.59	0.12	0.92
	Lanemark	1.33	1.20	0.72	0.92	0.34	0.66	0.05	0.36
Number of vehicles involved	Veh_num	4.89	4.41	2.65	3.38	1.28	2.45	0.18	1.34
Number of persons involved	Person_num	2.02	1.82	1.09	1.40	0.53	1.01	0.07	0.55
Truck involved in crash	Truck_involved	-2.80	-2.53	-1.44	-1.84	-0.67	-1.28	-0.09	-0.67
Light vehicle involved in crash	Lightvehinvolved	5.05	4.55	3.20	4.09	1.76	3.38	0.29	2.18
Crash type	C_angle	7.39	6.66	4.97	6.34	2.88	5.53	0.50	3.82
	C_opposite	9.55	8.60	7.32	9.35	4.74	9.10	0.96	7.26
	C_overturn	10.98	9.89	17.32	22.12	19.03	36.56	7.77	58.89
	C_fixedobj	7.96	7.17	5.32	6.79	3.07	5.90	0.54	4.08
	C_nonfixedobj	-3.70	-3.34	-1.85	-2.36	-0.83	-1.60	-0.11	-0.81
Contributing circumstances	Unsafespeed	5.79	5.22	3.72	4.75	2.07	3.98	0.34	2.61
	Inattention	2.69	2.42	1.48	1.89	0.72	1.39	0.10	0.77
	Improper	1.71	1.54	0.96	1.23	0.48	0.92	0.07	0.52
	Close	1.96	1.76	1.11	1.41	0.55	1.06	0.08	0.61
	Other_circ	1.95	1.75	1.10	1.41	0.55	1.06	0.08	0.61
Vehicle precrash action	Maketurn	-5.17	-4.66	-2.48	-3.16	-1.08	-2.07	-0.13	-1.01
	Interaction	-4.52	-4.08	-2.26	-2.88	-1.02	-1.95	-0.13	-0.99

4.4.6 Multi-level Crash Severity Analysis for Non-work Zone Crashes

Analyzing the characteristics of work zone crashes in terms of contributing factors for severity can be made possible by comparing the contributing factors for these with those of non-work zone crashes. Similar to the binary crash severity models comparison, a multilevel crash severity model comparison was conducted to derive a better understanding of the crash severity factors. To do so, two different multilevel severity models were developed for non-work zone crashes based on four levels of crash severity (killed, incapacitated, moderate injury, complaint of pain and no injury) as follows:

1. Modeling multilevel crash severity of non-work zone crashes by using the maximum crash severity level.
2. Giving weight to the severities based on crash costs as provided in (Table 4-9) and normalizing these values by using the level 1 severity costs.

4.4.6.1 Multi-level Severity Analysis for Non-Work Zone Crashes (Maximum Severity)

The maximum severity based multilevel non-work zone crash severity model was developed by using the same variables that were used in the multilevel work zone crash severity models. Ordered probit regression was performed to create the model by using the dependent variable, maximum severity of all occupants involved in a crash.

1. no injury = 0
2. complaint of pain = 1
3. moderate injury = 2
4. incapacitated = 3
5. killed = 4

The severity variable was defined by using Equation 4-10. Estimated coefficients give an idea about the impact of the related variable on crash severity roughly. To obtain a numerical impact for each parameter, the marginal effects were estimated by using four different severity levels as outcomes.

For the modeling component, 10.000 crashes were selected randomly for each year between 2006 and 2010. This dataset, used for binary level, was cleaned for multilevel crash severity. Based on the filtering process, 36374 sample crashes remained for the non-work zone multilevel severity analysis.

Multilevel Non-work Zone Crash Severity Modeling Results (Maximum Severity)

Fifty two variables were used to model the multilevel crash severity factors for the non-work zone crashes by using the maximum occupant severity item as a dependent variable. Eight of these 52 variables were omitted due to the issue of collinearity. Items such as rear-end crashes were omitted and the modeling results for crash types represented the difference compared to base level rear-end crashes. Thirty one of the 44 variables were found to be significant and are included in Table 4-14. The model's chi-square value was $\chi^2 = 5199.7$ and the p value was less than 0.001. The Wald-square test which shows the relationship between "maximum severity" and the independent variables was performed for each parameter and included within Table 4-14. Based on the Wald-square test of the non-work zone maximum severity model, the most significant relationship between the severity and the independent variables was found for non-fixed object crash types. The overturn crashes, angle type crashes and DUI were other significant variables influencing non-work zone crash severity.

Table 4-14 Multilevel Non-work Zone Crash Severity Modeling Results
(Maximum Severity)

Variable	Symbol	Estimat	Std.	Wald	Significanc
Time of day	Time	0.115	0.025	22.1	***
Light condition	Light	-0.034	0.020	2.8	.
Weather condition	Weather	-0.080	0.030	7.2	**
Driver gender	Drv_gender	0.073	0.015	22.6	***
Driver under the influence	DUI	0.558	0.032	302.6	***
Vehicle type	Light_veh	0.524	0.098	28.3	***
	Heavey_veh	-0.161	0.056	8.3	**
Vehicle age	Veh_age	0.007	0.001	23.3	***
Road class	Rd_classhigh	-0.147	0.037	15.4	***
	Rd_classmediu	0.043	0.021	4	*
Posted speed limit	Speedhigh	0.136	0.041	10.9	***
	Speedmedium	0.148	0.021	50.1	***
Traffic control type	Signalsign	0.191	0.022	74.7	***
	Lanemark	0.196	0.021	83.7	***
Number of vehicles involved	Veh_num	0.273	0.018	227	***
Number of persons involved	Person_num	0.094	0.006	238	***
Cell phone use	Cellphone	0.149	0.074	4.1	*
Light vehicle involved in	Lightvehinvolve	0.725	0.079	84.6	***
Crash type	C_angle	0.423	0.024	303.2	***
	C_opposite	0.485	0.042	131.6	***
	C_overturn	1.259	0.071	313.2	***
	C_fixedobj	0.526	0.032	273.1	***
	C_nonfixedobj	-0.566	0.029	368.5	***
Contributing circumstances	Unsafespeed	0.323	0.038	70.6	***
	Inattention	0.084	0.028	9	**
	Improper	0.099	0.031	9	**
	Close	0.111	0.037	9.9	**
	Other_circ	0.118	0.035	11.6	***
Vehicle precrash action	Maketurn	-0.268	0.024	124.5	***
	Slowmove	-0.206	0.020	102.5	***
	Interaction	-0.302	0.026	130.6	***

Significance codes: 0 ‘*’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1**

Findings can be interpreted from the ordered probit modeling results in Table 4-14. Variables that have an increasing effect on crash severity are listed according to their impact order as follows:

Time and environmental characteristics:

- Traffic control type: lane mark, signal sign
- Posted speed limit if between 40 mph and 60 mph,
- Posted speed limit if higher than 60 mph,
- Nighttime had a higher impact on multilevel work zone crash severity,

Driver and vehicle characteristics:

- Driving light vehicle or light vehicle involved in a crash
- DUI
- Cell phone usage
- Female drivers

Crash characteristics:

- Crash types: Overturn, fixed-object, opposite, angle crash types had a more marked effect on crash severity compared to rear-end crashes (from the most efficient to less efficient in order).
- Contributing circumstances: Unsafe speed, other circumstances, following too closely, improper lane change, and inattention had a greater effect on severity when compared to no error cases.
- Numbers of vehicle involved,
- Numbers of occupants involved had an increasing effect on multilevel work zone crash severity.

Besides factors increasing severity, the following variables were found to have an effect on decreasing multilevel non-work zone crash severity.

- non-fixed object as a crash type, the interaction as a contributing circumstances, making a turn and slow moving types, and as pre-crash action, interstate highways etc.

To examine the marginal effects of each variable, the STATA program was used. The “dy/dx” values were estimated for each variable and for each severity outcome by using model coefficients. Eq-23 was used to estimate the marginal effect ratio of each variable for each severity level. These results are included in Table 4-15. Findings from the marginal effects analysis can be categorized for each level as follows:

Level (1) – Complaint of Pain:

Similar to the work zone maximum crash severity modeling variable, the “overturn” crash type was found to have the highest marginal impact, which was 23.6 percent for level 1 severity. If a light vehicle was involved in a crash, 16.4 percent complained of pain, and if a DUI crash was included, it was 12.8 percent more likely to result in a complaint of pain or level 1 severity. “Fixed object”, “opposite”, and “angle” types of crashes had the effect of increasing level 1 crash severity probability by 11.9, 11.1 and 9.5, respectively. If the crash type was a “non-fixed object”, it was 10.8 percent less likely this would to result in a level 1 severity. “Unsafe speed” contributed to crashes that had marginal effects of 7.3 percent. If one more vehicle was involved in a non-work zone crash, this l increased the probability of a level 1 crash severity by 5.9 percent.

Level (2) – Moderate Injury:

Level 2 marginal effects had similar results to the level 1 marginal effects. If the same order is observed, the “overturn” type crash was 18.3 percent more likely to result in a moderate level of severity. “Light vehicles” involved in a crash, DUI, and fixed object type crashes had stronger marginal effects of 7.6 percent, 5.1 percent and 4.3 percent, respectively. If the crash was carried out at an “unsafe speed” this contributed 2.4 percent to these effects, and if a cellphone caused crash, this was 1 percent more likely to result in a moderate level injury.

Level (3) – Incapacitated:

If the crash was an overturn type, it was 3.2 percent more likely to result in an incapacitated type of injury. Light vehicle involvement in a crash and DUI were other variables which had a significant impact on the level 3, “incapacitated” severity. Findings can be interpreted in same way from the table. Since the sample size was lower for this level of severity, to better understand the effect of each variable this can be interpreted by using the ratio of marginal effects.

Level (4) – Killed:

As for the level 3 severity outcomes, the marginal effect ratios that were calculated can be used to better understand the impact of each variable. The overturn crash type had a 1 percent marginal effect; however, the ratio of this marginal effect was 54 percent among the absolute sum of all marginal effects. Similarly, light vehicles involved in a crash, DUI, opposite crash types, fixed object crash types, angle crash types, “unsafe speed” contributed crashes, numbers of vehicles involved were other important factors for estimating the importance of the killed level outcomes of non-work zones crash severity category.

Table 4-15 Marginal Effects of Each Variable for Different Levels of Severity (Non-WZ Maximum Severity)

Variable	Symbol	Complaint		Moderate		Incapacitated		Killed	
		dy/dx (%)	Ratio (%)	dy/dx (%)	Ratio (%)	dy/dx (%)	Ratio (%)	dy/dx (%)	Ratio (%)
Time of day	Time	2.52	1.40	0.72	1.04	0.05	0.71	0.01	0.48
Light condition	Light	-0.73	-0.41	-0.20	-0.28	-0.01	-0.18	0.00	-0.12
Weather condition	Weather	-1.68	-0.94	-0.44	-0.64	-0.03	-0.41	0.00	-0.26
Driver gender	Drv_gender	1.58	0.88	0.43	0.62	0.03	0.41	0.00	0.27
Driver under the influence	DUI	12.79	7.11	5.05	7.25	0.51	6.52	0.10	5.46
Vehicle type	Light_veh	12.04	6.69	4.76	6.83	0.47	6.13	0.09	5.12
	Heavey_veh	-3.30	-1.83	-0.82	-1.17	-0.06	-0.72	-0.01	-0.45
Vehicle age	Veh_age	0.14	0.08	0.04	0.05	0.00	0.04	0.00	0.02
Road class	Rd_classhigh	-3.05	-1.69	-0.77	-1.11	-0.05	-0.69	-0.01	-0.44
	Rd_classmedium	0.93	0.52	0.26	0.37	0.02	0.24	0.00	0.16
Posted speed limit	Speedhigh	2.99	1.66	0.88	1.26	0.07	0.87	0.01	0.60
	Speedmedium	3.22	1.79	0.91	1.31	0.07	0.89	0.01	0.61
Traffic control type	Signalsign	4.19	2.33	1.21	1.74	0.09	1.20	0.01	0.83
	Lanemark	4.23	2.35	1.18	1.70	0.09	1.14	0.01	0.77
Number of vehicles involved	Veh_num	5.86	3.25	1.59	2.28	0.12	1.49	0.02	0.98
Number of persons involved	Person_num	2.02	1.12	0.55	0.78	0.04	0.51	0.01	0.34
Cell phone use	Cellphone	3.31	1.84	0.99	1.42	0.08	1.01	0.01	0.70
Light vehicle involved in crash	Lightvehinvolved	16.40	9.11	7.62	10.94	0.87	11.27	0.18	10.50
Crash type	C_angle	9.53	5.29	3.16	4.54	0.27	3.54	0.05	2.66
	C_opposite	11.14	6.19	4.23	6.07	0.41	5.26	0.07	4.28
	C_overturn	23.62	13.12	18.26	26.21	3.18	41.02	0.94	53.74
	C_fixedobj	11.93	6.63	4.31	6.18	0.40	5.17	0.07	4.12
	C_nonfixedobj	-10.82	-6.01	-2.51	-3.61	-0.17	-2.14	-0.02	-1.34
Contributing circumstances	Unsafespeed	7.31	4.06	2.41	3.46	0.21	2.67	0.03	1.99
	Inattention	1.80	1.00	0.49	0.71	0.04	0.46	0.01	0.31
	Improper	2.15	1.19	0.60	0.87	0.05	0.58	0.01	0.39
	Close	2.42	1.35	0.70	1.00	0.05	0.69	0.01	0.47
	Other_circ	2.59	1.44	0.75	1.07	0.06	0.73	0.01	0.50
Vehicle precrash action	Maketurn	-5.41	-3.01	-1.31	-1.88	-0.09	-1.13	-0.01	-0.71
	Slowmove	-4.28	-2.38	-1.10	-1.57	-0.08	-0.98	-0.01	-0.63
	Interaction	-6.00	-3.33	-1.42	-2.04	-0.09	-1.20	-0.01	-0.74

4.4.6.2 Multi-level Monetary Weighted Severity Analysis for Non-work Zone Crashes

Similar to the multilevel work zone crash severity modeling approach, the non-work zone crash severity model was developed by using a monetary weighted severity variable. To create this variable, the severity level of each non-work zone crash was defined based on the total weighted severity (Table 4-9) values of the occupants involved in a crash. These values were categorized into 5 different levels and thresholds were defined as follow:

1. no injury = 0
2. Level 1 (complaints) = 1
3. Level 2 (moderate) = 2
4. Level 3 (incapacitated)= >2 & <8
5. Level 4 (killed) > 7

Ordered probit regression was used to the model monetary weighted non-work zone crash severity based on the thresholds listed above. Crash severity was defined based on Eq-24. In addition to model coefficients for each variable, the marginal effects were estimated in order to gain a better understanding of the relationships between the variables and the severity thresholds.

36,374 crashes were used to model non-work zone monetary weighted crash severity, which is the same as the maximum severity model dataset. No injury was defined as the base category and compared to other levels of severities.

Multilevel Non-work Zone Crash Severity Modeling Results (Monetary Weighted)

As used in the previously described models, 52 variables were included within the ordered probit model for the non-work zone multilevel monetary weighted severity factor. After omitting the base categories such as “no-error” as contributing factors, 44 variables remained for modeling purposes. Thirty of these 44 variables were found to have a significant relationship with crash severity. The chi-square value for the all variables was $\chi^2 = 5514.7$ and the *p* value was less than 0.001. The Wald-square test was also conducted to examine individual relationships between crash severity and the other variables. The model variable coefficients and the Wald-square test results are included in Table 4-16. According to the Wald-square test results, some of the variables had a stronger relationship with monetary based crash severity than others, including number of persons involved in a crash, non-fixed object crash type, angle crash type, overturn crash type, fixed object crash type, DUI, and the number of vehicles involved in a crash in decreasing order.

Table 4-16 Multilevel Non-work Zone Crash Severity Modeling Results (Monetary Weighted)

Variable	Symbol	Estimate	Std. Error	Wald χ2	Significance
Time of day	Time	0.116	0.024	22.6	***
Weather condition	Weather	-0.074	0.029	6.4	*
Driver gender	Drv_gender	0.084	0.015	30.5	***
Driver under the influence	DUI	0.513	0.032	257.7	***
Vehicle type	Light_veh	0.472	0.098	23.2	***
	Heavey_veh	-0.126	0.056	5.2	*
Vehicle age	Veh_age	0.007	0.001	25.5	***
Road class	Rd_classhigh	-0.139	0.037	14	***
	Rd_classmedium	0.040	0.021	3.5	.
Posted speed limit	Speedhigh	0.127	0.041	9.7	**
	Speedmedium	0.152	0.021	53.8	***
Traffic control type	Signalsign	0.201	0.022	84	***
	Lanemark	0.192	0.021	81.6	***
Number of vehicles involved	Veh_num	0.281	0.018	245.4	***
Number of persons involved	Person_num	0.136	0.006	508.1	***
Cell phone use	Cellphone	0.178	0.073	6	*
Light vehicle involved in crash	Lightvehinvolved	0.602	0.078	59	***
Crash type	C_angle	0.446	0.024	344.7	***
	C_opposite	0.535	0.042	164.9	***
	C_overturn	1.167	0.070	275.1	***
	C_fixedobj	0.515	0.032	264.5	***
	C_nonfixedobj	-0.565	0.029	368	***
Contributing circumstances	Unsafespeed	0.315	0.038	68.4	***
	Inattention	0.067	0.028	6	*
	Improper	0.083	0.031	7.2	**
	Close	0.088	0.036	5.8	*
	Other_circ	0.111	0.034	10.4	***
Vehicle precrash action	Maketurn	-0.271	0.024	130.2	***
	Slowmove	-0.203	0.020	102.1	***
	Interaction	-0.303	0.026	133.3	***

Significance codes: 0 ‘*’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1**

The following findings can be ordered based on the coefficients derived from the ordered probit results:

Time and environmental characteristics:

- Traffic control type: signal sign, lane mark,
- Posted speed limit if between 40 mph and 60 mph,
- Posted speed limit if higher than 60 mph,
- Nighttime had a higher impact on multilevel work zone crash severity,
- State roads

Driver and vehicle characteristics:

- DUI
- Driving light vehicle or light vehicle involved in a crash
- Female drivers
- Cell phone use
- Vehicle age

Crash characteristics:

- Crash types: Overturn, opposite, fixed-object, and angle crash types had a greater effect on crash severity compared to rear-end crashes (from the most efficient to less efficient in order).
- Contributing circumstances: Unsafe speed, other circumstances, following too closely, improper lane change, and inattention.
- Number of vehicles involved,

- Number of occupants involved, had an incremental effect on multilevel work zone crash severity.

Estimating the marginal effects for each outcome using STATA software provided a better understanding of the relationship between multilevel crash severity and the measured variables of interest. Table 4-17 shows the marginal effects and the marginal effect ratios estimated by Equation 4-11 within each severity level. Results were observed to be distributed normally when compared to the maximum severity modeling data.

According to the marginal effects for each monetary weighted severity level;

Level (1) –Complaint of Pain:

If the crash was of the “overturn” type, this was 12.4 percent more likely to result in a level-1 severity injury. Similarly, the light vehicle item had an 8.6 percent, the opposite type had a 7.8 percent; and the fixed object and DUI types had a 7.5 percent chance of heightening the chances of incurring a crash severity level-1 crash type. Non-fixed object non-work zone crashes were 7.6 percent less likely to result in a level -1 severity injury compared to rear-end crashes.

Level (2) – Moderate Injury:

The impact order for level-2 injuries based on the marginal effect was as follows: the “over turn” crash type, light vehicle involved crashes, the opposite crash type, DUI, fixed object etc. The “over turn” crash type had a higher marginal effect for level-2 severity than level-1 severity which was 14.6 percent. Except for this finding, all marginal effects were smaller when compared to those for the level-1 crash severity data.

Level (3) – Incapacitated:

The marginal effect for “overturn crashes” for the “incapacitated” crash severity level was 11.9 percent and the ratio among all marginal effect was 26.5 percent. Different from similar variables, if the contributing circumstance was “unsafe speed”, the severity level was 1.6 percent more likely to result in an “incapacitated” outcome. The marginal effects for the “opposite” crash type, DUI, and “fixed object” crash types were 7.5, 6.9 and 6.4 percent, respectively.

Level (4) – Killed:

The variables with the highest marginal effects were the “overturn” crash type, light vehicles involved in a crash, the “opposite” crash type, DUI, and the “fixed object” crash type. If the crash type was an overturn type, this crash was 3.6 percent more likely to result in a fatal crash severity outcome compared to rear-end crashes.

