MOUNTAIN-PLAINS CONSORTIUM

MPC 16-311 | S. Chen, F. Chen, and X. Ma

Investigation of Interaction between Traffic Safety, Law Enforcement and Environment

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September 2016

Acknowledgements

The funds for this study were provided by the United States Department of Transportation to the Mountain Plains Consortium (MPC). Matching funds were provided by Colorado State University. The data for this study was provided by Colorado State Patrol and Colorado Department of Transportation, which is greatly appreciated.

ABSTRACT

For highways located in different counties and cities across the country, specific conditions of weather, terrain, traffic characteristics, highway conditions, population and economic development are all different. Driving environments, traffic accidents and injury risks have strong interactions, which have not been fully explored. To effectively mitigate traffic accidents and injury severity on these highways, both rational risk prediction and law enforcement efforts are important. This study conducts an investigation on interactions between those traffic accidents, various driving environments and also mitigation efforts, such as law enforcement.

This study began with a literature review on state-of-the-art traffic accident prediction and mitigation. A comprehensive historical data analysis of traffic accidents in Colorado was conducted. Insights were given about interactions between traffic safety, critical variables, and terrain conditions. By developing advanced traffic accident frequency and injury severity prediction models, trends of two major interstate highways and of the entire state's highways could be discussed. Due to the lack of site-specific law enforcement data, the study related to law enforcement is still preliminary and focuses on a review study of existing law enforcement efforts in the United States.

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1. INTERACTION OF TRAFFIC SAFETY AND ACCIDENT MITIGATION

1.1 Overview of Traffic Safety and Accident Mitigation Through Law Enforcement

Traffic safety on highways has long been a concern to people and the local economy. Among all the prevention approaches for traffic accidents, law enforcement has been regarded as one of the most effective. Measures used for accident preventions typically are divided into three main categories (Lund and Aaro 2004): (1) attitude modification, (2) structural modification, and (3) behavior modification. Attitude modification usually is about changes of attitudes through persuasive messages in mass media campaigns, leaflets, films or posters, etc. Structural modification concerns the change of contextual factors, through legislation, regulation, and economy. Behavior modification is a more direct approach, such as training and law enforcement citations (Lund and Aaro 2004). Several popular topics potentially related to the accident mitigation efforts follow.

1.1.1 Safety Belt and Helmet Usage

Increasing seat belt usage of motor-vehicle occupants is an effective strategy used to reduce motor-vehicle-related injuries and deaths. Such a strategy encompasses educating motor-vehicle users (attitude modification) and enforcing a primary seat belt law (behavior modification). Most of the accident prevention research papers were found on investigating seat belt usage. Some recent findings, which may be potentially useful to the current study, follow.

According to the National Highway Traffic Safety Administration (NHTSA), adoption of lap/shoulder seat belts reduce the risk of fatal injuries for front seat vehicle occupants by 45%, and the risk of moderate to critical injury by 50% (USDOT 2000).

Assessments in Illinois and New England show primary enforcement laws (can be the sole reason for being stopped by law enforcement officers) are more effective than secondary enforcement laws (needs some other violation for being stopped by law enforcement officers) to increase seat belt usage (Perkins et al. 2009). Changing from secondary to primary enforcement was associated with percentage point increases in safety belt use: 18 in California, 16 in Louisiana, 17 in Maryland, 14 in Oklahoma, 12 in Washington, DC and 10 in Michigan, respectively (Matsen 2007).

1.1.2 Driving Under Influence (DUI)

DUI-related studies primarily are about how to set appropriate standards. Some useful information follows.

Several hundred statutory changes were implemented and reported across the United States from 1976 to 2002, in terms of penalties for driving after drinking or driving under the influence of alcoholic beverages (Wagenaar et al. 2007). These statutory changes include presumptive alcohol concentration limits, license suspensions, fines, and jail time, etc.

Some investigations focused on discovering appropriate Blood Alcohol Concentration (BAC) (Gorman et al. 2006; Homel 1994). It was found that explorations in more detailed conditions of publicity and enforcement, under which the law does or does not contribute to a decline in alcohol-involved accidents and fatalities, should be conducted, rather than simply regulating a BAC value, such as 0.08 (Wagenaar et al. 2007).

1.1.3 Policy and High Visibility Enforcement

Several studies were found by the study group to be potentially helpful, and to be considered in present and future studies.

The study conducted by Redelmeier et al. (2003) showed that traffic-law enforcement can effectively reduce the frequency of fatal motor-vehicle crashes in countries with high rates of motor-vehicle use. However, inconsistent enforcement could contribute to a large number of deaths each year around the world. The study showed that “Each conviction leads to a 35% decrease in the relative risk of death over the next month for drivers and other road users; conversely, each conviction not issued would lead to a corresponding increase in risk.”

Setting appropriate targets for reduction of traffic fatalities and injuries is one principal task used to carry out strategic highway safety plans by highway patrol or management agencies (Kweon 2010). In recent years, establishing data-driven reduction targets has been advocated. These targets are highly dependent on rational predictions of traffic accidents, forecasting of fatality and injuries (Levine 2006; Pande et al. 2005).

In addition, some recent studies researched optimizing patrol routes and some patrol algorithms, which have been developed targeting on event hotspot (Steil et al. 2011) (Note from Carla: The former sentence does not make sense.) Also, a network-wide traffic police deployment system recently was developed in Queensland Australia, which showed a 11% - 15% reduction in crashes (Newstead 2001).

The high visibility project on interactions between passenger vehicles and commercial vehicles conducted in Washington -- Ticketing Aggressive Cars and Trucks (TACT)-- was evaluated (Thomas et al. 2008) and found that an effective reduction (between 23% to 46%) of crashes could be achieved.

1.2 Intelligence-Led Policing Practices

According to definitions given by the Bureau of Justice Assistance (BJA) (BJA 2005), “intelligence-led policing is a collaborative enterprise based on improved intelligence operations and community-oriented policing and problem solving, which the field has considered beneficial for many years”. There are many fundamental changes in terms of the way information is gathered, assessed, and redistributed intelligence-led policing has been applied primarily in the prevention efforts in crimes and terrorist attack (Figure 1.1) (Weiss and Morckel 2007). In recent years, similar ideas have been adopted to incorporate traffic law enforcement. In the context of traffic law enforcement, intelligence primarily refers to data.

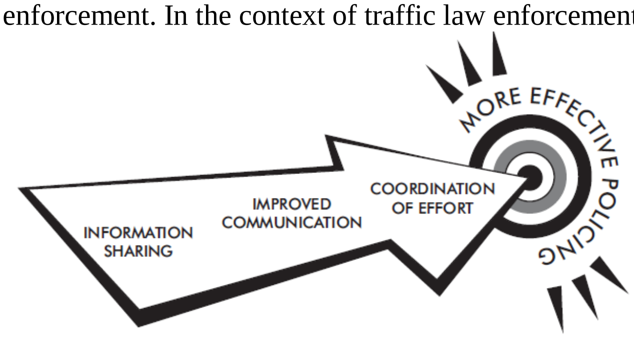

Figure 1.1 Key to more effective policing (Weiss and Morckel 2007)

As realized by more law enforcement officers, it is believed that traffic safety is a comparable, if not more significant, concern for causing injury and fatality compared to crime in many communities (BJA 2005).

Closely related to the intelligence-led policing, advanced resource allocation and staffing tools become critical. Several states have started developing these models. For example:

(1) Michigan State Patrol has started developing an advanced staffing tool (CMU 2010) through work with Central Michigan University.

(2) North Dakota Department of Transportation (NDDOT 2010) also has incorporated intelligence and resource allocation efforts in its highway safety plan (NDDOT 2010).

(3) A data-driven software tool was developed for the police departments in Camden, NJ, and Philadelphia, PA, to make decision-making on combating crime (Redmond and Baveja 2002). Such a system was an integrated tool for information and data gathering and sharing among different departments. Although not specifically designed for traffic law enforcement, similar ideas can be used for the state patrol on traffic safety prevention.

(4) The National Highway Traffic Safety Administration (NHTSA) has developed a popular software tool - Personnel Allocation Model (PAM). Despite well-known drawbacks and limitations, PAM is still one of the most popular software tools on resource allocation in the country.

(5) Ohio State Highway Patrol (OSHP) developed LifeStat 1.0 around 2005 to guide the effective assignment of traffic enforcement and to ensure communication among personnel. The LifeStat 1.0 includes five components: (1) implementation of new inspection process; (2) incorporating a monthly teleconference with district commanders; (3) incorporating trends in the monthly business plan; 4) using corridor safety information on Ohio highway safety to implement local enforcement; and (5) education and engineering solution (McClellan 2006). Such a model was based on the CompStat program originally developed by NYPD.

(6) Washington State has laid out an ambitious strategic highway traffic safety plan of "target zero" (zero traffic deaths and disabling injuries) by 2030 (Washington State 2007). Washington State Patrol, as the major player, will incorporate the "data-driven" management and performance system toward more effective law enforcement. Four priorities were identified, including impaired driving and speed-related collisions, occupant protection; young, old, aggressive and distracted and drowsy drivers and emergency medical services, etc (Washington State 2007). However, no further technical detail of the study could be found by the study group.

(7) Madison Police Department in Wisconsin conducted a police patrol staffing study in 2008 (MPD 2008). With the developed system, (1) appropriate levels of patrol staff for the department to meet patrol requirements can be determined, and (2) deployment strategies that use patrol staff can be developed in the most effective manner. With a few important refinements and improvements over the PAM, the model was found to lack rational demand and resource prediction models critical to any resource allocation model in the opinion of the study group.

Tennessee has developed the Tennessee Integrated Traffic Analysis Network (TITAN) system (https://www.tn.gov/safety/article/titan) for the electronic collection, submission and management of all traffic safety-related data in Tennessee. TITAN can "accept reports submitted by law enforcement agencies, validate the data contained within the report for completion and accuracy and then store the statistically valid information"

1.3 Three Representative Examples

Based on a comprehensive literature review, three successful studies have been conducted on an intelligence-based study:

(1) The Strategic and Tactical Approaches to Traffic Safety (STATS model) conducted by New York Police Department (NYPD)
(2) Crash Prediction model by Ohio Highway State Patrol
(3) Data-Driven Approaches to Crime and Traffic Safety (DDACTS) conducted through the national collaborative efforts

Case 1: The strategic and tactical approaches to traffic safety (STATS model) conducted by New York Police Department (NYPD)

In 2007, New York Police Department (NYPD) developed a new model focusing on the use of strategic and tactical approaches to traffic safety, or STATS (Weiss and Morckel 2007). The STATS approach has four goals (Weiss and Morckel 2007):

a. to enable law enforcement agencies to provide effective traffic law enforcement without depending on federal funding
b. to use data-driven models for allocating enforcement resources
c. to develop strategies for using traffic enforcement to reduce overall criminal activity
d. to develop and train a new generation of traffic safety professionals

Within the model, NYPD has developed the CompStat Program based on arguments that most law enforcement organization administrators focus on officer productivity, not traffic safety (Weiss et al. 2007). The STATS focuses on resource allocation and criminal prevention activities. The feature descriptions of STATS can give people a future vision of how the related studies could potentially be applied and integrated into the big picture of advanced resource allocation and optimizing practices of law enforcement in the future.

Case 2: Crash Prediction Model by Ohio State Highway Patrol

Ohio State Highway Patrol (OSHP) developed and implemented strategies for reducing the number of injury and fatal vehicle crashes on Ohio highways. As an extension of this project, OSHP planned to apply the findings in the resource allocation and other quantitative studies to provide a coherent plan for safety of the people of Ohio on metro roadways in the future (Holloman 2006). First, the study combined a master database from different resources, which would serve as an integrated data repository for future studies. Second, five-year historical accident data was analyzed in the exploratory analysis and also the developing forecasting model. Output of the forecasting model was a set of predicted crash rates for every one-mile segment of the metro roadways (Figure 1.2). Basic algorithms were applied, however the methodology used in the study had possible problematic conclusions. Detailed discussion about the different methodologies will be made in the following section of "traffic safety prediction methodology." Although that study was finished in 2006, the study group believed it was successful in providing some basic information, which could potentially help the current study.

Figure 1.2 Forecasted alcohol-related crash rates for Columbus on June 30, 2006 (Holloman 2006).

Case 3: Data-Driven Approaches to Crime and Traffic Safety (DDACTS) conducted through the national collaborative efforts

Recently, Data-Driven Approaches to Crime and Traffic Safety (DDACTS) has emerged as an integrated law enforcement operational model through the partnership and collaborative effort between the Department of Transportation, National Highway Traffic Safety Administration (NHTSA) and the Department of Justice, Bureau of Justice Assistance (BJA) and the National Institute of Justice (NIJ) (BJA 2010) (http://stko.maryland.gov/DDACTS/tabid/127/Default.aspx). Such a comprehensive model is designed to "aid communities of any size in improving their overall quality of life through the reduction of social harm." The DDACTS model provides a dynamic, evidenced-based problem-solving approach to crime and crashes. The Baltimore, MD, area has become one of the demonstration sites. Results show considerable reduction on both crime and accidents. DDACTS relies on seven guiding principles for its implementation: data collection, data analysis, community partnerships, strategic operations, information sharing and outreach, program monitoring, and measuring outcomes.

For unknown reasons, the technical details of each component, such as algorithms used to develop the model, and functions and limitations, were not available to the study group. DDACTS is a comprehensive system focusing on data integration, resource allocation optimization and evaluation, but it appears that DDACTS has incorporated the improved traffic safety prediction module, and this is the study group's primary interest. Some features of data integration and resource allocation are not discussed further because of limited relevance to the current study.

The three cases are summarized as follows:

1. These three cases represent current leading efforts on intelligence-led policing at the state level (Case 1 & 2) and national level (Case 3).
2. An obvious trend in the coming years will be development of integrated law enforcement resource allocation and management systems.
3. Advanced traffic safety prediction study is still in the emerging stage and shows potential.

2. HISTORICAL ACCIDENT AND ENVIRONMENT DATA

2.1 Historical Data

Historical traffic and environment data in the State of Colorado was collected for this study. Data format was converted to SAS-based to continue the remaining tasks. Detailed information of all data follows.

Crash Data

Time Period: 2007-2010
Data include 5 files: Crash Header file, Crash Injury file, Crash Trucks file, Crash Vehicle file and Crash Citation file.

Table 2.1 Variable classification of crash header file

Injury Outcome of Accident	Location Characteristic	Temporal Characteristic	Accident Characteristic	Road Characteristic
NumKilled	District	AccYear	NumVehicles	HighwayNumber
NumInjured	Troop	AccMonth	Crash Type	HwyInterchange
Highest Inj Level	City	AccDay	Cause	HighwayType
Crash Inj Level	CoCode	DateAccident	A_LocationDesc	RailCross
Fatal	County	AccHour	B_FirstHarmfulEvent	ConZone
Under1000	Road Code	TimeAccident	B_VehSecondHarmful	Bridge
	Milepoint		B_VehMostHarmful	D_RoadDesc
	Milepost		C_ApproachDesc_NA	E_RoadContour
	Latitude			F_RoadSurface
	Longitude			G_RoadCondition
	LocAt			H_LightingCondition
	LocOther			J_AdverseWeather

Table 2.2 Variable classification of crash injury file

Injury Outcome of specific person	Injured person Characteristic	Safety Equipment Characteristic
VehPos	Age	SafetyEquip
Severity	Sex	SafetyUse
	AlcoholUsage	SafetyHelmet
	DrugUsage	AirbagDep
	RestrictionComp	AirbagType
	EndorsementComp	
	InjZip	

Table 2.3 Variable classification of crash trucks file

Truck Characteristic	Hazardous Material Characteristic	Single-vehicle Accident Characteristic
Zip	Placard	Seq1
Weight	PlacNum4	Seq2
Axles	PlacNum1	Seq3
Config	Release	Seq4
CarrierType	LiquidHazMat	

Table 2.4 Variable classification of crash vehicle file

Vehicle Characteristic	Accident Characteristic	Driver Characteristic
K_VehType	Parked	DrvZip
T_VehicleDefect	NonContact	DrvLicState
VehYear	Towed	DrvCDL
VehMake	M_VehMovement	DrvLicRestrict
VehModel	N_Limit	DrvLicEndorse
VehState	P_Speed	DrvLicClass
VehOwnerZip	Q_DriverAction	DLDeny
VehInsurance	S_PedAction	DLRevoke
VehInsNone		DLExpired
VehInsNoProof		DrvSex
		DrvAge

Table 2.5 Variable classification of crash citation file

Citation Time	Citation Location	Citation Details
CitDate	Loc	Causal
CitTime	County	PatrolCode
	RoadCode	HVPTFlag
	MilePost	ViolCode
	HwyCode	ZONE
		CITCODE
		StatuteID

Highway Geometry Data

The Highway geometry data includes road design, traffic volume and other information of road segments. There are five files: Highway spatial, Highway curve data, Highway grade, ramp and structure. Tables 2.6-2.8 summarize variables in Highway spatial, Highway curve data and Highway grade files. In addition, this report also includes detailed spatial information of ramps and structures (bridges).

