PERFORMANCE MEASUREMENT FOR HIGHWAY WINTER MAINTENANCE OPERATIONS

by

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1. INTRODUCTION

A. Motivation and Background

Although winter highway maintenance has improved significantly over time (for instance, between 1995 to 2001, there was a 26% decline in crashes during sleet and snow weather conditions (Goodwin, 2003)), road users still experience delays and crashes due to unsatisfactory road conditions that result from poor winter weather. In 2001, approximately 1000 people were killed and 95,000 people were injured in crashes on snowy and slushy pavement (FHWA, 2002). Annually there are 500 million hours of delays in major US highways due to adverse weather conditions (NOAA, 2002). While maintenance operations aim to provide road users with a safe highway that has limited delays, to achieve this condition maintenance agencies spend 2.3 billion dollars annually on Winter Highway Maintenance (FHWA, 2002). Given this high expenditure, an important goal for a winter maintenance agency is to find the optimal usage of limited resources. One way to reach this goal is to develop a performance measurement system. Such a system is typically composed of a series of quantitative measures that evaluate how well maintenance activities have been performed to meet a variety of road users' expectations (Adams, 2003). By comparing the real-time performance outcome data with the pre-specified targets, performance measurement can inform winter maintenance agencies how well an operation has been conducted to improve mobility and safety. The feedback from the performance measures will help an agency to improve their maintenance actions over time.

The generally identified goals in the management of transportation systems are safety, mobility, effectiveness, environmental concern, and user-satisfaction. The two major goals of winter highway maintenance are safety and mobility. The commonly used outcome measures for mobility and safety are traffic speed and traffic flow rate and accident rate. However, in winter maintenance, it is more typical to measure either outputs (evaluate the result of maintenance activities, such as, cycle time, lane-miles maintained) or different outcome measures (e.g. road surface condition observations or pavement friction). Output measures are often relatively simply to collect, but they are not directly tied to maintenance goals and objectives and cannot be easily communicated to road users. Likewise, the outcomes currently used are not necessarily easy to collect, nor are they easily translatable into a publicly accepted form of outcome measure.

Based on the current literature search, it is clear that though there is a reasonable amount of performance measurement studies conducted in the winter maintenance area, few of them are comprehensive enough to evaluate winter maintenance outcomes (how safe and mobile traffic was able to get to its destination), while at the same time taking weather condition(the severity of individual storms), the specifications of road system being treated(Interstate or Primary, different AADT levels), various traffic specifications (urban vs. rural, day vs. night, traffic vs. non-peak, etc.) and the maintenance effort (frequency of plowing actions, quantity of chemicals, and other operational input) together into consideration.

To establish a performance measurement system for operational use, the proposed performance measurement system needs to take those factors above into consideration. Among the above factors, weather conditions, specifications of road system characteristics and traffic specifications (Peak-hour or not, Day time or not) are used in this study as normalizing factors or classification variables to ensure an appropriate comparison across different storm events and maintenance routes. Maintenance input measures the cost to agencies in fighting a storm, which is a major concern and easy to quantify, but not a dominant factor. Measures of winter maintenance outcomes is the most important factor, and can also be understood as the value-added benefit to road users by improved traveling conditions.

B. Challenges

There are two particular challenges when trying to develop a performance measurement system. First of all, maintenance efforts and outcomes are largely dependent on the variability of individual storms. Therefore to make the maintenance effectiveness comparable across different storms, the individual storm severity must be quantified. However, until this study, there were no examples of storm severity indices that measured severity on a storm by storm basis. Such weather indices measured behavior over a total winter season.

Second, the complexity of relationships involved in the performance of the winter maintenance operations means that they are not only dependent on the maintenance input or effort, but they are also sensitive to all the other conditions, including weather severity variables, road classifications, and various traffic specifications. Thus, different targets need to be developed to accommodate these differences. The appropriate targets can only be set based on a sound understanding of these relationships. Even though there are some studies that examine the effect of weather on mobility and safety, the research findings on the effect of weather on safety are quite conflicting. Also, there is an absence of studies that examine the effects of maintenance actions (Andrey, 2003), and no studies model how the effects of maintenance and weather changes with the various conditions mentioned above.

On the basis of these needs and challenges, this project constructs a performance measurement framework for the winter maintenance operational system. Operational goals have been established. Measures that evaluate the maintenance outcomes, as well as those sets of measurement variables upon which the winter highway maintenance outcomes depend have been identified and included in the performance measurement framework.

Chapter 2 reviews the existing literature in the field, including general guidelines for performance measurement, and current performance measurement in winter highway maintenance practice. The review also identifies deficiencies in current practice. Further, literature on the effects of weather and maintenance operations and their complex interactions on safety and mobility have been reviewed.

Chapter 3 develops a storm severity index used to quantify the severity of individual storms. Multiple regression is used to built the model and the model was validated by expert feedback.

Chapter 4 generalizes the current conflicting results of studies that have examined weather effects on safety. A hierarchical meta-analysis is applied. Effect size and proportional change in crash rates were used to standardize findings.

Chapter 5 investigates the effects of weather factors and maintenance actions on road surface conditions, and tests the possible interactions between these two sets of variables. CHAID (Chi-squared Interaction Detection) was applied in this step to identify the significant factors and interactions. MLR (Multinomial Logistic Regression) was used further to validate the result produced from CHAID, and quantify the effects.

Chapter 6 explores the direct and indirect casual effects of weather and maintenance actions on mobility and safety. Also the important interactions between light, and road classifications were tested and included in the models. Structural Equation Modeling (SEM) was used in this chapter to estimate the direct and indirect effects.

Chapter 7 presents the final performance measurement model, and shows typical results that would be obtained from the model. The results are evaluated by comparison with field data. This comparison shows that the performance model that has been developed is an effective measurement tool and can also be used for the planning use.

Chapter 8 presents conclusions of the project, together with recommendations for further work.

C. Contributions

This proposed measurement system can be used to enable winter maintenance agencies to evaluate how well operations have been conducted to meet road users' needs as specified in maintenance goals (as used for the post-event evaluation) by comparing the maintenance outcomes with the specified standards. Combining the modeling results, this work can enable the decision maker to determine the optimum decision through balancing the trade-offs between maintenance input and road user benefit in terms of traveling comfort and safety.

The constructed prediction model in chapter 5 can be used to predict the road surface condition for a specified weather event given the traffic volume and maintenance procedures. The structural equation modeling results have established the effects of maintenance actions, weather conditions, and road surface conditions on traveling speed and volume and crash rates. Thus for a specified weather event, a given time of the day, and a given road class and AADT, the model can estimate the traveling speed and traffic volume, as well as crash rates with different maintenance operation input. Thus, this model is a predictive tool for maintenance managers, and as such allows them to conduct "what if" experiments that will lead to optimization of maintenance practice over time.

Clearly, observations of the road surface condition will continue to be effective measures of maintenance outcomes in the near future. Thus road surface condition prediction based upon maintenance and weather conditions can be used by the maintenance agency to do pre-event evaluations, and to evaluate and facilitate the selection of the best strategies for a variety of scenarios. This established relationship between road surface condition and the speed and volume could be used as the rationale to establish a Mobility index (such as that used in MDSS, Mahoney, 2005). Further, the relative magnitudes of the effects of different maintenance methods on mobility and safety that is predicted by the models will enable agencies to assign priorities, and to compare maintenance outcomes based on the input resource.

Moreover, the study results can also be used to go from asking how maintenance affects mobility and safety to understanding how to maximize limited resources so as to improve maintenance effectiveness. For instance, by studying the relationship between performance outcomes and weather severity, road scope, and all the other variables, this study found some areas for potential improvement in current winter maintenance practice. On this basis, a series of recommendations for possible change in operational methods are presented herein.

2. LITERITURE REVIEW

This chapter covers the review of methods and guidelines for establishing an applicable performance measurement system. Studies of the current performance measurement practice in the winter maintenance field have been summarized and deficiencies have been identified. All the major components of performance measurement systems and how they and their interactions affect maintenance outcomes have been reviewed. Additionally, studies on the weather and maintenance related impact on road mobility and safety have been reviewed.

Information on the framework construction of performance measurement systems helps to identify the necessary components of such systems. The literature review on winter maintenance operations identified that the most widely used performance measures used in these operations are various measures of road surface condition. While such measures have the advantage of being relatively easy to collect and thus easy to use operationally it should be noted that such measures are not directly related to safety and mobility goals.

A. Performance Measurement System: A Review of the Literature

Performance measurement is a well-established concept in the transportation arena. The Federal Highway Administration (FHWA) has already conducted many studies on performance measurement. According to the FHWA definition (FHWA, 2004): "Performance measurement is a process of assessing progress toward achieving predetermined goals." Generally the following broad categories would be useful to identify goals for performance measures: Safety, Accessibility, Mobility, Environmental and resource conservation, and Operational efficiency (NCHRP, 2000).

Well-designed performance measures should be linked to objectives and goals (Neely, 1997). For instance, the likely performance measure to meet the goal of safety are rate of highway-related fatalities/ injuries (number of accidents per 100 million vehicle miles traveled) (FHWA, 2003). The likely performance measures for the goal of mobility are travel speed, delay, and quantity of travel (Vehicle miles traveled-VMT), and Average Annual Daily Traffic (AADT), together with both variability and reliability indexes (NCHRP, 2003). The likely measures for productivity and environmental conservation are monetary values for the maintenance agencies and society.

Principles in guiding performance measures selection have been discussed in a number of studies (Meyer 1995, TRB 2001, and Neely 1997): Performance measures should be customer-oriented and outcome-based (TRB, 2001). In addition to the traditional use of output-based performance measures that measure the product or service of the activity, outcome measures that measure progress toward achievement of the purpose should be combined with output measures (Cambridge, 2001). Generally, performance measures are classified in the following categories:

- Input measures, indicating the amount of resource used (such as types and quantity of material, frequency and types of mechanical removal, labor, equipment, etc.);
- Uncontrollable factors, indicating those factors that organizations can't change but contribute to the decreases of performance. (such as natural hazard and emergency, etc);
- Output measures, indicating effectiveness of resources transformed to service. (such as road surface condition, maintenance cycle time)
- Outcome measures, directly reflecting operation impact on goals (such as improved mobility and safety, or lower travel costs to customers).

To develop a comprehensive performance system, the above factors must be taken into account. The input measures are directly associated with agency spending, and the outcome measures clearly reflect how well operations meet the organization goals and customer expectations. Moreover, to make the selected performance measures applicable in operations, data availability, sample size, and frequency of measurement are all major considerations.

B. Performance Measurement in Winter Maintenance Operations

Maintenance operations are typically performed to minimize the adverse weather effects on traffic in terms of traveling speed, and volume, and to minimize the adverse weather effects on safety in terms of crashes. Effective performance measures have significant importance to any agencies involved in winter maintenance. Through measuring performance, a maintenance agency will be able to make more informed decisions, and to track the process over time toward a goal or objective (TRB, 2001). A variety of performance measures have been developed for different purposes in the winter maintenance area. For instance, Adams et al. (Adams, 2003) explored the business uses of data gathered by a new winter maintenance vehicle equipped with AVL (automated vehicle location) system, GPS (global positioning system) receivers, and material sensors and provided systematic performance measures for budgeting and monitoring use. To best meet the customer expectation, Caltrans (California Department of Transportation) collected data from a public satisfaction survey, and used a custom rating scale to evaluate operational effectiveness (Kuhl, 2000). Taking public perception into decision making can be good. However, public opinions may depend on personal preference and it is hard to evaluate each storm by survey.

This study is focused on evaluating the effectiveness of winter highway maintenance operations and as a result to facilitate decision making. The primary goal for winter highway maintenance operations is to reduce undesirable road surface conditions. By doing so, an agency can reduce accidents and minimize delays and changes in travel times compared to normal weather conditions. As the public survey results indicated, the goal of safety and mobility are also the road user's primary concerns (Alfelor, 1999). Perhaps the most relevant study is by Blackburn. For the purpose of evaluating the effectiveness of maintenance strategies and tactics, Blackburn established a Pavement Ice Condition Index (PSIC) by visual characterization of roadway surfaces descriptions (amount of ice/snow/slush on the road surface and condition of the interface: bonded or un-bonded). PSIC can be used to evaluate the during-storm performance, and the time needed to achieve a certain PSIC can be used to evaluate after-storm performance (Blackburn, 2004). This kind of road surface description is a typical measure to evaluate operation effectiveness around the world because of its ease of understanding and comparatively low cost to obtain, and also because it is associated with the maintenance end-goal of mobility and safety to some extent. However, there are two deficiencies associated with this measure. First, the measure, based on crew observation, is subjective. Second, the road surface description is not direct enough to indicate the safety and mobility effects to road users (speed, accident rate, traffic volume).

As proposed by Nixon, friction is another promising indicator of road condition (Nixon, 1998). The measure of the friction ranges between 0 and 1, with 0 indicating most slippery icy surface, and 1 indicating normally dry surface condition. Friction is normally measured by a locked-wheel skid-resistance device attached to the maintenance truck or patrol vehicles (Hagiwara, 1990). Finland has established Winter Maintenance Level-of-Service based on the friction value (Leppannen, 2001). Japan has constructed a traffic accident reconstruction model, and it is noted that improving friction value of the pavement could greatly influence the safety especially when the friction value is around 0.2 (Hosseinlou, 2000). However, the correlation between friction levels and traffic speed/volume is still less than clear, and a reliable friction measurement device is still in the development stage for heavily traveled highways (Al-Qadi, 2002).

C. Effect of Weather and Maintenance on Safety and Mobility

Generally the number of crashes during a certain time unit is related to many factors, such as driver behavior, geometric characteristics, e.g. grade and curve radius, weather related variables, interactions between geometrics and weather, etc. (Shankar V, 1995). Other important interactions have been identified in the literatures including interactions between weather and traffic volume, holidays and weekly patterning of social activities e.g. weekday travel patterns (Levine et al., 1995).

Sometimes researchers use crash rate, which is the ratio of crash counts and traffic exposure (flow rate, namely traffic volume per lane) as the measure of crashes (Amoros, 2002). Mean speed and variation in speed are found to be positively related to crash rates (e.g. see Garber and Gadiraju, 1990; Garber and Ehrhart, 2000; Dickerson et al., 2000). Also the effects of speed and traffic flow rate on crash rates depend on the type of highway (Garber and Ehrhart, 2000). In terms of crash severity, Golob and Recker (2003) found that more adverse conditions were associated with the lowest traffic volumes and high variations in traffic flow. Other studies that have modeled the relationship between road accidents and traffic flows are Dickerson et al. (2000) and Martin (2002).

Effect of Weather on Crash Rates

Research on crashes during adverse weather conditions suggests that adverse weather is associated with an increase in the number of less severe crashes, such as minor injury and property damage only crashes (Andrey, 2003). However, adverse weather has only a minor influence on severe crashes, severe injury or fatal crashes. For instance, Evans (1991) stated that “the effect of inclement weather [snow fall] is more to reduce mobility by deterring travel or reducing speeds than to change safety [fatality].”

Snow event type and poor visibility were found to be associated with both reductions in speed and increase of variation in speed (Idaho 2000, Liang 1998)). Moreover, the effect of rain depends on the time of the day. Keay (2005) found a 5.2% increase in crash rates at night compared to a 1.9% increase during the day. The effect also depends on the characteristics of the weather event (Andrey, 2003), and geometric and ambient temperature-related variation (Shankar V, 1995) and specific site or city characteristics. Eisenberg (2005) and Suggett (2002) both found that the risk of fatalities is significantly higher on the first snowy day of the season compared to subsequent snowy days during the same season.

In terms of crash characteristics, (Andrey, 2003) “Snow events are associated with disproportionately more single vehicle crashes; more collisions at locations without traffic control and on roads with speed limits of 60 kph or higher; and they are less likely to involve a turning maneuver than ‘normal’ driving.” These findings have been confirmed by other studies (Mercer, 1986; Andrey, 1989). Lane (1995) found “passing and lane changing were especially hazardous in winter driving conditions and the risk was increased by the tendency of slush and snow to build up between the right and left lanes and on the shoulders. Excessive vehicle speed for inclement roadway conditions was a factor in most of these crashes”.

In terms of precipitation type, Suggett (2002) has found crash risk is particularly high for freezing rain or sleet events, and low for drizzle or dry snow. In addition it has been demonstrated that even after precipitation ends, crash risks stay elevated. One possible reason is the accumulated precipitation may lead to slippery road surface conditions, a conjecture that this dissertation research examines further. The studies exploring the interactions of weather with other factors on crash rates suggest that the effect of weather type (rain/ no rain) depends on the rural or urban settings. Bertness (1980) found over 100% more vehicle accidents under rain compared to non-precipitation, particularly in urban areas, but the accident severity associated with rain was greater in rural areas.

Effect of Weather on Traffic Volume

Travelers can and do defer their trips during adverse weather. During rain fall, traffic volume on the highway decreases 1.35 to 2% depending on the precipitation rate. It also changes considerably with time of the day (Keay, 2005; Doherty et al. 1998, Colding, 1974). During snow fall, traffic volume decreases substantially from 7% to 56% (Hanbali, 1994) and 10% to 50% (Knapp, 2001).

In terms of the distribution of the traffic volume, it is likely to observe more frequent very low traffic volume, less frequent very high traffic volume during snow than non-precipitation or rain (EIDessouki, 2004).

Effect of Weather on Traveling Speed

There have been several studies that examined the relationship between weather and speed. Snow events and poor visibility were found to be associated with both reductions in speed and increase of variation in speed. For instance, the 2001 Traffic Flow Theory and Highway Capacity manual provide models that predict the average off-peak winter weather vehicle speed reduction is 3.9 mph for low visibility (visibility below 0.4 km/0.25 mi) and 7.3 mph for snow cover on road ways. Brown and Baass (1997) found a 10% to 30% reduction in free flow speed. Liang (1998) found a three times larger variation in speed during a snow event.

Moreover, these studies suggest that the decrease in speed and increase in speed variation during snow storms are influenced by road classification and vehicle type (passenger car or pick up trucks) (Padget 2001, Liang 1998). For instance, Hanbali and McBride (1994) found snowy/icy conditions are associated with an average 18% to 42% speed reduction on two-lane highways and 13% to 22% reduction on freeways (More reduction on lower level of road).

In a summary, previous literatures demonstrate clearly that speed and volume and various variations of the indexes (reliability index, miserable index, etc.) are critical measures of mobility. Crash rates (fatality rate, injury rate, property-damage-only rates) and levels of severity are critical measures of safety. However, to incorporate these measures into the performance measurement process of winter highway maintenance operations requires filling two main gaps.

First, Road Surface Conditions (RSC) as the traditional measure of maintenance outcome will continue be used as the primary performance measure in winter highway maintenance operations due to its low cost to obtain, and ease of use in making maintenance operation decisions. However, to date, there are not enough sound studies that link different types of RSC with direct measure of mobility and safety (speed, volume and crash rate). Lack of the studies in these areas make the evaluation of maintenance outcome obscure to road users and maintenance agencies, and makes the process of meeting the goals of mobility and safety more difficult.

Second, even when hourly measurement of speed and volume are possible to obtain, and maintenance agencies are willing to use speed and volume as their primary measure of the operational effectiveness, no study to date has accommodated appropriate targets with which real time performance measurement can be compared. Setting up the appropriate targets against which performance can be compared can be a daunting task, because it must be based on a thorough understanding of the system. However, there are no studies that quantify the influence of types and levels of maintenance methods on speed, volume and crash rates. Even though many studies examined the effects of adverse weather conditions, few of them include winter maintenance in to considerations. However, maintenance operations and weather conditions together influence the road surface conditions, and through changing road surface conditions, maintenance and weather have influence speed and volume and crash rates. Studies on effects of weather suggest that wind speed, precipitation, surface temperature, and visibility are all associated with different levels of reduction in speed and volume. Also interactions effects with light, Urban/Rural, Road Class etc. need to be taken in to consideration as well.

3. STORM SEVERITY INDEX

As discussed in the earlier chapters, in order to determine the performance of an agency in dealing with a particular winter storm it is critical that the severity of the storm be quantified in some way, so that the performance can be normalized with respect to the severity of the weather. In this chapter, the process of developing such an index is described, and the storm severity index is presented. The storm severity index quantifies to what extent an individual storm poses difficulty to maintenance activities.

No study to date has evaluated the severity of individual storms as opposed to the severity of the whole winter season. Decker, 1998 developed a weather index, which incorporates daily new snow fall into consideration; but this is still a winter season based index. The only relevant studies are those that describe individual storms by meteorological factors. One such is the storm description matrix developed in the FHWA Manual on Anti-Icing Practice (1996). Nixon and Stowe (2004) improved and extended the storm description matrix by incorporating pre and post storm behavior in the matrix.

The development of the storm severity index was conducted in three steps. First the appropriate storm event classification and descriptions were developed. Second, based on the storm description, a multiple regression model was built to produce a storm severity index between 0 and 1. Third, representative storms were ranked in severity by winter maintenance supervisors and the model was modified to reflect this ranking. The storm severity index thus produced can be used as an objective measure of the challenge that an individual storm poses to a maintenance agency.

A. Storm Event Classification and Description

The matrix of possible storms developed by Nixon and Stowe (2004) can be represented schematically as shown in Figure 3.1. This is based upon the storm matrix in the FHWA manual on anti-icing practice (1996), but extends it especially in how it considers pre- and post-storm behavior. By combining one from each of the five categories or factors, a large number of potential storms can be described. Nixon and Stowe (2004) discarded some unlikely storm scenarios and considered a total of 312 storm scenarios (96 for each of the snow events, and 12 each for the frost and freezing rain events).

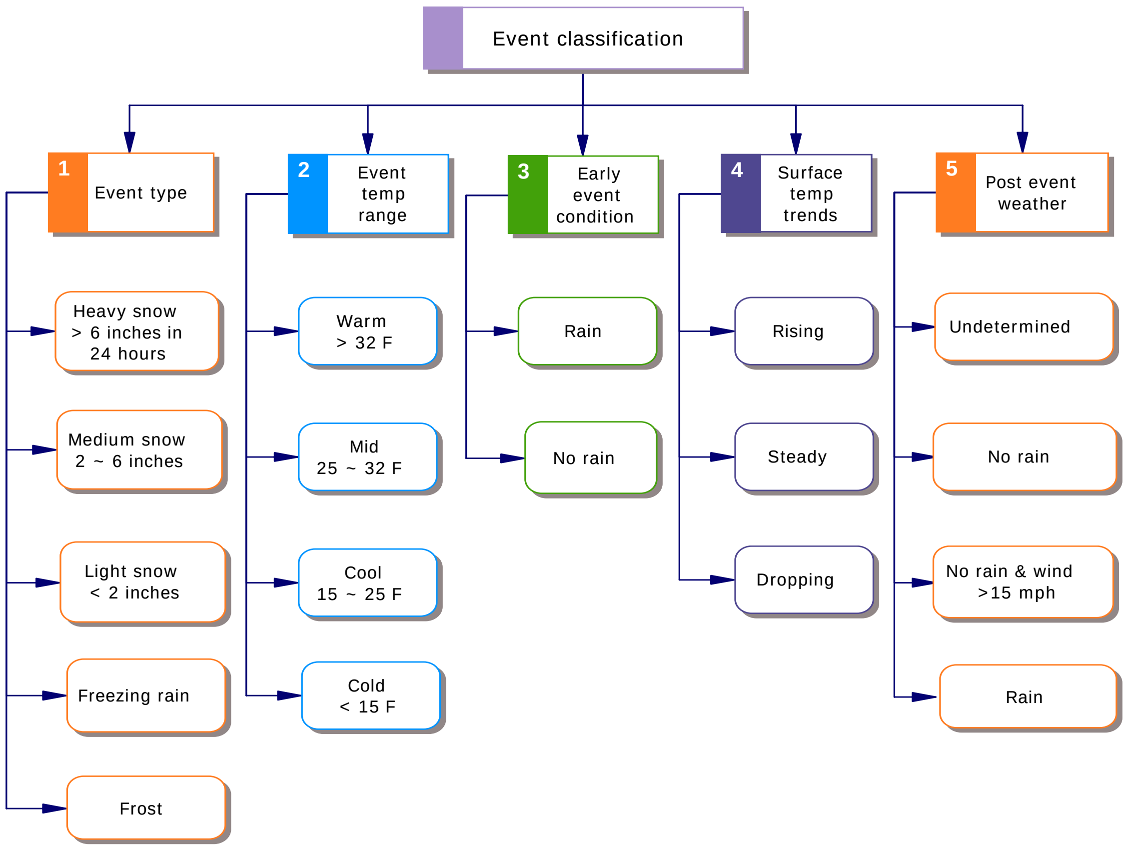

Figure 3.1. Event classification

For the purposes of generating the storm severity index, these storm scenarios were adapted as discussed below.

1. Because the focus of this effort was on storm events, it was decided to remove frost as a possible event type. Thus only four possible storm event types were considered: heavy snow, medium snow, light snow, and freezing rain.

2. Because the levels of wind during a storm can have a significant impact on the challenges faced while maintaining roads during the storm it was decided to incorporate the in-storm wind condition as another factor. Wind condition during a winter storm is an important factor to be taken into account, because wind speeds in excess of about 12 to 15 miles per hour may cause drifting snow problem and when the pavement is wet, cause retention of snow (e.g. see Illinois DOT, 1998).

3. It was decided to simplify the options for temperature ranges from four ranges (warm, mid, cool and cold) to three ranges by combining the cool range (15°F ~ 25°F) and the cold range (< 15°F) into one single range (< 25F) in this classification. Thus the storm severity index has only three temperature ranges – warm, mid, and cool.

4. The post-storm conditions seemed overly complex for the purposes of the storm index, and accordingly these were simplified into two categories rather than four. Thus the four conditions from Nixon and Stowe (2004) of "Undetermined", "No rain", "No rain with wind above 15 mph", and "Rain", are simplified to "Light wind" and "Strong wind" instead, because the impact of post-storm winds was considered to be much more important than the impact of post-storm rains. After these modifications, the event classification used in this study is as shown in Figure 3. 2.