Table 4-17 Marginal Effects of Each Variable for Different Levels of Severity (Monetary Weighted)

Variable	Symbol	Complaint		Moderate		Incapacitated		Killed	
		dy/dx	Ratio	dy/dx	Ratio	dy/dx	Ratio	dy/dx	Ratio
Time of day	Time	1.71	1.52	1.05	1.30	0.48	1.08	0.07	0.78
Weather condition	Weather	-1.08	-0.96	-0.62	-0.78	-0.27	-0.61	-0.04	-0.41
Driver gender	Drv_gender	1.24	1.10	0.73	0.91	0.33	0.73	0.05	0.51
Driver under the influence	DUI	7.47	6.63	5.58	6.94	3.09	6.88	0.56	6.25
Vehicle type	Light_veh	6.90	6.12	5.14	6.39	2.84	6.30	0.51	5.68
	Heavey_veh	-1.81	-1.61	-1.02	-1.26	-0.43	-0.97	-0.06	-0.64
Vehicle age	Veh_age	0.10	0.09	0.06	0.07	0.03	0.06	0.00	0.04
Road class	Rd_classhigh	-1.99	-1.77	-1.12	-1.39	-0.48	-1.07	-0.06	-0.71
	Rd_classmediu	0.58	0.52	0.35	0.43	0.16	0.35	0.02	0.24
Posted speed limit	Speedhigh	1.88	1.67	1.16	1.45	0.54	1.21	0.08	0.88
	Speedmedium	2.24	1.98	1.36	1.69	0.63	1.39	0.09	1.00
Traffic control type	Signalsign	2.97	2.63	1.83	2.28	0.85	1.90	0.12	1.39
	Lanemark	2.81	2.50	1.69	2.10	0.77	1.71	0.11	1.22
Number of vehicles involved	Veh_num	4.11	3.64	2.42	3.00	1.08	2.40	0.15	1.66
Number of persons involved	Person_num	1.98	1.76	1.17	1.45	0.52	1.16	0.07	0.80
Cell phone use	Cellphone	2.65	2.35	1.69	2.10	0.81	1.81	0.12	1.37
Light vehicle involved in	Lightvehinvolve	8.58	7.61	6.86	8.52	4.03	8.97	0.78	8.78
Crash type	C_angle	6.57	5.83	4.48	5.57	2.30	5.11	0.37	4.21
	C_opposite	7.75	6.87	5.93	7.36	3.35	7.45	0.62	6.94
	C_overturn	12.41	11.00	14.59	18.12	11.93	26.53	3.56	39.95
	C_fixedobj	7.54	6.69	5.38	6.68	2.87	6.38	0.49	5.54
	C_nonfixedobj	-7.60	-6.74	-4.00	-4.97	-1.64	-3.64	-0.21	-2.31
Contributing circumstances	Unsafespeed	4.68	4.15	3.15	3.91	1.59	3.53	0.25	2.83
	Inattention	0.99	0.87	0.58	0.72	0.26	0.58	0.04	0.40
	Improper	1.23	1.09	0.74	0.92	0.34	0.75	0.05	0.53
	Close	1.30	1.15	0.79	0.98	0.37	0.81	0.05	0.58
	Other_circ	1.64	1.46	1.01	1.25	0.47	1.03	0.07	0.75
Vehicle precrash action	Maketurn	-3.82	-3.38	-2.08	-2.58	-0.87	-1.93	-0.11	-1.24
	Slowmove	-2.92	-2.59	-1.65	-2.05	-0.71	-1.59	-0.09	-1.06
	Interaction	-4.22	-3.74	-2.26	-2.81	-0.93	-2.07	-0.12	-1.31

4.4.7 Comparison of Multilevel Severity Models for Work and Non-Work Zone Crashes

An estimated impact of each variable on crash severity for the work zone and non-work zones was undertaken as well. The essential point of this analysis was to estimate the difference between the work zone and non-work zone conditions. To do so, the impacts of the variables on work zone crash severity were defined precisely. For example, A can be an effective variable for work zone crash severity, but can be more effective or less effective for-non work zone crashes. Similarly, findings from multilevel severity models were compared based on the estimations and marginal effects of each variable. First, the maximum severity based models, and then the monetary weighted severity models were compared for the work zone and non-work zone conditions.

4.4.7.1 Comparison of Maximum Severity Based Crash Model

The maximum severity models for work zone and non-work zone conditions were discussed in a previous section. The comparison of these models in terms of the coefficient and marginal effect differences were investigated in detail. The comparison of the coefficients is included in the Table 4-18. The last column describes the difference between (Non-WZ – WZ) coefficients for each comparison. The precise impact could not be interpreted from the ordered probit coefficients directly. Thus a marginal effects comparison was conducted for each level of severity.

Table 4-18 shows results from the maximum severity models for work zone and non-work zone crashes and can be interpreted as follows:

- Nighttime had a lower impact on work zone crash severity.
- Female drivers had more risk of being involved in severe crashes at work zones.
- DUI was slightly less impactful in terms of severity on work zone crashes.
- Small vehicle or small vehicle involved crashes had a lower severity risk at work zones.
- Vehicle age had similar effects for both work zone and non-work zone crash severities.
- State roads had a higher severity risk for work zone crashes.
- Speeds over 60 mph posed more risk, speeds between 40-60 mph posed less risk for work zone crashes.
- As a traffic control type, “no control” was used as the base case. The “signal sign” had a similar effect on work zone and non-work zone crash severity, and “lane mark” reduced risk for work zone crashes.
- The number of vehicles involved in a crash had a stronger impact on the severity of non-work zone crashes; and the number of persons involved in a crash had a similar effect for both conditions.
- In terms of crash type, the impact of crash types was estimated compared to the “rear-end” crash type as base. The “non-fixed” object crash type had a significantly greater impact on work zone crash severity. Similarly, “overturn” and “opposite” crash types had a stronger impact on work zone crash severity.

"Angle" and "fixed-object" crash types caused less risk for work zone crashes when compared to non-work zone crashes.

- For the contributing circumstances of the crash, "unsafe speed" posed a lower risk of severity and "inattention" posed a higher severity risk for work zone crashes. "Following too closely" had similar effects on crash severity for both conditions.
- Pre-crash actions such as "making a turn", "moving slowly" or "interaction" were found to be more risky for work zone crashes when compared to non-work zone crashes.

To explore numeric differences between the maximum severity based model variables, the marginal effects were compared. Differences between the marginal effects and the percent changes between non-work zone and work zone crashes are provided in Table 4-19. Significant variables for both models were included in a comparison analysis. The non-work zone crash severity level marginal effect values were defined as the base case, and the percent changes for each marginal effect was estimated by subtracting the marginal effects of the model variable for the work zone crashes from the base scores. A comparison of the results is listed below as follows:

- Except for the "killed" level of severity, the nighttime marginal effect on crash severity was found to be 27 percent lower for the work zone crashes than the non-work zone nighttime crashes. For the "killed" level of severity, the nighttime marginal effect was 155 percent higher than the non-work zone nighttime "killed" level crashes.

- The marginal effect of being a female driver on work zone crash severity was significantly higher for all level of severity than non-work zone crashes. The marginal effects of “incapacitated” and “killed” levels of severity at work zones were 65 percent and 471 percent higher than the marginal effects of non-work zone crash female driver marginal effects on severity for the same levels, respectively.
- DUI had higher marginal effects for severity of work zone crashes. The difference was lower for level 1-3 severities which were about 4 percent on average. For the “killed” level of severity, DUI had a 2.4 times greater marginal effect for work zone crashes than the DUI marginal effect on non-work zone crashes.
- Except for the “killed” severity level, the marginal effect of driving a small vehicle at a work zone of 37 percent on average was lower than driving a small vehicle at a non-work zone.
- The marginal effect of “vehicle age” was slightly higher for work zone crashes. Since the marginal effects of vehicle age was too small, the percentage differences for the marginal effects for both conditions were higher.
- State roads were found to have approximately 2 times higher marginal effects on work zone crash severity rates for levels 1 to 3, and a 10 times higher impact for the “killed” severity level compared to the marginal effect of state highways on non-work zone crash severity.
- The marginal effect of higher posted speed limit (> 60mph) was 16 percent higher on average for levels 1 to 3 severity thresholds compared to the marginal

effects on non-work zone crash severity. For level 4 crash severity, the marginal impact of a higher posted speed limit was 3 times more than the marginal effects for non-work zone crash severity rates. Interestingly, the marginal effect of medium posted speed (40 mph < PSL < 60 mph) on work zone crash severity was 57 percent lower than the marginal effect of non-work zone crashes for level 1 to 3 severities.

- A comparison of the marginal effect of the traffic control type for the maximum severity models showed that the “signal sign” had as higher impact on work zone crash severity. On the other hand, the marginal effect of “lane mark” was 51 percent lower on average, on work zone 1 to 3 level crash severities and 69 percent higher for 4th level crash severity when compared to the marginal effect of “lane mark” on non-work zone crash severity rates.
- The number of vehicles involved in a crash increased the severity risk for level 1 to level 3 severities by 14 percent for non-work zone crashes, and 211 percent for level 4 work zone crashes when compared to the marginal effects for both conditions.
- The marginal effect of the number of occupants in a crash was similar for level 1 and level 2 severities and 9 percent and 274 percent higher for work zone crashes compared to the marginal impacts for non-work zone crashes for the mentioned level of severities.
- The marginal effect comparison for crash types showed that “angle”, “opposite” and “overturn” crashes had an 11, 40 and 23 percent higher marginal impact on

crash severity (level 1 to 3) at work zones compared to marginal effects on non-work zone crash severity. “Fixed object” and “non-fixed” object crashes had a 13 percent and 130 percent lower marginal effect for work zone crash severity (level 1 to 3) compared to non-work zone ones. For the “killed” level of severity, the “fixed object” crash type had a 180 percent higher impact and “non-fixed object” crash type had a 238 percent lower marginal effect on work zone crash severity when compared to the marginal effects of non-work zone crash severity.

- When we examine the marginal effects comparison in terms of contributing circumstance of the crash, “unsafe speed” had a similar effect for both work zone and non-work zone conditions except for the “killed” level of severity. “Unsafe speed” had a 226 percent higher marginal effect for the work zones “killed” level crash severity outcome compared to those of non-work zones. The marginal effect of “inattention” was 65 percent higher for work zone crash level 1 to 3 severities, and 5 times higher for level 4 severity. Similarly, “following too closely” had a 15 percent higher marginal effect for work zone levels 1 to 3 crash severity and a 3 times higher effect for level 4 severity.
- The marginal effects of the pre-crash actions seen in Table 4-19 show that, “making a turn” was on average 7 percent more impactful than the marginal effect for work zone crash level 1 to 3 and 285 percent more impactful for level 4 severities. The item “slow move” had a 73 percent lower marginal effect for work zone crash levels 1 to 3 severity and a 5 percent higher effect for level 4 compared to the marginal effect for non-work zone crash severity levels.

Table 4-18 Comparison of Maximum Severity Models

Maximum Severity Model / Variables	Symbol	Work Zone		Non-Work Zone		Comparison
		Coef.	Signif.	Coef.	Signif.	WZ-NonWZ
Time of day	Time	0.079	0.004	0.115	0.000	0.037
Driver gender	Drv_gender	0.102	0.000	0.073	0.000	-0.029
Driver under the influence	DUI	0.550	0.000	0.558	0.000	0.008
Vehicle type	Light_veh	0.348	0.005	0.524	0.000	0.175
Vehicle age	Veh_age	0.007	0.000	0.007	0.000	-0.001
Road class	Rd_classmedium	0.114	0.000	0.043	0.045	-0.071
Posted speed limit	Speedhigh	0.144	0.000	0.136	0.001	-0.008
	Speedmedium	0.061	0.015	0.148	0.000	0.087
Traffic control type	Signalsign	0.194	0.000	0.191	0.000	-0.002
	Lanemark	0.091	0.004	0.196	0.000	0.105
Number of vehicles involved	Veh_num	0.212	0.000	0.273	0.000	0.061
Number of persons involved	Person_num	0.088	0.000	0.094	0.000	0.006
Light vehicle involved in crash	Lightvehinvolved	0.386	0.000	0.725	0.000	0.339
Crash type	C_angle	0.414	0.000	0.423	0.000	0.009
	C_opposite	0.591	0.000	0.485	0.000	-0.106
	C_overturn	1.522	0.000	1.259	0.000	-0.263
	C_fixedobj	0.444	0.000	0.526	0.000	0.081
	C_nonfixedobj	0.112	0.002	-0.566	0.000	-0.677
Contributing circumstances	Unsafespeed	0.291	0.000	0.323	0.000	0.031
	Inattention	0.124	0.000	0.084	0.003	-0.040
	Close	0.117	0.002	0.111	0.003	-0.007
Vehicle precrash action	Maketurn	-0.264	0.000	-0.268	0.000	-0.004
	Slowmove	-0.048	0.038	-0.206	0.000	-0.158
	Interaction	-0.274	0.000	-0.302	0.000	-0.028

Table 4-19 Comparison of Marginal Effects of Each Variable Severity (Maximum Severity)

Maximum Severity Model Variables	Symbol	Complaint (1)		Moderate (2)		Incapacitated (3)		Killed (4)	
		Δ dy/dx	Δ %	Δ dy/dx	Δ %	Δ dy/dx	Δ %	Δ dy/dx	Δ %
Time of day	Time	0.65	25.83	0.22	30.25	0.01	24.86	-0.01	-155.12
Driver gender	Drv_gender	-0.83	-52.80	-0.21	-48.57	-0.02	-64.84	-0.02	-471.19
Driver under the influence	DUI	-0.54	-4.23	-0.08	-1.55	-0.03	-5.84	-0.23	-244.75
Vehicle type	Light_veh	3.52	29.24	1.91	40.12	0.21	43.22	-0.07	-73.18
Vehicle age	Veh_age	-0.04	-25.95	-0.01	-20.92	0.00	-33.09	0.00	-359.66
Road class	Rd_classmedium	-1.76	-189.48	-0.46	-179.82	-0.04	-209.22	-0.03	-970.82
Posted speed limit	Speedhigh	-0.47	-15.73	-0.10	-11.69	-0.01	-21.92	-0.03	-316.98
	Speedmedium	1.80	55.73	0.54	59.45	0.04	57.05	0.00	-44.22
Traffic control type	Signalsign	-0.45	-10.63	-0.09	-7.73	-0.02	-18.46	-0.04	-306.87
	Lanemark	2.10	49.72	0.63	53.34	0.04	50.08	-0.01	-68.61
Number of vehicles involved	Veh_num	0.86	14.75	0.29	18.16	0.01	9.83	-0.04	-211.39
Number of persons involved	Person_num	-0.05	-2.69	0.01	1.42	0.00	-8.60	-0.02	-274.92
Light vehicle involved in crash	Lightvehinvolved	6.97	42.50	4.38	57.51	0.56	64.31	0.00	1.18
Crash type	C_angle	-0.57	-5.94	-0.26	-8.32	-0.05	-19.73	-0.14	-308.76
	C_opposite	-3.10	-27.86	-1.57	-37.12	-0.22	-53.68	-0.32	-428.64
	C_overturn	1.06	4.50	-5.28	-28.90	-1.41	-44.23	-3.71	-395.99
	C_fixedobj	1.13	9.46	0.66	15.41	0.05	13.23	-0.13	-180.21
	C_nonfixedobj	-13.49	124.68	-3.25	129.35	-0.23	137.13	-0.06	238.53
Contributing circumstances	Unsafespeed	0.21	2.92	0.18	7.41	0.00	1.83	-0.08	-226.75
	Inattention	-1.13	-62.73	-0.28	-57.23	-0.03	-73.76	-0.03	-501.30
	Close	-0.37	-15.26	-0.07	-10.16	-0.01	-19.82	-0.03	-308.98
Vehicle precrash action	Maketurn	0.46	-8.50	0.02	-1.23	0.01	-11.22	0.04	-285.13
	Slowmove	-3.15	73.74	-0.81	73.77	-0.05	70.20	0.00	-4.98
	Interaction	0.16	-2.72	0.02	-1.11	0.01	-15.39	0.04	-309.24

4.4.7.2 Comparison of Monetary Weighted Multilevel Severity Based Crash Model

The monetary weighted model results for the work zone and non-work zone crashes were also analyzed. Similarly, a detailed comparison analysis was conducted for the monetary weighted crash severity modeling results. Table 4-20 shows the modeling estimations for both conditions and the difference between the coefficients (Non-WZ – WZ). Moreover, the marginal effects were compared to examine the difference for the impact of each variable. According to the preliminary results of the monetary weighted crash severity modeling approach, the findings are listed below as follows:

- Nighttime had a lower impact on work zone crashes severity compared to non-work zone crashes.
- Female drivers had more risk in the case of work zone crashes.
- DUI had more effect on work zone crash severity.
- Small vehicle or small vehicle involved crashes had a lower severity risk at work zones.
- Vehicle age had similar effects.
- Interstate highways had higher severity risk for work zone crashes.
- Speeds over 60 mph had more risk, speed between 40-60 mph had less risk for work zone crashes.
- As a traffic control type, “no control” was used as the base case. “Signal sign” had a similar effect on work zone and non-work zone crash severity rates, and “lane mark” reduced risk for work zone crashes.

- Numbers of vehicles involved in a crash had more impact on severity for work zone crashes; numbers of persons involved in a crash had a similar effect for both conditions.
- In terms of crash type, the impact of crash types was estimated and compared to the “rear-end” crash type as base. The “non-fixed” object crash type had a significantly greater impact on work zone crash severity. Similarly, “overturn” and “opposite” crash types had more impact on work zone crash severity. The “angle” and “fixed-object” crash types had a similar risk for work zone and non-work zone crashes.
- For the contributing circumstances of the crash, “inattention”, “unsafe speed”, “following too closely” and “improper lane change” were found to be more risky errors in terms of work zone crash severity.
- In terms of pre-crash actions, “making a turn” was found to be less risky for work zones and “interaction” was found to be more risky for work zone crashes when compared to non-work zone crashes.

To examine the difference between the impacts numerically, the marginal effects were compared at each level of severity. Table 4-21 provides a comparison for the marginal effects comparison for work zone and non-work zone crashes based on the monetary weighted crash severity models. Table 4-21 includes the change in the marginal effects for each level of severity and the percent change between the non-work zone and work zone conditions. Work zone values are used as subtrahend, in other words, the negative values show that the parameter had a greater impact on work zone crash severity than non-work zone crash severity. Based on the results of Table 4-21, findings can be summarized as follow:

- Sample interpretations from the table are as follows. For the complaint level of severity, the nighttime condition was 0.41 percent less risky for work zones when compared to non-work zone nighttime conditions. In other words, the nighttime effect on crash severity was 23.7 percent lower for work zones for the "complaint" level, 30.7 percent for the "moderate" severity, 26.3 percent for the "incapacitated" level of severity, and 26.47 percent for the "killed" level of severity. The rest of the table can be interpreted in the same way.
- For female drivers, work zone crashes were more risky than non-work zone crashes in terms of severity. With an increase in severity level, the impact of being female within work zone crash severity category was increased as well. Gender impacted on crash severity for female drivers, an on average, were 55 percent higher for work zones.
- DUI on average resulted in 20 percent more impact on work zone crash severity than the impact on non-work zone crash severity. Similar to the gender outcomes, when the severity level increased, the impact of DUI increased in terms of work zone crash severity as well.
- The marginal effects for driving a small vehicle had 2.19 percent less impact on level 1, 2.19 percent for level 2, 1.22 percent for level 3 and 0.24 percent for level 4 work zone crash severity. If we look at the percent differences of the marginal

effects, on average, driving a small vehicle had a 41 percent lower impact on work zone crash severity than the impact on non-work zone crash severity.

- The marginal effect of vehicle age was slightly different. The average change was 22.7 percent higher for work zone crash severity levels in terms of vehicle age.
- One of the biggest percent differences was observed for interstate highways. The average impact change in crash severity for driving on an interstate highway was 244 percent higher for work zone conditions. The marginal effect differences from level (1) to level (4) were 1.44, 0.77, 0.39 and 0.06, respectively.
- The posted speed limit above 60 mph was 46 percent higher on average for the impact on crash severity for work zone crashes compared to the impact on non-work zone crashes. On the other hand, the speed limit between 40-60 mph had a 52 percent lower impact on average on crash severity at work zones.
- Two of the traffic controls were found to be significant for both work zone and non-work zone models. The impact of “signal sign” and “lane mark” on crash severity was found to be 4.7 percent and 55 percent lower for work zone conditions compared to non-work zone crashes.
- There was no difference for the impact of the “number of occupants involved in a crash” on crash severity for both conditions. The impact of the “number of vehicles involved in a crash” on crash severity of 16.5 percent on average was higher for work zone conditions compared with non-work zone conditions.
- The biggest difference for the marginal effects of crash types was observed for “overturn” crashes. Except for the “complaint of pain” level, the “overturn” crash

type had a 65 percent higher impact on average on work zone crash severity, compared with non-work zone crash “overturn” crashes. Similarly, “opposite” and “angle” crash types had a 36 and 21 percent higher impact, on average, respectively. “Non-fixed object” crashes had the effect of decreasing crash severity for both conditions. “Non-fixed object” work zone crashes were 50 percent less severe on average than non-work zone “non-fixed object” crashes. Except for the moderate level of work zone crashes, “fixed object” type of crashes were 7 percent higher as regards impact on average on work zone crash severity compared to non-work zone crashes.

