Feasibility of Using Traffic Data for Winter Road Maintenance Performance Measurement

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Winter road maintenance (WRM) operations, such as plowing, salting and sanding, are significant to maintain both safety and mobility of highways, especially in countries like Canada. Traditionally, WRM performance is measured using bare pavement regain time and snow depth/coverage, which are reported by maintenance or quality assurance personnel based on periodic visual inspection during and after snow events. However, the increasing costs associated with WRM and the lack of objectivity and repeatability of traditional performance monitoring methods have stimulated significant interest in developing alternative performance measures.

This research is motivated by the need to develop an outcome based WRM performance measurement system with a specific focus on investigating the feasibility of inferring WRM performance from traffic state. The research studies the impact of winter weather and road surface conditions (RSC) on the average traffic speed of rural highways with the intention of examining the feasibility of using traffic speed from traffic sensors as an indicator of WRM performance. Detailed data on weather, RSC, and traffic over three winter seasons from 2008 to 2011 on rural highway sites in Iowa, US is used for this investigation. Three modeling techniques are applied and compared for modeling the relationship between traffic speed and various road weather and surface condition factors, including multivariate linear regression, artificial neural network (ANN), and time series analysis. Multivariate linear regression models are compared by temporal aggregation (15 minutes vs. 60 minutes), types of highways (two-lane vs. four-lane), and model types (separated vs. combined). The research also examines the feasibility of estimating/classifying RSC based on traffic speed and winter weather factors using multi-layer logistic regression classification trees.

The modeling results have shown the expected effects of weather variables including precipitation, temperature and wind speed, and verified the statistically strong relationship between traffic speed and RSC. The findings suggest that speed could potentially be used as an indicator of bare pavement conditions and thus the performance of WRM operations. It is also confirmed that the time series model could be a valuable tool for predicting real-time traffic conditions based on weather forecast and planned maintenance operations, and the multi-layer logistic regression classification tree model could be applied for estimating RSC on highways based on average traffic speed and weather conditions.

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To

My Family

And

All Winter Drivers

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List of Abbreviations and Notations

WRM	Winter road maintenance
RSC	Road Surface Condition
MTO	Ministry of Transportation Ontario
FHWA	Federal Highway Administration
LOS	Level of Service
NHTSA	National Highway Traffic Safety Administration
HCM	Highway Capacity Manual
FFS	Free Flow Speed
ANN	Artificial Neural Network
AVL	Automated Vehicle Location
GPS	Global Positioning System
DEA	Data Envelopment Analysis
TAS	Total Area Served
AADT	Annual Average Daily Traffic
PSIC	Pavement Snow and Ice Condition Index
DOT	Department of Transportation
BVSR	Base Value of Speed Reduction
SSI	Storm Severity Index
WPI	Winter Performance Index
WMI	Winter Mobility Index
RWIS	Road Weather Information Systems
CCTV	Closed Circuit Television
ESS	Environmental Sensor Systems
CFM	Continuous Friction Measurement
ARIMA	Autoregressive Integrated Moving Average
MLP	Multi-Layer Perceptron
ACF	Autocorrelation Factor
PACF	Partial Autocorrelation Factor
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion

Chapter 1
Introduction

1.1 Background

In countries like Canada and the United States (US), people's daily life can be significantly impacted by severe cold weather, wind chills and heavy snow storms during winter seasons. Highway transportation is one of the many aspects that could severely be impacted by adverse weather conditions. Snow covered road surface conditions (RSC), low temperature and poor visibility could result in slow traffic speed and a higher risk of fatal collisions.

Research has been carried out to address the impact of adverse weather on highway safety and mobility. According to the 2010 Ontario Road Safety Annual Reports, over 22.8% of fatal collisions, 24.8% of personnel injury collisions and 28.3% of property damage collisions are related to wet/snow/icy RSC. Among all types of collisions, over 19.1% occurred under adverse weather conditions. The Highway Capacity Manual (HCM 2010) also provided research results about the impact of weather conditions on freeway traffic speed, citing a drop of 8-10% in free flow speed (FFS) due to light snow, 30-40 percent due to heavy snow, compared with clear and dry conditions.

In order to keep road networks clear of snow and ice and for safe and efficient travel throughout winter seasons, many transportation authorities in countries like Canada and US are facing mounting challenges both monetarily and environmentally. According to the FHWA Statistics, WRM accounts for roughly 20 percent of state Department of Transportation (DOT) maintenance budgets with an average annual spending of more than 2.3 billion dollars on snow and ice control operations. (http://www.fhwa.dot.gov/policy/ohpi/hss/hsspubs.cfm). Similarly, Canada spends significant amounts of resources on WRM every year, including over 1 billion dollars of direct investment and use of an average of five million tons of road salt. The increasing maintenance costs and public concerns over the detrimental effects of road salt on the environment and vehicles stimulated significant interest in developing performance measures. It therefore becomes increasingly important to develop a rigorous performance measurement system that can show clear linkage between the inputs of WRM and its outcomes such as mobility and safety benefits.

1.2 Winter Road Maintenance and Performance Measurement

Generally, WRM are the maintenance activities conducted by governments, institutions and individuals to remove or control the amount of ice and snow brought by snow events on roadway surface, and to make travel easier and reduce the risk of collisions.

WRM methods can be divided into two primary categories: mechanical and chemical (Minsk, 1998). Mechanical methods include plowing, brooming and blowing using maintenance trucks and equipment. The main chemical method is the application of temperature suppressant chemicals on the road's surface. These chemicals, either liquid or solid, can lower the freezing-point, thus melting the snow/ice or preventing ice bonding on the road surface and making plowing easier.

Based on the timing of the operation, WRM operations can also be classified into three categories: before, during and after snow events. Before event operations include checking for changing road and weather conditions, planning and preparing operations, and applying liquid chemicals to the road's surface. During and after maintenance events includes operations such as plowing snow and ice; spreading salt and sand on road surface to provide traction and safer driving; cleaning up roadways and continually checking road, weather and traffic conditions after snow events.

The choice of appropriate and effective methods depends on various factors. These factors include the severity of the snow events, topology of the area, road surface temperature, wind speed, etc. Because of the high efficiency and effectiveness in clearing snow and ice, plowing and salting are the two most commonly used methods. Plowing involves removing the snow layer from the road surface with trucks. The snow layer is usually a mixture of snow, ice, water, chemicals, and dirt, and is not excessively bonded to the road surface so that it can be picked up by plow equipped maintenance trucks and casted off to the side of the road for storage. Salting involves the applications of solid and liquid chemicals, such as Magnesium Chloride (MgCl), Calcium Chloride (CaCl), and Sodium Chloride (NaCl), and can be divided into two types, anti-icing and de-icing. Anti-icing is the application of salt or brine to the roadway prior to snow events so as to prevent the bonding of snow and ice to the road surface. De-icing is the application of salt to snow and ice that is bonded to the road surface for the purpose of melting the snow or ice, thereby ensuring safe driving conditions. Operation frequency and the chemical application rate can be determined based on road weather and surface conditions as well as the level of service requirements. The priorities of WRM are different for different types of roadways. For example, the priorities of highways, arterial roads, business districts and bus lanes are higher while the priorities of local industrial roadways and residential streets are relatively lower.

WRM is a typical example that its activities and performance need to be measured so as to achieve the optimum maintenance outcome while utilizing the minimum amount of resources. According to a handbook published by the U.S. Department of Energy (1995), performance measures quantitatively summarize some important indicators of the products, services and the process that produce them. A performance measurement system should consist of a comprehensive set of measures, processes and standards that can be used by the government agencies and maintenance contractors to assess:

- How well we are doing?
- Are we meeting our goals?
- Are the customers satisfied?
- Is the process with statistical control?
- Are improvements necessary?

Many WRM performance measures have been developed in the past, which can be generally divided into three categories: input measures, output measures, and outcome measures. Input measures indicate the amount of resources utilized to perform WRM operations, therefore are directly associated with maintenance costs. Output measures represent the amount of work that is accomplished by transportation agencies or maintenance contractors using WRM resources. Outcome measures assess the effectiveness of winter maintenance operations, and can clearly reflect the impact of the operations on highway mobility and safety as well as customer satisfaction. Input measures such as salt usage, labor, and equipment investment are not directly linked to WRM objectives and goals, and cannot provide measures of quality, efficiency or effectiveness of WRM.

Although output measures such as lane-miles plowed or salted are more meaningful compared with input measures, they can only measure the physical accomplishment or the efficiency of WRM, and do not reflect the level of impact on the ultimate goal of WRM.

Outcome measures such as bare pavement regain time, friction level, delay and the number of collisions can produce the most meaningful results. However, these measures also have drawbacks. Firstly, because of the limitations of data collection methods, some data used in these measures are still subjective. Others highly depend on data quality and availability (e.g. friction models), therefore they cannot be applied without enough properly formatted datasets (Maze, 2009; Qiu, 2008). Secondly, models used for estimating outcomes are often relatively complex and are time-consuming to calibrate, which leaves a huge barrier to practical usage.

One of the performance measures that have the potential to overcome the limitations of these existing outcome measures is traffic speed. Traffic speed is directly linked to WRM goals and easy to monitor with existing traffic sensors. However, traffic speed has not been widely used as a WRM performance in practice. One of the main reasons for this lack of practical applications is that the relationship between traffic variables and road weather conditions, especially, road surface conditions (RSC), has not been clearly quantified. Some past studies have attempted to develop models to quantify the effect of weather and surface condition variables on traffic speed; however, most of these models were built on simplistic frameworks that have limitations in capturing the complex relationship between weather and traffic. Also, most of the past studies focused on freeways only, in which the effect of weather on traffic speed could be easily confounded by traffic congestion. These models used data with incomplete spatial/temporal representation, limiting their ability to take a full account of the variation in winter RSCs.

1.3 Research Objectives

With the problems of the current WRM performance measures mentioned in the previous section, this research has the following two major objectives:

1. To investigate the impact of winter weather and RSC on the average traffic speed of rural highways with the intention of examining the feasibility of using traffic speed from traffic sensors as a new WRM performance measure; and
2. To develop statistical models and methodologies to estimate/classify RSC based on traffic and weather data.

The main task for Objective 1 is to develop and compare models calibrated with different time aggregation intervals, highway types and statistical algorithms, quantify the impact of winter weather and road surface factors on average traffic speed, and examine if average traffic speed is sensitive to winter weather, especially RSC on rural highways. Objective 2 addresses the problem of inferring RSC based on traffic speed and other factors. The main task is to develop reliable RSC classification models/frameworks using data that is easy and inexpensive to collect such as traffic speed and weather factors.

1.4 Thesis Organization

This thesis consists of five chapters:

Chapter 1 introduces the research problem and objectives and some basic concepts.

Chapter 2 reviews the existing methods, standards, guidelines and policies used for WRM performance measurement in practice. It also reviews previous studies on the mobility impact of winter weather and road surface factors as well as RSC monitoring and estimation.

Chapter 3 calibrates and compares different types of models and describes the results of the investigation of the impact of winter weather and RSC on the average traffic speed of rural highways.

Chapter 4 presents the calibration process, validation and discussion of the RSC classification model/framework.

Chapter 5 summarizes the major findings and provides recommendations for future studies.

Chapter 2
Literature Review

Much research work has been carried out on WRM performance measurement. This chapter covers a review of the WRM performance measurement system and some of the most widely used WRM performance measures in practice. Additionally, past studies on factors affecting average traffic speed in winter seasons are reviewed and summarized. Finally, previous research on equipment and methodologies for winter RSC monitoring and estimation is presented and discussed.

2.1 WRM Performance Measurement

Winter road maintenance operations are performed to minimize winter weather related collisions and the impact of adverse winter weather on travel times. This section reviews the WRM performance measurement system and the pros and cons of traditional WRM performance measures.

2.1.1 Performance Measurement System

According to a handbook published by the U.S. Department of Energy (1995), performance measures quantitatively summarize some important indicators of the products, services, and the process that produces them. Performance measurement is the process of collecting and analyzing data and assessing the performance of a system, individual, or organization (FHWA, 1996). It demonstrates with convincing evidence that the activities and work have been done towards achieving the targeted results and pre-specified objectives (Schacter, 2002).

The fundamental reason why performance measurement is important is that it makes accountability possible, which is significant to decision making. Kane (2005) suggested that the purpose of measuring performance by transportation agencies is to advise customers how well transportation agencies are doing at improving transportation services. A report prepared by the Transportation Association of Canada (2006) also suggested that the most common purpose of conducting performance measurement is the need to be accountable to the public. The public expects to know how their funds are spent on maintaining the transportation system, and the effect of expenditures upon it. Performance measurement is essential to that process.

Central to a performance measurement system is a set of indicators, numerical or non-numerical, which measure different aspects of the activities. Most literature suggested that input, output, and outcome are considered to be the three most common aspects of performance related activities.

Delorme et al. (2011) in their report about performance measurement and its indicators from the perspective of government decision making and policy evaluation, classified performance measures into five types, namely input, output, outcome, impact and context. Similarly, Probst (2009) suggested that inputs, outputs, efficiency, service quality and outcome should be taken into consideration when measuring local government decision performance.

When it comes to selecting proper performance measures, firstly, it is important to determine what aspect of the activity is to be measured. Input measures reflect the resources that are used in the activity process, output measures reflect the products of the activity, and outcome measures reflect the impact of the products and are directly related with the agency's strategic goals (Dalton et al, 2005). Secondly, it is also significant to consider data availability, quality, the cost, and time in data collection. It must be possible to collect the necessary data with relatively high quality, but low cost. The performance measure that is to be adopted must be possible to be generated with the existing technology and resources available to transportation agencies. According to a report by the Transportation Research Board (TRB) (2000), there are other issues to be considered when selecting performance measures:

- Forecastability: Is it possible to compare future alternative projects or strategies using this measure?
- Clarity: Is it can be understood by transportation professionals, policy makers and the public?
- Usefulness: Does the measure reflect the issue or goal of concern? Does it capture cause-and-effect between the agency's actions and condition?
- Ability to diagnose problems: Is there a connection between the measure and the actions that affect it? Is the measure too aggregated to be helpful to agencies trying to improve performance?
- Temporal Effects: Is the measure comparable across time?
- Relevance: Is the measure relevant to the planning and budgeting processes? Will changes in activities and budget levels affect a change in the measure that is apparent and meaningful? Can the measure be reported with a frequency that will be helpful to decision makers?

2.1.2 WRM Performance Measurement System

Qiu (2008) proposed a general performance measurement system from the perspective of WRM, and suggested that to develop a comprehensive performance measurement system, the following factors need to be taken into consideration:

- Input measures: indicating the amount of resource used (e.g. equipment, material, and labor);
- Uncontrollable factors: indicating those factors that are controllable in normal conditions, but related with performance (e.g. natural hazard and emergency);
- Output measures: indicating efficiency of resources transformed to service (e.g. the lane-miles plowed or salted); and
- Outcome measures: reflecting effectiveness of the operation on pre-specified objectives (e.g. lower travel costs to customers).

Maze (2009) systematically summarized the performance measurement system for WRM. As shown in the 'Fish Bone Model' in Figure 2.1, the government pays contractors to invest in WRM equipment, chemical materials and personnel (i.e. the input). Contractors then conduct WRM operations before, during and after snow events and make sure that the road surface is clean and the bare-pavement regain time meets the standard specified on the WRM guidelines (i.e. the output). Roadway users benefited from WRM in terms of both safety and mobility while travelling (i.e. the outcome).

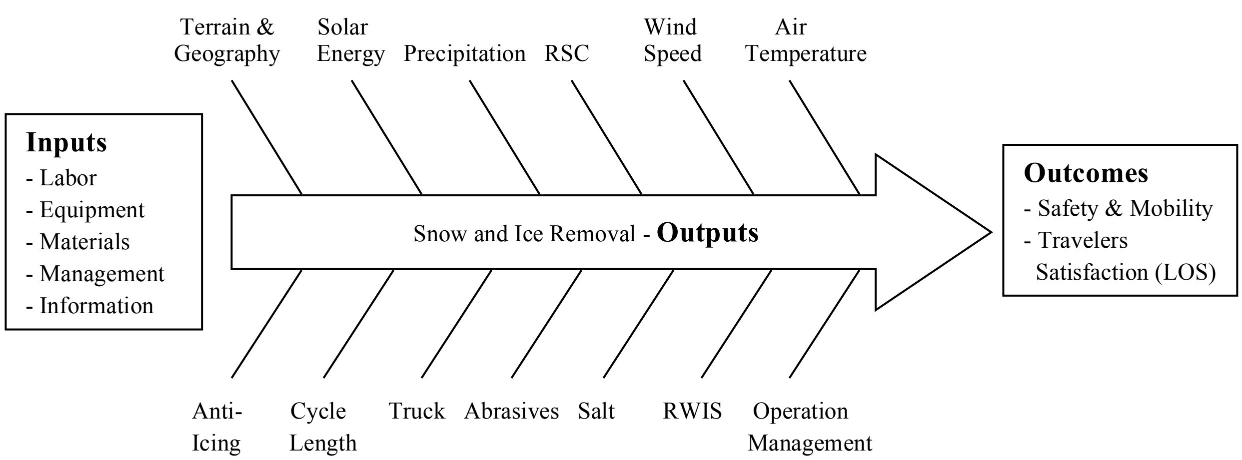

Figure 2.1 WRM Performance Measurement Model (Maze, 2009)

Qiu (2008) and Maze (2009) have suggested different types of measures that can be used as indicators of WRM performance while these measures vary from one to another in terms of cost, data availability, measuring frequency, reliability and repeatability. The next section will review some of the most widely used WRM performance measures in practice, and discuss their pros and cons.

2.1.3 Current WRM Performance Measures

Effective WRM performance measures are significant to both the government and maintenance contractors. On one hand, by measuring maintenance performance and benchmarking outcomes, the government is able to tell how well the job is done by maintenance contractors. On the other hand, maintenance contractors can make more informed decisions, and conduct better planned maintenance operations toward specific objectives (Qiu, 2008). Many performance measures have been developed in the past to measure different aspects of WRM.

(1) Input Measures

Input measures indicate the amount of resources (e.g. labor, equipment and materials) utilized to perform WRM operations, therefore are directly associated with maintenance costs. For instance, for studying the budget and forecast of maintenance equipment needs, Adams et al. (2003) utilized automated vehicle location (AVL), global positioning system (GPS), material sensors and equipment sensors to collect data, and systematically developed a set of performance measures dealing with material application rate, material inventory and equipment cost in the State of Wisconsin. For example, the following equations show the measures for quantity of material used for each event and patrol section:

$$Q_{salt,p,e} = [\sum_{y=1}^{Y_{salt,p,e}} MAR_{salt,y,p,e}/2Y_{salt,p,e}]L_{salt,p,e} \tag{2.1}$$

$$Q_{sand,p,e} = [\sum_{y=1}^{Y_{sand,p,e}} MAR_{sand,y,p,e}/2Y_{sand,p,e}]L_{sand,p,e} \tag{2.2}$$

$$Q_{pw,p,e} = [\sum_{y=1}^{Y_{pw,p,e}} MAR_{pw,y,p,e}/2Y_{pw,p,e}]L_{pw,p,e} \tag{2.3}$$

$$Q_{anti\_ice,p,e} = [\sum_{y=1}^{Y_{anti\_ice,p,e}} MAR_{anti\_ice,y,p,e}/Y_{anti\_ice,p,e}]L_{anti\_ice,p,e} \tag{2.4}$$

Where,

$Q_{material,p,e}$ = Quantity of material used for each event and patrol section

$MAR_{material,y,p,e} = y^{th}$ material application rate reading for patrol section p and for the event e

$L_{material,p,e}$ = Number of treated lane miles in patrol section p over which material was distributed during event e

$Y_{material,p,e}$ = Total number of material application rate readings for event e and patrol section p

y = Index for material application rate reading

e = Index for event

The authors suggested that developing new performance measures is time consuming, and the measures in the paper can serve as a quick starting point for agencies who want to utilize winter vehicle data to improve the performance of WRM.

Input measures have the advantages of controllability and are the easiest to monitor; however, as stated by Maze (2009), because inputs are applied at the beginning of the winter maintenance process, they are not directly linked to WRM objectives and goals, and cannot provide measures of quality, efficiency or effectiveness of WRM.

(2) Output Measures

Output measures represent the amount of work that is accomplished by transportation agencies or maintenance contractors using WRM resources. Typical output measures are lane-kms plowed/salted/sanded and lane-kms to which anti-icing chemical was applied (Maze, 2009; Qiu, 2008). Fallah-Fini & Triantis (2009) utilized Data Envelopment Analysis (DEA) in combination with regression analysis, analytic hierarchy process and classification methods to measure the efficiency of winter maintenance operations on highways from 2003 to 2007 within eight counties across the State of Virginia, US. According to the authors, the total area served (TAS), which represents the amount of road surface maintained by each county, was considered as one of the WRM output variables. The authors suggested that TAS can affect the performance of the maintenance crew and consequently the quality of the maintenance efforts performed to meet the required level of service. Similarly, Adams et al. (2003) also suggested that the following equations can be used measure the total operating distance for different equipment:

For plow and scraper units:

$$ED_u = \sum_{k}^{K_u}(LM_{up} - LM_{down})_k \tag{2.5}$$

For spreader and spray bar units:

$$ED_u = \sum_{k}^{K_u}(LM_{off} - LM_{on})_k \tag{2.6}$$

For truck units:

$$ED_u = \sum_{k}^{K_u}(LM_{truck\_leaves\_p} - LM_{truck\_enters\_p})_k \tag{2.7}$$

Where,

ED_u = Total operating distance for each attachment unitK_u = Total number of time periods equipment unit *u* was in use

k = Index for time period for equipment use

LM = Linear Measures

u = Index for equipment unit

Although output measures, like those mentioned above, are more meaningful compared with input measures, they can only measure the physical accomplishment of WRM, and cannot reflect the level of impact on the ultimate goal or the effectiveness of WRM.

(3) Outcome measures

Outcome measures assess the effectiveness of winter maintenance operations, and can clearly reflect the impact of the operations on highway mobility and safety as well as customer satisfaction. Therefore, outcome measures are considered the most meaningful to WRM management.

According to a survey conducted by the CTC & Associates LLC of Wisconsin DOT Research & Library Unit (2009), almost 70% of transportation agencies use bare pavement regain time or similar measures as the main indicator of WRM. One major problem of bare pavement regain time is that it is usually reported by maintenance or quality assurance personnel based on periodic visual inspection during and after snow events, therefore it lacks of objectivity and repeatability (Feng et al., 2010). Another problem is it can only reflect the road condition after snow storms, but it cannot capture the variation during snow storms.

Many transportation agencies around the world including US, Canada, Japan and Europe (especially Finland and Norway) have found that the friction level correlates to collision risk, traffic speed and volume so that it can be used as an acceptable measure for snow and ice control operations. Friction level is a value that ranges from 0 to 1 with 0 indicating the most slippery/icy surface condition and 1 indicating a bare/dry surface condition. Some studies have been conducted regarding using friction level as WRM performance measurement. For example, Jensen et al. (2013) from Idaho DOT proposed Winter Performance Index (WPI) with the following form:

$$Storm\ Severity\ Index = WS(Max) + WEL(Max) + 300/ST(Min) \tag{2.8}$$

Where,

WS = Wind Speed (mph)

WEL = Water Equivalent Layer (millimeters)

ST = Surface Temperature (degrees F)

$$Winter\ Performance\ Index\ =\ Ice\_Up\ Time\ (hours)\ /\ Storm\ Severity\ Index \tag{2.9}$$

Where:

$Ice\_Up\ Time$ is when the friction level is below 0.6 for at least a 30 minute period, and the goal is to have a Winter Performance Index of 0.50 or less.

Dahlen (1998) reported that Norway is also using friction level to measure WRM performance. On high volume roads, a friction level of 0.4 must be regained within a certain amount of time that is dependent on the road's annual average daily traffic (AADT). For example, a friction level of 0.4

must be regained within four hours after a snow storm on a road with an AADT of between 3001 and 5000.

Some literatures, however, claimed that friction models highly depend on data quality and availability, therefore its large scale application is still questionable at this stage (Al-Qadi, et al., 2002; CTC & Associates LLC, 2007).

Apart from the above measures, many other WRM performance measures have been proposed in the past. Blackburn et al. (2004) developed a pavement snow and ice condition index (PSIC) to evaluate the effectiveness of snow and ice control strategies and tactics (see Appendix B). The index was used to evaluate both within-event and end-of-event LOS achieved by winter maintenance treatments.

Table 2.1 and 2.2 show the within and after event LOS categories based on the PSICs and the time to achieve a PSIC of 1 or 2. Table 2.3 shows the LOS expectations for different strategies and tactics based on the LOS categories in Table 2.1 and 2.2.

Table 2.1 Within Event LOS Categories

Within Event LOS	PSIC
Low	5 and 6
Medium	3 and 4
High	1 and 2

Table 2.2 After Event LOS Categories

After Event LOS	Time to Achieve a PSIC of 1 or 2 (hour)
Low	> 8.0
Medium	3.1 – 8.0
High	0 – 3.0

Table 2.3 Strategies and Tactics and LOS Expectations

Strategies and Tactics	Within Event LOS			After Event LOS		
	Low	Medium	High	Low	Medium	High
Anti-icing			X			X
De-icing	X	X		X	X	
Mechanical Alone	X			X		
Mechanical and abrasives	X			X		
Mechanical and anti-icing			X			X
Mechanical and de-icing	X	X		X	X	
Mechanical and pre-wetted abrasives	X			X		
Anti-icing for frost/black ice/icing protection			X			X
Mechanical and abrasives containing > 100 lb/lane-mile of chemical	X	X	X	X	X	X
Chemical treatment before or early in event, mechanical removal during event, and de-icing at end of event	X				X	

A customer satisfaction survey is also used in some areas to measure the WRM performance. For example, Kreisel (2012) conducted a public satisfaction survey about the local government service in the Strathcona County, Alberta. In the section about WRM, the author found that more people living in the rural areas felt the quality of WRM was higher than those living in the urban areas (shown in Figure 2.2). By comparing historical data from 2008 to 2012, the author also found that the percentage of urban residents who felt the WRM work was either very high or high decreased to 44.4% in 2012, while it was 50.1% in 2011 and 45.7% in 2010. On the other side, the percentage of rural residents who felt the WRM work was either very high or high is 60.9% in 2012. This number is close to 2011 (61.1%), but higher than 2010 (56.3%), 2009 (53.1%) and 2008 (58.9%). Based on the survey results, the author finally suggested maintenance contractors to clear and sand residential side streets more often, and graders and sanders should get out earlier than they do to deal with the snow.

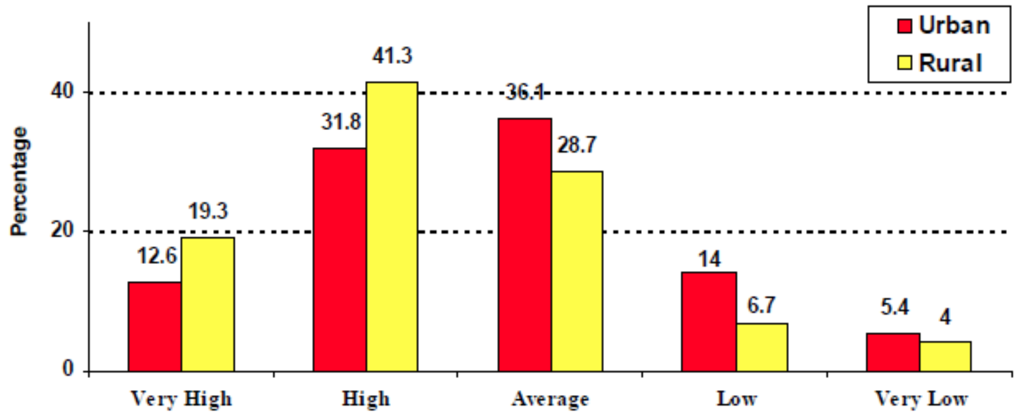

Figure 2.2 Quality of Winter Road Maintenance Urban and Rural Comparisons (Kreisel, 2012)

Although outcome measures can produce the most meaningful results, they also have a series of problems. Firstly, because of the limitation of data collection methods, some data used in these measures is still subjective and costly (e.g. bare pavement regain time). Other models highly depend on data quality and availability (e.g. friction models), therefore cannot be applied without enough properly formatted datasets (Maze, 2009; Qiu, 2008). Secondly, models used for estimating outcomes are often relatively complex and are time-consuming to calibrate. This leaves a huge barrier to practical usage. Table 2.4 illustrates some of the mostly used WRM performance measures and their evaluation metrics.

Table 2.4 Evaluation Metrics for WRM Performance Measures

Category	Measure	Meaningful	Controllable	Easy to Monitor	Robust	Support Benchmarking
Input	Salt Usage	L	H	H	H	L
	Work Hours	L	H	H	H	L
Output	Lane-km Plowed	M	M	H	H	L
	Lane-km Salted	M	M	H	H	L
	Total cost per lane-km	M	M	H	H	L
Outcome	Average Collision Rate	H	L	H	L	L
	BP Regain Time	H	M	H	M	M
	Friction Level	H	M	L	M	M

2.1.4 Using Traffic Speed as a WRM Performance Measure

Compared with other WRM performance measures, traffic speed is easier and cheaper to monitor and has high reliability. Therefore, it could be a meaningful performance measure of WRM, and can easily be used to support benchmarking. This section will review some of the previous studies of using traffic speed as a WRM performance measure.

Lee et al. (2008) conducted a study to investigate vehicle speed changes during winter weather events using the regression tree method, and proposed speed recovery duration (SRD) as a new WRM performance measure. A total of 954 winter maintenance logs collected from 24 counties in the State of Wisconsin over three seasons were analyzed. Figure 2.3 shows the definition of SRD, and the following linear model shows how SRD is calculated:

$$SRD = 9.68 + 9.926 * MSRPCENT$$
$$- 0.866 * StoS2MSR + 0.493 * CrewDelayed - 0.222 * SnowDepth \quad (2.10)$$

Where,

$MSRPCENT$ is maximum speed reduction percent

$StoS2MSR$ is time to maximum speed reduction after snowstorm starts

$CrewDelayed$ is time lag to deploy maintenance crew after snowstorm starts

$SnowDepth$ is snow precipitation

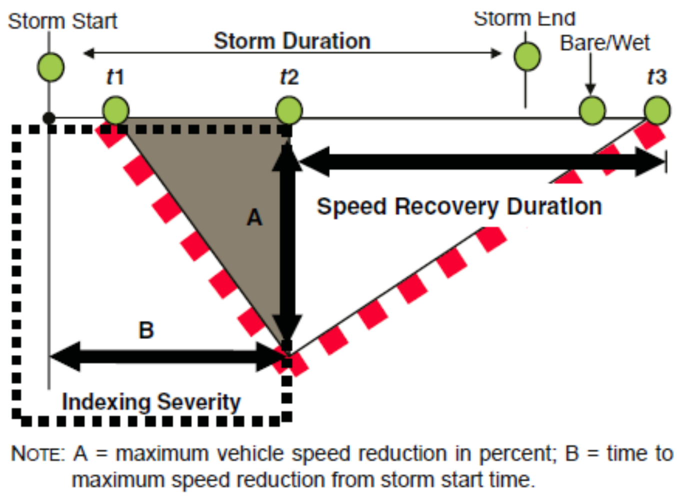

Figure 2.3 Speed Recovery Duration as a Performance Measure (Lee et al., 2008)

The author concluded that changes in vehicle speed are correlated with changes in RSC during winter snow events and thus recovery in vehicle speed can be a good indication that WRM has taken in effect. SRD derived from vehicle speed data was found to be a good performance indicator of WRM.

Qiu and Nixon (2009) used a traffic data related WRM performance measure, which is based on the comparison between the actual measured speed reduction with the acceptable speed reduction during a snow storm. The acceptable speed reduction is calculated based on a storm's severity, which is an index defined with the consideration of several weather-related factors.

$$Acceptable\ Speed\ Reduction\ =\ BVSR\ *\ SSI \tag{2.11}$$

Where,

$BVSR$ (Base Value of Speed Reduction) is the maximum acceptable speed reduction for a given route under the worst storm.

SSI (Storm Severity Index) is generated based on the storm type, wind level and pavement temperatures during and after the storm.

Figure 2.4 shows the base values of speed reduction and the SSI equation. As can be seen in the figure, different types of routes have different base values of speed reduction (i.e. type A, B and C). SSI is calculated by considering storm type, storm temperature, wind conditions in the storm, early storm behavior, post storm temperature and post storm wind conditions.

	Priority A	**Priority B**	**Priority C**
Base Value of Speed Reduction (mph)	17	22	24

$$\mathrm{SSI} = [\frac{1}{b} * [ST * Ti * Wi) + Bi + Tp + Wp - a]]^{0.5}$$

a = 0.0005, b = 1.6995

Storm Type (ST)	Freezing rain 0.72	Light Snow 0.35	Medium Snow 0.52	Heavy Snow 1
Storm Temperature (Ti)	Warm 0.25	Mid Range 0.4	Cold 1	
Wind Conditions in Storm (Wi)	Light 1	Strong 1.2		
Early Storm Behavior (Bi)	Starts as Snow 0	Starts as Rain 0.1		
Post Storm Temperature (Tp)	Same 0	Warming -0.087	Cooling 0.15	
Post Storm Wind Conditions (Wp)	Light 0	Strong 0.25		

Figure 2.4 Base Values of Speed Reduction and SSI Equation (Iowa Highway Research Board, 2009)

Based on Qiu and Nixon's model, Greenfield et al. (2012) proposed a revised SSI calculation model (shown below) and applied it for real-time winter road performance analysis. The new model takes into account uncertainty in the sensor-based inputs and yielded better performance both on estimating in-storm and post-storm effect on traffic speed.

$$SSI = c * (\frac{1}{b} * ((E_s * E_T * E_w) + B_i - a))^{0.5} \qquad (2.12)$$

Similarly, Kwon et al. (2012) developed a traffic data-based automatic process to determine the road condition recovered times that can be used as the estimates for the bare pavement regain time.