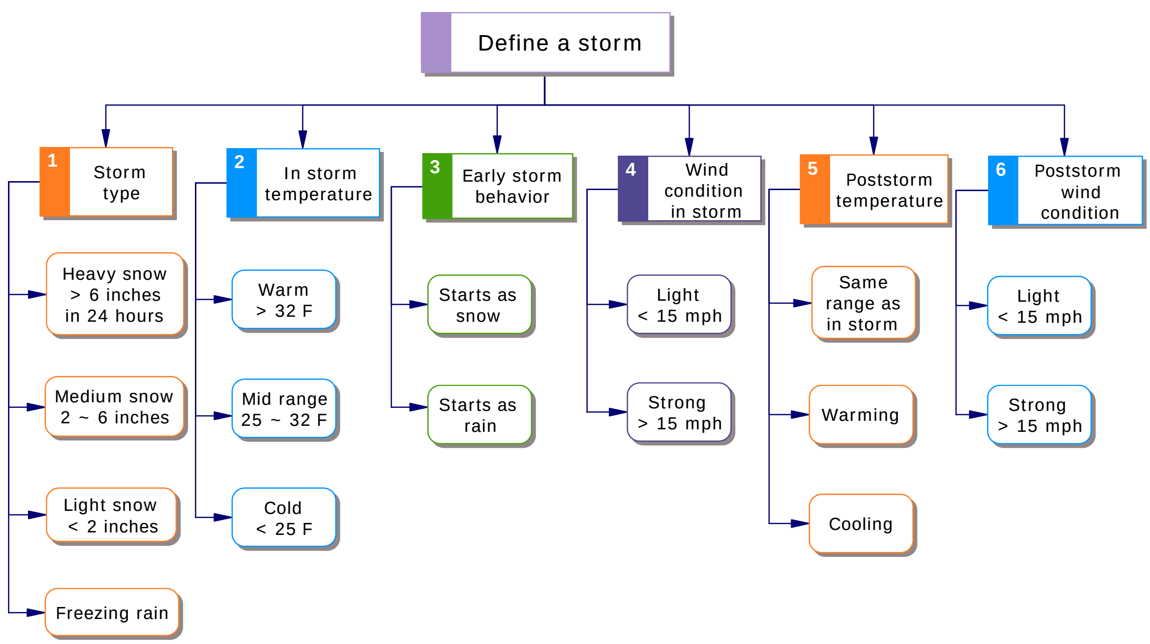

Figure 3.2. Modified Event Classification

B. Development of a Multiple Regression Model that Produces the Storm Severity Index

Using the above modifications, any given storm can now be described in terms of six variables: ST (Storm type); Ti (In storm road surface temperature); Wi (In storm wind condition); Bi (Early storm behavior); Tp (Post storm temperature); and Wp (Post storm wind condition). In order to develop a storm severity index between 0 and 1, each condition for the six variables must be assigned a score, and these scores must then be combined in some manner to create a composite score. This composite score can then be normalized so as to create the storm severity index.

The format of the storm severity index was based upon that used by SHRP-H-350 (Boselly, et al. 1993) for the development of a winter severity index. Thus the general form of the index equation is given as:

$$SSI = \left[\frac{1}{b} * [(ST * Ti * Wi) + Bi + Tp + Wp - a] \right]^{0.5} \qquad \text{Eq. 3.1}$$

Where SSI is the storm severity index and a, b are parameters to normalize the storm severity index from 0 to 1.

The storm type is clearly modified by the road surface temperature and the in-storm wind condition, thus these three terms are multiplicative. The various pre- and post-storm behaviors are considered, in contrast, to be additive to the main storm and are expressed as such in equation 1. The two constants “a” and “b” are used to normalize the storm severity index between 0 and 1.

Once the form of the equation is established, the relative scores between the values of the factors must be estimated. This involves attempting to assess how much worse a cold storm (with road surface temperatures below 25º F) is to handle than a warm storm (with surface temperatures above 32º F). A first approximation of these values can be obtained by studying the FHWA Manual of Practice recommended treatments (1999) and comparing how (for example) road temperature impacts treatment amounts and frequency, but this provides only an initial estimate. These initial estimates are listed in Table 3.1 (see below).

Table 3.1. Modified scores for each storm index factor

Storm Type	Freezing rain 0.4 (0.72)	Light Snow 0.35	Medium Snow 0.65 (0.52)	Heavy Snow 1
Storm Temperature	Warm 0.25	Mid Range 0.6 (0.4)	Cold 1	
Wind Conditions in Storm	Light 1	Strong 1.2		
Early Storm Behavior	Starts as Snow 0	Starts as Rain 0.1		
Post Storm Temperature	Same 0	Warming -0.087	Cooling 0.15	
Post Storm Wind Conditions	Light 0	Strong 0.15 (0.25)		

*Values inside parentheses indicate values modified after the Supervisors' evaluations.

After these initial values had been applied, the model was adjusted to get an approximately normal distribution. Using the estimates for the six factors listed in Table 3.1., the storm severity index was calculated for 252 different storms based on the initial algorithm and scores. Then the initial scores were modified (using the "a" and "b" constants) so that the computed storm severity index values have an approximately normal distribution (as shown in Figure 3.3.) The scores used for the six factors are shown in Table 3.1.

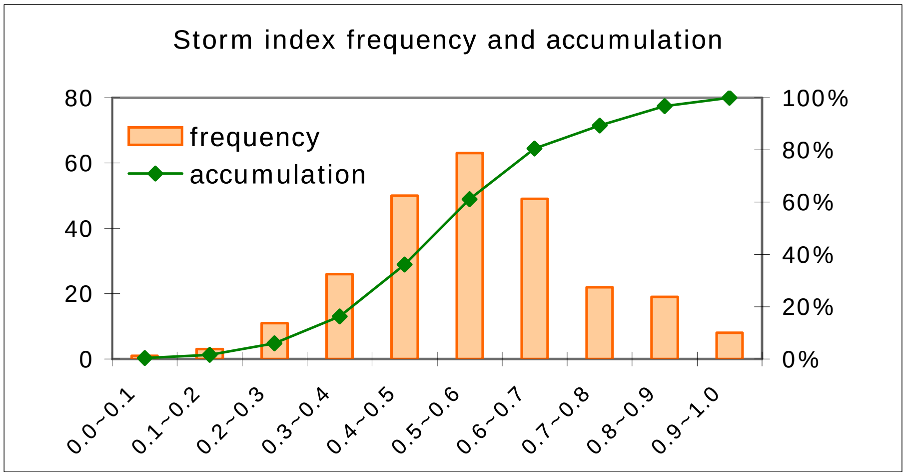

Figure 3.3. Storm severity index distribution

C. Adjustment of Index by Expert Input

To test and improve the accuracy and reliability of model, in the final step, ten storms were selected and were ranked in severity by winter maintenance garage supervisors. The ranks produced by the index were compared with the expert ranks provided by the supervisors. The major differences were discussed and the model was adjusted to ensure storm index ranks agree with the expert ranks.

Selected ten storms ranked in severity by Winter Maintenance Supervisors

Ten representative storm scenarios were selected out of 252 possible storm events and described in a survey form (Table 3.2). The storms were labeled A through J and their order on the survey form was randomized so as to minimize bias. Maintenance supervisors in Iowa ranked these ten scenarios according to the level of difficulty that these events would pose to them in their maintenance activities. The hardest was ranked as 10, and the easiest as 1. The storms were ranked by 38 supervisors around the State of Iowa.

Table 3.2. Storm scenarios description from the expert survey form

Storm scenarios	Description:
A	A storm with freezing rain and temperatures in the warm-range (above 33 F^o) that starts as rain. Winds in the storm are strong (over15mph). After the storm, winds become light and temperatures warm up.
B	A storm with heavy snow (above 6 inches) and temperatures in the midrange (25F^o to 32F^o) that starts as snow. Winds in the storm are strong (over 15 mph). After the storm, winds become light and temperatures cool down.
C	A storm with heavy snow (above 6 inches) and temperatures in the warm-range (above 33F^o) that starts as rain. Winds in the storm are light (less than 15 mph). After the storm, winds become strong and temperatures cool down.
D	A storm with heavy snow (above 6 inches) and temperatures in the warm-range (above 33F^o) that starts as snow. Winds in the storm are light (less than 15 mph). After the storm, winds become strong and temperatures cool down.
E	A A storm with light snow (up to 2 inches) and temperatures in the warm-range (above 33F^o) that starts as snow. Winds in the storm are light (less than 15 mph). After the storm, winds remain light and temperatures warm up.
F	A storm with freezing rain and temperatures in the cold-range (15F^o to 25F^o) that starts as rain. Winds in the storm are light (less than 15 mph). After the storm, winds remain light and temperatures remain cold.
G	A storm with medium snow (2 inches to 6 inches) and temperatures in the midrange (25F^o to 32F^o) that starts as snow. Winds in the storm are light (less than 15 mph). After the storm, winds become strong and temperatures warm up.
H	A storm with medium snow (2 inches to 6 inches) and temperatures in the midrange (25F^o to 32 F^o) that starts as snow. Winds in the storm are light (less than 15 mph). After the storm, winds remain light and temperatures remain in the midrange.
I	A storm with light snow (up to 2 inches) and temperatures in the midrange (25F^o to 32 F^o) that starts as rain. Winds in the storm are light (less than 15 mph). After the storm, winds remain light and temperatures warm up.
J	A storm with heavy snow (above 6 inches) and temperatures in the cold-range (15F^o to 25F^o) that starts as rain. Winds in the storm are strong (over 15 mph). After the storm, winds remain strong and temperatures remain cold.

Storm index ranks in comparison with expert ranks

The rankings of the ten storms were then compared with the initial storm severity index produced by the model. Table 3.3. shows the average rank that the 38 supervisors assigned to the ten storms, together with the rankings developed from the initial form of the storm severity index. It is clear that while there is general agreement between the supervisors and the initial index, there are also areas of significant disagreement, as discussed further below.

Table 3.3. Average expert rank vs. storm index rank for ten storm scenarios

Storm scenario	E	A	I	H	G	F	D	C	B	J
Storm Index rank	1	2	3	4	5	6	7	8	9	10
Avg. Expert rank	1	4	2	3	5	9	7	8	6	10

A more complete (and also more complex) representation of the responses obtained from the supervisors is given in Figure 3.4.

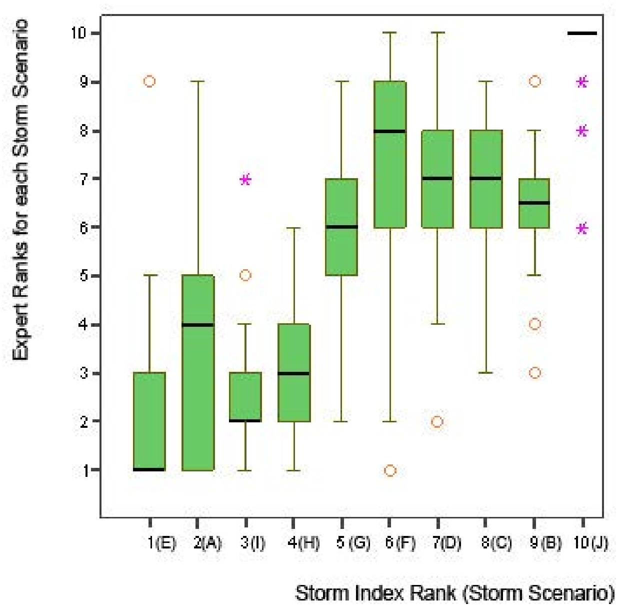

Figure 3.4. Expert ranks for ten storm scenarios

The ten storms are listed on the x-axis in Figure 3.4., and for each storm the solid black line is the mean response. The box represents the upper and lower quartiles, and the bars represent the high and low data values. The other symbols represent statistical outliers that were discarded from the final analysis.

Model adjustment to ensure storm index ranks agree with the expert ranks

As indicated in the above section, there was less than perfect agreement between the initial storm severity index and the supervisor rankings. Three major areas of difference are considered below. On the basis of this comparison, the numerical values for certain of the factors were adjusted so that the storm severity index scores for these ten storms are now in agreement with the rankings given by the garage supervisors.

1. Scenarios A, I, and H: Storm Scenario A (freezing rain) was ranked as more severe than storms H (medium snow) and I (light snow) by the supervisors, which contrasted markedly with the initial severity index. This indicated that the score assigned to freezing rain was relatively low and the score for medium snow was relatively high. The scores were adjusted accordingly (see the values in parentheses in Table 3.1).

2. Scenarios D and B: There was a significant degree of disagreement between the supervisors with regard to storms B and D. 63% of the supervisors ranked Storm scenario B as less severe than storm scenario D while 27% of the supervisors took the opposite view. It appears that the majority of supervisors think that post-storm winds are worse operationally than in-storm winds. On the basis of this, the score for post-storm winds was increased (see the values in parentheses in Table 3.1).

3. Scenario F, D, and B: Storm scenario F was ranked as more severe than storms D and B by the supervisors, again in contrast to the initial storm severity index. It appears that the lower temperature and the freezing rain condition (the latter as noted above) are considered to be operationally more severe conditions than a heavy snow storm. Thus the score for mid-range storm temperatures was also adjusted.

As indicated in the above analysis, the discordant scores have been adjusted according to the supervisor rankings. The adjusted scores are the scores inside the parentheses, shown in Table 3.1. While the index now matches the evaluations of winter maintenance supervisors in Iowa, it is not clear how well it would match with evaluations of similar supervisors in other Mid-western States (who would experience similar weather but may have differing operational responses) nor how it would compare with evaluations from supervisors from other climatic regions (e.g. Mountain States). While such comparisons are clearly of interest, they lie beyond the scope of the current study.

D. Result and Discussion

This chapter presents a model that takes the weather factors as the input and produces a storm severity index from 0 to 1, with 0 indicating very mild storm and 1 indicating very severe storm. The initial regression model was given as Eq. 3.1 and the assigned values are given in Table 3.1.

Using this model, the storm severity index for 252 different storm events can be provided. The index was compared with rankings provided by winter maintenance supervisors from the Iowa Department of Transportation, and was adjusted to agree with those rankings.

Development of the storm severity index is the first step in measuring the performance of winter maintenance operations. The index measures the level of difficulty that each individual storm events would pose to a maintenance agency in their maintenance activities. Thus it can be viewed as a normalizing factor that provides a basis for the fair comparison of the performance of maintenance operations under differing weather conditions.

4. WEATHER AND TRAFFIC SAFETY

Adverse weather conditions are known to be a major factor impacting traffic safety and mobility. A number of studies have attempted to quantify this impact, although the results of these studies are not consistent. The increased crash rate ranges from less than 100% to over 1000% during snowfall. There is also a debate on whether injury rate decreases during snowfall. Andrey (2002) noted that injury rate increased over 20% in Ottawa, Canada. Brown and Baass (1998) found fewer crashes involving injuries during winter in Quebec, Canada. The impact of severe weather on fatal crashes is even harder to quantify, because of the lower number of events involved and other confounding factors. Eisenberg and Warner (2005) estimated the effects of snowfall on US traffic crash rates between 1975 and 2000, and concluded that fatal crash rate decreased during snow days compared to dry days, but nonfatal-injury crash rate and property-damage-only crash rate increased, which seems to be in agreement with Knapp et al's (2000) study in the state of Iowa.

To present a clear idea of how weather impacts traffic safety, the method of meta-analysis has been applied to examine the impact of adverse weather on crash rates. The basic idea of meta-analysis is to identify relevant studies by a systematic search and then use effect size standardizing on each study result. In addition, this approach corrects sampling error and other artifacts and can present an estimate of the total effect with minimized subjectivity (Hunter et al., 2004). Further, since different studies might be influenced by methodologies, time span and regions, hierarchy meta-analysis has been applied using these factors as grouping variables. Separate analyses are conducted for each group.

A. Method

The process used in the meta-analysis is outlined in Figure 4.1. After careful review of the included articles, two meta-analyses were conducted separately for comparison studies and regression studies. The first step was to conduct a comprehensive literature search. An inclusion criterion filter was then applied to the found literature. After careful review of the included articles, two separate meta-analyses were conducted for "comparison studies" and "regression studies". Here, the "comparison studies" indicates those studies using binary weather indicators, for instance, comparing daily crash rates during snow and those during a non-snow condition. The "regression study" indicates those studies including continuous weather variables to predict the crash rates, such as inches of snow. Effect size and percent change in crash rate were both applied to standardize the research results. Due to insufficient data being available for effect size computation, only the percent change could be used to standardize research findings. In addition to the overall meta-analysis carried out for each weather factor category (snow, rain, snow depth, etc.), hierarchy meta-analyses were also conducted separately for the comparison studies stratified by validity score, by decades (time span) and by countries.

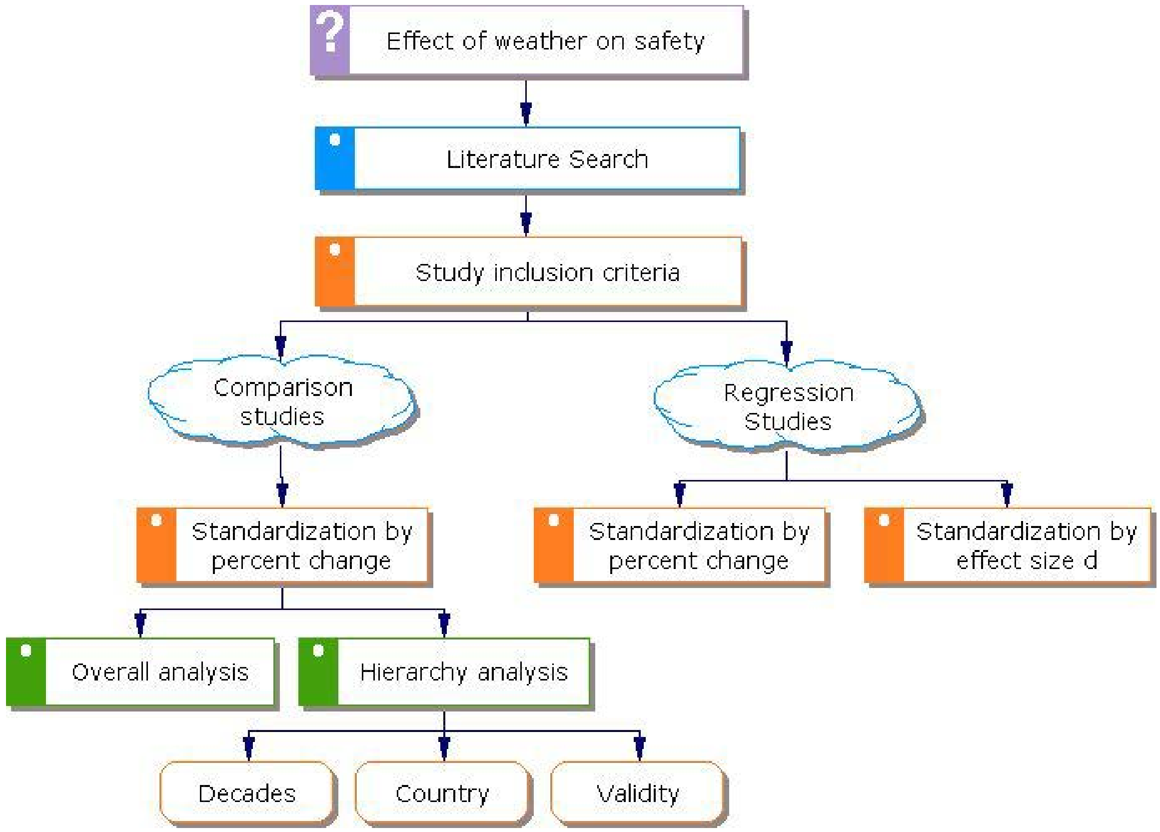

Figure 4.1. Study outline

Literature Search

A literature search for relevant studies published from 1970 to 2005 was conducted for both peer-reviewed literature and unpublished technical reports and theses. The search strategies used ensured this study contained enough primary studies for meta-analysis, because meta-analysis based on a large number of studies even with a small sample size has been shown to be more accurate than that based on small number of studies with large sample size (Hunter and Schmidt 2004).

After searching, 376 papers and reports were selected for further examination, of which 108 were determined to be pertinent. From these, 34 reports that provided 78 result records were selected for meta-analysis.

Study Inclusion Criteria

Previous studies that explored the association between weather conditions and traffic safety have investigated diverse variables. These studies have also applied a variety of methods and were based on different types of data. To ensure that the included studies were indeed comparable, the following study inclusion criteria were used:

Subject: only studies that explored the associations between traffic safety and weather factors were included.

Study design and method: Generally, two types of studies were included. One type of study used some form of comparison between adverse weather and normal weather conditions. Matched-pair study design was commonly used to control for extraneous factors in these studies: These studies identified the pairs similar in all respects (study area, time of a day, week or weekend), except for the weather factors being studied, so the other confounding factors were controlled. The studies then compared the crash rate during the precipitation days (events) to comparable non-precipitation days (events) to get an averaged relative risk ratio[1] (Bertness, 1980; Andrey and Olley, 1990; Andrey and Yagar, 1993; Sherretz and Farhar, 1978). Similar approaches include the Wet Pavement Index method, and the Difference-in-Means method, which are variations upon the matched-pair method. However, the wet pavement index method subtracts non-precipitation hours during the precipitation days based on assumptions of wet pavement durations. As a result of this subtraction, these study types will tend to give a higher estimation than a straightforward matched-pair approach (Brodsky, 1988).

Another type of study included was those using regression analyses. Most of the studies controlled for extraneous factors statistically. The results establish the change in crash rate or count associated with each unit change in a weather factor during a specified unit of time. Exposure measure[2] can be included as a normalizing factor for the accident count. Alternatively, exposure may be one of the independent variables in the study.

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1 In such studies typically the many accident rate ratios are averaged to produce a single value.

2 Exposure usually measured by million Vehicle Miles Traveled (VMT) or Average Daily Traffic Volume (ADT))

Either way, for this meta-analysis only those studies that consider exposure are included. The regression methods may vary from least-square regression (Andreescu and Frost, 1998) to a Generalized Poisson Regression (Fridstrom et al., 1995, Eisenberg, 2004 and Eisenberg, 2005). Generalized Poisson Regression is more commonly used due to its advantages. These two types of studies (comparison and regression) have been analyzed separately, and they will be discussed further in the method section.

Studies that investigated only the effect of weather conditions on crash frequency were excluded. Studies that investigated only the proportion of crashes with different levels of severity were also excluded, because the results are only informative about the relative frequencies of different types of crashes (Edwards, 1998; Bertness, 1980; Sherretz and Farhar, 1978).

Outcome measures: to be included, a study must have used an appropriate outcome measure such as counts or rates of traffic crashes, injuries, or fatalities; or measures of crashes likely to be affected by adverse weather, such as winter crashes or summer crashes. Examples of appropriate measures include: Crash counts defined by number of crashes during a certain time unit (e.g. as used by Andreescu, 1998); Crash rate usually defined by ratio of crash counts and traffic exposure (Amoros, 2002); Crash risk (also called relative accident risk ratio) usually estimated by crash rate during precipitation events divided by crash rate during non-precipitation events (e.g. as used by ElDessouki, 2004).

Measures of weather conditions: Snow and rain were the primary weather conditions among the identified studies. The commonly used measure in the comparison studies for the precipitation is whether it is a snow (rain) day (event) or not, which is mainly based on the precipitation type and total precipitation amount. For example, Andrey et al. define a snow event as snow or ice precipitation event of six-hours, in which total precipitation exceeds 0.4 mm (water equivalent).

In the case of weather measures in the regression studies, the continuous variable of snow depth, together with snow intensity, and the dummy variable of sudden snow[3]

[3] Sudden snow is defined as the first snowfall occurring during the winter or the year

(eg. Fridstrom et al, 1995) have all been used. These are all commonly used variables in the several studies being considered. Few studies investigated the effects of heavy or light precipitation, wind speed, or road surface conditions on traffic safety. However, to present a complete idea of how weather conditions can impact safety, data from this type of study were considered.

Data: Only studies that provided sufficient quantitative data to permit the calculation of the effect of adverse weather on crashes were included. This criterion is discussed further below.

Data Extraction

Coding: For each study that met the inclusion criteria, variables were coded into two tables. The general information table (see Table 4.1,) included document type, authors, publication year, country, study design, data source, and data on traffic volume. The study results information table (see Table 4.2.) included sample size, weather category (snow, rain, light snow, heavy snow, sudden snow, snow depth), weather specification, crash category (crashes, fatality, injury, property-damage-only), and percent change in crash rate. Table 4.1 and Table 4.2 show a few entries from the complete tables of this study to provide examples of these two table types.

Table 4.1 General information

Paper ID	Author	Document type	Publication Date	Study decade	Country	study method
2	Andrey	Journal	2002	1990-1998	Canada	Matched-pair
15	Fridtrom	Journal	1995	1975-1987	Finland	Negative Binomial regression

Table 4.2 Data information

ID	Paper ID	Sample size	weather Category	Crash Category	Percentage change in crash rate
12	2	469	rain	Crash	112%
15	2	302	snow	Crash	47.00%
16	2	159	rain	Injury	69.00%
17	2	128	snow	Injury	21.00%
48	15	144	snow depth	Injury	-1.46%
49	15	144	sudden snow	Injury	1.51%

Assessing study quality by validity score: As shown in Table 4.3., scores were assigned to each study on the basis that the validity of each study could be estimated by assigning a validity score in each of three categories: study design, traffic volume data, and level of aggregation. (e.g., as used by Elvik, 2001) The total validity score of a study is then the sum of these three scores. Validity classifications are shown in Table 4.3.

Table 4.3 Validity classification

	Description	Validity Score
Study design	Matched-pair approach	2
	Comparison study with certain controls	1
Traffic volume data	Hourly record from Automatic Traffic Recording (ATR) stations	3
	Averaged daily traffic data	2
	Approximation from state-year vehicle miles traveled	1
	Approximation from gasoline sale	1
Levels of Aggregation	Specified type of road	2
	Aggregate by state or region	1

B. Comparison Studies with Percent Change as the Standard Measure

This study calculated an effect size d as the standard measure for each of the analyzed studies, specifically, the study used:

$$Cohen's\,d = \frac{M_1 - M_2}{\sigma_{pooled}} \text{ (Hunter and Schmidt 1990).} \qquad \text{Eq. 4.1}$$

where M_1 and M_2 are the means of the two populations being considered, and σ_{pooled} is a function of the standard deviation of the two populations. To compute an effect size a parameter estimate and its standard error or variance estimation was needed. However, not all comparison studies consistently report those parameters. Thus as an alternative; percent change of crash rate (number of crashes per million vehicle miles traveled) to standardize outcome variables was selected.

For the comparison studies using relative crash risk ratio ($Risk_i$) as outcome variables, or for the studies providing crash rate ($Rate_i$) during precipitation vs. non-precipitation conditions ($Rate_{c\,ontrol}$), percent change (P_i) was computed directly as shown in Eq. 4.2 and Eq. 4.3.

$$P_i = Risk_i - 1 \qquad \text{Eq. 4.2}$$

$$P_i = \frac{Rate_i - Rate_{control}}{Rate_{control}} \qquad \text{Eq. 4.3}$$

where i represents different adverse weather events.

For some of the regression studies, information has been extracted to compute the percent change in crash rate during adverse weather. These computations were based on the expert knowledge of weather conditions; a certain range of weather factor was selected in the x –axis and from this computed the corresponding crash rate change was computed.

Traffic Volume Deduction Correction

To ensure all the percent changes are comparable, it is necessary to correct those studies that did not control for the reduced traffic volume associated with adverse weather. For studies that used relative accident risk ratio (crash count ratio) as outcome variables or studies that did not take traffic volume reduction into consideration because of the insufficient traffic volume data, the effect of reduced traffic volume on the crash rate was incorporated.