- Another higher percent difference observed for the marginal effect comparison of monetary weighted severity model variables was for “inattention” as a contributing factor. “Inattention” caused the impact of crashes to be 171 percent higher on average in work zone crashes than non-work zone crashes. Besides, when compared to non-work zone crashes, “unsafe speed”, “improper lane change” and “following too closely” were approximately 27 – 39 – 49 percent higher in terms of their marginal effects for work zone crashes, respectively.
- “Making a turn” and “interactions” as pre-crash actions had a 25 percent and 7 percent higher rate of risk severity for work zone conditions compared to same pre-crash action at non-work zone conditions.

Table 4-20 Comparison of Monetary Weighted Severity Models

Monetary Severity Model / Variables	Symbol	Work Zone		Non-Work Zone		Comparison
		Coef.	Signif.	Coef.	Signif.	WZ-NonWZ
Time of day	Time	0.082	0.003	0.116	0.000	0.034
Driver gender	Drv_gender	0.122	0.000	0.084	0.000	-0.037
Driver under the influence	DUI	0.568	0.000	0.513	0.000	-0.056
Vehicle type	Light_veh	0.296	0.020	0.472	0.000	0.176
Vehicle age	Veh_age	0.008	0.000	0.007	0.000	-0.001
Road class	Rd_classhigh	0.127	0.000	0.040	0.062	-0.088
Posted speed limit	Speedhigh	0.171	0.000	0.127	0.002	-0.044
	Speedmedium	0.074	0.003	0.152	0.000	0.078
Traffic control type	Signalsign	0.180	0.000	0.201	0.000	0.021
	Lanemark	0.084	0.010	0.192	0.000	0.108
Number of vehicles involved	Veh_num	0.309	0.000	0.281	0.000	-0.028
Number of persons involved	Person_num	0.127	0.000	0.136	0.000	0.008
Light vehicle involved in crash	Lightvehinvolved	0.317	0.001	0.602	0.000	0.285
Crash type	C_angle	0.473	0.000	0.446	0.000	-0.027
	C_opposite	0.643	0.000	0.535	0.000	-0.108
	C_overturn	1.516	0.000	1.167	0.000	-0.349
	C_fixedobj	0.510	0.000	0.515	0.000	0.005
	C_nonfixedobj	-0.241	0.000	-0.565	0.000	-0.324
Contributing circumstances	Unsafespeed	0.365	0.000	0.315	0.000	-0.050
	Inattention	0.169	0.000	0.067	0.015	-0.102
	Improper	0.107	0.009	0.083	0.007	-0.024
	Close	0.123	0.001	0.088	0.016	-0.035
	Other_circ	0.122	0.004	0.111	0.001	-0.011
Vehicle precrash action	Maketurn	-0.345	0.000	-0.271	0.000	0.074
	Interaction	-0.295	0.000	-0.303	0.000	-0.008

Table 4-21 Comparison of Marginal Effects of Each Variable Severity (Monetary Weighted)

Monetary Weighted Severity Model Variables	Symbol	Complaint (1)		Moderate (2)		Incapacitated (3)		Killed (4)	
		Δ dy/dx	Δ %	Δ dy/dx	Δ %	Δ dy/dx	Δ %	Δ dy/dx	Δ %
Time of day	Time	0.41	23.70	0.32	30.73	0.13	26.33	0.02	26.74
Driver gender	Drv_gender	-0.70	-56.26	-0.33	-45.35	-0.19	-58.08	-0.03	-61.56
Driver under the influence	DUI	-1.21	-16.17	-0.68	-12.10	-0.75	-24.23	-0.17	-30.83
Vehicle type	Light_veh	2.19	31.76	2.18	42.43	1.22	43.08	0.24	48.34
Vehicle age	Veh_age	-0.03	-25.50	-0.01	-15.48	-0.01	-24.45	0.00	-25.49
Road class	Rd_classhigh	-1.44	-248.08	-0.77	-222.64	-0.39	-249.96	-0.06	-256.71
Posted speed limit	Speedhigh	-0.85	-45.41	-0.42	-36.34	-0.27	-48.94	-0.04	-53.23
	Speedmedium	1.07	47.93	0.73	53.66	0.32	51.54	0.05	52.83
Traffic control type	Signalsign	0.09	3.00	0.19	10.40	0.03	3.39	0.00	2.30
	Lanemark	1.49	52.88	0.97	57.59	0.43	55.24	0.06	55.99
Number of vehicles involved	Veh_num	-0.78	-19.11	-0.23	-9.59	-0.20	-18.11	-0.03	-19.31
Number of persons involved	Person_num	-0.04	-1.87	0.07	6.27	-0.01	-1.02	0.00	-2.05
Light vehicle involved in crash	Lightvehinvolved	3.53	41.18	3.66	53.32	2.27	56.36	0.49	63.16
Crash type	C_angle	-0.82	-12.49	-0.48	-10.79	-0.58	-25.25	-0.13	-34.59
	C_opposite	-1.80	-23.17	-1.40	-23.55	-1.38	-41.22	-0.34	-54.91
	C_overturn	1.43	11.54	-2.74	-18.78	-7.10	-59.47	-4.21	-118.32
	C_fixedobj	-0.42	-5.51	0.06	1.16	-0.20	-7.01	-0.04	-9.08
	C_nonfixedobj	-3.90	51.29	-2.15	53.81	-0.81	49.21	-0.10	48.30
Contributing circumstances	Unsafespeed	-1.11	-23.77	-0.57	-18.21	-0.49	-30.61	-0.09	-36.60
	Inattention	-1.70	-172.88	-0.90	-153.70	-0.46	-176.03	-0.07	-182.58
	Improper	-0.48	-39.48	-0.22	-30.12	-0.14	-41.73	-0.02	-45.13
	Close	-0.66	-50.47	-0.31	-39.58	-0.19	-51.23	-0.03	-53.94
	Other_circ	-0.30	-18.51	-0.10	-9.80	-0.09	-18.78	-0.01	-20.66
Vehicle precrash action	Maketurn	1.36	-35.63	0.40	-19.26	0.21	-24.43	0.02	-20.90
	Interaction	0.30	-7.20	0.00	0.12	0.09	-9.32	0.01	-12.32

4.5 Summary

In this chapter, work zone crash severity was investigated to determine most important factors characteristic factors that are hypothesized to affect severity in a crash. New Jersey work zone crashes between 2004-2010 were the focus of the analysis. A sample of non-work zone crashes of similar size was extracted from the crash records for the same year intervals. Relationships between crash severity and numerous variables were tested by using detailed descriptive analysis. Significant variables were included within the binary level and multiple level severity models for both types of crashes.

First, binary level crash severity model was estimated by using significant variables for both work zone and non-work zone crashes. Logistic regression technique and stepwise processes were employed. The interpretation of model coefficients for the work zone and non-work zone crash severity were compared to see the difference for both conditions. According to the result of comparison, some of the major findings can be listed for binary level models as follows:

- Overturn types of work zone crashes were more likely to be resulted as an injury crashes when compared to same type of crashes at non-work zones.
- Compared to rear-end crashes, the most of the crash types have more potential risk for work zones.
- One more vehicle involved in a work zone crash created 50.2 more risk when compared to non-work zones.
- The work zone crash caused by “unsafe speed” was 42.2 percent more likely to be severe compared to non-work zone crash caused by unsafe speed.

- "Inattention" and "following too closely" had a higher impact on work zone conditions with numbers of 34.1 and 31.9, respectively.
- Light vehicles were 97.2 percent and trucks 9.8 percent less likely to be involved severe crashes at work zones compared to non-work zone conditions.

Relation between variables and crash severity varies based on level of severity outcome. The ordered probit regression was used to determine this relation. Multilevel severity modeling results provided better connections between the variables and the severity level of the crashes. First, the maximum severity based multilevel crash severity results, and secondly, the modeling results of the crash severity weighted by monetary value were compared for both conditions by using model coefficients and marginal effects. By using the monetary weighted models, total marginal effects distributed widely among more variables. Thus, more significant variables were found by this method. Some of the common major findings from both the maximum severity and the monetary weighted severity modeling results are as follows:

- The nighttime marginal effect on crash severity was found to be lower for the work zone crashes, except "killed" level of severity. The nighttime marginal effect is higher for "killed" level severity at work zone crashes.
- The marginal effect for being a female driver was higher for work zone crashes for all level of severity.
- DUI had a greater marginal effect for work zone crashes than the DUI marginal effect on non-work zone crashes.
- Driving a small vehicle was carrying more risk at work zones.

- Work zones at state highways are more likely to have risk in terms of crash severity.
- Higher speed limit (> 60mph) caused more risk in crash severity at work zones. The posted speed between (40-60 mph) was safer for work zone compared to non-work zone conditions.
- Both the higher number of vehicle or occupants involved in a work zone crash increased the severity compared to non-work zone crash.
- The “overturn” crash type had the highest impact for crash severity for both work zone and non-work zone. “Overturn”, “opposite” and “angle” crash types had the higher marginal effect and “fixed object”, “non-fixed object” crash types had the lower marginal effects on crash severity for work zones.
- Contributing circumstances which were “unsafe speed”, “inattention” and “following too closely” had higher impact on crash severity at work zones.
- “Making a turn” as a pre-crash action was found to be less risky for work zones and “interaction” was found to be more risky for work zone crashes when compared to non-work zone crashes.

CHAPTER 5 ESTIMATION THE IMPACT OF WORK ZONE PRESENCE ON THE ROADWAY CAPACITY

5.1 Introduction

This chapter provides a detailed analysis of the impact of work zones on traffic conditions in terms of changes in traffic conditions such as traffic flow, travel time, speed and occupancy. Several data sources were used to estimate the impact of the work zones for different cases, such as lane closure without crashes, non-injury crash and injury crashes. It is well-known that there is also strong relationship between capacity reduction and work zone crashes. For example, rear-end crashes, the major work zone crash type, is mainly observed in the presence of stop and go traffic conditions sometimes caused by the existence of work zones. Thus, it is important to understand the effect of work zones on roadway traffic conditions.

In this study, the NJ Turnpike data from the Exit 6-9 widening project, which is one of the biggest nationwide construction projects (costing 2.5 billion dollars) that began at the end of the 2009 with the goal of completion in 2014, was used. This project was the largest expansion project undertaken since the roadway opened in 1951. It was proposed that an additional 3 lanes between interchanges 6 and 8A and one outer lane for each direction between interchange 8A to interchange 9 would be constructed (Simpson et al. 2011). As well, it was anticipated that170 lane-miles would be constructed for a 35 mile roadway segment. This type of large scale project could be predicted to bring about an increase in work zone crash frequency. Figure 5-1 shows the monthly work zone and non-work zone crash counts in 2011. As can be seen from this graph, an increasing trend is observed for the rates of work zone crashes and overall crashes at this location, and a decreasing trend for non-work zone crashes. Although some of the non-work zone crashes may turn out to be misclassified as work zone crashes in such a large project, the increasing trend line for rates of overall crashes can be hypothesized to show the actual work zone impact on crash frequency.

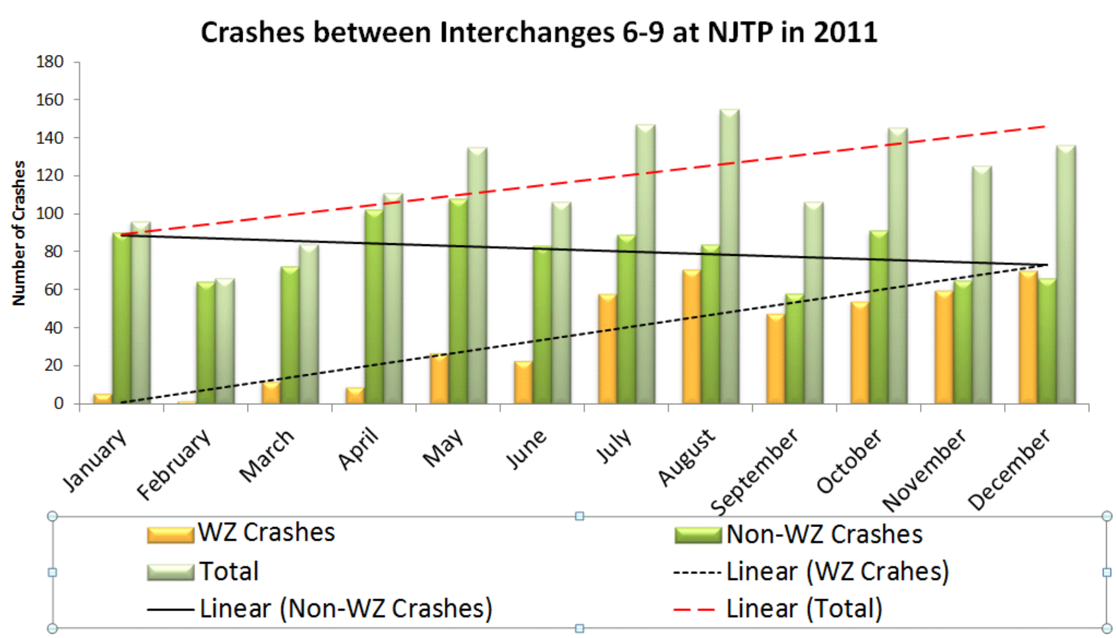


Figure 5-1 Work zone crashes at the NJ Turnpike between interchange 6-9 monthly (2011)

In this chapter, the effect of lane closure on traffic conditions was investigated for a specific location by using both remote traffic microwave sensor (RTMS) data and the Automatic Vehicle Identification (AVI) data obtained from the toll collection system. Thereafter, the impact of the crash rates within the lane closure areas was also investigated in terms of the change in traffic conditions. The statistical modeling approach used for examining lane closures and crashes within lane closures results is presented at the end of this section.

5.2 Data Sources

The effect of work zones on certain NJ roads where additional reliable traffic data is available including the New Jersey Turnpike (I-95) was investigated. To investigate the interactions between the work zones and the traffic conditions on the Turnpike between Exits 6 to 9 a primary database was created by combining the datasets shown in Figure 5-2. By using this combined database, various cases can be studied. The impact of the work zones will be evaluated in terms of delay, speed and capacity reduction.

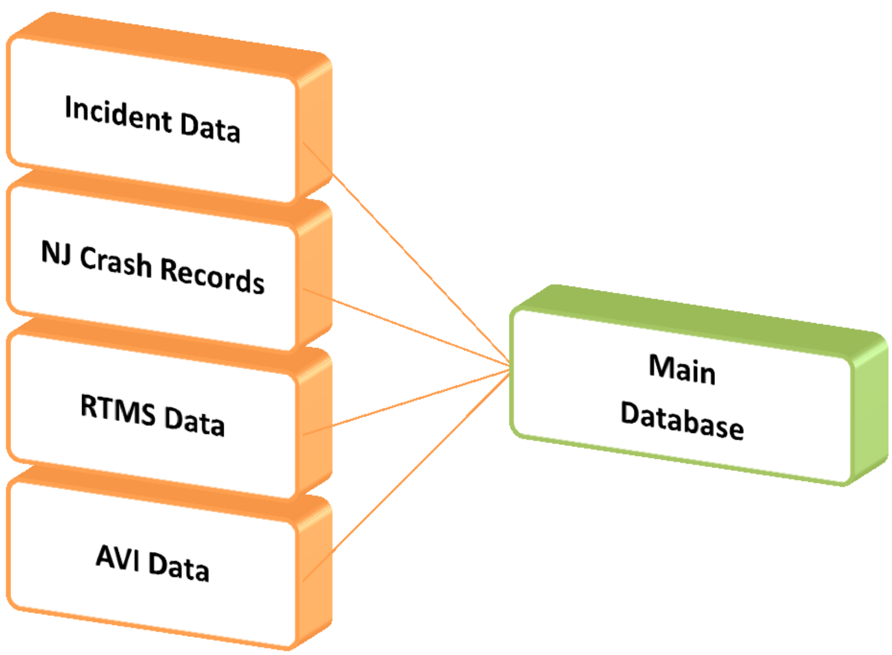


Figure 5-2 Data sources for the evaluation of the impact of work zones on roadway traffic

Summary of the information from the datasets is given below.

- The NJ crash records provided detailed information about rates of crashes.
- The incident data provided detailed information about the traffic condition such as lane closures, road works, delays, accidents etc.
- The RTMS features installed on the Turnpike between interchanges 6-9; recorded instant speed, volume and sensor occupancy data for each lane at 1, 5, 15, 30 and 60 minutes intervals.
- The AVI data is used to estimate individual travel times for given freeway sections.

5.2.1 The New Jersey Turnpike Authority Incident Information (NJTA)

The incident data provided detailed information about the roadwork and traffic conditions. The 2012 annual incident data for the New Jersey Turnpike (NJTP) was used in this study. The following information could be extracted from the incident data:

- Incident Start Time
- Incident End Time
- Incident Duration (min)
- Description of the Incident (Lane closure, crash severity etc.)
- Incident Type (Delay, roadwork, construction etc.)
- Location (From mile marker – to mile marker)

The incident data that was filtered for "roadwork" and "construction" types and sensor locations between the NJTP interchange 6 to interchange 8A was used to obtain work zone related information. Since the number of lanes changed between interchanges 8A and 9, this section was removed from the analysis. By applying a filtering process, the sample size available for the lane closure analysis became 587 incidents, and 489 of these incidents were defined in the dataset as road works and the remainder was defined as the construction type of work zones. After filtering based on the sensor location, 442 incidents were left for analysis. From these 442 lane closure operations, 129 of them were right-lane closure, 117 of them left-lane closure, 92 of them right and center lanes closure and 104 of them left and center lanes closure types of operations.

Data on lane closures and the direction of the operation was obtained through the description of the incident by using text filtering for right, left, right and center and left and center lanes closed to traffic, and northbound-southbound terms for describing direction. To do this the incident data were expanded to include the required information by adding detailed lane closure variables.

5.2.2 The Remote Traffic Microwave Sensor (RTMS) Data

Mimbela and Clein (2007) defined the RTMS sensors in the handbook prepared for FHWA as follows:

> "*The RTMS is a low-cost, all weather, true RADAR (Radio Detection and Ranging) device, which provides presence, multiple zone, vehicle detection. Its ranging capability is achieved by frequency-modulated continuous-wave (FMCW) operation. The RTMS is capable of detecting vehicle presence and measuring other traffic parameters in multiple zones.*"

Sensors located between the NJTP Interchange 6 to interchange 8A. 23 were used to analyze the work zone impact on traffic conditions. Sensor data provide information about vehicle counts, the average speed for a given time interval, and sensor occupancy information. Occupancy referred to the percentage of time during which there was a vehicle passing over the detector (Gordon and Tighe, 2005). By using this information, the change in the traffic conditions due to work zones could be investigated.

The RTMS locations on the NJTP between interchange 6 and interchange 8A are shown in Figure 5-3. Each sensor records vehicle counts, the average speed and occupancy for each lane, and for the directional road segment. Separate datasets from these 23 sensors were combined into a single dataset for the vehicle count, speed and sensor occupancy variables. Time interval for the sensor data was chosen as 5 minutes in view of the time and size involved in processing the data. For the period of 2012, about 2.5 million- 5 minutes sensor readings were utilized for recording each type of feature. Sensor selection was based on milepost marker incidents. On the NJ Turnpike, the roadway mileposts decrease for southbound traffic, and increase for northbound traffic. For each incident, five different sensors were extracted based on these mileposts. Thus upstream, second upstream, third upstream, downstream and second downstream sensors were selected to investigate the effects of incidents. Figure 5-4 shows the sensor selection process for the incidents. Sensor numbers were defined for each incident based on the incident location. The defined sensor readings were extracted from the main database by merging the incident dataset, crash records, and sensor datasets. The time interval selected for extraction was 1 hour before and 2 hours after the incident began.