Table 2.6 Highway spatial data variables

ROUTE	FUNCCLASS	AADT	SPEEDLIM
REFPT	ROUTESIGN	AADT20	PRISURF
ENDREFPT	NHSDESIG	AADTYR	THRULNQTY
SEG_LENGTH	ACCESS_	AADTDERIV	THRULNWD
REGION	PRIGFP	PKTRK	ISDIVIDED
TPRID	PRIRSL	OFFPKTRK	PRIOUTSHD
COMMDISTID	PRIIRII	AADTSINGLE	PRIOUTSHDW
CITY	PRIRUTI	AADTCOMB	MEDIAN
FIPSCITY	ALIAS	VCRATIO	MEDIANWD
COUNTY	DESCRIPTIO	VCRATIO20	TERRAIN
FIPSCOUNTY	SHAPE_LEN	VMT	

Table 2.7 Highway curve data variables

ROUTE	PRICURVE	SEG_LENGTH
REFPT	PRICURVECL	UPDATEYR
ENDREFPT	CTYPE	SHAPE_LEN

Table 2.8 Highway grade data variables

ROUTE	SECGRADE	SEG_LENGTH
REFPT	SECGRADECL	UPDATEYR
ENDREFPT	PRIGRADE	

2.1.1 Real-time road surface condition data

Table 2.9 lists variables in real-time road surface data, and Table 2.10 lists highways with real-time road surface data.

Table 2.9 Real-time road surface data variables

Column Name	**Description**
weather station common Name	Business name for the device. The format of the name is as follows: Three Digit Highway Direction Three Digit Mile Marker space Common Name Text (in upper case)';
weather station latitude	Latitude where the device is located
weather station longtitude	Longitude where the device is located
weather_station_Mile_Marker	Mile marker on the highway where the device is located
Sensor common Name	Sensor name from the SSI system
DEVICE_COLLECTION_DT	Date and time that surface data were collected by the RWIS weather station sensor
TYPE_RWIS_SURFACE_STATUS_CD	System generated identifier for the status of the surface data collected by the RWIS weather station sensor
ESS_SUBSURFACE_TEMPERATURE_NUM	Temperature approximately 43 cm (17 inches) below the top of the pavement, in degrees Fahrenheit
ESS_SURFACE_FREEZE_POINT_NUM	Freezing point of the moisture on the pavement sensor based upon the specific chemical in use, in degrees Fahrenheit
CHEMICAL_FACTOR_NUM	Relative indication of chemical present in the moisture on the surface. Chemical factor uses a relative scale ranging from 5 to 95 in increments of 5.

Column Name	Description
CHEMICAL_PERCENTAGE_NUM	Percent of chemical saturation in the moisture
ESS_WATER_DEPTH_FLT	Depth of water layer on the sensor, in inches
ICE_PERCENTAGE_NUM	Percentage of ice in the moisture
ESS_SURFACE_CONDUCTIVITY_NUM	Conductance of the ice/liquid mixture on the pavement
ESS_SURFACE_SALINITY_NUM	Number of grams of dissolved matter per kilogram of seawater, in parts per 100,000
TYPE_ESS_SURFACE_BLACK_ICE_CD	System generated identifier for an NTCIP 1204 value indicating if black ice is detected by the RWIS weather station senso
TYPE_ESS_PVMT_SENSOR_ERROR_CD	System generated identifier for the NTCIP 1204 value indicating the type of error at the RWIS weather station pavement sensor
WEATHER_STATION_ID	System generated identifier for the RWIS weather station collecting the atmospheric data

Table 2.10 Highways with real-time road surface data

Road ID	Road Name	Time Period
1	C470	07/01/2008 – 12/31/2010
8	CO 14	07/01/2008 – 12/31/2010
18	CO 7	07/01/2008 – 12/31/2010
19	CO 71	07/01/2008 – 12/31/2010
20	CO 72	07/01/2008 – 12/31/2010
27	CO 91	01/01/2010 – 12/31/2010
28	CO 93	07/01/2008 – 12/31/2010
30	I 225	07/01/2008 – 12/31/2010
31	I 25	07/01/2008 – 12/31/2010
32	I 70	07/01/2008 – 12/31/2010
33	I 76	07/01/2008 – 12/31/2010
34	US 160	07/01/2008 – 12/31/2010
35	US 24	07/01/2008 – 12/31/2010
36	US 285	07/01/2008 – 12/31/2010
37	US 287	07/01/2008 – 12/31/2010
38	US 34	07/01/2008 – 12/31/2010
40	US 36	07/01/2008 – 12/31/2010
41	US 40	07/01/2008 – 12/31/2010
42	US 50	07/01/2008 – 12/31/2010
46	US 550	07/01/2008 – 12/31/2010
84	CO 82	07/01/2008 – 12/31/2010
103	CO 121	07/01/2008 – 12/31/2010
107	CO 133	07/01/2008 – 12/31/2010
109	CO 135	01/01/2010 – 12/31/2010
112	CO 139	07/01/2008 – 12/31/2010
117	CO 145	07/01/2008 – 12/31/2010
159	CO 391	07/01/2008 – 12/31/2010
162	US 385	07/01/2008 – 12/31/2010

2.1.2 Real-time weather condition data

Table 2.11 lists variables in real-time weather data, and Table 2.12 lists highways that have real-time weather data available.

Table 2.11 Real-time weather data variables

Column Name	Descriptions
weather station common Name	Business name for the device. The format of the name is as follows: Three Digit Highway Direction Three Digit Mile Marker space Common Name Text (in upper case)';
weather station latitude	Latitude where the device is located
weather station longitude	Longitude where the device is located
weather_station_Mile_Marker	Mile marker on the highway where the device is located
WEATHER_STATION_ID	System generated identifier for the RWIS weather station collecting the atmospheric data
DEVICE_COLLECTION_DT	Date and time that atmospheric data were collected by the RWIS weather station';
ESS_AIR_TEMPERATURE_NUM	Air temperature at the RWIS weather station, in degrees Fahrenheit
ESS_RELATIVE_HUMIDITY_NUM	Percentage of moisture in the air at the RWIS weather station
ESS_DEW_POINT_TEMP_NUM	Temperature at which the air becomes saturated as it cools, in degrees Fahrenheit
ESS_WET_BULB_TEMP_NUM	Temperature of a thermometer whose bulb is wrapped in wet muslin, in degrees Fahrenheit
ESS_MIN_TEMP_NUM	Minimum temperature recorded during the 24 hours preceding the observation, in degrees Fahrenheit
ESS_MAX_TEMP_NUM	Maximum temperature recorded during the 24 hours preceding the observation, in degrees Fahrenheit';
ESS_ATMOSPHERIC_PRESSURE_FLT	Force per unit area exerted by the atmosphere, in inches
ESS_AVG_WIND_SPEED_NUM	Average speed of the wind during an evaluation cycle, in miles per hour
ESS_AVG_WIND_DIRECTION_NUM	Average wind direction during an evaluation cycle, in degrees
WIND_DIRECTION_TXT	Average wind direction during an evaluation cycle, in cardinal points
ESS_MAX_WIND_GUST_SPEED_NUM	Maximum wind speed measured during an evaluation cycle The time period over which wind gust speed is monitored can vary based on the type and manufacturer of the RWIS weather station.';
ESS_MAX_WIND_GUST_DIR_NUM	Maximum wind gust direction during an evaluation cycle, measured in degrees
WIND_GUST_DIR_TXT	Maximum wind gust direction during an evaluation cycle, measured in cardinal points
ESS_VISIBILITY_FLT	Average distance that a person can see, both day and night, computed every three minutes, in miles
weather station common Name	Business name for the device. The format of the name is as follows:Three Digit Highway Direction Three Digit Mile Marker space Common Name Text (in upper case)';

Column Name	**Descriptions**
weather station latitude	Latitude where the device is located
weather station longtitude	Longitude where the device is located
weather_station_Mile_Marker	Mile marker on the highway where the device is located
WEATHER_STATION_ID	System generated identifier for the RWIS weather station collecting the atmospheric data
DEVICE_COLLECTION_DT	Date and time that atmospheric data were collected by the RWIS weather station';
ESS_AIR_TEMPERATURE_NUM	Air temperature at the RWIS weather station, in degrees Fahrenheit
ESS_RELATIVE_HUMIDITY_NUM	Percent of moisture in the air at the RWIS weather station
ESS_DEW_POINT_TEMP_NUM	Temperature at which air becomes saturated as it cools, in degrees Fahrenheit
ESS_WET_BULB_TEMP_NUM	Temperature of a thermometer whose bulb is wrapped in wet muslin, in degrees Fahrenheit
ESS_MIN_TEMP_NUM	Minimum temperature recorded during the 24 hours preceding the observation, in degrees Fahrenheit
ESS_MAX_TEMP_NUM	Maximum temperature recorded during the 24 hours preceding the observation, in degrees Fahrenheit';
ESS_ATMOSPHERIC_PRESSURE_FLT	Force per unit area exerted by the atmosphere, in inches
ESS_AVG_WIND_SPEED_NUM	Average speed of the wind during an evaluation cycle, in miles per hour
ESS_AVG_WIND_DIRECTION_NUM	Average wind direction during an evaluation cycle, in degrees
WIND_DIRECTION_TXT	Average wind direction during an evaluation cycle, in cardinal points
ESS_MAX_WIND_GUST_SPEED_NUM	Maximum wind speed measured during an evaluation cycle The time period over which wind gust speed is monitored can vary based on the type and manufacturer of the RWIS weather station.';
ESS_MAX_WIND_GUST_DIR_NUM	Maximum wind gust direction during an evaluation cycle, measured in degrees
ESS_PRECIP_RATE_FLT	Average precipitation rate computed every minute, in inches
ESS_PRECIPITATION_START_DT	Time at which the most recent precipitation event began
ESS_PRECIPITATION_END_DT	Time at which the most recent precipitation event ended
TIME_SINCE_LAST_PRECIP_NUM	Time interval since the last precipitation event occurred, in minutes
PRECIPITATION_ACCUMULATION_FLT	Rainfall amount or snowfall liquid equivalent for the period from midnight GMT to the current time, in inches.
TEN_MINUTE_PRECIP_ACCUM_FLT	Rainfall amount or snowfall liquid equivalent for the previous 10 minute period, in inches
ESS_PRECIPITATION_1_HOUR_FLT	Rainfall amount or snowfall liquid equivalent for the previous 1 hour period, in inches
ESS_PRECIPITATION_3_HOURS_FLT	Rainfall amount or snowfall liquid equivalent for the previous 3 hour period, in inches

Column Name	Descriptions
ESS_PRECIPITATION_6_HOURS_FLT	Rainfall amount or snowfall liquid equivalent for the previous 6 hour period, in inches
ESS_PRECIPITATION_12_HOURS_FLT	Rainfall amount or snowfall liquid equivalent for the previous 12 hour period, in inches
ESS_PRECIPITATION_24_HOURS_FLT	Rainfall amount or snowfall liquid equivalent for the previous 24 hour period, in inches

Table 2.12 Highways which have real-time weather data

Road ID	Road Name	Time Period
1	C470	07/01/2008 – 12/31/2010
8	CO 14	07/01/2008 – 12/31/2010
18	CO 7	07/01/2008 – 12/31/2010
19	CO 71	07/01/2008 – 12/31/2010
20	CO 72	07/01/2008 – 12/31/2010
27	CO 91	01/01/2009– 12/31/2010
28	CO 93	07/01/2008 – 12/31/2010
30	I 225	07/01/2008 – 12/31/2010
31	I 25	07/01/2008 – 12/31/2010
32	I 70	07/01/2008 – 12/31/2010
33	I 76	07/01/2008 – 12/31/2010
34	US 160	07/01/2008 – 12/31/2010
35	US 24	07/01/2008 – 12/31/2010
36	US 285	07/01/2008 – 12/31/2010
37	US 287	07/01/2008 – 12/31/2010
38	US 34	07/01/2008 – 12/31/2010
40	US 36	07/01/2008 – 12/31/2010
41	US 40	07/01/2008 – 12/31/2010
42	US 50	07/01/2008 – 12/31/2010
44	US 6	07/01/2008 – 12/31/2010
46	US 550	07/01/2008 – 12/31/2010
84	CO 82	07/01/2008 – 12/31/2010
103	CO 121	07/01/2008 – 12/31/2010
107	CO 133	07/01/2008 – 12/31/2010
109	CO 135	01/01/2010 – 12/31/2010
112	CO 139	07/01/2008 – 12/31/2010
117	CO 145	07/01/2008 – 12/31/2010
159	CO 391	07/01/2008 – 12/31/2010
162	US 385	07/01/2008 – 12/31/2010

Real-time Traffic Speed Data

Table 2.13 Real-time speed data variables

MM_START_FLT	SEGMENT_LENGTH_MILES_FLT	AVG_SPEED_FLT	AVG_VOLUME_FLT
MM_END_FLT	CALCULATED_DT	SH.AVG_OCCUPANCY_FLT	TRAVEL_TIME_NUM

Data Used for Injury Severity Study

For multinomial logit model to study the injury severity, the variable needed for injury severity study is listed in Table 2.14.

Table 2.14 Variable needed for injury severity study

Injury Outcome	Time Characteristic	Accident Characteristic	Road Characteristic	Person Characteristic	Vehicle Characteristic
Injury outcome of accident(from CSP Crash Header file)	Temporal Characteristic (from CSP Crash Header file)	Accident Characteristic (from CSP Crash Header file)	Road Characteristic(from CSP Crash Header file)	Injured person Characteristic (from Crash Injury file)	Vehicle Characteristic (from CSP Crash Vehicle file)
Injury outcome of specific person (from Crash Injury file)		Accident Characteristic (from CSP Crash Vehicle file)	Highway geometry data(From Highway spatial data variables)	Safety Equipment Characteristic (from Crash Injury file)	
		Citation details (from CSP Crash Citation file)	Highway geometry data (Highway curve data variables and Highway grade data variables)	Driver Characteristic (from CSP Crash Vehicle file)	

Data Used for Accident Frequency Study

Table 2.15 shows the variable needed for the annual accident frequency study and data source using Negative Binomial model. Table 2.16 demonstrates the variable needed for the daily accident frequency study and data source using panel data model.

Table 2.15 Variable needed for accident frequency study (annual count accident frequency)

Annual accident frequency of each road segment	Highway geometry	Road surface data	Weather data	Speed data
Counted based on Location Characteristic (from CSP Crash Header file) and year	Highway spatial data variables (from CDOT Highway geometry data)	Annual average of real-time road surface data from CDOT	Annual average of real-time weather data from CDOT	Annual average of real-time speed data from CDOT
	Highway curve data variables (from CDOT Highway geometry data)			Some variables from Highway spatial data variables
	Highway grade data variables (from CDOT Highway geometry data)			

Table 2.16 Variable needed for accident frequency study (daily count accident frequency)

Daily accident frequency of each road segment	Highway geometry	Road surface data	Weather data	Speed data
Counted based on Location Characteristic (from CSP Crash Header file) and day	Highway spatial data variables (from CDOT Highway geometry data)	real-time road surface data from CDOT	real-time weather data from CDOT	real-time speed data from CDOT
	Highway curve data variables (from CDOT Highway geometry data)			
	Highway grade data variables (from CDOT Highway geometry data)			

3. ACCIDENT FREQUENCY AND ENVIRONMENT

3.1 Methodology

Annual accident data of each road section is typically studied for spatial analysis of accident frequency. The negative binomial (NB) model is used in crash-frequency modeling.