Firstly, the authors tried to identify speed change points in a speed-time space with smoothed and quantized speed data, for example, speed reduction starting time (SRST), low speed time (LST) and recovery starting time (RST) as shown in Figure 2.5. Secondly, the author's defined speed recovered time to FFS (SRTF) and speed recovered time to congested speed (SRTC) are as follows:

Time point t satisfies the following condition is considered as SRTF:

$$U_{s,i,t} \geq \left(U_{i,limit} - \Delta\right) for\ one\ hour \tag{2.13}$$

Where,

$U_{i,limit}$ is the speed limit at location i

Δ is parameter to reflect the measurement error, only for $U_{i,limit} \geq 60\ mph$

The initial SRTC is when time point i satisfies the following conditions in the quantized speed-time graph:

$$\begin{cases} U_j - U_i < 0 \\ K_j - K_i > 0 \end{cases} \quad where\ j > i\ for\ at\ least\ 2\ time\ inervals$$

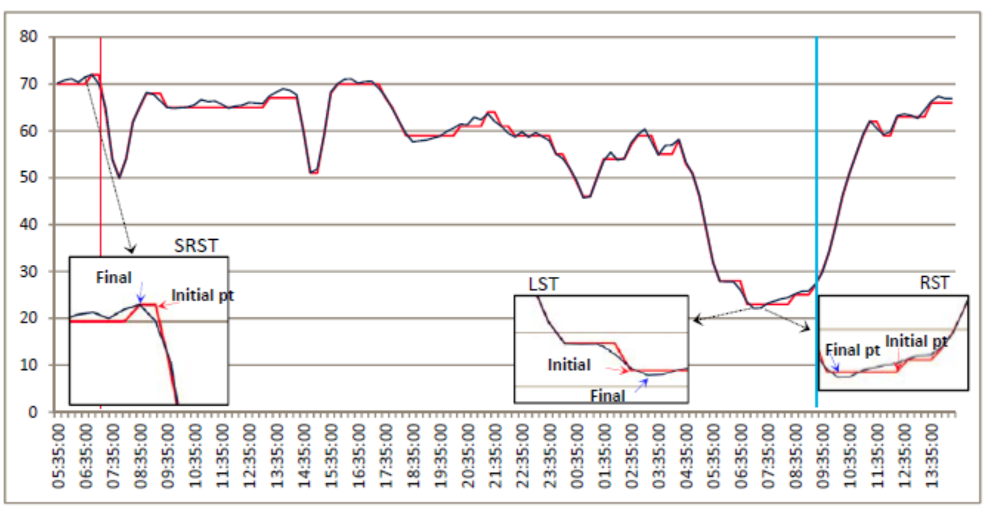

Figure 2.5 Identification of SRST, LST, RST of Speed Variation During Snow Event (Kwon et al., 2012)

Then, the authors tried to identify the road condition recovered (RCR) time with both SRTF and SRTC cases. For the case with SRTF, if the speed level at RST <= (50 – β) mph, RCR time equals the last significant speed change point before the speed reaches its posted speed limit. Else, RCR time equals the last significant speed change point before SRTF where β = the threshold range parameter, e.g., 2 mph. For the case with SRTC, RCR is defined as the time when the significant speed change occurs between RST and SRTC. The model was then validated with data collected on two routes for four snow events. It was found that three of the four events, 64-65% of all the segments have less than 30 minute differences between the estimated road condition recovered times and the reported bare pavement regain times. The fourth event on January 23, 2012, has only 44% of all the segments with less than a 30 minute difference.

Using traffic speed as a WRM performance measure is relatively new compared with traditional performance measures, and still lacks systematic research. Most of the above studies focused on the speed reduction during winter snow events; however, few studies systematically analyzed the effect of both weather and RSC on traffic speed. Since both weather and maintenance activities can impact traffic speed, the effect of weather must be considered before making any assumptions about the quality of the WRM using traffic speed (Greenfield et al., 2012). The next section will review some of the previous studies on both weather and RSC factors on traffic speed.

2.2 Factors Affecting Winter Traffic Speed

Traffic speed on highways can be influenced by many factors, such as time of day, driving habits, the vehicle, traffic volume, highway class and design, etc. During winter seasons, both weather and RSC play an important role in traffic speed change on highways. This section reviews studies on the effect of weather and RSC on winter road mobility and compares different modelling methodologies.

Much research work has been carried out to address the impact of adverse weather on traffic speed. HCM (2010) provides information about the impact of weather condition on traffic speed on freeways. Two precipitation categories are considered: light and heavy snow. Accordingly, there is a drop of 8-10 percent in FFS due to light snow while heavy snow can reduce the FFS between 30–40 percent compared with normal conditions. Another research conducted by FHWA (1977) reported that the freeway speed reduction caused by adverse road conditions are 13% for wet and snowing, 22% for wet and slushy, 30% for slushy in wheel paths, 35% for snowy and sticking and 42% for snowing and packed.

Ibrahim and Hall (1994) conducted a study to quantify the effect of adverse weather on freeway speed using the data collected on Queen Elizabeth Way (QEW), Mississauga, Ontario. It was found that light snow resulted in a drop of 3 km/h in FFS, while heavy snow resulted in a drop of 37.0 to 41.8 km/h (35 to 40 percent). Although the authors considered two intensity categories of rain and snow, other weather factors such as temperature and visibility were not considered. Also, the data used in this analysis is limited, covering only six clear, two rainy, and two snowy days. Therefore the results may not be reliable and applicable to other sites.

Both Liang et al. (1998) and Kyte et al. (2001) took additional variables into consideration: visibility, wind speed and RSC. Liang et al. (1998) reported that under the 10 km visibility threshold, every one km reduction in visibility resulted in a reduction of 3 to 5 km/h in average traffic speed. Every one degree reduction in temperature resulted in reduction of 2 to 4 km/h. Snow covered road surface resulted in a reduction of 3 to 5 km/h. The effect of wind speed was found to be significant over 40 km/h where it reduced vehicle speed approximately by 1.1 km/h for every kilometer per hour that the wind speed exceeded 40 km/h. The regression results are summarized in Table 2.5.

Table 2.5 Model Calibration Results (Liang et al., 1998)

	Visibility Threshold (km)	Intercept	Visibility	Snow Floor	Day/Night	Temperature	Wind Speed	Adjusted R^2
Fog Events								
All vehicles	10.0	98.72 0.0001	2.55 0.0001	---	2.12 0.0001	2.83 0.0001	---	0.52
Passenger car	10.0	104.83 0.0001	2.56 0.0001	---	1.27 0.024	1.74 0.0137	---	0.28
Truck	10.0	94.95 0.0001	2.09 0.0001	---	1.96 0.0001	*0.35* *0.44*	---	0.48
Snow Events								
All vehicles	10.0	89.13 0.0001	4.61 0.0001	-3.49 0.0001	2.58 0.0001	2.58 0.0001	-1.09 0.0001	0.384
Passenger car	10.0	92.78 0.0001	4.79 0.0001	-4.05 0.0001	1.32 0.0034	3.23 0.0001	-1.24 0.0001	0.373
Truck	10.0	86.78 0.0001	3.23 0.0001	-3.39 0.0001	1.34 0.0005	3.43 0.0001	-1.21 0.0001	0.396

Note: The first value in each cell is the regression coefficient. The second value is the p-value. Italic figures are statistically insignificant.

Kyte et al. (2001) reported that when visibility is lower than 0.28 km (the critical visibility), traffic speed reduced by 0.77 km/h for every 0.01 km below the critical visibility. Wet or snow covered pavement resulted in a speed reduction of 10 to 16 km/h. High wind speed resulted in a speed reduction of over 11 km/h. A combination of snow-covered pavement, low visibility and high wind speed resulted in a speed reduction of about 35 to 45 km/h. The model calibrated is shown below:

$$speed = 100.2 - 16.4snow - 9.5wet + 77.3vis - 11.7wind \tag{2.14}$$

Where,

$speed$ is passenger-car speed (km/h),

$snow$ indicating presence of snow on roadway,

wet indicating that pavement is wet,

vis is visibility variable that takes on value of 0.28 km when visibility exceeds 0.28 km and value of visibility when visibility is below 0.28 km, and

$wind$ indicating that wind speed exceeds 24 km/h.

Compared with Liang et al.'s study, Kyte et al. used more RSC categories (dry, wet and snow/ice covered) while Liang et al. used more factors such as temperature and day/night. However, both studies did not consider precipitation type and intensity. Using two RSC categories is also limited as it cannot capture the full range of the RSC variation during and after snow events.

Similar with Ibrahim and Hall's research, Knapp et al. (2000) utilized multiple regression analysis to model the relationship between traffic speed and weather factors using data collected over seven winter snow events in 1998 and 1999 in Iowa. As is shown in Table 2.6, poor visibility and the snow covered roadway resulted in about a 6.24 km/h (3.88 mph) and an 11.64 km/h (7.23 mph) reduction in average vehicle speed, respectively.

Table 2.6 Model Calibration Results (Knapp et al., 2000)

Explanatory Variable	Coefficient	T-Statistic	P-Value	Mean of Variable	Std. Dev. of Variable	Range of Variable
Traffic Volume[2] (vph[2])	0.00002	7.91	0.000	327,980	214,125	15,376 to 788,544
Visibility Index[3]	- 3.88	- 3.08	0.003	--	--	--
Roadway Cover Index[4]	- 7.23	- 4.28	0.000	--	--	--
Constant	55.7	52.90	0.000	--	--	--

[1]mph = miles per hour and vph = vehicles per hour
[2]**Model Summary Statistics:** Number of Observations = 83, F-Value = 42.55, P-Value = 0.000, Mean Square Error = 21.85, Coefficient of Multiple Determination = R-Squared = 0.618, and R-Square (Adjusted) = 0.603.
[3]The visibility index is equal to one when visibility is less than ¼-mile and zero when greater.
[4]The roadway cover index is equal to one when snow has begun to impact the roadway lanes and zero if snow is only on the shoulders or nonexistent on the roadway surface.

There are some limitations with this study. First, the research data is collected for the northbound traffic flow at one site only (i.e. only 83 data points were used). Second, due to the lack of data collection facilities, some of the RSC and visibility data were manually collected, therefore their reliability and objectivity are limited. As mentioned by the authors, the results generated by this study should be used with caution.

Agrwal et al. (2005) investigated the impact of different weather types and intensities on urban freeway traffic flow characteristics using traffic and weather data collected in the Twin Cities, Minnesota. Rain, snow, temperature, wind speed and visibility were considered, and each of these variables were categorized into 3 to 5 categories by intensity ranges. Average traffic speeds were calculated for different weather types and weather intensities. The research finally suggested that light and moderate snow show similar speed reductions with the HCM 2000 while heavy snow has significantly lower impact on speed reduction than those recommended by the manual. In addition, it was found that lower visibility caused 6% to 12% reductions in speed while temperature and wind speed had almost no significant impact on the average traffic speed. Table 2.7 shows the comparison between the model results and those values suggested on HCM 2000.

Table 2.7 Comparison of Model Results with HCM 2000 (Agrwal et al., 2005)

Variable	Range	Assumed corresponding categories from the Highway Capacity Manual (2000)	Capacities(percentage reductions)		Average Operating Speeds (percentage reductions)	
			Highway Capacity Manual (2000)	This Study	HCM 2000	This Study
Rain	0-0.01 inch/hour	Light	0	1-3	2-14	1-2.5
	0.01-0.25 inch/hour	Light	0	5-10	2-14	2-5
	>0.25 inch/hour	Heavy	14-15	10-17	5-17	4-7
Snow	<= 0.05 inch/hour	Light	5-10	3-5	8-10	3-5
	0.06-0.1nch/hour	Light	5-10	5-12	8-10	7-9
	0.11-0.5 inch/hour	Light	5-10	7-13	8-10	8-10
	>0.5 inch/hour	Heavy	25-30	19-28	30-40	11-15
Temperature	10°-1° Celsius		N/A	1	N/A	1-1.5
	0°- (-20)° Celsius		N/A	1.5	N/A	1-2
	<-20° Celsius		N/A	6-10	N/A	0-3.6
Wind Speed	16-32km/hr		N/A	1-1.5	N/A	1
	>32 km/hr		N/A	1-2	N/A	1-1.5
Visibility	1-0.51 mile		N/A	9	N/A	6
	0.5-0.25 mile		N/A	11	N/A	7
	< 0.25 mile		N/A	10.5	N/A	11

N/A- Not Available

Rakha et al. (2007) published results of a systematic study on the impact of inclement weather on key traffic stream parameters, including FFS, speed-at-capacity, capacity, and jam density. The analysis was conducted using weather data and loop detector data obtained from Baltimore and Twin Cities in the US. A general multiple regression model was proposed to estimate the weather adjustment factor (WAF) for key traffic stream parameters. The model is shown below and the calibration results are shown in Table 2.8:

$$F = c_1 + c_2\, i + c_3\, i + c_4\, v + c_5\, v + c_6 iv \tag{2.15}$$

Where,

F is WAF

i is the precipitation intensity (cm/h)

v is the visibility (km)

vi is the interaction term between visibility and precipitation intensity

Table 2.8 Model Calibration Results (Rakha et al., 2007)

Precip.	City	n	c_1	c_2	c_3	c_4	c_5	c_6	P-value	R^2_{Adj}	Normality Test A^2	Normality Test P-value	Levene Variance Test
Rain	Baltimore	32	0.963 (0.000)	-0.033 (0.001)	–	–	–	–	0.001	0.304	0.485	0.211	0.684
	Twin Cities	45	0.980 (0.000)	-0.0274 (0.000)	–	–	–	–	0.000	0.540	0.553	0.146	0.424
	Seattle	43	0.973 (0.000)	-0.0650 (0.000)	0.0240 (0.004)	–	0.0010 (0.044)	–	0.000	0.607	0.336	0.493	0.067
	Aggregate	111	0.981 (0.000)	-0.050 (0.000)	0.014 (0.011)	–	–	–	0.000	0.734	0.646	0.089	0.168
Snow	Baltimore	8	0.955	–	–	–	–	–	–	–	–	–	–
	Twin Cities	32	0.842 (0.000)	-0.131 (0.002)	–	–	0.0055 (0.000)	–	0.000	0.866	0.456	0.251	0.704
	Aggregate	40	0.838 (0.000)	-0.0908 (0.025)	–	–	0.00597 (0.000)	–	0.000	0.824	0.340	0.482	0.624

Note: Minitab reports a P-value of less than 0.0005 as 0.000.
Values in columns c_1 through c_6 represent coefficient value (p-value).

The results revealed that compared to normal conditions, light snow (0.01 cm/h) produces reductions in FFS of 5 to 16 percent. Heavy snow intensity (0.3 cm/h) resulted in FFS reduction of 5 to 19 percent. FFS reductions in the range of 10 percent are observed for a reduction in visibility from 4.8 to 0.0 km. However, Rakha et al.'s study suffered from small sample size (8 from Baltimore and 32 from Twin Cities) and few weather factors (visibility and precipitation intensity only).

Camacho et al. (2010) also utilized multiple regression analysis to model the relationship between FFS and traffic and weather factors such as truck percentage, visibility, wind speed, precipitation intensity, air temperature and snow layer depth. Data from 2006 to 2008 was collected from fifteen freeway sites in northwestern Spain. Four regression models were proposed correspond to four different types of climate: \

- Climate 1: without precipitation and air temperature is above 0°C:

$$v = a + b * I_t + c * \log\left(\frac{vis}{2{,}000}\right) + W * d * (V_w - 8) \tag{2.16}$$

- Climate 2: without precipitation and air temperature is below 0°C:

$$v = a + b * I_t + c * \log\left(\frac{vis}{2{,}000}\right) + d * V_w \quad (2.17)$$

- Climate 3: with precipitation and air temperature is above 0°C (rain condition):

$$v = a + b * I_t + c * \log\left(\frac{vis}{2{,}000}\right) + W * d * (V_w - 8) + \frac{f}{e^{I_p}} \quad (2.18)$$

- Climate 4: with precipitation and air temperature is below 0°C (snow condition):

$$v = a + b * I_t + c * \log\left(\frac{vis}{2{,}000}\right) + W * d * (V_w - 8) + \frac{f}{e^{I_p}} + g * s \quad (2.19)$$

Table 2.9 Model Calibration Results (Camacho et al., 2007)

Climate	Parameter	Estimation	Standard Error	*T*-Statistic	*P*-Value
Climate 1	*a*	129.72	0.0160621	8,076.15443	.000
	b	−0.353685	0.00055141	−641.420434	.000
	c	2.54137	0.0360639	70.4685295	.000
	d	−0.607541	0.0551818	−11.0098076	.000
Climate 2	*a*	127.749	0.169144	755.267701	.000
	b	−0.323244	0.0040076	−80.6577503	.000
	c	0.813488	0.143411	5.67242401	.000
	d	−0.229905	0.0376527	−6.10593663	.000
Climate 3	*a*	122.74	0.0967415	1,268.74196	.000
	b	−0.305221	0.00212833	−143.408682	.000
	c	2.27213	0.0648867	35.0168833	.000
	d	−0.596222	0.115342	−5.16916648	.000
	f	4.00669	0.102804	38.9740672	.000
Climate 4	*a*	116.028	0.330229	351.35618	.000
	b	−0.357527	0.00452176	−79.0681062	.000
	c	4.60032	0.14274	32.2286675	.000
	d	−1.08099	0.109376	−9.88324678	.000
	f	12.8298	0.313385	40.9394196	.000
	g	−0.133796	0.00414638	−32.2681472	.000

Model calibration results are shown in Table 2.9. The authors reported that snow layer depth could cause reduction in speed, ranging from 9.0 to 13.7 km/h. The effect of visibility loss had a logarithmical form and has a large effect on speed reduction when it is low. Wind speed affects speed only when it goes beyond 8 m/s. It was also found that the effect of weather factors (i.e. visibility, wind speed and precipitation intensity) on vehicle speed was higher in snow conditions than in the other three conditions; the effects differed between different locations.

Camacho et al.'s study was well designed, utilizing a large dataset covering three years and 15 sites. However, their study also suffers several limitations. For instance, like other studies, RSC was not considered in the study. Although snow layer factor was included in the models as one of the independent variables, its data was collected by meteorological stations at roadside rather than by embedded surface sensors. Secondly, the assumption made for classifying climate types is not reliable. The categorization of climate is helpful for understanding the relationship between speed reduction and weather factors under different weather conditions; but, the weather stations used in this research could not distinguish between rain and snow precipitation.Assumptions were introduced to distinguish rain and snow based on temperature (above 0°C was assumed as rain; below 0°C was assumed as snow).

Zhao et al. (2011) proposed a new weather indexing framework for weather factors. Instead of using sensor data directly, the framework transformed the data into weather indices. These indices areVisibility_Index, WeatherType_Index, Temperature_Index, WindSpeed_index and Precipitation_Index. The calibrated model is shown in the following equation:

$$Avg\ Speed = 7.23 + 0.770 * Visibility_{Index} + 0.358 * WeatherType_{Index} + 0.132 * Temperature\_Index - 0.0469 * WindSpeed\_Index - 1.92 * CumuPrecip\_Index\ (Update12am) + 0.853 * Norm\_Hr\_Speed - 0.935 * Day\_Index \quad (2.20)$$

The calibrated regression model suggested that an increase in the visibility index (better visibility) leads to higher speeds, with the speed increasing by about 2 km/h for each 1 km increase in visibility. The coefficient of WeatherType_Index indicated that the more severe the weather type, the slower the traffic speed. Moreover, temperatures above the freezing point results in a 1.58 km/h higher travelling speed compared to temperatures below freezing. High wind speed has a negative impact on traffic speed, with the speed decreasing by about 1.3 km/h for each 10 km/h increase in wind speed. The report mentioned that to ensure a proper match between weather (hourly data) and traffic data (10-minute interval data), traffic data observed during the last 10 minute interval of every hour was used to match the weather data (e.g. 0:50 – 1:00am, 1:50-2:00pm). This indicates that the traffic data (average traffic speed, volume) may not be representative of that hour. Moreover, RSC was not used in the weather indexing framework so that the relationship between traffic speed and RSC cannot be revealed by the model.

Kwon et al. (2013) examined the relationship between freeway traffic capacity and FFS and various weather and RSC factors. Traffic, weather and RSC data were used to calibrate multiple linear regression models for estimating capacity and FFS as a function of several weather variables, such as snow intensity, visibility, air temperature, road surface index (RSI) and wind speed. As is shown in Table 2.10, it was found that snow intensity is highly correlated with visibility while both can statistically significant affect FFS. Hourly snow intensity rates of 2.0 mm/h and 15.0 mm/h would cause percent reductions of 1.8% and 13.5% in FFS, respectively. As visibility increases, FFS also increases. Visibility greater than 1.0 km had less than 5% reductions in FFS. Increased RSI (i.e., better road conditions) are correlated with increased FFS. For example, under the given snow intensity of 5 mm/h, at RSI = 0.2 (snow covered), FFS is reduced by 17.01%, whereas at RSI = 0.8 (bare wet), FFS is reduced about 11.01%.

Table 2.10 Model Calibration Results (Kwon et al., 2013)

					95% Confidence Interval	
Predictor	Coefficient	SE	t	Sig.	Lower Bound	Upper Bound
1st Capacity Model: Calibrated Using All Variables ($R^2 = 91\%$)						
(Constant)	814.27	62.25	13.08	7.46 E–12	685.17	943.36
RSI	463.41	71.71	6.46	1.68 E–06	314.69	612.14
ln(visibility)	226.51	24.69	9.17	5.67 E–09	175.3	277.72
2nd Capacity Model: Calibrated Using All Variables Except ln(visibility) ($R^2 = 76\%$)						
(Constant)	1,222.89	103.71	11.79	5.57 E–11	1,007.8	1,437.98
Snow (mm/h)	–31.97	7.37	–4.34	2.66 E–04	–47.26	–16.68
RSI	619.06	108.52	5.7	9.75 E–06	394	844.12
1st FFS Model: Calibrated Using All Variables ($R^2 = 84\%$)						
(Constant)	75.33	1.77	42.6	7.10 E–22	71.65	79
RSI	5.15	2.09	2.47	2.23 E–02	0.81	9.49
ln(visibility)	5.84	0.73	8.02	7.86 E–08	4.32	7.35
2nd FFS Model: Calibrated Using All Variables Except ln(visibility) ($R^2 = 69\%$)						
(Constant)	85.81	2.57	33.4	1.09 E–19	80.47	91.15
Snow (mm/h)	–0.86	0.18	–4.7	1.21 E–04	–1.24	–0.48
RSI	9.54	2.7	3.53	1.98 E–03	3.92	15.16

NOTE: SE = standard error; sig. = significance.

The authors finally suggested that larger dataset with wider study area coverage can improve the applicability of the developed models. In addition, the potential non-linear effect should be tested and additional factors, such as number of lanes and road geometry, should be considered as well if possible.

Donaher (2014) conducted a research with six years' data collected from 21 sites in Ontario, Canada. The author developed two types of regression models, namely, hourly based and event based. For hourly based models, to isolate the effect of volumes approaching capacity on speed on non-rural freeways, the traffic data was divided into two groups "rural" and "urban" highways. Each event hour was paired with the typical median speed established based on non-event data. The difference between the observed median speed and the typical median speed was used as the dependent variable for regression modelling. Weather factors and RSI were used as independent variables. For event based models, each storm event was summarized in terms of weather and RSC factors over the duration of the event. Each event is also compared with average conditions of a clear weather period in the week before or after of the same duration. The event model is shown below:

Table 2.11 Event Based Model (Donaher, 2014)

Variable	Coef.	Sig	Std. Err.	z	Elasticity
Constant	69.082	0.000	0.787	87.790	
Temperature	0.089	0.000	0.022	3.980	-0.004
Wind Speed	-0.078	0.000	0.013	-6.060	-0.010
Visibility	0.310	0.000	0.019	16.380	0.034
Hourly Precipitation	-1.258	0.000	0.140	-8.960	-0.007
RSI	16.974	0.000	0.708	23.970	0.133
Volume to Capacity Ratio (V/C)	-4.325	0.004	2.966	-2.920	-0.004
Posted Speed Limit (80 km/hr)					
Posted Speed Limit (90 km/hr)	1.951	0.007	0.718	2.720	0.020
Posted Speed Limit (100 km/hr)	12.621	0.000	0.818	15.430	0.130
Site1					
Site2	-4.521	0.000	0.807	-5.600	-0.047
Site3	7.664	0.000	0.664	11.530	0.079
Site4	12.023	0.000	0.704	17.080	0.124
Site5	12.459	0.000	0.658	18.920	0.129
Site6	12.812	0.000	0.718	17.850	0.132
Site7	7.825	0.000	0.857	9.130	0.081
Site8	10.295	0.000	0.791	13.010	0.106
Site9	17.189	0.000	0.716	24.010	0.178
Site10	11.380	0.000	0.690	16.500	0.118
Site11	10.031	0.000	0.672	14.930	0.104
Site12	7.244	0.000	0.662	10.950	0.075
Site13					
Site14	8.408	0.000	0.600	14.010	0.087
Site15	9.897	0.000	0.807	12.270	0.102
Site16	8.411	0.000	0.817	10.300	0.087
Site17	15.273	0.000	0.926	16.490	0.158
Site18	0.740	0.276	0.679	1.090	0.008
Site19	13.331	0.000	0.676	19.720	0.138
Site20	8.230	0.000	0.720	11.430	0.085
Site21					
Observations	4822				
R-squared	0.5879				
Adj R-squared	0.5857				

The hourly model for rural sites is shown below:

$$\Delta V = -15.287 - 0.033 * WindSpeed + 0.246 * Visibility - 0.472 * Precipitation + 10.887 * RSI + 4.378 * V/C + 2.903 * Daylight \tag{2.21}$$

The hourly model for urban sites is shown below:

$$\Delta V = -22.192 + 0.420 * Temperature - 0.048 * WindSpeed + 0.527 * Visibility - 0.938 * Precipitation + 17.143 * RSI - 4.472 * V/C + 2.364 * Daylight \tag{2.22}$$

Some major findings include that for hourly based models, a 0.1 drop in RSI was correlated with a 1.09 km/h drop in median speed on rural highways while it is a 1.71 km/h drop for urban highways. For event based models, the same 0.1 drop in RSI was correlated with a 1.70 km/h drop in median speed.

Table 2.12 presents a summary of the literature related to which factors affecting winter traffic speed. While differing in research objectives, circumstances and data used, past studies have all confirmed that adverse winter weather has a negative effect on average traffic speed. However, there were inconsistency in the findings in terms of weather factors being significant and the size of the effects for these variables that were found significant. This is partially due to the different traffic and environmental characteristics of the study sites. It can also be caused by the sources and quality of the data used in these studies. Some of the limitations of previous studies include, firstly, most past studies focused on the differences in speed or other traffic variables between adverse and normal weather conditions using data under all weather conditions. Secondly, most of the past studies utilized linear regression models to quantify the effect of weather and surface condition variables on traffic speed, which cannot capture the possible non-linear effects of some factors. Thirdly, most studies focused on freeways only, in which the effect of weather on traffic speed could be easily confounded by traffic congestion, making the model less reliable. Lastly, few of the past studies have used large spatial/temporal coverage datasets and taken a full account of the variation in winter RSCs, and the results are therefore not immediately useful for showing the feasibility of using speed as a performance indicator of WRM.

Table 2.12 Summary of Literature Winter Traffic Speed Reduction

Source	RSC	Precipitation	Wind Speed	Temperature	Visibility
FHWA (1977)	3% for wet and snowing; 22% for wet and slushy; 30% for slushy in wheel paths; 35% for snowy and sticking; 42% for snowing and packed				
HCM (2010)		8-10% for light snow; 30-40% for heavy snow			
Ibrahim and Hall (1994)		3 km/h for light snow; 37.0 – 41.8 km/h (35-40%) for heavy snow			
Liang et al. (1998)	3-5 km/h for snow covered RSC		1.1 km/h for 1 km/h wind speed exceeded 40 km/h	2-4 km/h for 1 degree temperature reduction	3-5 km/h for 1 km visibility reduction
Knapp et al. (2000)	11.64 km/h for snow covered RSC				6.24 km/h if visibility is less than 0.4 km
Kyte et al. (2001)	10-16 km/h for wet/snow covered RSC		11 km/h if wind speed exceeded 24 km/h		0.77 km/h for every 0.01 km below 0.28km
Agrwal et al. (2005)		3-10% for light snow; 11-15% for heavy snow	No significant effect	No significant effect	6-12% for low visibility
Rakha et al. (2007)		5-16% for light snow; 5-19% for heavy snow			10% for a reduction from 4.8 to 0.0 km
Camacho et al. (2010)		9 km/h for light snow; 13.7 km/h for heavy snow	Has effect if goes beyond 8 m/s		Has large effect if visibility is low
Zhao et al. (2011)			1.3 km/h for each 10 km/h increase	1.58 km/h lower if temperatures below freezing	2 km/h for each 1 km reduction in visibility
Kwon et al. (2013)	Increased RSI (i.e., better road conditions) are correlated with increased FFS	1.8% and 13.5% for 2.0 mm/h and 15.0 mm/h snow			less than 5% if visibility is greater than 1 km

Donaher (2014)	Hourly: 1.09 km/h (rural) or 1.71 km/h (urban) for 0.1 drop of RSI; Event: 1.7km/h for 0.1 drop of RSI	Hourly: 0.47km/h (rural) or 0.97km/h (urban) drop for 1 cm increase Event: 1.3 km/h for 1 cm increase	Hourly: 0.33 km/h (rural) or 0.48km/h (urban) drop for 10km/h increase Event: 0.8km/h for 10km/h increase	Hourly: 4.2km/h (urban) for 10 degree increase Event: small effect	Hourly: 2.5km/h (rural) or 5.3km/h (urban) drop for 10km drop Event: 3.1km/h for each 10km/h drop

2.3 Winter RSC Monitoring and Estimation

Since many WRM performance measurements rely on the measures of RSC which has huge impact on road safety and mobility, it is of great importance for transportation agencies to monitor or estimate RSC during winter seasons. This section summarizes some major RSC monitoring and estimation technologies that are being used currently or proposed recently. Their pros and cons are discussed at the end of each subsection.

Traditionally, RSC is visually monitored and reported by highway maintenance or patrol staff during and after snow events. However, as mentioned in section 1.1, human report is labor intensive and lacks objectivity and repeatability, therefore is expensive and usually tends to be biased. With the development of modern sensing and network technologies, more and more RSC monitoring and estimation systems and methodologies have been proposed and developed. RSC indicators like road surface contaminant, contaminant type, temperature and friction can be measured by these sensors, and RSC can be inferred either directly or indirectly based on the measured indicators. By operation mechanism, RSC monitoring/estimation systems can be divided into two categories, namely stationary based and mobile based. Each category has its own advantages and disadvantages, and serves different purposes in terms of spatial and temporal coverage (Omer, 2011).

2.3.1 Stationary Based RSC Monitoring and Estimation

Stationary based systems rely on devices and infrastructure constructed at a fixed location close to highways for proper functioning. Video surveillance measuring, road weather information systems (RWIS) and spectral/optical sensor measuring are three typical stationary based RSC monitoring systems.

Video surveillance measuring refers to use close circuit television (CCTV) and web cams to collect RSC condition, and transfer data through the network to RSC monitoring staff and road users (Feng, 2013). Kido et al., (2002) introduced a CCTV based winter RSC monitoring and road management system as part of the local ITS project to the city of Sapporo, located in northern Japan. It was reported that the system effectively reduced the snow removal cost and significantly improved winter maintenance efficiency. Video surveillance is a good alternative to traditional methods as it does not require onsite patrolling and can continuously provide road information, however, because human judgment still plays an important role during the classification process, its reliability and classification objectivity are limited (Yamamoto et al., 2005).

RWIS, a combination of sensing technologies, however, does not rely on direct human judgment. It is capable of using both historical and current climatological data to provide real time road and weather condition, and aid in roadway-related decision making (http://www.aurora-program.org/rwis.cfm). With the environmental sensor systems (ESS), which is usually installed at the roadside or embedded in the roadway, RWIS is capable of collecting both weather and road surface data which can be transmitted and processed on a central server for reporting, forecasting, data archiving and distribution purposes. RWIS has been under continuous and active development in the past few years and is now the most widely adopted weather and road surface data collection system in North America. In spite of all the benefits that RWIS brought to road users, researchers and transportation agencies, the major limitation of RWIS is that its measurement is site-specific and cannot reflect the variation of RSC along highways. Moreover, the current installation cost of a single RWIS station with basic configuration is from $45,000 to $50,000 (CAD), which makes it financially difficult for transportation agencies to install RWIS stations with high spatial density along highways at this stage (Buchanan & Gwartz, 2005).

Another popular technique of stationary RSC monitoring is spectral/optical based sensing. The difference between video surveillance and spectral/optical sensing is that the latter not only utilizes visible spectrum to monitor RSC, but also applies built-in image detection algorithms or infrared band techniques. Yamamoto et al. (2005) studied the application of visible image road surface sensors for road surface management. According to the authors, the sensor can estimate RSC by applying image processing algorithms to road condition images captured by CCTV cameras, which makes it much easier for later judgment. Feng and Fu (2008) evaluated two new Vaisala sensors for road surface conditions monitoring located on highway 417, Ontario, Canada. Two infrared sensors are analyzed in the study, namely the Vaisala Remote Road Surface State Sensor (DSC111) and Vaisala Remote Road Surface Temperature Sensor (DST111). DSC111 is mainly used to detect RSC and DST111 is mainly used to detect road surface temperature. The validation shows that the matching rate of RSC measurements is over 85%, and the temperature measurements accuracy is generally high. The authors, however, also suggested that although Vaisala sensors have acceptable performance in terms of RSC and temperature monitoring, the spatial coverage of sampling area is limited and tend to underestimate the road surface condition severity while the road surface is snow or ice covered.

2.3.2 Mobile Based RSC Monitoring and Estimation

Mobile based RSC monitoring requires systems and devices that are installed on moving vehicles while functioning. It is significantly different with stationary based methodologies in terms of cost, modelling techniques, spatial and temporal coverage. Typical mobile based RSC monitoring systems include thermal mapping, friction based measuring and image detection based measuring.