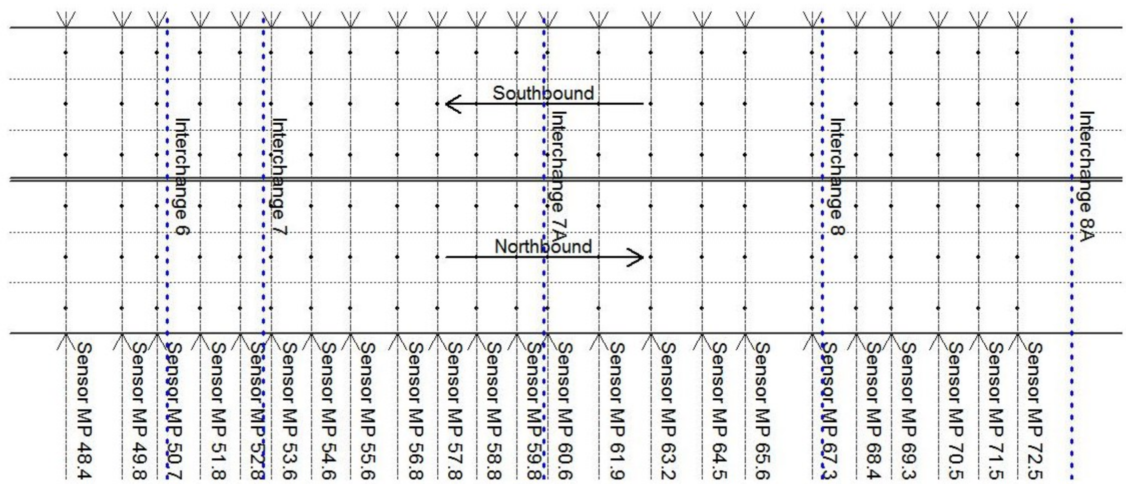


Figure 5-3 Sensor Location Mileposts on NJ Trunpike

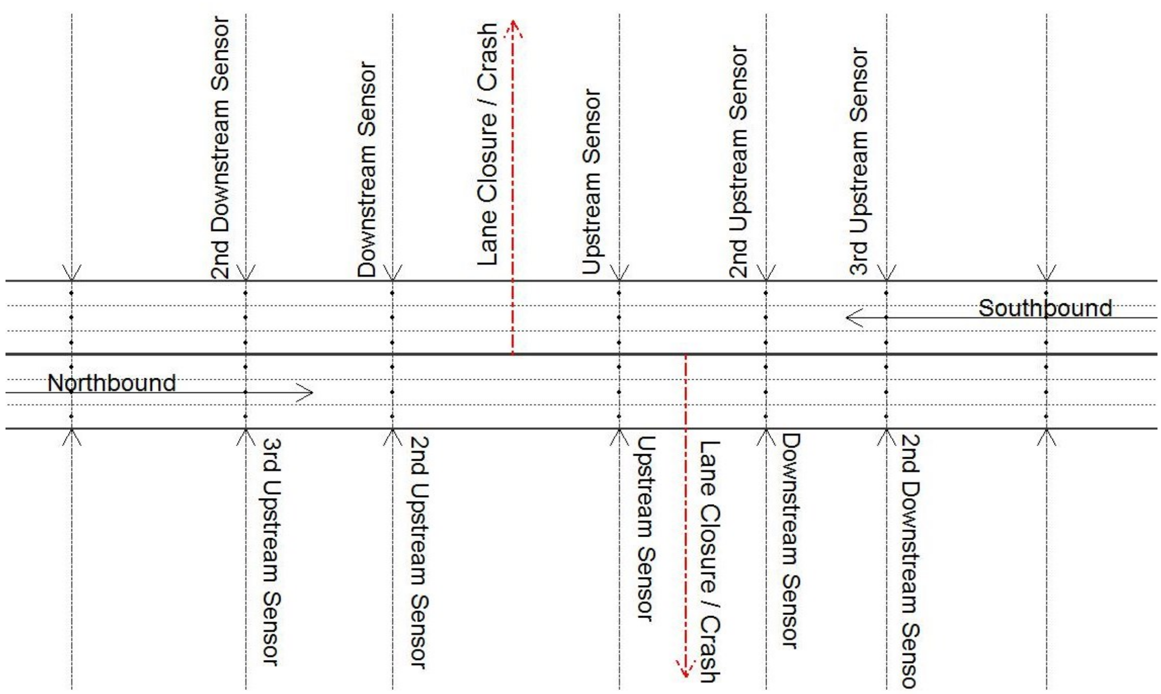


Figure 5-4 Sensor Selection Based on Incident Location and Direction

The sensor readings during lane closure and crash occurrences were removed to derive normal time traffic information for the selected sections. To do so, data were deleted from the main database during crash occurrences and lane closures from start to finish. Figure 5-5 shows the data cleaning process employed to obtain normal time traffic flow.

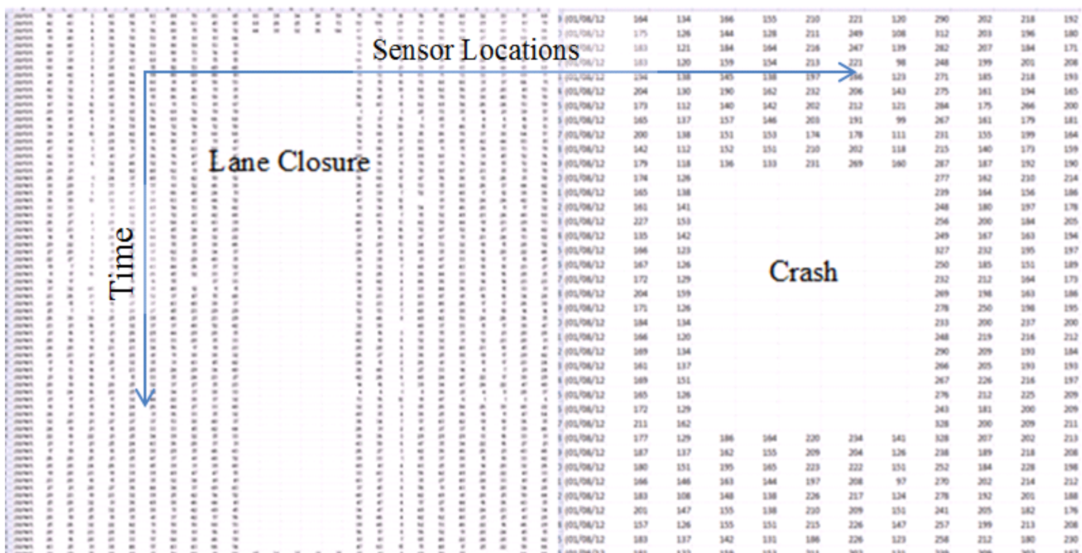


Figure 5-5 Data Filtering Process to Obtain Normal Condition Sensor Readings

The average traffic conditions for the analyzed section can be interpreted from the sensor data. The figure below shows the annual daily average traffic information for weekdays and weekends separately. This data represent 2012 data for NJ Turnpike interchanges between 6-8A. As can be seen from Figure 5-6, morning and evening peaks for vehicle counts are higher than weekday counts. The average weekend traffic flow is observed to be higher for the time intervals after 10:00 AM and peak flow was reached around noon. The average speed during the day was similar to that shown in the figure in the Banaei et al. (2011) study, which was created by using sensor data in Los Angeles.

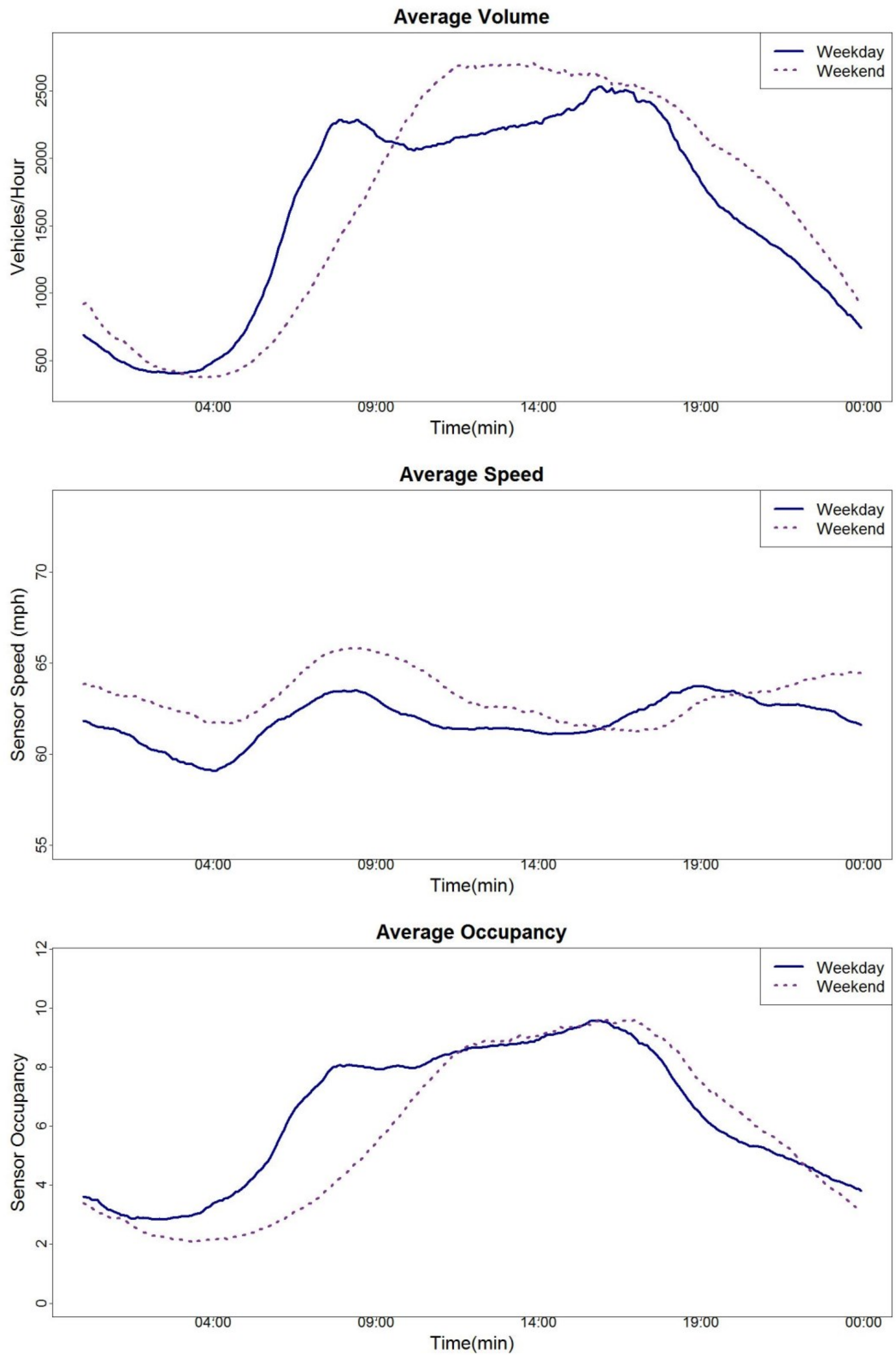


Figure 5-6 Average Annual Daily Traffic information for the NJTP Interchanges 6-8A

5.2.3 The Automatic Vehicle Identification (AVI) Data

The electronic toll collection data was employed to provide information on the vehicle transactions that took place between toll plazas located on the NJTP. Vehicle entrance - exit times, and entrance-exit toll plaza information are available within the AVI database. A computer code preciously developed by Rutgers Intelligent Transportation Systems (RIS) laboratory researchers was employed to extract travel times for defined intervals between travelers entering and exiting the interchanges (Bartin et al., 2007). By using the AVI data, travel times between the interchanges were gathered for 15 minute intervals for the year, 2012. Since lane closure operations are scheduled mainly for nighttime conditions, the sample size was not satisfactory for some of the time intervals. By using travel time data, the impact of lane closure operations and work zone crashes on travelers in terms of delay could be estimated. Figure 5-7 shows a snapshot of the analyzed section of the NJTP interchanges.

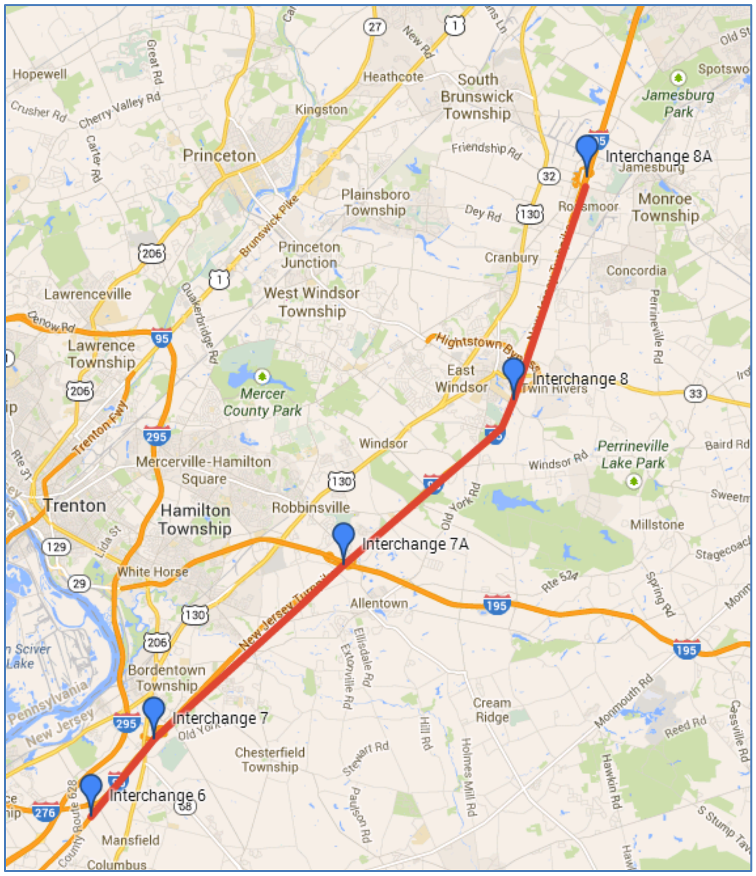


Figure 5-7 Snapshot from the NJTP between Interchange 6 to Interchange 8A (Google Maps)

5.3 Effect of Lane Closure on Traffic Flow, Speed and Occupancy

Roadway agencies schedule lane closures to minimize reductions in revenue coming from toll charges. A software tool named Rutgers Interactive Lane Closure Application (RILCA) was developed by Bartin et al. (2012), as a decision support tool for lane closure decisions by NJTP and NJDOT. Usually work zones are set up at nighttime or off peak time hours. Although work shifts are optimized for undersaturated traffic conditions, many people have experienced delays or stoppages in traffic flow due to work zone lane closures. Especially during the initial setup and removal activities queues have been observed on many occasions. To investigate this issue, traffic sensor data such as vehicle counts, occupancy and speed data were investigated for different types of lane closure. Change in traffic conditions was compared based on the normal time average traffic conditions data.

5.3.1 Difference in Sensor Readings (Count, Speed, Occupancy) Due to the Lane Closures

The main database for the RTMS was edited with respect to lane closures and crashes that occurred relative to the location and time in order to obtain vehicle counts, sensor speed and sensor occupancy data for the normal time conditions. Equation 5-1 below was used to estimate the average vehicle counts, speed and occupancy for the normal traffic conditions.

$$\mu(C_{t_i,m_j}), \mu(S_{t_i,m_j}), \mu(O_{t_i,m_j}) = \frac{\sum_1^N C_{t_i,m_j}, \sum_1^N S_{t_i,m_j}, \sum_1^N O_{t_i,m_j}}{N_{t_i,m_j}} \tag{5-1}$$

Where,

$\mu(C_{t_i,m_j})$: Average vehicle counts at time interval i, for month j, for a given sensor;

$\mu(S_{t_i,m_j})$: Average speed at time interval i, for month j, for a given sensor;

$\mu(O_{t_i,m_j})$: Average sensor occupancy at time interval i, for month j, for a given sensor;

N_{t_i,m_j}: Number of samples for time interval i, and for month j.

The average vehicle counts recorded at 5 minute intervals within a period of 24 hours was estimated for each month and weekday, as well as weekend separately for traffic conditions without lane closures and crashes. To determine normal condition sensor readings, data during the work zone lane closures was eliminated from all the sensor readings for the lane closure locations. In addition to this, sensor readings taken within 30 minutes before and 1 hour after the crash occurrences were eliminated from the main database.

Changes in sensor vehicle counts, average speed and sensor occupancy by time for right lane closure conditions are shown as an example in Figure 5-8. Upstream sensor, downstream sensor and average downstream sensor readings were included in Figure 5-8. The lane closure operation started on 6/11/2012 at 17:04. Monthly average hourly counts for normal conditions during this time interval were 1854 veh/hour, the average speed was 56.5 mph and the average occupancy rate was 5.9 at the downstream sensor of lane closure starting point. At the beginning of the lane closure operation, small oscillations were observed for the vehicle counts and sensor occupancy rates. This was possibly due to the presence of peak traffic that occurred 25-35 minutes after the lane closure start time, when vehicle counts decreased sharply to almost zero. Between 35-55 minutes after lane closure, the traffic flow seemed to recover in terms of vehicle counts and sensor occupancy. Sixty minutes after the operation started, sensor readings were closer to the average reading values, except for speed. This was possibly due to the reduction in the posted speed limit at the work zone area, and as a result the average speed at the downstream sensor kept going under the average speed of that location and time interval. The difference between the upstream speed and the average downstream speed shows that there was a posted speed limit differences for these locations for the given time intervals.

For the left lane closure, the sample operation which started on 5/10/2012 at 19:08 was analyzed graphically. Figure 5-9 shows the sensor reading plots for this incident. As shown, vehicle counts decreased sharply between 15-25 minutes after closure and recovered between 25-60 minutes after closure. The average downstream vehicle count showed a decreasing trend due to the reduced demand in the night time. The average hourly count for the normal conditions at this time interval was 1294 veh/hour, the average speed was 69.4 mph and the average occupancy was 7.5 at the downstream sensor at the start of the lane closures. The biggest decrease in the downstream sensor vehicle counts was observed 25 minutes after the lane closure with the value of about 15 vehicles. The minimum speed observed for the upstream sensor at 35th minute after lane closure was 22 mph. Traffic reached the highest occupancy rate 30 minutes after the lane closure for the upstream sensor. The recovery time for this operation was observed about 65 minutes after closure. As was expected, the two lanes closure operation affected traffic conditions more than the single lane closures. Although, the two lanes closure was mostly scheduled during the off-peak hours, greater differences were observed in terms of the sensor readings.