Two assumptions were made in order to do this correction as used in the study by Fridstrom et al. (2005):

- Exposure is proportional to traffic volume. This assumption is made because for a specified segment of road, the exposure measure vehicle miles traveled (VMT) is normally estimated by multiplying traffic volume on each road segment with the length of road segment and then summing them together to get an entire area VMT.
- Percent traffic volume reduction compare non-adverse weather condition can be defined as P_{vi}. Though traffic volume reduction data are not available for each study, it is reasonable to assume that the estimations are similar from comparable literatures.

Doherty et al. (1998) suggested that during rain, traffic volume in Canada reduced 2% in comparison with non-precipitation days; this estimation is the same as a study conducted in London (Colding, 1974). Keay (2005) showed that the traffic volume decreased 1.35% to 2.11% on wet days in winter and spring, and can decrease up to 3.43% for heavier precipitation (2-10 mm). In terms of snow, traffic volume has a substantial reduction range from 7% to 56% (Hanbali, 1994) and 10% to 50% (Knapp et al., 2000). Knapp also estimated the average traffic volume reduction is 29% during heavy snow for interstate highways. Based on these studies, traffic volume reductions as shown Table 4.4 for a variety of precipitations were used.

Table 4.4 Traffic volume reduction P_{vi} due to different weather conditions

Precipitation type	light precipitation	precipitation	rain	Light snow	Snow	heavy snow
Percent deduction in traffic volume, P_{vi}	1.35%	1.65%	2%	10%	15%	29%

According to the these assumptions and Table 4.4, the percent change (P_i) of each study that needs traffic volume correction has been modified by Eq. 4.4 to provide the corrected percent change in crash rate ($P_{i\,corrected}$).

$$P_{i\,corrected} = \frac{1}{1-P_{vi}} * (P_i + 1) - 1 \qquad \text{Eq. 4.4}$$

<u>Weight Each Study by Sample Size and Correct Sampling Error Variance</u>

The occurrence of crashes is subject to random variation (Fridstrom et al, 1995). Thus studies with small sample size tend to have great variability and may lead to biased results. Computing the mean percent change across studies can reduce the impact of sampling error because of the large sample size obtained in this manner.

Because studies based on a large sample size would normally provide a better estimation, each study was weighed by its sample size. Also in many areas of scientific research, sampling error has been found to account for most of the observed variance, thus the sampling error variance was corrected by the Hunter-Schmidt method (Hunter and Schmidt, 2004).

Sample size (N_i), and the percent change in crash rate (P_i) during adverse weather event were available for each study. For each weather factor category, the mean percent change was computed as shown in Eq. 4.5.

$$\overline{P} = \sum n_i P_i / \sum n_i \qquad \text{Eq. 4.5}$$

The observed variance is given in Eq. 4.6

$$\text{Variance} = \sum n_i (P_i - \overline{P})^2 / \sum n_i \qquad \text{Eq. 4.6}$$

Thus, the sample-size-weighted mean was obtained and the sample-size-weighted variance of observed crash rate change for each weather factor was calculated. The formula for the sampling-error variance of proportions is shown in Eq. 4.7.

$$\text{Sampling-Error Variance} = P_i * Qi/n \text{, where } Qi = 1 - Pi \qquad \text{Eq. 4.7}$$

A sample-weighted mean of the sampling-error variance of proportions to be cumulated was then obtained as shown in Eq. 4.8.

Mean of Variance of Proportions = $\sum P_i * Qi / \sum n_i$ Eq. 4.8

Then sampling error variance was corrected by subtracting the sampling-error variance from the observed variance. This provided an estimate of the true variance plus variance due to other artifacts. Because of the lack of necessary information to allow for correction due to other artifacts, this estimation was used as an approximation for the true variance and was also used to compute the confidence interval.

C. Regression Studies Effect Size d and Percent Change as the Standard Measure

The regression studies considered in this meta-analysis predicted the percent change in crash rate with a unit change in a certain weather factor. Most of the studies in this category applied Negative Binomial regression and provided sufficient information for effect size calculation. Thus effect size d (standardized mean different in crash rate) was applied to standardize each study result.

Effect Size

Normally effect size is the most reliable method to generalize studies. Effect size can be calculated in a number of different ways. Effect size d (Standardized mean difference) can be computed from a parameter estimate and its standard error or variance estimation, such as shown in Eq. 4.9. (Glass, 1981; Hunter and Schmidt, 1990). Note that this is the same as Eq. 4.1 above.

$$Cohen'sd = \frac{M_1 - M_2}{\sigma_{pooled}} \quad \text{Eq. 4.9}$$

Or effect size d can also be computed from test statistics t, chi-square, or Z as shown in Eq. 4.10, Eq. 4.11 and Eq. 4.12 (Glass, 1981).

$$d = 2\sqrt{\frac{t^2}{df}} \quad \text{Eq. 4.10}$$

$$d = 2\sqrt{\frac{\chi^2(1)}{N - \chi^2(1)}} \qquad \text{Eq. 4.11}$$

$$d = \frac{2r}{\sqrt{1-r^2}}, \text{ in which } r = \frac{Z}{\sqrt{N}} \qquad \text{Eq. 4.12}$$

Depending on the information provided by each study, effect size d was appropriately calculated for each study. Then each effect size d was weighted by its sample size, and the sampling error variance was subtracted from the pooled variance. Finally the confidence interval was calculated and is presented for the pooled effect size d at the 95% level.

Percent Change

Percent change (P_i) here represents the percent crash rate change with per unit weather factor change. For Negative binomial regressions, it can be computed by reducing the exponential of the regression coefficient (B_i) of weather variables by 1.

D. Results

General Findings for Comparison Studies

A total of twenty nine comparison studies provided fifty three records, among which twenty four record crashes, eight record fatalities and seventeen record injuries. In addition four studies recorded property-damage-only crashes. Table 4.5 presents the estimated crash rate change during various weather conditions using 95% confidence intervals. Most of the percent changes were positive, indicating that during adverse weather conditions all types of crashes (fatality, injury, property-damage-only) exhibit some kind of increase in crash rate. Results also indicate that most precipitation events are associated with considerable increased crash risk, together with a somewhat lesser increase in injury risk and a minor increase in fatal crash risk. Generally, as the precipitation intensity increased, all levels of crash risk increased. High winds are also associated with an increase of the traffic crash rate.

Table 4.5 Crash rate change compare to non-adverse weather conditions.

	Fatal			Injury			Crashes		
	N	Estimate (%)	95% C.I. (%)	N	Estimate (%)	95% C.I. (%)	N	Estimate(%)	95% C.I. (%)
Snow	1	9	(9, 9)	4	75	(54, 96)	8	84	(68, 99)
Rain	1	8	(8, 8)	7	49	(28, 70)	10	71	(31, 111)
Wet pavement	3	384	(308, 459)	\	\	\	3	380	(249, 511)
Heavy Snow	\	\	\	2	420	(350,490)	\	\	\
Light snow	\	\	\	\	\	\	1	169	(169, 169)
Heavy rain	\	\	\	\	\	\	1	93	(93, 93)
High wind	\	\	\	\	\	\	1	100	(100, 100)

* Heavy snow: hourly precipitation intensity above 5 mm

* Snow: total six hour precipitation amount above 2 mm

* Light snow: total daily precipitation less than 25 mm

* Rain: total six hour precipitation amount above 0.4 mm

* High wind: wind speed above 15 mph

The "Wet Pavement Index" method was used in most of the studies that explored wet pavement related crashes. This method tends to overestimate the real crash risk (Brodsky and Hakkert, 1988). Also the "wet pavement" included in this analysis indicate all wet pavement events during winter months or cold temperature conditions, so the wet pavement actually represents various undesirable road surface conditions during the winter. As indicated in Table 4.5 above, on average the wet pavement conditions would increase both crash rate and fatal crash rate by over 300%. The estimated relative risk of crashes was increased on a slippery road surface without precipitation present, with an estimated injury risk of 1.70 (Andrey, 2003). A Swedish study showed the highest crash risk was associated with road slipperiness due to rain or sleet on a frozen road surface and the estimated increase of crash rate can be over 1000% (Norrman, 2000).

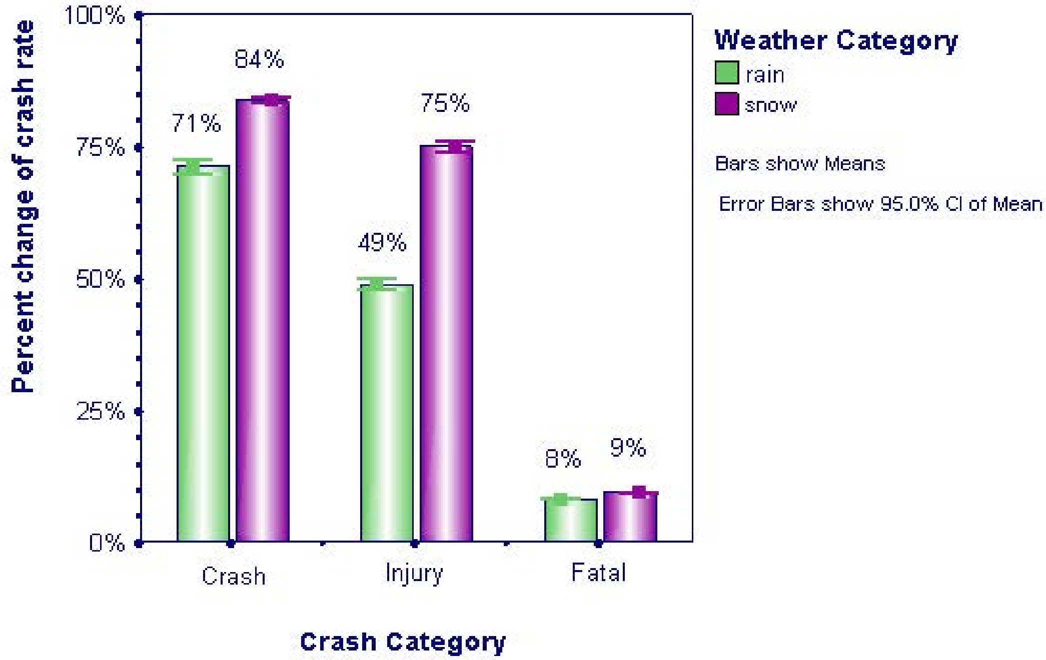

Figure 4.2 Effect of snow and rain on crash rate

As shown in Figure 4.2., the average percent change in crash rates for rain and snow are 71%, and 84% respectively. Compared to rain, snow has a more positive significant impact on crashes and injuries.

Contrary to some research findings that the fatal crash rate would decrease in adverse weather condition, the result shows that those who travel on the road during snow experience an 8% increase in fatality rate in comparison with dry days. Eisenberg suggested precipitation is negatively associated with fatal crashes (3.73% reduction per 10 cm of precipitation). (Eisenberg, 2004). However, he acknowledged that the reduced traffic volume is not controlled in this study. Indeed, in this meta-analysis study, before controlling for the reduced exposure, the estimated fatality rate has a decrease of 7% during snow. However once the results were corrected for traffic volume reduction, the fatality rate does positively associate with precipitation. This result suggests the decline in traffic volume may result in less car crashes, but for those who traveled in adverse weather, the risk of a fatal crash is nonetheless increased.

E. Hierarchy Analysis Findings for Comparison Studies

Results of Evaluating Studies by Decades

Since these prior studies have spanned several decades, a hierarchy meta-analysis was conducted to assess to what extent patterns have changed over time. Three subgroups were formed, using study decades as the grouping variable. However, in order to get meaningful results, it was not possible to simply consider each decade between 1950 and 2005 individually. Ranges of years were selected such that the number of studies in each range were approximately equal. Thus, three studies fall into the first range (1950-1979), two into the second (1980-1989), and three into the third (1990-2005). Separate analyses were conducted for each subgroup.

Table 4.6 Percent change of crash rate (fatal, injury and PDO) by decades

Study decade	Percent change of crash rate related with snow			Percent change of crash rate related with rain		
	N	Mean(%)	95% CI(%)	N	Mean(%)	95% CI(%)
All decades	8	84	(68, 99)	10	71	(31, 111)
1950~1979	3	113	(79, 146)	4	80	(43, 118)
1980~1989	2	71	(71, 72)	2	29	(10, 49)
1990~ 2005	3	47	(33, 62)	4	70	(30, 111)

Table 4.7 Percent change of injury rate by decades for rain

Study decade	Percent change of injury rate related with rain		
	N	Mean (%)	95% CI (%)
1950~1989	4	74	(22, 125)
1990~ 2005	3	47	(33, 62)

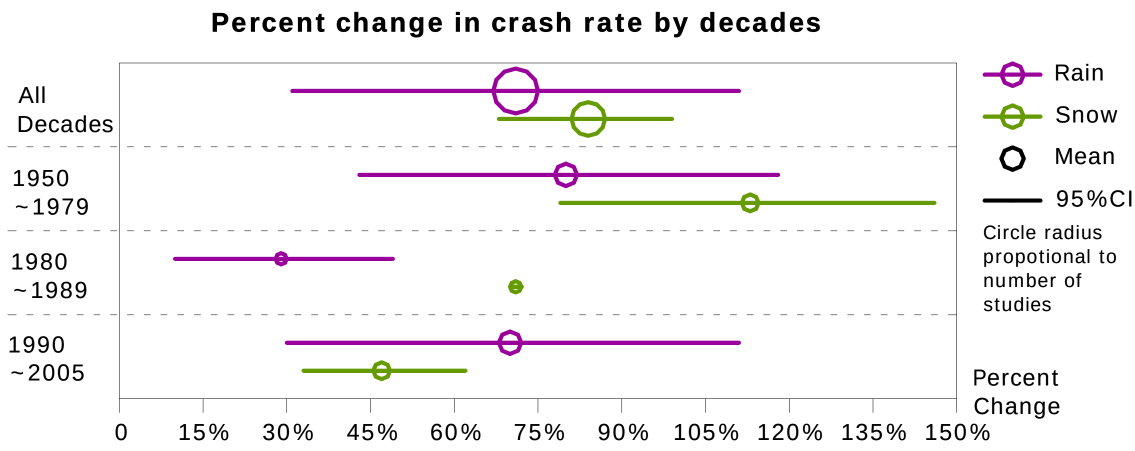

Figure 4.3 Percent change in crash rate by decades

As shown in Table 4.6 and Table 4.7, the percent change of crash rates during snow has decreased over time. It dropped from 113% during decades 1950~ 1979 to 47% during 1990~ 2005. This conclusion can be further confirmed from the 95% confidence interval of the percent change as shown in Figure 4.3: From 1950 to1979, the estimated percent change of crash rate has the confidence interval from 70.6% to 146%, while after 1990; the confidence interval is from 33% to 62%.

One possible explanation for this is that winter maintenance methods and technologies have improved over time. For example, the pro-active technology of anti-icing has been introduced into the U.S. since the early 1990s (Ketcham et al., 1996). While this strategy is not yet used throughout the U.S., there is clear evidence (Breen, 2001) that anti-icing reduces crashes in winter weather. It would be useful to know which snow and ice control strategies are the most effective at reducing crashes. This, however, lies beyond the scope of the current study.

In contrast, there is no statistically significant variation in the crash rate under rain conditions over this same time period. This tentatively suggested that any technological improvements related to safety in rain (e.g. improved tire design) have been overwhelmed by other factors.

Results of Evaluation Studies by Country

Since these prior studies have spanned a number of countries, hierarchy meta-analysis was conducted to assess how much results vary with country. USA, Canada and Britain tree subgroups were selected. Table 4.8 indicates the change in crash rate varies across countries.

Table 4.8 Percent crash and injury rate change for snow and rain by country

Country	Weather Category	Injury			Crashes		
		N	Estimate (%)	95% C.I. (%)	N	Estimate (%)	95% C.I. (%)
USA	Snow	1	45	(45, 45)	2	73	(72,73)
	Rain	1	21	(21, 21)	3	58	(28, 88)
Canada	Snow	2	79	(61, 96)	4	85	(69, 100)
	Rain	2	50	(39, 61)	5	73	(32, 113)
Britain	Snow	1	50	(50, 50)	1	1.00	(100, 100)
	Rain	2	42	(28, 56)	1	0.24	(24, 24)

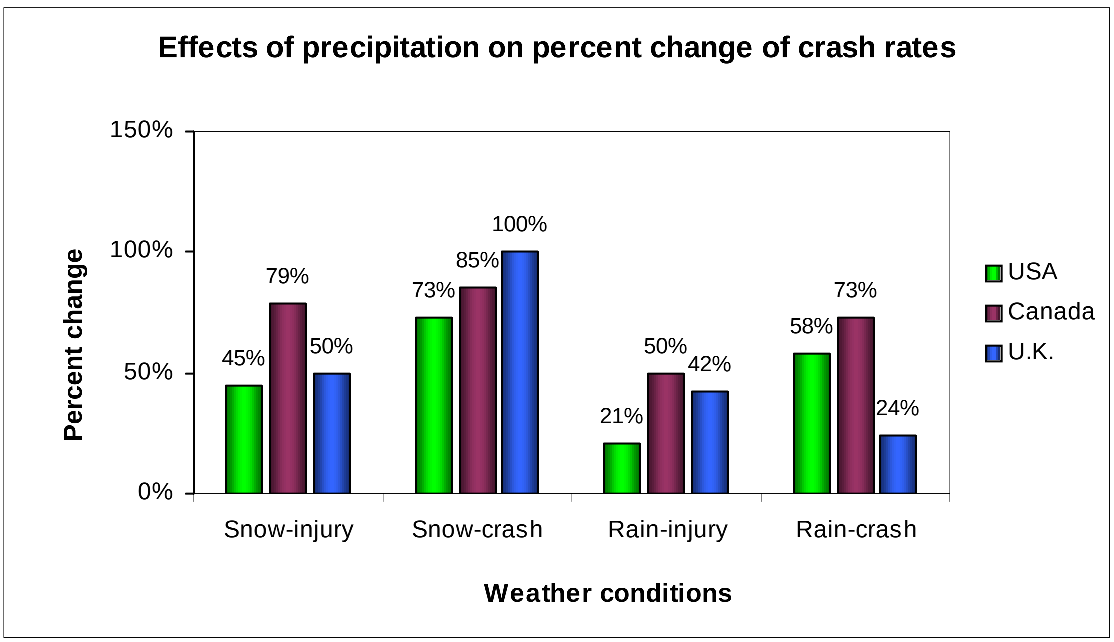

Figure 4.4 Effect of snow and rain on crash rate

In Figure 4.4, the impact of rain and snow on injury and crashes are shown for U.S.A., U.K. and Canada. When studies were evaluated by countries, there was considerable difference in the crash rate change, but there is no clear pattern. Different transportation policies, climate and the extent to which drivers can become accustomed to a specific weather driving condition might be an explanation for the differences.

The average crash rate under snowfall conditions of the British studies has a higher increase than the other two counties. One explanation for the difference might be that snowfall is less frequent in the U.K. than the other two countries, so drivers in the U.K. are not as experienced at driving under the snow condition as drivers in the regions with frequent snow precipitations. Thus the crash rate might be expected to have a higher increase. Again, further work would be needed to clarify this issue.

Results for Regression Studies

There are five studies that are fall into this category. They all applied Negative Binomial regression to predict the percent change in crash rate with a unit change in a certain weather factor. However different measures of weather conditions made the studies hard to generalize. For example, different measures in studies were maximum snowfall amount in a month, snow grade interaction factor, or the number of days with snowfall in a month. After reviewing the literature, there are only two studies, in which the common dependent and independent variables can be found. One is by Eisenberg (2004) and another is by Fridstrom(1995). Fridstrom provides four separate regressions for four different countries, and these four regression studies were considered to be four records used in meta-analysis. The effect size d for these studies is presented in Table 4.9.

Table 4.9 Effect size d for each study

Weather Category	Snow Depth (cm)		Precipitation (cm)		Applied Equation
Crash Category	Fatal	Injury	Fatal	Injury	
Eisenberg, 2004,U.S.A.	-0.0907	-0.0578	-0.1371	0.1743	(11)
Fridstrom, 1995,Demark	\	\	0.0002	0.0005	(8)
Fridstrom, 1995,Finland	\	-0.1207	\	\	(8)
Fridstrom, 1995,Norway	-0.0271	0.0106	\	\	(8)
Fridstrom, 1995,Sweden	-0.0431	-0.1023	\	\	(8)
… …	… …	… …	… …	… …	… …

The results of the meta-analysis by both methods are presented in Table 4.10 and Table 4.11. In Table 4.10 the variable d is the size effect (see Eq. 4.1. and 4.9). Var (d) is the variance in the size effect, while Var (e) is the variance of the sampling error, with the asterisk denoting the fact that this variance has been corrected for bias. The methods by which these statistics are calculated are discussed at length in Hunter and Schmidt (1990).

Table 4.10 Meta-analysis by effect size d

Weather Category	Snow Depth (cm)		Precipitation (cm)	
Crash Category	Fatal	Injury	Fatal	Injury
Average (d)	-0.073	-0.062	-0.121	0.090
Var(d)	0.001	0.003	0.002	0.008
Var(e) *	0.001	0.002	0.001	0.002
SD	0.010	0.035	0.038	0.074
95% CI upper	-0.093	-0.130	-0.195	-0.055
95% CI lower	-0.053	0.006	-0.047	0.235

Table 4.11 Meta analysis by percent change in crash rates

	Fatal			Injury		
	N	Estimate (%)	95% C.I. (%)	N	Estimate (%)	95% C.I. (%)
Snow depth (1cm)	3	-0.5	(-0.7, -0.4)	4	-0.3	(-0.5,-0.01)
Precipitation (1cm)	2	-0.3	(-0.5, -0.1)	2	0.12	(-0.03, 0.3)

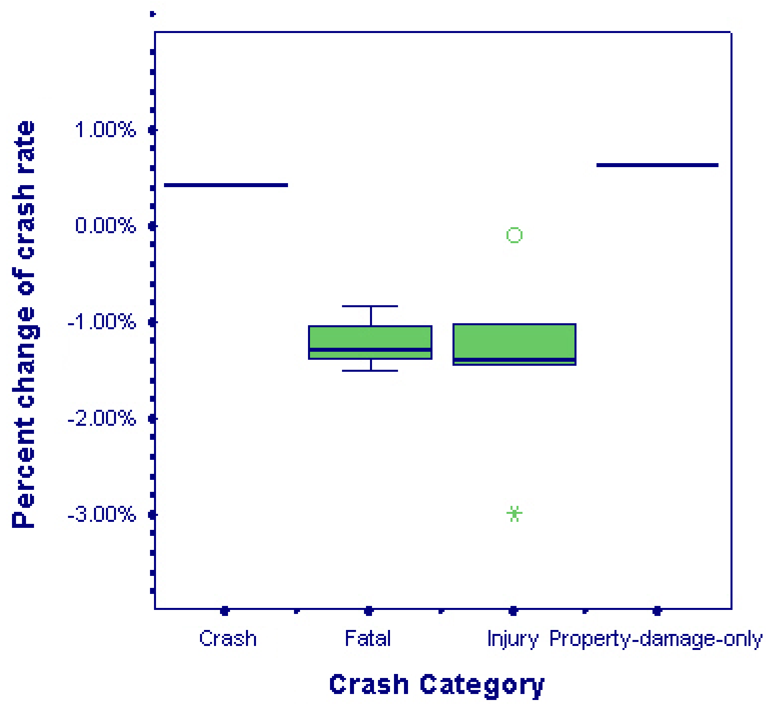

Figure 4.5 The association between snow depth (1cm) with percent change of crash rate.

Figure 4.5 shows how an increase in snow depth results in a change in crash rate. Based on the result from Table 4.11 and Figure 4.5, it would appear that snow depth has a negative impact on crash rate. For every one centimeter increase in snow depth, the predicted fatal crash rate decreases 0.5%, with 95% confidence interval (-0.7%, -0.4%).

The effect size for snow depth increase was -0.073, with 95% confidence interval (-0.093,-0.053) as shown in Table 4.11.

However the effect of snow depth on injury rate is less clear. The 95% confidence interval for effect size for snow depth ranged from -0.13 to 0.006. However, with one unit increase in snow depth, the associated crash rate appears to increase 0.4% (see Figure 4.5, the first category, "crash"). Thus, if the road surface is snow covered, road users would be likely to experience a decreased fatal crash risk or severe injury risk, but would be more likely to have less serious crashes, such as a property-damage-only crash. These results partly can be explained by the driver's behavior during the snowfall. As the visible snow depth increases, drivers may be more cautious and further decrease their driving speeds to compensate.

F. Summary and Discussion

The generalized results from studies that compared daily crash rates during adverse weather and those during non-adverse weather indicate the following: Most precipitation events are associated with a considerable increase in crash rate and injury rate. Snow has a greater effect than rain. It can increase the crash rate by 84 %(95% confidence interval [CI] =0.68, 0.99), and the injury rate by 75% (95% CI = 0.54, 0.96), while rain can increase the crash rate by 71% and the injury rate by 49%. As precipitation intensity increases, the crash risk also increases. Most studies focused exclusively on the effect of precipitation on crashes, while few estimated crash risk during other adverse driving conditions, such as high winds, fog, low temperature, and their interactions with precipitation. Thus to have a clear understanding, further research about how road surface condition and other weather factors relate to crash rates would be required.

Evans (1991) stated "The effect of inclement weather [snow fall] is more to reduce mobility by deterring travel or reducing speeds than to change safety (P.95)," after he analyzed the crash severity ratio from the province of Ontario. Although previous research show strong evidence that adverse weather is associated with reduced traffic and driving speed, and traffic speed and volume are clearly strong factors influencing crash rates, the effect of reduced traffic volume is not normally considered in most of the studies considered herein, and neither is reduced speed. In this study, from limited evidence, the fatal crash rate increased 9% during snow vs. no-snow when the effect of the reduced traffic volume on the crash rate was considered, compared to an increase of 7% when the effect is not considered. This estimation suggest the decline in the traffic volume may result in less car crashes, but for those who traveled in the adverse weather, the risk of a fatal crash is still increased.

Weather interaction with other factors might be another area to explore. Some of the studies have explored the interactions of weather variables with other factors such as lighting (Codling, 1974, Andrey, 2002), grades and curves (Shankar, 1995), and with urban or rural conditions (Bertness, 1980).

Goodwin (2002) stated that "Precipitation and undesirable pavement condition together constitute a greater hazard to the traveling public, than each alone, and the effects are a joint result of winter highway maintenance, weather and traffic." However, only Norrman (2000) considered whether maintenance action had been performed or not in his estimation of weather impact on crash rates. Because studies did not control for the benefits of winter maintenance, this may explain why the effect of snow on crash rate has a decreasing tendency over decades. The percent change of crash rate dropped from 113% during 1950-1979 to 47% during 1990-2005. The percent change of crash rate during rain does not have the same decreasing tendency. Overall improvements in safety may be the reason, but the improvement in winter maintenance methods might be also an explanation. Thus further research is needed to explore to what extent winter highway maintenance can reduce crashes.

