Empirical Studies on Traffic Flow in Inclement Weather

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16. Abstract

Weather causes a variety of impacts on the transportation system. While severe winter storms, hurricanes, or floodings can result in major stoppages or evacuations of transportation systems and cost millions of dollars, day-to-day weather events such as rain, fog, snow, and freezing rain can have a serious impact on the mobility and safety of the transportation system users. These weather events can result in increased fuel consumption, delay, number of accidents, and significantly impact the performance of the transportation system. The overall goal of the research work undertaken in this study was to develop a better understanding of the impacts of weather on traffic flow. The research was intended to accomplish the following specific objectives: (1)Study the impact of precipitation on macroscopic traffic flow parameters over a full range of traffic states; 2) Study the impact of precipitation on macroscopic traffic flow parameters using consistent, continuous weather variables; 3) Study the impact of precipitation on macroscopic traffic flow parameters on a wide range of facilities; 4) Study regional differences in reaction to precipitation; and 5) Study macroscopic impacts of reduced visibility.

The work documented in this report was conducted in two parts: 1) literature review and development of a data collection and analysis plan, and 2) analysis and interpretation of the results. The recommended plan combined the use of macroscopic traffic data archives with archived weather data in order to meet the research goals that include achieving better understanding of the impacts of weather on macroscopic traffic flow. The results of the research conducted for this study were helpful in identifying weather impacts of traffic flow in the three cities studied, Minneapolis-St. Paul, Baltimore and Seattle. No impacts were found on traffic stream jam density, but both rain and snow did impact traffic free-flow speed, speed-at-capacity and capacity and parameters varied with precipitation intensity. The results of these analyses are documented in the report.

This report concludes with some recommendations of future research related to weather and traffic flow. Several ideas are presented including enhancing the macroscopic analysis used in this study. Additional work is proposed related to human factors and microscopic traffic modeling.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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Executive Summary

BACKGROUND

Weather causes a variety of impacts on the transportation system. An Oak Ridge National Laboratory study estimated the delay experienced by American drivers due to adverse weather conditions in 1999 at 46 million hours. While severe winter storms, hurricanes, or floodings can result in major stoppages or evacuations of transportation systems and cost millions of dollars, day-to-day weather events such as rain, fog, snow, and freezing rain can have a serious impact on the mobility and safety of the transportation system users. These weather events can result in increased fuel consumption, delay, number of accidents, and significantly impact the performance of the transportation system.

Despite the documented impacts of adverse weather on transportation, the linkages between inclement weather conditions and traffic flow in existing analysis tools remain tenuous. This is primarily a result of limitations on the data used in research activities. For example a recent study of weather-related delay in northern Virginia documented that there are significant weather-related delays but was limited by the fact that the traffic data did not recognize average speeds that were over the speed limit. This influenced the ability to accurately estimate delay caused by weather during free-flow conditions. Measuring the impact of precipitation intensity has also been challenging due to limitations of weather data. Studies conducted in Canada (Ibrahim and Hall) and by the University of Virginia (Smith, et al 2004) differed in their conclusions about the impact of precipitation intensity on speed reduction. More research is needed to determine whether results reflect regional differences or the limitations of the weather data. Research has been limited on the microscopic driving behavior as well, particularly in the areas of vehicle following and lane changing. These are critical parameters in understanding the effectiveness of different traffic management strategies. Researchers and practitioners need improved weather data sets and analytical models that can connect traffic flow to specific weather impacts.

GOALS AND OBJECTIVES

The overall goal of the research work undertaken in this study was to develop a better understanding of the impacts of weather on traffic flow. The research was intended to accomplish the following specific objectives:

1. Study the impact of precipitation on macroscopic traffic flow parameters over a full-range of traffic states;

2. Study the impact of precipitation on macroscopic traffic flow parameters using consistent, continuous weather variables;
3. Study the impact of precipitation on macroscopic traffic flow parameters on a wide-range of facilities;
4. Study regional differences in reaction to precipitation; and
5. Study macroscopic impacts of reduced visibility.

These objectives reflect the needs identified through the literature searches conducted for this project as well as the research activity. Increasingly sophisticated ITS and traffic management systems provide an opportunity to improve safety and mobility during weather events. Before implementing these strategies, however, more needs to be understood about how weather impacts vary during congested and uncongested conditions and during different weather events. Differences in driver behavior response will also influence strategies, as well as regional differences. A better understanding of these differences is needed as well. Implementation of variable speeds limits, for example, requires an understanding of all the factors listed above.

Research Approach

The work documented in this report was conducted in two parts: 1) literature review and development of a data collection and analysis plan, and 2) analysis and interpretation of the results.

As the research plan was developed, it became clear that collecting new data would be expensive, and thus limit the resources available for analysis and interpretation. Therefore, the recommended plan combined the use of macroscopic traffic data archives with archived weather data in order to meet the research goals that include achieving better understanding of the impacts of weather on macroscopic traffic flow.

Traffic data archives with good geographic coverage were required to meet the objectives outlined in the research plan. In order to meet the study objectives, the traffic data archives had to be available in more than one region, associated with varying weather conditions, and cover regions that receive significant amounts of rain, snow, and fog. Traffic data sources were available from a number of cities that meet these criteria, and three cities that represent a variety of weather conditions were selected – Minneapolis-St. Paul, Baltimore and Seattle. Efforts were made to add a fourth, warm-weather city that does not generally experience severe weather. Several regions were considered but none could offer the desired combination of weather and traffic data.

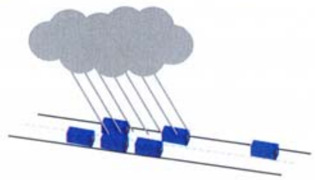
Data from Automated Surface Observing Systems (ASOS) and Automated Weather Observing System (AWOS) were the best available for this research. They represent high-quality, reliable weather information within a national network. One limitation of using this data set was limited local coverage, since

ASOS/AWOS are only located at airports. However, data were available from an adequate number of ASOS/AWOS stations close to desired traffic stations.

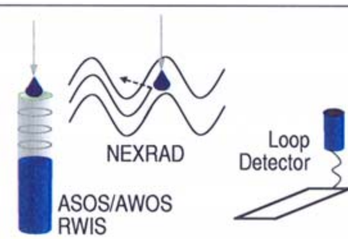
As stated above, the three metropolitan areas of Minneapolis, Baltimore and Seattle cover a wide-range of weather conditions appropriate for this study. Utilizing both weather data and loop detector traffic data, empirical models were calibrated by minimizing a normalized orthogonal error between field observations and model estimates. The optimum free-flow speed, speed-at-capacity, capacity, and jam density were computed for different weather conditions. Inclement weather adjustment factors were then developed for each precipitation level. In addition, statistical models were developed to characterize the behavior of these parameters as a function of the precipitation type and intensity. The general process is shown in the table below.

Table ES.1 Process for Developing Empirical Models on Weather and Traffic Flow

Weather Events & Traffic States Occur
First, weather events occur on a road network, affecting a particular traffic state.

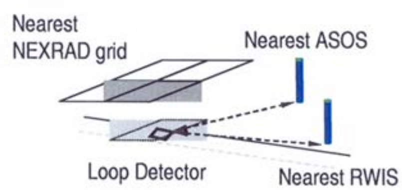


Measurement
Second, measurement devices (detailed in Section 5) measure aspects of the weather event and the traffic states.



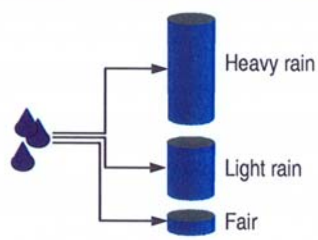
Goal:
Accurately reproduce reality with imperfect measurement instruments.
Issues:
Data may require cleaning and processing.

Data Fusion
Third, data from several weather measurement devices are matched with data from a single set of traffic measurement devices (Section 5).



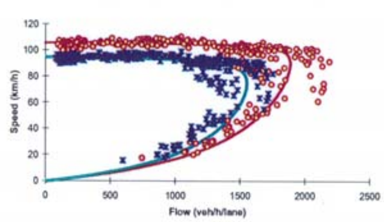
Goal:
Isolate weather events geographically and match to detectors.

Weather Categorization
Fourth, weather data are placed into categories, using a combination of statistical techniques and intuition (Section 6).



Goal:
Categorize weather into statistically significant bins.
Issues:
Categorization must be useful to engineers.

Traffic Analysis
Traffic data from differing weather categories are used to fit a model and estimate critical traffic stream parameters. The differences in model fit determine the impact of a weather category on traffic parameters. If needed, weather events are re-categorized until significant traffic parameter impacts are found (Section 6).



Goal:
Determine impact of different weather categories on traffic parameters.
Issues:
May need to iterate back to categorization until meaningful traffic differences are found.

MODEL FORM AND CALIBRATION

The functional form utilized in this study is the Van Aerde nonlinear functional form that was proposed by Van Aerde (1995) and Van Aerde and Rakha (1995). The model bases the distance headway (km) of a vehicle (*n)* on several parameters, including vehicle speed, facility free-flow speed, a fixed distance headway constant, a variable headway constant and a variable distance headway constant. This model provides a linear increase in vehicle speed as the distance headway increases with a smooth transition from the congested to the uncongested regime. This combination provides a functional form that allows the speed-at-capacity to differ from the free-flow speed.

The calibration of macroscopic speed-flow-density relationships requires identification of a number of key parameters, including the facility's expected or **mean** four parameters, namely; capacity (q_c), speed-at-capacity (u_c), free-flow speed (u_f), and jam density (k_j). Key decisions in the calibration process include definition of the functional form to be calibrated, identification of the dependent and independent variable, defining the optimum set of parameters and developing a technique to compute the parameter values.

A customized, heuristic tool was developed (SPD_CAL) to calibrate traffic stream models. The data were initially aggregated into traffic stream density "bins" in order to reduce computational requirements. The "bins" used reflected varying degrees of precipitation intensity and also distinguished between congested and uncongested conditions. After initializing the four traffic stream parameters the model functional form was constructed the objective function computed in an incremental process, varying the four parameters. A set of parameters was computed in an iterative manner that minimizes the objective function. The results have been summarized in various ways to represent the impact of different weather states on the traffic parameters. A sample of results is shown below in the executive summary and more detailed results are shown in Chapter 5.0 of the Report.

RESEARCH FINDINGS

The results of the research conducted for this study were helpful in identifying weather impacts of traffic flow in the three cities studied. No impacts were found on traffic stream jam density, but both rain and snow did impact traffic free-flow speed, speed-at-capacity and capacity and parameters varied with precipitation intensity. Capacity did not vary with snow intensity, although capacity reductions of 12 to 20 percent were found in snowy conditions. One of the more interesting findings was that the Twin Cities experienced more significant reductions in the traffic stream free-flow speed and speed-at-capacity under snowy conditions when compared to Baltimore (19 versus 5 percent reductions). This finding might appear to be counter intuitive given that the Twin Cities experience higher annual snow precipitation when compared to

Baltimore. A possible explanation for this finding is that drivers who are more accustomed to snow are more aware of the dangers of snow. This could also explain the higher reductions that were observed in the Canadian study (33 to 43 percent).

Results of the research are summarized in the table below.

Table ES.2 Research Summary

Traffic Parameter	Weather Condition	Range of Impact
Free-flow speed	Light Rain (<0.01 cm/h)	-2% to -3.6%
	Rain (~1.6 cm/h)	-6% to -9%
	Light snow (<0.01 cm/h)	-5% to -16%
	Snow (~0.3 cm/h)	-5% to -19%
Speed at Capacity	Light Rain (<0.01 cm/h)	-8% to -10%
	Rain (~1.6 cm/h)	-8% to -14%
	Light snow (<0.01 cm/h)	-5% to -16%
	Snow (~0.3 cm/h)	-5% to -19%
Capacity	Light Rain (<0.01 cm/h) and Rain (~1.6 cm/h)	-10% to -11%
	Light snow (<0.01 cm/h)	-12% to -20%

The research also produced more detailed, multidimensional analysis results that can be found in Chapter 5.0 of the report. The summaries and diagrams show how various parameters are influenced over a range of weather and traffic conditions. Figure ES.1 below demonstrates that the free-flow speed and speed-at-capacity Weather Adjustment Factors are impacted by both the snow precipitation rate and the visibility level in the Twin Cities.