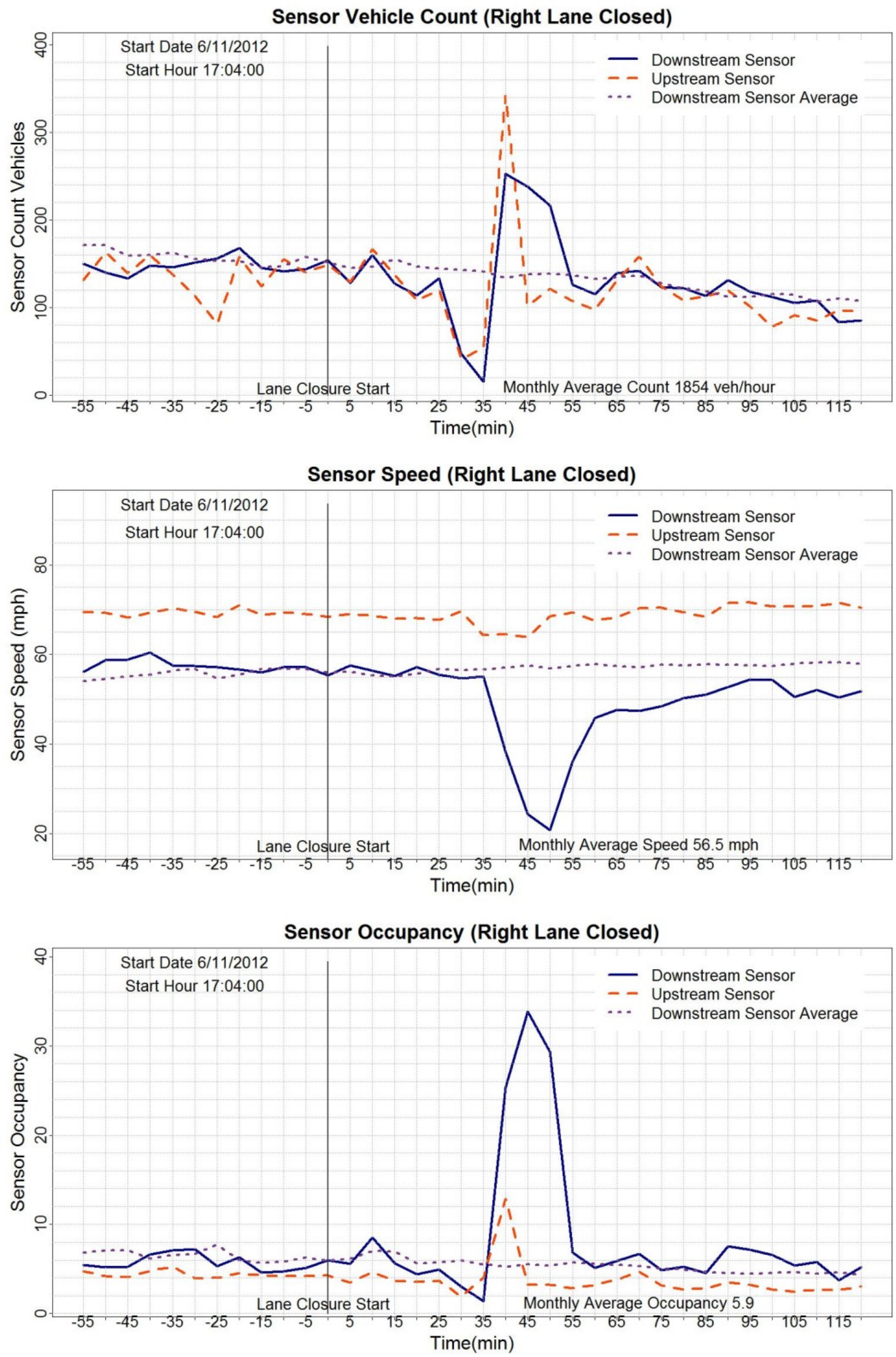


Figure 5-8 Sample Sensor Readings for the Scenario where Left Lane is Closed

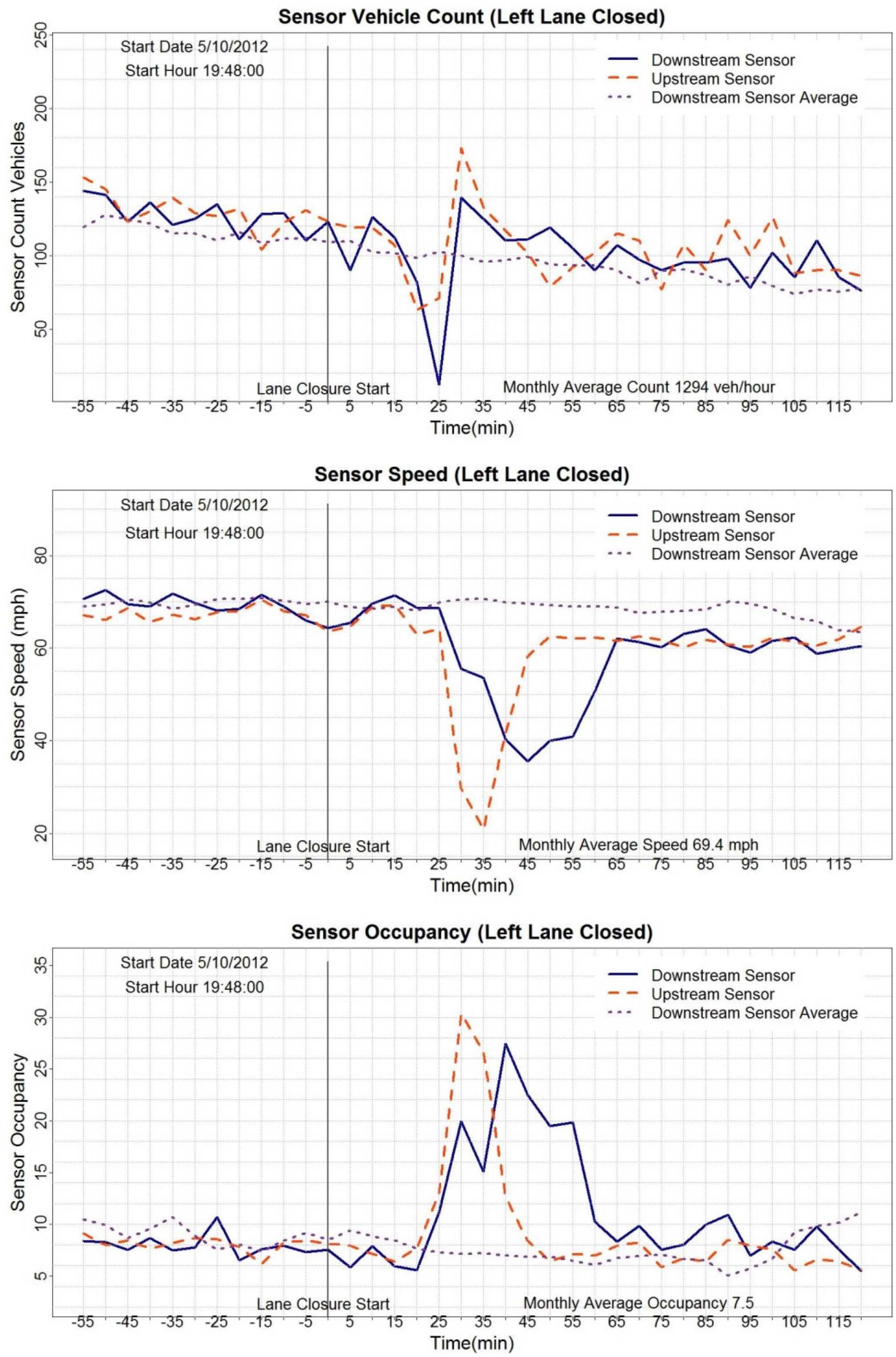


Figure 5-9 Sample Sensor Readings for the Scenario where Left Lane is Closed

Figure **5-10** shows the sample for right and center lane closures that started on 8/21/2012 at 18:52. The traffic flow rate started to oscillate at the beginning of the operation and decreased for a period of up to 35 minutes. It touched the minimum value for vehicle counts at the 35th minute where it was close to 0. Almost no vehicle passed from either upstream or downstream sensors for this 5 minute interval. For the sensor occupancy readings, the traffic flow reached its highest value at the 25th minute after closure for both upstream and downstream sensors. Recovery time for the vehicle counts was 65 minutes, and sensor occupancy was carried out for 80 minutes based if the return to the average readings is considered. When compared to the single lane closure samples, recovery times were higher for the right and center lanes closures. Due to the oversaturated traffic conditions oscillations were observed during the lane closure period.

The sample for the left and center lanes closure type is shown in Figure 5-11. This closure occurred on the 3/7/2012, at 18:14. The monthly average hourly traffic for the operation site was 2142 vehicles per hour, which is above average for the one lane capacity at lane closure conditions defined as 1610 vphpl (NJTA, 2011). Similar to the right and center lane closure, oscillations in vehicle counts were observed during the lane closure period until the recovery of the oversaturated traffic flow. Different from the previous samples, a sharp decrease in vehicle counts was observed at the beginning of the lane closure. The upstream sensor reached the lowest value in terms of the average speed and the highest in terms of the sensor occupancy readings at the 20th minute after closure. The upstream sensor returned to its average speed value at 70th minutes after the lane closure operation began. Compared to the right and center lane closures, the traffic conditions were less affected for the left and center lane closure samples. This was possibly due to the differences in traffic density and operation due to monthly differences, which were March and June in this case.

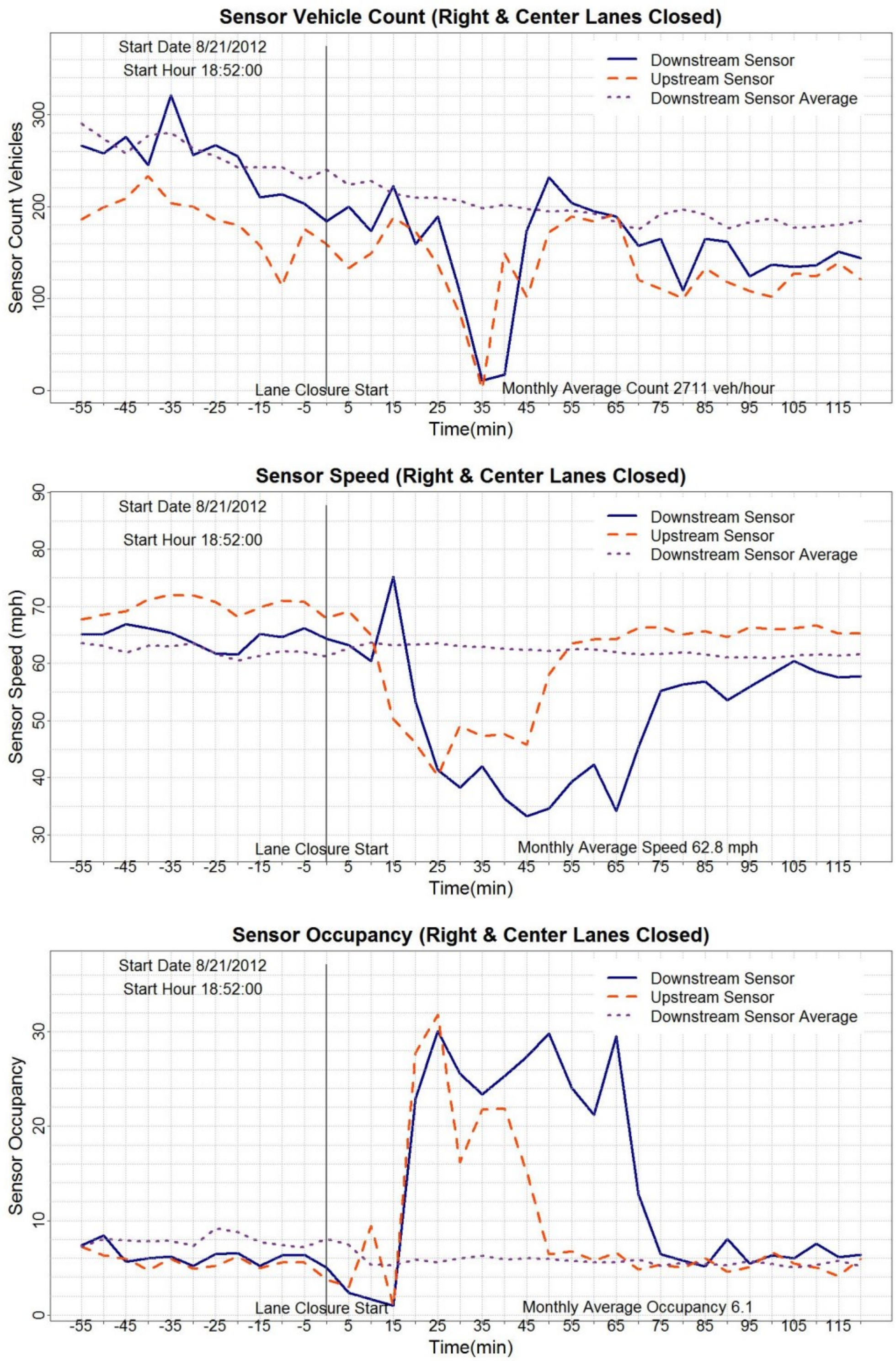


Figure 5-10 Sample Sensor Readings for the Scenario where Right and Center Lanes are Closed

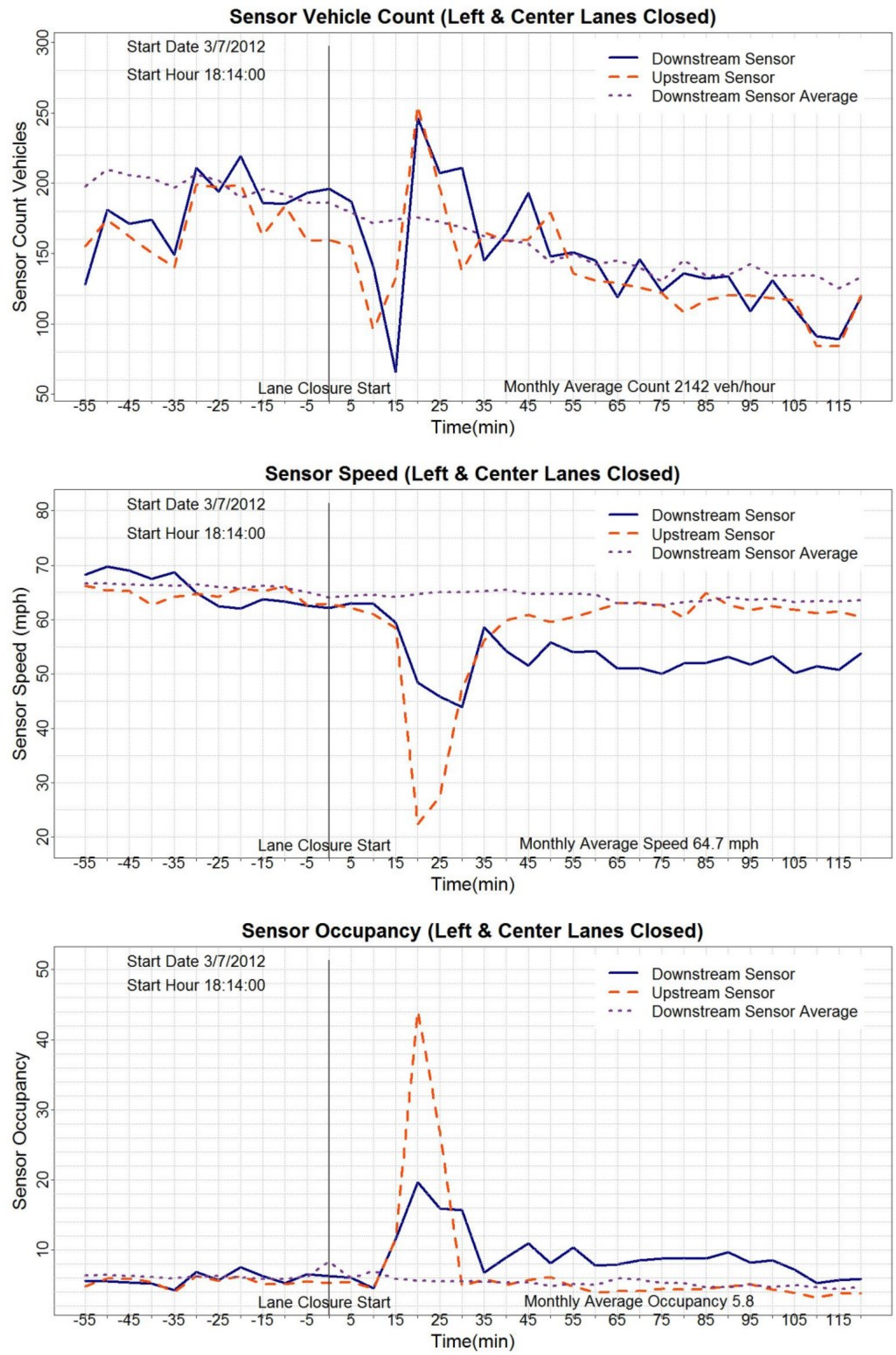


Figure 5-11 Sample Sensor Readings for the Scenario where Left and Center Lanes are Closed

5.3.2 Change in Count, Speed and Occupancy Ratios Due to Lane Closure

The average values $\mu(C_{t_i,m_j}), \mu(S_{t_i,m_j}), \mu(O_{t_i,m_j})$ were estimated for each time interval and sensor by weekday-weekend and monthly time bases. By using these numbers, the ratio of the traffic flow, the average speed and the occupancy rates were estimated for the time interval i for the lane closure operation period. The equation below was used to estimate the ratios.

$$RC_{t_i}, RS_{t_i}, RO_{t_i} = \frac{C_{t_i}, S_{t_i}, O_{t_i}}{\mu(C_{t_i,m_j}), \mu(S_{t_i,m_j}), \mu(O_{t_i,m_j})} \quad (5\text{-}2)$$

Where,

RC_{t_i}: Count ratio for time interval i,

RC_{t_i}: Speed ratio for time interval i, and

RC_{t_i}: Occupancy ratio for time interval i.

The general trend that emerged can be seen by plotting vehicle counts, speed and occupancy ratios for each type of lane closure. Figure 5-12 and Figure 5-13 show the ratios for each type of closure. The following findings can be interpreted from the figures:

- A sharp decrease was observed for vehicle counts and speed ratios and an increase was observed for the sensor occupancy ratio at the start of the lane closure operation.
- The increases and decreases in the amount of oscillations are higher for the two lane closure types for the vehicle counts, speed and sensor occupancy readings.

- Recovery time for the single lane closure type was shorter than that recorded for the two lanes closure type.
- Recovery time was longer for the downstream sensor readings compared to upstream sensor readings.
- The occupancy ratio at the downstream sensor had not recovered to its average value within a 2 hour interval.
- The speed ratio at the downstream sensor location was lower than the average ratio during the lane closing operations.
- Before the start of lane closure conditions, the average ratios for each type of feature were around 1.0, which means that the average ratios represented normal time traffic conditions.
- By using ratios for the sensor readings, the change in traffic conditions could be observed using a normalized diagram.
- This ratio chart can be useful for agencies for purposes of predicting the behavior of the traffic flow at the beginning of lane closing operations.

In estimating these values, the differences between sensor vehicle counts were based on data recorded under normal conditions. The ratios were estimated for 1 hour before and 2 hours after lane closure began. Although the lane closure operations take more than two hours, the initial impact of the set up was aimed to investigate change in the traffic conditions by estimating the ratios. These time intervals were defined based on observed sensor features for the different lane closure types. Trends in the ratios were examined starting during normal traffic condition up until the start of the operation. After that, the oscillations were observed during the lane closure operations for each type of sensor feature. The average value of the ratios was estimated based on a time axis. For instance, the average value of the ratios was measured for 20 minutes after lane closure for the right lane closure condition. Table 5-1 shows the maximum change in sensor features in terms of lane closure types.

Table 5-1 Change in Sensor Vehicle Counts, Speed and Occupancy Ratios after Lane Closure

Closure Type/ Max Decrease in Average Ratios (N=442)	**Count Ratio** (Δ %)	**Speed Ratio** (Δ %)	**Occupancy Ratio** (Δ %)
Right Lane (Upstream Sensor, N=129)	-15.9%	-10.8%	-5.7%
Right & Center Lanes (Upstream Sensor, N=92)	-19.8%	-22.1%	-3.3%
Left Lane (Upstream Sensor, N=117)	-11.6%	-16.9%	-8.6%
Left & Center Lanes (Upstream Sensor, N=104)	-19.4%	-17.7%	-7.7%
Right Lane (Downstream Sensor, N=129)	-21.8%	-16.8%	-3.4%
Right & Center Lanes (Downstream Sensor, N=92)	-29.7%	-21.3%	-5.7%
Left Lane (Downstream Sensor, N=117)	-20.4%	-12.9%	-8.8%
Left & Center Lanes (Downstream Sensor, N=104)	-25.0%	-18.6%	-7.3%
Closure Type/ Max Increase in Average Ratios (N=442)	**Count Ratio (Δ %)**	**Speed Ratio (Δ %)**	**Occupancy Ratio (Δ %)**
Right Lane (Upstream Sensor, N=129)	7.7%	0.4%	56.6%
Right & Center Lanes (Upstream Sensor, N=92)	15.5%	0.2%	128.7%
Left Lane (Upstream Sensor, N=117)	11.3%	2.2%	84.5%
Left & Center Lanes (Upstream Sensor, N=104)	25.0%	0.3%	100.9%
Right Lane (Downstream Sensor, N=129)	3.9%	1.1%	76.0%
Right & Center Lanes (Downstream Sensor, N=92)	17.5%	0.6%	164.8%
Left Lane (Downstream Sensor, N=117)	9.0%	2.0%	61.8%
Left & Center Lanes (Downstream Sensor, N=104)	20.3%	1.2%	135.7%