The negative binomial form is as follows:

$$P(y_i) = \frac{\Gamma(1/\alpha + y_i)}{\Gamma(1/\alpha) y_i!} \left(\frac{1/\alpha}{1/\alpha + \lambda_i} \right)^{1/\alpha} \left(\frac{\lambda_i}{1/\alpha + \lambda_i} \right)^{y_i} \qquad (3.1)$$

where $P(y_i)$ is the probability of roadway entity *i* having y_i crashes per time period. $\Gamma(.)$ is a gamma function. For each observation $\lambda_i = EXP(\boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i)$, where $\mathbf{X}_i$ is a vector of explanatory variables and $\boldsymbol{\beta}$ is a vector of estimable parameters. $EXP(\varepsilon_i)$ is a gamma-distributed error term with mean 1 and variance α.

3.2 Explanatory Variables

Spatial analyses of accident frequency consider the following information of the road sections: road geometry, traffic volume, traffic control, environmental condition, etc. As introduced in the Task 2 report, the study group received accident records from CSP and road geometry, traffic volume, and environmental conditions from CDOT. Thirty-seven parameters were significant in the final model.

Studies were conducted with several models covering different spatial dimensions in Colorado (using 2007, 2008 and 2009 accident data), such as whole state, different function class and two specific highways: I-25, I-70. These models will be respectively introduced in the following sections.

3.3 Whole State Crash Frequency Spatial Model

Model output is the annual accident number (accident frequency) of each road section. The inputs all are parameters that have significant influence on accident frequency. The hypothesis of no significant difference from zero for each parameter was tested using the likelihood ratio *t*-test. Parameters not significantly different from zero at the 90% confidence interval will be deleted from the model. This means the parameters remaining in the model all have a 90% confidence interval. Although the parameters are listed in several tables, the parameters are in one model together. They are separated into different tables for better illustration and comparison.

There are 93,512 highway sections in Colorado. In the following tables, *up arrow* means accident frequency increases if the parameter increases (for dummy parameter, the value increases from 0 to 1). d*own arrow* means accident frequency decreases if the parameter increases. Since traffic safety is a complex phenomenon reflecting the outcome caused by many factors of both driving environment and driving behavior, some interesting findings were observed.

Road Characteristics: Traffic Volume and Highway Road Geometry

Table 3.1 shows the influence of traffic volume and road geometry on accident frequency in the whole state model. Accident frequency increases when length, AADT or volume/capacity ratio of the road section increases. This phenomenon can be found in many existing studies. For Colorado Highways as a whole, road sections with higher speed limits are associated with higher accident frequency. If the number of lanes is larger, lane or outside shoulder is wider, accident frequency of the road section will decrease. Typically, these designs will make the highways physically safer to drive and drivers feel more comfortable. Although the same designs also may cause drivers to drive more aggressively, the resultant outcome seems to be positive in Colorado overall.

Table 3.1 Influence of traffic volume, road geometry on accident frequency (whole state)

Log of length	↑
Log of AADT	↑
Volume/Capacity ratio	↑
Speed limit	↑
Number of lanes	↓
Lane width	↓
Median width	↑
Outside shoulder width	↓
Peak percent of truck	↓

Other Road Characteristics

Table 3.2 shows the influence of other road characteristics on accident frequency in the whole state model. The road section on an urban highway appears to be related to fewer accidents compared to rural highways. As expected, interstate highways are associated with more accidents than other function classes of highways. Highways with truck restriction are related to more accidents than those without. Highways belonging to forest area will have more accidents.

Table 3.2 Influence of other characteristics of road on accident frequency (whole state)

Urban	↓
Interstate	↑
Truck restricted	↑
Forest	↑

Road Geometry and Pavement Conditions

Table 3.3 shows the influence of grade and curvature of roads on accident frequency in the whole state model. When the road section has steeper grade, more accidents occur, but when the road section has sharper curvature, the number of accidents decrease.

Table 3.3 Influence of grade and curvature of road on accident frequency (whole state)

Grade	↑
Curvature	↓

Table 3.4 shows the influence of road surface on accident frequency in the whole state model. Results suggest highways with bituminous road sections may experience fewer accidents than those with concrete road sections. When international roughness index is higher, meaning the road is smoother, more accidents occur. When the remaining service life for rutting is higher, meaning the road has less rutting, fewer accidents occur. When road pavement condition is fair or poor, more accidents tend to occur. The opposite trends of international roughness index and pavement conditions suggest pavement that is too smooth (e.g. very new pavement) or too rough (e.g. too old) both cause more accidents. This reflects the complex interaction and balance between physical driving conditions and corresponding driving behavior. Further studies may be needed to learn the optimal roughness range of pavements that lead to the minimum number of accidents. This information may help transportation authorities define the ideal initial roughness and criteria when repaving is needed for the safety perspective.

Table 3.4 Influence of road surface on accident frequency (whole state)

Road surface: Bituminous	↓
International roughness index	↑
Remaining service life for rutting	↓
Fair pavement condition	↑
Poor pavement condition	↑

Median and Shoulder Types

Table 3.5 shows the influence of median types on accident frequency in the whole state model. It was found that accident frequency is related to different median types. Road sections with Depressed - Guard Rail or Channelized – Painted medians are associated with more accidents, and Road sections with Painted, Level – Concrete or Raised Curb – Concrete medians are related to fewer accidents. This information is useful for Colorado transportation authorities when selecting safer guard rails and medians.

Table 3.5 Influence of median types on accident frequency (whole state)

Painted	↓
Level - Concrete	↓
Depressed - Guard Rail	↑
Raised Curb - Concrete	↓
Channelized - Painted	↑

Table 3.6 shows the influence of inside shoulder types on accident frequency in the whole state model. It was found that accident frequency also is related to different inside and outside shoulder types. Comparatively, more accidents occur on road sections with Bituminous, Portland-not tied or Portland-tied inside shoulders, while fewer accidents occur on road sections with Earth or Curbed inside shoulders.

Table 3.6 Influence of inside shoulder types on accident frequency (whole state)

Bituminous	↑
Portland-not tied	↑
Portland-tied	↑
Earth	↓
Curbed	↓

Table 3.7 shows the influence of outside shoulder types on accident frequency in the whole state model. More accidents occur on road sections with Bituminous, Portland-not tied, Portland-tied, Stabilized and Combination outside shoulders, while fewer accidents occur on road sections with Earth or Curbed outside shoulders. Future transportation infrastructure designs in Colorado may benefit from the findings illustrated in Tables 3.6 and 3.7.

Table 3.7 Influence of outside shoulder types on accident frequency (whole state)

Bituminous	↑
Portland-not tied	↑
Portland-tied	↑
Stabilized	↑
Combination	↑
Earth	↓
Curbed	↓

Function Class: Interstate, Arterial and Collector

Highways are separated into three different function classes: Interstate, Arterial and Collector. Three different models were built with different significant variables. Some variables have an opposite influence on the accident frequency of different function classes. Table 3.8 shows the numbers of road sections and significant variables of Interstate, Arterial and Collector, respectively.

Table 3.8 Number of significant variables of different function classes

Function class	Interstate	Arterial	Collector
Number of road sections	12122	68988	12139
Number of significant variables	25	33	17

Table 3.9 shows that some parameters have different influences on different function classes. For example, interstates with wider outside shoulders have higher accident frequency. Arterial and Collector highways show an opposite trend. These results may help to make highway design improvements, which consider specific contributions to accident frequency from median, inside and outside shoulders for different highways.

Table 3.9 Different influence of some parameters on different function classes

Function class	Interstate	Arterial	Collector
Outside shoulder width	↑	↓	↓
Median: Depressed	↓	↑	
Median: Channelized - Painted		↑	↓
Inside shoulder type: Bituminous	↑	↓	
Road surface: Reinforced Concrete	↑	↓	

3.4 Whole State Crash Frequency Temporal Model

For the temporal model, output is the accident number of each hour of the whole state model from 2007 to 2009, where 3×365×24=26,280 samples. Input variables are the hour, date and month information of each sample. Negative Binomial model also was adopted to develop the temporal model. The percentage shown in the following figures means that when the value of the variable of one specific road section (*x* axis) is changed from 0 to 1 and other variables of the road section remain the same, accident frequency of the road section will increase (if +) or decrease (if -) the particular percentage (as shown in *y* axis) compared to the corresponding value, when the variable is 0.

The temporal model of the whole state model demonstrates the time information of accidents. Figure 3.1 shows weekly and monthly information of the whole state accident model. Approximately 20% more accidents occurred on Friday compared to other days, with fewer accidents on Holidays. Days in December or in January had 30% or 10% more accidents compared to non-December and non-January days, respectively. Figure 3.1 shows the frequency of accidents from March to September. Days in the month of May had the fewest accidents in Colorado.

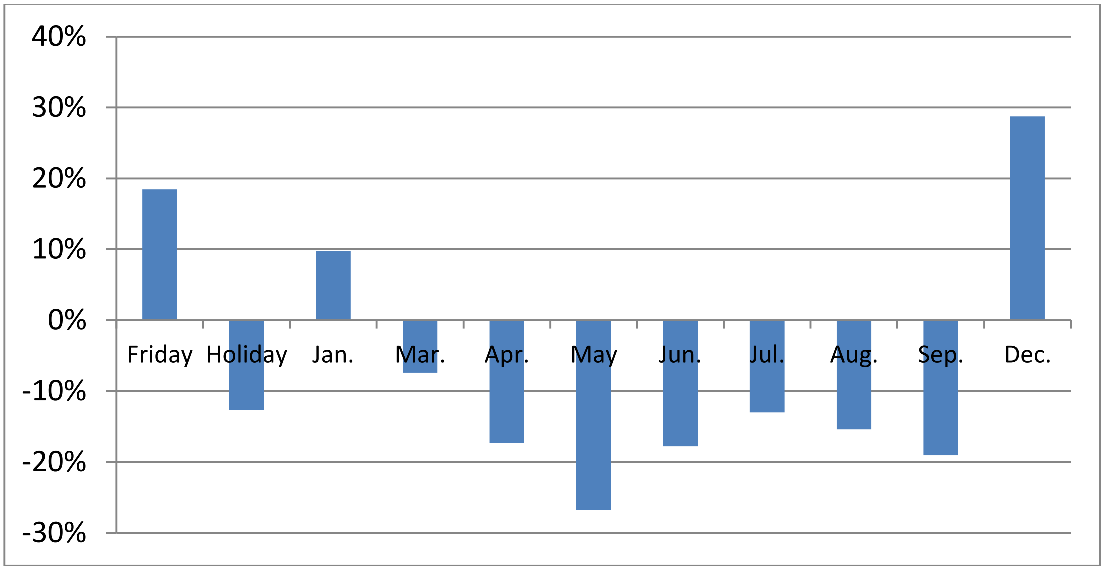

Figure 3.1 Weekly and monthly information of the whole state model

Figure 3.2 shows the hourly information of the whole state accidents, which is highly related to traffic volume. There are two peaks of accidents: h07-h08 and h15-h18. Both time instants are near the rush hours and comparatively, the afternoon peak has more accidents than the morning peak.

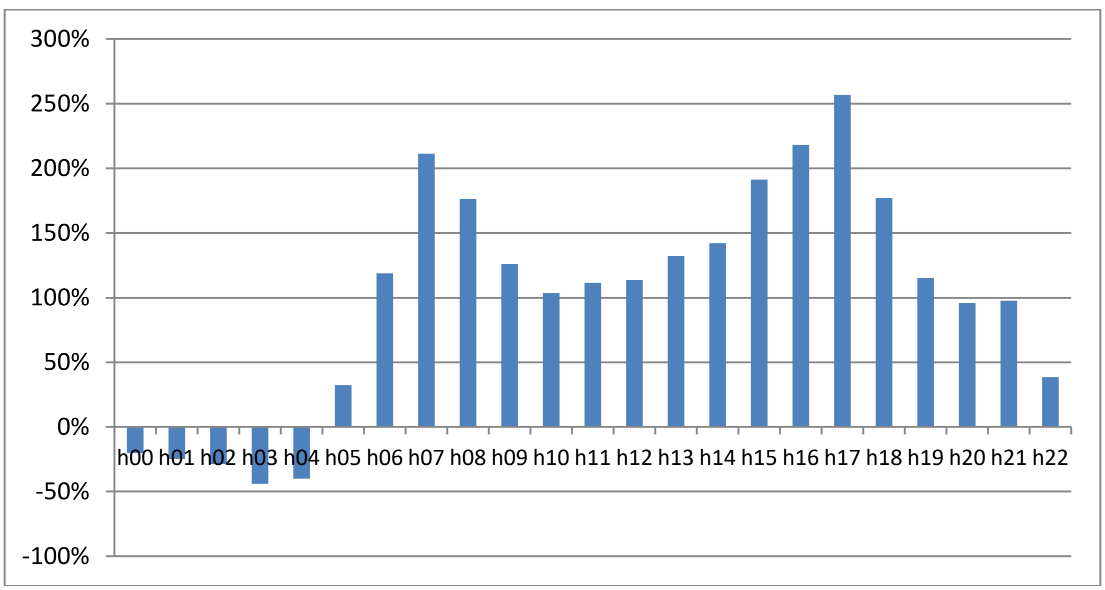

Figure 3.2 Hourly information of whole state accidents

Freeway Models: I-25 and I-70 (Spatial Model)

I-70 and I-25 are two major interstate freeways in Colorado, which deserve special attention. In addition, detailed traffic, weather, and surface data are only available on these two major interests. Therefore, more comprehensive analyses were conducted on these two freeways.

It was found that I-70 is unique compared to most other highways in Colorado. Table 3.10 shows the different influences of some parameters on the whole state model and I-70. Most previous researches showed that accident frequency increases with higher AADT. The whole state model in this study also shows this trend. But the influence of AADT is opposite in the I-70 model. In addition, the influence of some critical variables such as speed limit, number of lanes, and outside shoulder width also were opposite between the I-70 model and the whole state highway model. These phenomena suggest that further studies may be needed on studying crash mechanisms of highways like I-70.

Table 3.10 Different influence of some parameters on the whole state highway model and I-70

Parameters	**Whole state highway model**	**I-70**
Log of AADT	↑	↓
Speed limit	↑	↓
Number of lanes	↓	↑
Outside shoulder width	↓	↑

To add insight into this comparison, two major Interstate highways in Colorado: I-25 and I-70 were compared with results given in Table 3.11. There are 4,820 highway sections on I-25 and 5,171 highway sections on I-70. There are 18 significant variables in the I-25 model and 23 significant variables in the I-70 model. Similar to the whole state highway model, some critical variables exhibit opposite trends on crash frequency for I-70 and I-25: AADT, number of lanes, lane width, and two road surface types. More comprehensive investigations will be needed to discover why I-70 has unique characteristics of crash frequency compared to other highways, including I-25.

Table 3.11 Different influence of some parameters on I-25 and I-70

	I-25	**I-70**
Log of AADT	↑	↓
Number of lanes	↓	↑
Lane width	↑	↓
Road surface: Plain Concrete	↑	↓
Road surface: Reinforced Concrete	↑	↓

Special Crash Types

Negative Binomial models were used to analyze the time information of three special crash types: DUI-caused accidents, speeding-caused accidents, and truck-caused accidents. Results were compared to an all accidents model. The outcome is the number of specific accident types occurring each hour in the whole state from 2007 to 2009. The difference with the whole state model is the number of specific accident types, instead of all accidents.

DUI-Caused Accidents (Temporal Model)

Figure 3.3 shows weekly information of DUI-caused accidents. Typically, there are fewer accidents on weekends or holidays, but the results show that there are more DUI-caused accidents on weekends or holidays. The trend of increasing accidents on Friday is similar to all accidents (as a whole) and DUI-caused accidents. However, the increase of DUI-caused accidents is still much higher than all accidents (56% vs 18%). It was found that frequency of DUI-caused accidents is not related to the monthly information.