Figure ES.1 Variation in Weather Adjustment Factors as a Function of Visibility and Snow Intensity Levels (Twin Cities)

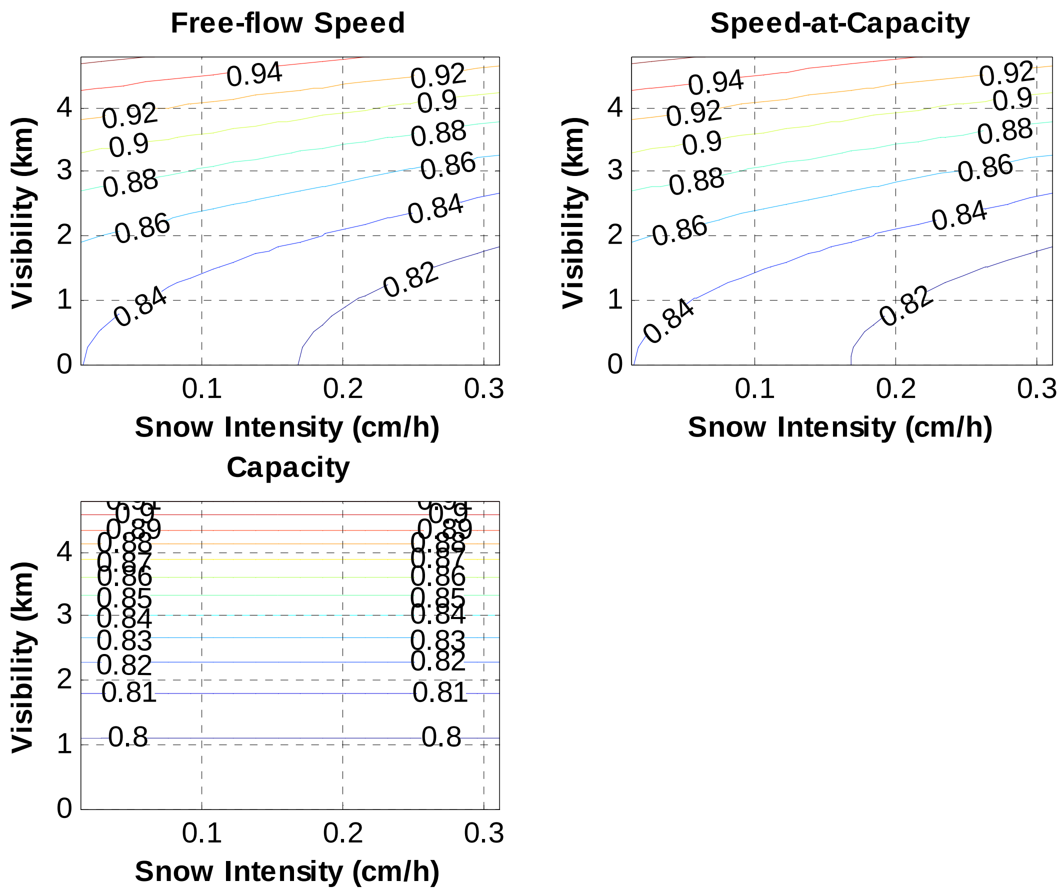
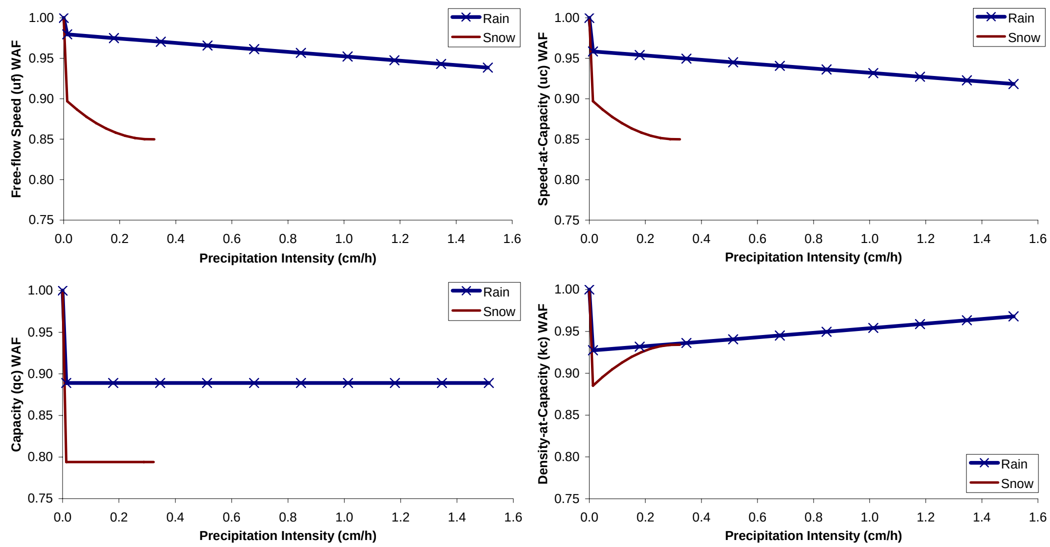


Figure ES.2 shows a comparison of the rain and snow free-flow speed, speed-at-capacity, and capacity Weather Adjustment Factors. The results demonstrate that snow impacts on traffic stream behavior are more significant than rain impacts, as would be expected. Furthermore, the results demonstrate that precipitation appears to produce a constant reduction (independent of the precipitation intensity) for the capacity. Alternatively, the free-flow speed and speed-at-capacity appear to be impacted by the precipitation level.

Figure ES.2 Sample Comparison Snow and Rain Weather Adjustment Factors (Twin Cities)



FUTURE RESEARCH

This report concludes with some recommendations of future research related to weather and traffic flow. Several ideas are presented, including enhancing the macroscopic analysis used in this study. This effort would involve original data collection with colocation of traffic detectors and environmental sensor stations. More detailed traffic and weather data would be collected and imaging cameras used to gain a better understanding of driver response to adverse weather conditions. The research also concluded that more work is needed to better understand the impact of weather on different types of facilities, including arterials. Additional cities need to be evaluated to better assess regional differences. For example, no warm weather cities were included in this study. Finally, additional analysis of visibility impacts is needed. While some analysis of visibility data was done, the amount of data was limited and the quality uneven. The inclusion of analysis of crash rates and crash types correlated to traffic flow and speed under adverse weather conditions should also be considered.

Additional work proposed related to human factors and microscopic traffic modeling include analysis of data being collected for the Next Generation Simulation (NGSIM) project and controlled field studies on a test track. The use of surveys to gauge driver reactions to pretrip weather and traffic information are discussed. Finally the Vehicle Infrastructure Initiative (VII) program provides the promise of a much more accurate and extensive database on driver reaction to adverse weather conditions. While privacy issues may limit the ability to obtain individual vehicle data, useful aggregate data will be available.

1.0 Introduction

1.1 Background

Weather conditions affect the operation of the national transportation system by changing the driving environment as well as the behavior of drivers, who modify their individual headways, target speeds, or other travel parameters in reaction to specific weather events. The individual reactions of these drivers to weather, in turn, directly impact overall system performance. From rain showers in Honolulu, to fog in San Francisco, to snow in Minneapolis, to storms in Boston, local transportation system managers understand the necessity of planning for the consequences of diverse weather conditions on a daily basis. However, at a national scale, universally applicable tools to understand and mitigate the effects of weather on transportation systems remain in short supply.

Weather causes a variety of impacts on transportation systems during and after weather events. These impacts can be short- or long-term, and direct or indirect. However, the linkages between inclement weather conditions and traffic flow in existing analysis tools remain tenuous. Transportation managers require information on the impacts of weather on traffic in order to apply advisory, control, and treatment strategies on their systems to deal with weather events. As a first step in strengthening this analysis capability, researchers and practitioners must have access to weather data sets and analytical models that can connect traffic flow to specific weather impacts. Without this information, managers will continue to rely on heuristic, local methods for determining impacts. This approach confounds coordination between managers and confuses the national approach to weather-related traffic flow impact analysis by failing to provide an acceptable knowledge base and techniques.

Oak Ridge National Laboratory conducted a study that estimated the delay experienced by American drivers in 1999 at 46 million hours on major United States highways due to adverse weather conditions defined for this study as fog, ice, and snowstorms (Han, et al., 2003). These conditions covered 65 percent of United States territory and impacted 68 percent of the nation's population. Researchers estimated that the occurrence of inclement weather increased overall travel times by approximately 7 to 36 percent. The weather events studied are highly seasonal events and occur most frequently during the winter months. Approximately two-thirds of traffic flow and delay impacts during the winter season can be attributed to adverse weather.

While severe winter storms, hurricanes, or excessive flooding can result in major stoppages or evacuations of transportation systems or evacuations and cost millions of dollars, day-to-day weather events such as rain, fog, snow, and freezing rain can have serious impacts on roadway mobility and the safety of the transportation system users. These weather events can result in increased fuel consumption, delay, number of accidents, and significantly impact the performance of the transportation system.

1.2 MOTIVATION FOR THIS STUDY

Transportation managers strive to improve safety and mobility within their systems. Currently, weather events add an element of variability to their day-to-day operations. However, these events can be forecast, and their impacts predicted, if data and decision support tools are available and utilized effectively. Improved predictive capabilities are critical to effective operational response. Tailored road weather observations and forecasts that provide information on the location, characteristics, and duration of weather events enable transportation managers to assess the scope, severity, and overall impacts of weather events on their systems.

Many municipalities have recently established Road Weather Information Systems (RWIS), a combination of technologies that use historic climate and current road weather data to develop information that aid roadway-related decisions. These systems improve the weather forecasts available to transportation managers and provide a wealth of information for analysis by providing weather and pavement condition data. While sensor station weather data provides benefit in reporting real-time conditions to managers, it has the potential to provide more value if archived and used to evaluate traffic management strategies.

Tools that use historic traffic data and weather forecast data to predict traffic flow conditions are important to help identify where and how weather events will impact traffic conditions. These can also enable managers to determine areas and conditions that are most vulnerable to incidents, and estimate the safety impacts of both weather events and response strategies. Long-term planning tools facilitate development and evaluation of weather-responsive traffic management strategies. Models that predict short-term traffic flow using historical and real-time data are useful in assessing its current impacts on the transportation system and determining implementation of a specific strategy. With these tools, transportation managers can implement effective advisory strategies that provide information on weather and traffic conditions to the public and control strategies that alter the state of roadway devices to regulate traffic flow and roadway capacity during a weather event by modifying signal timings/plans and speed limits, closing roads, and implementing detour routes.

The aim of this research is to investigate and quantify the impacts of various weather events on traffic flow in order to provide transportation managers with information and tools they can utilize to improve mobility and safety on the transportation network.

1.3 Scope of Report

The early phases of this project included background research on the impact of weather on traffic flow. The first activity, a literature review, is documented in Section 2. This was followed by a search of available data sources for both weather and traffic information. The results of this effort are summarized in Section 3. The research plan and models proposed for analysis are described in Section 4 and the research findings are detailed in Section 5. Section 6.0 contains recommendations for further research.