Thermal mapping is the technology that utilizes an infrared thermometer mounted on the operating vehicle for sensing the temperature on road surfaces. Joshi (2002) investigated and developed a lightweight, vehicle-mounted RSC sensor system based on backscatter of infrared radiation emitted by an onboard light source from the road surface. The detected temperature signals are transmitted to an onboard computer, processed by a microprocessor and displayed on a map for visualization in real-time. The developed prototype was calibrated and tested in Hanover, New Hampshire, US. The results revealed that the prototype has the potential to discriminate RSC types, but still needs to be adjusted in many ways to retrieve better results. One concern of thermal mapping is that the road surface temperature is affected by various factors, e.g. air temperature, traffic volume, maintenance operations and is usually site specific. The reliability of using temperature as the only indicator of RSC is yet to be proven.

Friction based measuring is the estimation of RSC based on measurements of the friction coefficient between the vehicle tires and the road surface. Similar with road surface temperature, friction measures can be used to estimate RSC using modelling techniques. Perchanok (2002) utilized three friction related measures: peak resistance (F_p), slip speed at which the peak resistance occurs (V_{crit}) and locked wheel resistance (F_{60}) to estimate RSCs. Feng et al. (2010) applied continuous friction measurement (CFM), sample standard deviation (Std), sample skewness ($Skew$) of friction measurements as well as the mean spectral power of the frequency range 0.0-0.2 periods/point ($LowFreq$) and mean spectral power of 0.3-0.5 periods/point ($HighFreq$), and calibrated multi-layer logistic regression classification tree to classify different RSC types. Both of these studies have shown the high correlation between road friction and RSC and the reliability of using CFM as an indicator of different RSC types. Because of the high performance of friction based RSC estimation models, friction has been used in many European countries as a powerful tool for RSC monitoring and estimation (Norwegian Ministry of Transport and Communication, 2003). The main limitation of friction based models is data collection and quality. Firstly, as claimed by Omer (2011), the operation cost of friction data collection is high due to the high cost of equipment (e.g. friction trailer, dedicated vehicles and drivers for operation). Secondly, friction trailers, acceleration/deceleration based friction measurement devices or optical sensor based friction measurement devices all suffer the drawback of measuring only a particular lane of a highway. This makes it difficult to model highways with multiple lanes especially those with different traffic patterns on different lanes (Haavasoja et al., 2012).

Another mobile based RSC measuring technique is using image detection/processing approaches to estimate RSC with data collected by onboard cameras or sensors. A similar system was developed by Omer (2011). With the application of onboard digital cameras and SVM classification algorithm on the server, Omer's system is capable of collecting, transferring and classifying RSC images in real-time. The author stated that since digital cameras are relatively cheap, and the system supports real-time RSC classification, it has huge potential for application in the near future. Similarly, Kim et al. (2013) published research results on the development of mobile road surface condition detection system utilizing image processing. The authors installed stereo cameras, GPS, temperature and humidity sensors on a probe car to collect road surface images, location, temperature and humidity data, and applied K-means clustering algorithm to classify RSC types. Although the above research results have demonstrated the high potential of the image detection/processing techniques, it is still relatively new to the RSC monitoring and estimation sector. One of the issues of image detection/processing is that the classification accuracy highly depends on the quality of the images (e.g. environment light, exposure accuracy, resolution, speed of the vehicle, etc.). Further research needs to be done in order to improve the quality of image collecting hardware configuration and image pre-processing techniques.

2.4 Summary

In summary, compared with input and output measures, outcome measures can produce the most meaningful results. However, outcome measures are usually hard to model and highly depend on data quality and availability. Data collection of some popular outcome measures like bare pavement regain time is still subjective and costly. Further studies are needed to either improve the current measures or come up with alternative measures to avoid these problems.

As a potential alternative WRM performance measure, traffic speed can be easily obtained with high quality and reliability. Past studies have all confirmed that adverse winter weather has a negative effect on traffic speed. However, most studies have limitations in terms of modeling methodologies and spatial/temporal coverage. Firstly, most past studies focused on the differences in speed or other traffic variables between adverse and normal weather conditions using data under all weather conditions. Secondly, most of the past studies utilized linear regression models to quantify the effect of weather and surface condition variables on traffic speed, which cannot capture the possible non-linear effects of some factors. Thirdly, most studies focused on freeways only, in which the effect of weather on traffic speed could be easily confounded by traffic congestion, making the model less reliable. Lastly, few of the past studies have used large spatial/temporal coverage datasets and taken a full account of the variation in winter road surface conditions. The results are therefore not immediately useful for showing the feasibility of using speed as a performance indicator of WRM.

For RSC monitoring and estimation, many methodologies and new technologies have been proposed and developed in the past few years. However, most stationary based systems suffer from high installation and maintenance cost and lack of spatial coverage. Mobile based systems are also costly in terms of the investment on equipment and personnel, and are not feasible to provide measures with high temporal coverage. This study proposed a method to estimate RSC based on traffic and weather data which are much easier to collect compared with other RSC related factors. With the rapid development of smart phone technologies, this modelling technique has a high potential to utilize speed data, GPS data and weather data collected from road users' smart phones to generate real time RSC estimation with high spatial and temporal coverage, which may potentially have the benefits of both stationary and mobile based systems, and dramatically reduce the overall cost.

Chapter 3
Effect of Weather and Road Surface Conditions on Traffic Speed of Rural Highways

3.1 Problem Definition

In order to study the feasibility of using traffic speed as an alternative WRM performance measure, it is essential to understand the relationship between traffic speed and different types of RSC. However, this relationship could be easily confounded by other human or environmental factors such as traffic volume, type of the highway, weather condition and time of the day, etc. In addition, a large dataset with high spatial/temporal coverage is also required for modelling this relationship.

To address these challenges, the study presented in this chapter focuses on the impact of winter weather and RSC on the average traffic speed of rural highways. Detailed data on weather, RSC, time of day, and traffic over three winter seasons from 35 rural highway sites in the State of Iowa, US, are used for this investigation. Three modeling techniques are applied and compared for modeling the relationship between traffic speed and various road weather and surface condition factors, including multivariate linear regression, Artificial Neural Network (ANN) and time series analysis.

3.2 Data Collection

This analysis was performed using three datasets: traffic, weather and surface condition, over three winter seasons from 2008 to 2011 collected from 35 rural highway sites in the State of Iowa, US. As shown in Figure 3.1, among the 35 sites, 14 are located on two-lane highways (shown in green) while 21 are located on four-lane highways (shown in blue).

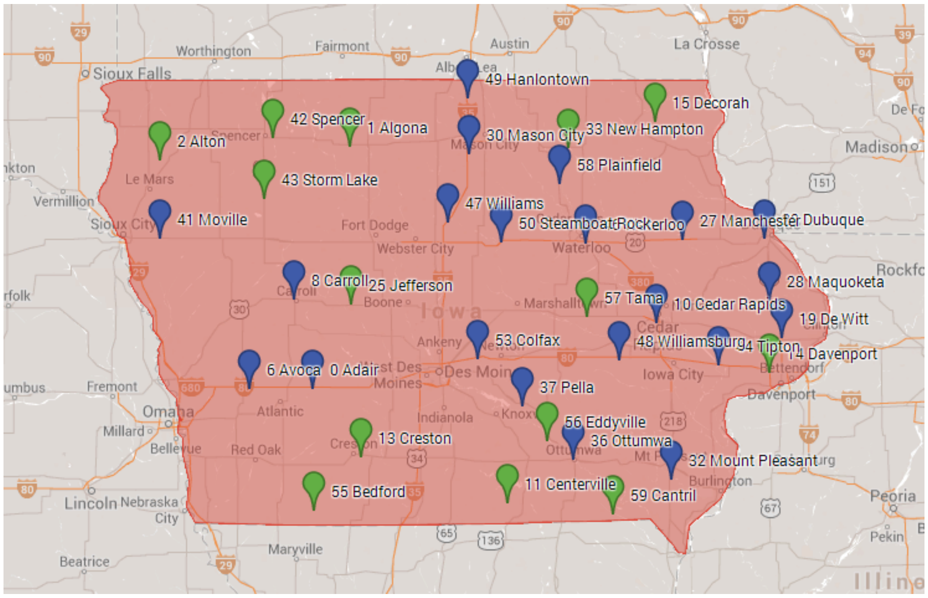

Figure 3.1 Study Sites in Iowa

The traffic, road weather, as well as RSC at each of these sites are monitored by a RWIS station located at a roadside. The traffic sensors are all radar detectors installed on the RWIS towers and can provide traffic speed and volume data. The RWIS weather sensors provide observations on atmosphere. The RWIS pavement sensors are embedded in the pavement and connected to the main tower by cables, and can provide RSC data of the site. Most of the traffic records have a time interval of 2 minutes while the time interval of the atmosphere and surface data ranges from 9 minutes to over 30 minutes with a majority of 10 minutes. Traffic data contains normal traffic volume, percentage of long traffic volume (i.e. truck and recreational vehicles) and average traffic speed. Atmosphere data includes precipitation, visibility, air temperature, and wind speed. Precipitation is given in two forms, precipitation intensity in centimeters per hour and categorical description of intensity, light snow (< 0.25 cm/15 min), moderate snow (0.25-0.755 cm/15 min) and heavy snow (>0.755 cm/15 min). RSC data includes surface temperature and road surface states with the following six types in order of severity from lowest to highest:

- Dry (moisture free surface, bare pavement)
- Trace Moisture (thin or spotty film of moisture above freezing and detected in absence of precipitation)

- Wet (continuous film of moisture on the pavement sensor with a surface temperature above freezing as reported when precipitation has occurred)
- Chemically Wet (continuous film of water and ice mixture at or below freezing with enough chemical to keep the mixture from freezing, it is also reported when precipitation has occurred)
- Ice Watch (thin or spotty film of moisture at or below freezing and reported when precipitation is not occurring)
- Ice Warning (continuous film of ice and water mixture at or below freezing with insufficient chemical to keep the mixture from freezing again, reported when precipitation occurs)

3.3 Data Processing

The dataset used in this analysis is collected by RWIS and traffic sensors. Due to software and hardware failures, the raw dataset may contain errors and outliers; therefore, cannot be used directly for this analysis. This section presents a data pre-processing framework developed for this dataset and a snow event extraction algorithm used to extract snow events from the data. Both the data processing framework and the snow event extraction algorithm can be easily modified to be applied to other datasets.

3.3.1 Data Processing Framework

For spatial aggregation, many previous traffic studies combined both directions together and developed site specific models based on the combined datasets. However, because driving habits, traffic patterns and surface conditions may be different in different directions of the same site, the effect of RSC on traffic speed on different directions may also have a big difference. To address this problem, this study separates the traffic and surface data collected on different directions from the same site, and calibrates models for each direction respectively. In other words, after the three data sources were aggregated, each sample was averaged over the lane based on the directional flow of traffic. Corresponding directional RSC data was used for each direction.

For temporal aggregation, as the three types of data were collected separately by different sensors, it is necessary to aggregate them based on a consistent time interval. In this study, both 15 minute and

60 minute intervals were selected to aggregate these three datasets. Note that the 15 minute and 60 minute intervals are also commonly used in many other traffic studies.

Figure 3.2 shows the data processing framework which is developed with the programming language Python. Algorithms Atmospheric, Surface, and Traffic clean up atmosphere, surface and traffic datasets, respectively, and remove obvious outliers and errors such as those with zero speed and volume as well as those attribute values do not make intuitive sense or exceeded low limit or high limit specified in the metadata file. TrafficCombine calculates directional average speed and volume. ATSFAggregate algorithm aggregates atmosphere and surface data into a single table based on time and surface sensor ID. TrafficAggregate algorithm converts the traffic data into a dataset with 15 minute or 60 minute time intervals and generates standard deviation of traffic speed, time of day etc. for each interval. AllAggregate is the core algorithm that combines all three data sources into a single table based on time and surface ID/lane ID, and generates the average temperature, wind speed and precipitation rate, etc. EventExtraction generates snow events utilizing an event generation algorithm which will be discussed in detail in the next section. Finally, GenerateAnalysis creates dummy variables of categorical variables, and changes the format of the data to make it analysis ready. All algorithms have been developed with flexibility to accept time intervals and site IDs as parameters to control the data processing and generate customized results.

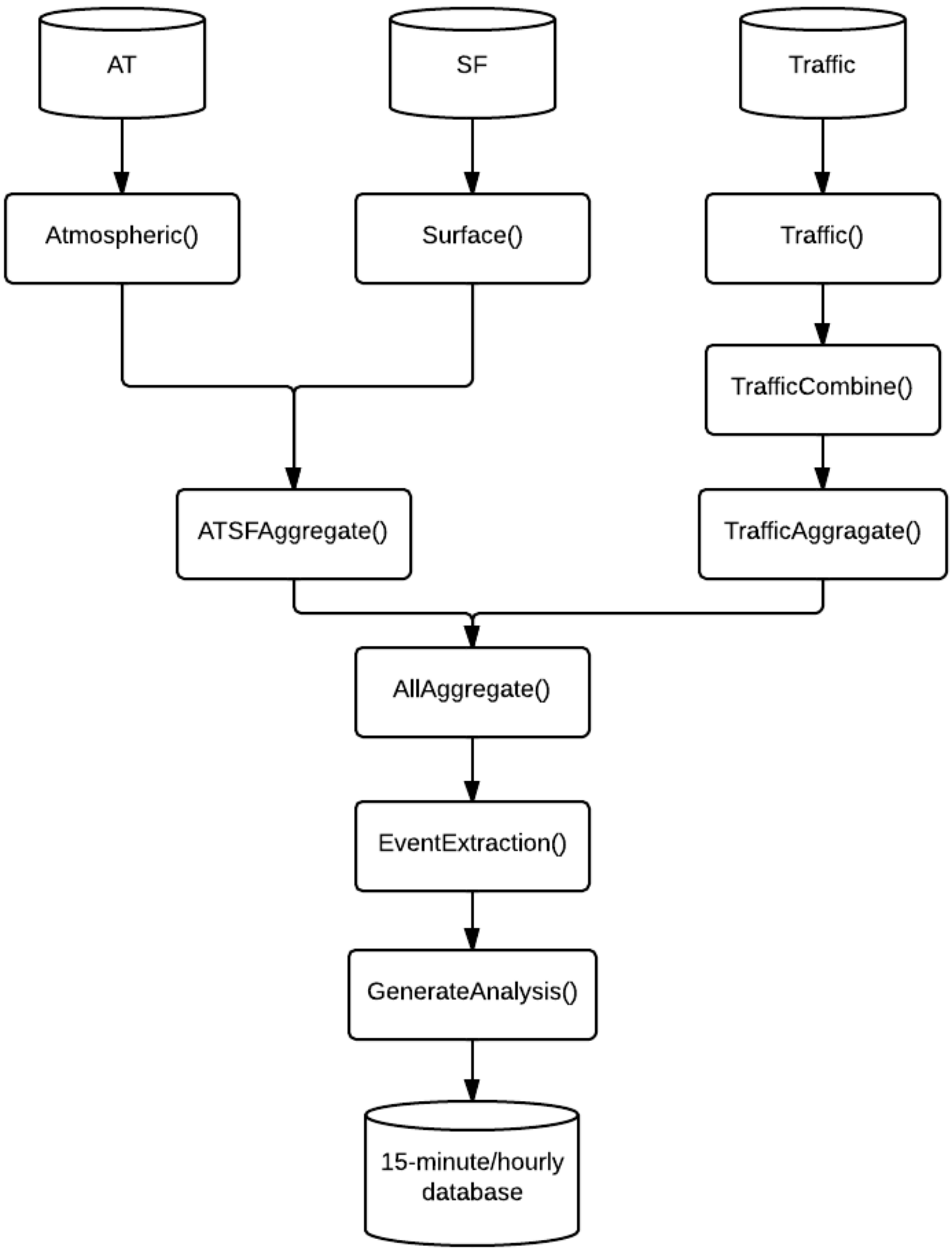

Figure 3.2 Data Processing Framework

Table 3.1 shows the data fields and units included in the final data table after applying the data processing framework. Note that dummy variables of categorical fields are generated and appended to the end of each row before the analysis.

Table 3.1 Summary of Final Data Fields

Data Source	Field Name	Unit	Note
General	System ID	N/A	System ID, i.e. 512
	Station ID	N/A	Station ID
	Station Name	N/A	Station Name
	Latitude	degrees	Latitude of the site
	Longitude	degrees	Longitude of the site
	Date & Time	N/A	Date and time
	Direction ID	N/A	Direction ID of the highway, e.g. 0 or 1
Traffic	Average Speed	km/h	Average speed over 15 minutes or 60 minutes
	Average Volume	veh/ln/h	Average total volume over 15 minutes or 60 minutes
	% Long Vehicles	percent	Percent of long vehicles
	SD of Speed	veh/ln/h	Standard deviation of speed over 15 minutes or 60 minutes
Atmosphere	Atmosphere Sensor ID	N/A	Atmosphere sensor ID
	Air Temperature	celsius	Average air temperature over 15 minutes or 60 minutes
	Wind Speed	km/h	Average wind speed over 15 minutes or 60 minutes
	Precipitation Type	categories	Precipitation Type (None or Snow)
	Precipitation Intensity	categories	Precipitation Intensity (None, Slight, Moderate or Heavy)
	Precipitation Rate	cm/h	Average precipitation rate over 15 minutes or 60 minutes
Surface	Surface Sensor ID	N/A	Surface sensor ID
	Surface Condition	categories	RSC types (Dry, Trace Moisture, Wet, Chemically Wet, Ice Watch or Ice Warning)
	Surface Temperature	celsius	Surface temperature
Others	Time of Day	categories	Day (6:00am – 6:00pm) Night (6:00pm – 6:00am)
	Event ID	N/A	The ID of each event

3.3.2 Snow Event Definition and Extraction

In this study, a snow event extraction algorithm was proposed and developed based on the data available in the datasets. To study the impact of both weather and RSC on traffic speed, snow events should not only include the periods with snow precipitation, but also include those with continuous ice/snow covered RSC during and after snow precipitation.

Figure 3.3 shows the definition of a snow event and the processes of the algorithm. The algorithm uses precipitation type equals snow as the start of each event, and then checks if snow or Ice Watch/Ice Warning surface condition occurs within the next hour (i.e. continuous snow precipitation or the RSC is ice/snow covered during or after a snow event). If any of these cases happens, the algorithm adds the next hour of data to the event bucket, and then repeats the process. If none of these cases happen, the algorithm will add one more hour of non-event data before and after the snow event to the event bucket, and write all data in the event bucket to an event file, the final output of the algorithm. Finally, the algorithm checks if this is the end of the file, if yes, save the event file and stop the process; otherwise, move to the next data row and repeat the whole process again.

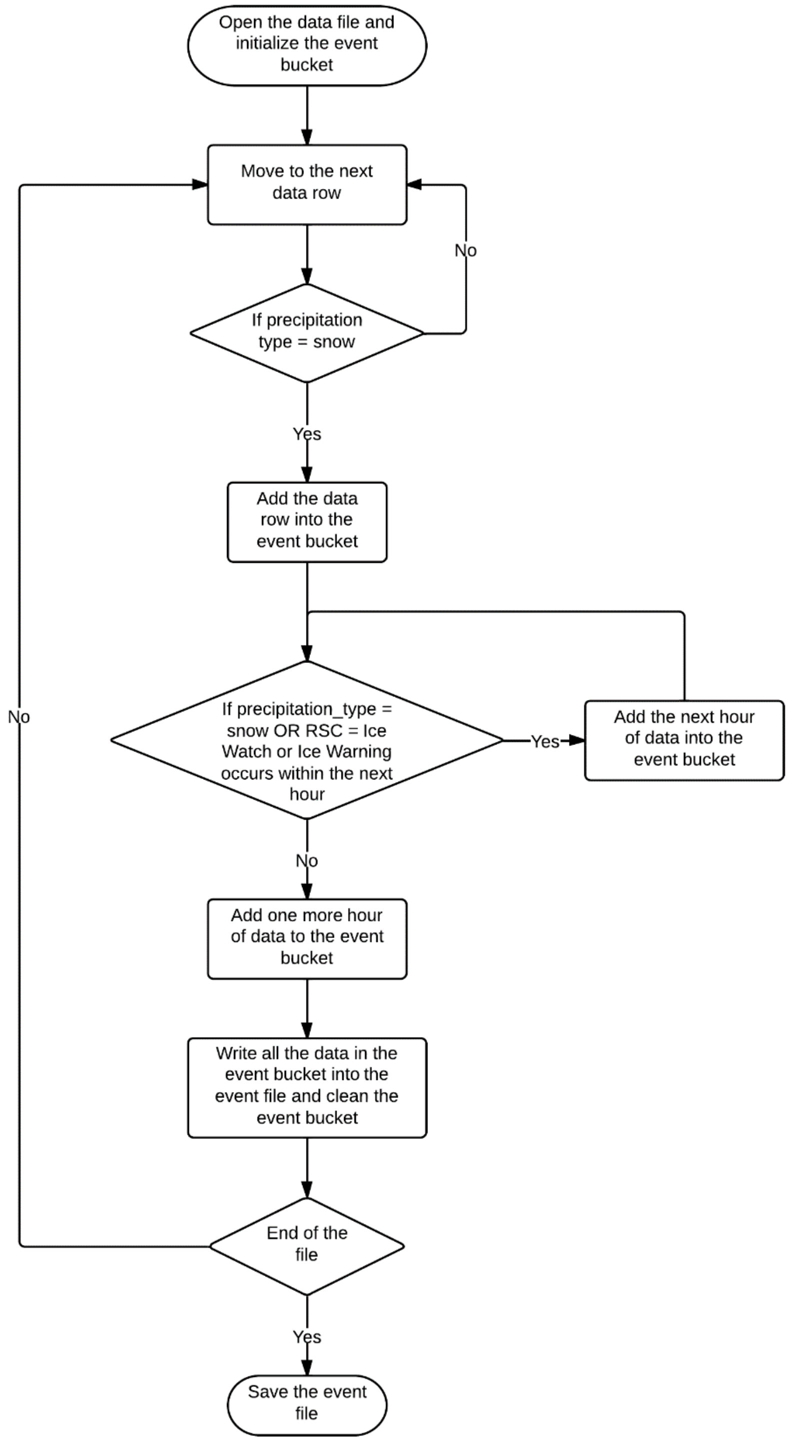

Figure 3.3 Snow Event Extraction Algorithm

3.4 Exploratory Analysis

Before proceeding with modelling, an exploratory data analysis was performed on the dataset to investigate the patterns of the data, potential outliers and correlation between variables. It was found that air temperature and surface temperature are highly correlated (i.e. 0.85 and 0.77 for two-lane and four-lane highways, respectively). Hence air temperature is removed from the dataset and is not considered in the subsequent modelling analysis.

Summary statistics are subsequently generated. Table 3.2 shows the summary statistics of all numerical variables that will be used in this analysis with different highway types and time intervals. Table 3.3 shows the sample size of each categorical variable. Table 3.4 and 3.5 show the sample size percentage of each site among all the sites of the same highway type.

As can be seen in Table 3.2, most summary statistics are identical for both 15 minute and 60 minute datasets, except that the standard deviations of the 15 minute datasets are higher than those of the 60 minute dataset. It can also be found that four-lane highways have relatively higher average speed and average volume than two-lane highways. Although the maximum volume for some highways (Site 13, 14 and 48) are relatively high (e.g. over 2500 veh/ln/h), the average volume for both two-lane and four-lane highways are only around 100 veh/ln/h and 300 veh/ln/h respectively. All highways have a maximum average volume equal to or under capacity, therefore traffic on these highways can be considered as free flow conditions. As can be found in Table 3.3, for both types of highways, the majority of precipitation intensity is none and slight snow. Ice watch is the most common category of surface condition, and dry is the second. Precipitation type and time of day are almost evenly distributed for the two categories, respectively. Table 3.4 and 3.5 reveals that data samples are almost evenly distributed among all the sites/directions for both highways types.

Table 3.2 Summary Statistics

15-Minute Interval									
		Two-Lane (67830 Obs.)				**Four-Lane (124314 Obs.)**			
Field Name	**Unit**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**
Average Speed	km/h	8.04	149.64	81.33	14.55	11.26	140.38	95.93	19.55
Average Volume	veh/ln/h	30.00	2730.00	111.42	84.15	30.00	4140.00	332.66	326.19
% Long Vehicles	%	0%	50%	18%	16%	0%	50%	31%	14%
Wind Speed	km/h	0.00	85.00	16.05	9.97	0.00	87.00	16.44	10.67
Precipitation Rate	cm/h	0.00	77.98	0.07	0.85	0.00	81.92	0.12	1.31
Visibility	km	0.00	114.26	34.20	43.56	0.00	162.54	13.11	27.81
Surface Temperature	Celsius	-30.15	36.35	-4.89	5.02	-24.80	39.55	-4.57	5.73
60-Minute Interval									
		Two-Lane (15905 Obs.)				**Four-Lane (30507 Obs.)**			
Field Name	**Unit**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**
Average Speed	km/h	8.04	145.97	80.00	14.48	11.26	136.87	93.86	19.39
Average Volume	veh/ln/h	30.00	2610.00	116.59	81.17	30.00	3930.00	309.37	302.78
% Long Vehicles	%	0%	50%	20%	14%	0%	50%	32%	14%
Wind Speed	km/h	0.00	85.00	16.44	10.43	0.00	70.00	16.35	10.88
Precipitation Rate	cm/h	0.00	49.55	0.09	0.83	0.00	62.75	0.13	1.12
Visibility	km	0.00	114.26	35.11	43.30	0.00	162.54	12.42	26.79
Surface Temperature	Celsius	-29.50	34.15	-5.05	4.92	-24.83	38.80	-4.98	5.68

Table 3.3 Categorical Variable Sample Size

	15-Minute Interval				
Field Name	Categories	Two-Lane		Four-Lane	
		Size	%	Size	%
Precipitation Intensity	None	32074	47.29%	58207	46.82%
	Slight	34445	50.78%	63014	50.69%
	Moderate	957	1.41%	2375	1.91%
	Heavy	354	0.52%	718	0.58%
Surface Condition	Dry	11756	17.33%	33726	27.13%
	Trace Moisture	2176	3.21%	6006	4.83%
	Wet	5299	7.81%	7495	6.03%
	Chemically Wet	2592	3.82%	3279	2.64%
	Ice Watch	42918	63.27%	69761	56.12%
	Ice Warning	3089	4.55%	4047	3.26%
Precipitation Type	None	32074	47.29%	58207	46.82%
	Snow	35756	52.71%	66107	53.18%
Time of Day	Day	37278	54.96%	66715	53.67%
	Night	30552	45.04%	57599	46.33%
	60-Minute Interval				
Field Name	**Categories**	**Two-Lane**		**Four-Lane**	
		Size	**%**	**Size**	**%**
Precipitation Intensity	None	5973	37.55%	11248	36.87%
	Slight	9487	59.65%	18292	59.96%
	Moderate	322	2.02%	737	2.42%
	Heavy	123	0.77%	230	0.75%
Surface Condition	Dry	2430	15.28%	7281	23.87%
	Trace Moisture	520	3.27%	1403	4.60%
	Wet	1165	7.32%	1733	5.68%
	Chemically Wet	635	3.99%	752	2.47%
	Ice Watch	10469	65.82%	18295	59.97%
	Ice Warning	686	4.31%	1043	3.42%
Precipitation Type	None	5973	37.55%	11248	36.87%
	Snow	9932	62.45%	19259	63.13%
Time of Day	Day	9072	57.04%	16988	55.69%
	Night	6833	42.96%	13519	44.31%

Table 3.4 Site Sample Size Percentage (15-Minute Interval)

Two-Lane					Four-Lane				
	Direction 0		Direction 1			Direction 0		Direction 1	
Site	**Size**	**%**	**Size**	**%**	**Site**	**Size**	**%**	**Size**	**%**
01	1419	2.09%	1451	2.14%	**00**	2439	1.96%	2842	2.29%
02	5033	7.42%	5263	7.76%	**06**	472	0.38%	709	0.57%
11	1902	2.80%	2027	2.99%	**08**	2596	2.09%	2310	1.86%
13	981	1.45%	1254	1.85%	**10**	1931	1.55%	2072	1.67%
15	3531	5.21%	3722	5.49%	**14**	5072	4.08%	4925	3.96%
25	4729	6.97%	4386	6.47%	**19**	1247	1.00%	1397	1.12%
33	4043	5.96%	4581	6.75%	**20**	3227	2.60%	3186	2.56%
42	295	0.43%	311	0.46%	**27**	2581	2.08%	2228	1.79%
43	796	1.17%	804	1.19%	**28**	1565	1.26%	2104	1.69%
55	1932	2.85%	1951	2.88%	**30**	2601	2.09%	3103	2.50%
56	4271	6.30%	4460	6.58%	**32**	1325	1.07%	1177	0.95%
57	3539	5.22%	3707	5.47%	**36**	4252	3.42%	4444	3.57%
59	749	1.10%	693	1.02%	**37**	7131	5.74%	6236	5.02%
Total			67830	100%	**41**	1825	1.47%	2599	2.09%
					44	371	0.30%	333	0.27%
					46	1441	1.16%	2956	2.38%
					47	3933	3.16%	3175	2.55%
					48	2970	2.39%	2818	2.27%
					49	4792	3.85%	4963	3.99%
					50	2586	2.08%	1943	1.56%
					53	3859	3.10%	3868	3.11%
					58	3552	2.86%	3158	2.54%
					Total			124314	100%

Table 3.5 Site Sample Size Percentage (60-Minute Interval)

Two-Lane					Four-Lane				
	Direction 0		Direction 1			Direction 0		Direction 1	
Site	**Size**	**%**	**Size**	**%**	**Site**	**Size**	**%**	**Size**	**%**
01	328	2.06%	328	2.06%	**00**	526	1.72%	573	1.88%
02	1149	7.22%	1208	7.60%	**06**	148	0.49%	212	0.69%
11	415	2.61%	428	2.69%	**08**	691	2.27%	604	1.98%
13	256	1.61%	342	2.15%	**10**	457	1.50%	457	1.50%
15	773	4.86%	823	5.17%	**14**	1074	3.52%	1082	3.55%
25	1177	7.40%	1084	6.82%	**19**	326	1.07%	385	1.26%
33	1049	6.60%	1112	6.99%	**20**	736	2.41%	736	2.41%
42	65	0.41%	65	0.41%	**27**	715	2.34%	634	2.08%
43	150	0.94%	152	0.96%	**28**	513	1.68%	646	2.12%
55	542	3.41%	565	3.55%	**30**	568	1.86%	677	2.22%
56	865	5.44%	848	5.33%	**32**	372	1.22%	358	1.17%
57	902	5.67%	908	5.71%	**36**	987	3.24%	1045	3.43%
59	188	1.18%	183	1.15%	**37**	1711	5.61%	1570	5.15%
Total			15905	100%	**41**	523	1.71%	666	2.18%
					44	75	0.25%	69	0.23%
					46	564	1.85%	777	2.55%
					47	859	2.82%	764	2.50%
					48	702	2.30%	679	2.23%
					49	1182	3.87%	1209	3.96%
					50	659	2.16%	574	1.88%
					53	827	2.71%	838	2.75%
					58	890	2.92%	847	2.78%
					Total			30507	100%

3.5 Methodology

3.5.1 Multivariate Linear Regression

In order to quantify the impact of adverse weather and surface factors on traffic speed, a multivariate linear regression analysis is carried out in this study. With the intention of investigating the feasibility of using traffic speed as an alternative measure of WRM, the regression models should be capable of revealing the relationship between traffic speed and weather and surface factors, especially the significance of RSC with the minimum confounding effects of traffic volume. For rural highways, traffic speed is less likely to be affected by volume due to lack of traffic congestion, thus making the models more reliable than using urban highways. This has been confirmed in the exploratory data analysis in the previous section.

Different directions of the same highway may have different traffic patterns, therefore with the 15 minute and 60 minute time intervals, a set of models are developed separately for both directions of each study site, and two combined models for all sites of the same type of highways are also developed for both two-lane and four-lane highways. This results in 144 models in total. The reason for developing combined models is that the effect of most external factors on speed is expected to be similar for a given type of highway. In addition, a combined model is expected to be more generalizable or transferable than a highway specific model.

Table 3.6 summaries the three dimensions of the regression analysis which includes aggregation interval, highway type and model type. The goal of setting these dimensions is to firstly investigate the impact of each dimension on the performance of the regression model; secondly, to find out similarities and improve the simplicity of the models; and thirdly, to find out the best modeling methodology that fits a specific dataset, which can also be used in the following advanced analysis.

Table 3.6 Dimensions of the Regression Analysis

Name	**Dimensions**
Aggregation Interval	15 minutes vs. 60 minutes
Highway Type	Two-Lane vs. Four-Lane
Model Type	Separated vs. Combined

The effect of precipitation on speed is tested in two representation forms, namely, categorical (precipitation intensity) and continuous (precipitation rate). It is found that the categorical form results in a higher explanation power, i.e., higher adjusted R^2 value suggesting its non-linear effect on traffic speed. Categorical form is thus used in the final models.

For each categorical variable such as RSC, dummy variables are created, and a base category is defined in advance. "Dry", "No Snow" and "Day" are used for RSC, precipitation intensity and Day/Night as the initial base conditions, respectively. Note that in the actual calibration, a combination of base conditions will be used if two or more categories show the similar effect with the initial base condition or not statistically significant compared with it. For example, as the effect of dry, trace moisture, wet and chemically wet are almost zero at Site 01 direction 0, the base condition, therefore, is the combination of all these four conditions.

For site variables in the combined models, dummy variables are also created for each site. Site 01 (direction 0) and Site 00 (direction 0) are used as base sites for the two-lane combined and four-lane combined models, respectively.

The statistical significance of each variable is decided using a significance level of 5%. Any variables with a p-value greater than 5% or that do not make intuitive sense are eliminated sequentially from the model. The data set from each direction of each site is divided into two parts randomly: one includes 90% of the data to be used for model calibration and the remaining 10% of data is held out for subsequent model validation. The overall performance of the regression model is assessed using adjusted R^2 and Root Mean Square Error (RMSE).

3.5.2 Artificial Neural Network

ANN is a non-parametric method for modelling complex non-linear relationships. Unlike regression models that need an explicitly defined function to relate the input and the output, the ANN can approximate a function and associate input with specific output through the process of training. Therefore, ANN can be used to evaluate the robustness of regression models (Martin et al., 1995).