5. EFFECTS OF WEATHER AND MAINTENANCE ON ROAD SURFACE CONDITION

The purpose of the next three chapters is to establish numerical links between weather and maintenance impacts and various possible performance measures. Specifically, these chapters aim to first establish how the condition of the road surface is impacted by a variety of factors, and then, how that road surface condition, together with other factors, impacts traffic volumes, traffic speeds, and crash rates. Once these relationships are established, it should be possible to determine suitable target values of speed reduction (for example) under given storm conditions, for a given level of service. These target values then become performance measures. If they are met or exceeded, then a given agency has achieved its performance goal. If not, then the agency has failed to achieve the goal.

The purpose of this chapter is to investigate the effects of weather, maintenance and traffic on the road surface condition as classified by the State of Iowa. In particular, this chapter considers the interaction between weather variables and maintenance procedures and how these interactions changed the possibility of a road surface being classified as SNOW/ICE. (Note that various capitalized terms such as SNOW/ICE, CHEMICAL, PLOW, TEMPERATURE, WIND, PRECIPITATION, SAND and BRINE represent variables in the models that are developed and described in this chapter). Moreover, effects of different CHEMICAL applications, and PLOW use on road surface types were compared for similar types of weather conditions, and the results of this study can also be used to predict the probabilities of different road surface conditions based on weather conditions and maintenance operations. A total of 16,980 cases were used in the study. Weather data were extracted from the ASOS/RWIS sites and maintenance operation data were extracted from maintenance logs.

This work is based on two combined methods: Chi-squared automatic interaction detector (CHAID, Kass, 1980) analysis was first used to identify the influential factors and the statistically significant (<0.05) interactions between weather variables and maintenance operations and how these interactions changed the possibility of road surface classifications or conditions. Then based on the segmentation and interaction identification from the CHAID analysis, a useful subset of weather and maintenance variables was used to build a Multinomial Logistic model for road surface condition prediction. The Multinomial Logistic Regression [MLR] (Hosmer and Lemeshow, 1989) results also indicate the strength of influence of weather factors, maintenance procedures, and interactions between them have upon the possibility of road surface conditions. This MLR model provides a tool for maintenance operations personnel to compare the effects of possible planned maintenance actions on the road surface conditions for specific weather scenarios.

The regression tree produced by CHAID indicated the data could be modeled in three separated subsets of maintenance activity: Anti-icing (activities before a storm starts), Phase I (activities during a storm) and Phase II (activities after a storm has ended). (No modeling of Frost Run activities was performed due to high levels (50%) of missing data). Multinomial Logistic Regression confirms and further extends the results learned with the answer tree: generally surface temperature, wind speed, and chemical usage are determinant factors. In Phase I and Phase II, two interactions (liquid rate and traffic volume, and plow and traffic volume) also impact the road surface condition significantly.

One of the primary goals of winter maintenance operations is to improve undesirable road surface conditions (Blackburn, 2004). Snow, ice and slush all create slippery road surfaces, and these surfaces are inherently less safe than dry roads. In the ideal, for a given weather condition, the result of a specific winter maintenance action on the road surface condition would be predictable. If this were the case, maintenance activities could be optimized to achieve the most desirable results with the least time and efforts.

Even though many previous studies have evaluated weather effects on traffic mobility and safety (Sherretz and Farhar, 1978; Bertness, 1980; Shankar, 1995; Andrey and Olley, 1990; Knapp, 2000), few of them qualified the effect of maintenance (Hanbali, 1994). Even fewer studies have evaluated how both weather and maintenance are associated with the road surface conditions. However, it appears that no study to date has evaluated how weather, maintenance and traffic together are associated with road surface condition. Road surface condition has considerable impact on traffic mobility and safety. However, the impact of maintenance on this condition is hard to qualify. The primary reason is that maintenance operations are not only dependent upon both the current and the forecast weather conditions and road surface conditions, but also the impact of these maintenance operations (chemical used, plowing or not, etc) vary with weather severity, road type, and traffic condition (mainly traffic volume). This situation presents a number of research questions, as discussed below.

- How do weather factors influence Road Surface Conditions (RSC)?

First we are interested in how weather factors: (e.g. Temperature, Wind, and Precipitation) influence the RSC. The problem is complicated by the interactions between weather variables. Previous research indicated that lower temperature (less than or equal to 15°F) and higher wind speeds (greater than 12 mph) combined would be a much more severe problem than either of these two conditions alone. One study that quantified the severity of weather events (Nixon & Qiu, 2005) has suggested that the severity of weather is mainly determined by TEMPERATURE, WIND, and PRECIPITATION, and the severity of weather is not related to these three factors in an additive form, but in a multiplicative manner. An example of such interaction is the issue of blowing snow, typically triggered when wind speeds exceed 12 mph. Blowing snow will not only reduce the visibility greatly, but also has the high possibility of increasing the risk of ice on the road surface when the road surface is wet and road surface temperature is lower than 32 ºF. The blowing snow problem depends on precipitation, temperature, and wind speed. Thus it is to be expected that wind speed interacts with temperature, and precipitation in its effect on the road surface condition.

- How do maintenance operations influence RSC?

More importantly, we are interested in how maintenance actions influence the RSC. Three types of maintenance action will be considered and are defined as: PLOWING (e.g. No-Plow, Wing-used, Ice-blade-used), SAND (e.g. Sand used or not, or Sand/Salt Percentage), CHEMICAL (e.g. Granular Salt, Brine, $CaCl_2$ solution) activities. However the effect of a given maintenance action is even harder to quantify, because this effect not only depends on the weather condition, but also on whether other maintenance actions have been performed at the same time. Using the effect of one CHEMICAL – Sodium chloride solution (Brine) as an example: BRINE of 23.3% concentration won't freeze until -6°F, but brine still can refreeze at relatively high temperature (e.g. 32°F) if brine has been diluted to near 0%. Therefore the possibility of a SNOW/ICE road condition after a certain amount of brine has been applied depends on not only the brine concentration and surface temperature, but also upon whether precipitation is ongoing and whether there is a large amount of snow currently on the road. Thus we cannot consider only how a given factor influences road surface condition, but we must also consider the strong interactions between maintenance actions and weather factors.

- How does traffic influence RSC?

An additional factor for consideration is how traffic influences road surface condition. Many maintenance agencies have long assumed that traffic can influence the road surface type in different ways. However past research indicates that the effects of traffic volume on RSC are neither direct, nor easy to quantify. Traffic can blow off chemical particles from roads. Vehicle tires can compact, or disperse snow. Heat from traffic exhaust or tire friction can heat the pavement surface and may melt the snow on the road surface. As noted in the FHWA anti-icing manual, when road surface temperature is low, “melted snow by the heavy traffic exhaust from the congestion, or stops at the intersection can refreeze and form black ice on the road surface” (FHWA, 1996). Clearly, traffic does influence road surface conditions both positively and negatively.

The effect of traffic volume on the road surface condition depends on the amount of snow on the road, whether the road has been plowed, the road surface temperature, and the nature of the maintenance activities that have been used. Since it is important to quantify the effect of traffic and using the traffic information to facilitate operation decision making, one goal of this work is to analyze and quantify how traffic influences surface conditions.

Driven by these research questions, and constrained by the data properties, the combined approach of CHAID and MLR have been used in this study. In this analysis, it is clear that there are complex interactions between the possible predictors considered in this study. In order to identify the influential factors and important interactions, the method of a classification tree has first been used to segment data and detect interactions. The classification tree method used herein provides detailed information and insights about interactions between weather factors and maintenance procedures. Moreover, the outcome variable (road surface condition or RSC) is presented as four mutually exclusive categories. It therefore cannot be treated as a continuous variable. Using the results produced by the tree, Multinomial Logistic Regression models (MLR) were constructed to predict road surface conditions classified into four mutually exclusive categories. In this chapter, first data preparation and a brief description of the data summary is given. Then the two classification methods – CHAID and the MLR, are described. Finally, results of the analysis are presented.

A. Method and Analysis

The methods used to determine the relationships described above are described in detail in Appendix A.

B.Results

Descriptive information of variables

An initial examination was conducted to discover the main features of the extensive data set. First, graphs and numeric summaries of each variable were examined as were relationships between the variables that may be thought to interact in their effect on the road surface conditions: such as chemical usage and surface temperature.

Table 5-1 shows the summary of the measures included in our analysis, and the summary of data consistent with expected behavior. In the ANTI-ICING stage, among total 1,792 observations designated as being ANTI-ICING, only 14 cases (1.3%) indicated that the PLOW was being used and 3.7% indicated that SAND was applied. In Phase I, with a total of 18,707 observations, about 57% of the observations indicated PLOW usage. Regardless of PLOW usage, almost all of the Phase I cases (96%) exhibited some form of CHEMICAL applied, and also 26% of the cases had SAND applied. In Phase II, about 50% of the observations were without PLOW operation. In 40% of the cases where no PLOW was used, no CHEMICAL was applied also.

Table 5.1 Summary of Measures

CASE SUMMARY	ANTI-ICING		PHASE I		PHASE II	
	N	% of Total	N	% of Total	N	% of Total
ROAD SURFACE CLASSIFICATION						
Dry	287	31.4	3151	30.4	433	35.9
Wet	198	21.7	1454	14.0	38	3.2
Snow/Ice	239	26.1	2228	21.5	321	26.6
Slush	190	20.8	3520	34.0	413	34.3
PLOW(1)						
No	902	98.7	4356	42.1	610	50.6
Yes	12	1.3	5997	57.9	595	49.4
PLOW(2)						
No	902	98.7	4356	42.1	610	50.6
Plowing	12	1.3	2106	20.3	262	21.7
Wing	\	\	753	7.3	97	8.0
Ice_Blade	\	\	1169	11.3	8	0.7
Wing & Ice_blade	\	\	1969	19.0	228	18.9
SAND						
None	880	96.3	7654	73.9	978	81.2
Sand	34	3.7	2699	26.1	227	18.8
CHEMICAL(1)						
Cacl2	\	\	1737	16.8	344	28.5
Brine	710	77.7	3342	32.3	72	6.0
Salt	151	16.5	4633	44.8	362	30.0
No Chemical	53	5.8	641	6.2	427	35.4
CHEMICAL(2)						
Brine rate 30	6	0.7	250	2.4	24	2.0
Brine rate 40	361	39.5	1287	12.4	45	3.7
Brine rate 50	271	29.6	1423	13.7	\	\
Brine rate 60+	72	7.9	382	3.7	3	0.2
Granular Salt	151	16.5	4633	44.8	362	30.0
CaCl2 missing	\	\	973	9.4	150	12.4
CaCl2 Rate 30	\	\	706	6.8	194	16.1
CaCl2 Rate 40/50	\	\	58	0.6		
No Chemical	53	5.8	641	6.2	427	35.4
TEMPERATURE (F)						
<15	131	14.3	1071	10.3	569	47.2
15-25	224	24.5	3141	30.3	411	34.1
25-32	258	28.2	3285	31.7	165	13.7
32-34	74	8.1	899	8.7	54	4.5
34+	227	24.8	1957	18.9	6	0.5
WIND SPEED (mph)						
>15	51	5.6	2056	19.9	162	13.4
12-15	61	6.7	1749	16.9	201	16.7
8-12	262	28.7	2695	26.0	335	27.8
2-8	488	53.4	3456	33.4	459	38.1
<2	52	5.7	397	3.8	48	4.0
Total cases	914		10353		1205	

Inevitably, while the data sets available were large, the study was constrained by a high percentage of missing data. The preliminary data analysis indicated that for the most of weather variables, the records are complete, but over 25% of the ASOS precipitation records were missing for most of the sites. Among maintenance records, variable liquid rate has the highest percentage of missing data among all the maintenance variables: 30% missing for BRINE RATE and 54% missing for liquid $CaCl_2$ RATE. This high percentage of missing data makes the analysis of the impact of different chemical rate on performance almost impossible. For this reason, the method of missing data imputation was applied (Royston, 2004) to substitute the missing value for the values by matching on other variables. For example, if an observation (Oi) from Site ID: “AL2070” has a missing value for the variable BRINE RATE, we know that the application rate is very likely to be the same at the same site for similar weather scenarios. Thus if we found another observation (Oj) from the same site, under similar weather conditions (temperature, wind speed) it is reasonable to assume that the missing observation of chemical rate (Oi) is the same as the chemical rate recorded in Oj. If there are several observations with similar patterns, any missing values are replaced by the average of these known observations.

A data validity check was also performed. The cross-tab of maintenance operation with the precipitation rate shows that in the anti-icing stage, there are still a few records indicating the precipitation rate is above 12 mm (0.47 inch). There might be two reasons for this discrepancy. First, the precipitation measures of ASOS/AWOS stations are not an accurate representation of the actual precipitation rate at the RWIS sites, even though the sites are within 10 miles distance of each other. Second, when the precipitation rate is recorded as 0, it does not necessarily mean that there is no precipitation. Thus OPERATION is used as a proxy for PRECIPITATION, with the understanding that ANTI-ICING and FROST-RUN both indicate winter maintenance operations performed before precipitation events. Phase I indicates that operations are during a precipitation event; and Phase II implies operations after precipitation has ended.

Results of CHAID

Major split: Temperature and Operation

Figure 5.1 presents the first split from the CHAID analysis. Node 0 is the root node containing the full sample, 16,148 cases. In the full sample, because the sample size is large enough, the frequencies, which can also be treated as probabilities, for the four different "ROAD SURFACE"[4] conditions are as follows: 24.1% for SNOW/ICE, 29.5% for SLUSH, 33% for DRY, and 12.7% for WET.

Moving down the tree, the total sample was branched into mutually exclusive subsets of data. One of the most significant predictors of road surface classifications is road surface temperature as shown in Figure 5.1. By default CHAID divided road surface temperature into approximately 8 categories of equal size. For each category, the probability of observing the road surface condition to be SNOW/ICE varies. Using the FHWA Manual on Anti-Icing Practice (1996), the following 5 categories were further defined: less or equal to 15°F, 15°to 25°F, 25°to 32°F, 32°to 34°F and above 34°F respectively, as shown in Figure 5.1. The highlighted category is the road surface condition category with the highest possibility for that subgroup. In other words, the road surface condition is most likely to be that category.

Consistent with the previous research, the general trend is that as temperature increases, the probability of SNOW/ICE decreases, but comparing the temperature subgroup, less than or equal to 15°F with the temperature subgroup, 15°F to 25°F, higher percentages of SNOW/ICE and SLUSH are found in the higher temperature group. One reason is that very low road surface temperatures are almost always associated with lower precipitation rates, and as a result, there are lower percentages of undesirable road surface conditions (i.e. SNOW/ICE, SLUSH).

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[4] "CAPITALIZED" Letters indicate the variables used in CHAID

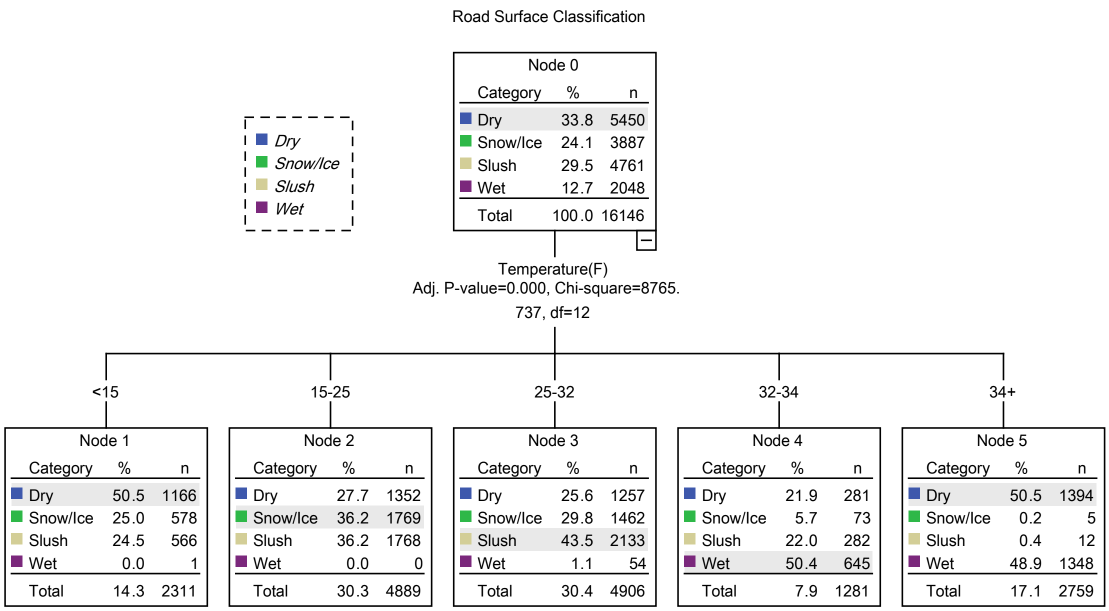

Figure 5.1 CHAID diagram: first split by road surface temperature

OPERATION is found to be another major factor that affects the road surface condition. One reason is that OPERATION is largely related to different road treatments, such as the amount of chemical solution; the frequency of plowing; and the use or not of abrasives. The regression tree branch for the temperature subgroup 25-32 F is shown in Figure 2. For the temperature subgroup 25°-32°F, the average possibility for SLUSH is 43% and 29.8% for SNOW/ICE. As figure 5.2 indicates when NO OPERATION is performed, the possibility of SNOW/ICE is 51.1%, an over 50% increase above the average of the temperature subgroup, which shows that maintenance activities do have a significant effect on reducing undesirable road surface conditions (as is to be expected). It is also noticeable the percentages of DRY and SNOW/ICE categories vary considerably across the temperature groups and the chi-squared tests are all significant at 0.001 levels. Thus the interaction of SURFACE-TEMP and OPERATION must be considered.

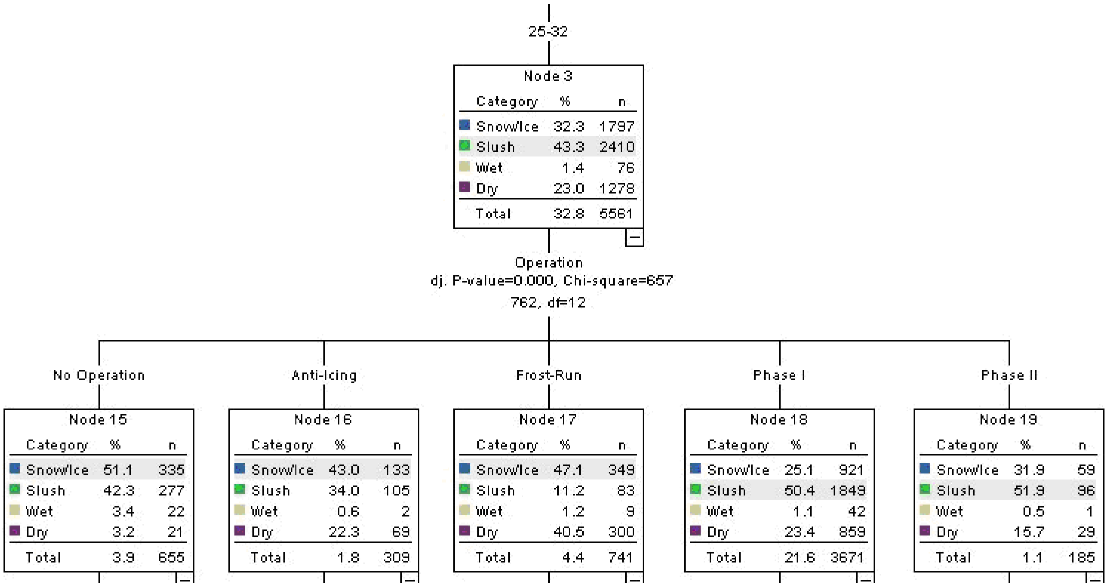

Figure 5.1. Segmentation by OPERATION for the subgroup temperature 25°– 32°F

<u>Important split: Traffic</u>

Traffic is shown to an important factor that influences road surface conditions across the various OPERATION stages. An example of this is shown in Figure 5.3: For the temperature subgroup 15° to 25°F, OPERATION is further split by AADT category. Traffic level is shown to be an important factor for the ANTI-ICING and PHASE II operation stages, but not for the PHASE I operation stage. The tree results tend to suggest that the higher the traffic volume, the more likely the road surface condition will be DRY than SNOW/ICE.

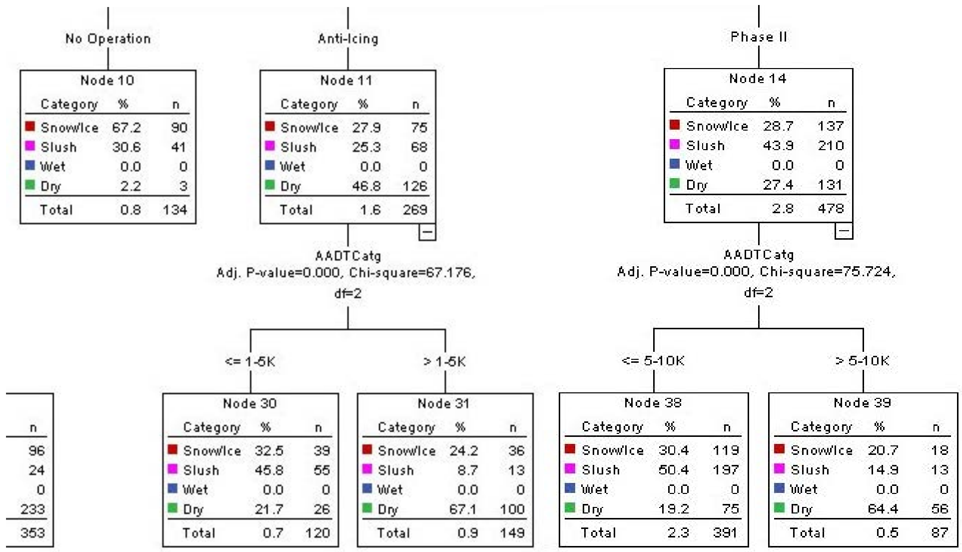

Figure 5.2 Segmentation by OPERATION and AADT category for the subgroup temperature 15°-25°F

The regression tree result also suggests that effect of WIND depends on levels of WIND and TEMPERATURE; that the variable PLOW interacts with OPERATION and surface TEMPERATURE in its effect on the road surface condition; and at the same TEMPERATURE and WIND level, there appears to be an interaction between CHEMICAL and the PLOW stages for the PHASE I and PHASE II but not for ANTI-ICING and FROST RUN subgroups.

The estimation accuracy of the regression tree is presented in Table 5-2. The risk of estimation is quite high with a value of 0.31, indicating that using this tree alone to predict the road surface condition will result in only a 70% chance that the prediction is right. Clearly, this model is not optimal.

Table 5.2 Risk Estimate of the Classification Tree

Actual Category / Predicted Category	Dry	Other	Wet	Snow/Ice	Chemical	Total
Dry	6499	413	1798	193	70	8973
Wet	374	74	720	35	42	1245
Snow/Ice W	356	81	8	698	142	1285
Chemical W	45	26	4	56	148	279
Total	7274	594	2530	982	402	11782

Risk Statistics	
Risk Estimate	0.315481
SE of Risk Estimate	0.00428124

Summary of CHAID findings

To improve the prediction accuracy, the results from the tree structure were used to construct a multinomial logistic regression model. The results from CHAID helped to determine the most important factors and interactions that should be considered in the model, but also provided important information regarding segmentations that should be used to split the sample to build different models. After running QUEST, C&RT and other algorithms and comparing those results to CHAID trees, it was decided to develop separate models for the three different OPERATION stages, even though TEMPERATURE as a variable provides the most distinct split. There are three reasons for this. First TEMPERATURE is a continuous variable, and splitting continuous predictor variables is associated with loss of information. Second, OPERATION interacts with several variables in its effect on the probability of road surface condition. For instance, the effect of WIND depends on different levels of WIND and TEMPERATURE and also different OPERATION stages. The effects of CHEMICAL and PLOW also depend on OPERATION. Thus to minimize the interactions that must be included, but still not bias the estimate, separate analyses were necessary for different OPERATION stages. Third and most importantly, while it is clear that PRECIPITATION will have a major impact on road surface condition, none of the tree result shows PRECIPITATION as a significant predictor. The reason is the reliability of the precipitation record. The large percentage of zero value record (90.6%) and 7% missing data makes PRECIPITATION not a valid predictor. Thus OPERATION is needed as a rough proxy for precipitation (this will be discussed in detailed in the section of MLR results).

Results of MLR

Multinomial Logistic regressions were used to build a model to predict road surface conditions. In the model, not only the main effect of each influential factor was tested, but also the possible interactions identified in the CHAID were tested to determine statistical significance in the MLR procedure.

The predictors includes TEMPERATURE, WIND SPEED, and non-linear component $WIND^2$, BRINE $RATE^2$, and also interactions between TEMP and PLOW, TEMP and WIND, OPERATION and WIND, PLOW and CHEMICAL, and finally PLOW and WIND. The non-linear component variables – $WIND^2$, BRINE $RATE^2$ were added to the regression equation because the tree splits also tend to suggest that WIND and BRINE RATE is non-linearly related to RSC. Interactions were tested by adding the cross-product variables (multiplying the two variables of interest) to the regression model and testing whether the cross-product term is statistically significant. If it was significant, the interaction was further explored by creating separate models for each level of the categorical variable, or splitting different levels of the continuous variable. Also for the categorical variables, different regroupings of these variables are tested.

With all the above considerations, the best performing models were selected as the final result. Finally models for the three operation stages were constructed. The final models exhibited overall chi-square test significance at the 0.0001 level, indicating that the final models outperform the null model. In addition the Pearson and Deviance goodness-of-fit statistics were above 0.5, suggesting that the models adequately fit the data. The pseudo r-square statistics (to a maximum of 1) of the model for PHASE I indicate that 56% of the variation is explained by the model (with the value of 0.56), and 51% for ANTI-ICING, 64% for PHASE II respectively.

The parameter estimate produced in the model quantifies the effect of each predictor. The results of the MLR for weather factors are shown in Table 5-3 for the operation stage Phase I and ANTI-ICING; MLR results for Maintenance variables for Phase I are shown in Table 5-4 and results for traffic variable are in Table 5-5 for Phase I and Phase II respectively. For the ease of interpretation, the estimated coefficients provided were in exponential form, sometimes termed the odds ratio.

Odds ratio is the ratio of the odds of the probability of choosing one outcome category over the probability of choosing the reference category. If odds ratios are above 1 and are significant at 0.05 level (noted as *) then the model indicates an increase in the likelihood of that response category (DRY, WET or SLUSH) with respect to the reference category (SNOW/ICE). Odds ratios less than 1 indicate a decrease in the likelihood of that response category. The coefficients for the continuous predictors answer the question, for a one unit change in the predictor variable, what is the predicted proportional change in the percentages of DRY vs. the reference category – SNOW/ICE.