2.0 Literature Review

This section synthesizes the research that has been conducted on the impacts of weather on traffic performance. The literature on research into this area can be divided into three general categories, although it is important to note that there are overlaps between them:

- **Secondary Data –** Secondary data studies use archived data collected by parties other than the researchers. This information is generally collected for other purposes than the objective of the research. Many research efforts have collected data from traffic count databases and weather stations in an attempt to identify the impact of adverse weather on traffic flow. Early efforts go back to the 1960s and 1970s when the University of Michigan used an early ITS system to collect traffic and speed data during different weather conditions on Detroit area freeways. Some efforts have looked only at speed impacts, while others have attempted to estimate changes in capacity and speed-density relationships. An increasing number of these research efforts are using microsimulation models to add value to the data. These models permit the analyst to fill in data gaps and test different assumptions regarding driver behavior. Much of the work to date has used tools such as CORSIM but increasingly sophisticated models are allowing researchers to disaggregate the traffic stream based on driver response. Different driver profiles can be developed based on their reactions to adverse weather (aggressive, cautious, moderate) and their interactions can be modeled. Some of the research projects identified in this category are listed in Appendix A.
- **Primary Data Collection –** Primary data studies use aggregate data collected by researchers specifically for the study. A number of researchers have been able to collect primary data on traffic speed and volumes during adverse weather. In some cases, data have been collected as part of traffic flow studies, while in other cases they have been collected to test driver response to traffic management system devices or other ITS technologies. Many of these studies have been conducted in Northern Europe, where both driving habits and roadway configurations will probably differ from those in the U.S. Increasingly there is recognition that primary, focused data collection efforts will provide a clearer picture of traffic flow impacts. This approach is still limited, however, as is secondary data collection, in its ability to disaggregate the market and identify how different classes of drivers will respond. A sampling of these research efforts is presented in Appendix A.
- **Human Factors Studies –** Human factors studies generally involve primary data collection, focused on individual reactions to driving conditions. There is increasing focus on the behavior of individual drivers or groups of drivers

based on the theory that gender, age, region of residence, and other factors impact driver behavior. Studying the response of individual drivers to adverse weather has a number of advantages. Field observations of decreased speeds and greater headways can be better understood by observing how individual drivers respond to certain stimuli, and how specific categories of drivers respond. This information is particularly helpful in light of the growing deployment of ITS technologies. Motorist warning systems that notify drivers through roadside Dynamic Message Signs (DMS) about weather-related conditions such as fog, flooding, or slippery pavement are deployed by some transportation agencies. The benefits of these systems can be maximized if agencies can optimize the location and provide the most effective warning on the sign itself. Human factors research is an important element in the analysis and design of these systems. A summary of these research efforts is presented later in this chapter.

The remainder of this chapter summarizes the results found in many of these studies. A discussion of macroscopic effects of weather on capacity, delay, volume, and speed is followed by a summary of much less understood microscopic behavioral and human factors impacts. Microscopic analysis looks at individual vehicle movements and their interactions while human factors research investigates driver response, which may or may not be manifested in vehicle response.

2.1 Operations and Macroscopic Traffic Research

This section describes the impact of weather on the relationships between traffic speed, flow, and density, and other macroscopic measurements. Following are key freeway traffic parameters that are impacted by adverse weather:

- **Capacity –** Capacity is the maximum number of vehicles that can pass a point during a specified time period and is a characteristic of the roadway.
- **Delay –** Delay is the time lost by a vehicle due to causes (i.e., adverse weather) beyond the control of the driver.
- **Traffic Volume/Demand –** Traffic volume is the number of vehicles passing a point during a specified time period or the number of vehicles desiring to pass that point during a specified period. Flow is traffic volume normalized to an hour, or vehicles per hour. Demand is the number of vehicles that desire to travel past a point during a specified period.
- **Speed –** Freeway speed is the average speed of vehicles in the absence of traffic control devices. Note that unless otherwise specified, speeds are averaged over time and over a number of traffic conditions. Free-flow speed refers to the average speed of vehicles under low-volume conditions.

Capacity

The Highway Capacity Manual (2000) asserts that adverse weather can significantly reduce capacity and operating speeds, and addresses the issues of when and how to take these effects into account. The manual references several studies in its discussion of weather effects. Lamm, Choueiri, and Mailaender (1990) conclude that speeds are not affected by wet pavement until visibility is affected, which suggests that light rain does not impact operating speeds, but heavy rain does and can be expected to have a noticeable effect on traffic flow.

Similarly, Ibrahim and Hall (1994) found minimal reductions in maximum observed flows and operating speeds (detailed in the discussion on speed) in light rain, but significant reductions in heavy rain. There is a 14 to 15 percent capacity reduction during heavy rain, compared to clear and dry conditions. The HCM does not define the intensity ranges associated with light and heavy rain and light and heavy snow classifications.

Similarly to rain, light snow was found to have minimal effects, while heavy snow was found to have a potentially large impact on capacity and operating speeds in the Ibrahim and Hall study. Light snow resulted in a five to 10 percent reduction in maximum observed flows (midway between the effects of light and heavy rain). Heavy snow resulted in a 30 percent drop in capacity. Snow accumulation obscures lane marking, which can cause drivers to seek greater lateral clearance in addition to longer headways.

The HCM notes that no studies have quantified the effects of fog on capacity, but several European studies have examined the effectiveness of fog warning systems. These studies, however, do not report how speeds or capacities are affected by fog. A 1995 Brilon and Ponzlet study examined the effect of environmental conditions and variability in capacity at 15 Autobahn sites in Germany. While the results cannot be directly translated to North American conditions, the study extends the research results cited above and identifies other environmental conditions that impact capacity. Combinations of daylight, darkness, dry, wet, weekend, and weekday, as well and four- and six-lane configurations were examined as shown in Table 2.1.

Table 2.1 Reduction in Capacity from Daylight and Dry Conditions

		Dark and Dry	Daylight and Wet	Dark and Wet
Six-lane	Weekday	13%	12%	38%
	Weekend	21%	27%	–
Four-lane	Weekday	19%	18%	47%
	Weekend	25%	29%	–

Source: Brilon and Ponzlet, 1995.

Given that the winter peak-periods often occur in darkness, these capacity reductions are important to recognize and study further. These research findings can be incorporated with the HCM methodology by using the speed-flow curve to model the effects of adverse weather and evaluate the expected traffic performance for certain sections of uninterrupted flow facilities.

In a University of Virginia study, Smith, et al. (2004), investigated the impact of rainfall at varying levels of intensity on freeway capacity and operating speeds to gain an understanding of the impact of weather conditions on key traffic parameters. Traffic and weather data were collected for a one-year period between August 1999 and July 2000, on two freeway links in Hampton Roads, Virginia. Traffic data (volume, time mean speed, and occupancy) were collected from the Smart Travel Laboratory at two-minute intervals. Average speed and flow rate were compiled at 15-minute intervals. Hourly weather data were collected from the weather station at Norfolk International Airport, three miles from the study freeway segments. Rainfall data were collected in inches per hour, and intensity was assumed to be the same for every 15-minute interval over the course of an hour. Rainfall was classified into light rain (0.01 to 0.25 inch per hour/0.25 to 6.4 mm per hour) and heavy rain (greater than 0.25 inch per hour/6.4 mm per hour), based on guidelines provided by the Swedish Meteorological and Hydrological Institute and the Philippine Atmospheric Geophysical and Astronomical Services Administration. Records during periods of darkness were removed from the study.

Analysis of the data began with plotting speed-flow curves. A maximum observed throughput approach was used to estimate freeway link capacity; the mean of the highest five percent flow rates was used to determine the percent changes in capacity due to rainfall. Capacity reduction was evident and statistically significant, as rainfall intensity became greater. Light rain decreased freeway capacity by 4 to 10 percent, and heavy rain decreased capacity by 25 to 30 percent.

Prevedouros and Chang (2004) analyzed video surveillance data of freeway and arterial roadways in Honolulu recorded between 1996 and 2000, focusing on measurements from traffic platoons collected during busy but fluid conditions. Headways were measured at identical locations under dry, wet pavement (no rain), and light-to-moderate rain conditions. Analysis of the data finds that, on average, freeway capacity is reduced by 8.3 percent.

Table 2.2 Summary of Rain Effects on Capacity

	Capacity Reduction			
Researcher	Ibrahim and Hall	Brilon and Ponzlet	Smith	Prevedouros and Chang
Location	Toronto, Ontario	Germany	Hampton Roads, Virginia	Honolulu, Hawaii
Year	1994	1995	2004	2004
Light Rain	–	12-47%	4-10%	8.3%
Heavy Rain	14-15%	12-47%	25-30%	8.3%

Delay

A 2003 Mitretek study (Stern, et al., 2003) attempted to quantify the amount of travel delay imposed upon drivers due to the effects of inclement weather. Using a metropolitan Washington D.C. network spanning from the eastern suburbs in Maryland to the western suburbs in Virginia and containing 33 roadway segments, researchers utilized travel time data for each weekday between December 1999 and May 2001. Traffic data were collected in five-minute increments between 6:30 a.m. and 6:30 p.m.

Researchers used two models to quantify the travel delay: a regression analysis using surface observations and an analysis by means of precipitation category using radar data. The regression analysis used weather data from Automated Surface Observing System (ASOS) stations at three International Airports in the Washington D.C. area. Air temperature, dew point, wind speed and direction, and rainfall accumulation were measured in hourly increments. In a two-step linear regression process, the travel time was regressed against weather variables for all ASOS sites. Final variables in the analysis were precipitation type and intensity, wind, visibility distance, and pavement condition (which was inferred from the other weather information). Then, the linear regression models were reduced for each segment to predict a base travel time and the increase due to weather.

Despite limitations in data (primarily, the absence of other variables affecting travel time and the temporal and spatial differences between weather and traffic data), the study found that, when weather phenomena occur, the average regional increase in travel time is 14 percent, with pavement condition the most frequent explanatory variable, followed by precipitation. Wind speed and surface visibility appeared in a few models.

Policy prevented the posting of travel times indicating speeds greater than the speed limit. This has tangible implications on the analysis of delay during congestion-free traffic periods, and may result in the study underestimating the effects of weather on travel times. Researchers recognized the need for an accurate travel time data source and recommended future studies focus on evaluating the relative impacts of weather and incident/congestion variables.

Traffic Volume

Adverse weather can reduce demand on the transportation system, as drivers postpone discretionary trips or activities get canceled. On the other hand, there may be increases in vehicular demand because some who travel by bicycle or on foot switch to motorized mode when adverse weather is forecast. Adverse weather can also have more complex effects on demand, such as peak-hour demand shifting as drivers leave early or late to avoid driving in dangerous conditions.

Hanbali and Kuemmel conducted a study in 1992 to measure reductions in traffic volumes during snowstorms on highways and freeways outside of urban areas in Illinois, Minnesota, New York, and Wisconsin. Automatic vehicle detectors collected traffic data during the first three months of 1991, including annual average daily traffic and actual 24-hour counts. Other data used in the study included highway characteristics, level of service (in terms of snow and ice removal), and road treatment to achieve bare pavement. Climate data, based on the National Climatic Data Center, included the storm period (start and end time and date), temperature range, snow depth, and type of snow.

Researchers measured the hourly traffic volumes during every snowstorm and compared it to the normal hourly traffic volumes corresponding to the same type of day/time/season. From that, hourly reduction factors were derived for each snowstorm, and compiled and correlated for each categorized group (shown in Table 2.3). Researchers concluded that volume reductions increased with total snowfall, but that the reductions were smaller during peak travel hours and on weekdays, likely due to the nondiscretionary nature of most weekday trips.

Table 2.3 Snowstorm Impacts on Volumes

Snowfall	Weekdays (Range of Volume Reduction)	Weekends (Range of Volume Reduction)
< 25 mm	7-17%	19-31%
25-75 mm	11-25%	30-41%
75-150 mm	18-34%	39-47%

Source: Hanbali and Kuemmel, 1992.

Knapp, et al. (2000) conducted a study to evaluate winter weather impacts on traffic volume and safety. Hourly traffic and weather information was collected and analyzed along interstates in Iowa for 1995, 1996, 1997, and 1998. Seven RWIS stations and nearby automatic vehicle detectors were used to approximate storm and nonstorm weather event parameters and traffic volumes.

The goal was to limit the research to relatively significant winter storm events, so event time periods were defined as those where an RWIS station recorded precipitation, air temperature below freezing, wet pavement surface, and a pavement temperature below freezing for at least four hours with an estimated snowfall of at least 5.1 mm per hour (0.2 inch per hour). The research compared and statistically analyzed volume and crash data from winter storm and nonstorm event time periods.