In this study, multi-layer perceptron neural network (MLP-NN), the most commonly used ANN, is selected for modeling the relationship between traffic speed and various influencing factors. As can be seen in Figure 3.4, MLP-NN consists of an input layer, one or more hidden layers, and an output layer. The input layer includes input nodes representing the weather, road and traffic factors which is the same as the independent variables used in a regression model, while the output layer includes the dependent variable to be predicted, i.e., traffic speed. The hidden layer provides a mechanism to transfer inputs to output through activation functions and weights (Martin et al., 1995). In this research, the popular sigmoid function is selected as the activation functions for the hidden layers, and a linear activation function is selected for the output layer. The weights of MLP-NN are calibrated by a back propagation algorithm with a learning rate of 0.1 and a momentum of 0.8. The back propagation algorithm minimizes the sum of squared deviation of the output from the target value at the nodes of the output layer by adjusting the value of weight at the nodes. For the sake of comparison, the significant independent variables found in the combined regression analysis will be used as the input factors of the MLP-NN.

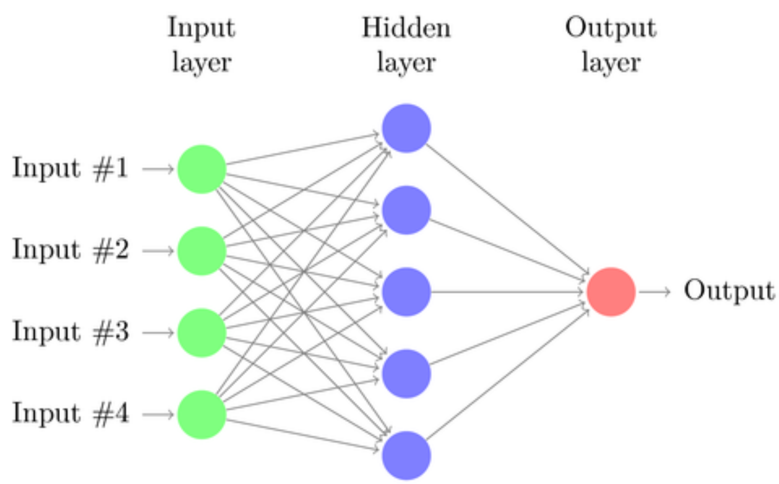

Figure 3.4 Typical MLP-NN Architecture (Huang & Ran, 2003)

3.5.3 Time Series Analysis

The data used in this research consists of a time series of observations over various snowstorm events. The observations within each event could therefore be correlated to each other due to the similarity in weather and environmental conditions. This auto correlation violates the assumption of randomness and independency between observations required by the multivariate regression method. To address this issue, time series analysis is attempted to explicitly model the correlation between successive observations by considering the effect on current behavior of variables in terms of linear relationships with their past values (Wei, 1989). In this research, one of the most popular time series models - univariate autoregressive integrated moving average (ARIMA) with additional exogenous variables (ARIMAX) - is utilized for predicting the traffic speed based on traffic volume, weather and surface data. Since the focus of this study is to investigate the speed variation during snow events, adjacent events are stitched together in model calibration.

According to Shumway and Stoffer (2006), a combination of an autoregressive integrated (AR(*p*)) process and a moving average (MA(*q*)) process is called ARMA(*p*,*q*), which can be expressed as below:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \omega_t + \theta_1 \omega_{t-1} + \cdots + \theta_q \omega_{t-q} \tag{3.1}$$

Where

x_t is a stationary time series

ω_t is white noise $N(0, \sigma^2)$

ϕ and θ are coefficients of the model

The above equation can be written in vector form:

$$\boldsymbol{\phi}(\boldsymbol{B})\boldsymbol{x_t} = \boldsymbol{\theta}(\boldsymbol{B})\boldsymbol{\omega_t} \tag{3.2}$$

If a *d* order differencing is added, the general form of ARIMA(*p, d, q*) model is given below:

$$\boldsymbol{\phi}(\boldsymbol{B})(\boldsymbol{1} - \boldsymbol{B})^{d}\boldsymbol{x_t} = \boldsymbol{\theta}(\boldsymbol{B})\boldsymbol{\omega_t} \tag{3.3}$$

Where

x_t is a stationary time series

ω_t is white noise $N(0, \sigma^2)$

B is the back slash operator, $Bx_t = x_{t-1}$

$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$

p is the number of autoregressive terms

d is the number of non-seasonal differences

q is the number of lagged forecast errors in the prediction equation

The ARMAX model is extended from general ARMA model by adding additional exogenous/explanatory variables. The general form of the ARMAX model is given below:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \omega_t + \theta_1 \omega_{t-1} + \cdots + \theta_q \omega_{t-q} + \Gamma \mathrm{U_t} \tag{3.4}$$

Where

x_t is a stationary time series (speed at time t)

ω_t is white noise $N(0, \sigma^2)$

ϕ and θ are coefficients of the model

$\mathrm{U_t}$ is the vector of exogenous variables (explanatory variables including AR, MA, weather and surface variables)

Γ is the coefficient vector of exogenous variables

The above equation is equivalent to:

$$\phi(B) x_t = \theta(B) \omega_t + \Gamma \mathrm{U_t} \tag{3.5}$$

If a d order differencing is added, the general form of ARIMAX(p, d, q) model is given below:

$$\phi(B)(1 - B)^d x_t = \theta(B) \omega_t + \Gamma \mathrm{U_t} \tag{3.6}$$

Where

x_t is a stationary time series

ω_t is white noise $N(0, \sigma^2)$

B is the back slash operator, $B x_t = x_{t-1}$

$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$

$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$

p is the number of autoregressive terms

d is the number of non-seasonal differences

q is the number of lagged forecast errors in the prediction equation

U_t is the vector of exogenous variables (explanatory variables including AR, MA, weather and surface variables)

Γ is the coefficient vector of exogenous variables

If the time series is non-stationary, it must be transformed into a stationary time series by the method of differencing first. This can be determined using autocorrelation factor (ACF) and partial autocorrelation factor (PACF). The model parameters are estimated using a maximum likelihood method with 95% confidence level. Therefore, covariates, AR and MA variables of different time lags with p-values greater than 0.05 are excluded.

3.6 Model Calibration

3.6.1 Multivariate Linear Regression

Statistical software R is used to calibrate the multivariate linear regression models. Appendix A-1 to A-4 shows the models developed for individual study sites. The average traffic speed constant of all two-lane highways are below 100 km/h while most four-lane highways have the average traffic speed constantly over 110 km/h. This makes sense as four-lane highways normally have a higher level of service than two-lane highways. Significant factors for highways of the same type are mostly identical: average volume, wind speed, all precipitation intensity categories, chemically wet, ice watch and ice warning are statistically significant and make intuitive sense for most two-lane highways. Average volume, % long vehicles, wind speed, all precipitation intensity categories, chemically wet, ice watch, ice warning and night are statistically significant and make intuitive sense for most four-lane highways. In terms of model performance, in general, four-lane highways have relatively higher adjusted R^2 (about 0.45 on average) than two-lane highways (about 0.25 on average). The reason is because four-lane highways have a relatively higher volume (larger sample size) which leads to less variation in average traffic speed while two-lane highways have higher variation in average traffic speed between vehicles due to a smaller sample size.

Table 3.7 and 3.8 show the combined models for two-lane and four-lane highways, respectively. For two-lane combined, except % long vehicles and night, all the variables are statistically significant and make intuitive sense for both 15 minute and 60 minute models. The adjusted R^2 of the 60 minute model is 0.34 which is slightly higher than the value of the 15 minute model (0.31). Both values are higher than the average adjusted R^2 generated by the separated models (about 0.25). The RMSE are 12.06 and 11.74 for the 15 minute and 60 minute model, respectively.

For four-lane combined, surface temperature and trace moisture are not significant for the 15 minute model while surface temperature, trace moisture and visibility are found not significant for the 60 minute model. Similar with two-lane models, the adjusted R^2 of both 15 minutes (0.68) and 60 minutes (0.70) are increased significantly compared with separated models (about 0.45). The RMSE are 11.01 and 10.64 for the 15 minute and 60 minute model, respectively.

The results above confirmed that, firstly, combined models have advantages over separated models and are acceptable to be used to estimate average traffic speed for most study sites. The adjusted R^2 of the combined models are higher than most separated models for both highway types. In addition, due to the lack of data on certain types of categorical variables at some sites, some categories' coefficients are zero in the separated models. For example, heavy snow for Site 20 and ice warning for Site 06 were observed rarely, which results in zero coefficients. With the combined models, this type of relationship could be captured utilizing the data from other sites of the same highway type. Secondly, the 60 minute models' performance is higher than the 15 minute model. Although the 15 minute models can generate average traffic speed estimations with higher temporal resolution, 60 minute models are based on smoother and more generalized dependent and independent variables and their adjusted R^2 are higher than the 15 minute models.

Based on these two conclusions, the combined models will be used to analyze the effects of each variable on average traffic speed, and the combined datasets with 60 minute time interval will be used in the subsequent ANN and time series analysis model calibration.

Table 3.7 Regression Model Calibration Results for Two-Lane Highways Combined

	15 Minutes Interval				60 Minutes Interval			
	Coef.	**Std. Error**	**t-value**	**P-value**	**Coef.**	**Std. Error**	**t-value**	**P-value**
(Intercept)	94.85	0.37	258.22	0.00	96.40	0.76	126.63	0.00
Average Volume	-0.01	0.00	-8.17	0.00	-0.01	0.00	-7.90	0.00
% Long Vehicles								
Wind Speed	-0.13	0.01	-25.89	0.00	-0.15	0.01	-15.41	0.00
Visibility	0.03	0.00	19.49	0.00	0.04	0.00	10.94	0.00
Surface Temp	0.05	0.01	4.49	0.00	0.10	0.02	4.16	0.00
Slight	-5.12	0.10	-52.82	0.00	-4.65	0.20	-22.92	0.00
Moderate	-13.14	0.41	-32.33	0.00	-10.52	0.70	-15.06	0.00
Heavy	-32.25	0.67	-48.09	0.00	-28.08	1.13	-24.87	0.00
Trace Moisture	-0.60	0.30	-1.99	0.05	-2.24	0.60	-3.71	0.00
Wet	-1.22	0.22	-5.68	0.00	-1.94	0.45	-4.31	0.00
Chemically Wet	-4.31	0.27	-16.11	0.00	-5.54	0.54	-10.34	0.00
Ice Watch	-7.81	0.13	-58.18	0.00	-9.13	0.28	-32.55	0.00
Ice Warning	-10.02	0.27	-37.80	0.00	-12.19	0.54	-22.48	0.00
Night	0.00		0.00		0.00		0.00	
01-1	-1.13	0.45	-2.51	0.01	-0.85	0.92	-0.93	0.35
02-0	-3.87	0.38	-10.32	0.00	-4.29	0.76	-5.63	0.00
02-1	-3.26	0.37	-8.73	0.00	-3.90	0.76	-5.14	0.00
11-0	-1.93	0.43	-4.49	0.00	-2.71	0.88	-3.08	0.00
11-1	2.05	0.43	4.83	0.00	1.64	0.88	1.87	0.06
13-0	-11.86	0.52	-22.98	0.00	-12.98	1.01	-12.82	0.00
13-1	-10.77	0.49	-22.15	0.00	-14.63	0.95	-15.34	0.00
15-0	3.28	0.39	8.43	0.00	3.64	0.79	4.59	0.00
15-1	2.47	0.39	6.41	0.00	2.50	0.79	3.18	0.00
25-0	-6.75	0.37	-18.15	0.00	-7.51	0.75	-10.02	0.00
25-1	-8.85	0.37	-23.69	0.00	-9.77	0.75	-13.00	0.00
33-0	-2.11	0.38	-5.51	0.00	-2.36	0.76	-3.08	0.00
33-1	1.14	0.38	3.02	0.00	0.78	0.76	1.02	0.31
42-0	-1.04	0.78	-1.32	0.19	0.78	1.61	0.48	0.63
42-1	-1.12	0.77	-1.46	0.14	0.66	1.61	0.41	0.68
43-0	-25.40	0.54	-46.93	0.00	-24.60	1.17	-20.98	0.00
43-1	-27.29	0.54	-50.60	0.00	-26.71	1.17	-22.89	0.00
55-0	2.90	0.43	6.82	0.00	2.73	0.83	3.30	0.00
55-1	4.78	0.42	11.26	0.00	3.97	0.82	4.82	0.00
56-0	-9.82	0.38	-25.99	0.00	-9.57	0.78	-12.34	0.00
56-1	-3.07	0.38	-8.16	0.00	-2.85	0.78	-3.67	0.00
57-0	-1.88	0.39	-4.82	0.00	-2.17	0.78	-2.79	0.00
57-1	0.07	0.39	0.18	0.86	-0.44	0.78	-0.56	0.57
59-0	-5.79	0.55	-10.57	0.00	-5.48	1.08	-5.07	0.00
59-1	-3.55	0.56	-6.32	0.00	-5.59	1.09	-5.12	0.00
	RMSE	12.06	**Adj. R^2**	0.31	**RMSE**	11.74	**Adj. R^2**	0.34

Table 3.8 Regression Model Calibration Results for Four-Lane Highways Combined

	15 Minutes Interval				60 Minutes Interval			
	Coef.	**Std. Error**	**t-value**	**P-value**	**Coef.**	**Std. Error**	**t-value**	**P-value**
(Intercept)	121.30	0.27	457.07	0.00	122.20	0.59	206.41	0.00
Average Volume	0.01	0.00	68.77	0.00	0.01	0.00	38.45	0.00
% Long Vehicles	-16.64	0.29	-56.47	0.00	-22.07	0.67	-32.72	0.00
Wind Speed	-0.18	0.00	-56.84	0.00	-0.21	0.01	-31.93	0.00
Visibility	0.01	0.00	4.92	0.00				
Surface Temp								
Slight	-4.69	0.06	-73.99	0.00	-4.19	0.14	-30.58	0.00
Moderate	-13.36	0.23	-58.73	0.00	-11.98	0.43	-27.83	0.00
Heavy	-15.62	0.41	-38.14	0.00	-17.25	0.75	-22.87	0.00
Trace Moisture	0.00		0.00		0.00		0.00	
Wet	-3.78	0.14	-27.49	0.00	-4.27	0.30	-14.30	0.00
Chemically Wet	-7.86	0.20	-39.69	0.00	-9.26	0.43	-21.57	0.00
Ice Watch	-9.10	0.07	-124.03	0.00	-9.94	0.16	-63.29	0.00
Ice Warning	-11.39	0.19	-60.63	0.00	-12.17	0.39	-31.34	0.00
Night	-0.94	0.06	-15.08	0.00	-0.41	0.13	-3.06	0.00
00-01	-0.50	0.29	-1.71	0.09	-0.73	0.67	-1.09	0.28
06-0	0.36	0.54	0.66	0.51	1.12	1.04	1.08	0.28
06-1	-3.39	0.46	-7.42	0.00	-2.14	0.90	-2.37	0.02
08-0	-28.90	0.31	-93.54	0.00	-27.87	0.65	-42.56	0.00
08-1	-29.48	0.32	-92.61	0.00	-29.18	0.68	-43.11	0.00
10-0	-13.70	0.33	-41.47	0.00	-14.18	0.72	-19.75	0.00
10-1	-16.68	0.32	-51.62	0.00	-18.00	0.72	-25.12	0.00
14-0	-9.21	0.28	-32.55	0.00	-9.87	0.64	-15.50	0.00
14-1	0.55	0.27	2.08	0.04	1.11	0.59	1.88	0.06
19-0	-7.81	0.37	-20.89	0.00	-8.29	0.78	-10.60	0.00
19-1	-9.14	0.36	-25.42	0.00	-9.09	0.74	-12.23	0.00
20-0	-45.98	0.30	-155.09	0.00	-46.10	0.65	-70.68	0.00
20-1	-47.68	0.29	-164.20	0.00	-46.36	0.64	-72.96	0.00
27-0	-6.75	0.31	-22.07	0.00	-7.40	0.64	-11.51	0.00
27-1	-7.07	0.32	-22.34	0.00	-10.10	0.66	-15.35	0.00
28-0	-11.28	0.35	-32.32	0.00	-13.39	0.69	-19.37	0.00
28-1	-1.84	0.32	-5.72	0.00	-3.56	0.66	-5.43	0.00
30-0	-6.64	0.31	-21.56	0.00	-8.60	0.68	-12.59	0.00
30-1	-0.80	0.29	-2.72	0.01	-1.42	0.65	-2.17	0.03
32-0	-8.88	0.37	-24.04	0.00	-9.49	0.76	-12.50	0.00
32-1	-3.42	0.38	-8.96	0.00	-3.89	0.76	-5.11	0.00
36-0	-44.68	0.29	-156.28	0.00	-44.96	0.63	-71.38	0.00
36-1	-40.08	0.28	-144.11	0.00	-39.85	0.61	-65.38	0.00
37-0	-1.48	0.26	-5.65	0.00	-1.92	0.57	-3.36	0.00
37-1	-0.79	0.27	-2.94	0.00	-1.23	0.58	-2.11	0.03
41-0	-34.63	0.34	-101.22	0.00	-35.11	0.71	-49.45	0.00
41-1	-40.07	0.31	-128.05	0.00	-39.87	0.67	-59.34	0.00
44-0	-13.90	0.60	-23.34	0.00	-13.80	1.37	-10.10	0.00
44-1	-3.69	0.62	-5.90	0.00	-3.67	1.42	-2.59	0.01
46-0	-14.62	0.36	-40.71	0.00	-14.59	0.68	-21.39	0.00
46-1	-12.54	0.30	-42.52	0.00	-12.76	0.63	-20.23	0.00
47-0	-1.13	0.28	-4.09	0.00	-1.31	0.62	-2.12	0.03
47-1	1.36	0.29	4.70	0.00	1.78	0.63	2.82	0.00
48-0	-6.84	0.30	-22.64	0.00	-6.86	0.66	-10.39	0.00
48-1	-10.38	0.30	-34.42	0.00	-11.24	0.66	-17.16	0.00
49-0	1.84	0.27	6.90	0.00	2.65	0.58	4.57	0.00
49-1	-0.81	0.26	-3.04	0.00	-0.25	0.58	-0.43	0.66
50-0	-3.76	0.30	-12.32	0.00	-4.32	0.65	-6.62	0.00
50-1	-4.92	0.33	-15.01	0.00	-5.71	0.67	-8.49	0.00
53-0	-2.84	0.28	-10.25	0.00	-3.54	0.62	-5.73	0.00
53-1	-3.65	0.28	-13.17	0.00	-3.75	0.62	-6.09	0.00
58-0	-6.85	0.28	-24.10	0.00	-6.57	0.61	-10.73	0.00
58-1	-2.31	0.29	-7.94	0.00	-2.49	0.62	-4.03	0.00
	RMSE	11.01	**Adj. R^2**	0.68	**RMSE**	10.64	**Adj. R^2**	0.70

- **Effect of Average Volume and % Long Vehicles**

Two-Lane Highways:

It can be found from Table 3.7 that traffic volume has the same negative effect on average traffic speed for both 15 minute and 60 minute models. The modeling results show that for each 100 veh/ln/h increase in average traffic volume, speed will decrease by 1 km/h. Considering the low average traffic volume on two-lane highways, this effect is relatively small. The proportion of truck and recreational vehicles is found to be not statistically significant for both the 15 minute and 60 minute models.

Four-Lane Highways:

Table 3.8 shows that, different from two-lane highways, traffic volume has a positive effect on average traffic speed for four-lane highways. Both 15 minute and 60 minute models have the same coefficient: for each 100 veh/ln/h increase in traffic volume, speed could increase by 1 km/h. This relationship is somehow counterintuitive as the opposite is commonly observed, at least, under normal weather conditions. This positive effect on traffic may be attributed to its positive effect on improving road surface conditions through tire compaction, which might not have been fully captured by the RSC variable on four-lane highways. Another possible reason could be the low presence of vehicles in visual range on rural highways may have a positive effect on how fast a driver would be comfortable driving under adverse weather conditions. The proportion of truck and recreational vehicles is found to have a negative effect on the average traffic speed. For the 15 minute model, every 10% increase in % long vehicles is expected to decrease average traffic speed by 1.7 km/h. For the 60 minute model, every 10% increase in % long vehicles is expected to decrease average traffic speed by 2.2 km/h.

- **Effect of Wind Speed**

Two-Lane Highways:

As expected, wind speed has a statistically significant effect on average traffic speed. Higher wind speed is found to be associated with a lower average traffic speed. One possible explanation is that high wind speed is normally associated with adverse weathers which will obviously slow down traffic. The results in Table 3.7 shows that on average, every 10 km/h increase in wind speed would slow traffic by approximately 1.3 and 1.5 km/h for the 15 minute and 60 minute models, respectively.

Four-Lane Highways:

Compared with two-lane highways, the effect of wind speed is slightly higher on four-lane highways. Every 10 km/h increase in wind speed would slow traffic speed by approximately 1.8 and 2.1 km/h for the 15 minute and 60 minute models, respectively.

- **Effect of Visibility**

Two-Lane Highways:

As is shown in Table 3.7, visibility has a positive effect on average traffic speed. On average, every 10 km increase in visibility would increase traffic speed by approximately 0.3 and 0.4 km/h for the 15 minute and 60 minute models, respectively. This makes intuitive sense, as high visibility indicates good weather and driving conditions which would have a positive effect on average traffic speed.

Four-Lane Highways:

Compared with two-lane highways, the effect of visibility is only statistically significant for the 15 minute model. Every 10 km increase in visibility would only increase traffic speed by approximately 0.1 km/h.

- **Effect of Surface Temperature**

Two-Lane Highways:

Surface temperature is found to have a positive effect on average traffic speed for two-lane highways. One possible explanation is that a lower road surface temperature had contributed to the worsening of road surface conditions and decreasing in road surface friction. However, the effect of this factor is relatively small, as for each degree of drop in road surface temperature, there was only an average reduction of equal to or less than 0.1 km/h in average traffic speed.

Four-Lane Highways:

Surface temperature is not statistically significant for four-lane highways.

- **Effect of Night**

Two-Lane Highways:

As is shown in Table 3.7, the categorical variable, night, doesn't have a statistically significant effect on average traffic speed for two-lane highways, which may be caused by a lack of vehicles during the night.

Four-Lane Highways:

For four-lane highways, night has a negative effect on average traffic speed. The average traffic speed at night time is approximately 0.94 km/h and 0.41 km/h lower than day time traffic speed for the 15 minute and 60 minute models, respectively. Like surface temperature, this effect is also considered to be very small.

- **Effect of Precipitation Intensity**

Two-Lane Highways:

Figure 3.5 shows a comparison of the coefficients of the three precipitation intensity categories. The modeling results suggest that precipitation has a huge negative effect on average traffic speed, especially heavy snow. Compared with no snow, heavy snow could cause an average reduction of about 32.25 km/h (34.0%) and 28.08 km/h (29.1%) in average traffic speed for the 15 minute and 60 minute models, respectively. Average speed reduction caused by moderate snow is 13.14 km/h (13.9%) and 10.52 km/h (10.9%) for the 15 minute and 60 minute models, correspondingly. Slight snow causes average speed reduction by 5.12 km/h (5.4%) and 4.65 km/h (4.8%) for the 15 minute and 60 minute model, respectively. The effects of precipitation intensity are very close in the two models with different time intervals. The effects in the 15 minute model are slightly higher than in the 60 minute model. The speed reduction caused by heavy and light snow is fairly close with the numbers suggested in HCM 2010 (30-40% for heavy snow and 8-10% for light snow).

Four-Lane Highways:

Similar to two-lane highways, the effect of precipitation intensity is also significant for four-lane highways. Compared with no snow, heavy snow could cause an average reduction of about 15.62 km/h (12.9%) and 17.25 km/h (14.1%) in average traffic speed for the 15 minute and 60 minute models, respectively. Compared with two-lane highways, these effects are lower for four-lane highways. Average speed reduction caused by moderate snow is 13.36 km/h (11.0%) and 11.98 km/h (9.8%) for the 15 minute and 60 minute models, respectively. Slight snow could cause an average speed reduction of 4.69 km/h (3.9%) and 4.19 km/h (3.4%) for the 15 minute and 60 minute models, respectively. Similarly, the effects of precipitation intensity are very close in the two models with different time intervals. Compared with the numbers suggested in HCM 2010, both heavy and slight snow result in relatively lower speed reduction on four lane highways.

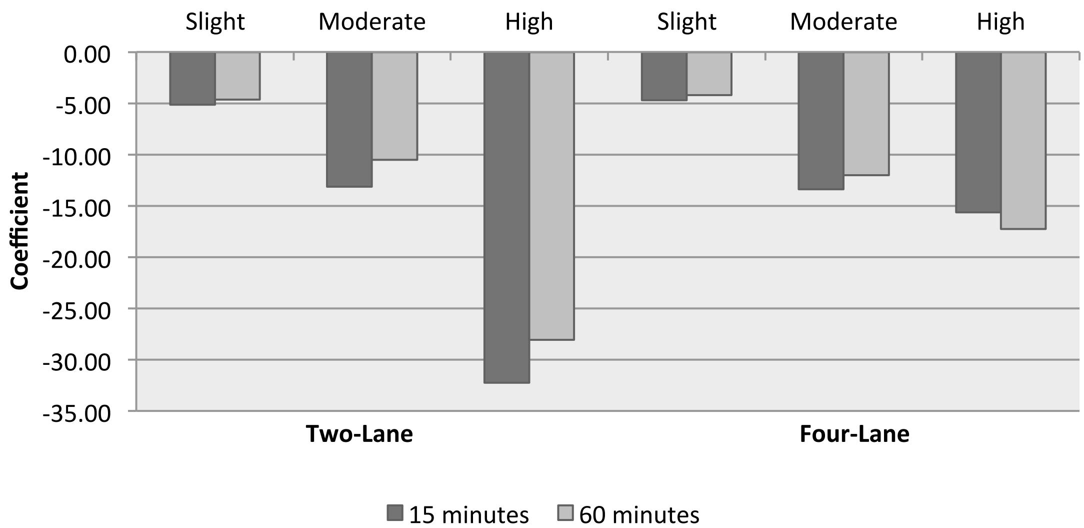

Figure 3.5 Effect of Precipitation Intensity

- **Effect of Road Surface Conditions**

Two-Lane Highways:

Figure 3.6 shows the coefficients of RSC categories. The modeling results suggest that RSC also has a significant negative effect on average traffic speed. Among all categories, ice warning causes the most significant speed reduction. Compared with dry conditions, it causes an average reduction of about 10.02 km/h (10.6%) and 12.19 km/h (12.6%) for the 15 minute and 60 minute models, respectively. Ice watch causes an average reduction of about 7.81 km/h (8.2%) and 9.13 km/h (9.5%) for the 15 minute and 60 minute models, respectively. Chemically wet causes an average reduction of about 4.31 km/h (4.5%) and 5.54 km/h (5.7%) for the 15 minute and 60 minute models, respectively. Compared with the first three categories, wet and trace moisture have limited effects on the average traffic speed. Wet causes an average reduction of about 1.22 km/h (1.3%) and 1.94 km/h (2.0%) for the 15 minute and 60 minute models, respectively. Trace moisture causes an average reduction of about 0.60 km/h (0.6%) and 2.24 km/h (2.3%) for the 15 minute and 60 minutes model, respectively. Again, the effects of RSC are very close in the two models with different time intervals. The effects in the 60 minute model are slightly higher than in the 15 minute model.

Four-Lane Highways:

The effects of RSC on average traffic on four-lane highways show the same pattern with two-lane highways. Compared with dry conditions, ice warning causes an average reduction of about 11.39 km/h (9.4%) and 12.17 km/h (10.0%) for the 15 minute and 60 minute models, respectively. Ice watch causes an average reduction of about 9.10 km/h (7.5%) and 9.94 (8.1%) km/h for the 15 minute and 60 minute models, respectively. Chemically wet causes an average reduction of about 7.86 km/h (6.5%) and 9.26 km/h (7.6%) for the 15 minute and 60 minute models, respectively. The effect of chemically wet is increased about 4 km/h than the effect in the two-lane models. Wet causes an average reduction of about 3.78 km/h (3.1%) and 4.27 km/h (3.5%) for the 15 minute and 60 minute models, respectively. These values are also doubled compared with the values in the two-lane highways. Trace moisture is found to be not statistically significant for four-lane highways. Again, the effects of RSC are very close in the two models with different time intervals. The effects in the 60 minute model are slightly higher than in the 15 minute model. These results clearly show the high degree of impact of the RSC on average traffic speed.

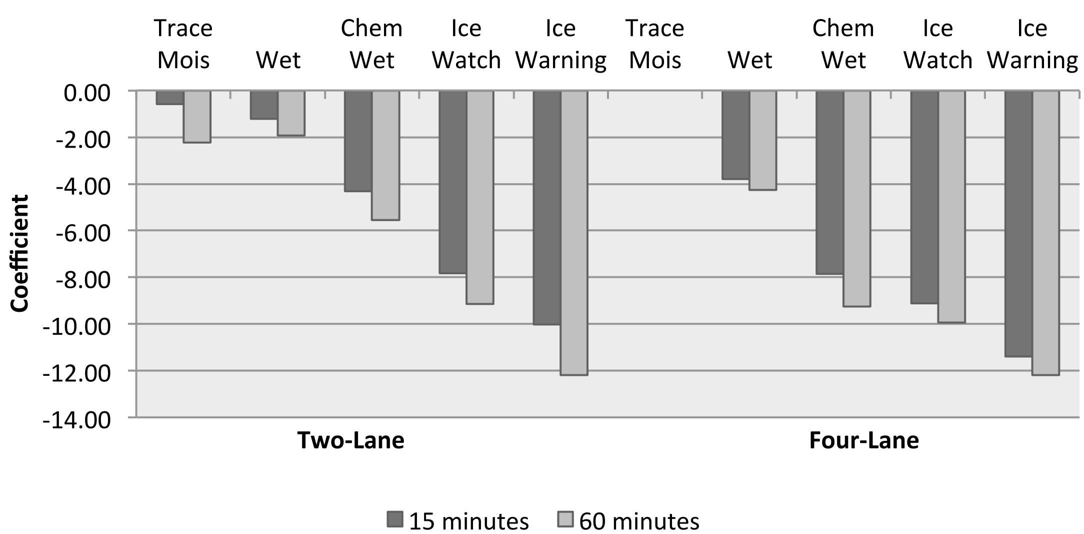

Figure 3.6 Effect of Road Surface Condition

- **Effect of Site with the Same Highway Type**

Two-Lane Highways:

Figure 3.7 shows the coefficients of sites of the two-lane models. The average speed constant of the base site is about 95 km/h. As can be seen in the figure, because of the lower speed limit or geometry (e.g. near intersection) at Site 13, 25 and 43, these sites have a relatively lower average speed than other sites. Except Site 13, 25 and 43, most two-lane highways' coefficients are between -5 and 5, which indicates that under the similar traffic and weather conditions, most two-lane highways tend to have similar average traffic speeds.

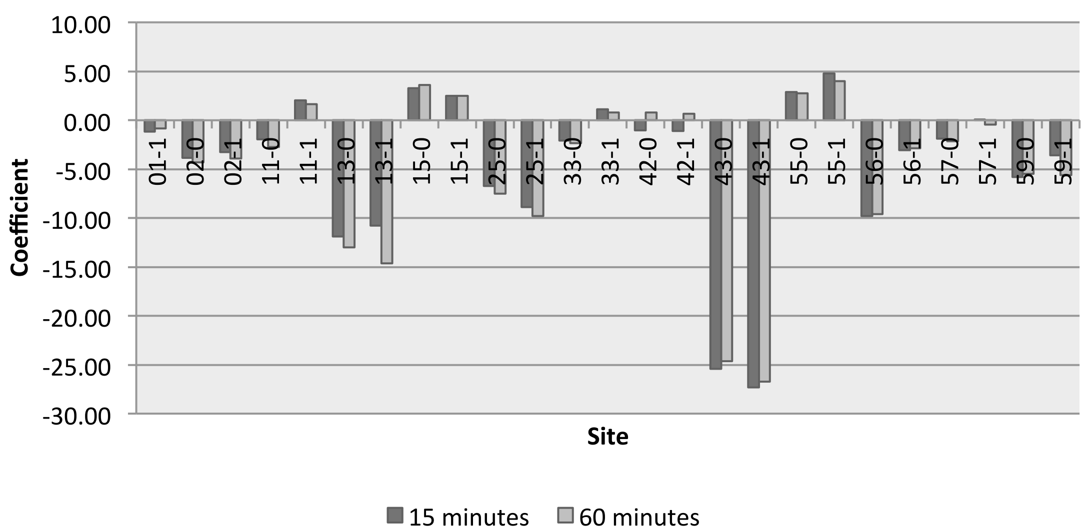

Figure 3.7 Site Effect of Two-Lane Highways

Four-Lane Highways:

Figure 3.8 shows the coefficients of sites of the four-lane models. The average speed constant of the base site is about 122 km/h. As can be seen in the figure above, most four-lane highways' site coefficients are negative, therefore under the default traffic and weather conditions, these highways' average traffic speeds are mostly lower than the base site. Also, because of the lower speed limit or geometry (e.g. near intersection) at Site 08, 20, 36 and 41, these sites have a relatively lower average speed than other sites. Most four-lane highways' coefficients are between -10 and 5, which indicates that under the default traffic and weather conditions, most four-lane highways also tend to have similar average traffic speeds (i.e. 112 km/h to 127 km/h). Note that the lower bound of this range (e.g. 112 km/h) is much higher than the higher bound of the two-lane highways' range (i.e. 100 km/h). This clearly shows the different traffic speed patterns on these two types of highways.