Effect of Weather

The developed models indicate that both TEMPERATURE and WIND have statistically significant and strong effect on the possibilities of RSC, and gives the estimates of changes. Further, the results confirmed that effects of TEMPERATURE depend on OPERATIONS (PRECIPITATION); effects of WIND depend on levels of WIND and TEMPERATURE; effects of the interaction of TEMPERATURE and WIND changes with the types of OPERATION. Thus a three way interaction exists between WIND, TEMPERATURE, and OPERATION.

Table 5.3 Effect of weather

	DRY			WET			SLUSH		
PHASE I	Estimate	95%CI		Estimate	95%CI		Estimate	95%CI	
Temperature	1.052*	1.043	1.060	1.296*	1.276	1.315	1.01*	1.003	1.018
Wind	0.886*	0.851	0.923	0.948	0.868	1.036	0.982	0.948	1.019
Wind*Wind	0.984*	0.978	0.989	1.009	0.999	1.020	0.994*	0.990	0.999
Temperature*Wind	1.005*	1.003	1.007	1.003*	1.001	1.006	1.002*	1.000	1.003
ANTI-ICING									
Temperature	0.917	0.848	1.007	2.558*	1.501	4.360	1.017	0.980	1.056
Wind	0.929	0.857	1.008	0.074*	0.009	0.639	1.093*	1.015	1.177
Wind*Wind	1.015*	1.000	1.031	0.507*	0.322	0.796	1.031*	1.016	1.047
Temperature*Wind	0.983*	0.971	0.995	1.784*	1.164	2.734	1.031*	1.013	1.049

* indicates odds ratio above 1 and are significant at 0.05 level

Effect of Temperature

In Phase I as shown in Table 5-3 , the odds ratio for the temperature variable is 1.052 for DRY, which suggests that for a one unit increase in the variable “SURFACE TEMPERATURE”, the odds of the “ROAD SURFACE” being “DRY” rather than “SNOW/ICE” are expected to increase by 1.052 . In other words, the road surface will be 5.2% more likely to be DRY than SNOW/ICE, similarly, the road surface is 29.6% more likely to be WET, and 1 % more likely to be SLUSH than SNOW/ICE with each additional one unit increase in TEMPERATURE. As previous research indicated that temperature is positively related to the road surface conditions, the results confirms that the increase in temperature is associated with rapid increase in possibility of WET; moderately increase in DRY, very slightly increase in possibility of SLUSH, and overall decrease in the possibility of SNOW/ICE.

It is also of interest to compare the coefficients for TEMPERATURE in PHASE I to those in ANTI-ICING. There are noticeable changes in the coefficients: In the ANTI-ICING phase, TEMPERATURE is not a significant predictor to differentiate DRY from SNOW/ICE, or SLUSH from SNOW/ICE. However, TEMPERATURE has a statistically significant and strong effect on the possibility of WET. With one F increase in TEMPERATURE, the road surface is 156% ((2.558-1)*100%) more likely to be WET than SNOW/ICE. Since the coefficients are different across the OPERATION stages, it indicates that surface temperature has differential effect for “Before precipitation” and “During Precipitation”. Thus it confirms that TEMPERATURE interacts with PRECIPITATION in its effect on the possibilities of road surface conditions.

Effect of WIND

The MLR test results confirm that the effect of WIND on road surface conditions depends on levels of WIND and TEMPERATURE.

For the ease of interpretation, first we use the effect of WIND at TEMPERATURE 26 ^{o} F in PHASE I as an example (the centered TEMPERATURE variable has the value of zero, because the average of TEMPERATURE is 26 ^{o}F). Then the total effect of wind can be expressed as:

$$P(Dry) \Big/ P(Snow/Ice) = \exp(a + bX + cZ) = \exp(a) * \exp(b)^X * \exp(c)^Z$$

$$= (0.886)^{WIND} * (0.984)^{WIND*WIND}$$

The odds for the WIND variable are less than 1 and significant at 0.05 level(marked with * in the table), which suggests as a general trend - with one MPH increase in WIND speed, the Road Surface condition will be less likely to be DRY than SNOW/ICE. The non-linear component WIND^2 is also significant, which indicates that the downward trend is also non-linear, and thus the likelihood of DRY is nonlinearly related to WIND.

In a similar manner to the variation with TEMPERATURE, the WIND variable is centered at 9 mph, and thus the non-linearity has a critical point at (9-0.886 = 8.1mph). It means when surface temperature is at 26°F, before wind speed reach 8.1 mph, with one MPH increase in wind speed, the possibility of DRY will increase slightly, about (0.86+0.984(WIND-9)) %. However, once WIND exceeds 8.1 mph, as wind speed increases further, the possibility of DRY as a road surface condition will decrease quickly.

The multiplication term WIND*TEMPERATURE is significant at the 0.05 level. It confirms that WIND and TEMPERATURE do interact in their effect on the possibility of the road surface condition. For example, during PHASE I operations, at a surface temperature of 15°F, with one mph increase in wind speed, the possibility of DRY would be further reduced by (1.005^11)*100% -1=5.6% compared to the reduction in likelihood at a surface temperature of 26°F. This result confirms that wind is a more severe problem at lower temperatures. This relationship is shown in Figure 5.4 below.

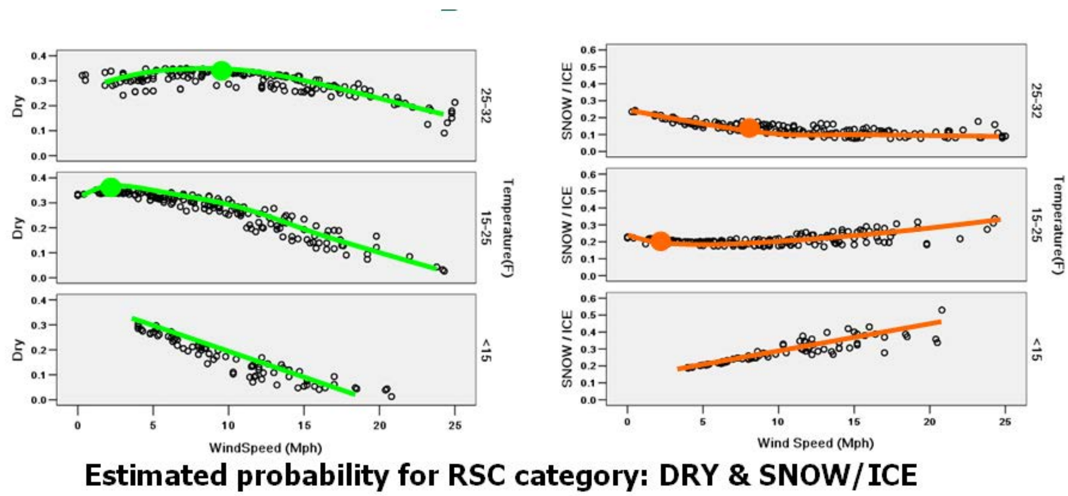

Figure 5.3. Effect of Wind on RSC depends on levels of Wind and temperature

The odds ratio for the TEMP*WIND variable changes with the OPERATION variable: 1.005* in Phase I, compared with 0.983 in anti-icing mode. This suggests that the effect of the interaction of TEMP and WIND changes with the type of OPERATION. This strongly suggests a three way interaction between TEMPERATURE, WIND and PRECIPITATION.

Effect of Maintenance

In the same model, when the effects of weather variables have been controlled, the effects of maintenance variables were quantified. The likelihood-ratio tests confirm that PLOW, CHEMICAL and the interaction between them are statistically significant in differentiating the likelihood of the road surface conditions being SNOW/ICE in PHASE I and PHASE II. To further explore these interactions, different models were developed for the PLOW or NOT PLOW groups.

Table 5.4 Effect of maintenance at three operations stages

PHASE I OPERATION		Dry		Wet		Slush	
Plow (Yes/No)		No	Yes	No	Yes	No	Yes
Traffic	AADT<5000 vs. AADT<5000	2.032*	0.656*	5.255*	1.558*	3.653*	1.543*
	Volume	1.001*	1	1.001*	1	1.001*	0.999*
Chemical (a)	Brine-Rate	1.038*	0.966*	1.005	0.977	1.015	0.972*
	Brine-Rate*Brine-Rate	0.993*	1.004*	0.998	0.998*	0.999	1
	Temperature*Brine-Rate	0.993*	1.001	0.995	1.006*	1.002*	1.004*
Chemical (b)	Liquid CaCl2 vs. Granular Salt	0.37*	1.38*	0.17	0.84	0.59*	0.88
	Liqiuid NaCl vs. Granular Salt	0.87	0.92	0.08	0.53	1.04	1.16
	Liquid CaCl2 * Temp_Cent	0.99	1.11*	1.35	1.02	1.03	1.06*
	Liqiuid NaCl * Temp_Cent	1.01	0.97*	1.86*	1.23	0.97*	1.01

* indicates odds ratio above 1 and are significant at 0.05 level

Effect of Plow

In PHASE I, the likelihood ratio tests show that PLOW is a significant predictor of the road surface condition probabilities. The odds for the PLOW variable suggest that if there is no PLOW action during the previous hour, the road surface is 53% less likely to be DRY than if PLOW action is performed, and 119% more likely to be SLUSH than if PLOW action is performed after other variables are controlled for. It is reasonable to get these results, because plowing action will easily remove packed snow or slush from road. After the mechanical removal, if there is no more precipitation, the road surface is more likely to be dry; however, there are situations when the temperature is low, after the plowing of snow, when a very thin layer of snow that is left after maintenance will change to ice.

When chemical is applied, but plowing action is not performed, the melted snow will take the form of slush and thus there is almost no possibility of road surface being dry under these operational conditions.

To further explore these interactions, separate models were developed for the two groups of data: PLOW or PLOW_NOT. The CHEMICAL effect was tested based on this split. As expected, the odds ratios are different for these two groups (plow vs. no plow).

This indicates that brine rate has different effects on road surface condition for plow and non-plow conditions. These different effects mean that the regression coefficients associated with the possibility of the road being snow/ice will be different for the two groups if separate regressions are conducted for plow and non-plow conditions.

Effect of Chemical

After checking with the frequency of each variable, it was determined that brine rates should be re-grouped as brine rate less than 50 gallons per lane mile, and 50 or more gallons per lane mile. Therefore there are four categories for the variable CHEMICAL: Granular Salt, and $CaCl_2$ solution, Brine less than 50 and Brine 50+. For the variable CHEMICAL, GRANULAR SALT is chosen as the comparison group(sometimes termed as reference group). For the reason that across the OPERATION stage, GRANULAR SALT has a relatively large sample size for each subgroup thus making the comparison valid. Because the probability of the reference group is the denominator for calculating the odds ratio, if any of the other categories were used as the reference group, it is possible that there would be no observations for that category, making the denominator zero and the comparison invalid.

Compared with the roads that were treated with Dry Salt, those that received no chemical treatment were significant less likely to have slushy road surface conditions than SNOW/ICE and those with brine treatment were significantly more likely to have slushy than snow/ice. Alternatively, the model can isolate only those instances in which BRINE was used. The exact application rate of Brine is recorded, so it can be treated as a continuous variable.

BRINE_RATE was found to be significant. For example, the road treated with an brine application rate of lower than 30 gallons/lane mile was significantly more likely to be DRY than SNOW/ICE covered, and those that received a BRINE_RATE of 50 gallons per lane mile and over were significantly less likely to be Dry than snow/Ice compared with the roads treated with 40 gallons/lane mile. A one unit increase in LIQUID_RATE results in1.5 times more likelihood of SLUSH than SNOW/ICE. It is worth nothing here that similar to the interaction between VOLUME and PLOW, and between PLOW and CHEMICAL, there is an interaction between BRINE RATE and PLOW, as well as

BRINE RATE with VOLUME. For example, after all the other variables are controlled, a higher BRINE_RATE and high traffic volume tend to result in a slight increase in the probability of SNOW/ICE rather than SLUSH. Also, when there is heavy traffic volume, as liquid rate increases, together with heavier traffic volume on the road, the ROAD SURFACE is more likely to be DRY than SNOW/ICE.

Effect of Traffic

The effect of TRAFFIC has shown to be interact with PLOW and OPERATION. As shown in table 5-6. During precipitation (in Phase I), when PLOW is not used, heavily traveled roads would be much more likely to be Dry (203% times likely), Wet (525%), or Slush (365%), compared with a low traffic road.

In comparison, when PLOW has occurred in the previous hour, the road surface condition of a heavily traveled road is more likely to be Wet (150%) and Slush (154%) rather than Snow/Ice, but also has a higher risk of Snow/Ice (36%) when compared with a low volume road

This suggests that generally the heavily traveled roads have better road surface conditions at the same weather condition and maintenance operations than the low traffic road. However, when there is a low amount of snow on the road (no precipitation or during precipitation and after plowing), the heavily traveled road has a higher risk of Snow/Ice rather than dry compare to the low traffic road.

Table 5.5 Effect of traffic volume

AADT>5000 vs. AADT<5000	Dry		Wet		Slush	
Phase I	2.032*	0.656*	5.255*	1.558*	3.653*	1.543*
Phase II	2.452*	0.259*	/	/	1.08	0.665

Prediction Ability

Using the models developed above, it is possible to estimate each of the road surface classifications' probability (see Table 5.6). With the input of the previous hours' weather information and maintenance procedures, the models output the probability of each of the four types of road surface conditions for the next hour. Conventionally, for each case, the predicted road surface type is assigned as the category with the highest model-predicted probability. For instance, during precipitation (at Phase I operation stage) when the surface temperature is 27°F, wind speed is 12.8 mph, and if plowing is not performed, the next hours' road surface probability of being dry is 46%, being wet is 7% and being snow/ice is 30%. In this circumstance, the model prediction is given as indicating that the road surface is more likely to be Dry than anything else.

Table 5.6 Prediction results of maintenance actions based on the MLR model

Operation		Anti-Icing	Anti-Icing	Phase I	Phase I	Phase I	Phase I	Phase II	Phase II
Surface Temp (°F)		9.8	26.9	10	14	11.7	36.8	10	14.8
Wind Speed (Mph)		20	12.8	16	14.7	4.8	13.6	9.8	6
Plow(Yes/No)		No	No	Yes	Yes	Yes	Yes	No	No
Chemical Type		Brine	Brine	Salt	No Chemical	Brine	Brine	Salt	Salt
Liquid Rate(Kg/Lane*km)		40	60	/	/	50	50	/	/
AADT		<=5000	>5000	<=5000	<=5000	>=5000	>=5000	<=5000	<=5000
Road Class		1	1	2	2	1	1	2	2
Volume (vehicle/hr)		150	670	91	65	433	1053	83	115
Estimated RSC Probability	Dry	27.91%	46.25%	4.12%	11.31%	41.04%	36.18%	47.53%	33.34%
	Wet	1.61%	7.10%	0.08%	0.47%	0.01%	36.72%	0.00%	0.00%
	Snow/Ice	40.27%	29.64%	43.04%	30.59%	25.34%	8.11%	23.96%	21.61%
	Slush	30.20%	17.01%	52.76%	57.63%	33.61%	18.99%	28.51%	45.04%
Predicted RSC		Snow/Ice	Dry	Slush	Slush	Dry	Wet	Dry	Slush
Observed RSC		Snow/Ice	Dry	Slush	Snow/Ice	Dry	Wet	Dry	Slush

Road Class: 1. Interstate; 2. Primary

6. EFFECTS OF WEATHER AND MAINTENANCE ON MOBILITY – STRUCTURAL EQUATION MODELING

A. Introduction

Previous literatures do suggest that weather factors are all associated with different levels of reduction in speed and volume (See Chapter Two for more details). However, there are no studies that quantify the influence of types and levels of maintenance methods on speed and volume. Lack of studies in the area of winter highway maintenance make the evaluation of maintenance outcome obscure to road users and maintenance agencies, and complicates the process of meeting the goals of mobility.

Thus the purpose of this Chapter is to quantify the relationship between weather, maintenance and traffic: how a variety of weather conditions and maintenance operations directly and indirectly influence traffic volume and speed. In particular, this chapter addresses the question of whether effects of weather and maintenance in nature are different across different road characters and traffic conditions: Interstate highways and primary roads with different levels of AADT and speed limit.

While weather and maintenance actions have a clear effect on road surface conditions as results in Chapter 5 indicated, it is expected that they also have indirect effects on mobility through the road surface conditions, as well as direct effects as represent graphically in Figure 6-1. An example of the direct effect of winter maintenance on mobility is that plowing the road will tend to slow down traffic on an interstate highway, since plows do not operate at typical interstate speeds. Examples of the direct effects of weather on traveling speed are: Drivers may adjust to the undesirable weather conditions by reducing their driving speed, such as under conditions when precipitation reduces visibility, or when strong wind reduces vehicle stability. However, in addition to these direct effects of weather and maintenance on vehicle speed, it is necessary to consider the indirect benefits of maintenance actions on mobility through improved road surface conditions. In other words, by plowing and applying chemicals and abrasives, the road surface condition will likely be improved. This improved condition will likely result in increased mobility.

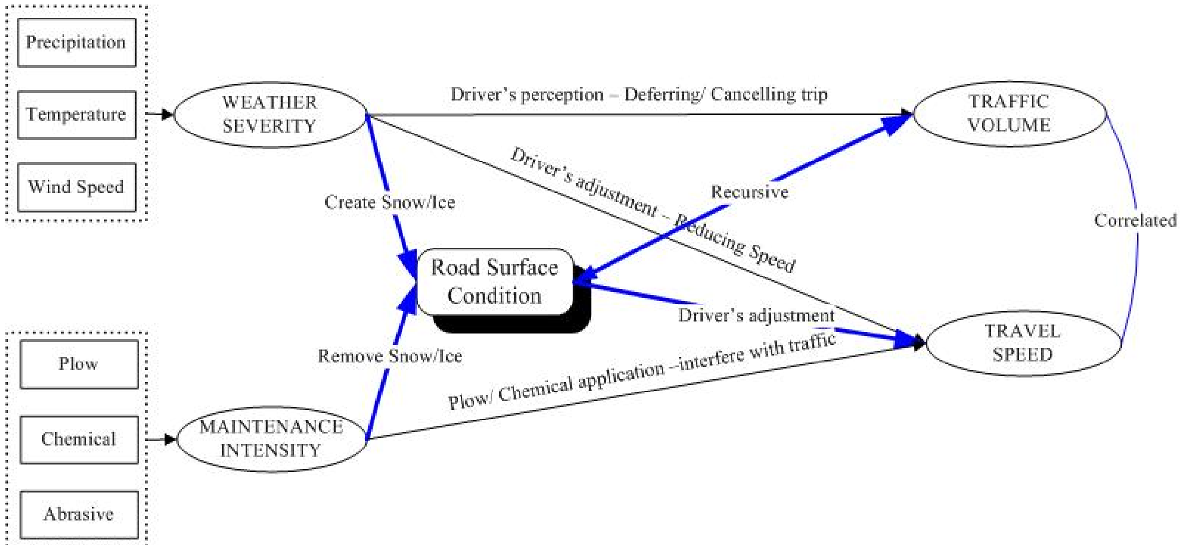

Figure 6.1 . Weather and maintenance effects on mobility

By using Structural Equation Modeling (SEM) the direct and indirect effects of weather and maintenance actions on mobility have been quantified in this chapter. The model uses road surface condition as an intermediate variable. Because the mediator is the categorical variable, and various maintenance variables are categorical, a particular type of SEM, termed Categorical Variable Methodology (CVM), was employed in dealing with the non-normal and ordinal data in this model. Also multiple group analysis in SEM was applied to determine whether the nature of influences of weather and maintenance on mobility is different across different road characteristics and traffic specifications.

Understanding the effects of winter maintenance operations using structural equation models could offer significant advantages for winter highway maintenance decision making. For instance, with understanding of how performing plowing and applying chemicals can increase speed during the hour of a winter precipitation, decision makes can better deploy maintenance operations according to pre-designed mobility goals. Also comparison of the effects between different highway groups could assist maintenance decision makers to prioritize the maintenance routes under the resource constraints that are faced.

Method

The methods used to develop the structural equation modeling for the study are presented in Appendix B.

Result and Analysis

For the illustration, we first considered a sub-set of the data consisting of traffic on the Non-peak hour during the day. Also to quantify the maintenance effect, the measure of speed and volume were taken after the hour that maintenance operations were performed. As explained in the method section, the underlying latent continuous variables were assumed for the categorical variables used in the analysis and for each latent continuous variable, the thresholds for entering categories were generated. PRELIS was used to compute the polychoric and asymptotic covariance matrices. Then Weighted Least Squares (WLS) were used to estimate the fit of the model. The structure model provides an overall acceptable fit as indicated by various fit indices: the RMSA is 0.062 RMSEA (The root mean square error of approximation) less or equal to 0.06 indicates an acceptable fit.) The NNFI (Non-normed Fit Index) and IFI (Incremental fit index) for this model is 0.951 and 0.972 respectively. (For both NNFI and IFI values above 0.9 indicate a good fit.). Further, even the chi-square test is significant (Chi-square = 33.96, df= 7, P-value= 0.0002), which is reasonable since a very large sample was used to fit the model (sample size more than 1,769 for each tested subgroup), which created excess power and resulted in easily detectable differences between the observed and implied covariance matrix.

Given that the model fit the data well, as described above, as a first step, the relative importance of variables were compared. Because the coefficient estimates of various weather and maintenance measurement are affected by the different scales being used, the standardized path coefficient estimates were used to facilitate the comparison, as presented in Figure 6-2. The standardized coefficient can be interpreted as, for a standard deviation increase in the predictor variable, the increase in the response variable's standard deviation is the same as the estimated coefficient.

Chi-square = 33.96, df= 7, P-value= 0.0002, RMSEA=0.082

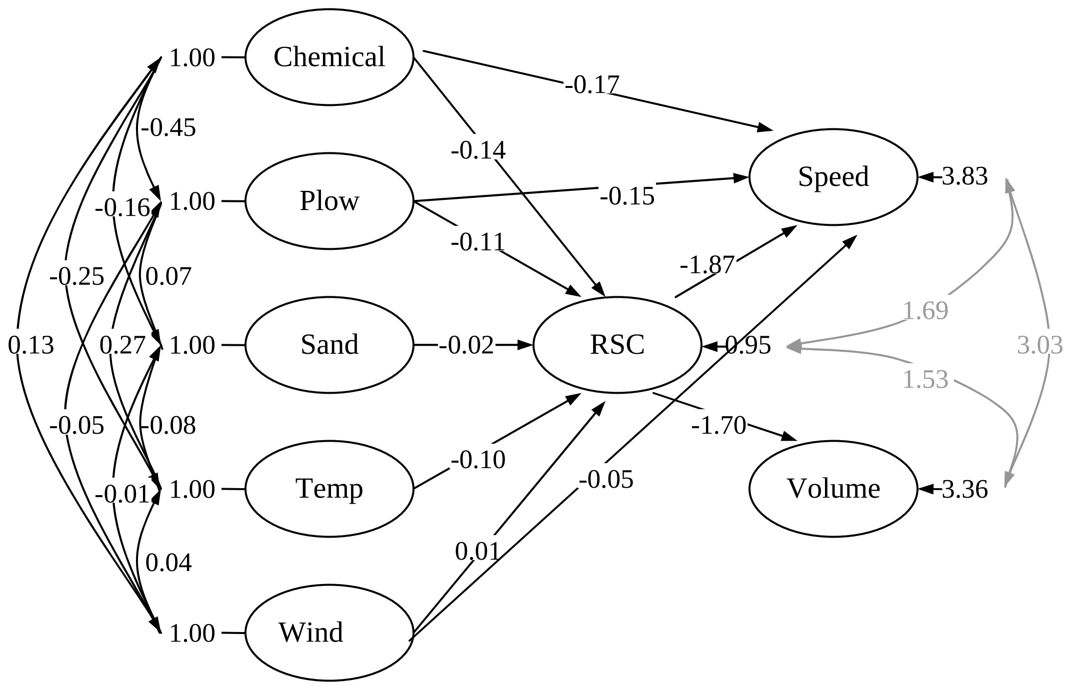

Figure 6.2. Standardized solution of the structural model of effects of weather and maintenance on traffic mobility

Strength of Influence of the Variables

First, the statistically significant correlations between various maintenance and weather variables were confirmed. Not surprisingly, we see that the influences of PLOW action (-0.11) and CHEMICAL application (-0.14) on road surface conditions are much larger than the influence of SAND application (-0.02). Also road surface temperature (-0.10) has as much greater influence on road surface condition than the influence of wind speed (0.01). For example, for a unit change, a standard deviation decrease in road surface temperature produced a roughly 10% standard deviation decrease in road surface slipperiness during a winter precipitation.

Direct and Indirect Relationships

Further, the indirect effect and the total effect can be derived from the path coefficients. For instance, the indirect effect of TEMP on SPEED intermediated through road surface condition is 0.187 = (-0.10)*(-1.87). It means a unit increase in road surface temperature is associated with 19% standard deviation increase in traveling speed. Since TEMP has no direct effect on SPEED, thus the total effect of TEMP on SPEED is the same as the indirect effect. Similarly, the indirect effect of PLOW on SPEED is 0.2057 = (-0.11)*(-1.87), and the direct effect of PLOW on SPEED is -0.15. The total effect of PLOW on SPEED is the sum of the direct and indirect effect, which is 0.0557. Similarly the total effect of CHEMICAL is 0.092. Thus it is concluded that even though during the hour that the maintenance operations are performed, vehicles driving behind trucks probably are slowed down about 15%~17% standard deviation of speed, the improved road surface friction after the maintenance operation more than compensated for the temporary reduction in speed.

Associations between Maintenance and Weather Variables

Considering associations between maintenance methods and weather factors, the correlation between the maintenance and weather variables is freed, to allow them to be correlated. As was speculated earlier, there are different levels of association between maintenance and weather factors. Notably, the associations between CHEMICAL and PLOW (-0.45), between CHEMICAL and TEMP (-0.25), between PLOW and TEMP (0.27) are quite strong compared to associations between other variables. The sign of the associations indicate that when large amount of chemical is applied, it is less likely that an ice-blade is used at the same time; similarly, when the road surface temperature is higher, it is less likely that large amount of chemical is applied.

Multiple Groups

In order to compare if the nature of influence is different across groups, subgroups of data were created using the variables Operational stage, Time of the day(Dawn&Night, Daytime, Peakhour), ROAD CLASS (Interstate / Primary), AADT (10k+, 5k-10k, 1k-5k, <1k), and SPEED LIMIT (55/65). These classifications make different subgroups for comparison. The following charts shown in Figure 0-3 give graphic displays of the interrelationships between those variables. The different lines in the charts represent the four maintenance operations. “Other” indicates no operation performed, “Before” indicates the pro-active anti-icing operational stage, “During” indicates during a snow storm, and “After” indicates after the snow storm.