The traffic volume analysis covered 64 winter storm events (618 hours). There was large variability in winter storm traffic volume impacts, ranging from 16 percent to 47 percent reduction. The overall average reduction was approximately 29 percent, with a 95 percent confidence interval of 22.3 percent to 35.8 percent. A regression analysis indicated that percent volume reduction had a statistically significant relationship with total snowfall and the square of the maximum wind speed. Storm event duration, snowfall intensity, and minimum and maximum average wind speed either were correlated to the explanatory variables or were not found to be statistically significant. The coefficients indicated that volume reduction increases with each variable and the adjusted R-squared value indicates that the model had some explanatory power.

Ibrahim and Hall's (1994) flow reduction results of 10 to 20 percent for heavy rain were consistent with a previous study by Jones and Goosby (1970). Little or no effect on flow was observed under light rain conditions. Light snow resulted in a 5 to 10 percent reduction in maximum observed flows (or midway between the effects of light and heavy rain).

Freeway Speed

A Federal Highway Administration (FHWA) study found that interstate speeds decrease in inclement weather. Table 2.4 describes the average percent speed reduction for a variety of weather conditions.

Table 2.4 Speed Reductions in Inclement Weather

Condition	Percent Speed Reduction
Dry	0%
Wet	0%
Wet and snowing	13%
Wet and slushy	22%
Slushy in wheel paths	30%
Snowy and sticking	35%
Snowing and packed	42%

Source: FHWA, 1977.

Ibrahim and Hall's (1994) study discussed in the Highway Capacity Manual used traffic data from the freeway traffic management center for the Queen Elizabeth Way (QEW) in Mississauga, Ontario, with volume, occupancy, and speed data recorded in 30-second intervals during the months of October, November, and December 1990; and January and February 1991. Weather records for Pearson International Airport were obtained and it was confirmed that the records accurately reflected the weather conditions at the QEW freeway location.

The study site was selected so that it would not be influenced by ramp or weaving sections, and the time period from 10:00 a.m. to 4:00 p.m. was chosen to focus on uncongested data and eliminate periods of darkness, which literature had shown to impact driver behavior and operating speed.

Regression analyses were conducted on the clear weather data to select models for the uncongested flow-occupancy and speed-flow relationships. A quadratic model was the best fit for the flow-occupancy relationship, while a simple linear model with dummy variables was used for the speed-flow relationship.

The comparison analysis showed that both the difference in slope and the difference in intercept of the speed-flow function within the rainy (snowy) condition (i.e., difference between light and heavy conditions) were more important than the differences between clear and rainy (snowy) weather. Comparing rainy and snowy conditions allowed the researchers to conclude that, while light rain and light snow have nearly the same effect on traffic operations, heavy snow has a much greater impact than heavy rain.

In light rain, a 1.9 km/hr (1.2 mph) and 6.4 to 12.9 km/hr (4 to 8 mph) reduction in operating speeds can be expected during free-flow conditions and at a flow of 2,400 vehicles per hour, respectively. In heavy rain, a 4.8 to 6.4 km/hr (3 to 4 mph) and 12.9 to 16.0 km/hr (8 to 10 mph) reduction in speed can be expected. Light snow resulted in a significantly significant drop of 0.96 km/hr (0.6 mph) in free-flow speeds, while heavy snow resulted in a 37.0 to 41.8 km/hr (23 to 26 mph) (35 to 40 percent) free-flow speed reduction.

Ibrahim and Hall concluded that, while adverse weather affects both the flow-occupancy and speed-flow relationships, other factors, including the driver's familiarity with rainy and snowy conditions, may affect these relationships. Regional differences are expected to be a factor in speed reductions. Additionally, facilities and capabilities to deal with adverse weather (i.e., quality of drainage or effective plowing operations) can also affect the magnitude of speed reduction and flows.

A study examining the importance of weather in performing a capacity or level of service analysis was conducted on a rural interstate in Idaho (Kyte, et al., 2001). Data were collected from the same location on a four-lane, level-grade freeway between 1996 and 2000, with high-truck volumes and flow rates almost always less than 500 passenger cars per hour per lane (pcphpl). Traffic data (time, speed, and length of vehicle), visibility distance, and weather data (wind speed and direction, air temperature, relative humidity, roadway surface condition, and type and amount of precipitation) were recorded in five-minute intervals.

In good weather, there was a nearly constant relationship between vehicle speed and flow rate, resulting in an estimated free-flow speed of 122 kilometers per hour (76 miles per hour) in ideal conditions (9 km/hr greater than the value computed using the HCM method). The study evaluated visibility reduction, wind, and pavement condition (wet or snow covered) factors. In this field study, for visibility levels greater than one kilometer (0.625 mi), speeds were nearly constant and near the ideal condition free-flow speed. As visibility decreased below one kilometer, speed decreased, with a substantial decline when visibility dropped below 0.3 kilometer (0.18-mile). Wind conditions did not have as clear a relationship, perhaps due to wind gust that are not reflected in average wind speed or variable driver responses to wind. Despite these limitations, data indicated that the critical wind speed was 24 kilometers per hour (14.9 miles per hour).

To determine the individual effects of weather variables on speed, speed was regressed against pavement condition, wind speed, and visibility, using the critical values described above. The results indicated that all coefficients were statistically significant, but with a high-degree of variability in the results as shown in Table 2.5.

Table 2.5 Impact of Environmental Conditions on Speed

Factor	Speed Reduction	
	(km/h)	(mph)
Wet	9.5	5.9
Snow	16.4	10.2
Wind > 24 km/h	11.7[a]	7.3[a]
Visibility < 0.28 km	0.77 per 0.01 km below critical	0.48 per 33 ft below critical

[a] Variation of speed drop is high.

Source: Kyte, et al., 2001.

The results for wet pavement and snow correspond closely with other studies. Researchers concluded that, since these factors indicated different free-flow speeds and since one-third of cities experience rain at least 125 days per year, weather should be considered in capacity and level of service analysis.

Research in the University of Virginia study (Smith, et al., 2004) has shown that speed is relatively insensitive to increasing flow rates until congestion sets in. Therefore, the mean speeds were calculated for uncongested conditions for each station/weather combination, and percent changes in speeds based on rainfall intensity were tested for statistical significance.

Operating speed reductions were not quite as dramatic as the capacity reductions discussed previously. Results indicated that the presence of rain is a more important factor than the difference in intensity, and decreased operating speeds by three to five percent. The difference between speed reductions during light and heavy rain is not statistically significant. This conclusion contradicts the results of the studies performed by Lamm, Choueiri, and Mailaender; and Ibrahim and Hall utilized in the HCM. Perhaps the low speed reduction is a result of an upper limit on free-flow speed not exceeding the speed limit. This data restriction may result in underestimating the effects of rain on operating speed. Researchers find that the study indicates rainfall has a greater impact on capacity than is currently presented in the HCM, and that the impact of heavy rainfall may be overstated.

Summary of Existing Literature on Weather Impacts on Macroscopic Traffic Parameters

Low Visibility

There is very limited research on the impact of low visibility on traffic flow. The Brilon and Ponzlet study in Germany indicated a 13 to 47 percent reduction in capacity in darkness, relative to daylight conditions. Additionally, the Kyte study found a 0.77 kilometer per hour (0.48-mile per hour) reduction in speed for every 0.01 kilometer (0.0062-mile) below the critical visibility of 0.3 kilometer (0.18-mile). There is anecdotal evidence that, in reduced visibility, drivers unconsciously increase their speed as they acclimate to foggy conditions. In a laboratory simulation, the more foggy environmental conditions were, the more drivers underestimated their speed (Snowden, et al., 1998).

Rain

There have been a number of studies investigating the impact of rain on traffic flow, particularly freeway speed and capacity. Table 2.6 summarizes the results of the studies.

Table 2.6 Summary of Rain Effects on Speed

	Speed Reduction		
Researcher	Ibrahim and Hall	Kyte	Smith
Location	Toronto, Ontario	Idaho	Hampton Roads, Virginia
Year	1994	2001	Smith
Light Rain	1.9-12.9 km/h (1.2-8 mph)	9.5 km/h (15.3 mph)	3-5%
Heavy Rain	4.8-16.1 km/h (3-10 mph)	9.5 km/h (15.3 mph)	3-5%

The Mitretek study indicated that travel time was increased between 3.4 to 25 percent during rain.

Snow

Similar to rain, there have been a significant number of studies investigating the impact of snow on freeway flow as presented in Table 2.7 and 2.8.

Table 2.7 Summary of Snow Effects on Volume

	Volume Reduction		
	Freeway		Arterial
Researcher	Hanbali and Kuemmel	Knapp	Maki
Location	Illinois, Minnesota, New York, Wisconsin	Iowa	Minneapolis, Minnesota
Year	1992	1995-1998	1999
Light Snow	7-31%	–	–
Heavy Snow	11-47%	16-47%	15-30%

Table 2.8 Summary of Snow Effects on Speed

	Speed Reduction			
	Freeway		Arterial	
Researcher	Ibrahim and Hall	Kyte	Maki	Perrin
Location	Toronto, Ontario	Idaho	Minneapolis, Minnesota	Salt Lake City, Utah
Year	1994	2001	1999	2001
Light Snow	0.97 km/h (0.6 mph)	16.4 km/h (26.4 mph)		13%
Heavy Snow	37.0-41.8 km/h (23-26 mph)	16.4 km/h (26.4 mph)	40%	25-30%

Heavy snow was also found by Ibrahim and Hall to decrease capacity by 30 percent, and light snow was found to decrease flows by five to 10 percent.

The following table summarizes the findings of research studies. A blank cell indicates that there are no empirical studies investigating a particular relationship. Most of these results reflect localized, mostly small sample research studies.

Table 2.9 Summary of Research Results – Freeway

	Volume	Maximum Observed Flow	Capacity	Speed
Low Visibility				↓ 13%
Rain		↓ 0-20%	↓ 4-47%	
Snow	↓ 7-47%	↓ 5-10%	↓ 30%	↓ 13-40%
Wind				↓ 10%

2.2 MICROSCOPIC BEHAVIOR RESEARCH

Macroscopic impacts on traffic flow resulting from adverse weather are the aggregate results of microscopic driver behavior. Microscopic driver behavior includes acceleration, deceleration, car-following, lane changing behavior, and gap acceptance. Though microscopic driving behavior models have been used for decades, knowledge of microscopic driving behavior remains limited, because human behavior is so complex and microscopic data collection is expensive.

To date, scarce research has been conducted on how weather events impact microscopic driving behavior logic, such as vehicle following and lane changing. While it is logical to conclude that adverse weather results in a more challenging driving environment, the exact mechanisms for a motorist's response to weather events are limited. Knowing which critical parameters within a driving behavior model should be changed under various weather conditions would aid in the development of weather-responsive traffic management strategies.

Colyar, et al. (2003) conducted a study to identify and assess the sensitivity of a range of model parameters that could be affected by weather events and which most impact the quality of traffic flow. However, this study did not research field data of microscopic driver behavior under different weather conditions.

Sterzin (2004) used aggregate weather and traffic data to refine and enhance microscopic driving behavior models used in a traffic simulator. Field data from a case study indicated that the presence of precipitation was significant in reducing speeds, and was incorporated into the acceleration and lane changing models with aggregate calibration. A sensitivity analysis of eight parameters within four key components of driving behavior – free-flow acceleration, car-following acceleration, lane changing, and gap acceptance – was performed. The sensitivity analysis indicated that car-following parameters had the most impact on modeling driving behavior in inclement weather, with desired speed and gap acceptance also playing a role. Calibration results found that car-following acceleration and deceleration were negatively affected by the presence of precipitation, while the critical gap (in lane changing behavior) was increased, indicating more cautious driving behavior. Additionally, the mean of desired free-flow speed decreased, while the spread of the distribution around the mean increased, in adverse weather. Sterzin reasoned that the range of aggressiveness of drivers increases the variability of desired speed in inclement weather, as some modify their behavior due to environmental conditions, while others do not.