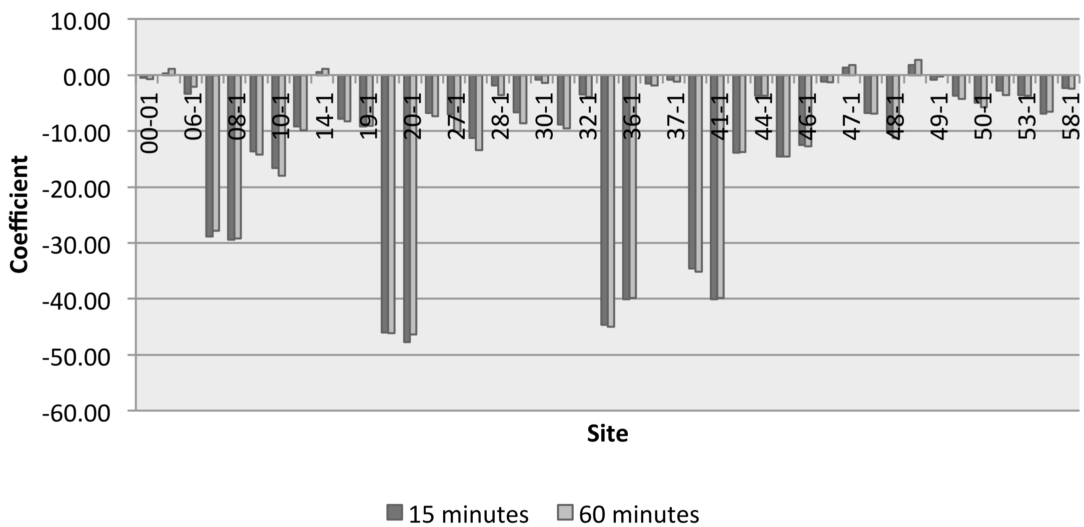

Figure 3.8 Site Effect of Four-Lane Highways

3.6.2 Artificial Neural Network

The two combined datasets with the 60 minute time interval are used for MLP-NN model calibration in the statistical software R. The significant independent variables found in the previous combined regression models are included as the input factors of the MLP-NN. Table 3.9 shows the results of MLP-NN for the two types of highways. Note that a single hidden layer with nine nodes was found to be optimal for the two-lane highways, and two hidden layers with nine nodes in the first layer and two nodes in second layer was found to be optimal for the four-lane highways. The corresponding RMSE is 10.13 and 9.68, which are slightly higher than the RMSE of the combined regression models. Detailed model comparison will be given in the next section.

Table 3.9 MLP-NN Model Calibration Results

Site	Variables	MLP-NN Architecture (Hidden Layers & Nodes)		Overall RMSE
		First Layer	Second Layer	
Two-Lane Combined (60-Minute Interval)	Average Volume, Wind Speed, Visibility, Surface Temp, Precipitation Intensity, RSC and Sites	9	0	10.13
Four-Lane Combined (60-Minute Interval)	Average Volume, % Long Vehicles, Wind Speed, Precipitation Intensity, RSC, Night and Sites	9	2	9.68

3.6.3 Time Series Analysis

Similar to the previous two analyses, time series analysis is also calibrated in the statistical software R. It is found that observed speed does not show any trend of being non-stationary; therefore, no differentiation was required for the data. All independent variables used in the regression model calibration are included as the independent variables of the ARIMAX model. Based on the investigation of several combinations of ARIMAX models, ARIMAX (2,0,2) is found to be optimal and finally selected and calibrated for both two-lane and four-lane highways.

Note that the goodness of fit of the model is estimated based on the model statistics generated by R called Akaike Information Criterion (AIC) and AICc (i.e. AIC with a greater penalty for extra parameters) which are measures of the relative quality of a statistical model for the trade-off between the goodness of fit of the model and the complexity of the model (Akaike, 1974). The lower the AIC/AICc values, the better quality the model has. Another model statistic generated by R that could be potentially used is Bayesian Information Criterion (BIC). However, a comparison of AIC/AICc and BIC given by Burnham & Anderson (2002, 2004) suggest that AIC/AICc can be derived in the same Bayesian framework as BIC, and has theoretical advantages over BIC. As a result, only AIC/AICc is used to justify the model quality in this analysis.

Table 3.10 and 3.11 show the final results of ARIMAX model for two-lane and four-lane highways, respectively. The results show that % long vehicles and night are not found to be significant for two-lane highways while visibility and night are not significant for four-lane highways. The results also suggest that similar with the multivariate linear regression results, precipitation intensity (i.e. up to -

6.62 and -7.80) and RSC (i.e. up to -6.28 and -6.84) have a significant effect on the average traffic speed. The RMSE values are 8.92 and 8.05, respectively, which are improved significantly compared with the values in the regression analysis (11.74 and 10.64), and also better than MLP-NN (10.13 and 9.68).

Table 3.10 ARIMAX Model Calibration Results for Two-Lane Combined (60-Minute Interval)

Intercept	**AR1**	**AR2**	**MA1**	**MA2**
89.45	1.68	-0.70	-1.19	0.26
(2.60)	(0.04)	(0.03)	(0.04)	(0.02)
Average Volume	**% Long Vehicles**	**Wind Speed**	**Visibility**	**Surface Temperature**
-0.01		-0.09	0.01	0.23
(0.00)		(0.01)	(0.00)	(0.03)
None	**Slight**	**Moderate**	**Heavy**	
0.00	-1.08	-3.73	-6.62	
0.00	(0.17)	(0.56)	(0.99)	
Dry	**Trace Moisture**	**Wet**	**Chemically Wet**	**Ice Watch**
0.00	-0.77	-0.53	-2.95	-3.80
0.00	(0.59)	(0.42)	(0.47)	(0.29)
Ice Warning	**Day**	**Night**		
-6.28				
(0.52)				
01-0	**02-0**	**11-0**	**13-0**	**15-0**
0.00	-4.08	-2.71	-19.26	1.54
0.00	(2.95)	(3.42)	(3.79)	(3.10)
01-1	**02-1**	**11-1**	**13-1**	**15-1**
-1.99	-4.43	0.44	-9.99	2.42
(3.40)	(2.93)	(3.41)	(3.71)	(3.07)
25-0	**33-0**	**42-0**	**43-0**	**55-0**
-5.46	-0.46	2.48	-24.87	2.10
(2.94)	(2.98)	(5.09)	(4.30)	(3.27)
25-1	**33-1**	**42-1**	**43-1**	**55-1**
-8.12	2.84	1.53	-27.15	4.41
(2.96)	(2.96)	(5.15)	(4.24)	(3.25)
56-0	**57-0**	**59-0**		
-10.07	-0.46	-6.26		
(3.05)	(3.03)	(4.04)		
56-1	**57-1**	**59-1**		
-4.16	1.31	-5.00		
(3.05)	(3.03)	(4.19)		
AIC	**AICc**	**BIC**	**Log Likelihood**	**Overall RMSE**
114854.30	**114854.50**	**115184.30**	**-57384.15**	**8.92**

Table 3.11 ARIMAX Model Calibration Results for Four-Lane Combined (60-Minute Interval)

Intercept	**AR1**	**AR2**	**MA1**	**MA2**
112.68	1.65	-0.67	-1.02	0.12
(1.76)	(0.03)	(0.03)	(0.04)	(0.01)
Average Volume	**% Long Vehicles**	**Wind Speed**	**Visibility**	**Surface Temperature**
0.01	-15.61	-0.14		0.03
(0.00)	(0.61)	(0.01)		(0.02)
None	**Slight**	**Moderate**	**Heavy**	
0.00	-1.31	-4.78	-7.80	
0.00	(0.10)	(0.33)	(0.60)	
Dry	**Trace Moisture**	**Wet**	**Chemically Wet**	**Ice Watch**
0.00	0.00	-0.72	-4.83	-4.61
0.00	0.00	(0.28)	(0.33)	(0.17)
Ice Warning	**Day**	**Night**		
-6.84				
(0.33)				
00-0	**06-0**	**08-0**	**10-0**	**14-0**
0.00	5.01	-26.39	-11.27	-5.23
0.00	(3.24)	(2.18)	(2.39)	(2.03)
00-1	**06-1**	**08-1**	**10-1**	**14-1**
-0.47	-0.76	-27.81	-16.16	3.22
(2.22)	(2.93)	(2.24)	(2.38)	(2.01)
19-0	**20-0**	**27-0**	**28-0**	**30-0**
-7.57	-43.86	-5.84	-10.48	-3.92
(2.60)	(2.15)	(2.16)	(2.33)	(2.27)
19-1	**20-1**	**27-1**	**28-1**	**30-1**
-8.19	-45.00	-8.95	-1.94	1.59
(2.49)	(2.15)	(2.21)	(2.21)	(2.19)
32-0	**36-0**	**37-0**	**41-0**	**44-0**
-7.45	-42.58	1.09	-32.48	-4.76
(2.51)	(2.04)	(1.89)	(2.32)	(3.96)
32-1	**36-1**	**37-1**	**41-1**	**44-1**
-2.72	-38.13	1.97	-38.34	-1.82
(2.54)	(2.02)	(1.91)	(2.20)	(4.04)
46-0	**47-0**	**48-0**	**49-0**	**50-0**
-13.04	-0.59	-3.51	4.23	-3.01
(2.28)	(2.09)	(2.18)	(1.98)	(2.20)
46-1	**47-1**	**48-1**	**49-1**	**50-1**
-11.38	2.62	-8.33	0.91	-4.21
(2.13)	(2.13)	(2.19)	(1.97)	(2.26)
53-0	**58-0**			
-1.63	-5.58			
(2.10)	(2.07)			
53-1	**58-1**			
-1.83	-1.39			
(2.10)	(2.10)			
AIC	**AICc**	**BIC**	**Log Likelihood**	**Overall RMSE**
213970.50	**213970.80**	**214478.40**	**-106924.30**	**8.05**

3.6.4 Model Comparison

Figure 3.9 shows the overall RMSE comparison of the regression, MLP-NN and ARIMAX models calibrated based on the 60 minute combined datasets. As can be seen in the figure, the regression models have the highest RMSE, about 12 and 11 for two-lane and four-lane highways. The MLP-NN models have slightly better performance than the regression models, about 10 for both two-lane and four-lane highways, which validates the robustness of the combined regression models. The ARIMAX models have the best performance among the three, about 9 and 8 for two-lane and four-lane highways.

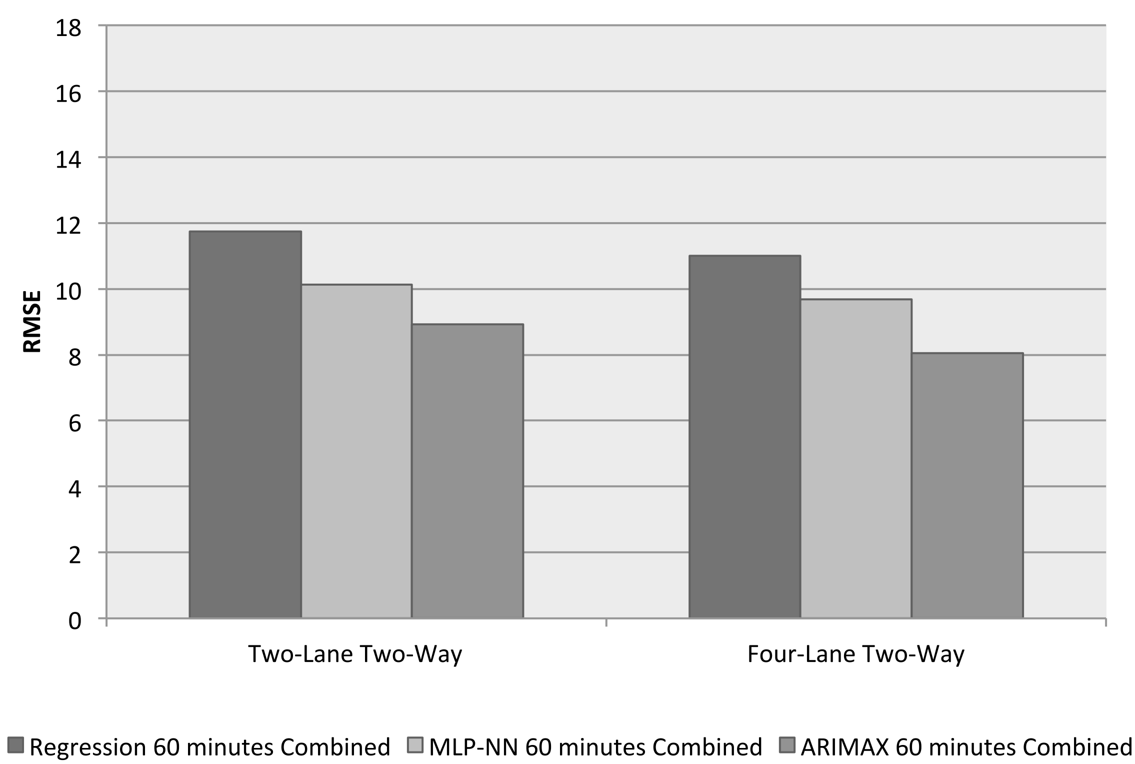

Figure 3.9 Overall RMSE Comparison for Combined Models

Figure 3.10, Figure 3.11 and Figure 3.12 show the observed vs. predicted scatter plots of the three models using the 60 minute combined calibration data. Ideally, all the points should be aligned on the diagonal blue line. These figures reveal similar results with Figure 3.9. Figure 3.10 clearly shows that the two-lane regression model tends to overestimate when the average traffic speed is low and underestimate when the average traffic speed is high. Particularly when the observed average traffic speed is between 0 to 20 km/h, the predicted speed ranges from 0 to over 80 km/h. The four-lane regression model is slightly better, however, there are still some points with observed speed between 40 to 60 km/h that are predicted as 80 to 100 km/h. As can be seen in Figure 3.11, the MLP-NN models show very similar pattern with the regression models for both two-lane and four-lane highways. Although the overestimate and underestimate issue still exists in both models, performance improvement can be observed compared with the regression models, especially four-lane highways. By comparing the pattern in Figure 3.12 with the previous two figures, it can be found that most points of the ARIMAX models are roughly diagonally distributed, therefore the ARIMAX models have the best prediction performance among the three types of models.

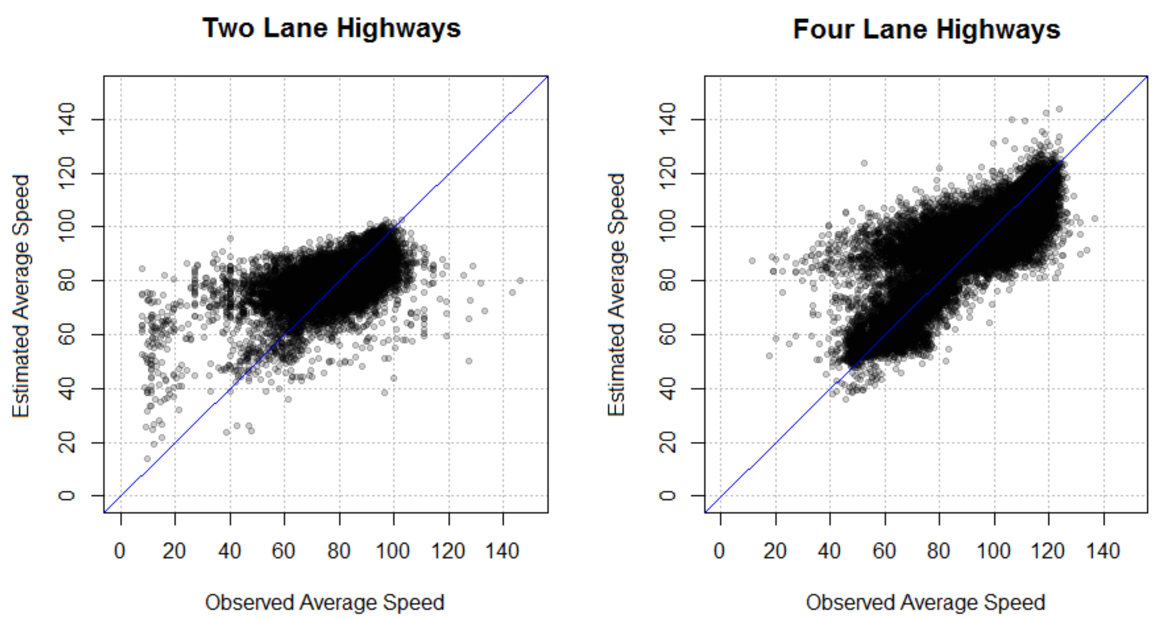

Figure 3.10 Observed vs. Estimated by Regression Combined (60-Minute Interval)

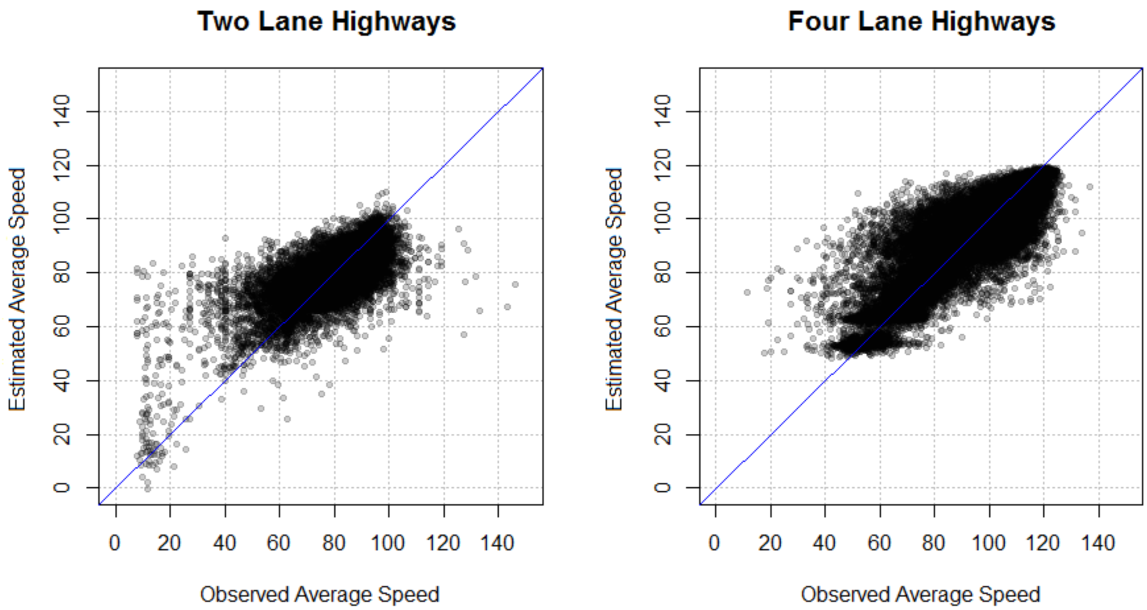

Figure 3.11 Observed vs. Estimated by MLP-NN Combined (60-Minute Interval)

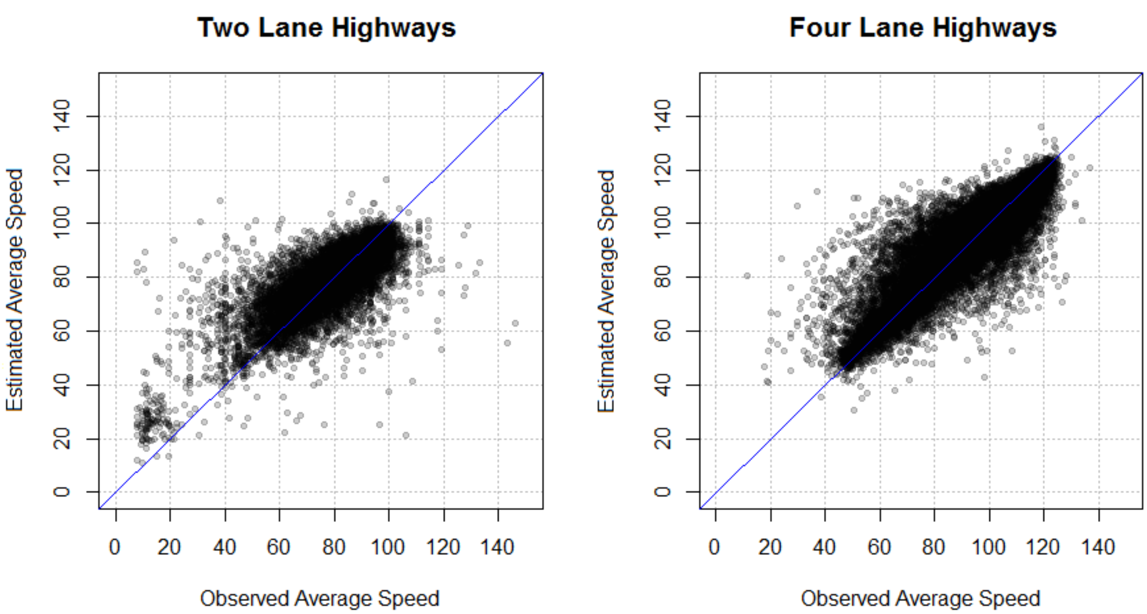

Figure 3.12 Observed vs. Estimated by ARIMAX Combined (60-Minute Interval)

3.7 Model Validation

3.7.1 Model Validation for Each Site

This section demonstrates the model validation using the 10% holdout data for each site. Since the ARIMAX model requires continuous time series data, it will be validated with the holdout event data and compared with other models in the next section. Therefore, only separated regression models, combined regression models and MLP-NN will be validated in this section.

Table 3.12 and Figure 3.13 show the model validation for two-lane highways. RMSE values of each site are summarized both numerically and graphically. As can be seen in Table 3.12, most sites have RMSE lower than 10 for all three models. The RMSE of MLP-NN is the lowest among all the three models for most sites, which indicates that MLP-NN's performance is the best among the three models. The RMSE of the separated regression model is slightly higher, but very close to the MLP-NN for most sites. The RMSE of the combined regression model is slightly higher than the separated regression model and the MLP-NN for most sites. In general, all the three models have very similar RMSE (i.e. performance) for most sites. Therefore, similar with the model calibration results, the results of the validation of two-lane highways confirm the robustness of the regression models, both separated and combined.

The only exception, as can be seen in Figure 3.13, is Site 13 in which the RMSE of the MLP-NN is much lower than both the separated regression model and the combined regression model. This reveals that MLP-NN probably works the best for Site 13, and regression models may not be the best choice for speed prediction purposes.

Table 3.12 RMSE Comparison for Two-Lane Highways 10% Holdout Data

	Regression 60 minutes by Site	Regression 60 minutes Combined	MLP-NN 60 minutes Combined
01-0	7.65	8.16	7.06
01-1	7.12	7.96	7.19
02-0	8.63	9.92	8.05
02-1	9.08	9.45	8.17
11-0	9.15	10.1	7.2
11-1	8.79	9.53	8.08
13-0	19.09	21.83	11.64
13-1	22.98	27.4	19.19
15-0	6.95	7.91	6.83
15-1	7.34	8.65	6.89
25-0	11.14	10.96	10.05
25-1	13.55	13.82	12.89
33-0	9.81	10.54	9.49
33-1	8.39	8.56	7.87
42-0	4.69	5.28	4.43
42-1	9.81	10.9	11.69
43-0	4.48	7.39	5.76
43-1	5.49	6.84	5.46
55-0	9.53	10.92	9.22
55-1	13.89	14.26	13.16
56-0	10.38	10.54	9.8
56-1	8.45	8.9	7.91
57-0	13.14	14.52	11.97
57-1	13.2	13.96	12.89
59-0	10.43	10.86	9.95
59-1	11.17	11.74	9.47

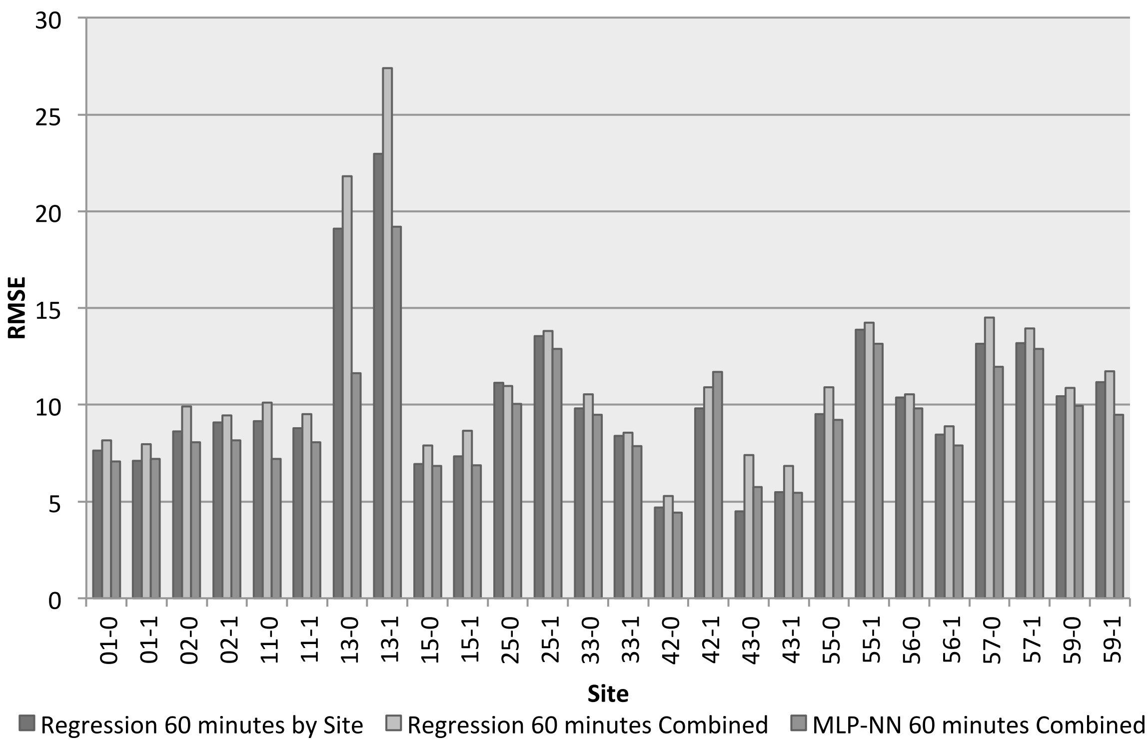

Figure 3.13 RMSE Comparison for Two-Lane Highways 10% Holdout Data

Table 3.13 and Figure 3.14 show the model validation for four-lane highways. As can be seen in Table 3.13, the RMSE ranges from lower than 5 to higher than 25. Most sites have RMSE lower than or around 10 for all three models. Again, similar with two-lane highways, the RMSE of MLP-NN is the lowest among all the three models for most sites. This indicates that MLP-NN's performance is the best among the three models for four-lane highways as well. The RMSE of the separated regression model and combined regression model also follow a similar pattern with two-lane highways. In general, the results of the validation of four-lane highways also confirms the robustness of the regression models, both separated and combined.

Table 3.13 RMSE Comparison for Four-Lane Highways with 10% Holdout Data

	Regression 60 minutes by Site	Regression 60 minutes Combined	MLP-NN 60 minutes Combined
00-0	8.2	8.62	7.65
00-1	10.64	11.21	8.53
06-0	5.85	7.67	5.19
06-1	8.3	8.83	7.53
08-0	6.98	27.67	7.07
08-1	6.15	28.4	6.28
10-0	8.63	24.58	12.05
10-1	9.88	25.49	21.46
14-0	11.54	10.81	9.56
14-1	9.05	9.65	8.19
19-0	10.61	11.2	9.52
19-1	11.51	12.1	10.7
20-0	5.12	6.88	5.23
20-1	7.48	9.39	7.06
27-0	11.89	13.35	10.43
27-1	17.1	18.88	15.22
28-0	18.56	19.69	17.65
28-1	15.47	17.17	13.04
30-0	10.38	12.02	10.24
30-1	11.12	11.72	11.08
32-0	8.86	9.12	7.85
32-1	11.79	12.84	13.15
36-0	4.12	5.48	3.83
36-1	3.61	4.95	3.69
37-0	8.73	9.05	8.49
37-1	8.12	8.11	8.03
41-0	6.06	6.62	6.32
41-1	6.65	6.82	7.15
44-0	15.32	19.28	11.24
44-1	3.93	6.34	5.76
46-0	11.34	12.21	11.94
46-1	8.41	8.7	8.73
47-0	11.87	14.39	10.92
47-1	11.08	12.88	10.23
48-0	9.96	9.85	9.44
48-1	11.47	11.41	8.75
49-0	7.82	8.19	8.11
49-1	10.13	10.25	10.46
50-0	11.89	12.43	11.62
50-1	10.89	11.85	11.08
53-0	11.98	12.57	11.93
53-1	12.77	13.01	12.52
58-0	8.39	9.09	7.74
58-1	11.41	11.94	11.43

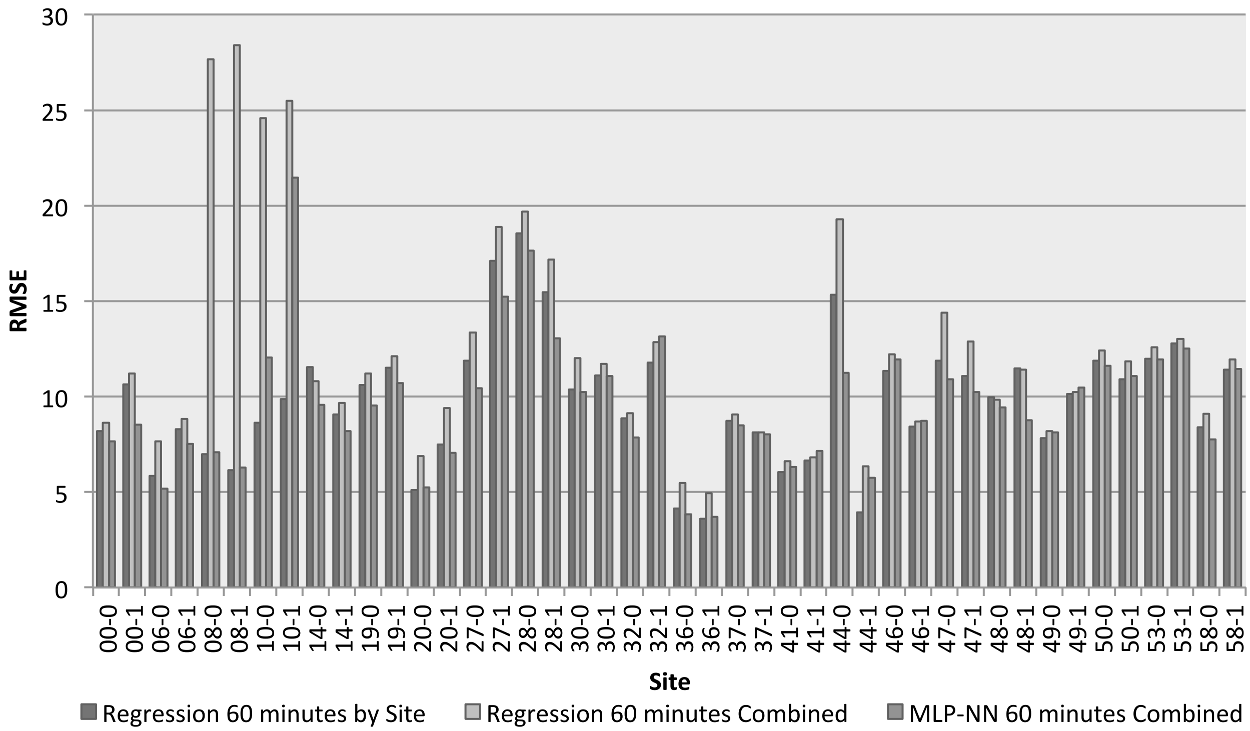

Figure 3.14 RMSE Comparison for Four-Lane Highways 10% Holdout Data

There are also exceptions. For example, both Site 08 and 10's combined regression models have extremely high RMSE values (i.e. over 25) indicating that combined regression models may not the best choice among the three models. For both sites, the model with the best performance is the separated regression model rather than the MLP-NN. This again suggests the need of developing different types of models for each site, therefore different models can be compared and the one with the best performance can be found.

3.7.2 Case Studies

To show the performance of the ARIMAX model for estimating traffic speed, the calibrated ARIMAX model is applied to estimate the traffic speed at a given time over two selected events based on past speed observations and current weather conditions. The calibrated regression models (both separated and combined) and MLP-NN model are also used to predict the traffic speed over the same events for comparison purpose.

Figure 3.15 shows the results of speed estimation by the four models on Site 01-0 which is one of the two-lane highways. The y-axis represents the average speed and the x-axis represents the time in hours. It can be observed that the regression models and MLP-NN model have fairly accurate estimation for the first 20 hours. However, underestimation begins after hour 20, and clear overestimation can be observed from hour 26 to hour 30 at the second significant speed drop. The estimated speed of the ARIMAX model, on the other hand, has a very similar pattern with the observed speed over the whole event. Some minor overestimate issues can be found at the first and second significant speed drop.