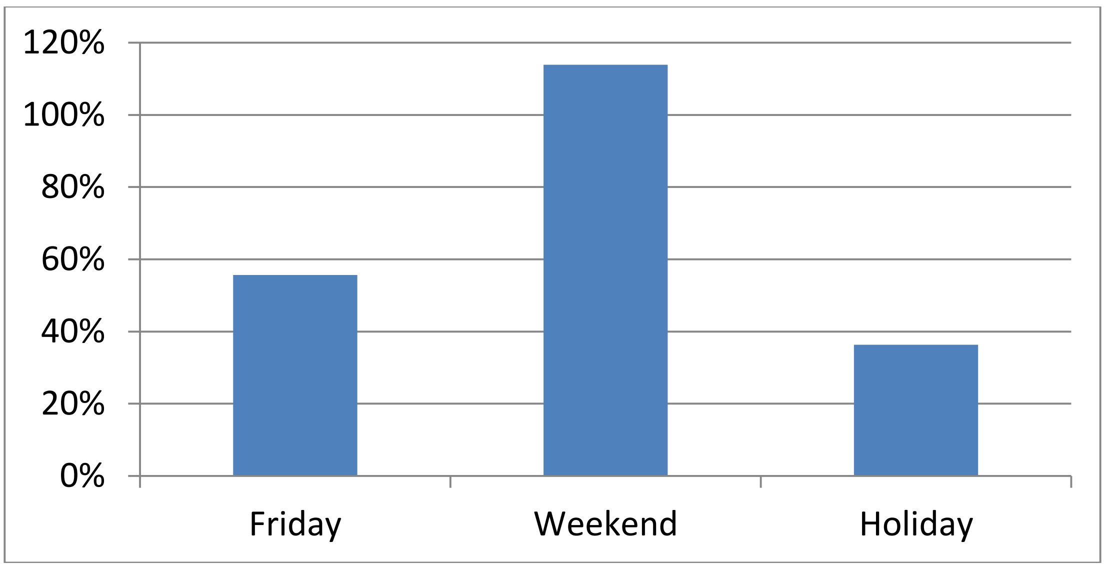

Figure 3.3 Weekly information of DUI-caused accidents

Figure 3.4 shows the hourly information of DUI-caused accidents. Two peaks of accidents exist: h20-h22 and h01-h02. The trend is different with all accidents as a whole. Not surprisingly, the frequency of DUI-caused accidents seems to be related to party time instead of traffic volume.

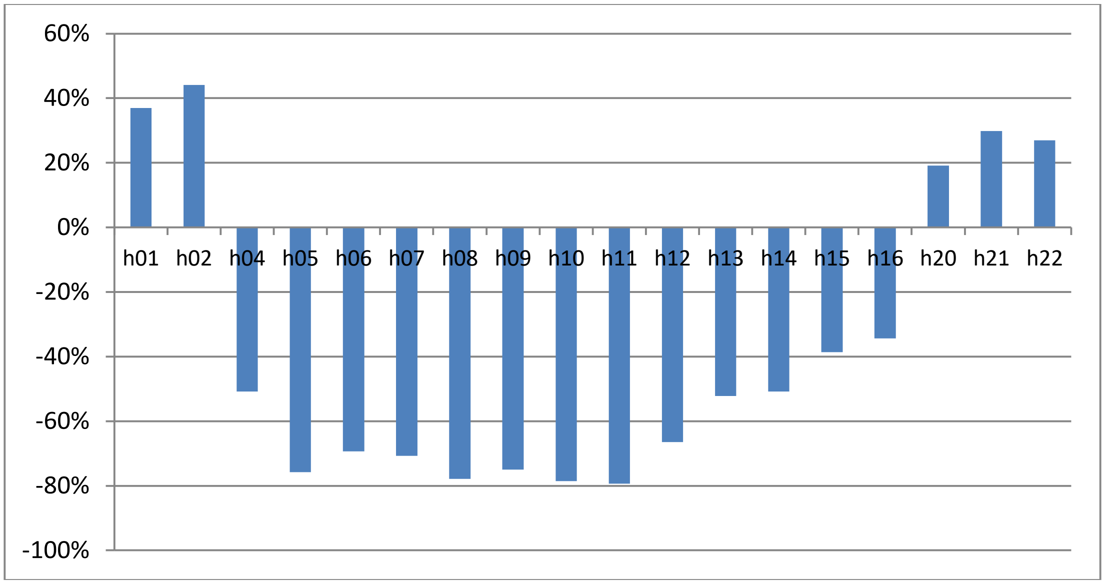

Figure 3.4 Hourly information of DUI-caused accidents

Speeding Related Accidents (Temporal Model)

Figure 3.5 shows the weekly and monthly information of speeding-caused accidents. Typically, there are fewer accidents (all types) on weekends, but there are more speeding-caused accidents in weekends as shown in Figure 3.5. There also will be more speeding-caused accidents when the day is Friday or the day is before a long weekend. The monthly information of speeding-caused accidents is similar to that of all the accidents as a whole. Only the month of March is different for speeding-caused accidents compared to that of all the accidents.

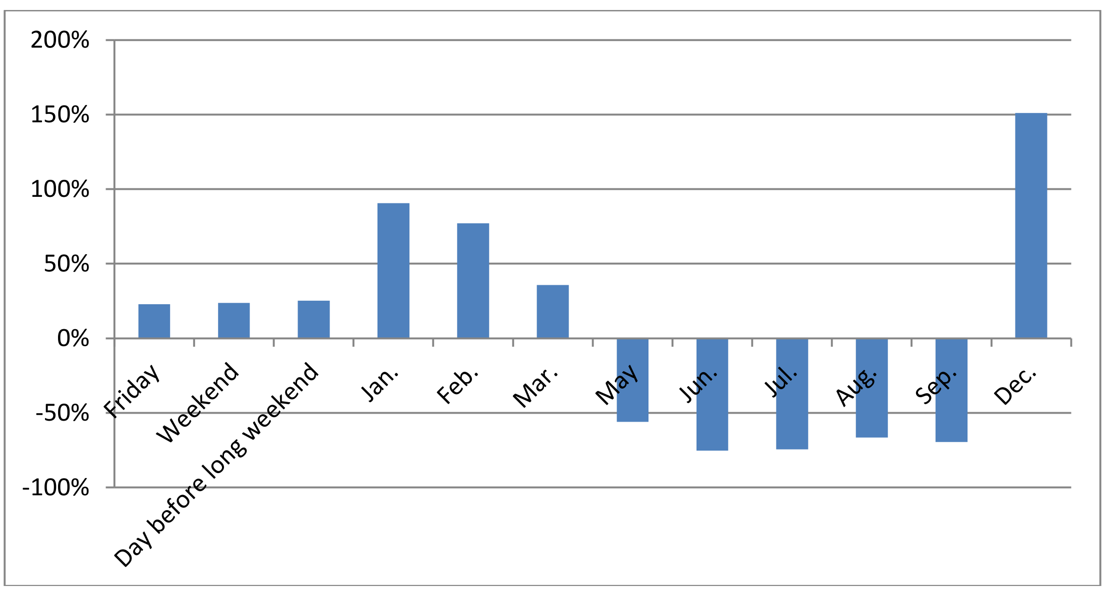

Figure 3.5 Weekly and monthly information of speeding-caused accidents

Figure 3.6 shows the hourly information of speeding-caused accidents, which is similar to that of all the accidents as a whole. Figure 3.6 shows that the results also are highly related to traffic volume. Two peaks of accidents occur: h06-h09 and h15-h17. These time instants are near two peak-hour periods with the only difference that the morning peak has relatively more accidents than the afternoon peak.

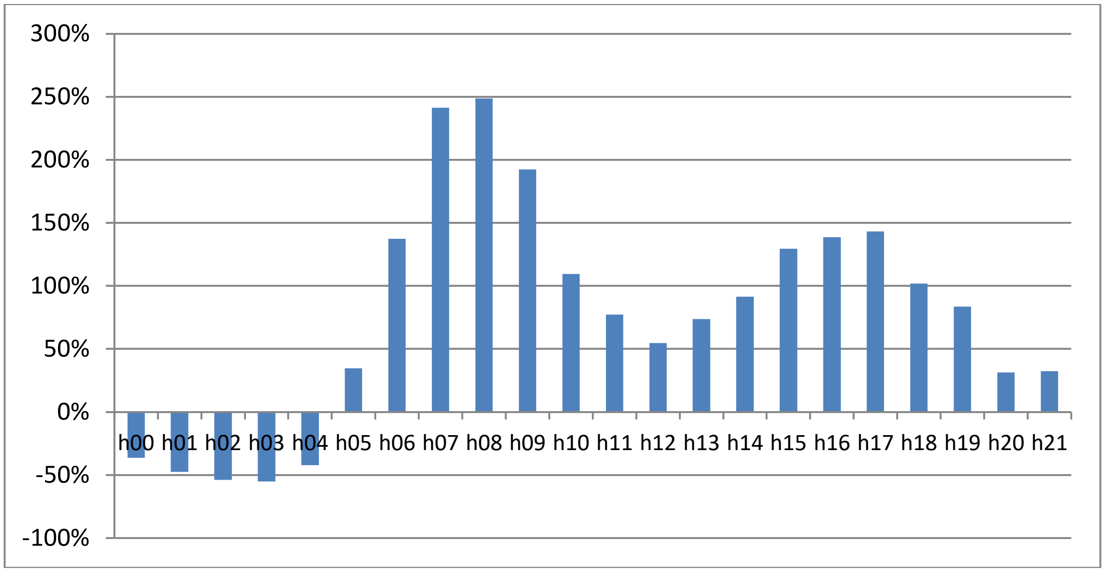

Figure 3.6 Hourly information of speeding-caused accidents

Truck Caused Accidents (Temporal Model)

Figure 3.7 shows weekly and monthly information of truck-caused accidents. Fewer accidents were found to occur on Mondays, weekends, holidays and the day before a long weekend. Days in May have the fewest truck-caused-accidents of a typical year in Colorado.

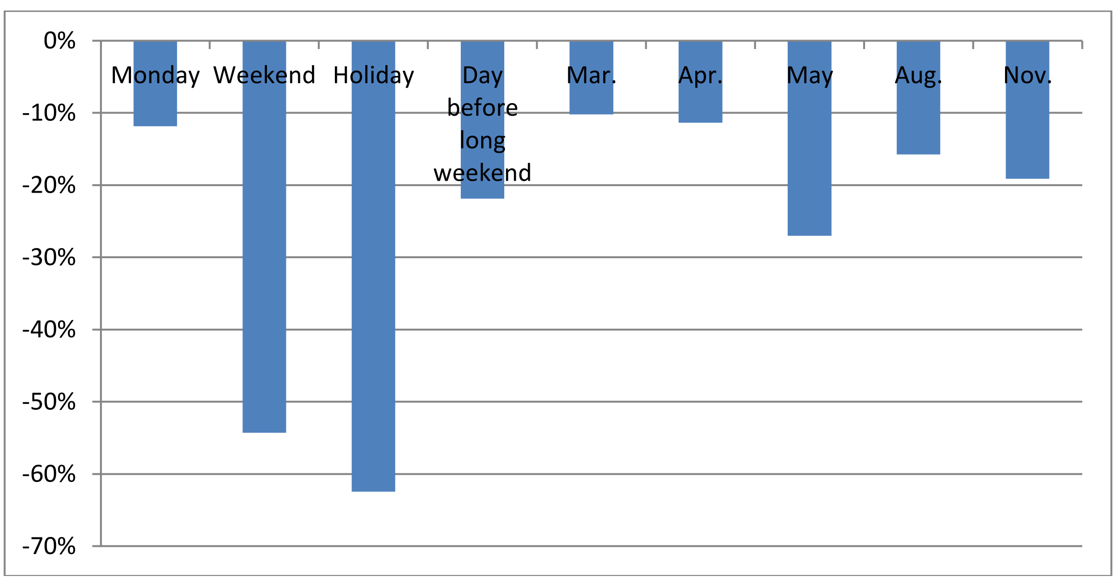

Figure 3.7 Weekly and monthly information of truck-caused accidents

Figure 3.8 shows hourly information of truck-caused accidents. The tendency is different from that of all accidents as it does not show obvious peaks during rush hours. Accident frequency is distributed nearly uniformly between h07 and h16.

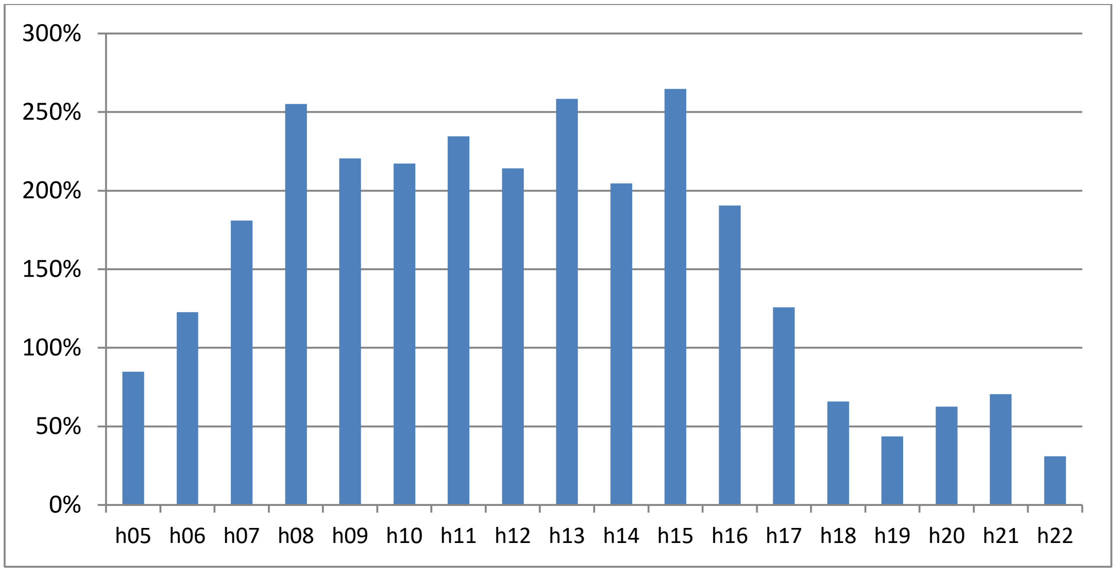

Figure 3.8 Hourly information of truck-caused accidents

4. INJURY RISK AND ENVIRONMENT

The detailed accident data between 2007-2009 was used to develop accident injury severity models. Only the accidents recorded with HighwayType= 1 (Interstate) or 2(State Hwy) were considered to happen on highways. The study also included some records coded as “HighwayType=3,” however the “HighwayNumber” indicates that the accidents actually happened on highways. There are 51,778 accidents which happened on highways in Colorado between 2007-2009.

4.1 Methodology

Three frequently used methods for injury severity analysis exist: Ordered logit/probit model, Multinomial logit/probit model, and Mixed logit model. In this study, multinomial logit models were developed to investigate injury severity.

Let $P_n(i)$ be the probability of the accident n causing the injury severity category i:

$$P_n(i) = P(\beta_i \mathrm{X}_n + \varepsilon_{ni} \geq \beta_{i'} \mathrm{X}_n + \varepsilon_{ni'}) \quad \forall i' \in I,\ i' \neq i \qquad (4.1)$$

where I is a set of all possible discrete outcomes, mutually exclusive severity categories. i and i' are different injury severity categories. β_i and $\beta_{i'}$ are vectors of estimated parameters of severity category i and i', respectively. X_n is the vector of characteristics (e.g. driver, vehicle, roadway and environmental) for the accident observation n that influences the injury severity category i and i'. ε_{ni} and $\varepsilon_{ni'}$ are random components (error terms) that explain the unobserved effects on injury severity of the accident observation n.

If ε_{ni} is assumed to be in a type I extreme-value distribution, a multinomial logit model can be expressed as:

$$P_n(i) = \frac{e^{\beta_i \mathrm{X}_n}}{\sum_{\forall i' \in I} e^{\beta_{i'} \mathrm{X}_n}} \qquad (4.2)$$

where the parameter β_i is typically estimated by the maximum likelihood method.