The FHWA is currently sponsoring the Next Generation Simulation (NGSIM) program, which has a primary focus on microscopic modeling, including supporting documentation and validation data sets that describe the interactions of multimodal travelers; vehicles and highway systems; and interactions presented to them from traffic control devices, congestion, and other features of the environment. As part of this program, a variety of traffic microsimulation stakeholders were surveyed about the parameters and mechanisms used to capture a variety of influencing factors (weather and environment included). Responses showed that the models used to simulate acceleration and lane changing generally do not have any parameters that explicitly relate to weather and its effects.

This NGSIM effort is expected to provide enhanced understanding of microscopic driving behavior. However, evaluating the impacts of weather on this behavior is complicated by the fact that efforts to collect the trajectory data – detailed, subsecond vehicle position data that are typically used in simulation models development, estimation, and validation – are hindered by inclement weather. To date, the video recording technology is not sophisticated enough to capture vehicle trajectory data in low visibility or precipitation.

2.3 Human Factors Research

Studies that look at individual driver response to adverse weather are limited in number. Techniques used include use of driving simulators, use of video to observe individual vehicles in the traffic stream or installation of video in the vehicle to observe driver behavior under varying conditions. Driving simulators have a long history and have been used extensively in automobile design and safety evaluations. Use of video is increasing and has a variety of applications. The Next Generation Simulation project (NGSIM) being sponsored by FHWA is currently using video to help refine car-following and lane changing algorithms for the next generation of simulation models. The University of Michigan Transportation Research Institute (UMTRI) is currently videotaping a group of drivers to evaluate their reactions to curve and lane departure warning systems. The UMTRI application could also be matched with weather data, from either outside sources or the vehicle's "black box" to help evaluate driver response to adverse road weather conditions.

The Vehicle Infrastructure Integration (VII) Initiative is another source of research on driver behavior in adverse weather. Among the many applications of VII will be utilization of data available from the vehicle's "black box," and location data, to identify unsafe situations and address them through driver warnings. Automated control of the vehicle is the next possible step in extreme circumstances. Field tests currently getting underway will look at various uses of weather data collected directly through the vehicle. Temperature data as well as data on antilock braking system engagement and windshield wiper usage, for example, may be used in combination or individually to collect data on driver response to weather events.

The sources below document a variety of techniques to evaluate driver response to adverse weather. Driving simulators and surveys are the techniques that have been used most often. Driving simulators are a valuable tool with numerous applications but it is important to note that the driver is not under the same pressure as on the road. There are no consequences to mistakes and as a result drivers are not likely to behave in exactly the same manner. Surveys are based on recall or perception that may not match the actual performance of a driver in the field. One would anticipate that respondents might consider themselves better drivers than they actually are, and answer questions accordingly. However, surveys can be useful when targeted toward specific types of information.

Because the goals and methods of these studies vary so widely it is hard to draw clear conclusions regarding driver behavior in adverse weather. A number of the surveys conducted and some of the observational studies do indicate that drivers have a realistic view of the risks involved in adverse weather. While they do modify their behavior to some extent, the research indicates that the changes do not reflect the level of risk involved. This indicates a need for better driver education and also additional research into management and information systems that will help to modify driver behavior. There are some indications that real-time information systems placed in the field can help reduce the speed differential during times of adverse weather. There are also hopeful indications that high-quality pretrip information may influence driver behavior.

The findings have implications for research into the impact of adverse weather on traffic flow. It is important to obtain a better understanding of driver behavior during adverse weather and it is also critical to understand what strategies will influence behavior in a way that will improve safety.

A summary of research efforts targeted toward individual drivers is included in Table 2.10.

Table 2.10 Literature and Research on Focused on Individual Drivers

Reference	Authors	Year	Comment
Effects of Variable Message Signs on Driver Speed Behavior on a Section of Expressway under Adverse Fog Conditions	V. Ganesh Babu Kolisetty, Takamasa Iryo, Yasuo Asakura and Katsuhiko Kuroda, Kobe University Japan	2006	The authors used a driving simulator in a laboratory setting to examine the effect of VMS on driver speed behavior while viewing the information provided through VMS. The simulation focused on 8.5 km of an Expressway in Japan under foggy conditions in cases with and without VMS. Results showed that 40% of subjects were clearly impacted by the VMS, 40% were marginally impacted and 20% were not impacted at all.
Road Safety Evaluation Using a Driving Simulation Approach: Overview and Perspectives	A. Benedetto and L.V. Sant'Andrea, University of Roma, Italy	2005	This paper reviews current practice in the use of driving simulators and identifies an approach for using simulators to investigate the role of human factors in a multidisciplinary approach. Three promising areas of study are identified 1) theoretical investigations 2) road project validation 3) road safety audit and assessment. Weather is one of the suggested areas of research.
Analysis of ATIS Effect on Mode and Route Choice	Mohamed Abdel Aty and Fathy Abdella	2005	The objectives of this paper were to evaluate driver behavior in response to traveler information. Issues evaluated included mode choice, route diversion and adherence to pretrip route plan. A travel simulator was used as a data collection tool. The simulator uses a realistic network, two modes of travel, actual historical volumes and different weather conditions. Among the findings were that as the level of information is increased, including both pretrip and en-route, drivers are more likely to divert from their normal route.
Impact of Traveler Advisory Systems on Driving Speed: Some New Evidence	Linda Ng Boyle and F. Mannering	2004	This study used a full sized driving simulator to collect information on the effect of real-time weather/incident hazard information provided by VMS and in-vehicle information systems. The study found that these systems were effective in reducing speeds under adverse conditions but that drivers tended to increase their speed downstream of the hazardous area in an attempt to make up the lost time.
Road Safety and Weather Information: Weather and Transportation in Canada	J. Andrey, B.N. Mills and J. Vandermolen, University of Waterloo, Canada	2003	This paper summarizes current knowledge regarding weather-related crash risks and the role of weather information in road safety. It notes the lack of information due to the difficulties in monitoring weather-related driver behavior. A review of research found that most drivers access weather information prior to their trip but do not change their travel patterns. More research is needed to determine what level of information is needed to influence traveler decisions.
Motorists Perceptions of and Responses to Weather Hazards: Weather and Transportation in Canada	J. Andrey and C. Knapper, University of Waterloo, Canada	2003	This study used group interviews and a large sample public survey to explore driver reaction to weather hazards in southern Ontario. A parallel study was carried out with driving instructors. The survey results were then compared to objective measurements of risk, based on accident statistics. The study found that both drivers and instructors have a realistic view of driving risks in hazardous weather but that drivers do not tend to modify their behavior. Another problem identified was that driver education does not provide helpful strategies for coping with hazardous weather.

Table 2.10 Literature and Research on Focused on Individual Drivers (continued)

Reference	Authors	Year	Comment
Integrating Human Factor Evaluation in the Design Process of Roads – A Way to Improve Safety Standards for Rural Roads	S. Cafiso, G. LaCava, R. Heger, R. Lamm, University of Catania, Italy	2003	The objective of this project was to improve highway design standards with respect to human factors needs. A field data collection effort used an instrumented car traveling in traffic on two-lane roads. The car was equipped with GPS equipment, speed and acceleration sensors, a video camera recording a view of the driver and a suite of equipment to collect psycho-physiological responses. Based on the data a procedure was developed to categorize good and poor driving conditions.
Field Operational Test of the Freightliner/Meritor Wabco Roll Stability Advisor and Control at Praxair	C. Winkler, J. Sullivan, S. Bogard, R. Goodsell and M. Hagan, University of Michigan Transportation Research Institute	2002	The report documents the experience with a Field Operational Test of the Freightliner/Meritor Roll Stability Advisor and Control. The system is intended to reduce rollover risk and improve driver performance through in-cab messages. Where necessary it can slow the vehicle automatically. The system was tested under actual operating conditions with 14 drivers completing the study. Weather was one of the factors considered in system performance.
The "Darwin" Driver Vision Support System: Its Potential Impact on Driving Behavior and Road Safety in Conditions of Reduced Visibility	Phillip Barham, Luisa Andreone, Xiang Hua Zhang and Maxime Vache, University of Leeds, Oskar Faber TPA	2000	This paper described the Darwin project which tested a vision support system used to aid drivers during periods of low visibility. The system included the use of an onboard infrared camera for detecting objects and a virtual image to present the objects to drivers. A driving simulator was used to conduct a number of human factors evaluations. Useful information was provided on system design and the evaluation indicated that the system could encourage drivers to reduce headways.
Naturalistic Driving Studies: A Tool for the Development and Evaluation of In-Vehicle Systems	Robert Llaneras, University of Minnesota	1999	This study summarizes the results of an expert panel on naturalistic analysis methods, defined as those employing unobtrusive in-vehicle instrumentation to record driver behavior and vehicle performance over extended periods of time. The paper lists a number of research topics suitable for these types of studies.
Estimates of Driving Abilities and Skills in Different Conditions	T. Galski, T.H. Ehle and J.B. Williams, Kessler Institute for Rehabilitation, East Orange, New Jersey	1998	This research was a preliminary effort to determine whether various driving situations required different driving skills and abilities. Experienced driver evaluators and trainers estimated the magnitude of driving abilities and skills for different photographed driving situations. Results found some driving situations more demanding than others, but interestingly did not find a difference between good weather and adverse weather.
Driver Acceptance of Weather-Controlled Road Signs and Displays	P. Rama and J. Louma	1997	The study was designed to investigate driver acceptance of weather controlled signs on Finland's south coast. A series of VMS and Variable Speed Limit Signs are used to provide information and modify speeds based on information gathered from road weather monitoring systems. 590 drivers were interviewed at various intervals after implementation to assess their reactions. Survey responses indicated that only a small percentage of respondents modified their behavior. However the study pointed out the need for study based on real-time monitoring rather than recall.

Table 2.10 Literature and Research on Focused on Individual Drivers (continued)

Reference	Authors	Year	Comment
Estimates of Driver Mental Workload: A Long-Term Field Trial of Two Subsidiary Tasks	L.R. Zeitlin, City University of New York	1995	This human factors study evaluated driver mental workload in two vanpools over a four-year period in New York. The test took place on a variety of roadways and different conditions were recorded, including time of day, traffic conditions, vehicle density, speed, weather, and brake applications. It was noted that weather influenced drivers' ability.
Car-Following Measurements, Simulations, and a Proposed Procedure for Evaluating Safety	S. Chen,	1995	This paper describes how video data of highway traffic were used to study the effect of illumination, weather and traffic density on driver behavior. Results showed that environmental factors influence driver behavior mainly in congested traffic but not in free flow traffic.
The Advanced Transportation Weather Information System (ATWIS)	Mark S. Owens, University of North Dakota		The ATWIS project was designed to provide a current road and forecasted weather report to the traveling public and commercial vehicles across the Interstate system in the Dakotas and Minnesota. This five-year project helped demonstrate the feasibility of in-vehicle traveler information.
Commuters' Propensity to Change Transportation Decisions in Adverse Travel Conditions: Results from Behavioral Survey in Brussels	Asad Khattak and Andre de Palma, PATH Program, University of California Berkeley	1994	This study used a comprehensive behavioral survey to help understand traveler behavior under normal and unexpected travel conditions.
Weather Hazards: The Motorist's Perspective	J. Andrey and C. Knapper	1993	The study is based on a telephone survey of 200 drivers in Hamilton, Ontario and 200 drivers in Ottawa. The survey focused on whether various driver groups differed in their perceptions of weather hazards and their adjustments to them. The survey results indicated that most drivers have a realistic understanding of the risks of driving in adverse weather but that the adjustments they reported making did not reflect the magnitude of the hazard. The results indicated a need for both improved education and active measures to encourage more cautious behavior.

2.4 Research Needs and Approach

The preceding literature review shows that there is an initial base of research regarding the impacts of precipitation (both rain and snow) and other weather events on macroscopic traffic flow parameters and system performance. However, the results of these studies in terms of weather impacts on speed, capacity, and volumes are variable and often apply only to certain traffic states, on particular types of facilities, and in specific locations. Therefore, there is a need to improve and/or expand our understanding of how these common weather events impact driving behavior and traffic flow under varying demands, on heterogeneous facilities, and in different locations.