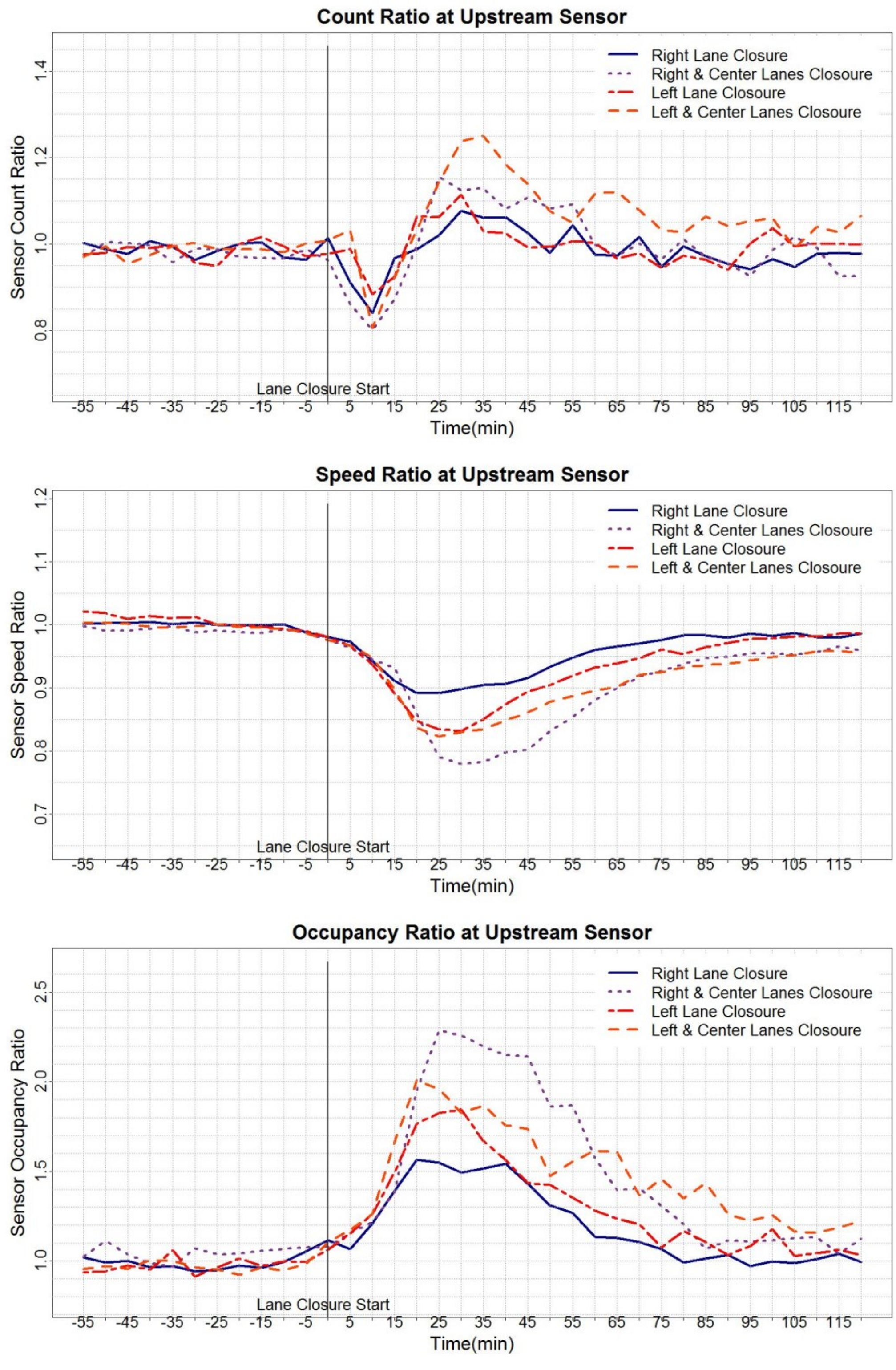


Figure 5-12 Change in Ratios vs Lane Closure Type at Upstream Sensor

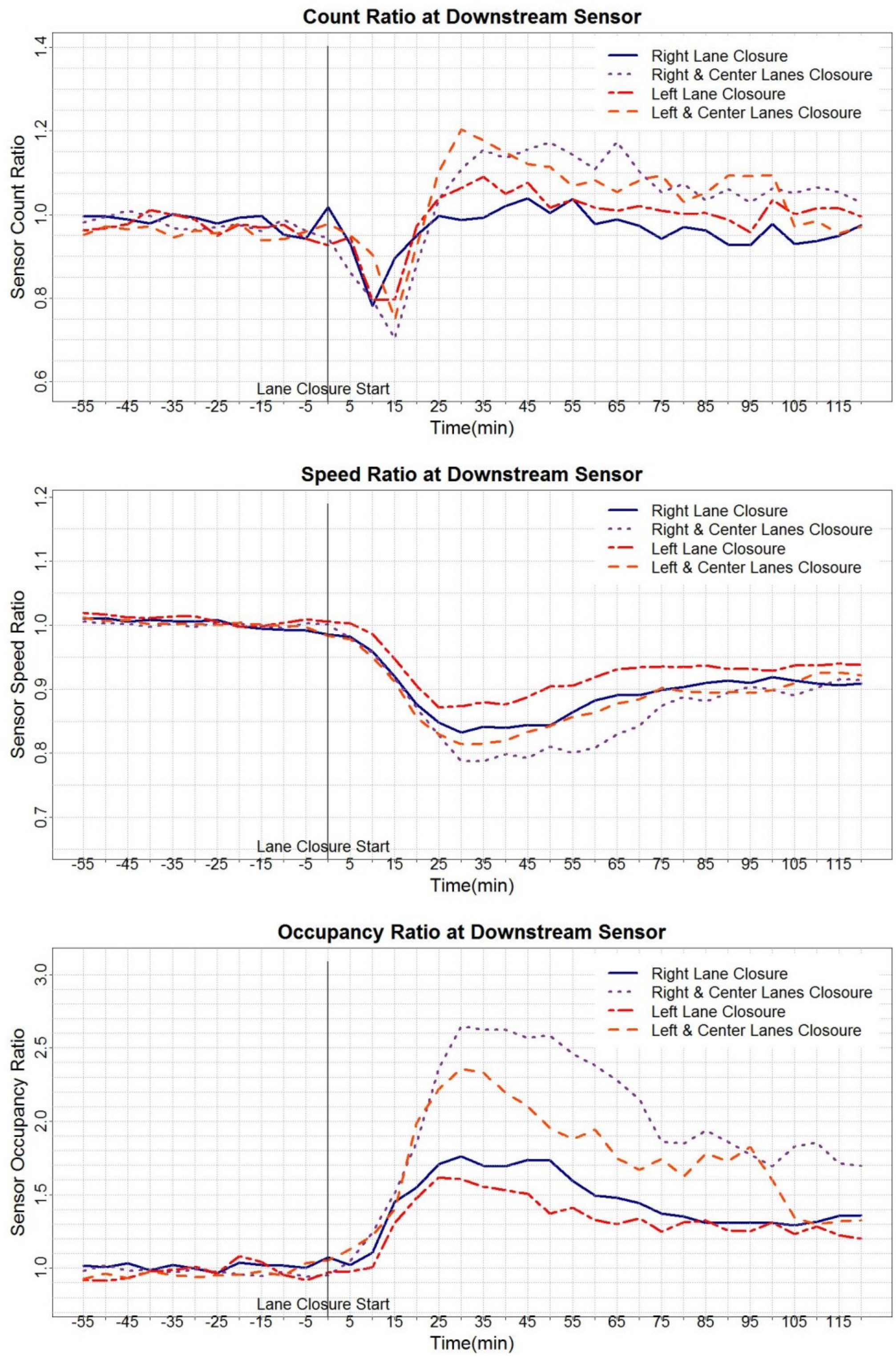


Figure 5-13 Change in Ratios vs Lane Closure Types at Downstream Sensor

According to the findings presented in Table 5-1, the maximum decrease observed at upstream sensor vehicle counts was 19.8 percent and at the downstream sensor it was 29.7 percent for the right and center lanes types. The maximum decrease in average speed ratios at the upstream sensor was 22.1 percent and at the downstream sensor it was 21.3 percent for the right and center lanes closure types. The increase in travel times due to lane closure can be interpreted from this value describing the decreased speed values. Since speed was used as the denominator for the travel time estimation, a decrease in speed value caused an increase in travel time due to the inverse ratio relationship between these variables.

$$TT = \frac{L}{S_N},\ \Delta TT = \frac{L}{S_L} - \frac{L}{S_N} = \frac{L}{S_N}\left(\frac{S_N}{S_L} - 1\right) = TT * \left(\frac{S_N}{S_L} - 1\right) \tag{5-3}$$

Where,

TT: Travel time (mins),

S_N, S_L: Sensor speed for normal and lane closure conditions, respectively,

L: Length of segment traveled (miles).

For instance, a 25 percent decrease in a segment caused $\left(\frac{1}{0.75} - 1\right) = 33.3\%$ increase in travel time during the lane closure operations. A maximum decrease in the average occupancy ratio change was observed to be 8.6 percent for the upstream and 8.8 percent for the downstream sensors for the conditions where left lane was closed.

Due to the backup in traffic, there was an increase in vehicle counts observed while traffic was recovering to its normal condition after the lane closure had started. The maximum increases in upstream and downstream vehicle counts were observed for the left and center lanes closed conditions by 25.0 and 20.4 percent, respectively. As was expected, a higher increase in average speed ratio was not observed compared to vehicle counts and occupancy, since average speed for the normal condition was very close to the free flow speed value. The maximum increase observed for the upstream sensor was 2.2 percent and for the downstream sensor it was 2.0 percent for the scenario where the left lane was closed. Interestingly, the maximum increase in occupancy was observed for the upstream sensor with a value of 128.7 percent and for the downstream sensor it was 164.8 percent for right and center lane closure. In other words, sensors recorded these percentage values as a result of there being more vehicles. This type of increase was possibly caused by the presence of stop and go traffic due to the lane closure operations.

5.3.3 Analyzing Travel Time Change Due to Lane Closure by AVI Data

The AVI data provides information about travelers using the highway for entrance and exit time based on transactions at toll plazas. This data was processed by using a special code developed by RITS lab researchers (Bartin et al., 2007). The extracted database included travel time averages for 15 minute intervals for 2012. Data was filtered for the roadway section between interchange 6 to interchange 8A on the NJTP.

Travel times were extracted for 1 hour before and 2 hour after the reported crash time in a similar way to that of the RTMS data analysis. These data were categorized for 15 minute averages for each section, 6-7, 7-7A, 7A-8 and 8-8A. Travel times versus time intervals were plotted for these sections as shown in Figure 5-14. The length of the segment, sample size, free flow travel time and travel times based on each type of lane closure were included in the figure. As can be seen from Figure 5-14, the average travel times were increased for all types of lane closure at the beginning of the roadway operation. Travel times for two lanes closures increased more markedly compared to single lane closures. For instance, interchange travel time for two lanes closures at 7A-8 were almost twice as much as those for free flow travel times.

The maximum increases in travel times for each section based on lane closure types are included in Table 5-2. According to the presented values in Table 5-2, a maximum increase was observed at interchange 8-8A for the left and center lanes closure types. Generally, the maximum increase in average travel time for single lane closure types was lower than the two lane closure types travel times. The shorter section length caused the lowest increases in travel times due to the lane closure when compared to the longer section lengths.

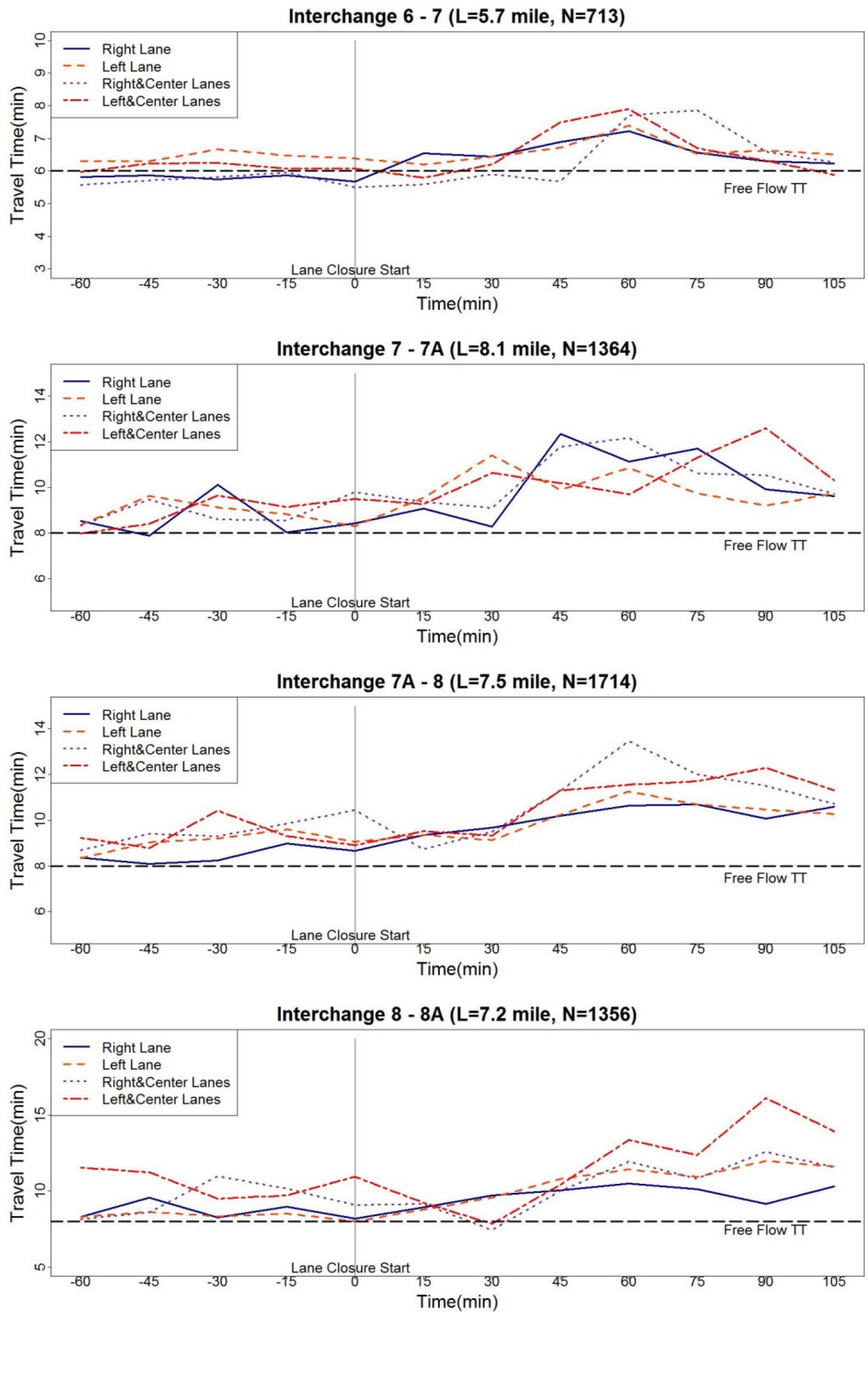


Figure 5-14 Change in Exit to Exit Travel Times by AVI Data

Table 5-2 The Maximum Increase in Travel times vs Lane Closure Type for Each Section

Section	Right	Left	Right & Center	Left & Center
Interchange 6-7	20.4%	23.2%	30.9%	31.7%
Interchange 7-7A	54.2%	42.5%	52.2%	57.4%
Interchange 7A-8	33.5%	40.9%	68.4%	53.8%
Interchange 8-8A	31.3%	49.7%	57.2%	101.4%

5.4 Work Zone Crashes within Lane Closure

As was expected, delays caused by crashes within lane closure areas are supposed to be higher than crashes that occur under-closure conditions. As Ryan et al. (2007) and Ozbay et al. (2009) suggested in their studies, strategies such as detours or diverting the traffic by using incident detection technology may be helpful to apply for crashes that occur at lane closure conditions in order to reduce any back up in traffic flow.

The NJ crash records, the incident data and the RTMS datasets were merged to create an integrated database of crashes that occurred during the lane closure conditions. The crash records imported included the lane closures' time and space coordinates. The merging of the datasets was processed based on the crash time and crash location records and when the lane closure began-and the end time interval and start-end mileposts. The database was then created by joining the information from both sources noted above. Figure 5-15, Figure 5-16 and Figure 5-17 show the sensor readings for the 4 different crash types within the different types of lane closure. Similar to the lane closure impact analysis, the time period of 1 hour before and 2 hour after the reported crash time was plotted on the time axis. The readings from the upstream and downstream sensors of the crash locations were extracted from the main RTMS database. After the filtering process, 35 work zone crashes were included in the database.

5.4.1 Difference in Sensor Readings Due to the Crashes within Lane Closure

As mentioned above, sensor readings for 4 different sample crashes within lane closures were plotted to examine changes in traffic conditions. The first (top-left) plot is a sample crash in the case of a right lane closure (RLC), the second (top-right) is a sample crash at a left lane closure (LLC), the third (bottom-left) is a sample crash for a case where right and center lanes are both closed (RLC&CLC) and the last one (bottom-right) is a sample crash for left and center lane closure (LLC&CLC). Severity information of the crashes was also included in the plots. There were 3 people injured and 1 person was killed for the first crash, there was 1 injury for the second crash, 1 person was killed in the third crash and 4 injuries occurred for the last crash as shown in Figure 5-15.

As can be seen in Figure 5-15, the vehicle counts for the fatal crashes decreased to zero under the RLC and RLC&CLC conditions 15 minutes after the crash occurred. There were no vehicles that passed the sensors for 60 minutes for the RLC condition and for more than 105 minutes for the RLC&CLC samples. Traffic recovery times were 90 minutes for the RLC crash and more than 2 hours for the RLC&CLC crash conditions. Vehicle counts for the other two samples under the LLC and LLC&CLC conditions hit the minimum peak at 15 minutes after the crash occurrence. Different from the fatal crashes, traffic flow started to recover after hitting the minimum peak of vehicle counts.

Figure 5-16 and Figure 5-17 show this relationship fairly well in terms of speed and occupancy. If we look at the upstream sensors of the fatal crashes, we note the sensor speeds didn't return to their average values, which means that traffic was not regulated within a 2 hour period after the crash occurred. For injury crashes under LLC conditions, traffic flow returned to normal after 45 minute for the upstream and 90 minutes for the downstream sensors. For crashes under the LLC&CLC conditions, speed returned to its normal value within 105 minutes. The occupancy at upstream sensor returned to its average value only for the LLC crash sample. The occupancy at other samples didn't return to their average value within the 2 hour observation period. The sensor occupancy for the RLC&CLC sample crash seemed to be zero for a while, which means no vehicle passed during that time interval. This was possibly due to the possibility that the traffic flow was stopped by a police officer until safer conditions prevailed. When the maximum occupancy rate was observed for crashes under the LLC&CLC conditions, the occupancy rate increased up to 100% 5 minutes after the crash occurrence, which means that the traffic stopped completely for at least 5 minutes in this case.

If we look at the crash occurrence time and decreasing start time for the speed readings in Figure 5-16, there are time gaps between the police crash report time and the real time of occurrence. The real time for crashes seems to be 15 to 25 minutes earlier than the reported crash times. Probably, this time gap was due to the time needed for the officer to arrive at the crash site.