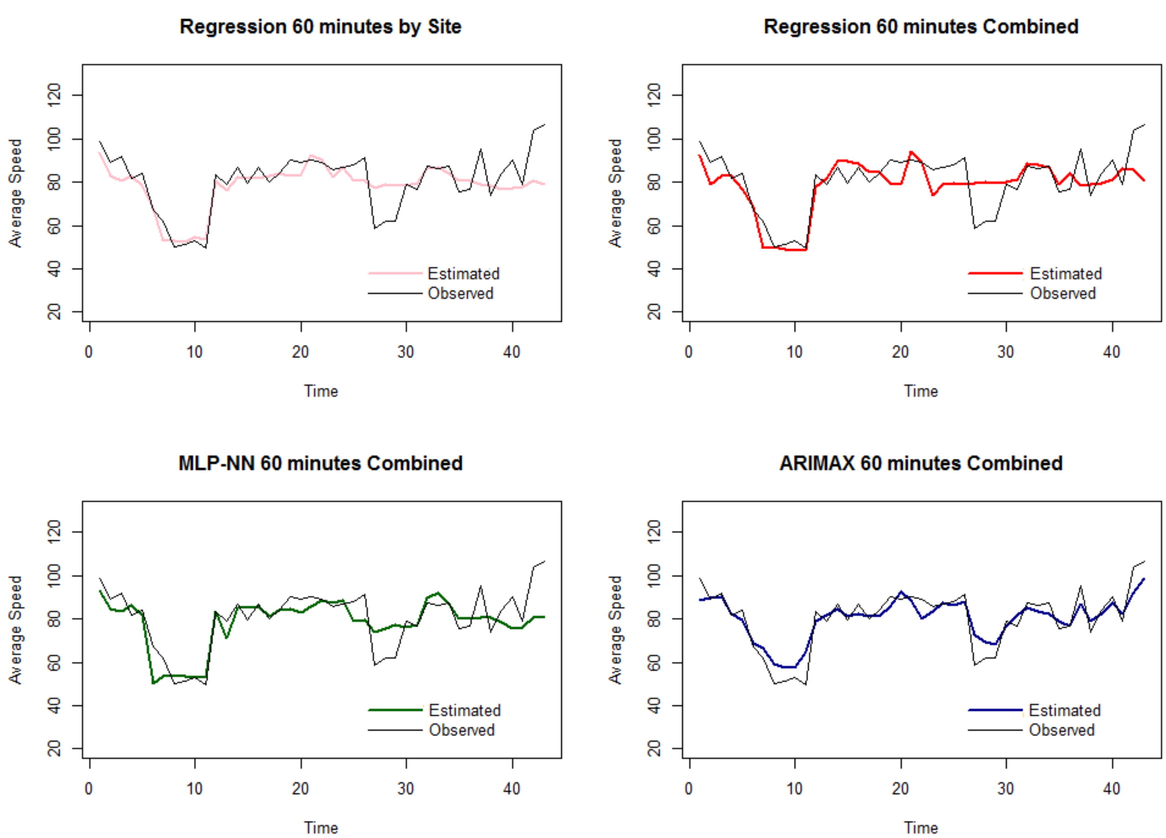

Figure 3.15 Estimation on Two-Lane Highways (Site 01-0 on Dec. 11th.-12th., 2010)

Figure 3.16 shows the results of speed estimation by the four models on Site 00-0 which is one of the four-lane highways. It can be seen that the pattern of the speed estimated by the regression models and MLP-NN roughly matches with the pattern of the observed speed, especially the separated regression model and the MLP-NN. Some overestimation issues can be found when the speed is lower than 80 km/h. Again, the ARIMAX model has the best performance among the four. The pattern of the estimated speed is almost the same with the observed speed except for the fact that the estimated speed is slightly higher (i.e. about 5 to 10 km/h) than the observed speed when the observed is lower than 80 km/h.

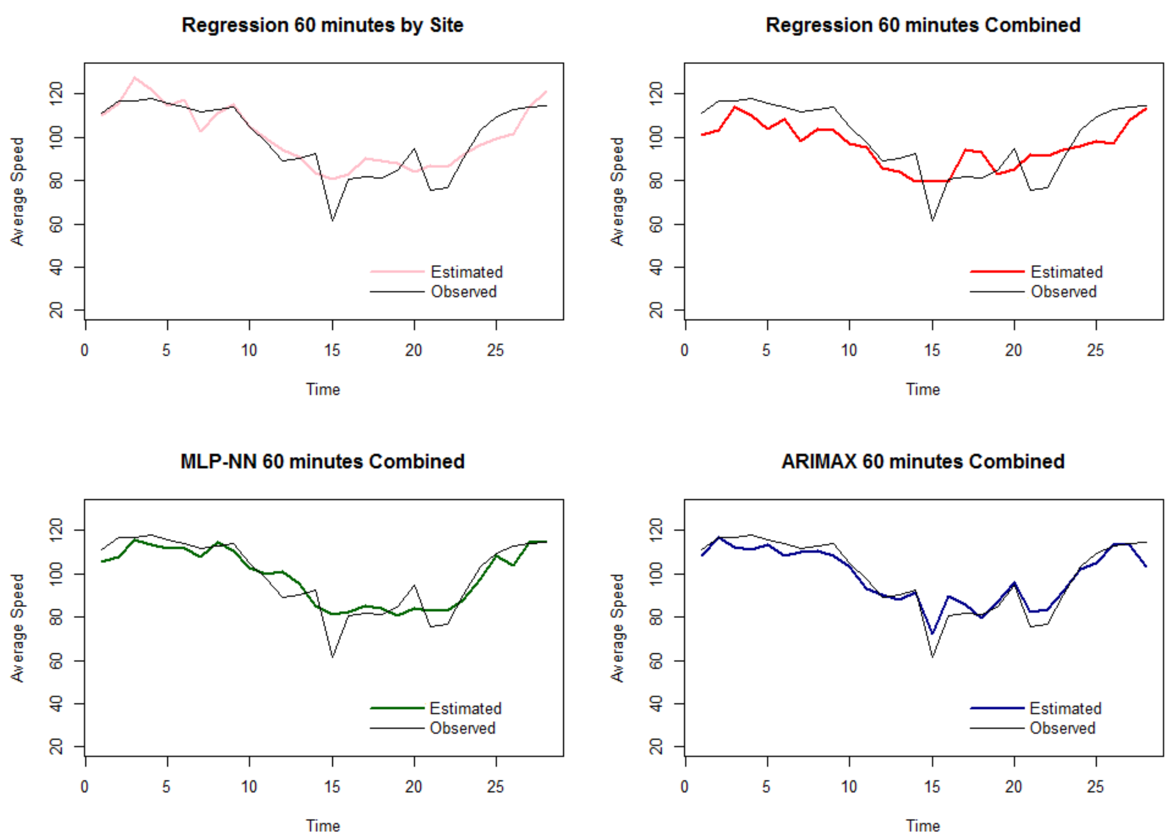

Figure 3.16 Estimation on Four-Lane Highways (Site 00-0 on Jan 10th., 2009)

Overall, the two regression models and the MLP-NN have been outperformed by the ARIMAX model. This result is somehow expected as the latter used the past speed observations and thus has the advantage of making use of more information than the other three alternatives.

3.8 Summary

This chapter investigates the impact of adverse weather and road surface conditions on traffic speed with the intention of exploring the feasibility of applying speed as a performance indicator of WRM. Data from 35 sites, 14 on two-lane and 21 on four-lane highways, in Iowa, US, are used in the analysis. Separated and combined regression models, MLP-NN and ARIMAX models are developed for these two highway types.

It is found that precipitation and road surface conditions have a relatively higher effect on the average traffic speed than other factors such as surface temperature and wind speed. Different from the linear regression models, the MLP-NN could capture the non-linear effect of independent variables on the average traffic speed. However, the modeling results do not confirm the superiority of the MLP-NN over the regression models. This indifference validates the appropriateness of the multivariate linear regression models. By taking into account both the autocorrelation nature of the data as well as the effects of cross-sectional variables, the ARIMAX model provided much improved explanatory and prediction power as compared to regression models and MLP-NN. It should be noted that the ARIMAX model makes use of recent past observations in estimating the travel speed of the current time period. In contrast, the regression models and MLP-NN models estimate speeds based on external factors only.

The analysis results clearly indicated the dependency of traffic speed on road surface conditions, suggesting the feasibility of applying speed as a performance monitoring tool. For example, under a given weather and traffic condition, the reduction in speed can be established from a comparison to baseline values and attributed to the change in surface conditions. Based on the degree of speed reduction, the road surface condition can be predicted and their performance can be gauged accordingly and/or maintenance activities can be mobilized.

This chapter focused on investigating the correlation between traffic speed and RSCs. To address the reverse part of the problem, the next chapter focuses on developing quantitative models that can be used to infer RSCs (e.g. bare pavement status) based on observed traffic speed and other known road and weather parameters.

Chapter 4
Inferring Road Surface Condition from Traffic and Weather Data

4.1 Problem Definition

One of the purposes of studying the effect of weather and RSC factors on traffic speed in the previous chapter is to confirm the relationship between traffic speed and RSC so that the feasibility of using traffic speed as WRM performance measure can be investigated. The results showed that adverse RSC is highly correlated with significant speed reduction on both two-lane and four-lane rural highways.

On the other hand, it is essential for WRM management to accurately determine the RSC during snow storms. Traditional RSC monitoring by visual observation and web cams are subjective and/or costly requiring high workload. Additionally, modern embedded surface monitoring sensors suffer from high installation and maintenance costs, low reliability and scalability, therefore cannot be deployed in a large scale at this point.

This chapter studies the reverse problem of Chapter 3, and proposes a model to estimate RSC based on traffic and weather data which are often readily available from existing traffic sensors. With the rapid development of smart phone technologies, this modelling technique has a high potential to utilize speed data, GPS data and weather data collected from road users' smart phones to generate real time RSC estimation with high spatial and temporal coverage, which may potentially have the benefits of both stationary and mobile based surface monitoring systems, and dramatically reduce the overall cost.

4.2 Data Collection

The dataset used in this chapter is the same with Chapter 3. To ensure enough sample size of each RSC category, Site 11-1 (two-lane) and 00-0 (four-lane) with both 15 and 60 minute time intervals are selected for model calibration and validation. The following variables in Table 4.1 are used as explanatory variables in model calibration. Note that the analysis assumes no surface data is available and only traffic and weather data is available. Due to lack of enough valid data points, visibility is not included in this analysis.

Table 4.1 Explanatory Variables used in Model Calibration

Data Source	Field Name	Unit	Note
Traffic	Average Speed	km/h	Average speed over 15 minutes or 60 minutes
	Average Volume	veh/ln/h	Average total volume over 15 minutes or 60 minutes
	% Long Vehicles	percent	Percent of long vehicles
	SD of Speed	N/A	Standard deviation of speed over 15 minutes or 60 minutes
Atmosphere	Wind Speed	km/h	Average wind speed over 15 minutes or 60 minutes
	Air Temperature	celsius	Air temperature
	Precipitation Intensity	categories	Precipitation Intensity (None, Slight, Moderate or Heavy)
Others	Time of Day	categories	Day (6:00am – 6:00pm) Night (6:00pm – 6:00am)

4.3 Methodology

4.3.1 Road Surface Condition Classification

RSC used in this analysis is collected by surface sensors embedded in the pavement. As is shown below, six types are recorded by the sensors in the order of severity from lowest to highest. The rest of the chapter will reference the RSC with type ids instead of type names.

- Type 0: Dry (moisture free surface, bare pavement)
- Type 1: Trace Moisture (thin or spotty film of moisture above freezing and detected in absence of precipitation)
- Type 2: Wet (continuous film of moisture on the pavement sensor with a surface temperature above freezing as reported when precipitation has occurred)
- Type 3: Chemically Wet (continuous film of water and ice mixture at or below freezing with enough chemical to keep the mixture from freezing, it is also reported when precipitation has occurred)
- Type 4: Ice Watch (thin or spotty film of moisture at or below freezing and reported when precipitation is not occurring)

- Type 5: Ice Warning (continuous film of ice and water mixture at or below freezing with insufficient chemical to keep the mixture from freezing again, reported when precipitation occurs)

4.3.2 Logistic Regression

Logistic regression is a special form of generalized linear model (Mc-Cullagh & Nelder, 1999) and is one of the supervised classification methods. A logistic regression model has the following form:

$$ln \frac{P(Y=C_k)}{1-P(Y=C_k)} = \eta(X) \qquad \forall C_k \in C \tag{4.1}$$

Where

Y is the categorical response variable

C is the set of classifications. In this case, it represents the set of different RSC types

C_k is a state in C

$P(Y = C_k)$ is the probability of Y in the state of C_k

X is the explanatory variable vector of d features

$\eta(X)$ is a linear function describing the dependence of Y on the explanatory variables defined as follows:

$$\eta(X) = \beta_0 + \beta_1 x_1 + \cdots + \beta_d x_d \tag{4.2}$$

Where β_0, $\beta_1 \cdots \beta_d$ are model coefficients to be estimated. With this special model format, the probability of Y belonging to any specific state can be estimated by explanatory variables.

The logistic regression model can be rewritten as

$$P(Y = C_k) = \frac{e^{\eta(X)}}{1+e^{\eta(X)}} \tag{4.3}$$

4.3.3 Multi-Layer Logistic Regression Classification Tree

RSC classification is a typical classification problem and can be addressed by various traditional classification modeling approaches, e.g. supervised and unsupervised methods. The basic idea of the classification tree is to partition the space of explanatory variables into successively smaller hyper-rectangles in order to make the sample more and more pure in terms of response variable's class within the new hyper-rectangles that are created (Breiman et al., 1984).

One of the major problems of the classification tree is that some classes are usually similar with other classes, and it is insufficient to use only one explanatory variable to discriminate two classes at each split. To solve this problem, in this chapter, a multi-layer logistic regression classification tree is proposed and used to classify RSC categories. At each split of the classification tree, a binary logistic regression model with multiple explanatory variables is calibrated. Figure 4.1 shows a sample classification tree.

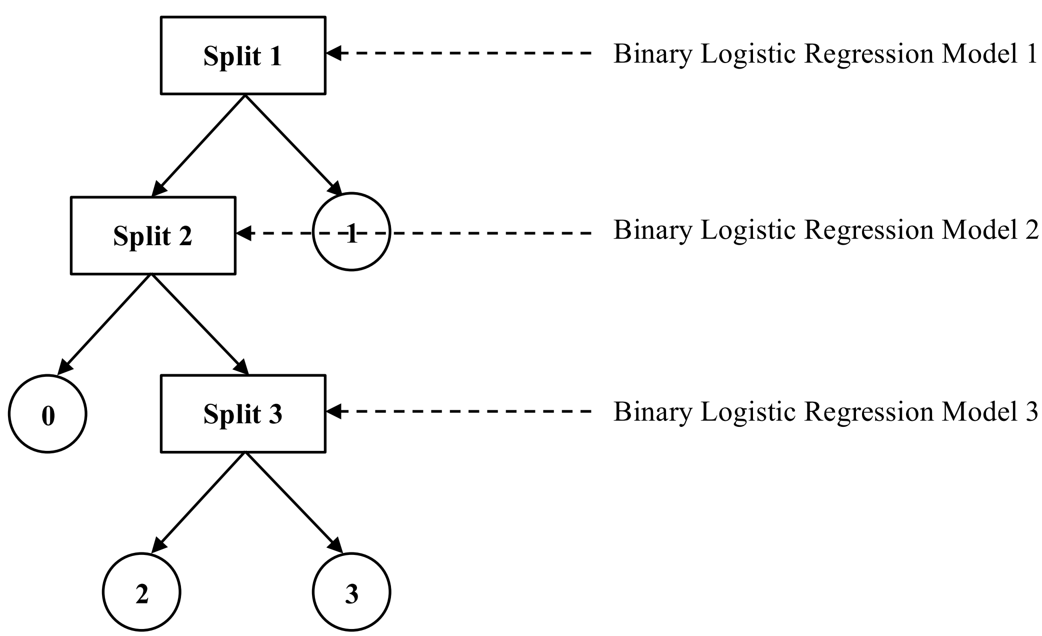

Figure 4.1 Sample Multi-layer Logistic Regression Classification Tree for RSC Discrimination

For each dataset, firstly, a multi-layer logistic regression classification tree with the best discriminant performance will be developed. Secondly, 90% of all the data records will be randomly selected from the database to calibrate the logistic regression models at each split using the backward stepwise likelihood ratio method. Finally, the developed models will be validated using the rest of the data records (10%), and the classification hit rate of the models will be evaluated and compared. The significance level threshold of the explanatory variables is set to 0.05.

4.3.4 Evaluation of Classification Quality

The quality of the logistic regression classification is measured by an evaluation matrix (i.e. confusion matrix) as shown in Table 4.2. The diagonal cells represent the number of points for which the predicted type is equal to the observed type, while those off-diagonal cells are mispredicted by the classifier. The higher the diagonal values of the confusion matrix or the higher percentage correct, the better performance the classifier has.

Table 4.2 Example of Logistic Regression Evaluation Matrix

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	7	3	70.0	20	5	80.0
	1	1	9	90.0	25	50	66.7
Overall Percentage				80.0			70.0

4.4 Exploratory Analysis

Figure 4.2 and Figure 4.3 show the box-plots of all variables, i.e. average speed, standard deviation of traffic speed, average volume, % long vehicles, wind speed and air temperature of each RSC type on Site 11-1 with 15 minute and 60 minute time intervals, respectively. It can be found from both figures that the average speed under chemically wet, ice watch and ice warning conditions are mostly lower than those under dry, trace moisture and wet conditions. Standard deviation of traffic speed of all the six types overlapped a lot, however, ice watch and ice warning generally tend to have a relatively higher standard deviation of traffic speed. The air temperature for trace moisture and wet are mostly above zero while it is mostly below zero for chemically wet, ice watch and ice warning. Although the box-plot of air temperature shows some difference among all the six types, the other five types are all bracketed by dry. Average volume, % long vehicles and wind speed overlapped a lot, and no obvious pattern can be found.

Figure 4.4 and Figure 4.5 show the same box-plots for Site 00-0 with 15 minute and 60 minute time intervals, respectively. The patterns of average speed, standard deviation of traffic speed as well as air temperature are mostly similar with the patterns found in Figure 4.2 and Figure 4.3. No obvious pattern can be found in average volume, % long vehicles and wind speed as well. The overlapped patterns of the six RSC types suggest that nested logistic regression models are needed.

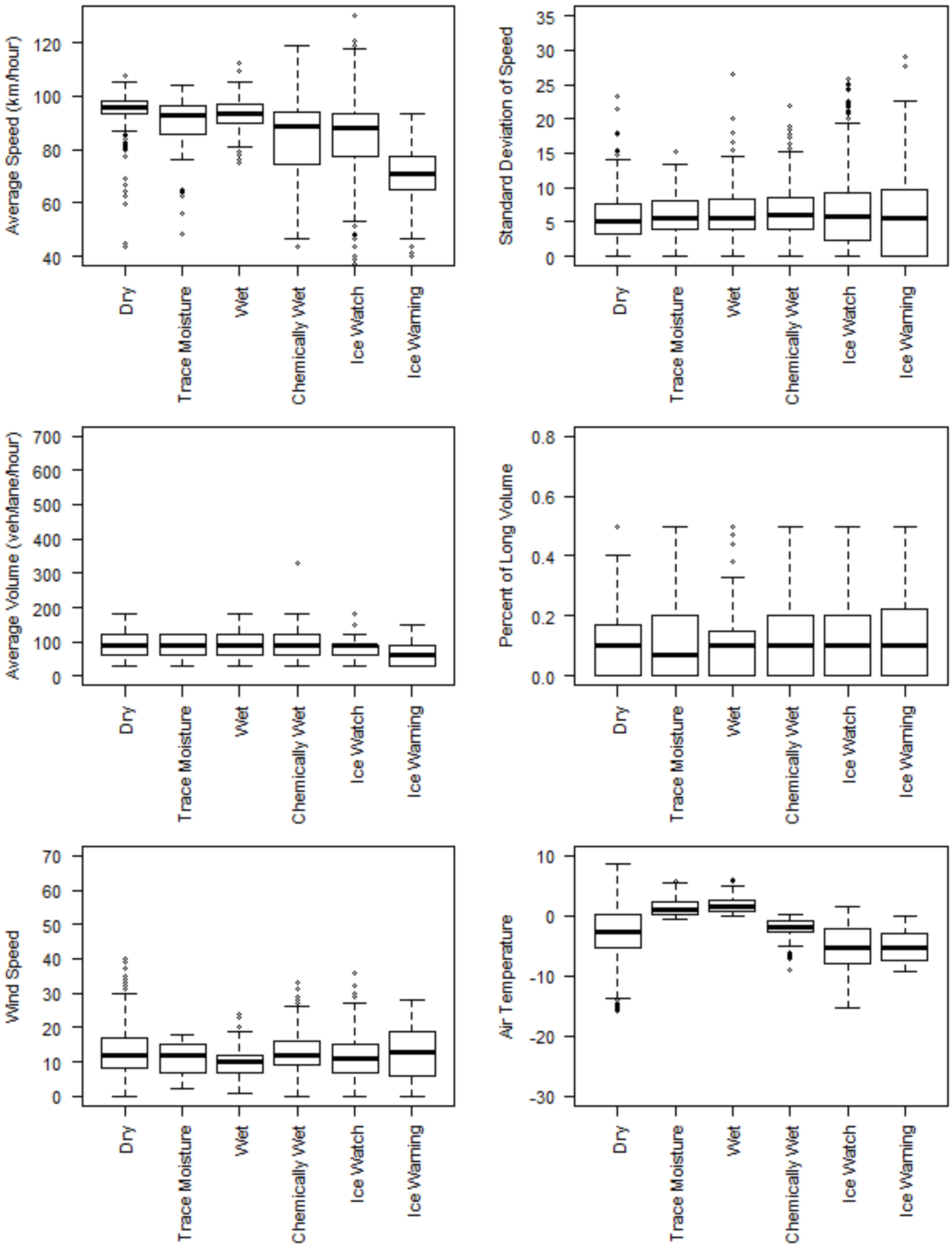

Figure 4.2 Boxplots for Site 11-1 (15-Minute Interval)

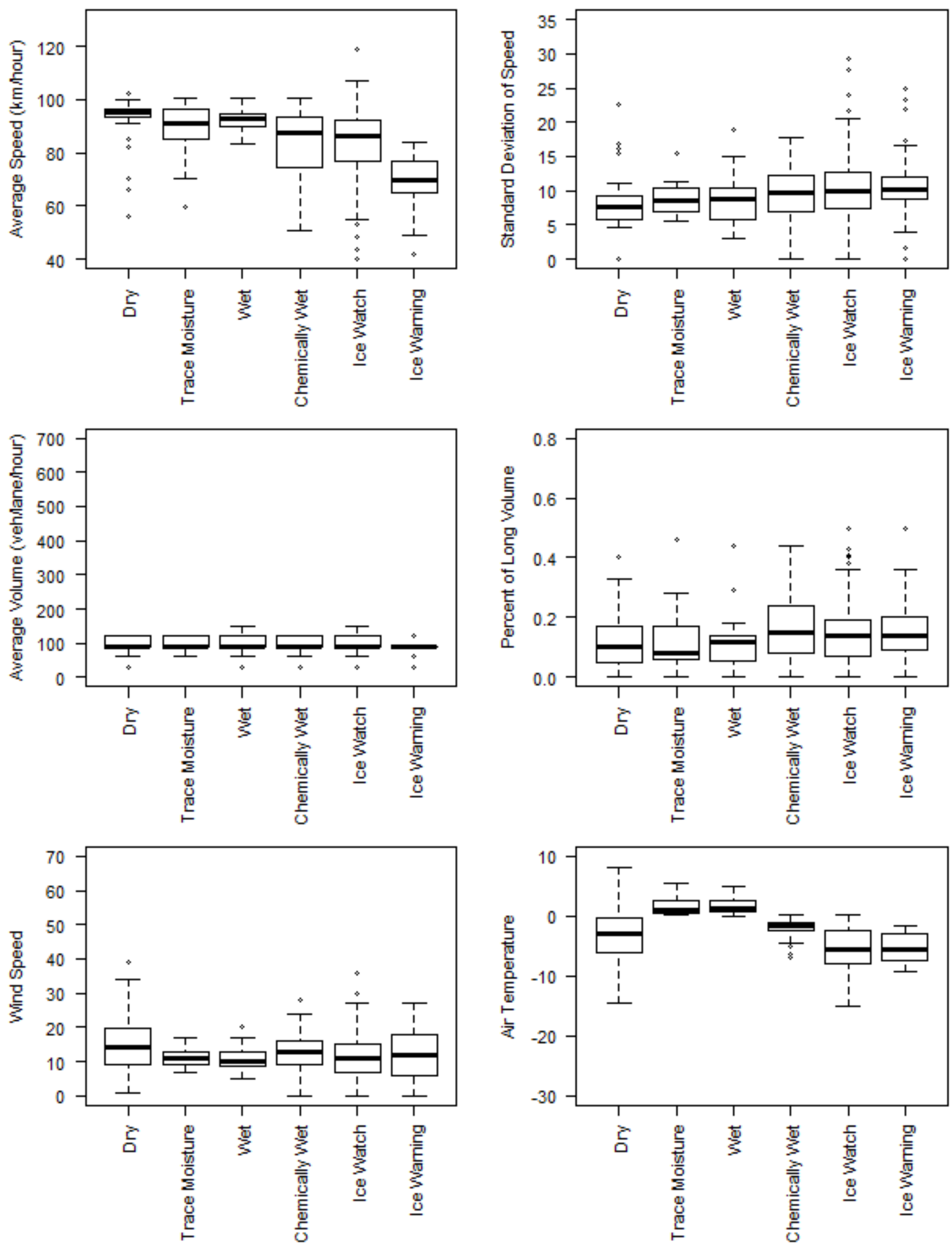

Figure 4.3 Boxplots for Site 11-1 (60-Minute Interval)

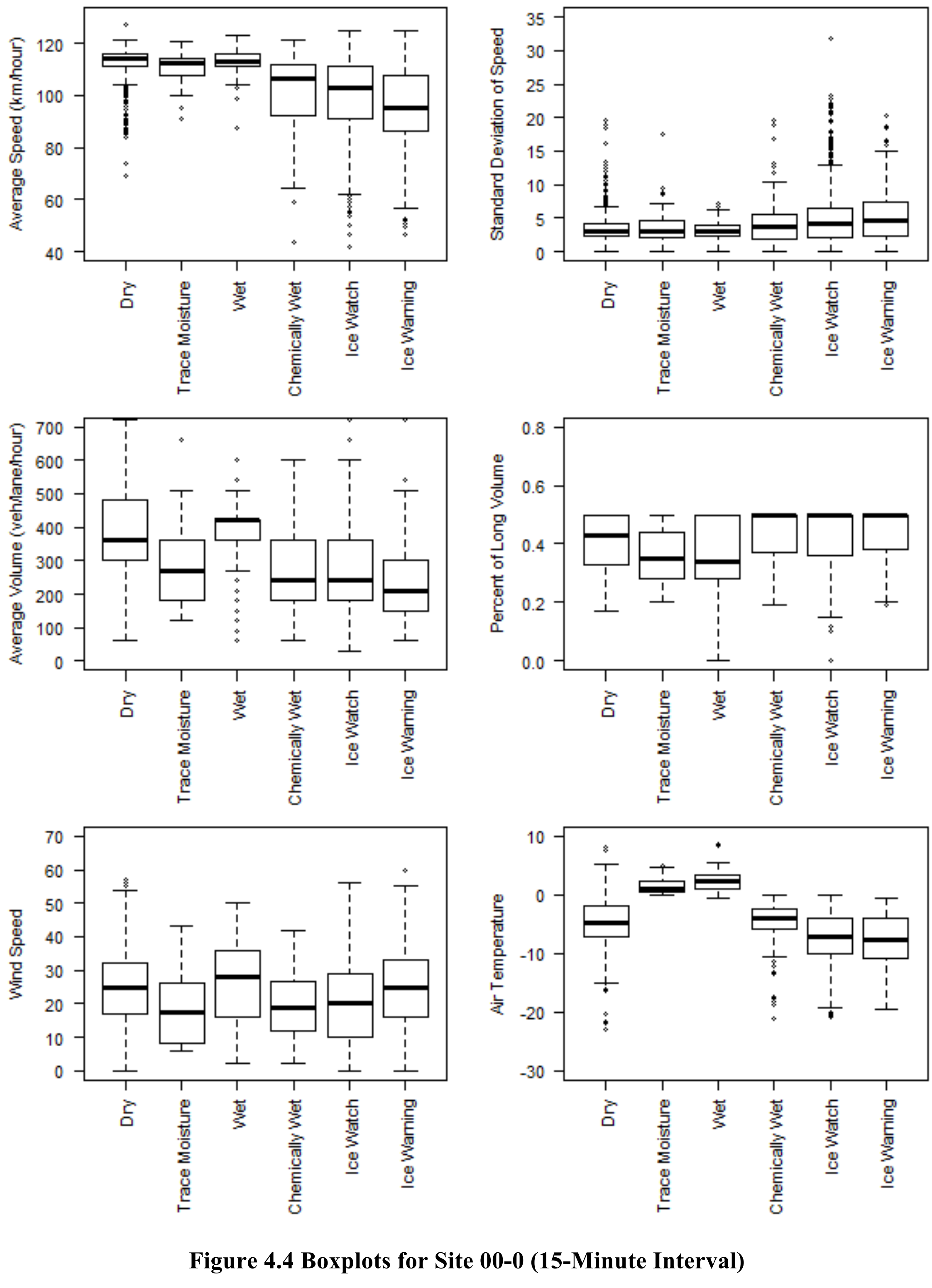

Figure 4.4 Boxplots for Site 00-0 (15-Minute Interval)

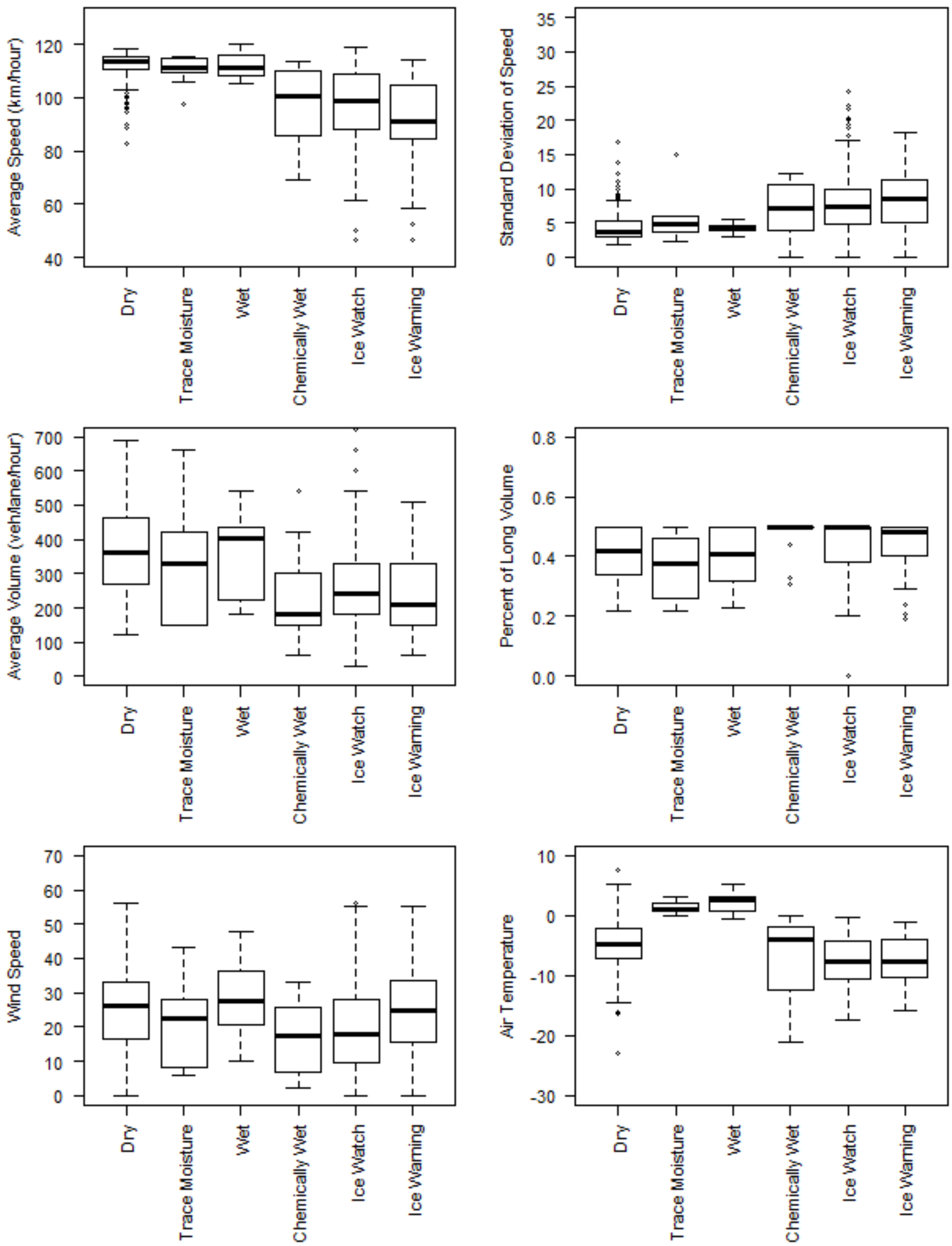

Figure 4.5 Boxplots for Site 00-0 (60-Minute Interval)

4.5 Model Calibration and Validation

4.5.1 Two Lane Highways

Based on the exploratory analysis as well as the calibration results of different alternative tree designs, it is found that the multi-layer classification tree in Figure 4.6 yields the best discriminant performance on Site 11-1 for both the 15 minute and 60 minute datasets. Note that because of the similarity of Type 1 and Type 2 as well as Type 4 and Type 5 at Site 11-1, the calibrated models lack of discriminate power to separate them with acceptable hit rate. Therefore, Type 1 and Type 2 have been combined together as a single Type, and the same with Type 4 and Type 5. Split 1 at the root of the tree firstly estimates the two probabilities respective to Type (0, 1, 2, 3) and Type (4, 5). Split 2 then estimates the two probabilities respective to Type 0 and Type (1, 2, 3). Accordingly, Split 3 estimates the two probabilities respective to Type (1, 2) and Type 3. Based on this classification tree, three logistic regression models in total are calibrated.

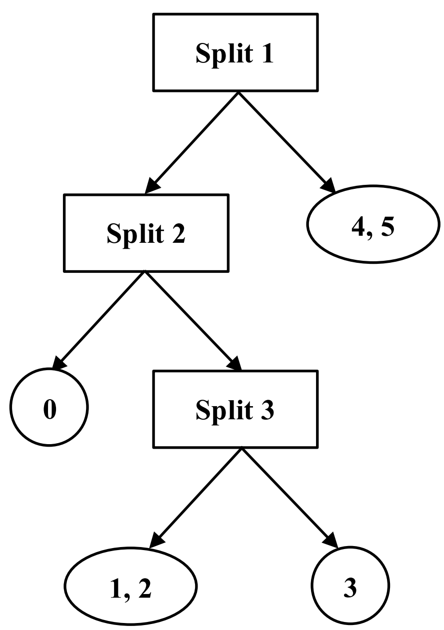

Figure 4.6 Calibrated Classification Tree for Site 11-1

Table 4.3 shows the calibration results of Split 1 with a 15 minute time interval for Site 11-1. As can be seen above, average speed, standard deviation of traffic speed, average volume, wind speed, air temperature as well as night are all statistically significant. The negative coefficients suggest that the higher the average speed, average volume, wind speed, air temperature and if the time is night, the more likely that the RSC is Type (0, 1, 2, 3). The positive coefficients suggest that the higher standard deviation of traffic speed, the higher probability that the RSC is Type (4, 5). The results make intuitive sense and are consistent with the pattern found in the box-plots in the exploratory data analysis.