Research Focus

The next sections of this report describe the research work undertaken to better understand the impacts of weather on traffic flow. The research is intended to accomplish the following specific objectives:

1. Study the impact of precipitation on macroscopic traffic flow parameters over a full-range of traffic states.
2. Study the impact of precipitation on macroscopic traffic flow parameters using consistent, continuous weather variables.
3. Study the impact of precipitation on macroscopic traffic flow parameters on a wide-range of facilities.
4. Study regional differences in reaction to precipitation.
5. Study macroscopic impacts of reduced visibility.

The work was divided into two phases: Phase I involved developing a data collection and analysis plan, and Phase II focused on conducting the analysis and interpreting the results.

This report also describes the work that needs to be done for Phase III research that will examine human factors and their influences on microscopic traffic parameters such as desired speed, acceleration, and minimum gap during common weather conditions such as rain and snow precipitation. The proposed research includes human studies of individual characteristics and behavior.

3.0 Research Methodology

This chapter presents a research plan aimed at compiling appropriate data for the analysis of weather impacts on traffic flow behavior and critical traffic stream parameters, namely free-flow speed (u_f), speed-at-capacity (u_c), capacity (q_c), and jam density (k_j). The research plan fuses weather and loop detector data to address two critical issues, namely:

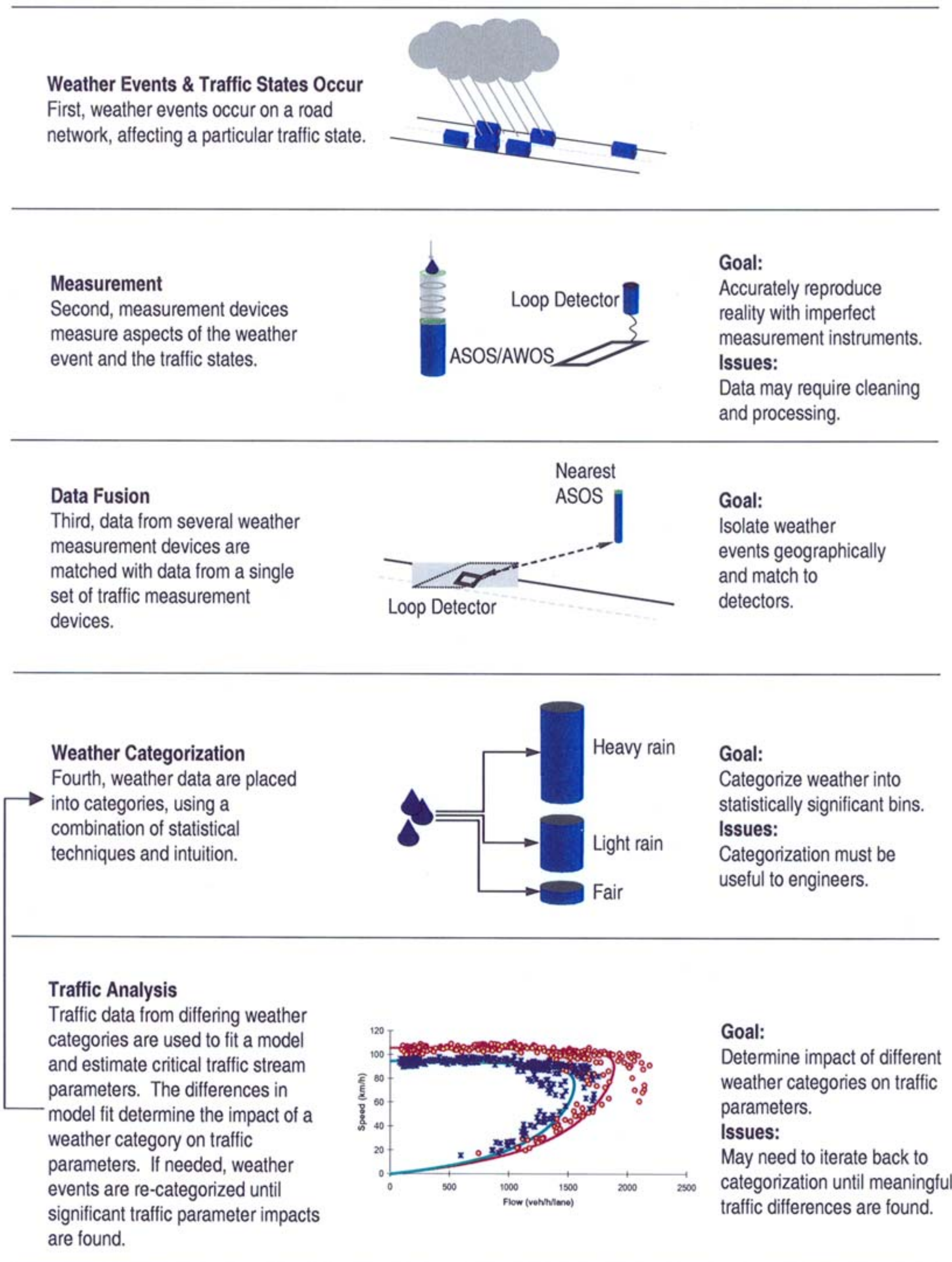
1. Study the impact of precipitation on macroscopic traffic flow indicators over a full-range of traffic states, and

2. Investigate the potential for regional differences in precipitation impacts.

The study analyzes data from three metropolitan areas that cover a wide-range of weather conditions within the U.S. These sites include Baltimore, the Twin Cities, and Seattle. Loop detector data aggregated to a five-minute level of resolution are analyzed as part of the study. In addition, real-time local weather data including precipitation rates are assembled. Utilizing the loop detector data, fundamental diagrams are fit to the data by minimizing a normalized orthogonal error between field observations and model estimates. The optimum free-flow speed, speed-at-capacity, capacity, and jam density are computed for different weather conditions and inclement weather adjustment factors are developed for each precipitation level. Furthermore, statistical models are developed to characterize the behavior of these parameters as a function of the precipitation type and intensity. The procedures developed as part of this project can be easily implemented within the basic freeway procedures of the Highway Capacity Manual (HCM) given that the level of service (LOS) and capacity of a basic freeway segment is characterized using two of the four critical traffic stream parameters, namely: free-flow speed and capacity. It is envisioned that the inclement weather adjustment factor will be applied in a similar fashion to the standard HCM adjustment factors (lane width, lateral clearance, heavy vehicle, etc.) to estimate a final free-flow speed and capacity that is reflective of both traffic and weather conditions.

The steps required for this approach are illustrated in the flowchart below:

Figure 3.1 Research Methodology Steps



The specifics of the proposed research approach are described in this section. Initially, key traffic stream variables are described. Subsequently, different forms of the fundamental traffic equation are discussed together with the reasoning for selecting the Van Aerde functional form. Subsequently, the statistical techniques that are utilized to analyze the data and develop models that characterize the behavior of critical traffic stream variables as a function of precipitation rates are discussed.

3.1 KEY TRAFFIC VARIABLES

Prior to describing the specifics of the research plan, a brief introduction of traffic stream variables is presented to set the stage for the analysis. Traffic stream motion can be formulated either as discrete entities or as a continuous flow. Microscopic car-following models, which form the discrete entity approach, characterize the relationship between a vehicle's desired speed and distance headway h) between it and the preceding vehicle traveling in the same lane. Alternatively, traffic stream models describe the motion of a traffic stream by approximating the flow of a continuous compressible fluid. Traffic stream models relate three traffic stream variables, namely:

- **Traffic stream flow rate (*q*) –** the number of vehicles that pass a point per unit of time,
- **Traffic stream density (*k*) –** the number of vehicles along a section of highway and
- **Traffic stream space-mean-speed (*u*) –** a density weighted average speed (the average speed of all vehicles on a given section of the highway at any given time).

In solving for the three traffic stream variables (q, k, and u) three relationships are required. The first relationship among is inherent in the quantity definition, which states that

$$q = ku . \qquad [1]$$

The second relationship is the flow continuity relationship, which can be expressed as

$$\frac{\partial k}{\partial t} + \frac{\partial q}{\partial x} = S(x,t) \qquad [2]$$

where $S(x,t)$ is the generation (dissipation) rate of vehicles per unit time and length. This equation ensures that vehicles are neither created nor destroyed along a roadway section.

Both of the above relationships are true for all fluids, including traffic and there is no controversy as to their validity. However, it is the controversy about the third equation, that gives a one-to-one relationship between speed and density or between flow and density, which has led to the development of many fundamental diagrams, also known as first-order continuum models. These models state that the average traffic speed is a function of traffic density. These functional forms describe how traffic stream behavior changes as a function of traffic stream states. Furthermore, they define the values of the critical traffic stream parameters, namely: free-flow speed, speed-at-capacity, capacity, and jam density.

The research plan uses macroscopic traffic stream models to estimate a facility's free-flow speed, speed-at-capacity, capacity, and jam density during normal and inclement weather conditions. Subsequently, procedures for characterizing inclement weather impacts on traffic stream behavior and critical traffic stream parameters are developed.

3.2 Selected Traffic Stream Model – Van Aerde

Why Traffic Stream Models?

The basic premise of the Lighthill, Whitham and Richards (LWR) theory is a fundamental diagram that relates the three basic traffic stream parameters; flow, density, and space-mean speed. The calibration of traffic stream or car-following behavior within a microscopic simulation model can be viewed as a two-step process. In the first step, the steady-state behavior is calibrated followed by a calibration of the nonsteady state behavior. Steady-state or stationary conditions occur when traffic states remain practically constant over a short time Δt and some length of roadway Δx. The calibration of the steady-state behavior involves characterizing the fundamental diagram that was described earlier and is critical because it dictates:

- the maximum roadway throughput (capacity),
- the speed at which vehicles travel at different levels of congestion (traffic stream behavior), and
- the spatial extent of queues when fully stopped (jam density).

Alternatively, the calibration of the nonsteady state behavior influences how vehicles move from one steady-state to another. Thus, it captures the capacity reduction that results from traffic breakdown and the loss of capacity during the first few seconds as vehicles depart from a traffic signal (commonly known as the start loss). Under certain circumstances, the non-steady-state behavior can influence steady-state behavior. For example, vehicle dynamics may prevent a vehicle from attaining steady-state conditions. A typical example of such a case is the motion of a truck along a significant upgrade section. In this case, the actual speed of the truck is less than the desired steady-state speed because the vehicle dynamics prevent the vehicle from attaining its desired speed. The analysis of such instances is beyond the scope of this study but is provided elsewhere (Rakha and Lucic, 2000; Rakha et al., 2004; Rakha and Ahn, 2004; Rakha and Pasumarthy, 2005).

State-of-Practice Single Order Continuum Models

In selecting the appropriate model for this analysis it is useful to note that traffic models developed over the years have used the same basic variables as those discussed in Section 2. Various functions and relationships have been developed between speed, jam density and/or capacity. Later research attempted to look at differences in driver behavior; specifically the fact that some drivers tend to leave less separation in congested conditions.

Further research on each of the above single regime models revealed deficiencies over some portion of the density-range. The most significant problem that these model development efforts have not solved is their inability to track the measured field data near capacity conditions (May, 1990). This led several researchers to propose two- and multi-regime models with separate formulations for the free-flow and congested-flow regimes.

As a result several multi-regime models have been proposed over the past 40 years. These models developed different formulations depending on the level of congestion with separate formulations for free-flow and congested-flow. Some models included a third category called "transitional flow." Other models developed identified different relationships for the inside lanes and the outside lanes using the theory that more aggressive higher performance vehicles tend to travel in the left lanes.