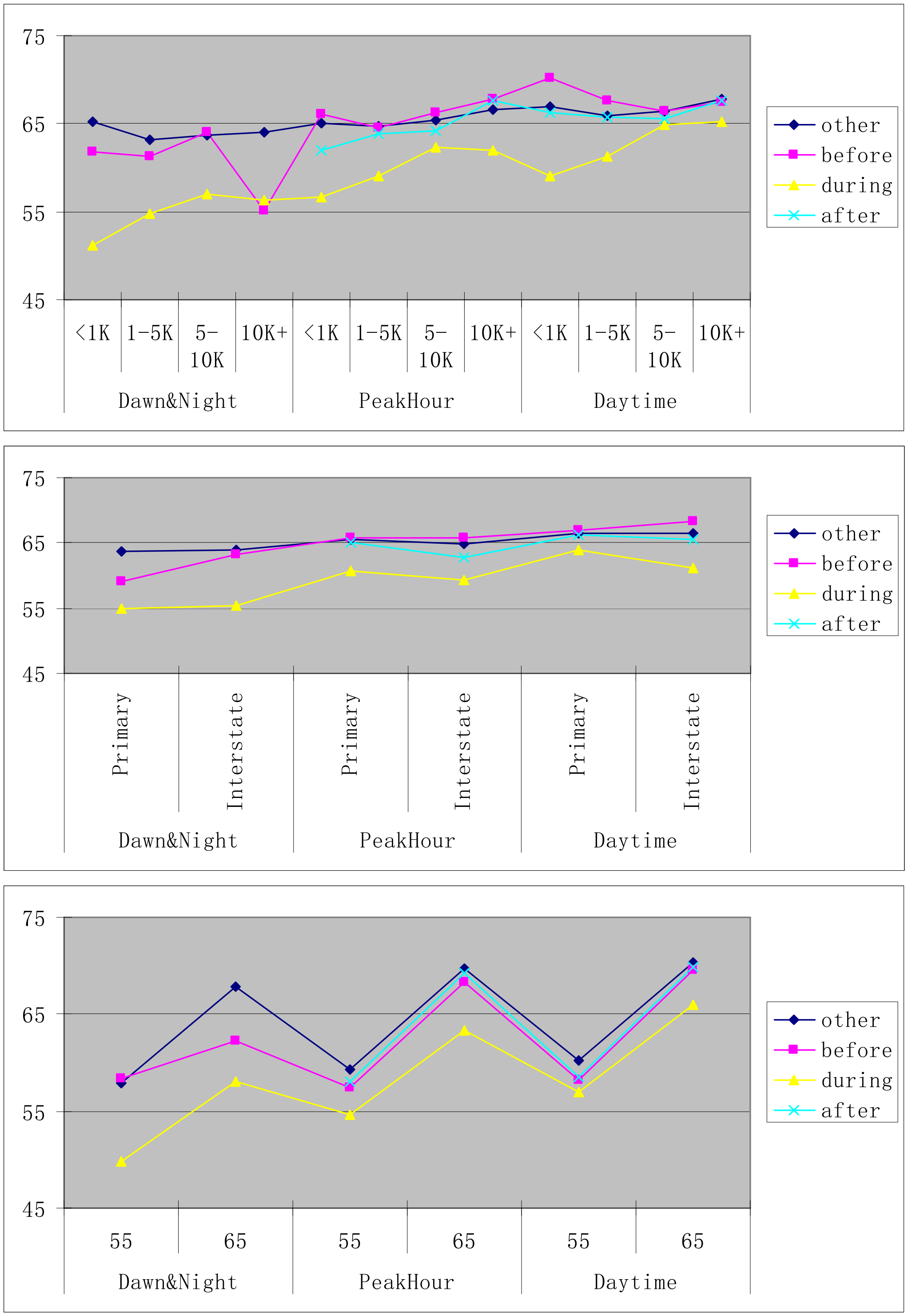

Figure 6-3: Differential effects of storm events on speed by AADT, Road Class, Speed limit during different time of the day.

In addition, the equation and Table 6-1 presents part of the comparison results.

Traffic speed = a + b* WINDSPEED + c*Road Surface + d*Plow + e*CHEMICAL

* Traffic speed in miles/ h

* Wind speed is in miles/h

* Chemical is the measure of Brine rate in lbs/lane-mile

Table 6.1 Estimated coefficients for subgroups

		Primary < 1k, 55mph	Primary 1-5k, 65mph	Interstate 5-10k, 65mph	Interstate 10k+, 55mph
a		56.13	69.07	67.41	54.67
b		-0.29	-0.28	-0.19	-0.19
c	Dry	5.21	6.49	4.68	4.49
	Wet	4.22	5.23	2.72	2.58
	Snow/Ice(1)	0.00	0.00	0.00	0.00
	Chemical(2)	0.00	0.00	0.00	0.00
d	[Plowing=0]	-3.03	-1.82	-2.67	-2.83
	[Plowing=1] (3)	0.00	0.00	0.00	0.00
e		0.015	0.018	0.014	-0.016
R Square/Adjusted R2		0.658/0.629	0.442/0.416	0.566/0.515	0.430/0.402

The comparison group is (2) With Chemical, but most of the chi-square tests do not show that (1) Snow/Ice condition is statistically significant from the With Chemical condition. Thus both categories have the number of zero. The number in Dry, can be interpreted as compare the Dry surface condition to With Chemical condition,

Parameter a is the intercept, which means the average traveling speed for each type of highway when no maintenance actions were performed. It is noticeable that the Interstate highways with 10k+ traffic volume have the biggest speed reduction. During a typical winter storm, the driving speed reduced below the speed limit for this type of highway, which it is not the case for other type of highway (The average traveling speed for most highways are roughly 5~6 mph above the speed limit.) The loss of mobility can in general be roughly estimated by the value of parameter a.

Parameter b is the estimate coefficient for WIND. We noticed that drivers on interstate highways are not reducing their traveling speed (a 0.19 mph reduction in speed when wind increases 1 mph) as much as when they travel on the primary roads (a 0.28~ 0.29 mph reduction in speed when wind increases 1 mph). The reason for this needs to be further investigated.

Parameter c can be interpreted as the influences of the road surface condition. It is clearly evident that as the road surface condition worsened, the traffic speed decreased. As indicated in parameter c, we can see compared to dry road surface conditions, the surface with snow or ice reduces the speed by 4~6 miles/h, and the speed reduction varies depending on different subgroups.

Parameters d and e combined show the effect of PLOW. We found when PLOW is used in the previous hour, the traveling speed are likely to increase 2 to 3 mph during the next hour, if plowing does not occur during the next hour

Parameter e is the effect of CHEMICAL. However, we found the chemical does not have a consistent effect for each subgroup (the effects are negative for interstate highways with 10k+, while the effects are positive for other highways), although chemical application rate does have a positive effect on speed when all data are analyzed as a whole. One cause for this result might be that due to a large percentage of missing data in precipitation and visibility measurement, variable PRECIPITATION and VISIBILITY are not included in the model, while these two variables both appear to be influential factors upon driving speed and travel decision based on the existing literature. Thus there might be a situation that even for the same storm, higher application rates would be more likely to associate with better maintenance results. However, when we have no precipitation data to control the severity of the storm, the higher application rate might indicate a more severe storm condition (with higher precipitation rate). Because the effect of precipitation can not be accounted for in the model, this uncertainty of effects occurs.

For this reason, the estimated coefficients may not precisely reflect the structural relationships being tested. Also several important interaction effects and reciprocal relationships between traffic and road surface conditions need to be further explored in the future. However, this method has been demonstrated to be able to identify the causal effects of maintenance and weather. In the future, when reliable precipitation data can be included in the model, the performance of the model will likely to improve.

In summary, in this chapter explanatory models are used to estimate how the types and levels of maintenance actions together with weather factors effect changes in speed and volume. We also estimated how road surface condition impacts speed and volume and what is the strength of these effects. In particular, we estimated if the nature of these effects differs across different road classifications. The challenge of the chapter is that the joint effects of winter maintenance and weather conditions normally are not easily separable. The results will be used in forming performance goals related to speed reductions.

CHAPTER 7
CRASH ANALYSIS DURING ADVERSE WEATHER

A. Introduction

The purpose of this chapter is to establish the contribution of various road attributes, together with weather conditions, and maintenance operations, to the possibility of crash involvement and the severity of crashes. In the absence of comprehensive theories of how winter maintenance operations influence on safety, the structure of the influence of maintenance on safety was first hypothesized. Then, Multiple Classification Analysis (MCA) was applied to give the estimates.

While weather and maintenance actions have a clear (and quantifiable, see above chapter 5 and chapter 6) effect on mobility, in terms of traveling speed and traffic volume, they can also have indirect effects on safety as represent graphically in Figure 7-1. On the one hand, it is expected that adverse weather reduces vehicle stability (for example, strong winds create particular difficulties for high-sided vehicles) and controllability (by way of reduced pavement friction, should ice form on the road surface). Those suboptimal physical conditions are all associated with an increased risk of crashes and with different levels of increase in crash severities. At the same time, the effects of maintenance cannot be neglected. Maintenance is performed to increase the friction on the road surface (an icy road surface exhibits much lower friction when compared to dry surface conditions). Previous research has shown that the reduction in road surface friction is associated with an increase in crash risk; one reason for this is that low friction is associated with a longer stopping distance.

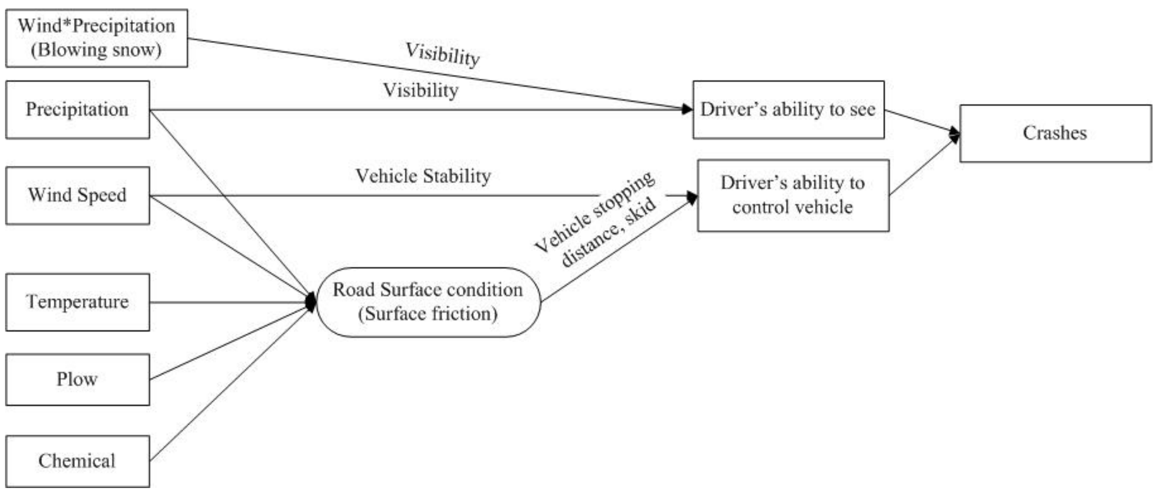

Figure 7.1. Weather and road surface conditions' direct effects on safety

On the other hand, undesirable weather conditions are associated with reduced traffic demand (traffic volume) on the road (Keay, 2005), and the reduced exposure is related to a smaller number of crashes. In addition, experienced drivers may adjust to the undesirable weather or road surface conditions by reducing their driving speed and being more cautious. These adjustments will depend on drivers' experience in driving during adverse weather conditions. In summary, because of trip cancellation and drivers' adjustments to the adverse weather conditions, we expect that adverse weather conditions and the corresponding maintenance operations may be related to both a reduced number of accidents and a reduction in the severity of crashes as illustrated in Figure 7-2.

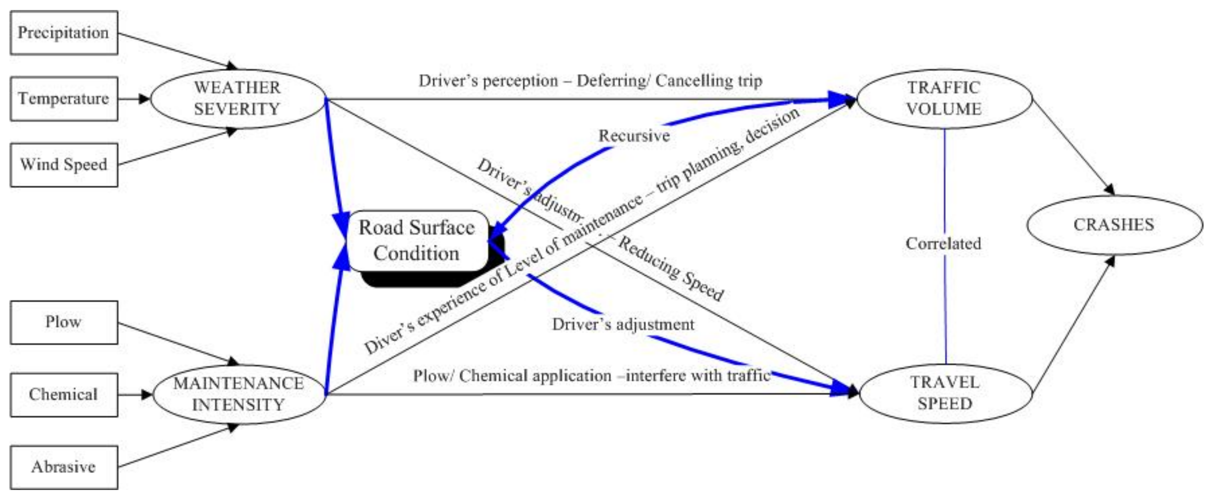

Figure 7.2. Weather and maintenance indirect effect through speed and volume

In this chapter, two separate analyses have been conducted: a crash probability analysis and a crash severity analysis. The relationships mentioned above are estimated to provide important information to road users, and to allow maintenance managers to make effective assessments[5]. The results may allow managers to understand how maintenance operations are related to performance goals, which may lead to further improvement in operations.

B. Method

The methodology used to develop the models of crash probability and crash severity is described in detail in Appendix C.

C Results

Crash probability

Table 7-1 summarizes the results of the four preliminary MCA's. Because of the 0 or 1 coding of the dependent variables, the unadjusted and adjusted mean scores are

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equivalent to the proportion of the hours in each category during which an injury crash happened, and the proportion of the hours during which a PDO happened, or in another words, the probability of having an injury or a PDO. Eta and Beta are produced to evaluate the relative importance of the variables contributing to crashes.

Table 7-1 Preliminary MCA results

		Injury		PDO	
INDEPENDENT		Eta	Beta	Eta	Beta
MCA-1	AADT	0.018*	0.095*	0.042*	0.048*
	Road Class	0.022*	0.104*	0.028*	0.048*
	Speed Limit	0.018	0	0.037	0.018
		R	R Squared	R	R Squared
		0.055	0.003	0.056	0.003
MCA-2	Maintenance	0.006	0.007	0.015	0.001
	Plowing	0.031*	0.03*	0.010	0.008
	Sanding	0.009	0.004	0.002	0.004
	Chemical	0.008	0.009	0.020	0.020*
		R	R Squared	R	R Squared
		0.032	0.001	0.022	0.000
MCA-3	Snow	0.018	0.022	0.040	0.037*
	Visibility	0.017	0.028*	0.026	0.016
	Temperature(F)	0.026	0.029*	0.040	0.038*
	Wind Speed(mph)	0.027	0.027*	0.022	0.020
		R	R Squared	R	R Squared
		0.048	0.002	0.061	0.004
MCA-4	Volume	0.024*	0.027*	0.019*	0.028*
	Speed Variance	0.022*	0.029*	0.038*	0.05*
	Speed	0.016	0.018	0.019	0.021
	RSC	0.028*	0.026*	0.042*	0.039*
	Day	0.002	0.001	0.024	0.014
	Peak Hour	0.008	0.008	0.019	0.014
		R	R Squared	R	R Squared
		0.047	0.002	0.067	0.004

*p<0.005

Eta measures the strength of relationship between a dependent variable and a predictor variable considered alone. Beta measures the strength of relationship between a dependent variable and a predictor while holding constant the effects of all other predictors included in this analysis. R and R squared indicate the proportion of variance in a dependent variable explained by all predictors jointly.

Table 7-2 presents the MCA results of probability of injury involvement. On average during the adverse weather conditions the probability of having an injury is 1.05%, driving on interstate or primary highways. Together 11 variables account for 11% of the variance in probability of injury involvement. Two sets of coefficients are provided: unadjusted and adjusted deviations from the grand mean on the dependent variable. The unadjusted gives deviations from the grand mean when the variable was considered alone, and the adjusted gives deviations from the grand mean when the confounding effects of all other variables in the table are taken into account. A positive coefficient indicates that the subgroup has an injury rate above the overall average in the sample, and a negative coefficient indicates a lower rate than the average.

Table 7.2 Probability of injury and PDO involvement during adverse weather conditions

			INJURY Deviation from Grand Mean (0.00105)		PDO Deviation from Grand Mean (0.00306)	
		N	Unadjusted	Adjusted	Unadjusted	Adjusted
Road Class	Primary	6308	-0.001	-0.0027	-0.0015	-0.0022
	Interstate	3248	0.002	0.0053	0.0028	0.0042
AADT	<1K	1402	-0.001	0.0025	-0.0027	0.0015
	1-5K	5964	0.0003	0.0014	0.0003	0.0013
	5-10K	2190	-0.0001	-0.0054	0.0009	-0.0044
SNOW	before	2557	-0.001	-0.0016	-0.0027	-0.0025
	during	6228	0.0006	0.001	0.0015	0.0010
	after	771	-0.001	-0.0016	-0.0027	-0.0018
Temperature(F)	<15	1566	-0.001	-0.0009	-0.0027	-0.0009
	15-25	2822	-0.001	-0.0011	-0.0020	-0.0017
	25-32	3092	0.0002	0.0001	0.0005	0.0008
	32+	2076	0.0018	0.002	0.0040	0.0017
Wind Speed(mph)	>15	1498	0.0003	0.0002	0.0013	0.0000
	12-15	1372	0.0019	0.0017	0.0017	0.0009
	8-12	2256	-0.001	-0.0009	0.0008	0.0009
	2-8	3932	-0.0005	-0.0005	-0.0012	-0.0006
	<2	498	0.003	0.0033	-0.0027	-0.0021
VisiCatg	<2mph	1444	-0.001	-0.0015	0.0028	0.0012
	2-7mph	3346	-0.0004	-0.0008	0.0015	0.0005
	7-10 mph	4766	0.0006	0.001	-0.0019	-0.0007
RWIS_S0Cond	Dry	3008	0.0009	0.0003	-0.0014	-0.0008
	Wet	1106	0.0008	-0.0015	0.0063	0.0030
	Snow/Ice	2522	-0.0003	0.0008	-0.0027	-0.0016
	Slush	2920	-0.001	-0.0004	0.0014	0.0010
Volume (Banded)	< 83	4070	-0.0008	-0.0006	-0.0008	-0.0004
	84- 300	4053	0.0009	0.001	0.0007	0.0007
	301-797	1416	-0.0003	-0.0013	0.0001	-0.0008
	>797	17	-0.001	-0.0013	-0.0027	-0.0030
SpeedVarCatg	<40	3832	-0.0005	0	-0.0014	-0.0004
	40-60	2141	-0.0006	-0.0007	0.0005	0.0004
	60-100	1725	0.0013	0.0004	-0.0010	-0.0018
	>100	1858	0.0006	0.0004	0.0032	0.0020

Road attributes

Road attribute variables were used as the control variable. As table 7-2 indicates the probabilities of both injury and PDO involvements are higher on Interstate highways than primary roads. Also highways with lower AADT and higher speed limit tend to have higher crash probabilities. This result corroborates an earlier study by Maze (2004) examining crash data in the state of Iowa.

In Iowa, Rural Interstate highways may have a speed limit of 65 mph and receive Level A winter maintenance service, and Primary highways may have a speed limit of 55 when AADT is no more than 5K and receive level B or C winter maintenance service (See table 7-3 for more basic site information). Thus, speed limit is eliminated as a control variable in the final model, because it is highly correlated with road classification and AADT, and it a weaker predictor than the other two (as indicated by the beta values in table 7-1).

Table 7.3 Road attributes of selected highways

Road Class	Speed Limit	AADT	Winter maintenance Level of Service
Primary	55	<IK	C
		1-5K	B
	65	1-5K	B
		5-10K	B
Interstate	65	1-5K	A
		5-10K	A
		10K+	A
	55	10K+	A

In addition CHAID analysis was performed to assist in the comparison of crashes that happened under normal conditions with crashes during adverse weather conditions.

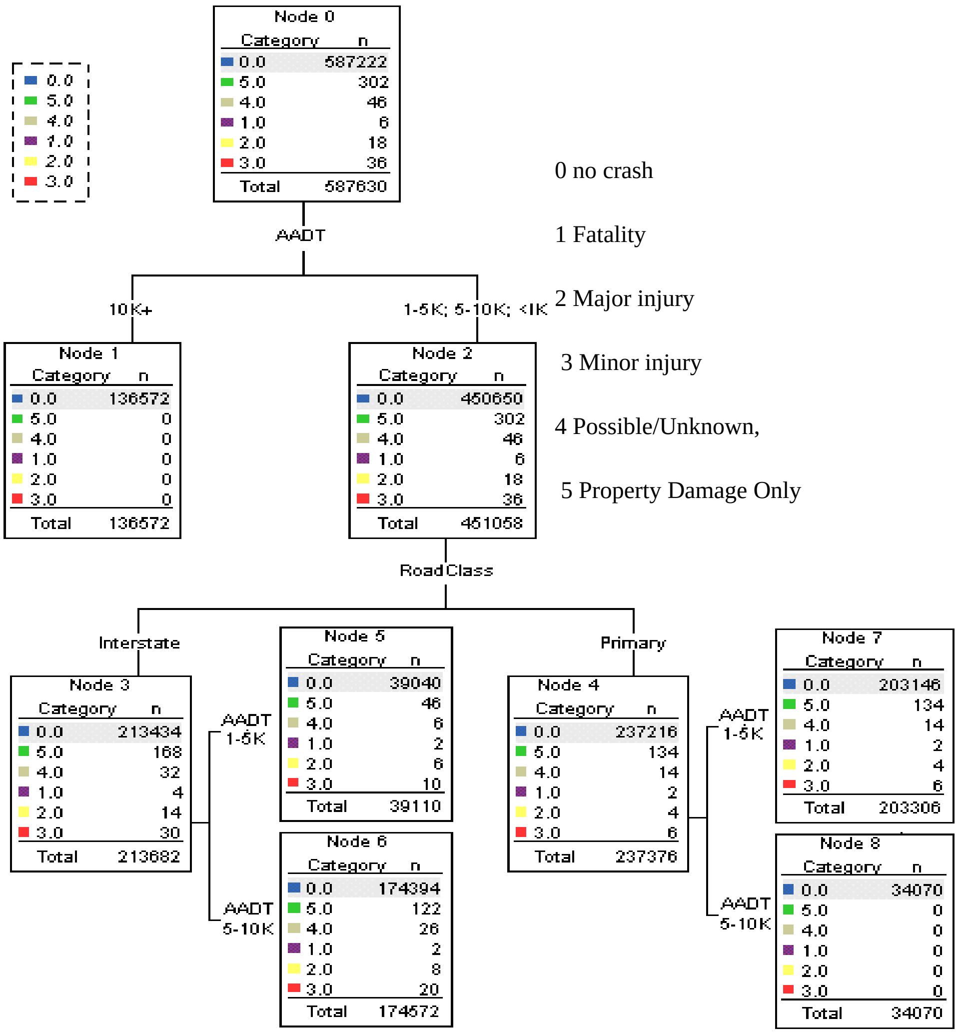

Figure 7.3. CHAID diagram of crash during normal driving conditions by AADT, ROAD CLASS, and speed limit.

For figure 7.3, it is notable that no crashes happened on interstate highways with AADT above 10K (including samples from 2 rural interstate and 1 municipal interstate). Compared with primary highways, interstate highways are likely to have more crashes and when crashes happened, they tended to be more severe.

Because AADT emerges as the most influential factor to crash probabilities, another MCA was conducted to compare the crash probabilities during normal driving conditions to adverse driving conditions.

Table 7.4 Probability of Injuries and PDOs during normal driving conditions

			INJURY Deviation from Grand Mean (0.00105)		PDO Deviation from Grand Mean (0.00306)	
		N	Unadjusted	Adjusted	Unadjusted	Adjusted
Road Class	Primary	145,805	-0.0001	-0.0003	0.0001	-0.0019
	Interstate	194,918	0.0001	0.0002	-0.0001	0.0014
AADT	<1K	34,674	-0.0001	0.0001	0.0023	0.0050
	1-5K	109,424	0.0001	0.0002	0.0010	0.0022
	5-10K	105,297	0.0001	0.0000	-0.0001	-0.0007
	10K+	91,328	-0.0002	-0.0003	-0.0020	-0.0037

Comparing the results in Table 7-2 and Table 7-4, it is further concluded that on average the probability of experiencing a crash with injuries increased during adverse weather conditions (the mean for injuries increased from 0.0002 in normal to 0.00105 in adverse weather), while at the same time the probability of having PDOs increased slightly from 0.002 during normal weather to 0.003 during adverse weather.

Maintenance operations

MCA -2 examines the relationships of winter maintenance operations to crash possibilities as shown in table 7-1. The etas and betas indicate that Plowing emerges as the strongest predictor of injury and chemical treatment seems to be related to PDO probabilities. However, the results can be accounted for by the fact that these two maintenance operational variables are inter-correlated with weather factors and road surface conditions (RSC) as shown in chapter 6. When the weather factors and RSC are included in the model, none of the maintenance variables (Plowing or Chemical) were shown to be significant predictors of crash probability. Because maintenance operational variables do not directly contribute to crash probabilities, they are not shown in Table 7-2.

Weather factors

MCA-3 in table 7-1 examines the relationships of weather factors to crash possibilities. Temperature appears to be the most influential factor on crash likelihood, more so than visibility and wind speed. The second best predictor is the variable Snow, which describes whether the hour being considered is before, during or after a snow storm. As table 7-2 indicates for those crashes that happened during adverse weather conditions, the probability of having a crash are much higher during a snow storm as opposed to before or after the snow storm.

Prevailing conditions

MCA-4 examines the relationships of prevailing conditions to crash possibilities. Hourly traffic volume and speed variation are both shown to have relatively strong relationships with Injury crashes and PDOs. Comparatively, the average speed is a weaker predictor. For further analysis, speed is eliminated as the control variable, because it highly correlates with speed variance (0.87) and modestly with hourly volume (0.42), and it is a weaker predictor than the other two. What is also found is that RSC emerges as a strong predictor while neither Day nor Peak-Hour is a strong predictor when the effects of the other variables are held constant.

As shown in table 7-2 crash probability increases steadily with speed variance. The higher the speed variance is, the higher the probability of getting involved in injuries or PDOs. This result is in accord with the findings of Garber and Gadiraju (1990) and Golob and Recker (2003).