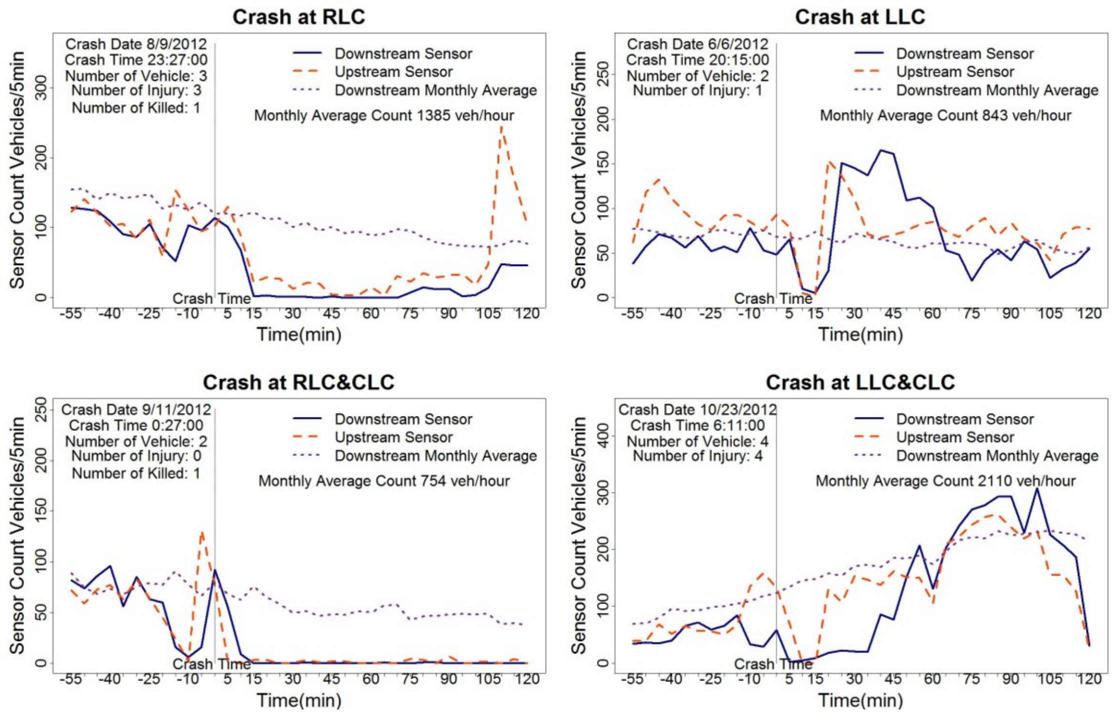


Figure 5-15 Sensor Vehicle Counts for Sample Crashes by Lane Closure Types

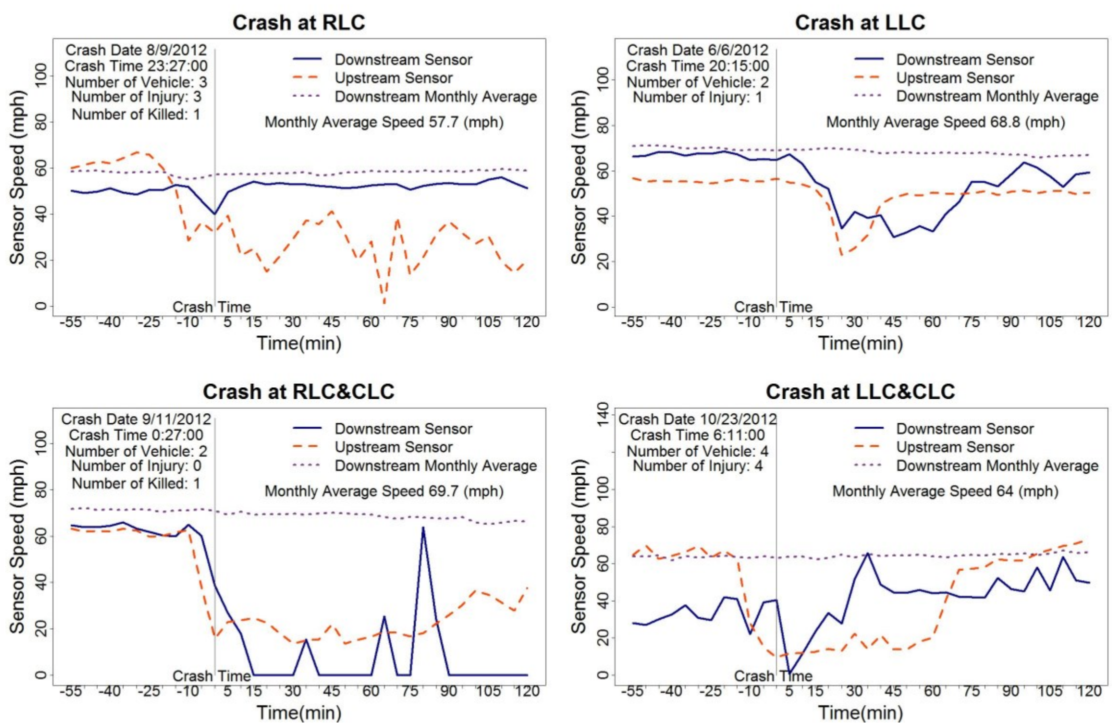


Figure 5-16 Sensor Speed Readings for Sample Crashes by Lane Closure Types

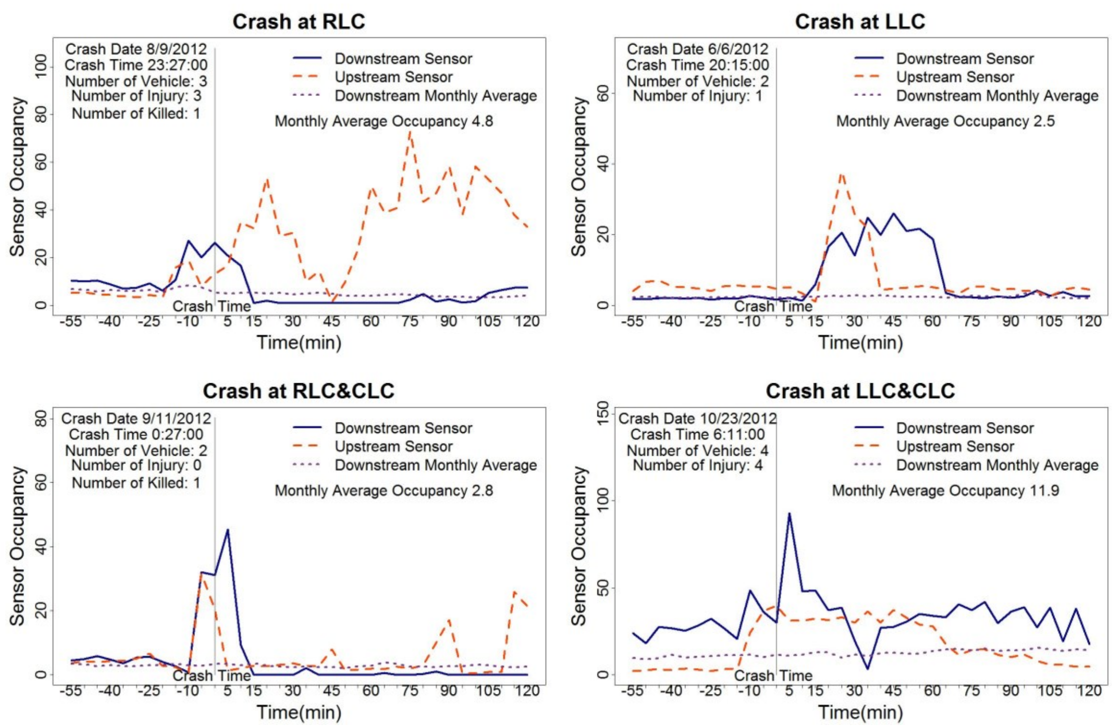


Figure 5-17 Sensor Occupancy for Sample Crashes within Different Lane Closure Types

5.4.2 Change in Count, Speed and Occupancy Ratios Due to Crashes within Lane Closure

The ratios for crashes under the various lane closure conditions were estimated by dividing the crash time readings by average monthly non-crash non-closure readings (Eq-26). By using the crash information data, the severity of the crashes was considered as a salient parameter in terms of traffic parameters. Figure 5-18 and Figure 5-19 show the upstream sensor ratios in terms of vehicle counts, speed and sensor occupancy for the PDO and injury crashes, respectively. Compared to the lane closure ratios plots, oscillations within the sensor readings had a higher frequency rate for the crash occurrence cases. Similar to the previous sample crash plots, the crash time seemed to be earlier than the reported time by the officer.

As can be seen from Figure 5-18 and Figure 5-19, PDO crashes under the lane closure conditions did not affect the traffic as much as the injury crashes did. For PDO crashes, the minimum vehicle count ratio was observed for the left lane closure at the upstream sensor followed by the right and center lanes closure conditions, the left and center lanes closure and the right lane closure conditions. When we look at the speed ratio which provides a better idea about the traffic conditions at the upstream location, the PDO crashes did not change the speed ratio which was around average speed. For the injury crashes, the speed ratio decreased quite markedly in relation to the crash occurrence. Only the speed ratio recovered within a 2 hour period for the left and center lanes closure. The occupancy ratio for the PDO crashes increased up to 2-2.5 of their baseline values, and for injury crashes, they increased up to 10 times higher than the average conditions.

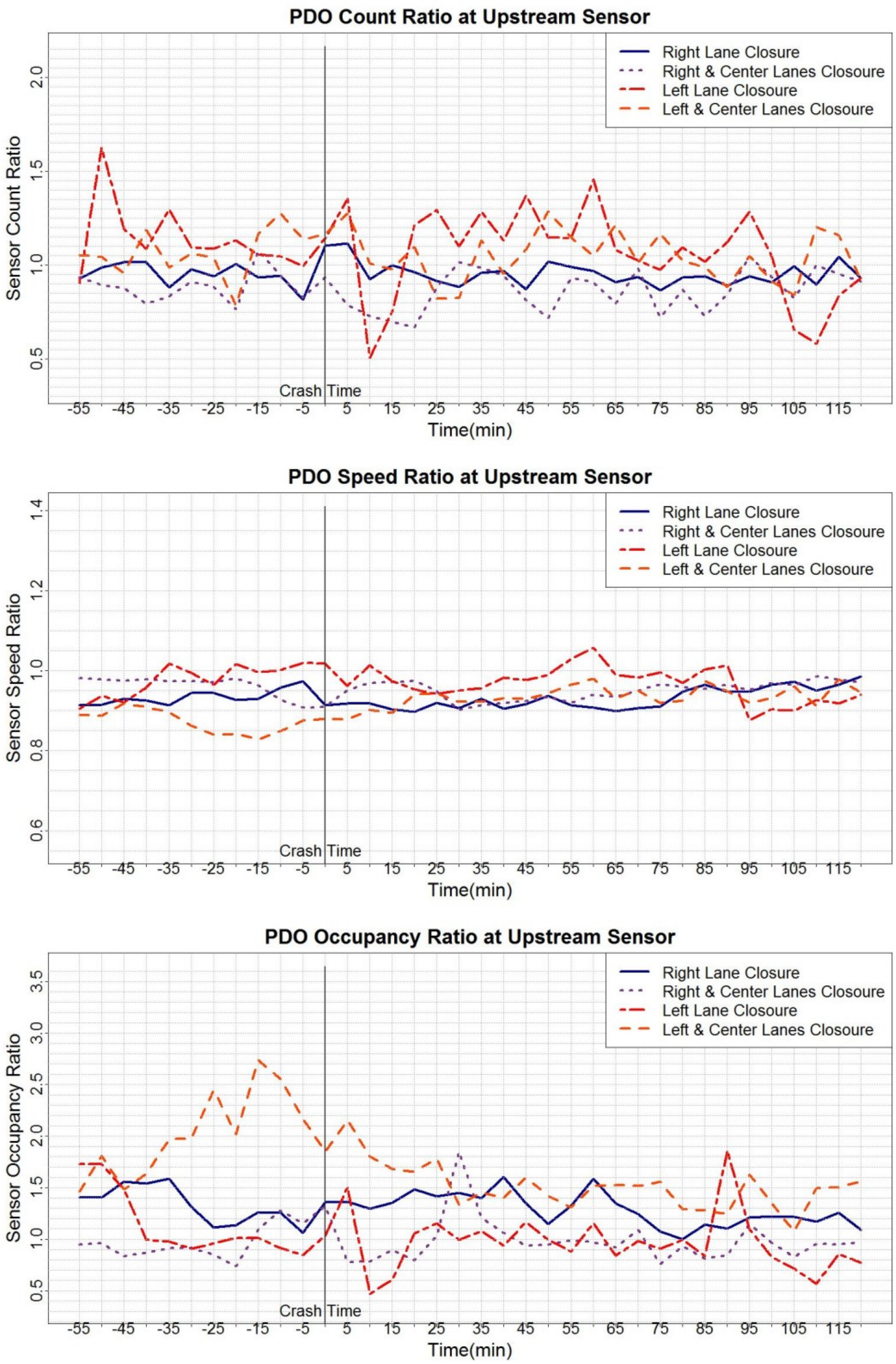


Figure 5-18 Sensor Reading Ratios for PDO Crashes within Lane Closure

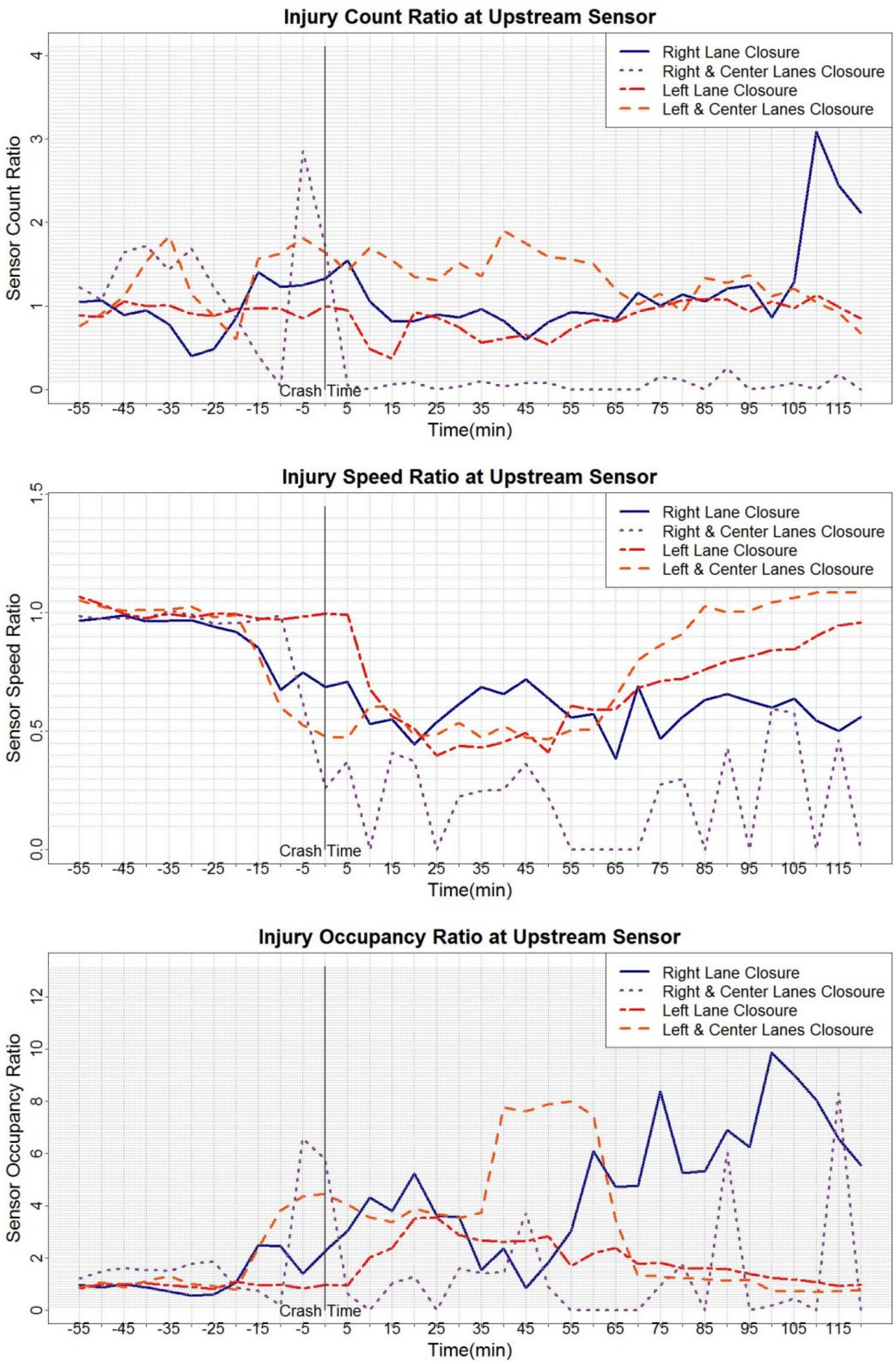


Figure 5-19 Sensor Reading Ratios for Injury Crashes within Lane Closure

These differences were categorized for each type of closure. Table 5-3 provides information about the maximum decrease and increase due to each crash type in relation to the sensor reading ratios. Based on the findings presented in Table 5-3, the maximum decrease in the vehicle count ratio was observed to be 59.1 percent for the PDO crashes within the context of the left lane closure condition and 98.2 percent for the injury crashes within the context of the right and center lanes closure conditions at the downstream sensor. The speed ratios decreased up to 24.5 percent at the downstream sensor for the right lane closure PDO crashes and 77.8 percent at the upstream sensor for the right and center lanes closure injury crashes. This decrease in speed ratio resulted in approximately 3.5 times longer travel times for a given time interval and sections. This can clearly be interpreted from Table 5-3, where a decrease in the speed ratios for the injury crashes are up to 8 times higher than the PDO crashes for some closure types. The maximum increase in vehicle count ratios due to delayed traffic flows was observed for the PDO crashes to be 77.3 percent for the downstream sensor left lane closure condition and for injury crashes it was 208.2 percent for the upstream sensor right lane conditions. Another way of saying this is that the traffic volume increased up to more than twice the average traffic value due to stopped traffic. When we look at the maximum increase in occupancy ratios, the highest one was observed for the PDO crashes at the downstream sensor, which was 346.4 percent higher for the right lane closure and for injury crashes at the upstream sensor it was 886.4 percent higher for the right lane closure. The maximum increase in occupancy ratios for injury crashes was up to 15 times higher than those recorded for the PDO crashes. This shows that the traffic stopped longer for the injury crashes when compared to the PDO crashes.

Table 5-3 Change in Sensor Vehicle Counts, Speed and Occupancy Ratios by Crash Type

Closure Type/ Max Decrease in Average Ratios	**Ratio Changes for PDO Crash**			**Ratio Changes for Injury Crash**		
	Count (Δ %)	**Speed** (Δ %)	**Occupancy** (Δ %)	**Count** (Δ %)	**Speed** (Δ %)	**Occupancy** (Δ %)
Right Lane (Upstream Sensor) (N=12)	-18.24%	-10.27%	-0.11%	-59.96%	-61.58%	-45.20%
Right & Center Lanes (Upstream Sensor) (N=6)	-33.16%	-9.80%	-26.39%	-96.70%	-77.77%	-83.92%
Left Lane (Upstream Sensor) (N=6)	-49.34%	-12.35%	-52.87%	-62.32%	-60.30%	-19.11%
Left & Center Lanes (Upstream Sensor) (N=9)	-21.41%	-17.18%	0.00%	-39.81%	-53.31%	-31.51%
Right Lane (Downstream Sensor) (N=12)	-30.76%	-24.51%	0.00%	-85.83%	-17.29%	-77.26%
Right & Center Lanes (Downstream Sensor) (N=6)	-38.41%	-12.37%	-20.21%	-98.24%	-76.64%	-91.76%
Left Lane (Downstream Sensor) (N=6)	-59.41%	-24.13%	-39.07%	-49.20%	-40.94%	-15.78%
Left & Center Lanes (Downstream Sensor) (N=9)	-22.51%	-18.22%	-4.61%	-37.74%	-48.66%	-4.14%
Max Increase in Average Ratios	**Count** (Δ %)	**Speed** (Δ %)	**Occupancy** (Δ %)	**Count** (Δ %)	**Speed** (Δ %)	**Occupancy** (Δ %)
Right Lane (Upstream Sensor) (N=12)	11.65%	0.00%	60.48%	208.24%	0.00%	886.41%
Right & Center Lanes (Upstream Sensor) (N=6)	7.86%	0.00%	85.10%	185.51%	0.60%	730.30%
Left Lane (Upstream Sensor) (N=6)	62.46%	5.80%	85.81%	13.31%	6.78%	253.20%
Left & Center Lanes (Upstream Sensor) (N=9)	28.66%	0.00%	173.41%	90.31%	8.62%	699.25%
Right Lane (Downstream Sensor) (N=12)	43.81%	0.00%	346.43%	0.84%	1.75%	178.38%
Right & Center Lanes (Downstream Sensor) (N=6)	25.97%	0.00%	84.55%	30.61%	0.00%	725.71%
Left Lane (Downstream Sensor) (N=6)	77.30%	8.24%	170.16%	81.08%	0.58%	321.33%
Left & Center Lanes (Downstream Sensor) (N=9)	51.64%	0.00%	107.00%	60.53%	0.00%	489.20%

Compared to the lane closure ratio results, the difference in sensor reading ratios was higher for both the PDO and injury crashes. Traffic recovery times for sensor features were also higher for the analyzed crash time interval. Since the ratios oscillated within the wide range of values, more focus on injury crashes is needed to better understand the reasons behind change in traffic parameters.

5.4.3 Analyzing Travel Time Change Due to Crashes within Lane Closure by AVI Data

Crashes within lane closure areas were investigated in terms of changes in link travel times by using the AVI data. Travel time ratios for crashes within the lane closure areas were estimated based on free flow travel time for each section. Figure 5-20 shows the change in travel time by lane closure. From Figure 5-20, crashes within lane closure increased travel times more than the lane closures analyzed within section 5.3.3.

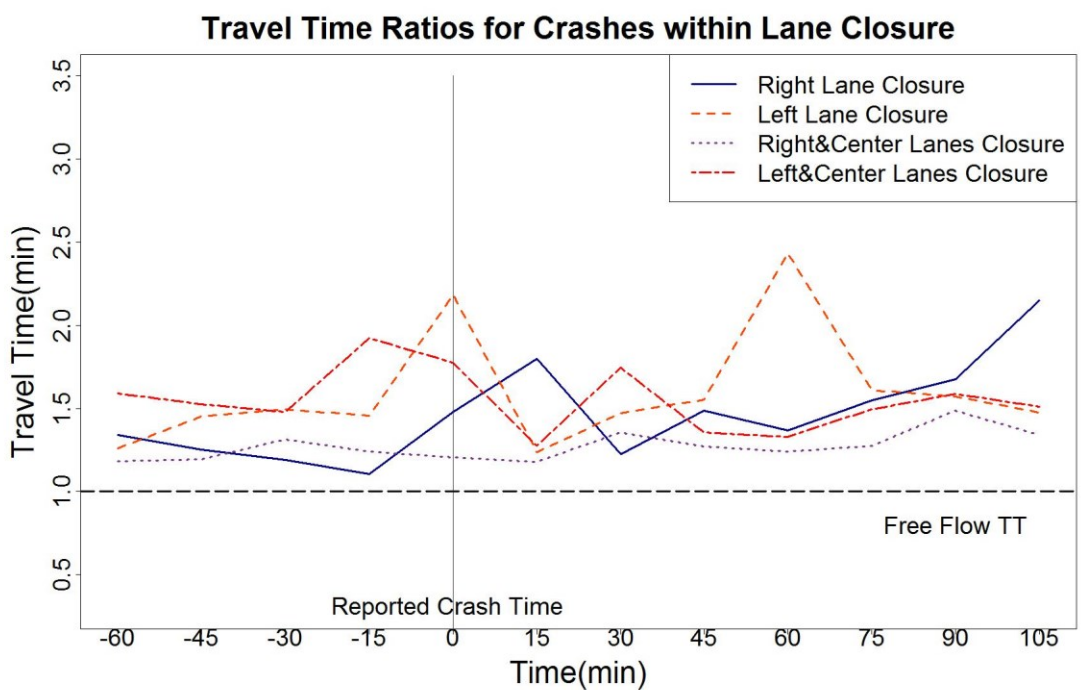


Figure 5-20 Change in the Travel Time Ratios for Crashes within Lane Closure

The increased amount of travel time for each section due to crashes for the lane closure conditions was included in Table 5-4. The maximum increase in travel times was observed between interchanges 8 to 8A and was 372.9 percent for the left and center lane closure conditions. This increase is equal to approximately a 30 minutes delay whereas the free flow travel time is 8 minutes. For the left and center lanes closure types, any crash was observed for Interchanges 7 to 7A and 7A to 8. Similar to the previous findings, travel times increased more incrementally for two lanes closed conditions compared to single lane closed conditions.

Table 5-4 The Maximum Increase in Travel times for Crashes within Lane Closure

Section	Right	Left	Right & Center	Left & Center
Interchange 6-7	11.6%	15.8%	96.2%	53.5%
Interchange 7-7A	180.4%	110.7%	294.6%	-
Interchange 7A-8	20.3%	36.5%	28.2%	-
Interchange 8-8A	12.9%	264.4%	50.9%	372.9%

5.5 Modeling Traffic Flow at Different Lane Closure Scenarios

According to the modeling strategies reported in the literature, capacity is estimated by subtracting or multiplying the original capacity by reduction factors for similar lane closure cases. Especially for toll roads, lane closure is predicted to optimize revenue which is mainly less than desirable due to undersaturated conditions. Instead of estimating capacity, modeling traffic flow can provide an idea about lane closure impact on traffic flow conditions.