Estimated parameters of logit model analysis sometimes are not sufficient to explore how changes in the explanatory variables affect the outcome probabilities because the marginal effect of a variable depends on all parameters in the model. Therefore, in addition to the estimated parameters, elasticity often is used to describe magnitude of the impact of explanatory variables on the outcome probabilities. Because the exogenous variables explored later are discrete instead of continuous (coded as 0 and 1 indicator values), a direct pseudo-elasticity of the probability $E_{x_{nk}}^{P_n(i)}$ was introduced to measure the effect in percentage that a 1% change in x_{nk} (the indicator varies from 0 to 1 or from 1 to 0) has on the severity probability $P(i)$. For example, a pseudo-elasticity of 50% for a variable in the fatal severity category means that when the value of the variable in the sub-set of the observations is changed from 0 to 1, the probabilities of fatal severity outcome for these observations in the sub-set increase by 50% on average. This method has been used in previous studies by several researchers:

$$E_{x_{nk}}^{P_n(i)} = e^{\beta_{ik}} \frac{\sum_{\forall i' \in I} [e^{\beta_{i'} x_n}]_{x_{nk=0}}}{\sum_{\forall i' \in I} [e^{\beta_{i'} x_n}]_{x_{nk=1}}} - 1 \qquad (4.3)$$

where $E_{x_{nk}}^{P_n(i)}$ is the direct pseudo-elasticity of the k^{th} variable from the vector x_n for observation n. x_{nk} is the value of the variable k for the outcome n. β_{ik} is the k^{th} component of the vector β_i of severity category i. $[e^{\beta_{i'} x_n}]_{x_{nk=0}}$ is the value of $e^{\beta_{i'} x_n}$ with the x_{nk} in x_n being set to zero and $[e^{\beta_{i'} x_n}]_{x_{nk=1}}$ is the value of $e^{\beta_{i'} x_n}$ with the x_{nk} in x_n being set to one.

The hypothesis of no significant difference from zero for each parameter of severity category was tested using the likelihood ratio *t*-test, where parameters not significantly different from zero at the 90% level will be restricted to zero.

4.2 Typical Explanatory Variables

All the information in historical accident data should be considered in injury severity models, including driver characteristics, vehicle characteristics, roadway characteristics, environmental characteristics, accident characteristics and so on. More than 300 parameters in the CSP accident data were considered, and 113 parameters were found to be significant (90% confidence interval). Elasticity (marginal effects) was calculated to demonstrate the influence of each parameter on three different injury levels.

Temporal Information

Figure 4.1 shows the influence of temporal characteristics on injury severity. Generally speaking, the influence of temporal characteristics on injury severity is not significant- less than 10%. One major finding showed that accidents which happen on Mondays have higher probability to cause serious injury.

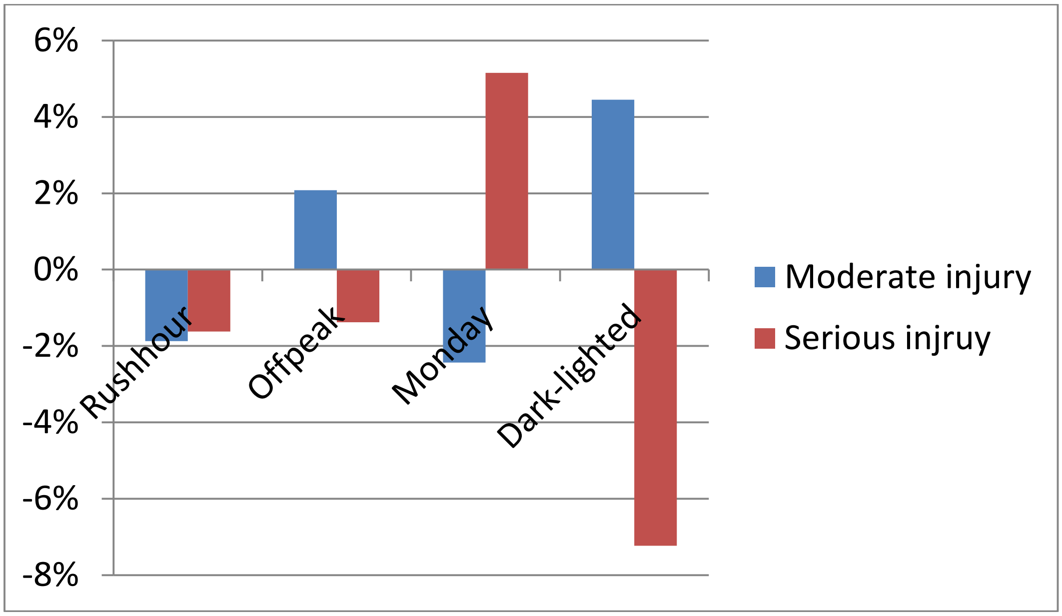

Figure 4.1 Influence of temporal characteristics on injury severity (whole state)

Driver Characteristics

Figure 4.2 shows the influence of driver characteristics on injury severity. Drivers registered in Colorado or female drivers have a slightly higher possibility to experience both moderate injury and serious injury. Young drivers have less possibility, while old drivers have much higher possibility, to have a serious injury. Drivers with driver licenses denied or revoked have much higher possibility to suffer from serious injury. Also, if the driver at fault has no insurance or no proof of insurance, the accident caused is more likely to be associated with serious injury. From an injury prevention and law enforcement perspective, these drivers warrant further attention.

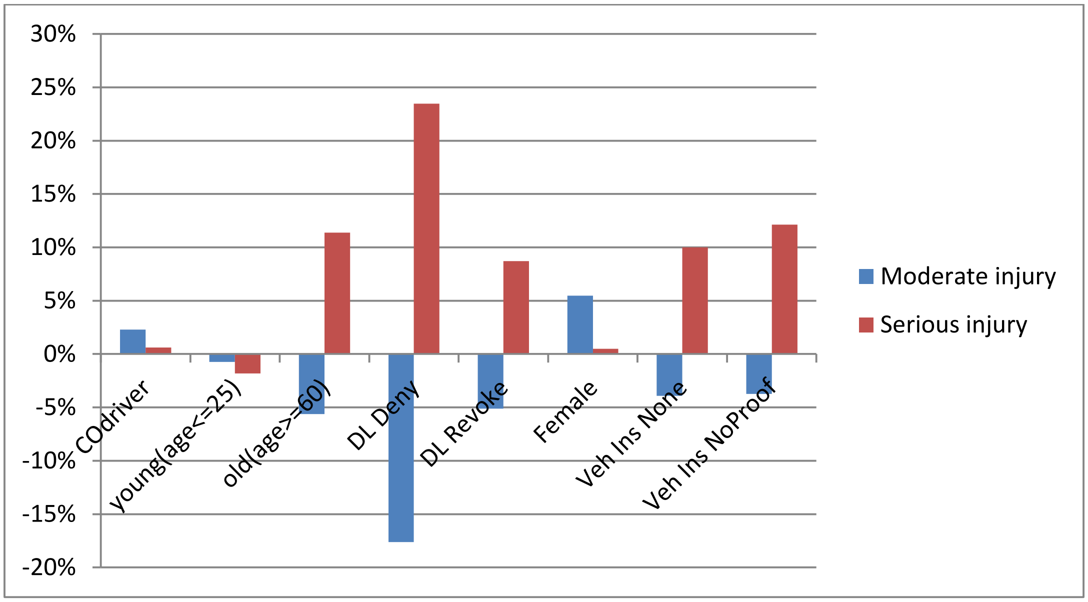

Figure 4.2 Influence of driver characteristics on injury severity (whole state)

Figure 4.3 shows the Influence of driver characteristics on injury severity. Many driver situations exist that increase the possibility of serious injury, such as driving with fatigue, illness/medical, aggressive driving or driving when upset and distracted by passenger. The influence of these parameters is significant, with elasticity higher than 15%. These phenomena underscore the importance of law enforcement focusing on these driver conditions.

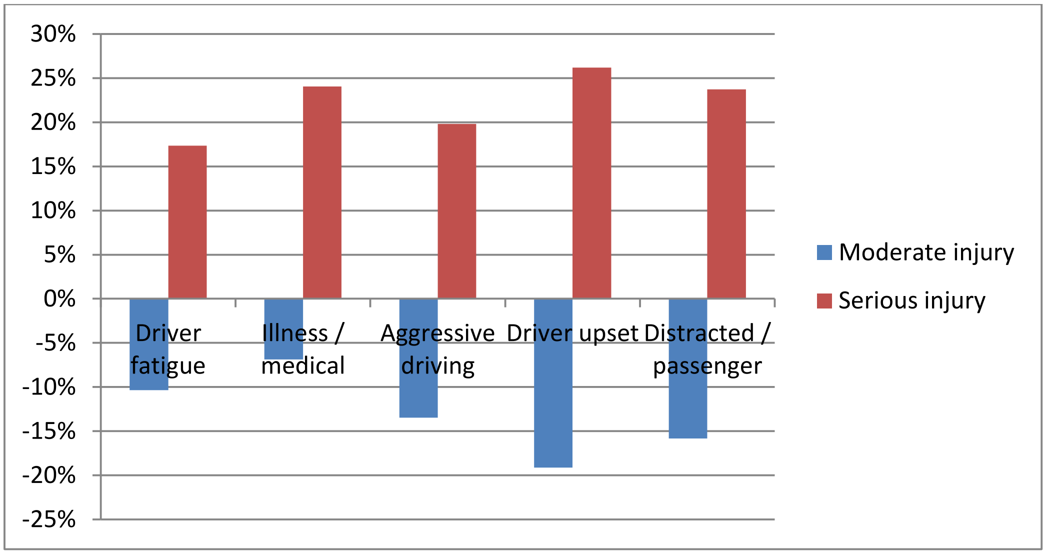

Figure 4.3 Influence of driver characteristics on injury severity (whole state)

Vehicle Characteristics

Figure 4.4 shows the influence of vehicle characteristics on injury severity and demonstrates that multi-vehicle accidents have much higher possibility to cause serious injury. When a vehicle is brake-defective or tire-defective, the possibility of experiencing serious injury also will be much higher. This finding may assist highway patrol and transportation management authorities during law enforcement.

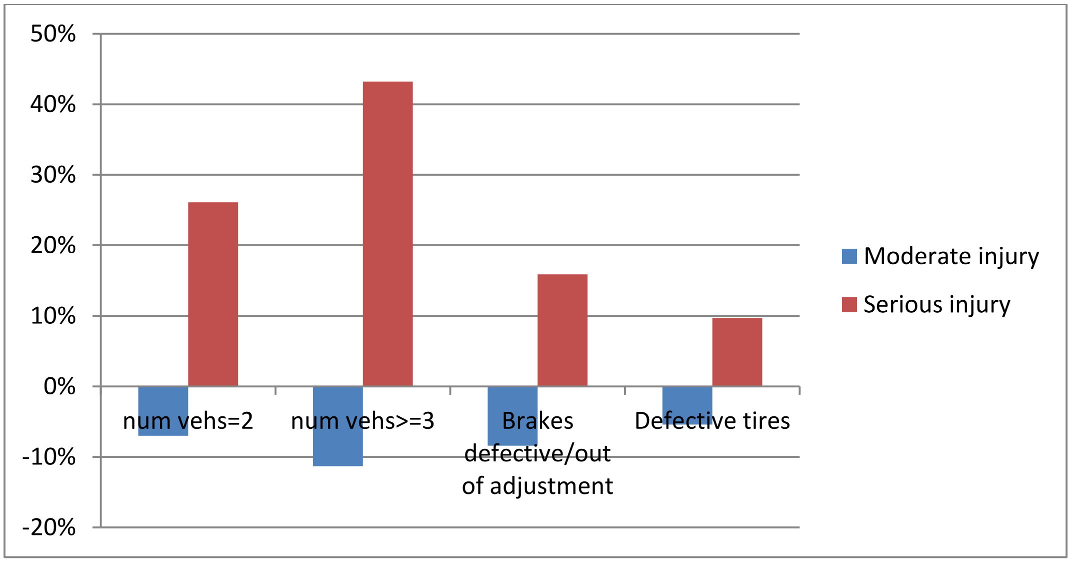

Figure 4.4 Influence of vehicle characteristics on injury severity (whole state)

Figure 4.5 shows the influence of vehicle characteristics on injury severity, including the different influence of new vehicles, old vehicles and no contact vehicle on the injury severity. A more important finding is the different influence of different vehicle types. For example, transit buses and motorcycles have a much higher possibility to cause serious injury. Other vehicle types decrease the possibility of serious injury.

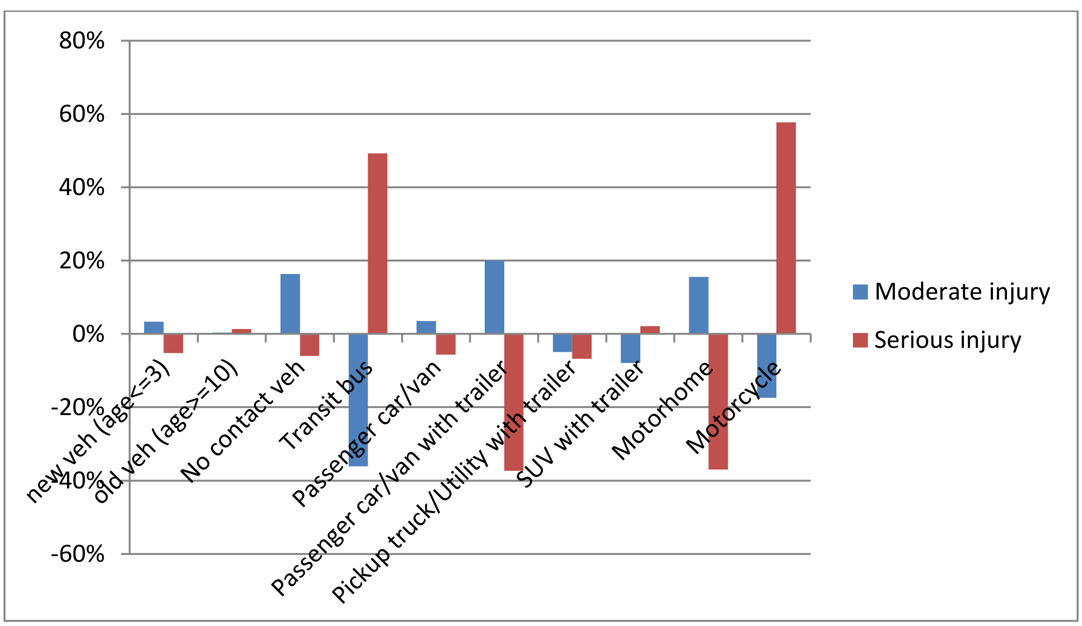

Figure 4.5 Influence of vehicle characteristics on injury severity (whole state)

Road Characteristics

Figure 4.6 shows the influence of road characteristics on injury severity. Generally speaking, the influence of road characteristics is not very significant. Some characteristics increased the possibility of serious injury, such as no evident rutting, speed limit= 75 mph, light traffic (small AADT), truck restricted roads, heavy truck percentage (off peak time) and poor pavement condition.