Crash severity analysis

All the crash records during the 3 year study period were then used for a crash severity analysis. Two types of crash severity index were created. One crash severity index is created by assigning 1 to Fatality, 2 to Major injury, 3 to Minor injury, 4 to

Possible/Unknown, 5 to Property Damage Only. The other index was created by assigning money values to different crash types, based on FHWA “Highway safety manual”, (3,000,000 for Fatal, 208,000 for Type A Injury, 42,000 for Type B Injury, 22,000 for Type C Injury and 2,300 for PDO). The weighted severity index was created by calculating the total costs during a crash event and the money value was scaled from 1 to 100. As in the crash probability analysis above, MCA is still the primary method of analysis. In addition, correspondence analysis was applied to facilitate the MCA analysis. Table 7-5 shows the results from MCA analysis.

Table 7-5. Effects of weather event and surface conditions on crash severity with controlling for road attributes and exposure

CSeverity		N	Unadjusted	Adjusted for Factors	Beta
Road Class	Primary	133	0.085	0.222	0.13
	Interstate	335	-0.034	-0.088	
AADT	<1K	37	0.359	0.292	0.14
	1-5K	153	-0.102	-0.186	
	5-10K	278	0.009	0.063	
Speed Limit	55	111	0.018	0.007	0.04
	65	357	-0.010	-0.002	
Weather Event	Blowing sand/soil/dirt/snow	16	0.031	-0.155	0.11
	Snow	55	0.074	-0.119	
	Severe winds	12	0.073	-0.066	
	Rain	18	-0.066	-0.020	
	Clear & Cloudy	341	-0.033	0.023	
	Sleet/hail/freezing rain	26	0.271	0.095	
Surface Condition	wet	39	-0.062	-0.096	0.23
	dry	292	-0.063	-0.079	
	ice	81	0.113	0.117	
	snow	42	0.132	0.237	
	slush	14	0.442	0.523	
Maintenance	N	354	-0.047	-0.005	0.08
	Y	114	0.147	0.014	

Road attributes

Because of the coding of the crash severity index, the lower the number is, the more severe the crash would be. The results from table 7-5 indicate crashes that occur on interstate highways tend to be more severe than crashes occurring on primary roads. In addition, highways with AADT 1-5K are more likely to have severe crashes than highways with AADT less than 1K. Highways with volume 5-10K are less likely to have severe crashes compared to the other two groups.

Maintenance & surface conditions

Winter highway maintenance is a weak predictor of crash severity, as indicated by the Beta value. However, it appears that crashes that occur during the time when winter maintenance operations are being performed tend to be less severe (with deviation from grand mean, 0.014) than crashes when there is no maintenance operation (with -0.005).

Given this result, more analyses were conducted to establish the relationship between road surface condition and crash severity, in order to give insight into how maintenance is related to crash severity.

First, road surface conditions were ranked by severity of crashes from most severe to least severe: wet, dry, ice, snow, slush. The results indicates crashes occurred under wet conditions are likely to be most severe while crashes that occurred under slushy conditions seems to be least severe.

The results could be explained in two ways. First, as found in the speed analysis results in the previous chapter, for interstate highways, the traveling speed was reduced about 5 mph for Snow/Ice surface conditions. A slushy road surface is associated with the highest speed reduction compared to dry, of 7 mph, while the driving speed on wet surface appears to be very close to that on dry surfaces. Since a lower traveling speed in general gives rise to a less severe crash, the different speed reductions for various road surface conditions may provide a partial explanation. Second, correspondence analyses were conducted to analyze the relations between surface type and crash manner, and also between crash types with crash manner. The relationships revealed from correspondence analysis as shown in Figure 7.4 and Figure 7.5 give an explanation from another perspective.

Figure 7.4 graphically illustrates how surface condition is associated with crash manner, figure 7.5 illustrates the relationship between crash manner and crash severity. In figure 7.4 and figure 7.5 row/column points that are close together are more alike than points that are far apart. It is easy to tell that crashes on wet surfaces are more likely to be Angle or Head-on collisions, whilst crashes on snow are closest to side swipe, opposite direction, and those on ice are associated with side-swipe and non-collision. Finally, slush seems to not be strongly associated with any particular crash manner. Figure 7.5 shows that head-on crashes are closest to fatal, while rear-end crashes are most strongly associated with injuries.

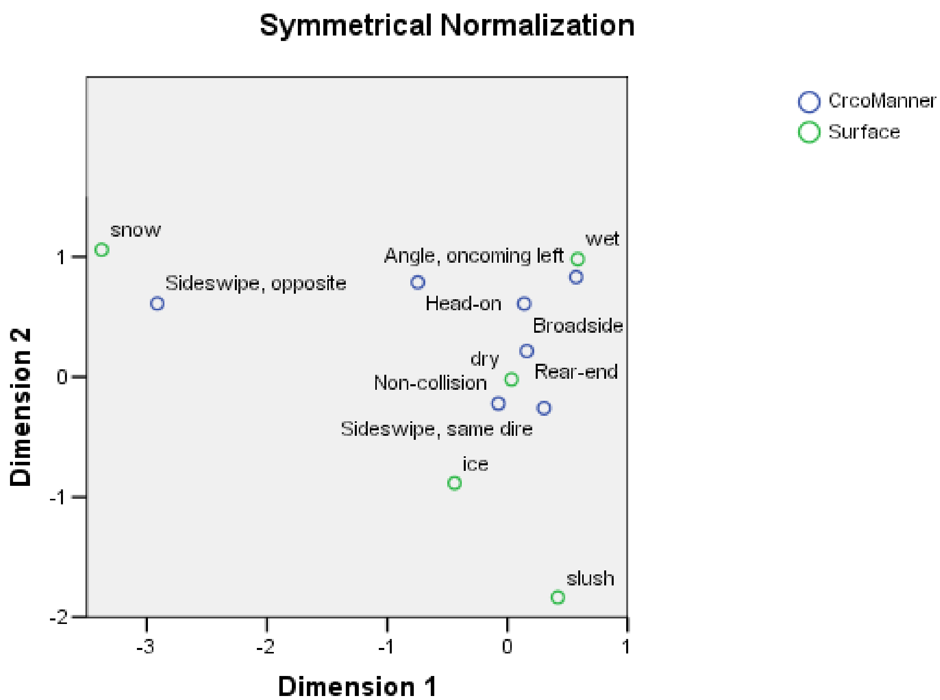

Figure 7.4. Relationship between crash cross manner and surface condition

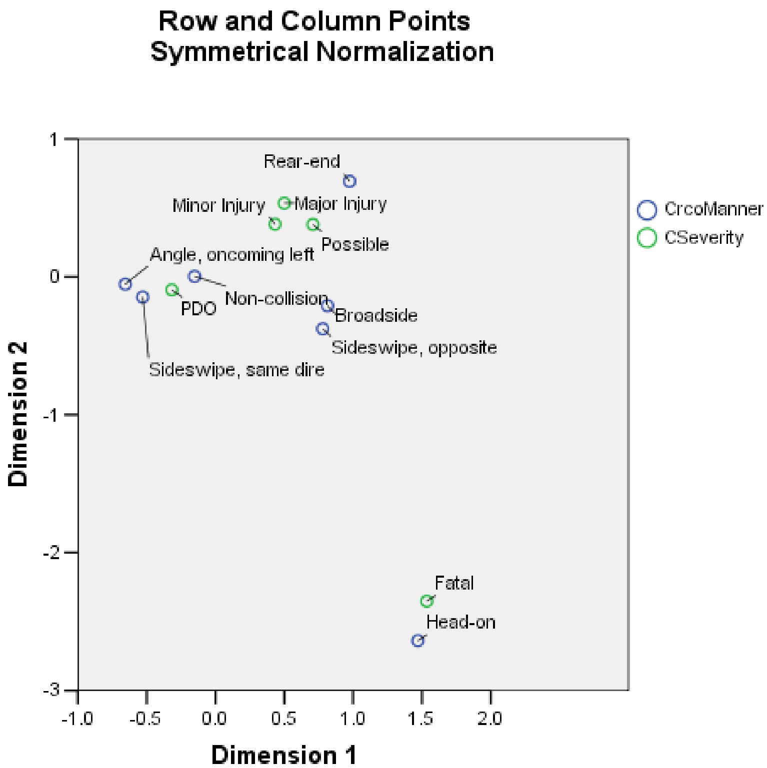

Figure 7.5. Relationship between crash cross manner and crash severity

D. Discussion

As mentioned in the method section (see Appendix C), in order to verify the structural theory proposed earlier in the chapter, three separate models were constructed: in model 1, the included independent variables are road attributes, weather and maintenance factors. For model 2, road surface conditions were added to the variables in model 1. In model 3, traffic volume and speed variance were further added to model 2. The basic ideas behind these three stepwise models are to give understandings of the direct and indirect influence of weather, maintenance and road surface conditions on crash probabilities.

Direct and indirect effects of maintenance operations

It is found from model 1 that none of the maintenance variables are shown to be significant predictors of crash probability when weather and road attributes have been controlled, while road surface condition has a relatively strong effect upon crash probability, with a beta of 0.028 as indicated by model 2. Further the results in MCA-4 indicate road surface condition is a strong contributing factor to both injury crashes and PDO crashes, with betas of 0.026 and 0.039 respectively. As shown in Table 7.2, injury probability peaks with a snow surface condition. Thus it is concluded that the effects of maintenance actions on crash probability are fully mediated through the road surface conditions. In other words, maintenance operations have no direct effects on safety, but indirectly impact safety through reducing snow/ice surface conditions.

Direct effects of road surface conditions and undesirable weather

The effects estimated from model 3 (results shown in Table 7.2.) are the direct effects of weather and undesirable road surface conditions on crash probabilities. It is found that during a snow storm, the injury probability is 95% above the average (0.001/0.00105*100%), and the likelihood of PDOs is about 33% (0.001/0.00306*100%) above the average. Injuries and PDOs peaks at wind speeds 12-15 mph, about 160% and 30% above the average respectively. A road surface condition that is snow/ice covered is associated with the highest injury and PDO probabilities, about 76% and 98% above the average.

Indirect effects of weather and maintenance through speed and volume.

After adding volume and speed in model 3, it was found that the effect of road surface condition decreased from 0.028 to 0.026. The effects of precipitation and surface temperature dropped slightly from 0.027, and 0.036 to 0.025, and 0.033 respectively. Wind effects remained the same, with a value of 0.028. These results indicate that the probability of involvement in an injury crash could be slightly reduced because of a driver's adjustment to the adverse weather conditions by either canceling a trip or reducing the driving speed. The probability of injuries is not reduced much due to exposure.

8. DEVELOPMENT OF A PERFORMANCE INDEX

There are a number of possible uses for a performance index. At least one bifurcation of uses concerns the strategic versus the tactical. In terms of winter maintenance, this may be thought of as the difference between performance in a single winter storm versus performance over a whole winter. There are benefits and drawbacks to each type of index, but if the purpose of having an index is, ultimately, for improvement in practice, then it is more likely that a storm by storm index will provide more readily identified opportunities for improvements than a winter long index.

This distinction is particularly important in the matter of winter maintenance. The two main goals of winter maintenance can be thought of as safety and mobility of the traveling public. Safety can be measured by the crash rate and as discussed in chapter 4 this is known to increase in winter weather. Presumably, the better the winter maintenance, the lower the increase in crash rate will be. Mobility can be measured by both traffic speed and traffic volume, and both are negatively impacted by winter weather (again, see above for discussion of these factors). However, traffic volume is not a good measure to be used as a performance index, since the traveling public is often advised to not travel during winter weather, and thus there could be conflicting reasons for a reduction in volume during a winter storm. It might be that people have heeded the advice not to travel, or it could be that winter maintenance has resulted in a less than optimal road surface condition.

Ultimately, of course, it is the condition of the road surface that determines how safe it is to travel on the road, and how mobile the traffic will be upon that road (see Figure 7-2). And it is winter weather which causes the road surface condition to deteriorate and winter maintenance which strives to return that road surface condition to "normal" as quickly, efficiently, and effectively as possible. In some ways, it would seem that the best possible performance index would be some measure of the road surface condition. However, this is hampered by two factors. First, as discussed extensively above, the relationship between the road surface condition, safety and mobility is not straightforward. Second, measuring the road surface condition is also rather difficult. Current methods for doing this include either some form of visual observation, or some form of friction measurement. Neither method provides an ideal measure, and even if one did, the step from there to safety and mobility is complex.

Given this, it would seem that the best approach to a performance index for winter maintenance would be some form of direct measure of either safety or mobility. And probably the best measures of these two factors are crash rate and traffic speed. However, as discussed in Chapter 7, crashes are fortunately rare occurrences. While clearly beneficial in and of itself, because crashes are so infrequent, it is difficult to use them, even on a winter by winter basis, as a measure of winter maintenance performance. This means that the best possible tool to use as a performance index for winter maintenance is traffic speed. The hypothesis behind this is that if winter maintenance, for a given storm, is done well, traffic will be slowed down less than if the winter maintenance is done poorly.

Table 8.3 Speed targets for different operational stages by road class, speed limit, AADT and time of the day

		Primary			**Interstate**		
		55		65	55	65	
		<1K	1-5K	1-5K	10K+	1-5K	10K+
Daytime	Normal	60	59	69	61	69	71
	Anti-icing	0	0	0	-2	0	0
	During storm	-5	-2	-3	-3	-6	-4
	After Storm	-1	-1	0	0	0	0
Peak Hour	Normal	60	59	69	61	69	70
	Anti-icing	-2	-2	-2	-2	-2	0
	During storm	-8	-4	-6	-6	-7	-5
	After Storm	-3	0	0	0	-1	0
Dawn & Night	normal	58	58	68	59	67	69
	Anti-icing	-2	-2	-8	-5	-3	-2
	During storm	-13	-8	-12	-10	-9	-8
	After Storm	-9	-5	-9	-1	-4	-2

Table 8-1 shows how traffic speeds are impacted during a winter storm on different road types, at different times of day, and at different stages of the storm. These results can be used to provide a basis for a performance index, in the following way. First, the difference in impact on the different road types suggests strongly that roads with a different priority will experience, in the normal run of a winter storm, differing impacts on speed. Second, while there are clear differences in the speed reduction with time of day, it creates perhaps needless complications to differentiate between the various times of day in order to determine performance. Thus, the speed reductions will be grouped together into three road priority levels, and one value for any time of day. Third, the values in table 8-1 are average values (or predicted model values) and do not represent extreme values. Accordingly, such values will be adjusted by a factor to allow for the most extreme conditions. Finally, the base values obtained from these three steps will be scaled using the storm severity index developed in chapter 3. Thus if two storms are considered, one with a severity index of 0.9 and one with an index of 0.4, and if the base value of speed reduction for a given road classification is 10 miles per hour, then for the more severe storm, and reduction in speed less than 9 mph (0.9 x 10 mph) would indicate successful winter maintenance, while for the less severe storm, the reduction in speed would have to be less than 4 mph to indicate success.

Table 8-2 indicates the "base" values of speed reduction for the three priority levels of the road way. These have been obtained from the modeling done in Chapter VI.

Table 8.2 Base Speed Reduction (mph) for Road Priorities

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

These values are then modified by the storm severity index developed in Chapter 3. That index was of the form:

$$SSI = \left[\frac{1}{b} * [(ST * Ti * Wi) + Bi + Tp + Wp - a] \right]^{0.5} \qquad \text{Eq. 3.1}$$

In this equation, the value of a is 0.0005, and the value of b is 1.6995. The values of the other variables are obtained from table VIII-3 which shows the final value of these variables (which brought the index into full agreement with the experts surveyed on the index).

Table 8.3 Values of Variables in Equation 3.1

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		

Thus, using a multiplicative combination of the Storm Severity Index and the Base Speed Reduction, a target speed reduction for a given storm and priority level of highway is given. If speed reduction is less than this, winter maintenance has been satisfactory. Clearly, this index can be improved, and with experience it should be refined significantly, but given the uncertainties (discussed throughout this report) in determining the effects of the many varied factors on road mobility, it is felt that this index is a good place to begin.

9. SUMMARY AND CONCLUSIONS

Adverse weather during winter has significant impacts on roadway safety, mobility. Winter highway maintenance operations are performed to minimize the impact. For the purpose of achieving further improvement in the field, we constructed a performance measurement system that evaluates how well operations have been conducted to meet road users' needs as specified in maintenance goals. In the previous chapters, the goals for maintenance operations to meet were identified, the critical measured used in measuring how well maintenance were performed in meeting with the maintenance goals were selected. Moreover, important relationships between weather, maintenance with mobility and safety were established, as well as the important interaction effects on mobility and safety. Thus the proposed measurement system can be not only used for the post storm evaluation, the system combined with the modeling results can also be used for the pre-event prediction and evaluation.

For instance, the constructed prediction model in chapter 5 can be used to predict the road surface condition quite accurately for a specified weather event given the traffic volume and maintenance procedures, also at the same time, the structural equation modeling results from chapter 6 established the effects of the maintenance, weather intermediate by road surface condition on traveling speed and volume, and results from chapter 7 of effects on crash rates. Thus for a specified weather event, a given time of the day, road class and AADT, we can estimate the traveling speed and traffic volume, as well as crash probability with different maintenance operation input.

Summary

Maintenance effect on road surface condition

Winter maintenance actions do have significant influence on road surface conditions as explored in Chapter 5. Plowing actions, applying chemicals are both found to be influential factors affecting road surface conditions. The effects of maintenance operations depend upon the temperature and wind speed and traffic on the road.

Maintenance effect on speed and volume

Mainly, winter maintenance actions have considerable positive effects on speed, although in some cases maintenance trucks do slow down traffic, and this effect is especially stronger during peak hours. Because the effect of maintenance depends on time of day, and peak hour, we would recommend that maintenance be performed ahead of peak hours, with application rates increased during night operations.

Maintenance operations also have positive effects on traffic volume. We found only a slight reduction in traffic volume during average winter storms for service routes that receive a high level of maintenance, especially for highways with constant 24-hour flow rates. In general, road users tend to make their trip decisions based on weather forecasts. Their trust and previous experiences of winter maintenance operations also play an important part in their decision-making.

Maintenance effect on crash rates

We found that the effects of maintenance operations on crash rates are fully meditated through road surface conditions. In other words, maintenance only has indirect effects on crashes. The modeling results suggest that: 1) maintenance operations have clear effects on speed and volume intermediated through road surface conditions; 2) maintenance is not a significant predictor of crash rates and crash types; and 3) road surface conditions have indirect effects on crash rates and crash types through the effects of speed and volume, as well as direct effects on crash rates and crash types.

Finally, a performance index has been developed, based upon a target reduction in traffic speed during a storm. The target reduction is a function of the road priority level and the storm severity. If traffic speeds reduce less than the target level, winter maintenance has been satisfactory.

Future Work

Data needs

A big constraint of the study is the availability and validity of the data. We found that the atmospheric data (i.e. wind speed, temperature, visibility, etc.) are highly accurate, and are available from both ASOS and AWOS sites. In comparison, data on precipitation amounts and visibility are only provided by ASOS, and are not consistently recorded, and there are no records at all for precipitation type. Improved data of this type would be extremely valuable.

Besides mobility and safety, environmental quality and productivity are also goals for winter highway maintenance activities. How to select measures to meet the other goals, and how to facilitate the decision making using multiple criteria based on developed performance measures would be an important task for future research.

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APPENDIX A: Methods used to determine the relationships between Road Surface Condition, Weather, Traffic, and Maintenance Activities.

Data Preparation

The research database includes 4 years of hourly data from 2001 to 2004. The road surface condition data is taken from RWIS (Road Weather Information System) stations in the State of Iowa. The atmospheric data are taken from ASOS (Automated Surface Observing System) or AWOS (Automated Weather Observing System) stations within 10 miles distance of each RWIS. Data were selected depending on which station (ASOS or AWOS) was closer to the RWIS. The maintenance data used in this analysis are taken from the winter highway maintenance garage log files provided by the Iowa Department of Transportation. For each snow event operation, the maintenance operators complete a report of that garage area. The report recorded the maintenance operations for three levels of service A, B or C (Interstate highways received the highest level of maintenance-Level A, most of the primary road receives level B and low volume primary roads receives the lowest level-C). For each level of maintenance routes, it recorded the time when the maintenance actions started, when it ended, together with what type of material (Sand or Sand salt mix) applied, what kind of liquid and how much used during the maintenance operations. The garage area within which each RWIS sites was located within were identified, and the weather data of each RWIS were merged together with the corresponding Level of winter maintenance data that the highway upon which the RWIS is located at receives. The selected sites' information is shown in Table A-1.

Table A-1. Sites Selection and Data Integration

ATR_ HWY	Road Class	RWIS Station	ATRID	RWIS _ID	ASOS/ AWIS_ID	Garage _ID
IA 110	State Highway	Storm Lake (US 71/IA 3)	SC2330	RSTO	SLB	553805
US 18	US Highway	Algona (US 18)	AL2070	RALG	AXA	552655
I-74	Interstate	Davenport (I-80/I-280)	BE7050	RDAV	DVN	556812
IA 2	State Highway	Sidney (I-29/IA 2)	SI2400	RSID	SDA	554808

I-29	Interstate	Missouri Valley (I-29)	HO1000	RMIS	CBF	554810
US 65	US Highway	Altoona (I-80/US 65)	PO2500	RALT	IKV	551806
I-29	Interstate	Sidney (I-29/IA 2)	PA1020	RSID	SDA	554808
US 20	US Highway	Fort Dodge (US 20)	WE2470	RFOD	EBS	551611
I-80	Interstate	Altoona (I-80/US 65)	AL1173	RALT	IKV	551806
I-80	Interstate	Davenport (I-80/ I-280)	LE1190	RDAV	DVN	556812
I-80	Interstate	Avoca (I-80)	SH1100	RAVO	HNR	554802
I-380	Interstate	Urbana (I-380)	BR1130	RURB	VTI	556602
US 20	US Highway	Waterloo (US 20)	JE2450	RWAT	IIB	552807
I-80	Interstate	Altoona (I-80/US 65)	AL1177	RALT	IKV	551806
I-35	Interstate	Williams (I-35)	JE1040	RWIL	EBS	551609
I-80	Interstate	Williamsburg (I-80)	WI1110	RWBG	CID	556606

Measures of RSC, weather, maintenance, and traffic

The outcome variable in this study is the Road Surface conditions classified by the State of Iowa. The original record of the ROAD SURFACE CONDITION retrieved from the RWIS stations has seven categories: DRY, DAMP, WET, WITH-CHEMCIAL, SNOW/ICE, NO-REPORT, and NONE. Outcomes were grouped into 4 mutually exclusive categories for the purposes of modeling and prediction: DRY, WET, SLUSH (WITH-CHEMCIAL), and SNOW/ICE. DAMP and NO REPORT situations accounted for less one 1% of the total sample, thus were excluded from the analysis. NONE was recoded as missing, which account for 15.4% in the total sample.

Predictor variables include three weather factors (TEMPERATURE, WIND, and PRECIPITATION). TEMPERATURE is the measure of the road surface temperature, measured in F. WIND is the measure of the wind speed, in mph; PRECIPITATION is the measure of the precipitation rate, measured in inches/hr. These weather variables were selected based on the results of a factor analysis (FA). The factor analysis identified the variables that are highly correlated, and only one of those variables was selected to avoid the multi-colinearity problem. For example, with road surface temperature included, air temperature and dew point temperature are excluded, since they were found to be highly correlated with surface temperature.

The included maintenance variables are: OPERATION and CHEMICAL (BRINE-RATE), PLOW_NOT (PLOW), and OPERATION (The variables inside the parenthesis indicate the coding or representation of the same variable). The maintenance variables were selected based on a categorical principle component analysis (CAPCA) (Nishisato, 1980). As for the factor analysis, the CAPCA is used to identify the common structure of 12 maintenance measurements (most of them are categorical variables). The results of CAPCA analyses suggest that PLOW and CHEMICAL represent two distinct dimensions of maintenance operations. SAND application is related to the CHEMICAL choice. SAND was normally applied with granular SALT or CACL2 solution. The results also suggest that PLOW is moderately correlated with OPERATION. It can be easily understood that in ANTI-ICING and FROST RUN operations, no plow is used, while with Phase I operations, the plow is used intensively, and in Phase II, the plow is used less frequently than in Phase I. Because OPERATION also contains other important maintenance information, it was retained as well.

OPERATION is one of the primary maintenance variables that describes the type of the maintenance activity performed. In the maintenance record, four types of activities were recorded: ANTI-ICING is a proactive maintenance procedure to apply chemicals on the road ahead of the precipitation, to prevent the formation of bond between road surface and snow; PHASE I normally denotes the common snow and ice control practice during a storm; Phase II denotes the subsequent cleaning stage after the storm; and FROST RUN is another common operation during winter weather. Because of the lack of reliability of precipitation records as described in the descriptive information of variables, also because precipitation is an influential factor to the road surface condition as indicated by previous research, OPERATION STAGE is used as a proxy for precipitation.

The "PLOW" activities can be categorized as three different types of PLOW use: PLOW, WITH_WING, or WITH_ICE_BLADE. To facilitate the analysis, plow action also has a dummy coding – PLOW_NOT; coded 0 for No Plow, and 1 for Plow[6].

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[6] Sometimes, the MLR regression with many categorical variables might be hard to converge, but the regrouping of the categorical variable into a new variable with fewer categories might solve the problem. Alternative coding of the maintenance variables with less categories were mainly provided for this reason.

CHEMICAL is categorized as Sodium Chloride Solution (BRINE), Calcium Chloride Solution (CACL2), or Granular Salt (SALT). Ideally, the application rate of different types of CHEMICAL would be recorded as a quantity as well as an action; however the quantity of CHEMCIAL were only recorded for the two CHEMCIAL solutions, BRINE and CACL2. Thus BRINE-RATE, which is the measure of the liquid rate in gallons per lane mile[7] is included as an alternative measure of CHEMICAL. The SAND variable is also coded into dummy variables with 0 for no sand applied, and 1 for sanding activity.

The measure of traffic is traffic VOLUME in vehicle per hour. Other factors that might be influential to the RSC were Peak-Hour, AADT, and Speed-limit. Those variables were kept in the data file as well.

Whether sand is used depends on the temperature range, road classification, and material availability. The dominant factor for sand being used is the temperature range - sand was applied to increase the vehicle traction rapidly when the temperature was extremely low (and thus when salt would have minimal effect). Previous studies suggest that sand might prevent salt from melting snow, and also suggest that the beneficial effect of sand diminishes after 50 vehicles has passed or 20 minutes after application. Thus sand was not included in the prediction model, but rather was used as a cross-tab to check the compliance of sand use verse the Surface Temperature.