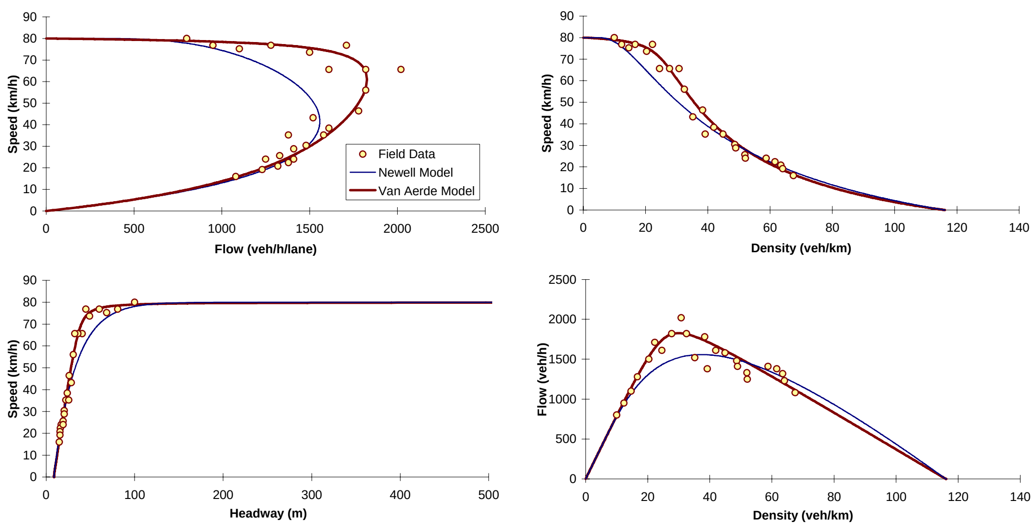
While multi-regime models are more advanced than the single-regime models it should be noted that a major disadvantage of multi-regime models are issues related to model calibration. Specifically, the calibration of these multi-regime models is challenging because one needs to identify the cut-points for each of the model regimes and identify which regime field observations fall into.

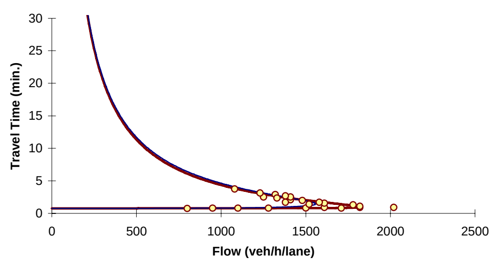
Figure 3.2 illustrates two sample fits to field observed data for five domains: the speed-flow, speed-density, density-flow, speed-headway, and speed-travel time domains. A visual inspection of the figure provides some good insight into model calibration. Table 3.1 summarizes the effectiveness of various models in estimating key parameters.

- First, an accurate estimation of the critical traffic stream parameters (u_f, u_c, q_c, and k_j) hinges on a good functional form.
- Second, a functional form that provides a good or reasonable fit in one domain does not necessitate a good fit in other domains. For example, the Newell model provides a reasonable fit in the speed-headway and speed-density relationships; however does a poor job in the speed-flow domain.
- Third, it is difficult to produce a good fit for all traffic states. For example, the Newell model provides a good fit for minimal and maximal flow conditions (free-flow speed and jam density); however the quality of the fit deteriorates as traffic approaches capacity. Table 3.1 also demonstrates that the Van Aerde functional form provides sufficient degrees of freedom to produce a good fit for all traffic states across the various regimes and

domains. A brief description of the Van Aerde model is provided in the following section. The quality of traffic stream parameter estimation is clearly demonstrated in Table 3.1. The results for all models except the Van Aerde model that are presented in Table 3.1 were obtained from May (1990) and demonstrate that apart from the Van Aerde model, all single- and multi-regime models do not provide a good estimate of the four traffic stream parameters. Consequently, the Van Aerde functional form will be used to estimate the four critical traffic stream parameters.

Figure 3.2 Van Aerde and Newell Model Fit to Freeway Data
(Data Source: May, 1990; page 292)





Parameter	Van Aerde Model	Newell Model
Free-Speed (km/h):	80	80
Capacity (veh/h):	1,827	1,558
Speed-at-Capacity (km/h):	61	41
Jam Density (veh/km):	116	116
Wave Speed (km/h):	-24	-28

Table 3.1 Comparison of Flow Parameters for Single-Regime, Multiple-Regime Models, and Proposed Model

Type of Model	Model	Free-flow speed (km/h)	Speed-at-Capacity (km/h)	Capacity (vph/lane)	Jam density (veh/km)
Valid Data Range [3]		80-88	45-61	1,800-2,000	116-156
Single-Regime	Greenshields	91	46	1,800	78
	Greenberg	∞	37	1,565	116
	Underwood	120	45	1,590	∞
	Northwestern	77	48	1,810	∞
	Newell	80	41	1,558	116
Multi-Regime	Edie	88	64	2,025	101
	2-Regime	98	48	1,800	94
	Modified Greenberg	77	53	1,760	91
	3-Regime	80	66	1,815	94
Van Aerde Model		80	61	1,827	116

Note: Highlighted cells are outside the valid data range for specified parameter.
Source: May, 1990 pages 300 and 303.

Van Aerde Model

The functional form that is utilized in this study is the Van Aerde nonlinear functional form that was proposed by Van Aerde (1995) and Van Aerde and Rakha (1995). The model bases the distance headway (km) of a vehicle (*n*) on:

- the speed of vehicle *n* (km/h);
- the facility free-flow speed (km/h);
- a fixed distance headway constant (km);
- a variable headway constant (km^2/h); and
- a variable distance headway constant (h^{-1}).

This combination provides a linear increase in vehicle speed as the distance headway increases with a smooth transition from the congested to the uncongested regime. This combination provides a functional form with four degrees of freedom by allowing the speed-at-capacity to differ from the free-flow speed or half the free-flow speed, as is the case with the Greenshields model. Specifically, the equation provides the linear increase in the vehicle speed as a function of the distance headway, while the third parameter introduces curvature to the model and imposes a constraint on the vehicle's speed to ensure that it does not exceed the facility free-flow speed through the use of a continuous function.

Ignoring differences in vehicle speeds and headways within a traffic stream and considering the relationship between traffic stream density and traffic spacing, the speed-density relationship can be derived as a function of the traffic stream density (veh/km) and the traffic stream space-mean speed (km/h) assuming that all vehicles are traveling at the same average speed (by definition given that the traffic stream is in steady-state). A more detailed description of the mathematical properties of this functional form can be found in the literature (Rakha and Van Aerde, 1995 and Rakha and Crowther, 2002), including a discussion of the rationale for its structure.[1]

Table 3.2 illustrates the critical traffic stream parameter estimates using the Van Aerde functional form for a number of facility types, demonstrating the flexibility of the model.

Table 3.2 Estimated Flow Parameters for Various Facility Types

Source	Facility Type	No. Obs.	Free-Flow Speed (km/h)	Speed-at-Capacity (km/h)	Capacity (veh/h/lane)	Jam density (veh/km/lane)
May, 1990	Freeway	24	80.0	61.0	1,827.0	116.0
May, 1990	Tunnel	24	67.5	33.8	1,262.5	125.0
May, 1990	Arterial	33	45.0	22.5	581.5	101.9
Orlando	I-4 Fwy	288	87.0	75.5	1,906.3	116.0
Toronto	401 Fwy	282	105.6	90.0	1,888.0	100.0
Amsterdam	Ring Road	1,199	99.0	86.3	2,481.3	114.7
Germany	Autobahn	3,215	160.0	105.0	2,100.0	100.0

Model Calibration

The calibration of macroscopic speed-flow-density relationships requires identification of a number of key parameters, including the facility's capacity, speed-at-capacity, free-flow speed, and jam density.

This section describes the proposed method for calibrating steady-state car-following and traffic stream behavior using the Van Aerde steady-state model,

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[1] Of interest is the fact the Van-Aerde Equation reverts to Greenshields' linear model, when the speed-at-capacity and density-at-capacity are both set equal to half the free-flow speed and jam density, respectively (i.e. $u_c=u_f/2$ and $k_c=k_j/2$). Alternatively, setting $u_c=u_f$ results in the linear Pipes model given that

$$c_1 = \frac{1}{k_j} = h_j; \quad c_2 = 0; \quad c_3 = \frac{1}{q_c} - \frac{1}{k_j u_f}.$$

which is described elsewhere in the literature (Van Aerde, 1995; Van Aerde and Rakha, 1995). The Van Aerde functional form is selected because it offers sufficient degrees of freedom to capture traffic stream behavior for different facility types, which is not the case for other functional forms. Van Aerde and Rakha (1995) presented a calibration procedure that has been enhanced to address field application needs. The technique considers macroscopic speed, flow, and density as dependent variables, and that relative errors in speed, density, or volume of equal magnitude should be considered to be of equal importance. The technique involves the optimization of a quadratic objective function that is subject to a set of nonlinear constraints. This optimization, which requires the use of an incremental optimization search, is demonstrated for several sample and field data sets. The results are compared to several previous analyses that also attempt to fit a linear or nonlinear relationship between the independent variable density and the dependent variable speed. An extensive review of the historical difficulties associated with such fits can be found in the literature (May, 1990).

It is common in the literature to utilize the traffic stream space-mean speed as the dependent variable and the traffic stream density as the independent variable in the calibration of speed-flow-density relationships. However, such a regression fit can only be utilized to estimate speed from density given that the regression minimizes the speed estimate error. To overcome this shortcoming, a concept of fitting a relationship between speed, flow, and density, which does not consider one variable to be more independent than another was considered. The calibration of macroscopic speed-flow-density relationships requires identification of a number of key parameters, including the facility's expected or **mean** four parameters, namely; capacity (q_c), speed-at-capacity (u_c), free-flow speed (u_f), and jam density (k_j). The overall calibration effort requires that four decisions be made, namely:

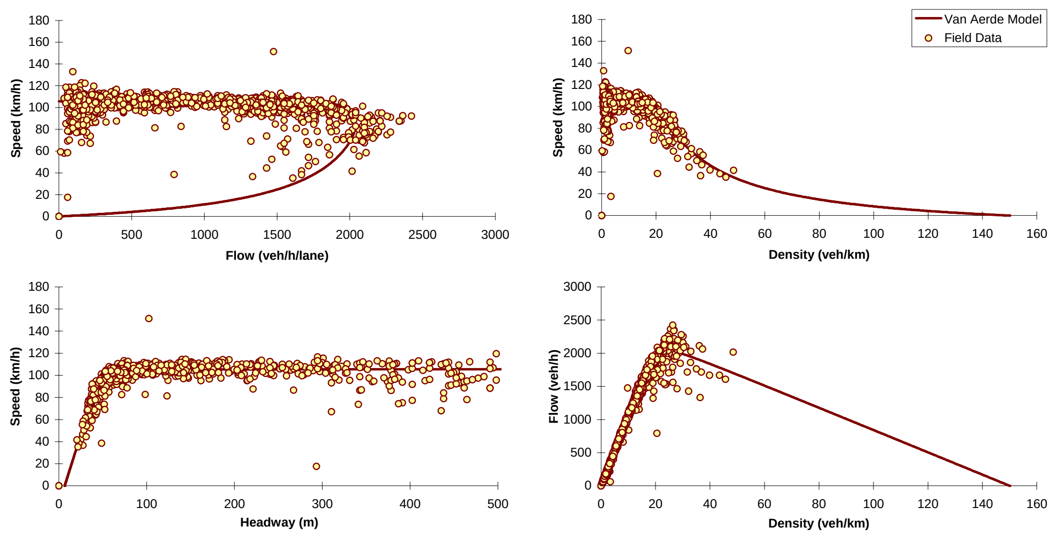
1. define the functional form to be calibrated;
2. identify the dependent and the independent variables;
3. define the *optimum* set of parameters; and
4. develop an optimization technique to compute the set of parameter values.

A heuristic tool was developed (SPD_CAL) and described in the literature to calibrate traffic stream models (Rakha and Arafeh, 2007). The procedure can be summarized briefly as follows:

- Aggregate the raw data based on traffic stream density bins in order to reduce the computational space;
- Initialize the four traffic stream parameters u_f, u_c, q_c, and $k_{j;}$
- Construct the model functional form and move along the functional form incrementally to compute the objective function. The accuracy of the objective function computation and the computational speed will depend on the size of the increments used;

- Vary the four parameters between minimum and maximum values using a specified increment;
- Construct the model functional form for each parameter combination and move along the function form incrementally to compute the objective function. Note that the computational accuracy increases as the iteration number increases;
- Compute the set of parameters u_f^i, u_c^i, q_c^i, and k_j^i that minimize the objective function;
- Compute minimums and maximums for each variable at specified increments; and
- Go to step 3 and continue until either the number of iterations is satisfied or the minimum change in objective function is satisfied.