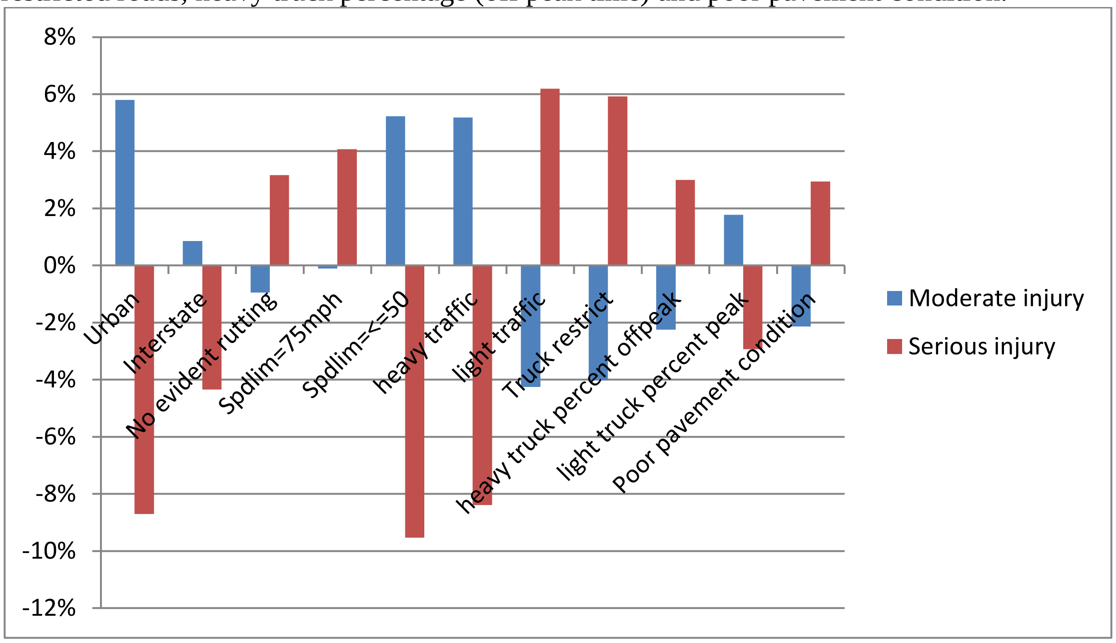

Figure 4.6 Influence of road characteristics on injury severity (whole state)

Weather Characteristics

Figure 4.7 shows the influence of weather characteristics on injury severity. Serious injury possibility increases only in rainy conditions. Serious injury possibility decreases during wet, snowy, icy, and slushy road conditions (with or without road treatment). Similar to other states, drivers in Colorado usually drive more carefully during adverse weather conditions. However, the increased injury severity during rainy days may deserve more attention by the state patrol and the department of transportation for developing more effective injury mitigation strategy.

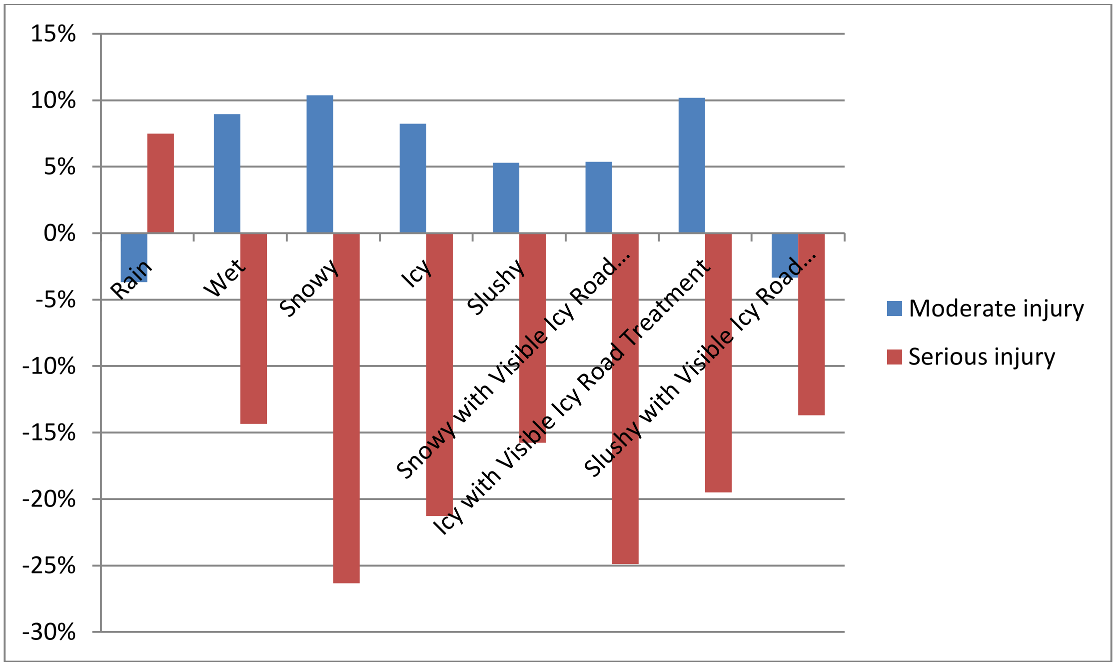

Figure 4.7 Influence of weather characteristics on injury severity (whole state)

Road Design Characteristics

Figure 4.8 shows the influence of road design characteristics on injury severity. Some road designs significantly increase serious injury possibility, such as median width is 0 and curbed inside shoulder. Other road designs decrease the serious injury possibility, such as level-concrete median and earth outside shoulder.

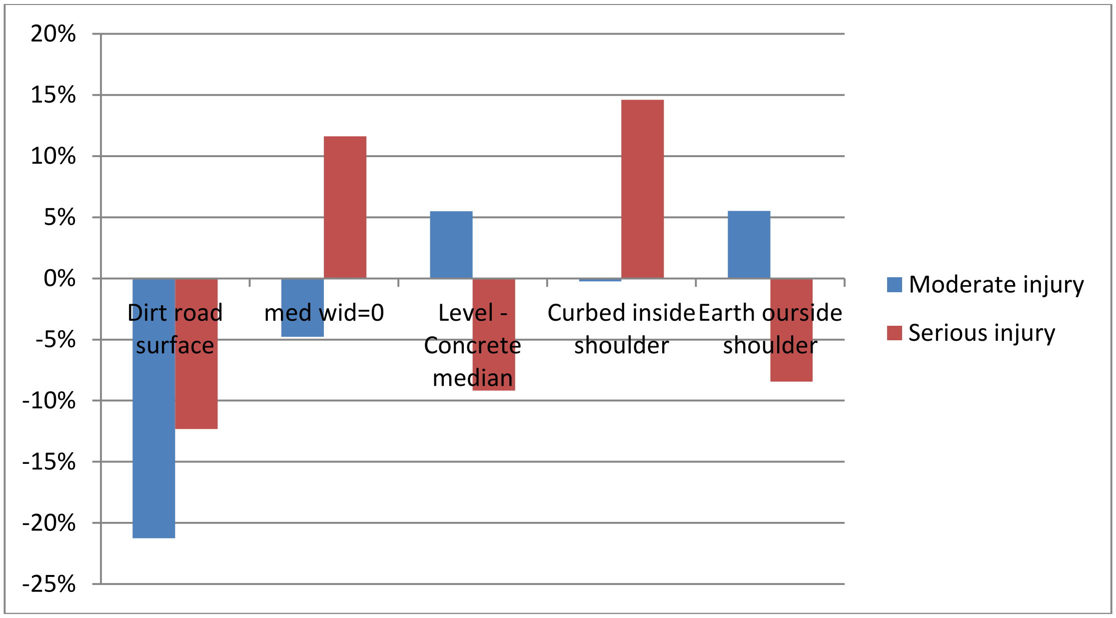

Figure 4.8 Influence of road design characteristics on injury severity (whole state)

Vulnerable Locations for Injuries

Figure 4.9 shows the influence of location characteristics on injury severity. Accidents that happen on highway bridges have a higher possibility of experiencing serious injury. Vehicles that run off left side or cross center median and get into opposing lanes, have a significant increase of serious injury.

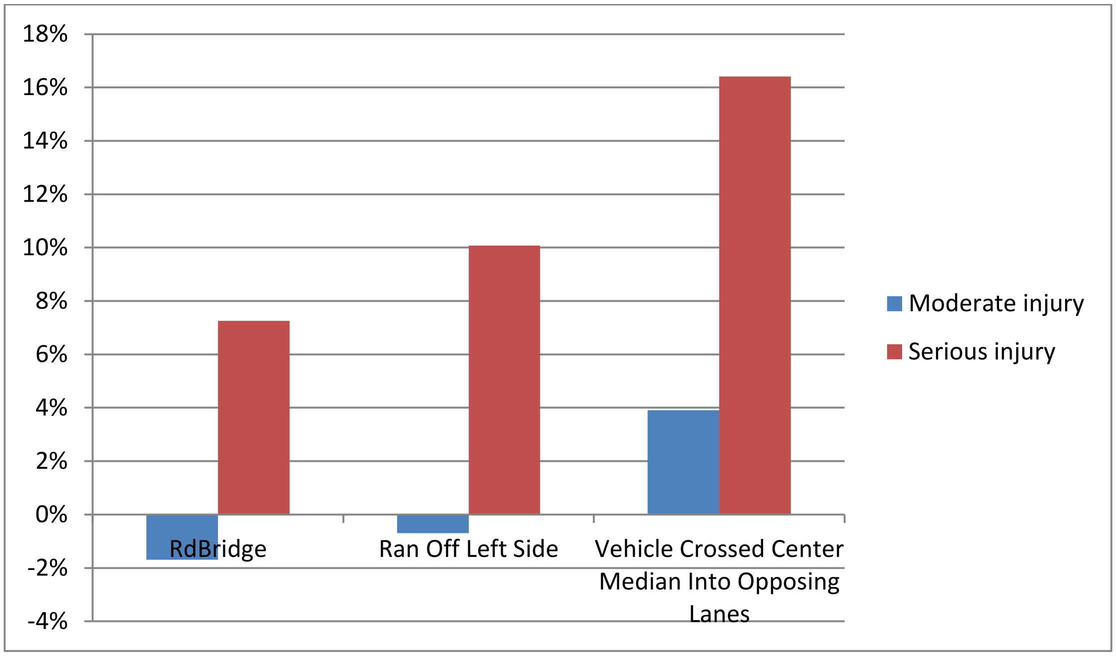

Figure 4.9 Influence of location characteristics on injury severity (whole state)

Cause Characteristics

Figure 4.10 shows the influence of cause characteristics on injury severity. Many cause characteristics exist that increase serious injury severity: DUI alcohol, DUI drug, exceeding legal speed, lane violation, wrong side of road, driving while asleep, inattentive to driving, and disregarding stop sign. For example, the possibility of serious injury will increase more than 30% when an accident is caused by DUI alcohol, DUI drug or exceeding legal speed. These phenomena reflect the importance of enhanced law enforcement on correcting toward correcting hazardous driver conditions/behaviors.

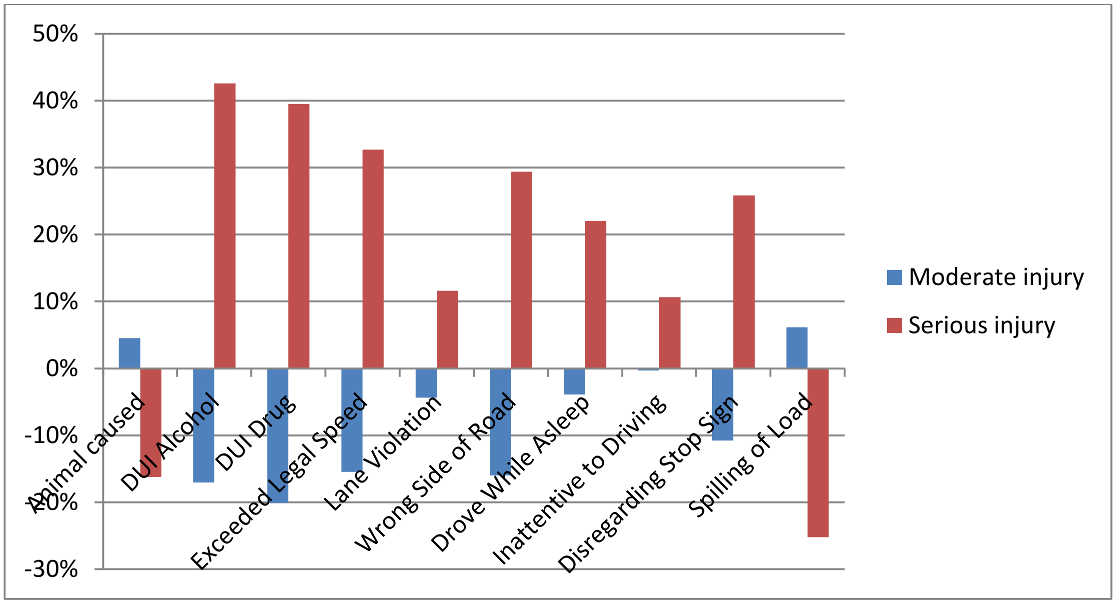

Figure 4.10 Influence of cause characteristics on injury severity (whole state)

First Harmful Event

Figure 4.11 shows the influence of first harmful event characteristics on injury severity. Hitting pedestrians or pedestrians with bicycles are most likely to be associated with serious injury. And the serious injury severity also increases under the following situations: overturning, front to front, front to side, rear to side, and parked motor vehicle.

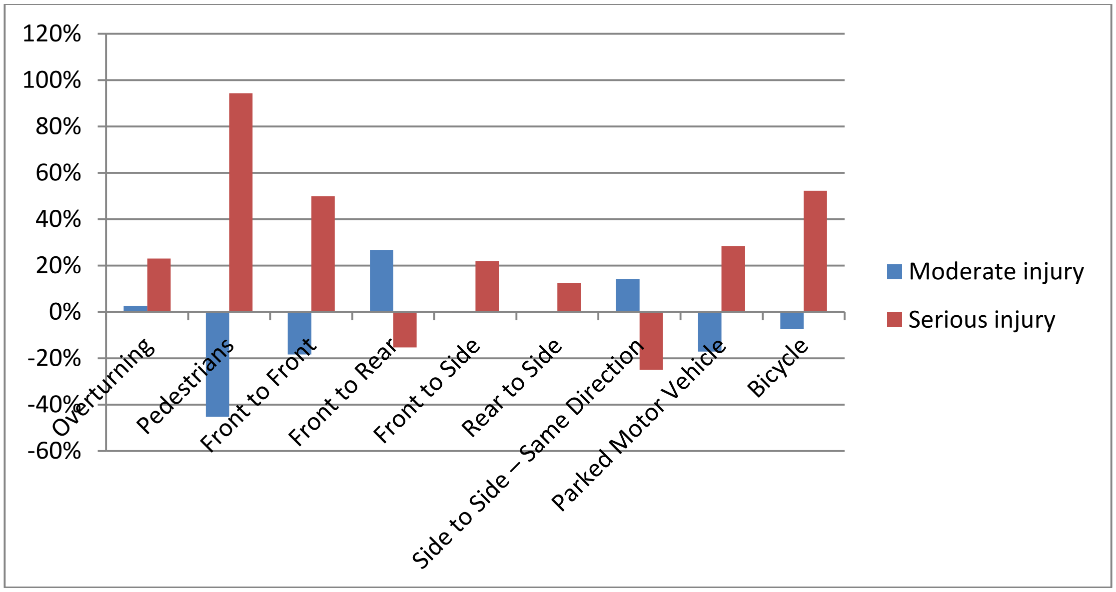

Figure 4.11 Influence of first harmful event characteristics on injury severity (whole state)

Figure 4.12 shows the influence of first harmful event characteristics on injury severity. Crashes involving road maintenance equipment and mailbox experience moderate injury severity. Serious injury severity increases significantly under the following situations: pole, culvert or headwall, embankment, delineator post, tree, large rocks or boulder, and crash cushion/traffic barrel.