Chi-squared automatic interaction detector (CHAID)

As the first stage in analyzing the data sets, the Chi-squared automatic interaction detector (CHAID) method (Bagozzi,1994) was applied to determine the important weather factors and maintenance actions that are most influential to the road surface conditions. In addition, CHAID was used to identify possible interactions between these variables. The software package applied in the data analysis is an add-in to SPSS version 10.0 (SPSS, 1999) called Answer Tree. CHAID uses chi-squared statistics to identify

[7] CACL2 RATE has not been included, since in 53% of cases where CACL2 was used, the rate was not recorded.

optimal splits (Kass, 1980). CHAID automatically searches the data and tests each categorical variable to determine which variable categories make a significant split with respect to the dependent variable. Using the Chi-square statistics, it was determined which variables were significant and which were not. In other words, the first split results in the most distinctive subgroups. Also CHAID merges those categories that are not distinct from each other, and regroups these categories in order to construct significant categories. Further, for continuous variables, CHAID decides the critical values for splitting the variable into significant categories. When the stopping rules (sample size, significance level) specified by the user are met, CHAID stops searching the subgroups. The resulting subgroups will be more homogeneous than the original data set. (Breiman, 1984). In this study, for the stopping rule, the significance level is specified at 0.05 and the minimum subgroup size is set at 40.

Multinomial Logistic Regression (MLR) Method

The Multinomial Logistic Regression (MLR) was used to validate and further extend the results learned from the decision tree. MLR (Hair, 1998) is chosen because the outcome variable, road surface classification, is multinomial (with more than two categories). The goal of multinomial logistic regression (MLR) is to describe, infer and predict the variable of interest. Compared with a logistic regression, MLR is more general because the dependent variable is not restricted to two values (Hosmer, 2000). Also compared with probit model(Borooah, 2002), "it is computationally tractable and offers a closed-form representation of the choice probability". Logistic regression transforms the dependent into a logit variable and uses maximum likelihood estimation (MLE) to estimate the coefficients. MLR has two assumptions. First MLR assumes a linear relationship between log transformed outcome (Road Surface Conditions) and predictors. Second, the error terms are assumed to be independent (Lattin, 2003). With these assumptions, the probability of one category being selected rather than another can be calculated. In this study, there are multiple categories for the outcome variable (the road surface condition): DRY, WET, SNOW/ICE, CHEMICAL. Traditionally previous research has indicated, SNOW/ICE surface condition is the most undesirable driving conditions -- road users want to avoid SNOW/ICE and maintenance agencies try to minimize the amount of SNOW/ICE on the road. Thus the category “Snow/Ice Covered” (represented as SNOW/ICE) is the base category for the outcome variable, which may thus also be considered to be the comparison group.

As mentioned earlier, MLR is also used to test and further explore the interactions identified by the regression tree. Interactions in the MLR are tested by creating a multiplication term. An important concern in testing interactions is that introducing interaction terms will increase multicolinearity (multicolinearity means linear relationship among two or more predictor variables). Severe multicolinearity makes the estimates sensitive to the specifications and thus the variance of the coefficient will increase. Hence for those interactions involving continuous variables, the centered new variables were created prior to the multiplication, in order to avoid multicolinearity (Aiken & West, 1991).

Centering is accomplished by subtracting the mean score of the variable from that variable. For instance, the interaction term of TEMPERATURE and WINDSPEED is created by multiplying the two centered variables: TEMP_CENT and WIND_CENT. TEMP_CENT was created as a centered version of SURFACE TEMPERATURE, by subtracting the mean for surface temperature (27.7 F,) from each hour’s temperature record. Similarly WIND_CENT values were created by subtracting the mean for wind speed (8 mph) from each hour’s wind speed. The centered variables have the same correlation with other variables, but a great reduction in multicolinearity with components (for example, an interaction term between temperature and wind built on the uncentered temperature variable correlated 0.875 with temperature, whereas the interaction term built on the centered variable correlated 0.23 with temperature).

APPENDIX B: Methods used in Structural Equation Modeling

To study the effects of maintenance on mobility, it is possible to apply the multiple regression analyses by including weather factors, and road surface conditions all as the control variables in the models. However there are two particular reasons that such an analysis requires more advanced techniques than multiple regression analysis.

First, the nature of relationships between these variables presents severe multicolinearity problems for the assumption of the regression analysis. Almost inevitably, the winter maintenance actions and weather factors are inter-correlated, since according to winter maintenance theory, most maintenance actions vary according to different weather events, presented or forecasted. Also, depending on the maintenance policy, we would expect that the various maintenance methods performed would be correlated. For instance, higher application rates (or a better freezing point depressant) are recommended for low temperature-storm situations; therefore it is likely that we will find that temperature is associated with chemical application rate or chemical choice. Second, the relationships between weather, maintenance and road surface condition can't be revealed. As we presented in Figure 6-1., the presence of direct and indirect effects makes quantifying the maintenance impact on speed and volume complex. Lack of such understanding creates difficulties in selecting the optimum maintenance strategies and performing operations to fight with winter storms.

General Description of the SEM

For the above reasons, SEM (Structure equation modeling) has been chosen to facilitate analysis. Structural equation modeling (SEM) is a method similar to multiple regressions, but may be used as a more powerful alternative to multiple regression, path analysis, factor analysis, time series analysis, and analysis of covariance. SEM can be viewed as "an extension of the general linear model (GLM) of which multiple regression is a part[8]". Also SEM has advantages over the general linear model because it can handle inaccurate input data, a capability the GLM lacks. Further, it can model the direct and indirect relationships between variables, and is more effective at resolving problems of multicolinearity. Put simply, SEM can be understood as several models that depict the relationships between variables optimized simultaneously.

SEM as a powerful data analysis tool has strict assumptions. The popular normal theory (NT) estimators (maximum likelihood and generalized least square) used in SEM require the following four assumptions (Bentler and Dudgeon 1996, Bollen and Stine 1992): Independent observations, large sample size, correctly specified model, and continuous and multivariate normally distributed data. Since violation of the assumptions can produce biased results in terms of model fit, parameter estimate and significance test (Austin and Calderon 1996, Tremblay and Gardner 1996), the data were checked to determine if they met these assumptions. Preliminary analyses suggest that the presence of ordinal variables and also non-normal continuous variables used in the model violated the multivariate normality assumption. Moreover, the presence of different groups imposed particular challenges to the SEM. To address these problems, the method of Categorical Variable Methodology (CVM) and the multiple-group analyses of SEM were employed.

Categorical Variable Methodology (CVM)

In this study, not only are most of the maintenance variables to be modeled ordered categorical variables, but also the endogenous variable – Road Surface Condition (RSC) is categorical. Even though sometimes researchers treat ordinal data as if continuous in SEM, not only is bias present when ignoring the nature of the data, but also doing this can pose a great difficulty in the interpretation of data in the model. First, the inherently assumed equal distance between categories is not reflective of the true population. For instance, the record of Road Surface Conditions (RSC) provided by Iowa

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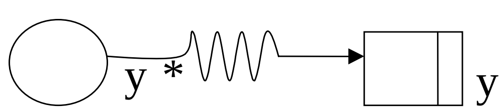
[8] Retrieved from: http://www2.chass.ncsu.edu/garson/pa765/structur.htm

Department of Transportation is an ordinal variable, with four categories: Dry, Wet, Snow/Ice covered, or With Chemical. If we treats the ordinal variables RSC as continuous, by assigning value 1 to 4 to from DRY to With Chemical categories, we inherently assumed when the road condition changed from Dry to Wet or from Wet to Snow, the impact of changes in RSC on traveling speed are the same. Second, ignoring the categorical nature of the variables, correlations between them are attenuated, and the fewer categories, the more severe the attenuation (Babakus, Ferguson and Joreskog 1987).

Categorical Variable Methodology (CVM) was recommended by Browne (1984) and Muthen (1985) when modeling non-normal and ordinal data. In the first step, an Asymptotically Distribution-Free (ADF) estimator was used in CVM. Unlike the ML estimator, ADF makes no assumption of normality (Browne 1984). After that an underlying continuous latent response variable was assumed for each ordinal variable and latent correlations were estimated to represent the theoretical relations; and then polychoric correlations were estimated instead of using more usual Pearson correlation (Muthen 1985). This strategy is explained below, using the covariance between road surface condition and chemical application as an example.

First, a non-linear function relates y (the ordinal variable, such as road surface condition) to y* (an underlying continuous latent response variable, which can be understood as the slipperiness of the road surface). Here road surface condition is treated as an ordinal variable is based on the previous findings that from Dry to ICY, the road surface friction value is decreasing (the road surface is more slippery)(Leppannen, 2001). Similarly, we can assume an underlying variable for the chemical application.



$$y = \begin{cases} 1, (Dry) & if \quad y^* \le \tau_1 \\ 2, (Wet) & if \quad \tau_1 < y^* \le \tau_2 \\ 3, (Snow/Ice) & if \quad \tau_2 < y^* \le \tau_3 \\ 4, (With \quad Chemical) & if \quad \tau_1 < y^* > \tau_3 \end{cases}$$

where τ_i = thresholds for entering categories. Then τ_i were calculated using

$$\tau_i = \Phi^{-1}\left(\sum_{k=1}^{i} \frac{N_k}{N}\right), \text{ i = 1, 2, …, c-1}$$

where $\Phi^{-1}(.)$ = the inverse of the standard normal distribution function

c = number of categories

N_k = number in kth category

As such, the polychoric correlations can be estimated for the underlying continuous variables. As illustrated in Figure B-1.

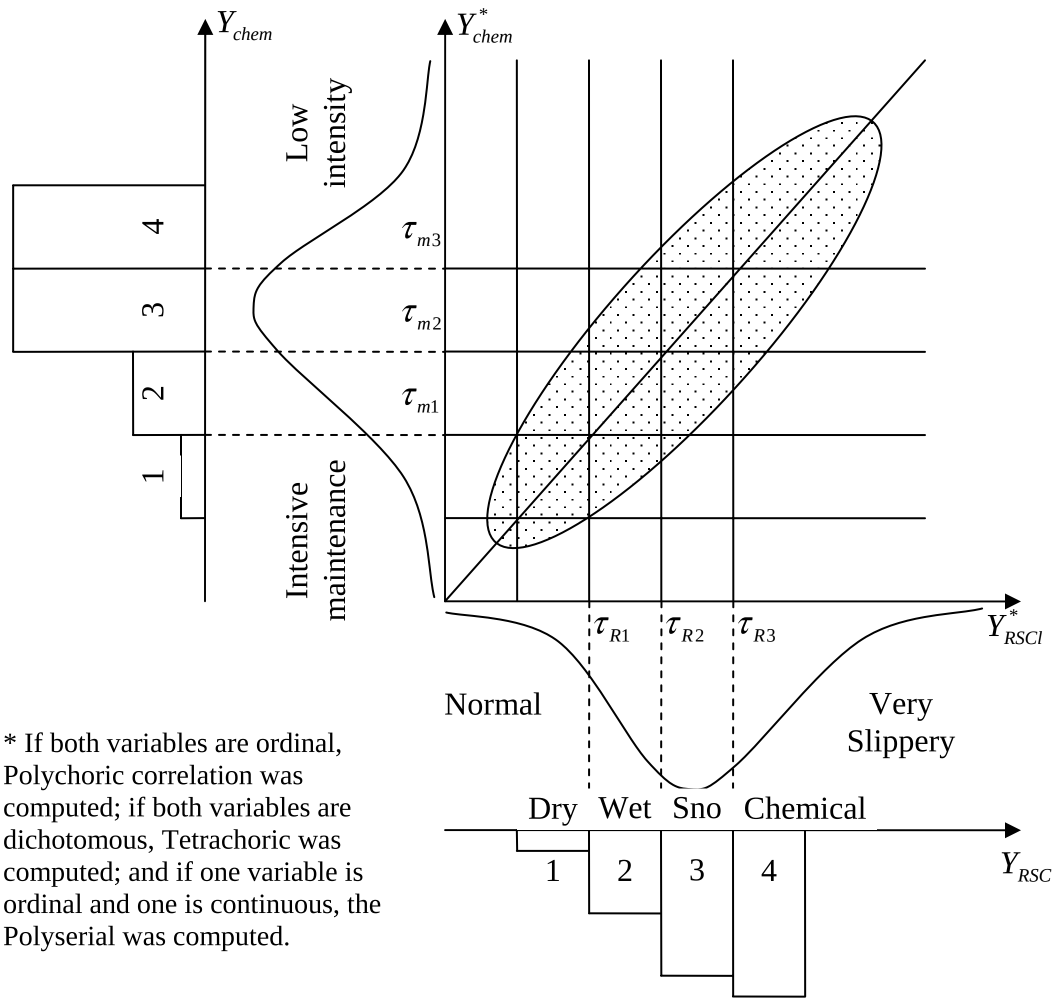


Figure B-1. Polychoric correlation between the underlying latent variables of the ordinal variables

PRELIS (Joreskog and Sorbom 2004) will use maximum likelihood to estimate all possible correlations and then assemble into the polychoric correlation matrix ($\hat{\Sigma}*$). Then ADF estimator was employed, as illustrated in the following equation.

$$F_{WLS} = [\,\hat{\rho} - \boldsymbol{\sigma}(\theta)]'\,\mathbf{W}^{-1}[\,\hat{\rho} - \boldsymbol{\sigma}(\theta)]$$

where $\hat{\rho}$ = vector of ½(p+q)(p+q+1) elements containing the non-redundant polychoric, polyserial, and Pearson correlations among all pairs in $\mathbf{x}^*$ and $\mathbf{y}^*$.

$\boldsymbol{\sigma}(\theta)$ = vector of ½(p+q)(p+q+1) elements corresponding to $\boldsymbol{\Sigma}(\theta)$

$\mathbf{W}$ = weight matrix, optimal $\mathbf{W}$ is asymptotic covariance matrix.

The multiple-group analyses of SEM

The data property in our analysis requires that SEM be conducted in multiple groups for the following two reasons. The primary reason is that previous literatures suggested the existence of interaction effects of adverse weather with Light, Urban/Rural, Road Class etc. on speed and volume (Hanbali, 1994; Liang, 1998; Padget, 2001; Knapp and Thomas, 2001). Similarly, we would suspect that effect of winter maintenance actions and road surface conditions also interacts with those variables in their effects on speed and volume. Normally there are two ways in dealing with interactions in SEM: either by including created interaction variables in the structural model or by modeling the data in subgroups. More importantly, the homogeneity test[9] of the complete set of observation failed in the preliminary analysis, suggesting data have to be modeled in multiple groups in order to meet the homogeneity rule of the variable, otherwise

9 homogeneity of the variable: the variance of the variable is due to random errors rather than some systematic reason

structural equation models can produce misleading results. If we develop separate models by sites, we no longer have the problem of violating the homogeneity. However the models do not have much implication or application use for other sites in the state of Iowa that haven't been sampled. Thus, three variables used in our analysis to capture the characteristics of the basic road conditions: ROAD CLASS, SPEED LIMIT, AADT, and also included Time of the day to capture the traffic flow characteristics.

Data Preparation

The research database includes 4 years of hourly detector data, comprising roughly 11 million records. Traffic volume and speed data are from 22 ATRs (Automatic traffic record) in the state of the Iowa. The road surface condition data is from 18 RWIS (Road weather information system) stations that are selected within 10 miles distance of ATRs, also on the same Highways as the ATR. Because the road surface conditions may vary over short distance (Andrey & Olley 1990, Gustavsson 1995) The atmospheric data are from 11 ASOS (Automated Surface Observing System)/ AWOS (Automated Weather Observing System) stations within 10 miles distance of ATRs. The selection of a 10-mile maximum separation was tested by examing 18 different sites, treated as 9 pairs. In these pairs, distance between sensors varies from 3 to 21 miles. Correlation of temperature, wind speed and visibility (especially the later two) diminished significantly for separations above 10 miles. For separations of 10 miles or less, temperature correlations were 0.97 to 0.99, while wind speed and visibility were 0.76 to 0.89. The maintenance data used in this analysis are taken from the winter highway maintenance garage log files. Maintenance data were merged into the data set in a similar way as discussed in the previous chapter. After the sites selected, weather data and traffic data were merged by the criteria of the same hour at the same day of the same year. The basic sites' traffic information is shown in Table B-1.

Table B-1. Sites Selection and Data Integration

ATRID	M-LOS	Speed Limit	Urban/Rural	AADT	Road Class	ATR_HWY	Total count	Maintenance (% of total)
AL1173	A	65	Rural	10K+	Interstate	I-80	21644	4
AL1177	A	65	Rural	10K+	Interstate	I-80	21796	4
WI1110	A	65	Rural	10K+	Interstate	I-80	47610	5
BE7050	A	55	Urban	10K+	Interstate	I-74	45522	3
AT1150	A	65	Rural	5-10K	Interstate	I-80	47694	6
BR1130	A	65	Rural	5-10K	Interstate	I-380	25162	5
HO1000	A	65	Rural	5-10K	Interstate	I-29	46862	5
JE1040	A	65	Rural	5-10K	Interstate	I-35	42878	5
LE1190	A	65	Rural	5-10K	Interstate	I-80	32820	2
ON1050	A	65	Rural	5-10K	Interstate	I-29	10740	4
SH1100	A	65	Rural	5-10K	Interstate	I-80	48714	5
PA1020	A	65	Rural	1-5K	Interstate	I-29	39110	4
AF2160	B	55	Rural	1-5K	Primary	US 34/169	47766	4
AL2070	B	55	Rural	1-5K	Primary	US 18	46756	5
OS2190	B	55	Rural	1-5K	Primary	US 34	46984	4
JE2450	B	65	Rural	1-5K	Primary	US 20	28382	5
WE2470	B	65	Rural	1-5K	Primary	US 20	45342	5
PO2500	B	65	Rural	5-10K	Primary	US 65	34070	4
WE8160	B	55	Urban	5-10K	Primary	US 34	8912	2
SC2330	C	55	Rural	<1K	Primary	IA 110	45322	5
WI2300	C	55	Rural	<1K	Primary	US 169	46068	4
SI2400	C	55	Rural	<1K	Primary	IA 2	37504	4

Extreme values were checked because the casual models can be very sensitive to the unusual observations. However, simply delete the extreme or influential values might overlook the fact that some of these outlier are represents some unique situations. Thus we identified the outliers and removed those observations only if we have justified reasons. In an example, 42 cases recorded that speed is zero. We looked through those observations case by case to check if traffic volume were recorded as 0 as well, or if any crashes happened during that hour. If either condition satisfied, the observations were removed from records.

Variables selection

The prerequisite of SEM is to formulate the models to be tested based on strict theory. Analytical methods itself can't uncover the model. Our research questions and the understanding of the field determine the construct of the theoretical model and the variables of interests. In this study, we are interested in what precepts of maintenance are critical in understanding the nature of effects, and how the results could be used helping agencies in improving winter maintenance operations. For these reasons, primarily variables must be selected to represent different dimensions of influence. In addition, confounding factors need to be considered as much as possible in order to make unbiased estimates.

As indicated in the literature, there are a variety of weather and maintenance indicators that could have potential influence upon speed and volume. In particular, maintenance garages keep record of a variety of variables as presented in Table B-2. Thus prior to constructing the model, the selection of the representative weather and maintenance indicators was first conducted based on previous literature and the data analyses.

Table B-2. Maintenances records from maintenance log

Variable Name	Variable type	Variable Categories / Scale
Operation	Categorical	Anti-icing, Frost-Run, Phase I, Phase II
Maintenance	Categorical	Maintenance, No Maintenance
Chemical type	Categorical	Brine, Salt, CaCl2
Liquid rate	Continuous	Gallons/Lane mile
Granular rate	Continuous	Gallons/ lane mile
Plowing	Categorical	Plow, No plow
Ice-blading	Categorical	Ice-blading, No Ice-blading
Material	Categorical	Sand, Salt, Sand/Salt Mix
Rotate snow blower	Categorical	Rotating, No rotating

Factor analysis (FA) was applied to facilitate the selections of weather variables. The factor analysis identifies those variables that are sharing the common construct, and only one of those variables sharing the same construct was selected to simplify the problem. For example, with road surface temperature included, air temperature and dew point temperature are excluded, since they were found to be highly correlated with surface temperature. Three selected weather factors are TEMPERATURE, WIND, and PRECIPITATION. TEMPERATURE is the measure of the road surface temperature, measured in F. WIND is the measure of the wind speed, in mph; PRECIPITATION is the measure of the precipitation rate, measured in inches/hr.

Categorical Principle Component Analysis (CAPCA) was conducted to facilitate the selection of maintenance factors out of 9 maintenance measurements (most of them are categorical variables). Merging and Regrouping of the variables were conducted prior to the analysis. The included maintenance variables are: OPERATION and CHEMICAL (BRINE-RATE), PLOW_NOT (PLOW), and SAND. The variables inside the parenthesis indicate another coding or representation of the same variable. The results of CAPCA analyses suggest that PLOW and CHEMICAL represent two distinct dimensions of maintenance operations. SAND application is related to the CHEMICAL choice. SAND was normally applied with granular SALT or CACL2 solution. The results also suggest that PLOW is moderately correlated with OPERATION. It can be easily understood that in ANTI-ICING and FROST RUN, no plow is used, while with Phase I operations, the plow is used intensively, and in Phase II, the plow is used less frequently than in Phase I. Because OPERATION also contains other important maintenance information, it was retained as well.

APPENDIX C: Methods Used in Crash Modeling.

As previous studies have indicated, many factors (the driver, the vehicle, road conditions and other circumstances) contribute to crash rates and crash severity. There is also a complex and subtle relationship between those factors and crashes (such as the curvilinear relationship between traffic volume and number of crashes). A variety of measures of safety have been used in previous research: crash counts, crash rates, crash risk, or crash severity. Although crash rates were used as the dependent variable in many previous studies, recent publications have scrutinized this measure, because of the pre-assumed linearity between crash counts and traffic flow rate. (NCHRP SYNTHESIS 295: Statistical Methods in Highway Safety Analysis).

To model crash counts, the commonly used regression methods are Negative binomial regression or Poisson regression. Compared with Poisson regression, Negative binomial regression is better with over-dispersed data, such as when the variance is large than the mean. In addition, because during the majority of hours, no crash happened, most of the hourly crash and injury counts are zero. Normally the Zero-inflated Negative Binomial or Poisson model has been suggested for this situation. However initial attempts to regress crash counts on weather and maintenance factors have not yielded significant results.

The original plan was to use structural equation modeling to estimate the direct and indirect effects of weather and maintenance on safety by way of an intermediate relationship with speed and volume. A major challenge in utilizing SEM is that the endogenous variables are the either count (number of crashes) or categorical variables (road surface condition). Thus transformation of these variables is required before modeling relations can be conducted. (Kupek, 2006). However, the following difficulties emerged as the analysis proceeded. The validity check of the critical variables revealed that apparent errors and distinct discrepancies existed between different measuring practices. For example, the road surface condition recorded in a police report in the crash file rarely matched those provided by the Road Weather Information System. Another difficulty was that the dependent variable- crash counts was for most of the time at a value of zero (because most of the time no crashes happened during the hour of the observation) which made the sample extremely unbalanced and as a result, the initial check revealed a very weak relationship between either the number of crashes or the severity of crashes and all the variables of interests. These data properties made using the transformation or two level analyses infeasible. Because of these factors, Multiple Classification Analysis (MCA) was used as the primary method for crash analysis.

Method of Multiple Classification Analysis (MCA)

The technique of Multiple Classification Analysis (MCA) developed by Andrews, et al. (1973) for social studies was employed. The analytical package incorporated in the ANOVA program in the Statistical Package for the Social Sciences (SPSS) was employed to do the analysis. MCA is an analysis of variance, but it examines the interrelations between categorical independent variables and an interval-scaled or dichotomous dependent variable more effectively than performing many cross-tabulations. The technique of “dummy variable multiple regression” is similar, but that technique is more cumbersome and difficult to describe and execute than MCA (Andrew, 1973).

Unlike regression, MCA does not require interval-scaled predictor variables, and linear relationships are not required, and also distributions need not be bivariate normal. MCA can be used to estimate the relationships of a set of predictors and a dependent variable, while simultaneously controlling for the remaining predictors.

Since the MCA coefficients are expressed as adjustments to the grand mean, to make the results more interpretable, the coding of the dependent variables were simplified. Rather than using crash counts during an hourly observation as the dependent variable, a zero or one coding is used to indicate where crashes (injuries or property damage only – PDO - events) happened during the hour of the observation.

Data

Weather, traffic and maintenance information was complemented by crash data. During the 4 years study period the total number of crashes that happened on the same stretch of highways where 27 ATR sites are located and within 10 miles distance of a suitable weather station totaled 1879. Of the 28 fatalities that occurred close to the study sites, 7 happened when adverse environmental conditions may have contributed to the crashes. Of the total hours included in the data, more than 99% had no crashes occurring during the given hour. The crash sample was further delimited so as to include only the crashes that occurred on interstate and primary highways segments, with no traffic control present.

Some of the ATR stations were not working all the time, and the maintenance information is not always complete, thus reducing the data set with complete information further. In addition, for many events, precipitation and visibility data were not available. Accordingly two separate data files were prepared. The first one includes all the adverse weather conditions with variables indicating if there a crash happened, and if so what type of crash it was during the hour when the observations were taken. The second file comprises all the crash data during the 4 years study period, with weather, traffic and maintenance data supplemented to each crash record as available.

Crash probability analysis

A key purpose of this study is to establish the various contributions of road attributes, weather, maintenance actions, and other circumstances surrounding the crash involvement during adverse weather conditions.

Two dependent measures were considered[10]: (a).Probability of having an injury crash (b) probability of having a Property-Damage-Only crash. Eighteen independent variables were selected as suggested by theory and previous research. The independent

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10 The probability of having a fatal crash is not analyzed in this study due to limited observations during the study period: Two fatal crashes happened when adverse weather conditions were present, out of a total of 28 fatal crashes during the study period.

variables can be categorized into the following groups: 1. Road attributes: including road classification, speed limit, urban/rural setting, AADT. 2. Weather condition, including different stage of winter precipitation (before, during or after snow storm), wind speed, road surface temperature, and visibility 3. Maintenance efforts, including winter maintenance level of service, whether maintenance has been performed, plowing, sanding, and chemical application. 4. Other prevailing conditions, including road surface condition, day or night, peak hour or not. The intermediate measures, including hourly traffic volume, mean speed, and speed variance were included as the control variables.

A preliminary MCA was first conducted for each group of variables. From each group the strong predictors are used for estimates in a final MCA. In addition, to verify the structural theory proposed earlier in the chapter, three separate models were constructed:

- Model 1, the included independent variables are road attributes, weather and maintenance factors.
- Model 2, road surface conditions were included in addition to those in model 1.
- Model 3, traffic volume and speed variance were further added to the second regression.

The basic ideas behind these three stepwise models are every time when we add an intermediate variable into the model the effect estimates should be attenuated. The effects estimated from model 1 can be understood as the total effects of weather and maintenance on crash probabilities. The effects estimated from model 3 are the direct effects of weather and maintenance on crash probabilities. The effect difference between model 2 and model 1 is the indirect effect of weather and maintenance through road surface conditions, and the effect difference between model 2 and 3 are the indirect effects of weather and maintenance through speed and volume.