Table 4.4 shows the classification results, which consists of two parts, the calibration data and the 10% holdout validation data. Class 0 represents Type (0, 1, 2, 3) and class 1 represents Type (4, 5). A cutoff value of 0.5 is used to define these two classes. When the estimated probability of belonging to class 1 is equal to or greater than 0.5 and the observed class is 1, the model is considered as making a correct prediction. When the estimated probability of belonging to class 1 is less than 0.5 and the observed class is 0, the model is also considered as making a correct prediction. Otherwise, it is considered as a missing. The overall percentage is the ratio of correct predictions to the total number of observations in the group.

For the calibration data, 399 and 1061 samples are correctly classified for class 0 and class 1, respectively. The hit rates for the two classes are 62.9% and 88.6%, respectively. The validation data shows the similar results: 39 and 117 cases are correctly classified for class 0 and class 1, respectively. The hit rates for class 0 and 1 are 60.9% and 88.6%, respectively. The overall hit rates for the calibration data and the validation data are 79.7% and 79.6%.

Table 4.3 Model Calibration of Site 11-1 Split 1 (15-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Speed	-.048	.006	70.364	1	.000	.954
Average Volume	-.004	.002	5.331	1	.021	.996
SD of Traffic Speed	.031	.013	5.211	1	.022	1.031
Wind Speed	-.060	.010	34.947	1	.000	.942
Air Temp	-.296	.019	248.607	1	.000	.744
Night	-.356	.121	8.590	1	.003	.701
Constant	4.695	.550	72.905	1	.000	109.432

Table 4.4 Classification Results of Site 11-1 Split 1 (15-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	399	235	62.9	39	25	60.9
	1	136	1061	88.6	15	117	88.6
Overall Percentage				79.7			79.6

Table 4.5 shows the calibration results of Split 2 with a 15 minute time interval for Site 11-1. It shows that the higher the average speed and wind speed, the more likely that the RSC is Type 0 while the higher air temperature and precipitation intensity is slight, the higher probability that the RSC is Type (1, 2, 3). Table 4.6 shows that for the calibration data, the hit rates for class 0 and 1 are 70.4% and 77.3%, respectively. For the validation data, the hit rates for class 0 and 1 are 80.6% and 66.7%, respectively. The overall hit rates for the calibration data and the validation data are 74.3% and 73.4%.

Table 4.5 Model Calibration of Site 11-1 Split 2 (15-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Speed	-.075	.013	30.900	1	.000	.928
Wind Speed	-.074	.016	21.017	1	.000	.928
Air Temp	.158	.025	39.053	1	.000	1.171
Slight	1.861	.210	78.335	1	.000	6.430
Constant	7.270	1.304	31.071	1	.000	1.436E3

Table 4.6 Classification Results of Site 11-1 Split 2 (15-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	195	82	70.4	25	6	80.6
	1	81	276	77.3	11	22	66.7
Overall Percentage				74.3			73.4

Table 4.7 shows the calibration results of Split 3 with 15 minutes as the time interval for Site 11-1. It can be found that only the air temperature is statistically significant, and the higher the air temperature, the higher the probability that the RSC is Type (1, 2). Table 4.8 shows the classification results. Compared with the previous two splits, the hit rates of both classes are much higher for both the calibration and validation data. The overall percentages for the calibration data and the validation data are 96.9% and 93.9%, respectively.

Table 4.7 Model Calibration of Site 11-1 Split 3 (15-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Air Temp	-7.155	1.468	23.753	1	.000	.001
Constant	-.623	.336	3.433	1	.064	.537

Table 4.8 Classification Results of Site 11-1 Split 3 (15-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	193	4	98.0	19	1	95.0
	1	7	153	95.6	1	12	92.3
Overall Percentage				96.9			93.9

Table 4.9 shows the calibration results of Split 1 with 60 minutes as the time interval for Site 11-1. Compared with the 15 minute model, only average speed, wind speed and air temperature are statistically significant. The coefficients of these independent variables remain similar with the 15 minute model. Table 4.10 reveals that for the calibration data, the hit rates for class 0 and 1 are 64.1% and 89.5%, respectively. For the validation data, the hit rates for class 0 and 1 are 63.6% and 82.1%, respectively. The overall percentages for the calibration data and the validation data are 81.0% and 76.9%.

Table 4.9 Model Calibration of Site 11-1 Split 1 (60-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Speed	-.060	.013	22.562	1	.000	.942
Wind Speed	-.084	.022	14.881	1	.000	.919
Air Temp	-.377	.047	63.587	1	.000	.686
Constant	5.611	1.150	23.814	1	.000	273.496

Table 4.10 Classification Results of Site 11-1 Split 1 (60-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	84	47	64.1	7	4	63.6
	1	27	231	89.5	5	23	82.1
Overall Percentage				81.0			76.9

Table 4.11 displays the calibration results of Split 2 with 60 minutes as the time interval for Site 11-1. The model has the same significant independent variables with the 15 minute model, and the coefficients of these explanatory variables are also identical with the 15 minute model. It can be found in Table 4.12 that for the calibration data, the hit rates for class 0 and 1 are 66.7% and 86.2%, respectively. For the validation data, the hit rates for class 0 and 1 are 60.0% and 100.0%, respectively. The overall percentages for the calibration data and the validation data are 78.6% and 81.8%.

Table 4.11 Model Calibration of Site 11-1 Split 2 (60-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Speed	-.098	.032	9.122	1	.003	.907
Wind Speed	-.095	.036	6.848	1	.009	.909
Air Temp	.236	.069	11.844	1	.001	1.267
Slight	1.830	.497	13.573	1	.000	6.235
Constant	9.865	3.155	9.779	1	.002	1.925E4

Table 4.12 Classification Results of Site 11-1 Split 2 (60-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	34	17	66.7	3	2	60.0
	1	11	69	86.2	0	6	100.0
Overall Percentage				78.6			81.8

Table 4.13 demonstrates the calibration results of Split 3 with 60 minutes as the time interval for Site 11-1. Again, only air temperature is statistically significant, and the effect of surface temperature is also identical with the 15 minute model. As is shown in Table 4.14, for the calibration data, the hit rates for class 0 and 1 are also high, 97.8% and 95.1%, respectively. For the validation data, the hit rates for class 0 and 1 are both 100.0%. The overall percentages for the calibration data and the validation data are 96.5% and 100.0%.

Table 4.13 Model Calibration of Site 11-1 Split 3 (60-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Air Temp	-9.755	1.589	4.519	1	.034	.000
Constant	-.092	.726	.016	1	.899	.912

Table 4.14 Classification Results of Site 11-1 Split 3 (60-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	44	1	97.8	4	0	100.0
	1	2	39	95.1	0	4	100.0
Overall Percentage				96.5			100.0

4.5.2 Four Lane Highways

The classification tree of Site 00-0 (shown in Figure 4.7) is similar with the one of Site 11-1, except that Type 1 and 2 are no longer combined as they can be separated with an acceptable hit rate. Split 1 at the root of the tree firstly estimates the two probabilities respective to Type (0, 1, 2, 3) and Type (4, 5). Split 2 then estimates the two probabilities respective to Type 0 and Type (1, 2, 3). Split 3 then estimates the two probabilities respective to Type (1, 2) and Type 3. Finally, Split 4 estimates the two probabilities respective to Type 1 and Type 2. Based on this classification tree, four logistic regression models in total are calibrated.

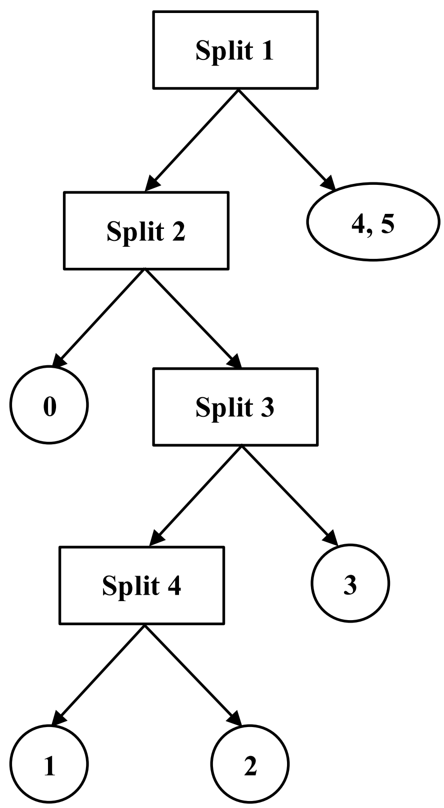

Figure 4.7 Calibrated Classification Tree for Site 00-0

Table 4.15 demonstrates the calibration results of Split 1 with 15 minutes as the time interval for Site 00-0. As can be seen, average speed, standard deviation of traffic speed, average volume, wind speed, air temperature, slight as well as night are all statistically significant. The negative coefficients suggest that the higher the average speed, average volume, wind speed, and if the air temperature, precipitation intensity is slight and the time is night, the more likely that the RSC is Type (0, 1, 2, 3). The positive coefficients suggest that the higher the standard deviation of traffic speed, the higher probability that the RSC is Type (4, 5). The results make intuitive sense and are consistent with the pattern of the box-plots obtained in the exploratory analysis. Table 4.16 reveals that for the calibration data, the hit rates for the two classes are 65.4% and 86.0%, respectively. For the validation data, the hit rates for class 0 and 1 are 62.2% and 85.0%, respectively. The overall percentages for the calibration data and the validation data are 78.7% and 77%.

Table 4.15 Model Calibration of Site 00-0 Split 1 (15-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Speed	-.101	.007	193.251	1	.000	.904
Average Volume	-.001	.000	5.224	1	.022	.999
SD of Traffic Speed	.062	.021	8.908	1	.003	1.064
Wind Speed	-.021	.005	18.397	1	.000	.980
Air Temp	-.122	.014	75.811	1	.000	.885
Slight	-.563	.120	21.928	1	.000	.570
Night	-.595	.114	27.061	1	.000	.552
Constant	11.265	.857	172.697	1	.000	7.804E4

Table 4.16 Classification Results of Site 00-0 Split 1 (15-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	507	268	65.4	56	34	62.2
	1	197	1213	86.0	25	142	85.0
Overall Percentage				78.7			77.0

The calibration results of Split 2 with 15 minutes as the time interval for Site 00-0 is shown in Table 4.17. The results reveal that the higher the average speed, average volume, wind speed and if time is night, the more likely that the RSC is Type 0 while the higher surface temperature and if the precipitation intensity is slight or moderate, the higher probability that the RSC is Type (1, 2, 3). It can be found in Table 4.18 that for the calibration data, the hit rates for class 0 and 1 are 95.8% and 55.6%, respectively. For the validation data, the hit rates for class 0 and 1 are 94.8% and 60.0%, respectively. The overall percentages for the calibration data and the validation data are 85.4% and 87.6%.

Table 4.17 Model Calibration of Site 00-0 Split 2 (15-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Speed	-.055	.013	17.500	1	.000	.946
Average Volume	-.004	.001	24.459	1	.000	.996
Wind Speed	-.030	.009	12.477	1	.000	.970
Air Temp	.302	.029	105.907	1	.000	1.352
Slight	.685	.213	10.363	1	.001	1.984
Moderate	1.657	.574	8.338	1	.004	5.243
Night	-.427	.204	4.361	1	.037	.652
Constant	7.116	1.496	22.626	1	.000	1.232E3

Table 4.18 Classification Results of Site 00-0 Split 2 (15-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	546	24	95.8	73	4	94.8
	1	88	110	55.6	8	12	60.0
Overall Percentage				85.4			87.6

Table 4.19 shows the calibration results of Split 3 with 15 minutes as the time interval for Site 00-0. Similar with Site 11-1, only the air temperature is statistically significant, and the higher the air temperature, the higher the probability that the RSC is Type (1, 2). Table 4.20 also shows similar results with Site 11-1. Compared with the previous two splits, the hit rates of both classes are much higher for both the calibration and validation data. The overall percentages for the calibration data and the validation data are 97.5% and 95.0%, respectively.

Table 4.19 Model Calibration of Site 00-0 Split 3 (15-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Air Temp	-7.821	1.449	10.200	1	.001	.000
Constant	-1.034	.648	2.544	1	.111	.356

Table 4.20 Classification Results of Site 00-0 Split 3 (15-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	100	2	98.0	12	1	92.3
	1	3	93	96.9	0	7	100.0
Overall Percentage				97.5			95.0

The calibration results of Split 4 with 15 minutes as the time interval for Site 00-0 can be found in Table 4.21. The results reveal that the higher the standard deviation of traffic speed and if the time is night, the more likely that the RSC is Type 1 while the higher average volume and wind speed, the higher probability that the RSC is Type 2. Table 4.22 reveals that for the calibration data, the hit rates for class 0 and 1 are 67.4% and 83.3%, respectively. For the validation data, the hit rates for class 0 and 1 are 75.0% and 100.0%, respectively. The overall percentages for the calibration data and the validation data are 76.4% and 88.9%.

Table 4.21 Model Calibration of Site 00-0 Split 4 (15-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Volume	.006	.002	10.785	1	.001	1.006
SD of Traffic Speed	-.292	.124	5.523	1	.019	.747
Wind Speed	.076	.022	12.582	1	.000	1.079
Night	-1.046	.508	4.248	1	.039	.351
Constant	-2.123	.783	7.346	1	.007	.120

Table 4.22 Classification Results of Site 00-0 Split 4 (15-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	31	15	67.4	3	1	75.0
	1	10	50	83.3	0	5	100.0
Overall Percentage				76.4			88.9

Table 4.23 shows the calibration results of Split 1 with 60 minutes as the time interval for Site 00-0. Compared with the 15 minute model, only average speed, wind speed, air temperature and night are statistically significant. The coefficients of these independent variables remain similar with the 15 minute model. As can be seen in Table 4.24, for the calibration data, the hit rates for class 0 and 1 are 68.9% and 88.8%, respectively. For the validation data, the hit rates for class 0 and 1 are 77.3% and 90.5%, respectively. The overall percentages for the calibration data and the validation data are 82.3% and 85.9%.

Table 4.23 Model Calibration of Site 00-0 Split 1 (60-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Speed	-.118	.015	64.602	1	.000	.889
Wind Speed	-.024	.010	5.594	1	.018	.976
Air Temp	-.112	.028	15.814	1	.000	.894
Night	-.660	.252	6.868	1	.009	.517
Constant	13.204	1.671	62.407	1	.000	5.423E5

Table 4.24 Classification Results of Site 00-0 Split 1 (60-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	104	47	68.9	17	5	77.3
	1	35	278	88.8	4	38	90.5
Overall Percentage				82.3			85.9

Table 4.25 demonstrates the calibration results of Split 2 with 60 minutes as the time interval for Site 00-0. Average speed, wind speed, air temperature, slight and moderate are statistically significant, and the coefficients of these independent variables are also identical with the 15 minute model. Table 4.26 shows that for the calibration data, the hit rates for class 0 and 1 are 96.7% and 58.3%, respectively. For the validation data, the hit rates for class 0 and 1 are 92.3% and 100.0%, respectively. The overall percentages for the calibration data and the validation data are 88.0% and 93.3%.

Table 4.25 Model Calibration of Site 00-0 Split 2 (60-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Speed	-.104	.030	12.348	1	.000	.902
Wind Speed	-.058	.019	9.699	1	.002	.944
Air Temp	.273	.064	18.068	1	.000	1.313
Slight	1.006	.495	4.130	1	.042	2.734
Moderate	2.334	.968	5.814	1	.016	10.316
Constant	11.726	3.416	11.780	1	.001	1.237E5

Table 4.26 Classification Results of Site 00-0 Split 2 (60-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	118	4	96.7	12	1	92.3
	1	15	21	58.3	0	2	100.0
Overall Percentage				88.0			93.3

Table 4.27 shows the calibration results of Split 3 with 60 minutes as the time interval for Site 00-0. Again, only air temperature is statistically significant. The coefficient of air temperature is changed from -7.821 to -4.552. Table 4.28 reveals that for the calibration data, the hit rates for class 0 and 1 are also high, 95.0% and 93.3%, respectively. For the validation data, the hit rates for class 0 and 1 are both 100.0%. The overall percentages for the calibration data and the validation data are 94.3% and 100.0%.

Table 4.27 Model Calibration of Site 00-0 Split 3 (60-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Air Temp	-4.552	2.959	2.366	1	.024	.011
Constant	-1.091	1.113	.961	1	.327	.336

Table 4.28 Classification Results of Site 00-0 Split 3 (60-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	19	1	95.0	2	0	100.0
	1	1	14	93.3	0	1	100.0
Overall Percentage				94.3			100.0

The calibration results of Split 4 with 60 minutes as the time interval for Site 00-0 can be found in Table 4.29. Except for the standard deviation of traffic speed, the other significant variables are the same with the 15 minute models, and the coefficients are close to the 15 minutes as well. Table 4.30 displays that for the calibration data, the hit rates for class 0 and 1 are also high, 85.7% and 90.0%, respectively. For the validation data, the hit rates for class 0 and 1 are 66.7 and 100.0%. The overall percentages for the calibration data and the validation data are 88.2% and 80.0%.

Table 4.29 Model Calibration of Site 00-0 Split 4 (60-Minute Interval)

	B	S.E.	Wald	df	Sig.	Exp(B)
Average Volume	.012	.002	10.785	1	.001	1.012
Wind Speed	.086	.022	12.582	1	.000	1.09
Night	-1.021	.508	4.248	1	.039	.36
Constant	-1.112	.783	7.346	1	.007	.329

Table 4.30 Classification Results of Site 00-0 Split 4 (60-Minute Interval)

		Calibration Data			Validation Data		
		Predicted		Percentage Correct	Predicted		Percentage Correct
		0	1		0	1	
Observed	0	6	1	85.7	2	1	66.7
	1	1	9	90.0	0	2	100.0
Overall Percentage				88.2			80.0

4.6 Discussion

Table 4.31 shows the summary of models for both Site 11-1 and Site 00-0. Based on this table, the effects of each variable for all the splits can be summarized below:

Table 4.31 Model Summary for Site 11-1 and Site 00-0

	Site 11-1						Site 00-0							
	Split 1		Split 2		Split 3		Split 1		Split 2		Split 3		Split 4	
	15 min	60 min	15 min	60 min	15 min	60 min	15 min	60 min	15 min	60 min	15 min	60 min	15 min	60 min
Average Speed	-0.048	-0.06	-0.075	-0.098			-0.101	-0.118	-0.055	-0.104				
Average Volume	-0.004						-0.001		-0.004				0.006	0.012
% Long Vehicles														
SD of Speed	0.031						0.062						-0.292	
Wind Speed	-0.06	-0.084	-0.074	-0.095			-0.021	-0.024	-0.03	-0.058			0.076	0.086
Air Temperature	-0.296	-0.377	0.158	0.236	-7.155	-9.755	-0.122	-0.112	0.302	0.273	-7.821	-4.552		
Slight			1.861	1.83			-0.563		0.685	1.006				
Moderate									1.657	2.334				
Heavy														
Night	-0.356						-0.595	-0.66	-0.427				-1.046	-1.021
Constant	4.695	5.611	7.27	9.865	-0.623	-0.092	11.265	13.204	7.116	11.726	-1.034	-1.091	-2.123	-1.112
Calibration Overall Percentage Correct	79.7	81.0	74.3	78.6	96.9	96.5	78.7	82.3	85.4	88.0	97.5	94.3	76.4	88.2
Validation Overall Percentage Correct	79.6	76.9	73.4	81.8	93.9	100.0	77.0	85.9	87.6	93.3	95.0	100.0	88.9	80.0

- **Impacts of Average Speed**

  Based on the results of Split 1, it can be found that average speed is statistically significant in distinguishing good RSC (Type 0, 1, 2, 3) from poor RSC (Type 4, 5), and the higher the speed, the higher probability that the RSC belongs to Type (0, 1, 2, 3) – good conditions. For Site 11-1, every one km/h increase in average speed, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.048 and 0.06 based on the 15 minute and 60 minute models, respectively. For Site 00-0, every one km/h increase in average speed, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.101 and 0.118 for the 15 minute and 60 minute models, respectively.

  In addition, average speed is also statistically significant in classifying Type 0 and Type (1, 2, 3) at Split 2, and the higher the value, the higher probability that the RSC is Type 0. For Site 11-1, every one km/h increase in average speed, the log odds of Type (1, 2, 3) versus Type 0 decreases by 0.075 and 0.098 for the 15 minute and 60 minute models, respectively. For Site 00-0, every one km/h increase in average speed, the log odds of Type (1, 2, 3) versus Type 0 decreases by 0.055 and 0.104 for the15 minute and 60 minute models, respectively.

- **Impacts of Standard Deviation of Traffic Speed**

Standard deviation of traffic speed is also statistically significant in distinguishing good RSC (Type 0, 1, 2, 3) from poor RSC (Type 4, 5). The more varied the speed, the higher probability that the RSC is in poor conditions. For Site 11-1, every one unit increase in standard deviation of traffic speed, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) increases by 0.031for the 15 minute model. For Site 00-0, every one unit increase in standard deviation of traffic speed, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) increases by 0.062 for the 15 minute model.

In addition, it turns out that standard deviation of traffic speed is also statistically significant in classifying Type 1 and Type 2. For Site 00-0, every one unit increase in standard deviation of traffic speed, the log odds of Type 2 versus Type 1 decreases by 0.292 for the 15 minute model.

- **Impacts of Average Volume and % Long Vehicles**

% long vehicles is found not statistically significant in all models. Average volume is in distinguishing good RSC (Type 0, 1, 2, 3) from poor RSC (Type 4, 5), and the higher the % long vehicles, the higher probability that the RSC is Type (0, 1, 2, 3). For Site 11-1, every one veh/ln/h increase in average volume, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.004 for the 15 minute model. For Site 00-0, every one veh/ln/h increase in average volume, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.001 for the 15 minute model.

In addition, average volume is also found statistically significant in classifying Type 0 and Type (1, 2, 3) as well as Type 1 and Type 2. For Site 00-0, every one veh/ln/h increase in average volume, the log odds of Type (1, 2, 3) versus Type 0 decreases by 0.004 for the 15 minute model. For Site 00-0, every one veh/ln/h increase in average volume, the log odds of Type 2 versus Type 1 increases by 0.006 and 0.012 for the 15 and 60 minute models.

- **Impacts of Wind Speed**

Wind speed is statistically significant in distinguishing good RSC (Type 0, 1, 2, 3) from poor RSC (Type 4, 5), and the higher the wind speed, the higher probability that the RSC is Type (0, 1, 2, 3). For Site 11-1, every one km/h increase in wind speed, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.06 and 0.084 for the 15 minute and 60 minute models, respectively. For Site 00-0, every one km/h increase in wind speed, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.021 and 0.024 for the 15 minute and 60 minute models, respectively.

In addition, wind speed is also statistically significant in distinguishing Type 0 from Type (1, 2, 3), and the higher the wind speed, the higher probability that the RSC is Type 0. For Site 11-1, every one km/h increase in average speed, the log odds of Type (1, 2, 3) versus Type 0 decreases by 0.074 and 0.095 for the 15 minute and 60 minute models, respectively. For Site 00-0, every one km/h increase in average speed, the log odds of Type (1, 2, 3) versus Type 0 decreases by 0.03 and 0.058 for the15 minute and 60 minute models, respectively.

Lastly, wind speed is also statistically significant in distinguishing Type 1 from Type 2. For Site 00-0, every one km/h increase in wind speed, the log odds of Type 2 versus Type 1 increases by 0.076 and 0.086 for the 15 minute and 60 minute models, respectively.

- **Impacts of Air Temperature**

Air temperature is statistically significant in distinguishing good RSC (Type 0, 1, 2, 3) from poor RSC (Type 4, 5).The higher the air temperature, the higher probability that the RSC is Type (0, 1, 2, 3). For Site 11-1, every one degree increase in air temperature, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.296 and 0.377 for the 15 minute and 60 minute models, respectively. For Site 00-0, every one degree increase in air temperature, the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.122 and 0.112 for the 15 minute and 60 minute models, respectively.

In addition, air temperature is also statistically significant in distinguishing Type 0 from Type (1, 2, 3), and the higher the air temperature, the higher probability that the RSC is Type (1, 2, 3). For Site 11-1, every one degree increase in air temperature, the log odds of Type (1, 2, 3) versus Type 0 increases by 0.158 and 0.236 for the 15 minute and 60 minute models, respectively. For Site 00-0, every one degree increase in air temperature, the log odds of Type (1, 2, 3) versus Type 0 decreases by 0.302 and 0.273 for the15 minute and 60 minute models, respectively.

Lastly, air temperature is also statistically significant in distinguishing Type (1, 2) from Type 3.The higher the air temperature, the higher probability that RSC is Type (1, 2). For Site 11-1, every one degree increase in air temperature, the log odds of Type (1, 2, 3) versus Type 0 decreases by 7.155 and 9.755 for the 15 minute and 60 minute models, respectively. For Site 00-0, every one degree increase in air temperature, the log odds of Type (1, 2, 3) versus Type 0 decreases by 7.821 and 4.552 for the15 minute and 60 minute models, respectively.

- **Impacts of Precipitation Intensity**

  Slight is statistically significant in distinguishing good RSC (Type 0, 1, 2, 3) from poor RSC (Type 4, 5). For Site 00-0, slight can cause the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decrease by 0.563 for the 15 minute model.

  Additionally, both slight and moderate are statistically significant in distinguishing Type 0 from Type (1, 2, 3) at Split 2. For Site 11-1, slight can cause the log odds of Type (1, 2, 3) versus Type 0 increase by 1.861 and 1.83 for the 15 minute and 60 minute models, respectively. For Site 00-0, slight can cause the log odds of Type (1, 2, 3) versus Type 0 increase by 0.685 and 1.006 for the 15 minute and 60 minute models, respectively. Moderate can cause the log odds of Type (1, 2, 3) versus Type 0 increase by 1.657 and 2.334 for the15 minute and 60 minute models, respectively.

- **Impacts of Night**

  Night is statistically significant in distinguishing good RSC (Type 0, 1, 2, 3) from poor RSC (Type 4, 5). For Site 11-1, night can cause the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decreases by 0.356 for the 15 minute model. For Site 00-0, night can cause the log odds of Type (4, 5) versus Type (0, 1, 2, 3) decrease by 0.595 and 0.66 for the 15 minute and 60 minute models, respectively.

  In addition, night is also found statistically significant in distinguishing Type 0 from Type (1, 2, 3) as well as Type 1 and Type 2. For Site 00-0, night can cause the log odds of Type (1, 2, 3) versus Type 0 decrease by 0.427 for the 15 minute model. For Site 00-0, night can cause the log odds of Type 2 versus Type 1 decrease by 1.046 and 1.021 for the 15 and 60 minute models.

Figure 4.8 and Figure 4.9 show the overall validation hit rate summary for each split of Site 11-1 and Site 00-0, respectively. As can be found in Figure 4.8, both Split 1 and 2 of Site 11-1 have the overall hit rate at around 80% for both the 15 minute and 60 minute models. Split 3 has an even higher overall hit rate than Split 1 and 2, i.e. over 90% for the 15 minute model and 100% for the 60 minute model. Figure 4.9 reveals that, similar with Site 11-1, both Split 1 and 2 of Site 00-0 have the overall hit rate at around 80%. Again, Split 3 has the highest overall hit rate, i.e. over 90% for the 15 minute model and 100% for the 60 minute model. Split 4 of Site 00-0 also has relatively high hit rate. It is about 90% for the 15 minute model, and about 80% for the 60 minute model.

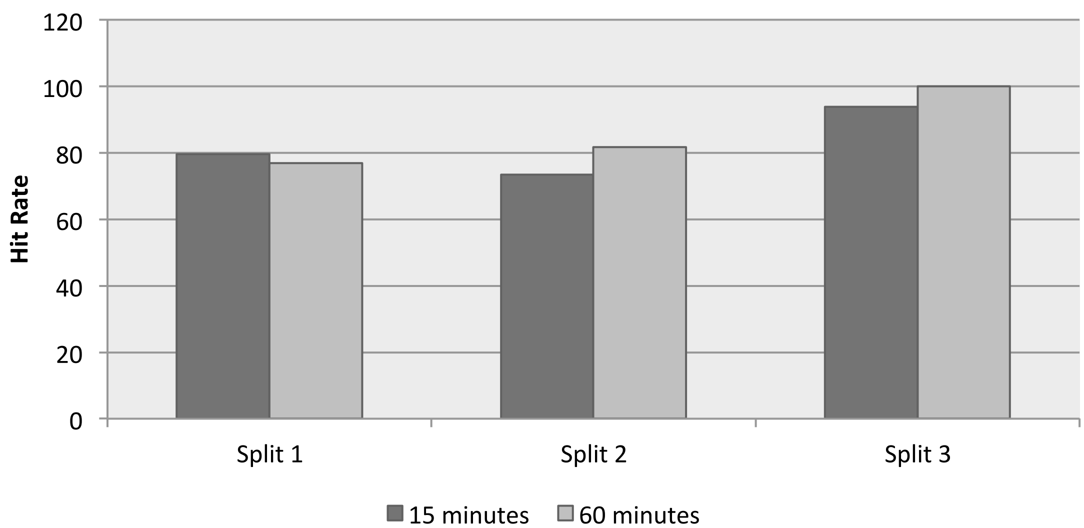

Figure 4.8 Overall Validation Hit Rate Summary of Site 11-1

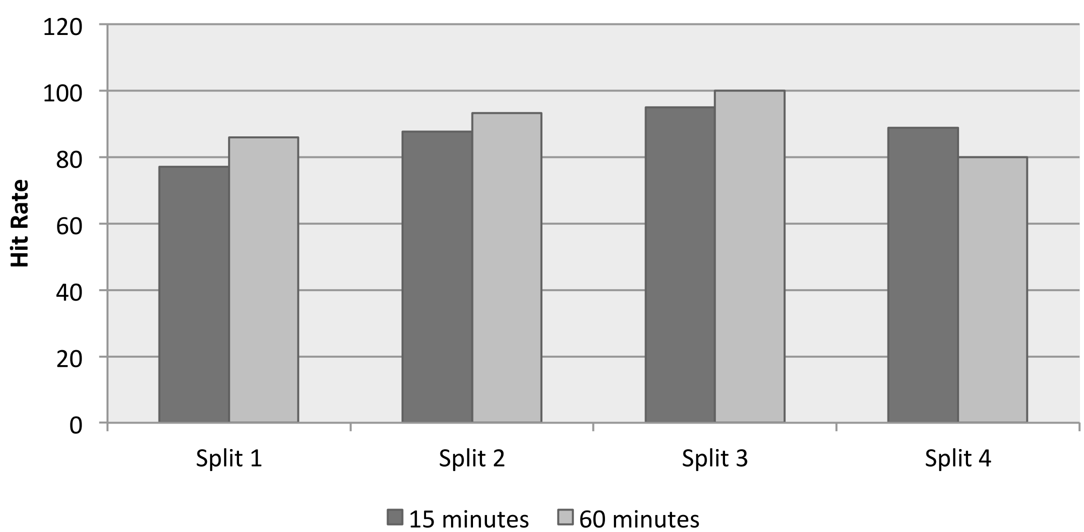

Figure 4.9 Overall Validation Hit Rate Summary of Site 00-0

4.7 Summary

This study investigates the feasibility of classifying different RSC types on uninterrupted traffic flow using a multi-layer logistic regression classification tree based on both traffic and weather data. A wide range of factors are examined for the effects on RSC, including average speed, average volume, % long vehicles, standard deviation of traffic speed, wind speed, air temperature, precipitation intensity and time of day. The results clearly show that with the proper classification trees, traffic and weather data can be utilized to discriminate major RSC types.

It is found that splits that classify the same RSC types for both Site 11-1 (two-lane two-way) and Site 00-0 (four-lane) have similar significant explanatory variables. For example, for discriminating Type (0, 1, 2, 3) and Type (4, 5) at Split 1 of both sites, average speed, average volume, standard deviation of traffic speed, wind speed, air temperature and night are all statistically significant for the 15 minute models while average speed, wind speed and air temperature are all statistically significant for the 60 minute models. For discriminating Type 0 and Type (1, 2, 3) at Split 2 of both sites, average speed, wind speed, air temperature and slight are all statistically significant for both the 15 minute and the 60 minute models. For discriminating Type (1, 2) and Type 3 at Split 3 of both sites, air temperature is statistically significant for both the 15 minute and the 60 minute models. In terms of model performance, the overall hit rates for models of all splits are around 80% or higher, which indicates that the calibrated models have a relatively high performance and reliability.

Chapter 5
Conclusions and Future Work

5.1 Major Findings

This research has, firstly, investigated the impact of adverse weather and RSC on traffic speed with the intention of exploring the feasibility of applying speed as a performance indicator of WRM. Traffic, weather and surface condition data, over three winter seasons from 2008 to 2011, collected from 35 rural highway sites (i.e. 14 on two-lane and 21 on four-lane highways) in Iowa, US, are used in this research. Multivariate linear regression models with both 15 minute and 60 minute time intervals, MLP-NN and ARIMAX models are developed for the two highway types.

The results of the multivariate regression analysis confirm that both adverse weather conditions (e.g. snow precipitation) and snow/ice coverage can result in a significant speed reduction during snow events on both two-lane and four-lane rural highways. The MLP-NN is capable of capturing the non-linear effect; however, it is only slightly better in speed estimation performance than the multivariate linear regression models. This result suggests the robustness of the multivariate linear regression models. Compared with the multivariate regression models and the MLP-NN model, the ARIMAX model provides much improved explanatory and prediction power in estimating the travel speed of the current time period by making use of both recent past speed observations and external factors. The analysis results clearly indicated the dependency of traffic speed on RSC, suggesting the feasibility of applying speed as a performance monitoring indicator.