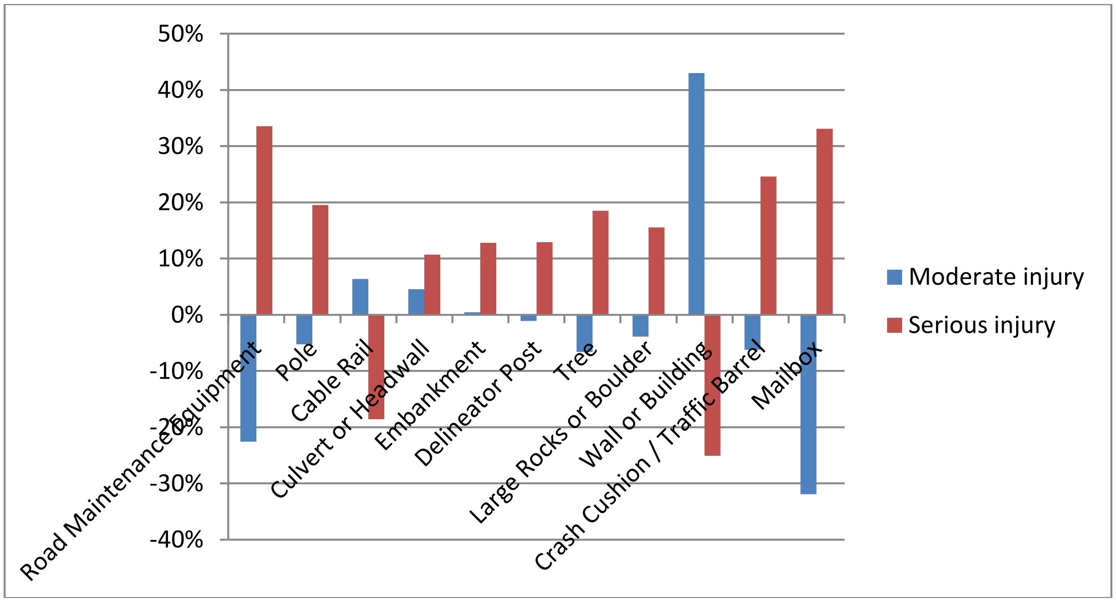

Figure 4.12 Influence of first harmful event characteristics on injury severity

4.3 Comparison Between Injury Studies on I-70 and the Whole State Model

For injury severity study, I-70 also was found to be unique in terms of trend and the critical impact factors. Some unique results of I-70 are introduced in the following sections.

Temporal Information

Figure 4.13 shows the time information of I-70 accident injury severity. There is no considerable difference on I-70 compared to the whole state accident injury severity.

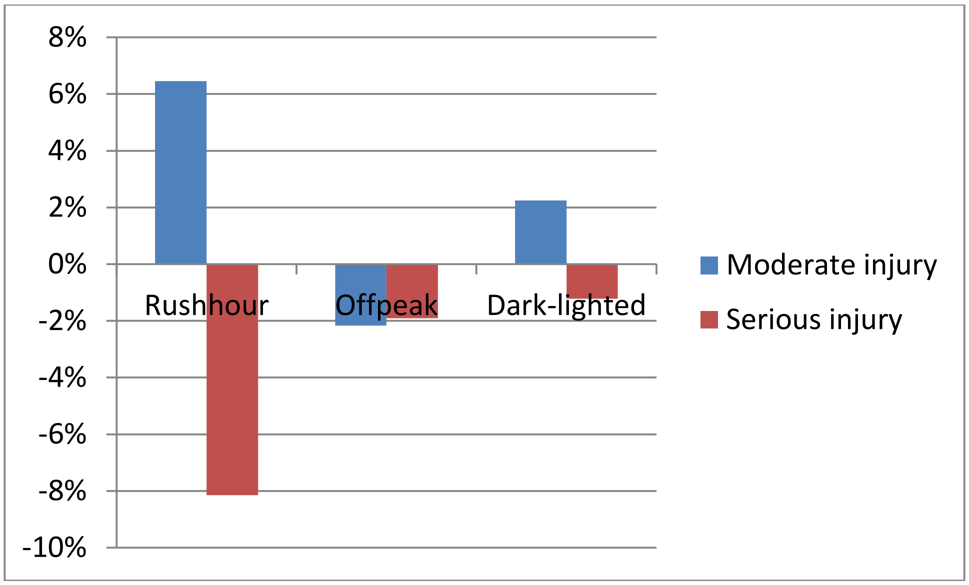

Figure 4.13 Time information for I-70 accident injury severity

Vehicle Number

Figure 4.14 shows the vehicle number information for I-70 accident injury severity. The major difference compared to the whole state injury severity model is that of the opposite influence of two-vehicle accidents (as compared to Figure 4.4).

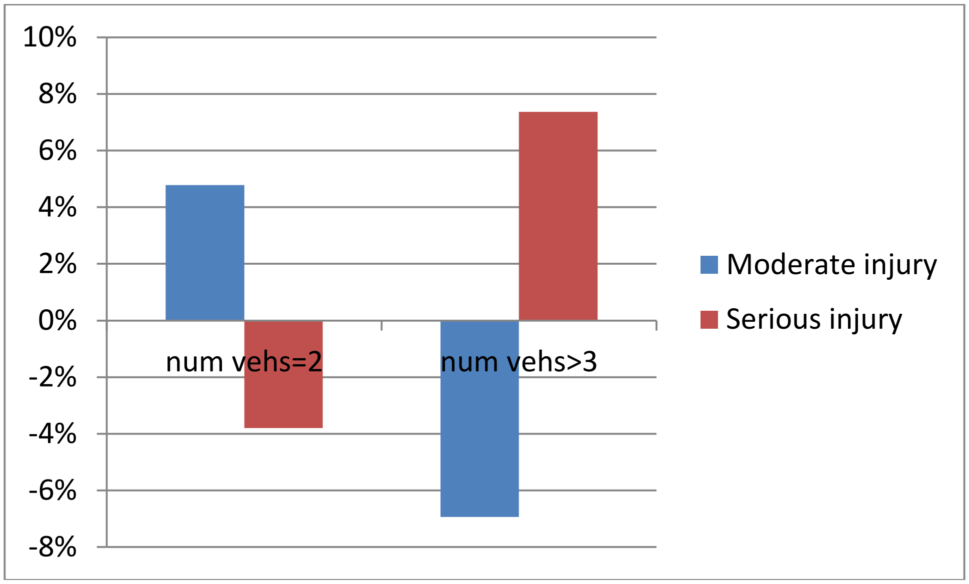

Figure 4.14 Vehicle number information for I-70 accident injury severity

Driver Information

Figure 4.15 shows the driver information for I-70 on accident injury severity. There are opposite trends of CO (what does this mean?) driver, young driver, old driver and female driver between I-70 and the whole state models (Figure 4.2).

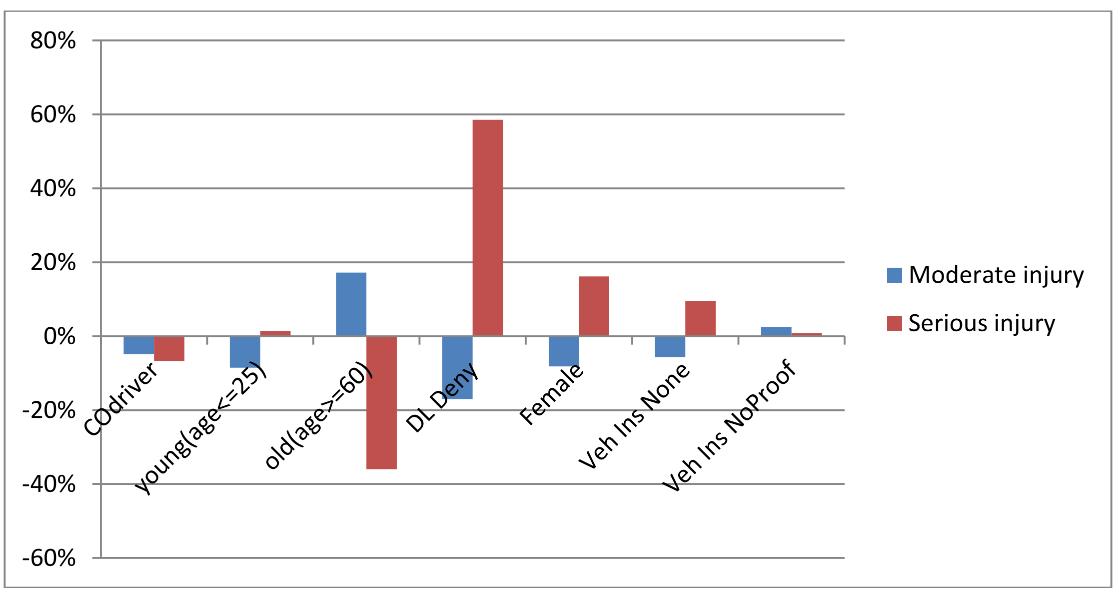

Figure 4.15 Driver information for I-70 accident injury severity

Road Information

Figure 4.16 shows the road information for I-70 on accident injury severity. Opposite trends exist for speed limit<=50, heavy traffic, and light truck percentage between I-70 (Figure 4.16) compared to the whole state models. (Figure 4.17)

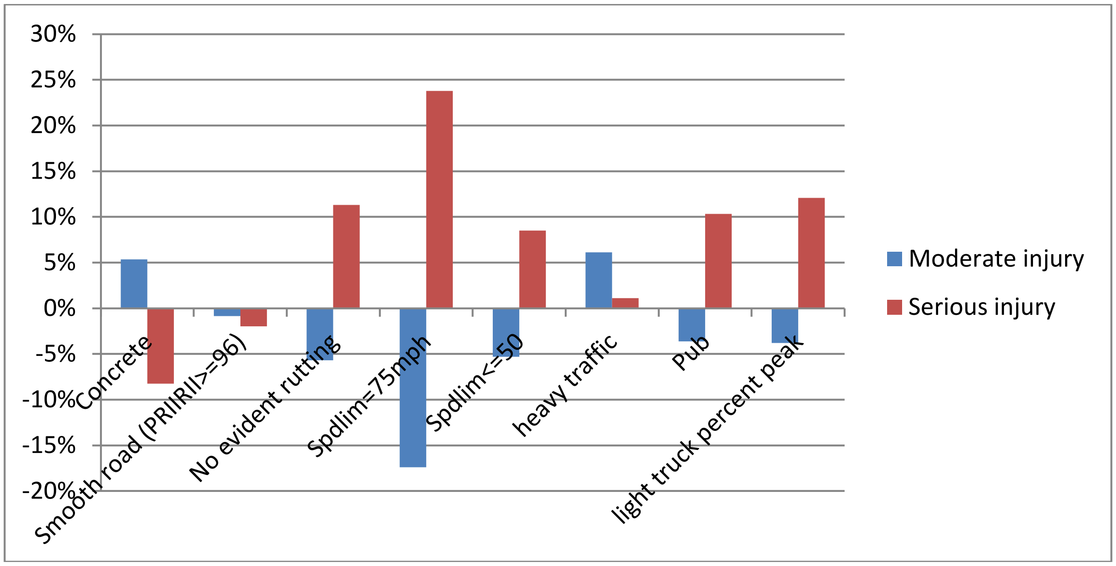

Figure 4.16 Road information for I-70 accident injury severity

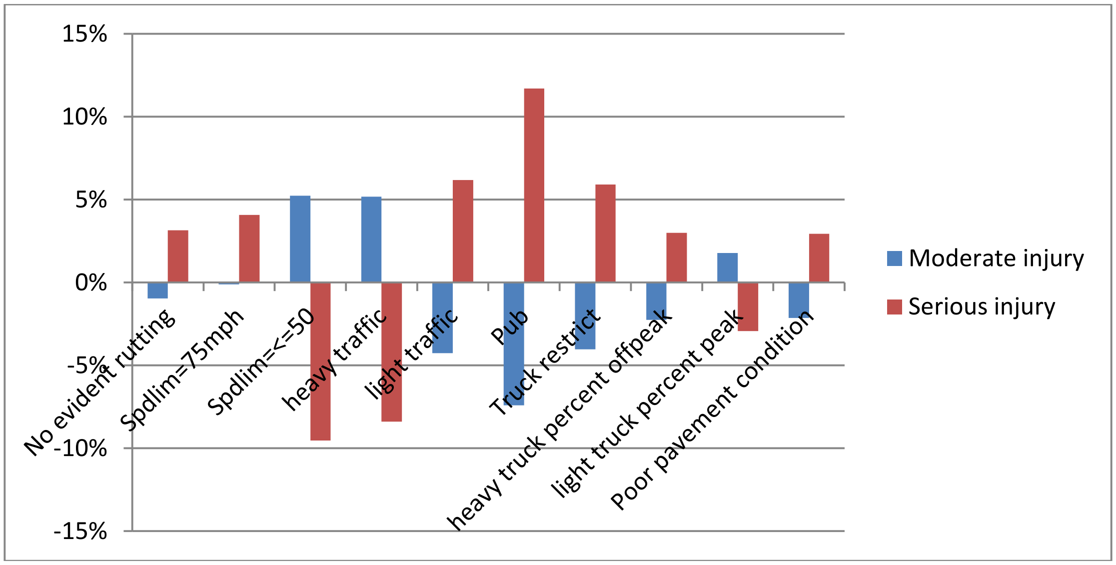

Figure 4.17 Road information for whole state accident injury severity

Vulnerable Locations of Injury

Figure 4.18 shows the location information for I-70 on accident injury severity. The trends of bridge structures are opposite between I-70 and the whole state models (Figure 4.9).

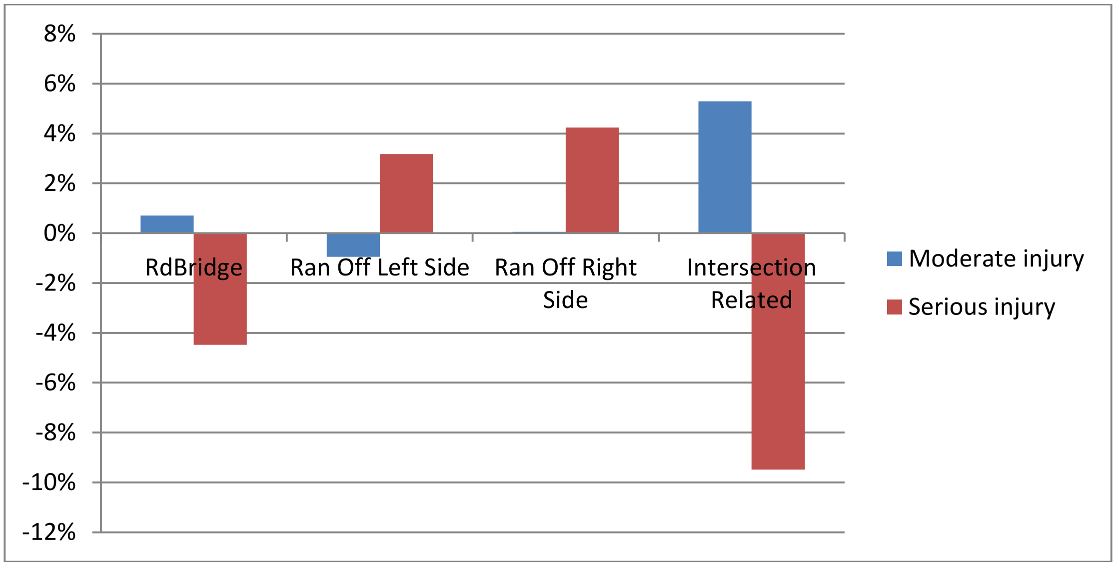

Figure 4.18 Location information for I-70 accident injury severity

Weather and Road Surface Information

Figure 4.19 shows weather information for I-70 on accident injury severity. Opposite trends exist for most surface conditions between I-70 and whole state models (Figure 4.7). Not surprisingly, most weather and road surface conditions cause a significant increase of the risk-causing serious injury (Figure 4.19). Therefore, it is extremely important to develop advanced traffic management strategy for I-70's adverse weather conditions.

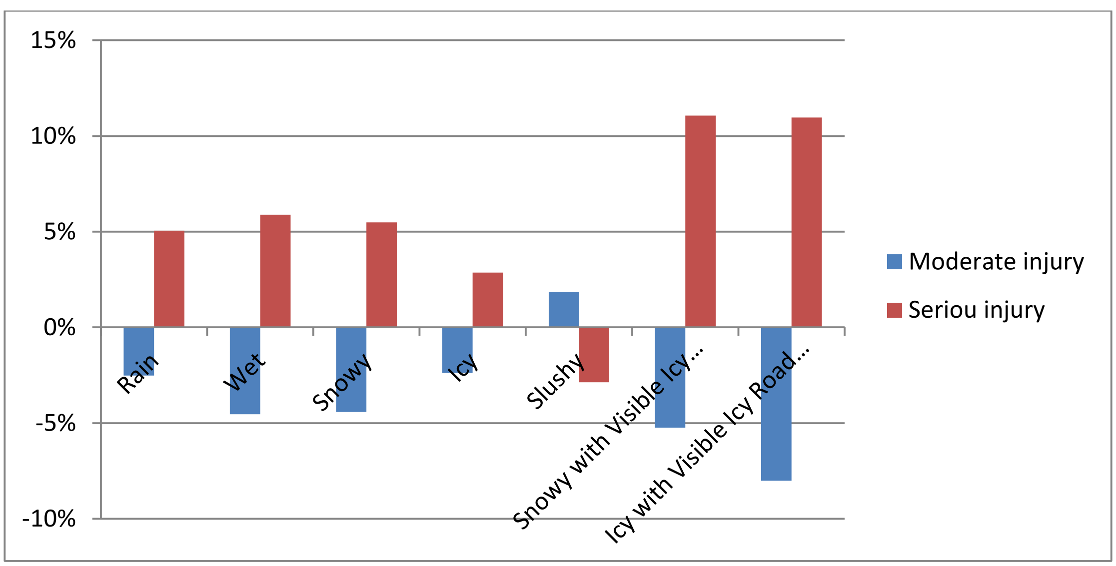

Figure 4.19 Weather and road surface information for I-70 accident injury severity

Crash Cause Information

Figure 4.20 shows the cause information on accident injust severity for I-70. Significant differences in the trends of many parameters can be found between the I-70 and the whole state models (Figure 4.10).