Based on sensor data, the relationship between traffic flow and lane closures can be modeled by using sensor vehicle count data at the incident locations. The simple flow–density relationship can be computed by utilizing sensor data. Alhassan and Ben-Edigbe (2012) used sensor data in their methodology to estimate highway capacity losses due to rainfall. Based on Greenshield's (1935) model, the relationship between flow, density and speed was as follows:

$$q = k * v \tag{5-4}$$

$$v = a - b * k \tag{5-5}$$

$$q = ak - b * k^2 \tag{5-6}$$

Where,

q: flow veh / hour / lane

k: density veh / mile

v: speed mile/hour

Occupancy was defined as the fraction of time that vehicles spend in the context of the detector. Hall (2001) defined occupancy in his book using the following equations.

$$occupancy = \frac{\sum_i (L_i + d)/(u_i)}{\mathrm{T}} \tag{5-7}$$

The key point here was the ability to estimate density by using occupancy values from the sensor readings. There is also a way of converting the relationship between occupancy and density based on vehicle length. Martin et al. (2003) and Coifman (2005) stated this relationship in their sensor data based studies. For example, if we assume that the RTMS sensor length is zero, there will only be vehicle length to compute. The following equation can be used to convert occupancy to density.

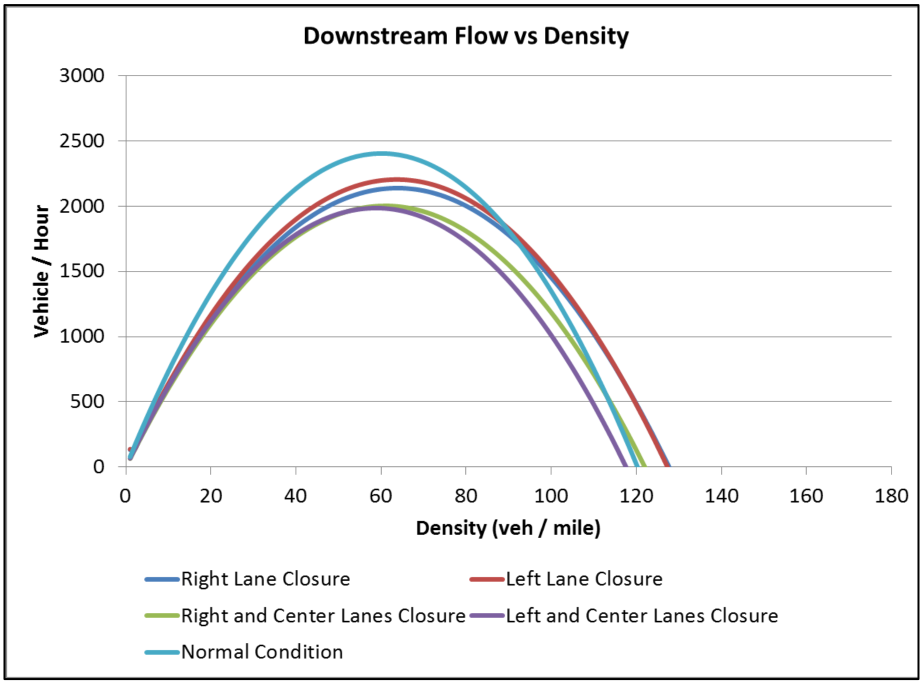
$$k = \frac{Sensor\ Occupancy}{100 * Vehicle\ Length} \tag{5-8}$$

The speed density relationship at downstream sensors for different types of lane closures was modeled by using density values estimated from Equation 5-8. Normal regression was utilized to model the relationship shown in Equation 5-5. Findings from the regression models were implemented into Equation 5-6. Table 5-5 shows the flow modeling coefficients for the different type of lane closure scenarios. Coefficients for the flow model, sample size, mean square error (MSE), and R-square values are included in the table. All models were significant at the 95 percent level of confidence.

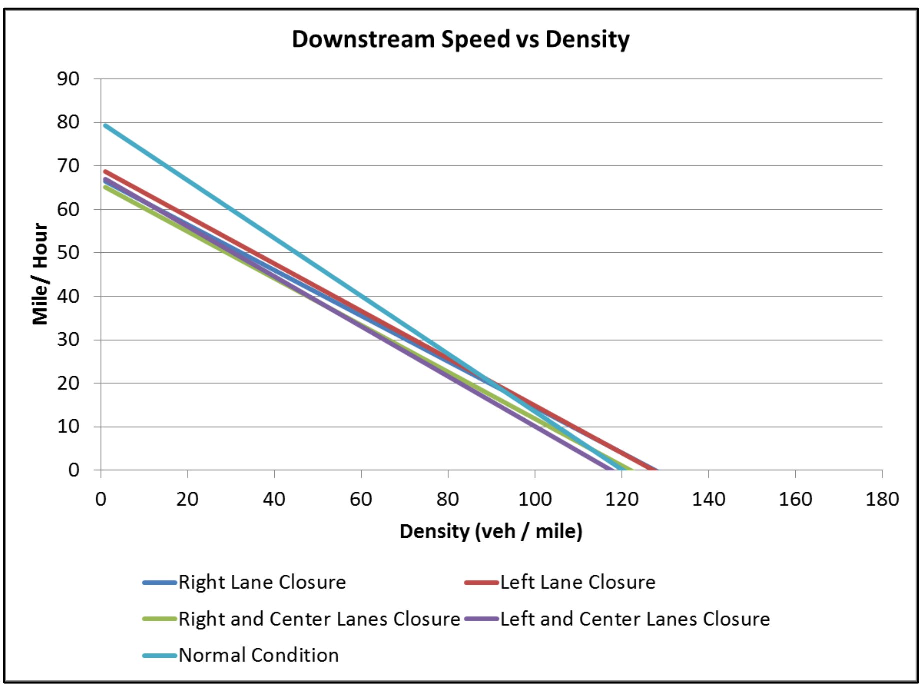
Table 5-5 Flow Modeling Coefficient for the Lane Closure Scenarios

Closure Type	k^2	Std(k^2)	t (k^2)	k	Std (k)	t (k)	N	MSE	R^2
Right	-0.52	0.04	-14.56	67.0	1.02	65.71	111	6.8	0.66
Left	-0.54	0.05	-11.02	69.3	1.21	57.26	95	7.1	0.57
Right and Center	-0.54	0.05	-10.01	65.7	1.56	42.05	80	7.1	0.56
Left and Center	-0.57	0.04	-13.81	67.6	1.20	56.32	90	6.4	0.68

Flow–density and speed-density diagrams were plotted by using modeling coefficients. Figure 5-21 shows these relations for each type of lane closure scenario and normal traffic. As it is seen from Figure 5-21, single lane and two lane closure types have lower maximum flow rates when compared to the maximum flow rate of normal traffic. This maximum flow is dependent to the vehicle length since density was estimated by using vehicle length and occupancy. Traffic flow reduced about 9 percent for single lane closure types and 18 percent for the two-lane closure types when compared to normal traffic flow. Similarly, free flow speed is about 11 mph lower for single lane closure and 15 mph for two-lane closure scenarios when compared to free flow speed at normal traffic conditions.



(a)



(b)

Figure 5-21 Flow Density and Speed Density Curves

5.6 Summary

This chapter studied the impact of work zones on various traffic related variables such as volume, speed, travel time and occupancy. To achieve this objective, a large dataset was created by using different sources such as Automatic Vehicle Identification (AVI) and the RTMS data. The section of New Jersey Turnpike between interchange 6-8A was selected as the test area for the purposes of investigating the impact of work zone activity on the above mentioned factors.

First, different types of lane closure scenarios were studied to examine if there would be a change in traffic conditions compared to normal traffic conditions at the upstream and downstream locations relative to the work zone operations. Right lane, left lane, right-center lanes and left-center lanes closure types were analyzed to determine whether these had an influenced in terms of volume, speed and occupancy. The ratios for each variable were estimated based on normal traffic conditions. A sharp decrease was observed for volume and speed ratios and an increase was observed for the sensor occupancy ratios with the onset of a lane closure operation. Based on the average ratio change, a maximum decrease in traffic volume of 29.7 percent was observed under right and center lanes closure scenario. The negative impact of the two-lane closure was higher than the single lane closure in terms of travel time, and traffic flow. Similarly, recovery times for returning to the average traffic condition parameters were observed to be higher for two-lane closure operations. Figure 5-12 and Figure 5-13 may be useful for agencies to have an idea about the change in the traffic parameters for each type of lane closure operations. The travel time data for the study area was obtained from AVI data. A change in travel times for each exit to exit link was then investigated for different lane closure types. A maximum increase of 101.4 percent was observed for the left and center lane closure types. Shorter sections were affected to a lesser degree than longer sections.

After analyzing the lane closure operations, the impact of the crashes within the lane closure areas was investigated with respect to PDO and injury crashes. Similar to the lane closure analysis procedures, volume, speed and occupancy ratios were estimated. According to the results, the maximum decrease for the volume ratio was observed for the injury crashes under right and center lanes closure scenarios. While speed ratio was decreased by 22.4 percent for PDO crashes, this number increased up to 77.8 percent for "injury crashes within the lane closure" conditions. The maximum observed occupancy ratio for injury crashes was observed to be 8 times more than normal occupancy observations. Travel time changes were investigated by using the AVI data for crash occurrences in the context of different lane closures. Based on the statistical analysis of the crashes that occurred within the lane closure areas, a maximum increase was observed for crashes during right and center lane closures, which were about 3 times higher than those occurring during free flow travel times.

The new traffic flow models were developed by using the regression technique for different lane closure scenarios. Flow-density diagram plotted by the model estimation shows that single lane and two-lane closure operations have lower maximum flow when compared to normal traffic. Similarly, free flow speed at normal traffic conditions is observed higher than the single and two-lane closure scenarios.

CHAPTER 6 CONCLUSIONS

6.1 Conclusions

In this dissertation, the impact of the work zone presence on traffic conditions as defined by crash frequency, crash severity, and roadway capacity were investigated by using descriptive analysis and different statistical modeling methods. Statistically accurate models were developed by incorporating enhanced datasets that could identify significant factors effecting crash frequency, severity and resulting roadway volume into the models that were used. To achieve this, the impact of work zone presence for crash frequency, crash severity, and roadway traffic conditions were compared with non-work zone cases. To this end, the present dissertation study focused on three major factors: the crash frequency at work zones, the crash severity at work zones and the change in traffic parameters at work zones. Following list shows the contributions of this dissertation:

- A novel approach proposed to find out work zone crash characteristic by comparing crash frequency and crash severity models.
- Different from the previous studies, relative impact of work zones is found out compared to non-work zone cases.
- Initial impact of the work zone was modeled first time.
- Multilevel severity was modeled by using monetary weighted total severity approach.
- Trend of traffic condition for the beginning of work zone operation was plotted for each type of lane closure. Flow prediction models were proposed to estimate flow for different types of work zone scenarios.

6.1.1. Crash Frequency at Work Zones

One key research question was whether or not a given roadway experiences an increased number of crashes in the presence of an active work zone. Although a number of studies focused on modeling crash frequency rates related to work zones, very few of them directly examined the change in crash rates under work zone conditions versus normal non-work zone periods for the same road section. This section of the dissertation focused on examining the relationship between work zone presence and crash occurrence through a detailed descriptive analysis and by developing related crash frequency models.

First, a comparison of the work zone and non-work zone crashes in terms of descriptive statistics was focused on. From the descriptive results, it was observed that the average number of crashes and crash rates increased by 18.8 and 24.4 percent respectively for work zones compared to pre-work zone conditions. Rear-end crash frequency was found to be 8.6 percent higher for work zone conditions compared with non-work zone conditions (Ozturk et al., 2014).

By identifying the effects of work zone length, daily traffic exposure, and other explanatory variables on the frequency models the present results can provide considerable information to transportation agencies (Ozbay et al., 2013). Based on the results obtained through the presently developed crash frequency models using work zone specific parameters, length and duration of the work zone, and AADT were found to be the most important factors. Nighttime shifts were found to be safer when compared to daytime crash frequency rates at work zone presence. Lane closure had an incremental effect on the work zone crash frequency. Speed variance between posted speed limit and work zone speed limit was observed to increase the rate of PDO crashes. The number of ramps and intersections was also found to be an important factor increasing crash frequency (Ozturk et al., 2013). In addition to the modeling frequency, the initial impact was examined for the work zone sites. The initial impact indicator added model was developed for examining work zone crashes in more depth. Based on the preliminary results, crash frequency for the initial period of the work zone was found 22.7 percent higher than that of the following time periods win the context of a work zone presence. This shows that familiarity of the work zone conditions over time reduced the risk of crashes. Thus, extra caution should be deployed for the initial setup period of long term work zones.

Modeling work zone frequency provides an idea about the effective parameters, however, the difference of this effect for work zone and non-work zone is more important if indeed there is a specific impact for different work zone cases. Both work zone and non-work zone crash frequency models were created by using the same parameters. One of the major findings from this comparison was the nighttime condition is safer in terms of PDO and injury work zone crashes when compared with the same types of non-work zone crashes. Traffic exposure parameters such as AADT, segment length or number of operating lanes are found to have higher impact for work zone crash frequency. The posted speed, number of ramps and state highways increase the probability of crashes at work zone sites.

6.1.2. Crash Severity at Work Zones

Most project managers consider roadway safety during work zone projects by investing large amount of money. Therefore, safety improvement is an important issue for work zone crashes. To examine risk factors related to work zone crashes, severity models were developed by using binary level and multilevel severity outcomes and by employing logistic regression and the ordered probit technique, to examine the data, respectively. The models tested were statistically significant at the 99.5 percent confidence interval. Work zone and non-work zone crash severity models were compared to determine the impact of each parameter on work zone crash severity.

According to the binary level modeling results, the overturn crash type was found to have about 8 times more risk at work zones when compared to the same crash type at non-work zones. Except for the rear-end crash type, all other crash types had a higher severity impact in work zones than those occurring in non-work zones. The binary level crash severity model parameters such as the numbers of vehicles involved, inattention, unsafe speed, and following too closely were found to be more predictive of increasing work zone crash severity compared to similar crashes in non-work zones (Ozbay et al., 2013)

The "complaint of the pain" and "incapacitated" were applied to describe both injury crashes for binary level outcomes. To overcome this problem, multilevel severity models were developed by employing the maximum severity and the monetary weighted total cost of the occupant's physical conditions. These models were investigated separately for both work zone and non-work zone crashes by using both the model coefficients and marginal effects of each parameters. The multilevel severity modeling results provided better connections between the variables and the severity level of the crashes. According to the comparison of both modeling results for work zone and non-work zone conditions, the nighttime marginal impact was found to be lower for work zone crashes, except for the “killed” level of severity. Being a female, DUI, driving a small vehicle and work zones at state highways were found to have more impact on crash severity at work zones. By using the monetary weighted models, the total marginal effects distributed widely to include more variables. Thus, more significant variables were found by using these methods.

6.1.3. Change in Traffic Conditions at Work Zones

Even though system engineers schedule work zone shifts for under saturated capacity conditions, most people have experienced delays at the beginning of the work zone period. The present research question focused on how the different types of work zone lane closures change the traffic flow conditions. To address this question, the impact of work zone presence on a variety of traffic conditions was investigated in terms of the change in volume, speed, occupancy and travel times by using different dataset sources. In addition to the lane closures, a key question of interest was what if the crash occurred within the active work zone? There are few studies focused on predicting traffic volume by using sensor dataset at work zone condition, especially crash included cases. Thus, both descriptive analysis and modeling were performed to examine the work zone impacts for a variety of traffic conditions in detail and to address the study goals.

The data from the sensor readings located on the NJ Turnpike between interchange 6-8A was utilized in this present study, and from these data, ratios were estimated for each element so these could be compared to normal time traffic condition parameters. The aggregated ratio plots were generated to provide an idea for agencies about how the traffic conditions change in relation to lane closure operations. Based on a preliminary statistical analysis, there was a sharp decrease observed for the traffic volume and the speed and an increase was observed for sensor occupancy when the lane closure operations began. The maximum reduction in traffic volume observed for right and center lanes closures was 29.7 percent. In addition to sensor data, the AVI data was used to determine differences in terms of travel times for various lane closure cases. Based on averaged changes, a maximum increase of 101.4 percent was found for the left and center lanes closed conditions. The decrease in traffic volume was higher for the two-lanes closure type compared to the single lane closure type.

Besides the lane closure itself, crashes were examined within the context of different types of lane closures. The impact of the PDO crashes on traffic volume was found to be lower than those of the injury crashes within the lane closure conditions. The maximum decrease was observed for the injury crashes for the right and center lanes closure conditions. The aggregated speed ratios decreased up to 77.8 percent for the injury crashes within lane closures and the occupancy ratio increased up to 8 times compared to the normal traffic travel time. Similarly, travel times were compared for work zone crashes and the maximum increase in travel time was found to be 3 times higher than free flow travel time for the right and center lanes closure type.

The new traffic flow models were developed by using the regression technique for different lane closure scenarios. Flow-density and speed-density diagrams were plotted by using the model coefficients show that single lane and two-lane closure scenarios had lower maximum flows when compared to the maximum flow at normal traffic conditions. Similarly, free flow speed at normal traffic conditions was observed higher than the single and two-lane closure scenarios.

6.2 Summary of Key Findings and Recommendations

The findings from this dissertation can be found in the Table 6-1. Recommendations belonging to the key findings were included as well.

Table 6-1 Key Findings and Recommendations

Type	Key Findings	Recommendations
Crash Frequency	Crash frequency is increased by work zone presence	Increase awareness of the road users for work zones.
	Initial period of the work zone is found to be more risky compared to ongoing periods of long term work zones.	Extra cautions should be deployed at the beginning of long term work zone projects to increase driver familiarity.
	Nighttime shifts are safer than daytime shifts.	Work zones should be scheduled, if possible, in the nighttime.
	State highways are found to have higher impacts on increasing work zone crash frequency than other highways.	This issue should be further investigated to find out possible reasons.
	Exposure parameters such as AADT, length or duration of the work zones are highly correlated with crash occurrences.	By using optimization techniques, these exposure parameters should be minimized for work zone projects.

Crash Severity	Crash types other than rear-end types such as “overturn”, and “angle” types are found to have a higher impact on work zone crash severity compared to the same types of crashes at non-work zones.	Possible reasons behind crash types and work zone crash frequency relationships should be further investigated.
	DUI has a higher impact on work zone crash severity.	Road users can be better informed and educated about effects of DUI on crash severity.
	Unsafe speeds and higher posted speed limits (>60 mph) are highly correlated with crash severity.	The posted speed limit at work zones should be lower than 60 mph. For unsafe speeds, different enforcement techniques can be employed such as photo radar enforcement.
	“Inattention” and “following too closely” as a contributing error are highly correlated with work zone crash severity.	Alertness of the drivers at work zone areas, and additional following distance warnings can be encouraged within the or before the work area.
	Light vehicles are found to pose more risk in terms of crash severity at work zone locations compared to non-work zones.	Reasons behind this relationship should be further investigated for light vehicle involved crashes.
Roadway Traffic Conditions	Lane closure operations are found to have a decreasing effect on traffic flow, especially after the initial 15-20 minutes of the operation.	Agencies should avoid unnecessary lane closures, and increase the speed of initial lane closure set up conditions.
	Two-lane closures are found to have a greater impact on reducing traffic flow and increasing travel time compared with single lane closures.	Time periods where very low demand conditions should be identified for two-lane closures by using tools such as RILCA software that can make use of historical demand data (Bartin et al., 2012)
	Real time traffic information can be acquired by using sensor.	If congestion occurs, traffic should be diverted whenever possible, or drivers should be informed about the work zone related delay.
	Injury crashes especially within two-lane closures are found to have the most significant impact on increasing travel time and decreasing throughput.	Emergency information providers such as 511 should try to disseminate information to reduce congestion. Speedy incident / accident clearance technologies should be deployed in the presence of two-lane closure conditions.

6.3 Future Work

Future research should focus on providing more detailed data for analyzing traffic conditions when using sensor datasets. In addition to the models presented in chapter 5, examining travel time modeling for different types of lane closure will be beneficial for agencies who want to learn about the factors that influence delays once they deploy lane closure operations. Also, by having more crash data available within the context of any lane closure, more comprehensive traffic volume prediction models can be developed. These data can be collected by efforts to use all sensor features in the context of a mixed-model. This investigation can be conducted to the instant application such as google travel time, and reflect changes in traffic conditions within work zones for road users. Lane closure strategies can be improved to prevent congestion at the beginning of the work zone, by deploying real time traffic management.

Instead of solely improving the prevailing models by adding new parameters, the economic impact of any work zone presence should be estimated in terms of both crashes and volume reduction. Based on the findings from this dissertation, a detailed cost-benefit analysis should be conducted for all work zone projects.

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