Secondly, the research investigates the feasibility of classifying different RSC types using a multi-layer logistic regression classification tree based on both traffic and weather data. The results show that splits that classify the RSC types for both Site 11-1 (two-lane) and Site 00-0 (four-lane) have similar significant explanatory variables. In particular, to discriminate ice watch/warning and other RSC types at Split 1, standard deviation of traffic speed is found statistically significant in the 15 minute model while average speed, wind speed and air temperature are all statistically significant for both the 15 minute and 60 minute models. The overall hit rates for models of all splits are 80% or higher, which confirms the reliability of the multi-layer logistic classification regression tree in discriminating RSC types using traffic and weather data on both two-lane and four-lane highways.

5.2 Limitations and Future Work

There are still limitations of this research. The following improvements can be pursued to gain a better understanding of the relationship between traffic speed and RSC and improve the reliability of applying the results in WRM performance measurement:

- This study only considered the first order of the independent variables in the multivariate linear regression analysis. Further studies can be performed to investigate the need to consider higher orders and interaction among variables.
- This study analyzed three winter seasons data collected from 35 sites. General models have been developed for both two-lane and four-lane highways. More sites should be covered to improve the transferability of the models.
- Data used in this study is collected at stations located on highways, which indicates that the dataset is point measurement only. To improve the spatial coverage of the RSC classification models, mobile data (e.g. GPS, real time speed and weather condition) collected from highway users or patrol personnel needs to be utilized.
- This study only applied logistic regression for classifying RSC types. Further studies need to be conducted to investigate other classification algorithms, especially machine learning algorithms, for example, a support vector machine.

Appendix A-1: Two-Lane Regression Results (15-Minute)

Sites	Constant		Avg Volume		% Long Vehicles		Wind Spd		Visibility		SF_Temp		Slight		Moderate		Heavy		Trace Moisture		Wet		Chemically Wet		Ice Watch		Ice Warning		Night		Adj. R^2
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	
01-0	88.23	0.00	0.02	0.00					0.02	0.03			-3.16	0.00	-8.08	0.00	-27.91	0.00			-3.10	0.00	-5.83	0.00	-9.33	0.00	-7.86	0.00			0.29
01-1	90.36	0.00	0.01	0.03									-3.77	0.00	-11.72	0.00	-28.28	0.00					-10.98	0.00	-6.82	0.00	-12.41	0.00	-1.48	0.00	0.24
02-0	88.74	0.00	0.04	0.00			-0.24	0.00					-5.17	0.00	-13.91	0.00	-19.77	0.00					-8.00	0.00	-8.53	0.00	-9.80	0.00			0.29
02-1	88.75	0.00	0.03	0.00	-4.30	0.00	-0.16	0.00					-5.55	0.00	-14.71	0.00	-16.83	0.00					-4.93	0.00	-7.28	0.00	-16.55	0.00			0.27
11-0	89.99	0.00	0.06	0.00	-13.26	0.00	-0.13	0.00					-4.03	0.00	-13.90	0.00	-30.87	0.00	-3.65	0.00			-5.09	0.00	-8.39	0.00	-16.39	0.00	-2.02	0.00	0.32
11-1	90.33	0.00	0.09	0.00	-17.10	0.00							-6.33	0.00	-16.56	0.00							-7.08	0.00	-7.03	0.00	-16.40	0.00			0.31
13-0	97.11	0.00	-0.04	0.00			-0.28	0.00					-5.66	0.00	-7.11	0.03	-35.00	0.00					-9.26	0.00	-12.54	0.00					0.40
13-1	99.64	0.00	-0.03	0.00			-0.54	0.00					-4.98	0.00			-32.76	0.00					-17.30	0.00	-13.44	0.00	-19.17	0.00			0.42
15-0	90.49	0.00	0.04	0.00	-5.74	0.00	-0.08	0.00					-4.09	0.00	-23.35	0.00							-4.22	0.00	-5.29	0.00	-13.70	0.00			0.30
15-1	87.45	0.00	0.04	0.00			-0.04	0.02					-5.58	0.00	-28.35	0.00							-2.93	0.00	-3.72	0.00	-14.51	0.00	-1.04	0.00	0.28
25-0	81.29	0.00	0.03	0.00			-0.13	0.00	0.04	0.00			-2.76	0.00	-11.48	0.00	-34.25	0.00							-5.51	0.00			-0.91	0.01	0.12
25-1	83.52	0.00	0.02	0.00			-0.24	0.00	0.04	0.00	0.23	0.00	-2.87	0.00	-8.87	0.00	-20.85	0.00					-2.27	0.00	-6.58	0.00					0.19
33-0	82.76	0.00	0.05	0.00					0.06	0.00			-3.16	0.00	-12.07	0.00	-29.25	0.01			-3.64	0.00			-8.46	0.00	-4.47	0.00			0.20
33-1	89.21	0.00	0.01	0.01			-0.03	0.04	0.06	0.00			-4.42	0.00	-12.45	0.00	-27.73	0.00							-6.26	0.00	-3.23	0.00			0.20
42-0	89.54	0.00	0.02	0.00					0.08	0.00	0.16	0.00					-26.84	0.00	-3.77	0.00					-10.09	0.00	-25.56	0.00	-6.59	0.00	0.51
42-1	85.82	0.00					-0.15	0.04	0.13	0.00	0.25	0.00			-8.95	0.00	-19.87	0.01											-4.51	0.00	0.40
43-0	68.57	0.00	0.03	0.00	-28.46	0.00					0.30	0.00	-2.36	0.00	-7.68	0.00	-14.02	0.00			-14.02	0.00			-6.31	0.00					0.52
43-1	67.28	0.00	0.02	0.00	-23.61	0.00	-0.06	0.00			0.36	0.00	-3.34	0.00	-6.52	0.00									-3.82	0.00			-2.50	0.00	0.41
55-0	93.42	0.00	0.04	0.00	-12.84	0.00			0.04	0.00			-7.17	0.00	-21.72	0.00	-28.70	0.00					-3.80	0.00	-5.49	0.00					0.21
55-1	94.12	0.00	0.06	0.00	-17.52	0.00			0.04	0.00			-7.76	0.00	-25.40	0.00	-33.77	0.00							-4.21	0.00			-1.16	0.04	0.22
56-0	72.37	0.00	0.04	0.00			-0.14	0.00					-3.81	0.00	-14.78	0.00	-9.52	0.00													0.09
56-1	83.93	0.00	0.02	0.00	-12.60	0.00	-0.14	0.00					-3.98	0.00	-17.35	0.00	-12.12	0.00													0.10
57-0	85.15	0.00	0.03	0.00			-0.09	0.00	0.04	0.00	0.33	0.00	-5.81	0.00	-16.64	0.00	-22.98	0.00	-4.91	0.04					-5.73	0.00					0.16
57-1	86.41	0.00	0.02	0.00					0.05	0.00			-6.46	0.00	-20.48	0.00	-20.14	0.00							-5.55	0.00			-1.93	0.00	0.19
59-0	88.27	0.00					-0.09	0.02					-3.22	0.00	-17.29	0.00	-47.34	0.00							-8.63	0.00					0.19
59-1	91.22	0.00			-6.05	0.03							-4.51	0.00	-19.52	0.00	-33.42	0.00	-6.25	0.00					-8.58	0.00					0.23

Appendix A-2: Four-Lane Regression Results (15-Minute)

Sites	Constant		Avg Volume		% Long Vehicles		Wind Spd		Visibility		SF_Temp		Slight		Moderate		Heavy		Trace Moisture		Wet		Chemically Wet		Ice Watch		Ice Warning		Night		Adj. R^2
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	
00-0	113.64	0.00	0.03	0.00	-15.16	0.00	-0.14	0.00					-6.78	0.00	-10.86	0.00	-20.96	0.00					-6.96	0.00	-8.91	0.00	-6.89	0.00	-1.48	0.00	0.44
00-1	104.45	0.00	0.04	0.00			-0.16	0.00					-7.97	0.00	-13.93	0.00	-19.55	0.00					-4.07	0.00	-8.07	0.00	-9.13	0.00	-1.42	0.00	0.47
06-0	117.30	0.00					-0.21	0.00			0.51	0.00	-1.69	0.04							-3.15	0.00			-11.23	0.00					0.35
06-1	107.08	0.00	0.01	0.00							0.91	0.00									-2.20	0.00			-7.37	0.00			-2.45	0.00	0.42
08-0	86.09	0.00	0.01	0.00	-14.05	0.00					0.18	0.00	-3.84	0.00	-14.39	0.00	-15.41	0.00							-3.95	0.00	-5.32	0.00	-2.12	0.00	0.25
08-1	83.65	0.00	0.03	0.00	-23.79	0.00							-4.07	0.00	-10.51	0.00	-20.14	0.00							-4.54	0.00	-5.74	0.00	-1.50	0.00	0.32
10-0	113.80	0.00	0.01	0.00	-43.38	0.00	-0.02	0.00			0.19	0.00	-6.07	0.00	-15.20	0.00	-18.69	0.00					-5.12	0.00	-8.49	0.00	-7.58	0.00			0.50
10-1	104.60	0.00	0.01	0.00	-31.61	0.00	-0.02	0.00					-6.87	0.00	-16.90	0.00	-22.04	0.00					-4.19	0.00	-6.92	0.00	-6.90	0.01	-0.85	0.03	0.45
14-0	136.30	0.00			-56.20	0.00	-0.10	0.00	0.02	0.00			-4.15	0.00	-23.33	0.00	-15.89	0.00			-2.48	0.00	-7.99	0.00	-13.10	0.00	-19.56	0.00	-3.40	0.00	0.45
14-1	122.50	0.00	0.01	0.00	-11.52	0.00	-0.06	0.00	0.02	0.00			-4.20	0.00	-20.45	0.00	-8.32	0.03	-2.44	0.00	-2.87	0.00	-9.08	0.00	-15.65	0.00	-26.65	0.00	-1.12	0.00	0.38
19-0	112.12	0.00	0.03	0.00	-29.34	0.00	-0.08	0.02			0.44	0.00	-6.50	0.00	-15.23	0.00							-10.61	0.00	-8.04	0.00	-16.33	0.00			0.37
19-1	101.72	0.00	0.03	0.00			-0.07	0.04			0.39	0.00	-8.46	0.00	-26.13	0.00	-34.02	0.00							-9.49	0.00	-11.35	0.01			0.39
20-0	78.38	0.00			-18.03	0.00	-0.23	0.00			0.09	0.00	-2.90	0.00	-11.24	0.00					-1.73	0.00	-4.98	0.00	-5.83	0.00	-1.91	0.01	-3.23	0.00	0.32
20-1	100.10	0.00	-0.01	0.00	-61.96	0.00	-0.38	0.00			0.13	0.00	-2.36	0.00							-6.04	0.00	-6.38	0.00	-6.67	0.00			-0.99	0.00	0.37
27-0	109.59	0.00	0.05	0.00	-28.06	0.00	-0.13	0.00					-4.49	0.00	-23.53	0.00			-4.01	0.03			-12.53	0.00	-7.97	0.00	-20.76	0.00			0.33
27-1	98.35	0.00	0.05	0.00									-9.17	0.00	-28.13	0.00							-26.92	0.00	-8.65	0.00	-14.23	0.00			0.29
28-0	108.05	0.00	0.04	0.00	-37.50	0.00	-0.23	0.00							-25.19	0.00					-7.54	0.00	-13.00	0.00	-12.52	0.00	-15.60	0.00			0.18
28-1	118.59	0.00	0.03	0.00	-36.32	0.00							-6.72	0.00	-22.20	0.00							-14.97	0.00	-10.31	0.00	-25.10	0.00			0.34
30-0	110.10	0.00	0.01	0.00	-10.63	0.00	-0.13	0.00	0.04	0.00			-6.23	0.00	-17.82	0.00	-32.06	0.00													0.23
30-1	113.00	0.00	0.01	0.00			-0.09	0.00	0.03	0.00			-4.78	0.00	-13.67	0.00	-25.60	0.00					-6.37	0.00	-8.46	0.00	-10.22	0.00	-1.17	0.00	0.30
32-0	114.75	0.00	0.02	0.00	-19.30	0.00	-0.28	0.00			0.33	0.00	-3.99	0.00	-21.78	0.00	-26.32	0.02	-3.61	0.01	-3.43	0.00	-11.44	0.00	-12.35	0.00	-18.05	0.00			0.36
32-1	98.22	0.00	0.06	0.00							0.25	0.02	-3.98	0.00	-18.24	0.00	-56.21	0.00							-10.64	0.00	-24.40	0.00			0.39
36-0	68.47	0.00	0.01	0.00	-19.16	0.00	-0.08	0.00					-1.52	0.00	-10.54	0.00	-11.53	0.00							-3.24	0.00	-1.61	0.00	-2.00	0.00	0.41
36-1	76.41	0.00			-22.78	0.00	-0.11	0.00					-1.89	0.00	-8.70	0.00	-8.11	0.00							-3.69	0.00	-1.53	0.00	-2.05	0.00	0.45
37-0	118.04	0.00	0.01	0.00	-18.75	0.00	-0.31	0.00			0.06	0.00	-1.33	0.00	-23.16	0.00					-1.42	0.00	-8.67	0.00	-6.07	0.00	-32.50	0.00	-0.80	0.00	0.34
37-1	115.61	0.00	0.02	0.00	-14.27	0.00	-0.20	0.00					-1.22	0.00	-17.00	0.00	-12.57	0.00	-2.48	0.00	-2.48	0.00	-5.90	0.00	-6.70	0.00	-32.52	0.00	-1.72	0.00	0.26
41-0	85.30	0.00	0.01	0.00	-33.47	0.00	-0.07	0.00			0.31	0.00	-2.76	0.00	-9.59	0.00	-8.91	0.03	-2.62	0.00	-2.33	0.00	-8.15	0.00	-5.87	0.00	-8.87	0.00			0.47
41-1	76.70	0.00	0.02	0.00	-21.68	0.00							-3.52	0.00	-9.48	0.00	-11.48	0.00	-2.46	0.00	-1.64	0.00	-9.20	0.00	-7.38	0.00	-12.47	0.00	-1.56	0.00	0.40
44-0	110.55	0.00	0.02	0.00	-36.16	0.00	-0.43	0.00	0.07	0.00	0.94	0.00			-17.57	0.00	-22.47	0.02					-5.01	0.00	-7.79	0.00			-3.44	0.00	0.68
44-1	132.15	0.00			-56.78	0.00	-0.15	0.02			1.08	0.00			-17.82	0.00							-3.75	0.01	-5.69	0.00					0.55
46-0	119.65	0.00			-30.07	0.00	-0.37	0.00			0.74	0.00	-3.59	0.00	-14.44	0.00	-16.03	0.00	-4.61	0.02	-7.61	0.00	-15.26	0.00	-10.53	0.00	-18.02	0.00	-1.26	0.04	0.37
46-1	117.37	0.00			-37.81	0.00	-0.14	0.00			0.10	0.02	-5.44	0.00	-15.44	0.00	-22.95	0.00			-3.11	0.00	-7.91	0.00	-7.17	0.00	-10.96	0.00	-2.79	0.00	0.37
47-0	120.74	0.00	0.02	0.00	-19.46	0.00	-0.23	0.00					-5.64	0.00	-14.65	0.00	-38.70	0.00	-7.24	0.00	-11.70	0.00	-10.95	0.00	-5.37	0.00	-9.21	0.00			0.31
47-1	120.34	0.00	0.03	0.00	-8.81	0.00	-0.34	0.00					-4.59	0.00	-15.17	0.00	-34.30	0.00	-9.38	0.00	-13.88	0.00	-14.34	0.00	-6.87	0.00	-7.67	0.00	-2.12	0.00	0.36
48-0	108.85	0.00	0.01	0.00			-0.16	0.00					-6.71	0.00	-15.58	0.00	-20.42	0.00					-11.22	0.00	-8.94	0.00	-14.53	0.00	-2.47	0.00	0.39
48-1	117.70	0.00	0.01	0.00	-32.35	0.00	-0.12	0.00					-6.37	0.00	-14.41	0.00	-18.26	0.00			-3.11	0.00	-11.14	0.00	-10.18	0.00	-18.34	0.00	-1.95	0.00	0.43
49-0	113.50	0.00	0.02	0.00	-9.62	0.00	-0.11	0.00	0.04	0.00			-2.59	0.00	-14.32	0.00	-20.13	0.00					-6.54	0.00	-7.10	0.00	-8.69	0.00	-1.17	0.00	0.33
49-1	113.41	0.00	0.01	0.00	-10.31	0.00	-0.14	0.00	0.04	0.00			-3.45	0.00	-20.97	0.00	-26.65	0.00					-7.51	0.00	-7.52	0.00	-3.59	0.00	-1.59	0.00	0.33
50-0	121.73	0.00	0.02	0.00	-39.55	0.00	-0.19	0.00					-4.59	0.00	-12.20	0.00	-25.14	0.04					-10.46	0.00	-10.09	0.00	-13.27	0.00			0.36
50-1	116.05	0.00	0.03	0.00	-26.07	0.00	-0.21	0.00					-4.00	0.00	-8.16	0.01							-10.11	0.00	-9.85	0.00	-15.67	0.00			0.35
53-0	119.50	0.00	0.01	0.00	-4.70	0.01	-0.30	0.00			0.60	0.00	-4.63	0.00	-14.71	0.00	-20.29	0.00			-4.07	0.00	-12.16	0.00	-10.81	0.00	-18.07	0.00			0.46
53-1	124.40	0.00	0.01	0.00	-16.83	0.00	-0.34	0.00	0.01	0.01	0.48	0.00	-3.82	0.00	-8.84	0.00	-13.30	0.00			-4.61	0.00	-13.36	0.00	-11.05	0.00	-18.56	0.00			0.42
58-0	106.99	0.00	0.02	0.00	-8.40	0.00	-0.22	0.00	0.01	0.00			-3.06	0.00	-3.52	0.00	-5.09	0.00					-3.25	0.00	-9.12	0.00					0.32
58-1	114.23	0.00	0.03	0.00	-11.36	0.00	-0.31	0.00	0.01	0.03			-3.83	0.00	-4.61	0.00	-8.57	0.00			-2.33	0.04	-2.60	0.00	-9.86	0.00			-1.72	0.00	0.34

Appendix A-3: Two-Lane Regression Results (60-Minute)

Sites	Constant		Avg Volume		% Long Vehicles		Wind Spd		Visibility		SF_Temp		Slight		Moderate		Heavy		Trace Moisture		Wet		Chemically Wet		Ice Watch		Ice Warning		Night		Adj. R^2
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	
01-0	86.71	0.00	0.05	0.00									-3.64	0.00	-15.76	0.00	-28.34	0.00							-9.26	0.00	-9.06	0.00			0.38
01-1	92.51	0.00											-4.16	0.00	-9.61	0.00	-47.01	0.00					-9.42	0.03	-8.66	0.00					0.41
02-0	84.05	0.00	0.07	0.00			-0.25	0.00					-3.59	0.00	-12.94	0.00							-8.83	0.00	-9.14	0.00	-18.28	0.00			0.37
02-1	85.63	0.00	0.05	0.00	-11.14	0.00	-0.19	0.00					-4.00	0.00	-13.23	0.00							-8.06	0.01	-8.30	0.00	-18.26	0.00			0.33
11-0	81.94	0.00	0.17	0.00	-37.03	0.00	-0.17	0.03					-3.72	0.00	-10.62	0.00							-4.83	0.00	-5.37	0.00	-15.09	0.00	-4.29	0.00	0.39
11-1	87.48	0.00	0.12	0.00	-30.23	0.00							-5.34	0.00	-16.76	0.00							-6.30	0.00	-6.33	0.00	-16.18	0.00			0.41
13-0	88.39	0.00	-0.05	0.00									-6.42	0.04			-37.15	0.00							-9.41	0.00					0.34
13-1	98.81	0.00	-0.03	0.00			-0.81	0.00									-29.19	0.00					-18.42	0.00	-12.79	0.00	-18.35	0.00			0.40
15-0	89.79	0.00	0.05	0.00	-18.67	0.00	-0.09	0.01					-3.60	0.00	-13.08	0.00			-5.96	0.00			-5.39	0.00	-6.16	0.00	-14.86	0.00			0.38
15-1	85.06	0.00	0.06	0.00									-5.06	0.00	-21.30	0.00			-6.16	0.00			-4.18	0.00	-4.56	0.00	-15.90	0.00	-2.17	0.00	0.31
25-0	79.55	0.00	0.06	0.00			-0.13	0.00	0.04	0.00			-3.45	0.00	-13.39	0.00	-31.58	0.00							-6.71	0.00					0.16
25-1	82.68	0.00	0.07	0.00	-9.11	0.00	-0.18	0.00			0.24	0.00	-3.77	0.00	-12.11	0.00	-12.88	0.01					-3.86	0.02	-8.11	0.00					0.24
33-0	79.65	0.00	0.05	0.00					0.07	0.00			-1.95	0.00											-8.03	0.00	-4.14	0.01			0.22
33-1	88.16	0.00							0.07	0.00			-3.43	0.00	-10.89	0.00									-7.38	0.00	-4.37	0.01			0.26
42-0	87.03	0.00	0.04	0.01											-11.12	0.01									-12.04	0.00			-3.75	0.04	0.51
42-1	83.19	0.00							0.10	0.00	0.26	0.00																			0.31
43-0	70.78	0.00	0.02	0.01	-37.63	0.00					0.38	0.00	-2.05	0.01	-6.44	0.02	-20.04	0.00							-5.26	0.00					0.66
43-1	71.61	0.00			-31.80	0.00	-0.07	0.01			0.49	0.00	-3.20	0.00	-7.12	0.02	-10.42	0.01							-3.77	0.00					0.58
55-0	91.15	0.00	0.07	0.00	-20.38	0.00			0.04	0.01			-6.31	0.00	-18.22	0.00	-28.51	0.00							-5.63	0.00					0.24
55-1	96.83	0.00	0.07	0.00	-30.11	0.00			0.12	0.01			-9.02	0.00	-24.50	0.00	-36.47	0.00					-5.67	0.04	-7.58	0.00					0.33
56-0	69.86	0.00	0.06	0.00			-0.11	0.01					-4.15	0.00	-14.11	0.00	-7.84	0.04													0.12
56-1	80.79	0.00	0.04	0.00	-19.93	0.00							-3.92	0.00	-18.21	0.00	-13.64	0.00													0.15
57-0	81.03	0.00	0.05	0.00			-0.25	0.00	0.06	0.00	0.26	0.03	-4.62	0.00											-5.20	0.00					0.27
57-1	80.87	0.00	0.06	0.00					0.05	0.00			-6.22	0.00	-17.11	0.00	-24.25	0.00	-7.01	0.02					-5.64	0.00			-2.29	0.01	0.29
59-0	89.89	0.00			-15.19	0.01													-23.34	0.00					-9.25	0.00	-26.60	0.00			0.21
59-1	85.69	0.00	0.08	0.03	-33.15	0.00													-23.72	0.00					-8.35	0.00	-26.13	0.00			0.25

Appendix A-4: Four-Lane Regression Results (60-Minute)

Sites	Constant		Avg Volume		% Long Vehicles		Wind Spd		Visibility		SF_Temp		Slight		Moderate		Heavy		Trace Moisture		Wet		Chemically Wet		Ice Watch		Ice Warning		Night		Adj. R^2
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	
00-0	107.30	0.00	0.04	0.00	-16.01	0.00	-0.11	0.00					-4.90	0.00	-8.39	0.00	-20.29	0.00					-5.49	0.04	-8.84	0.00	-7.88	0.00			0.49
00-1	94.99	0.00	0.06	0.00			-0.11	0.00					-5.23	0.00	-10.51	0.00	-17.07	0.00							-7.69	0.00	-9.25	0.00	-2.08	0.03	0.55
06-0	112.50	0.00									0.96	0.01	-3.23	0.04											-5.78	0.02	-27.33	0.00			0.31
06-1	106.75	0.00									1.42	0.00													-5.12	0.00					0.43
08-0	88.62	0.00			-17.35	0.00					0.20	0.00	-3.49	0.00			-14.77	0.04							-4.90	0.00	-6.18	0.00	-2.76	0.00	0.27
08-1	84.59	0.00	0.03	0.00	-26.64	0.00							-3.72	0.00											-5.44	0.00	-6.53	0.00	-1.31	0.02	0.35
10-0	117.17	0.00			-59.80	0.00	-0.02	0.00					-4.94	0.00	-14.80	0.00	-16.83	0.00					-6.31	0.00	-8.73	0.00					0.55
10-1	109.52	0.00	0.01	0.00	-61.36	0.00	-0.02	0.00					-4.47	0.00	-15.50	0.00	-16.90	0.00					-4.55	0.00	-6.38	0.00					0.49
14-0	158.60	0.00	0.01	0.00	-101.50	0.00	-0.19	0.00					-2.12	0.00	-21.22	0.00					-3.56	0.01	-7.91	0.00	-13.57	0.00	-16.90	0.00	-3.53	0.00	0.46
14-1	141.20	0.00	0.01	0.00	-57.16	0.00	-0.13	0.00					-1.59	0.02	-17.82	0.00			-3.59	0.02	-3.64	0.01	-9.57	0.00	-16.13	0.00	-21.18	0.00			0.42
19-0	116.21	0.00	0.05	0.00	-53.19	0.00							-7.68	0.00									-12.59	0.00	-9.76	0.00	-25.98	0.00			0.38
19-1	89.94	0.00	0.08	0.00									-7.88	0.00	-20.84	0.00	-36.26	0.00							-9.58	0.00	-13.97	0.02			0.43
20-0	79.52	0.00			-31.06	0.00	-0.22	0.00					-2.19	0.00	-11.18	0.00							-4.22	0.00	-5.72	0.00			-3.18	0.00	0.40
20-1	121.00	0.00	-0.01	0.00	-115.00	0.00	-0.34	0.00					-1.74	0.00					-4.75	0.01	-5.77	0.00	-4.56	0.02	-6.61	0.00			-1.62	0.01	0.48
27-0	114.32	0.00	0.07	0.00	-49.56	0.00	-0.23	0.00					-5.25	0.00	-10.91	0.02							-11.35	0.00	-7.55	0.00	-23.16	0.00			0.42
27-1	87.10	0.00	0.10	0.00									-9.50	0.00	-13.84	0.04							-27.41	0.00	-9.60	0.00					0.36
28-0	104.33	0.00	0.06	0.00	-51.36	0.00	-0.40	0.00															-13.42	0.03	-8.68	0.00					0.21
28-1	123.71	0.00	0.03	0.00	-48.21	0.00							-8.39	0.00	-21.70	0.00							-23.23	0.00	-12.14	0.00	-25.61	0.00			0.38
30-0	108.61	0.00	0.02	0.00	-11.12	0.01	-0.22	0.00	0.05	0.05			-5.38	0.00	-17.54	0.00	-35.64	0.00							-12.75	0.04					0.32
30-1	113.58	0.00	0.01	0.00			-0.19	0.00	0.04	0.02			-5.60	0.00	-13.40	0.00	-32.36	0.00					-12.65	0.00	-9.10	0.00	-11.85	0.00			0.36
32-0	120.12	0.00			-37.19	0.00	-0.42	0.00			0.33	0.02			-13.80	0.00							-17.01	0.00	-12.38	0.00					0.43
32-1	97.38	0.00	0.06	0.00			-0.21	0.02			0.40	0.04									-5.74	0.02			-12.97	0.00	-39.70	0.00			0.41
36-0	68.02	0.00	0.01	0.00	-27.88	0.00	-0.09	0.00					-0.70	0.03	-8.93	0.00	-11.40	0.00							-2.81	0.00			-2.48	0.00	0.54
36-1	78.17	0.00	0.01	0.00	-37.65	0.00	-0.11	0.00					-0.94	0.00	-5.21	0.00	-6.27	0.00							-2.91	0.00			-2.21	0.00	0.61
37-0	120.25	0.00	0.01	0.04	-26.48	0.00	-0.33	0.00					-2.19	0.00	-16.40	0.00							-13.80	0.00	-6.93	0.00	-34.10	0.00			0.39
37-1	114.96	0.00	0.03	0.00	-15.61	0.00	-0.24	0.00					-1.62	0.01	-24.84	0.00	-37.04	0.00					-13.06	0.00	-7.47	0.00	-24.41	0.00	-1.58	0.00	0.34
41-0	84.36	0.00	0.01	0.01	-40.06	0.00					0.19	0.00	-3.19	0.00									-7.96	0.00	-6.48	0.00	-15.07	0.00			0.58
41-1	75.79	0.00	0.03	0.00	-24.51	0.00							-3.62	0.00	-8.69	0.00	-14.87	0.00					-9.86	0.00	-7.16	0.00	-12.67	0.00	-1.80	0.00	0.45
44-0	80.98	0.00	0.06	0.00			-0.50	0.00									-18.42	0.02											-9.14	0.00	0.60
44-1	129.98	0.00			-64.71	0.00					1.55	0.00																			0.53
46-0	121.04	0.00			-36.00	0.00	-0.47	0.00			0.67	0.00	-2.85	0.00	-8.48	0.00	-14.61	0.01			-9.85	0.00	-10.38	0.01	-10.82	0.00	-23.70	0.00			0.37
46-1	122.28	0.00			-55.31	0.00	-0.16	0.00					-5.29	0.00	-14.33	0.00	-31.09	0.00					-9.47	0.00	-7.94	0.00			-2.98	0.00	0.42
47-0	121.86	0.00	0.03	0.00	-29.85	0.00	-0.28	0.00					-5.62	0.00	-10.54	0.00	-44.66	0.00	-6.64	0.00	-11.36	0.00	-18.43	0.00	-4.60	0.00	-8.89	0.02			0.40
47-1	112.09	0.00	0.05	0.00			-0.36	0.00					-4.23	0.00	-16.25	0.00	-36.16	0.00			-10.64	0.00	-17.27	0.00	-5.90	0.00	-8.21	0.04	-2.58	0.01	0.38
48-0	107.20	0.00	0.01	0.00			-0.21	0.00					-6.12	0.00	-13.82	0.00							-13.48	0.00	-8.72	0.00	-21.80	0.00	-2.76	0.00	0.40
48-1	117.48	0.00	0.01	0.00	-42.70	0.00	-0.17	0.00					-5.85	0.00	-11.34	0.00							-12.48	0.00	-9.07	0.00	-21.52	0.00	-1.93	0.04	0.44
49-0	111.42	0.00	0.02	0.00	-10.55	0.00	-0.11	0.00	0.05	0.00			-2.13	0.00	-15.83	0.00	-23.10	0.00							-7.17	0.00	-8.87	0.01	-1.30	0.02	0.37
49-1	112.50	0.00	0.02	0.00	-12.89	0.00	-0.18	0.00	0.04	0.00			-3.11	0.00	-22.87	0.00	-31.67	0.00					-8.49	0.00	-8.27	0.00	-5.78	0.02	-1.63	0.01	0.38
50-0	119.50	0.00	0.03	0.00	-41.75	0.00	-0.12	0.00					-3.14	0.00									-12.34	0.00	-12.27	0.00	-13.38	0.00			0.35
50-1	109.88	0.00	0.04	0.00	-26.05	0.00	-0.11	0.00					-2.83	0.01	-10.92	0.04							-13.21	0.01	-11.22	0.00	-17.50	0.00			0.34
53-0	115.23	0.00	0.02	0.00			-0.39	0.00			0.46	0.00			-10.11	0.00	-16.26	0.00			-5.32	0.02	-14.73	0.00	-12.76	0.00	-21.09	0.00			0.52
53-1	118.58	0.00	0.01	0.00	-9.09	0.04	-0.38	0.00			0.36	0.00	-2.08	0.02	-7.05	0.00	-11.52	0.00					-12.12	0.00	-11.81	0.00	-18.24	0.00			0.45
58-0	106.57	0.00	0.02	0.00	-9.41	0.00	-0.25	0.00					-2.31	0.00	-3.98	0.00	-7.59	0.00							-10.28	0.00					0.36
58-1	115.00	0.00	0.03	0.00	-16.19	0.00	-0.37	0.00					-3.69	0.00	-5.72	0.00	-12.59	0.00							-11.10	0.00			-1.67	0.04	0.38

Appendix B: Description of Pavement Snow and Ice Conditions

Condition 1: All snow and ice are prevented from bonding and accumulating on the road surface. Bare/wet pavement surface is maintained at all times. Traffic does not experience weather-related delays other than those associated with wet pavement surfaces, reduced visibility, incidents, and "normal" congestion.

Condition 2: Bare/wet pavement surface is the general condition. There are occasional areas having snow or ice accumulations resulting from drifting, sheltering, cold spots, frozen melt-water, etc. Prudent speed reduction and general minor delays are associated with traversing those areas.

Condition 3: Accumulations of loose snow or slush ranging up to 5 cm (2 in.) are found on the pavement surface. Packed and bonded snow and ice are not present. There are some moderate delays due to a general speed reduction. However, the roads are passable at all times.

Condition 4: The pavement surface has continuous stretches of packed snow with or without loose snow on top of the packed snow or ice. Wheel tracks may range from bare/wet to having up to 4 cm (1.5 in.) of slush or unpacked snow. On multilane highways, only one lane exhibits these pavement surface conditions. The use of snow tires is recommended to the public. There is a reduction in traveling speed with moderate delays due to reduced capacity. However, the roads are passable.

Condition 5: The pavement surface is completely covered with packed snow and ice that has been treated with abrasives or abrasive/chemical mixtures. There may be loose snow of up to 5 cm (2 in.) on top of the packed surface. The use of snow tires is required. Chains and/or four- wheel drive may also be required. Traveling speed is significantly reduced, and there are general moderate delays with some incidental severe delays.

Condition 6: The pavement surface is covered with a significant buildup of packed snow and ice that has not been treated with abrasives or abrasives/chemical mixtures. There may be over 5 cm (2 in.) of loose or wind-transported snow on top of the packed surface due to high snowfall rate and/or wind. There may be deep ruts in the packed snow and ice that may have been treated with chemicals, abrasives, or abrasives/chemical mixtures. The use of snow tires is the minimum requirement. Chain– and snow tire–equipped four-wheel drive is required in these circumstances. Travelers experience severe delays and low travel speeds due to reduced visibility, unplowed loose or wind-compacted snow, or ruts in the packed snow and ice.

Condition 7: The road is temporarily closed. This may be the result of severe weather (low visibility, etc.) or road conditions (drifting, excessive unplowed snow, avalanche potential or actuality, glare ice, accidents, vehicles stuck on the road, etc.).

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