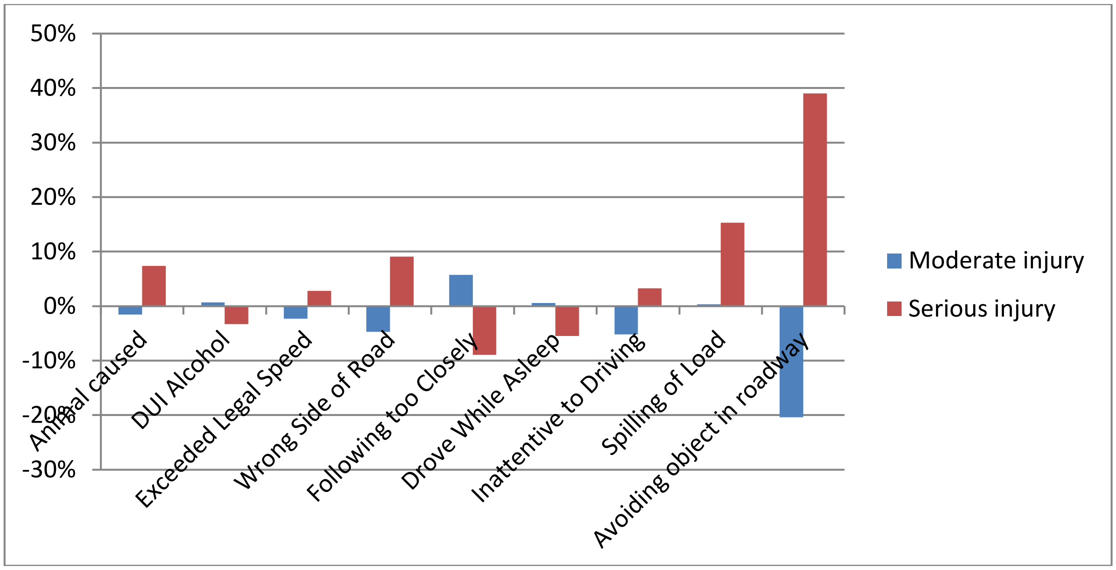

Figure 4.20 Cause information for I-70 accident injury severity

Crash Information

Figure 4.21 shows the crash information of I-70 on accident injury severity. Most safety prevention features on I-70 are effective for reducing risk of serious injury, except for the "crash cushion/traffic barrel." Significant differences exist between the trends of these parameters of the I-70 and the whole state models (Figs. 4.11 & 4.12).

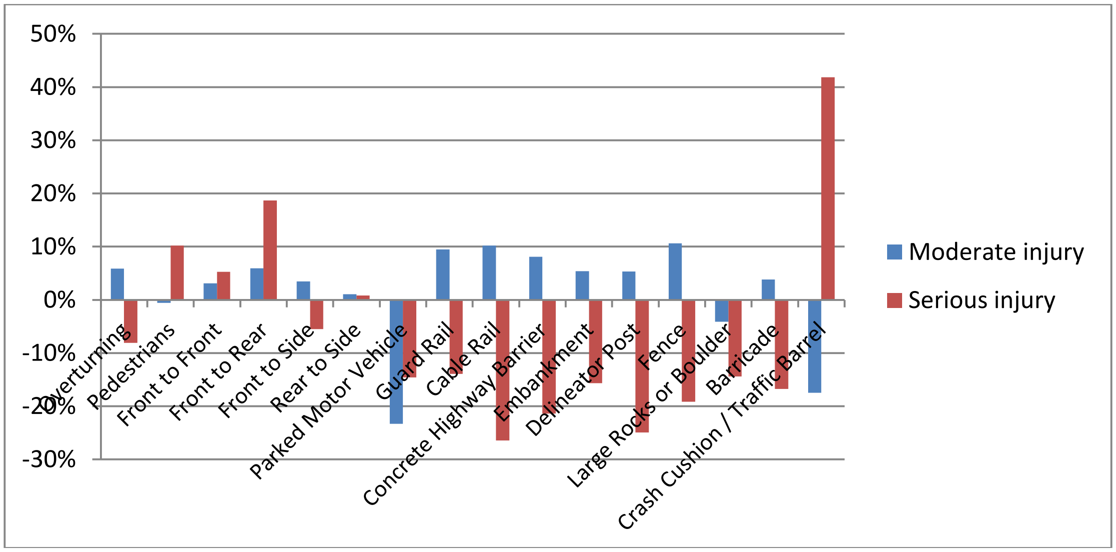

Figure 4.21 Crash information of I-70 accident injury severity

Driver Information

Figure 4.22 shows driver information of I-70 on accident injury severity. Two unique critical factors exist on the I-70 model: Driver inexperience and Distracted by cell phone.

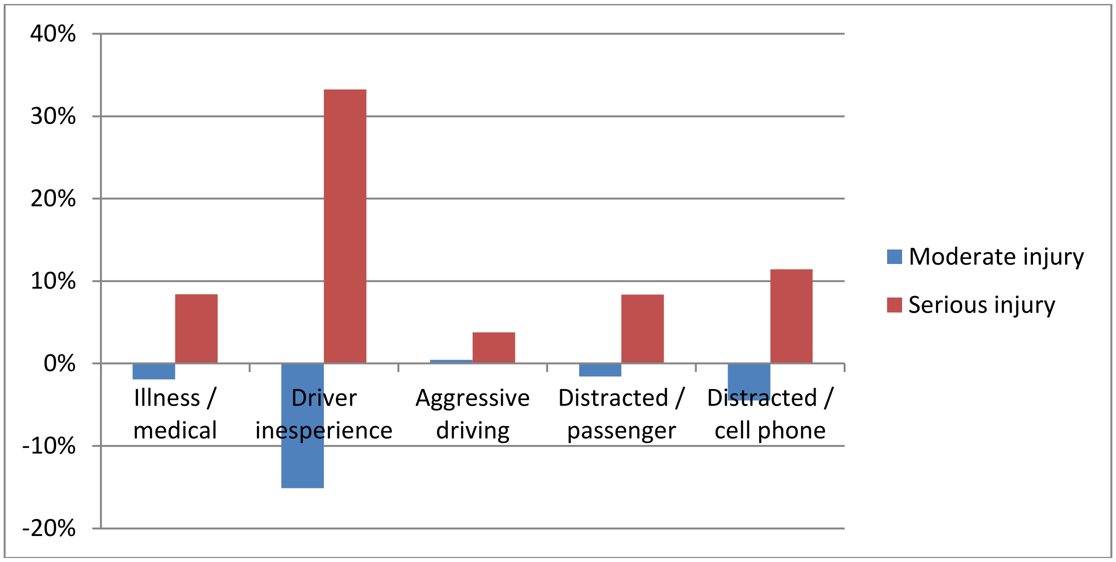

Figure 4.22 Driver condition information on I-70 accident injury severity

5. CONCLUSION AND FUTURE WORKS

Traffic safety is a long-time challenge faced by modern society. Traffic accidents cause the most injuries and fatalities. For decades, people have tried all possible approaches to reduce the number of traffic accidents and associated injury severity. Even 1% reduction of accident numbers, no matter the means − active traffic management, law enforcement, modern vehicle technology or education, can significantly benefit society and its citizens. This study was conducted to investigate state-of-the-art of interaction research of law enforcement, traffic safety and the environment. The crash frequency prediction models on major highways in Colorado were developed after a detailed historical accident data analysis was conducted. A comprehensive analysis of crash frequency and injury severity was conducted for the state of Colorado. Model results revealed how each explanatory variable impacted crash risk and injury severity levels. Some findings can provide valuable information about traffic characteristics, vulnerable spots and driver groups.

Because of the lack of detailed data, only limited law enforcement-related data was directly incorporated into the model development. However, findings in the present study can shed light on carrying out future studies on mitigating traffic accidents and injury. For future studies, detailed law enforcement data may be incorporated into model development. This could be accomplished by obtaining information on how police forces are allocated and including that data as the explanatory variable in crash models.

REFERENCES

Beck, L. F. and R. A. Schults, 2009, Seat belt use in states and territories with primary and secondary laws—United States, 2006, J Safety Res. 40, pp. 469–472.

Carpenter, C. S. and M. Stehr, 2008, The effects of mandatory seatbelt laws on seatbelt use, motor vehicle fatalities, and crash-related injuries among youths, J. Health Econ. 27 (3), pp. 642–662.

Chiu, W. T. , C. Y. Kuo, C. C. Hung and M. Chen, 2000, The effect of the Taiwan motorcycle helmet use law on head injuries, American Journal of Public Health 90(5) pp.793–796.

Conner, K. A., H. Xiang, G. A. Smith, 2010, The impact of a standard enforcement safety belt law on fatalities and hospital charges in Ohio. J Safety Res 41, pp. 17-23.

Davis, J. W., L. Bennink, K. L. Kaups and S. N. Parks, 2002, Motor vehicle restraints: primary versus secondary enforcement and ethnicity, J. Trauma 52, pp. 225–228.

Dee, T. S. 1998, Reconsidering the effects of seat belt laws and their enforcement status, Accid. Anal. Prev. 30, pp. 1–10.

Dinh-Zarr, T. B., D. A. Sleet, R. A. Shults, S. Zaza, R. W. Elder, J. L. Nichols, R. S. Thompson, D. M. Sosin and the Task Force on Community Preventive Services, 2001, Reviews of evidence regarding interventions to increase the use of safety belts, Am. J. Prev. Med. 21 (Suppl. 4), pp. 48–65.

Eby, D. W., J. M. Vivoda and T. A. Fordyce, 2002, The effects of standard enforcement on Michigan safety belt use, Accid. Anal. Prev. 34, pp. 815–823.

Gorman, D. M., J. C. Huber and S. E. Carozza, 2006, Evaluation of the Texas 0.08 BAC law, Alcohol Alcohol. 41 (2), pp. 193–199.

Homel, R. 1994, Drink-driving law enforcement and the legal blood alcohol limit in New South Wales. Accid. Anal. Prev. 26 (2), pp. 147–155.

Houston D. J. and L. E. Richardson, 2002, Traffic safety and the switch to a primary seat belt law: the California experience, Accid. Anal. Prev. 34 (6), pp. 743–751.

Kim, K., E. Yamashita, 2003, Click it or ticket boosting seat belt use in Hawaii, Transport. Res. Rec. 1830, 18–24.

Kweon, Y. J. 2010, Data-driven reduction targets for a highway safety plan, Transport Policy 17(4), pp. 230-239.

Leggett, L. M. W. 1997, Using Police Enforcement to Prevent Road Crashes: The Randomised Scheduled Management System. In R. Homel (Ed.), Policing for Prevention: Reducing Crime, Public Intoxication and Injury. Crime Prevention Studies, Vol. 7, pp.175–97. Criminal Justice Press, Monsey, N.Y.

Levine, N. 2006, Houston, Texas, metropolitan traffic safety planning program, Transport. Res. Rec., 1969, 92–100.

Levine, R. S., N. C. Briggs, D. G. Schlundt, N. Stinson, R. C. Warren and I. A. Goldzweig, 2006, Seatbelt law enforcement and motor vehicle crash fatalities among blacks and whites in Louisiana and Mississippi, Southern Medical Journal 99(2), pp. 143-148.

Lund J. and J. E. Aarø, 2004, Accident prevention. Presentation of a model placing emphasis on human, structural and cultural factors, Safety Science 42 (4), pp. 271–324.

Madison Police Department (2008), Patrol staffing and deployment study, http://legistar.cityofmadison.com/attachments/1f4da04e-a583-479d-aa12-f9fd3f621790.pdf

Masten, S. V. 2007, Do states upgrading to primary enforcement of safety belt laws experience increased daytime and nighttime belt use? Accid. Anal. Prev. 39(6), pp. 1131-1139.

McCartt, A. T. and V. Shabanova-Northrup, 2004, Factors related to seat belt use among fatally injured teenage drivers, J. Saf. Res. 35, pp. 29–38.

McClellan, P.D. 2006, Ohio state highway patrol: can individual troopers make a difference? Police Chief

Miles-Doan, R. 1996, Alcohol use among pedestrians and the odds of surviving an injury: evidence from Florida law enforcement data, Accid. Anal. Prev. 28 (1), pp. 23–31.

Newstead, S. V., M. H., Cameron and L.M.W. Leggett, 2001, The crash reduction effectiveness of a network-wide traffic police deployment system, Accid. Anal. Prev. 33, pp. 393–406.

Pande, A., M. Abdel-Aty, and L. Hsia, 2005, Spatio-temporal variation of risk preceding crash occurrence on freeways, Transportation Research Record, 1908, 26–36.

Perkins, B. J., S. D. Helgerson and T. S. Harwell, 2009, Attitudes toward a primary seat belt law among adults in a rural state with a secondary seat belt law, J. Safety Res. **40**, pp. 49–52.

Redelmeier, D. A., R. J. Tibshirani and L. Evans, 2003, Traffic-law enforcement and risk of death from motor-vehicle crashes; case-crossover study, Lancet 361 (9376), pp. 2177–2182.

Retting, R. A. and S. Y. Kyrychenko, 2002, Reductions in injury crashes associated with red light camera enforcement in Oxnard California, American Journal of Public Health 92, pp. 1822–1825.

Rivara, F. P., D. C. Thompson and P. Cummings, 1999, Effectiveness of primary and secondary enforced seat belt laws, Am. J. Prev. Med. 16 (1S), pp. 30–39.

Servadei, F., C. Begliomini, E. Gardini, M. Giustine, F. Taggi and J. Kraus, 2003, Effect of Italy's motorcycle helmet law on traumatic brain injuries, Inj. Prev. 9, pp. 257–260.

Steil, D. A., J. R. Pate, N. A. Kraft, R. K. Smith, B. Dixon, Ding Li and A. Parrish, 2011, Patrol routing expression, execution, evaluation, and engagement, IEEE Transactions on Intelligent Transportation Systems 12(1), pp. 58-72.

Strine, T. W., L. F. Beck, J. Bolen, C. Okoro, S. Dhingra and L. Balluz, 2009, Geographic and sociodemographic variation in self-reported seat belt use in the United States, Accid. Anal. Prev. 42(4), pp. 1066-1071.

Thomas, F. D., R. D. Blomberg, R. C. Peck, L. A. Cosgrove and P. M. Salzberg, 2008, Evaluation of a high visibility enforcement project focused on passenger vehicles interacting with commercial vehicles, J. Safety Res. 39 (5), pp. 459–468.

USDOT 2010, traffic safety facts 2009, US Department of Transportation.

Wagenaar, A. C., M. M. Maldonado-Molina, D. J. Erickson, L. Ma, A. L. Tobler and K. A. Komroa, 2007, General deterrence effects of U.S. statutory DUI fine and jail penalties: long-term follow-up in 32 states, Accid. Anal. Prev. 39(5), pp. 982–994.

Weiss, A and K. Morckl, 2007, Strategic and tactical approaches to traffic safety, The Police Chief, 74, 20-23, 73 (12).

Washington State DOT, 2007, Target zero: strategic highway safety plan, http://www.wsdot.wa.gov/planning/SHSP.htm