Figure 3.3 Van Aerde Model Fit to Freeway Data (Twin Cities, USA)



Free-Speed:	106 km/h
Capacity:	2041 veh/h/lane
Speed-at-Capacity:	85 km/h
Jam Density:	150 veh/km/lane
Wave Speed (wj):	-17.0 km/h

The fit to five-minute data from the Twin Cities, Minnesota, demonstrates that the calibration tool is able to capture the functional form of the data, as illustrated in Figure 3.3. The figure clearly demonstrates the effectiveness of the proposed calibration tool together with the Van Aerde functional form to reflect steady-state traffic stream behavior on this facility over multiple regimes.

3.3 DATA ANALYSIS AND MODEL DEVELOPMENT

The first step in the data analysis will be to obtain a subset of reliable data for processing, by screening the data as follows:

1. Incident data will be removed from the dataset so that the dataset only includes data during incident-free conditions;
2. Detectors in the merging lanes and weaving sections will be removed from the data processing;
3. Using the weather data, the loop detector data will be grouped into different categories. For example, data may be grouped based on the intensity of precipitation. Data from multiple days may be grouped together to ensure that data cover a significant range of traffic states; and
4. Data will be screened for any missing and unrealistic data.

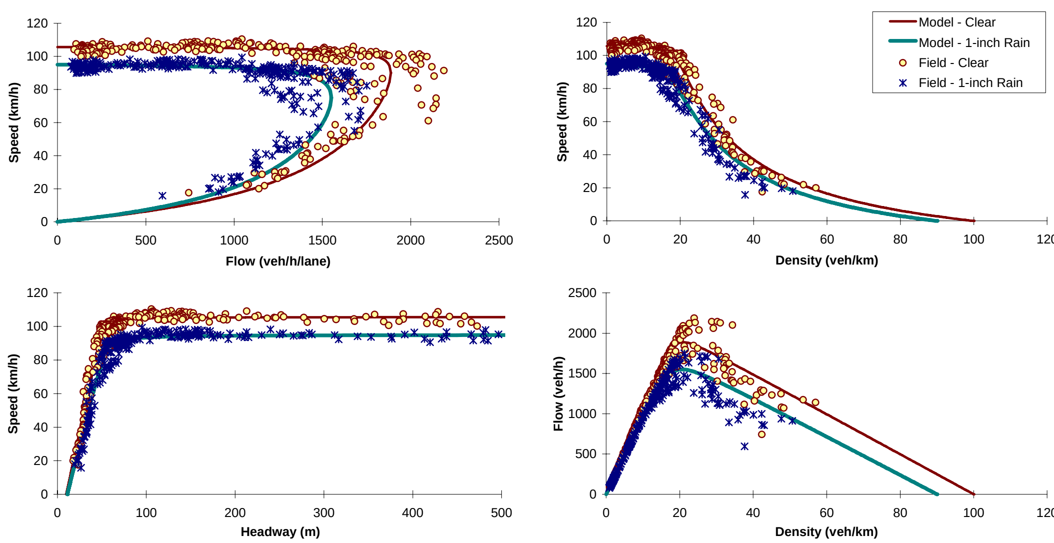
The processed data will be used to study:

- the impact of precipitation on macroscopic traffic flow indicators over a full range of traffic states.
- the impact of precipitation on macroscopic traffic flow indicators using consistent, continuous weather variables.
- the impact of precipitation on macroscopic traffic flow indicators on a wide range of facilities.
- regional differences in reaction to precipitation.
- macroscopic impacts of reduced visibility.

Impacts of Precipitation

The short-term direction of the research, as defined by the first four research questions described earlier deal with answering how precipitation affects driving, as a factor of: 1) Traffic State, 2) Intensity, 3) Facility, and 4) Region. The fifth research question addresses the affect of visibility on driving. In order to study the impacts of precipitation on traffic flow and precipitation intensity, the optimum four traffic stream parameters (free-flow speed, speed-at-capacity, capacity, and jam density) will be calibrated for a number of days. A distribution of typical parameter values will be constructed. Depending on the number of inclement weather conditions and the range of states that the inclement weather conditions cover, either a single or multiple repetitions of the data may be available for each site. The distribution of each parameter for the base conditions (ideal weather) will then be compared to the inclement weather parameters. Subsequently, t-statistics will be used to test if the mean parameter values are statistically different. In addition, analysis of variance (ANOVA) tests will be conducted on the data to identify any potential statistical differences for various parameters, including weather, regional differences, and the combination of both weather and regional differences. Figure 3.4 illustrates a sample functional relationship for ideal and inclement weather conditions. The figure also summarizes the key four parameter estimates for both instances and computes a multiplicative inclement weather adjustment factor. The statistical tests that will be conducted will investigate if these adjustment factors are statistically significant, or within the range of typical daily variations.

Figure 3.4 Impact of Precipitation on Traffic Stream Behavior and Parameters



Parameter	Normal	Inclement	F
Free-Speed (km/h):	106	95	0.90
Capacity (veh/h):	1888	1550	0.82
Speed-at-Capacity (km/h):	90	75	0.83
Jam Density (veh/km):	100	90	0.90
Wave Speed (wj) (km/h):	-25.0	-24.3	0.97

The first two research issues:

1. The impact of precipitation on macroscopic traffic flow indicators over a full range of traffic states; and
2. The impact of precipitation on macroscopic traffic flow indicators using consistent, continuous weather variables

will be addressed within the context of the analysis procedure shown above. Different states of congestion can be defined along different portions of the curves. Additional curves can be defined based on the characteristics of weather events, with categories based on precipitation type and intensity. These sets of curves can ultimately be utilized to define different adjustment factors as shown in Table 3.3 below:

Table 3.3 Hypothetical Capacity Adjustment Factors

Congestion State	Weather State				
	Clear	Light to Moderate Rain	Heavy Rain	Light Snow	Heavy Snow
Uncongested	1.0	0.95	0.85	0.9	0.75
Transitional	1.0	0.90	0.7	0.8	0.55
Congested	1.0	0.75	0.55	0.6	0.40

Statistical Analysis

Crow et al. (1960) state that "the data obtained from an experiment involving several levels of one or more factors are analyzed by the technique of analysis of variance. This technique enables us to break down the variance of the measured variable into the portions caused by the several factors, varied singly or in combination, and a portion caused by experimental error. More precisely, analysis of variance consists of 1) partitioning of the total sum of squares of deviations from the mean into two or more component sums of squares, each of which is associated with a particular factor or with experimental error, and 2) a parallel partitioning of the total number of degrees of freedom. The assumptions of the analysis of variance (ANOVA) technique are that the dependent variable populations have the same variance and are normally distributed (Littell et al., 1991). Consequently, tests were conducted to ensure that the dependent variables were normally distributed using the Shapiro-Wilk statistic which produces a score ranging from 0 to 1. The closer the score is to 1, the more likely the data are normally distributed.

The distinction between normality and non-normality of data and what should be done in the case non-normality exists are two controversial issues. Some researchers, on the one hand, believe that the ANOVA technique is robust and can be used with data that do not conform to normality. On the other hand, other researchers believe that nonparametric techniques should be used whenever there is a question of normality. Research has shown that data that do not conform to normality due to skewness and/or outliers can cause an ANOVA to report more type 1 and type 2 errors (Ott, 1989). Conover (1980) recommends use of ANOVA on raw data and ranked data in experimental designs where no nonparametric test exists. The results from the two analyses can then be compared. If the results are nearly identical then the parametric test is valid. If the rank transformed analysis indicates substantially different results than the parametric test, then the ranked data analysis should be used. As a result, an approach using both an ANOVA on the normalized data and an ANOVA on rank-transformed data may be utilized depending on the normality of the data. We suggest ranking the data when the Shapiro-Wilk test is less than 0.85.

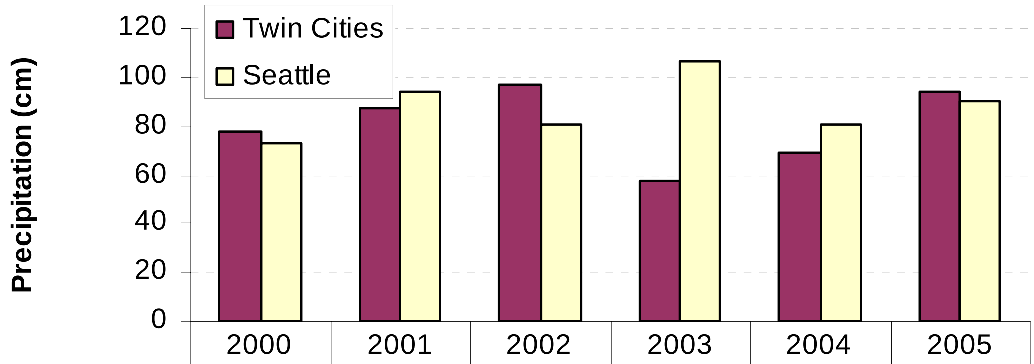
4.0 Data Collection

This section summarizes the weather and traffic field data collection used in the research study. A description of the data sources is followed by a discussion of the dataset construction and data analysis.

4.1 Field Data Description

The data used in this study were obtained from three major metropolitan areas in the U.S.: the Twin Cities, MN; Seattle, WA; and Baltimore, MD. For each city two sets of data were obtained for the analysis: traffic data and weather data. Traffic data included traffic stream speed, flow, and density estimates obtained from inductive loop detectors (in the case of Seattle and the Twin Cities) or microwave radar detectors (in the case of Baltimore). Weather data were available from two sources; the Road Weather Information System (RWIS) stations operated by DOTs, and the Automated Surface Observing System (ASOS) stations located at airports. An initial analysis of RWIS data in the Twin Cities Area revealed that the precipitation and visibility readings were either missing or invalid. Consequently, only the ASOS data were utilized for the entire analysis in order to maintain a level of consistency across the various locations. For each study area two years worth of data were utilized for the analysis. The highest total precipitation year was selected for the analysis for Seattle and the Twin Cities, respectively along with the most recent year of data. In the case of Baltimore, the latest data were used for the analysis. Using this criterion the following years were selected for the study; 2002 and 2004 for the Twin Cities, 2003 and 2004 for Seattle, and 2002 and 2003 for Baltimore. The analysis included data for 2004 because this represented the latest available five-minute weather data at the time of the study for the Twin Cities and Seattle Areas. The analysis also included data for 2003 and 2002 because these years had the highest annual precipitation rates in the five-year timeframe for which weather data were available, as illustrated in Figure 4.1. In the case of Baltimore the analysis was confined to 2002 and 2003 because traffic and weather data were only available for these two years.

Figure 4.1 Annual Precipitation Rates for Twin Cities and Seattle



	2000	2001	2002	2003	2004	2005
Twin Cities	77.42	86.94	97.10	57.71	69.57	93.73
Seattle	72.87	94.06	80.29	106.53	80.19	90.35

Year

This section briefly describes the weather and traffic data used in the analysis.

Weather Data

The weather data used for all cities were obtained from the ASOS system. This system is sponsored by the Federal Aviation Administration (FAA), National Weather Service (NWS), and the Department of Defense (DOD). ASOS provides weather observations which include: temperature, dew point, wind, altimeter setting, visibility, sky condition, and precipitation. Five hundred sixty-nine (569) FAA-sponsored and 313 NWS-sponsored ASOS stations are installed at airports throughout the USA. The weather reports by ASOS that were used in this study were of METAR type (Aviation Routine Weather Reports) and contained precipitation type, precipitation intensities (inch/h), visibility readings (mile), at five-minute intervals. ASOS also provided other climatic parameters such as temperature, dew point, wind, altimeter setting, and sky condition, however these factors were not considered in this study. The ASOS stations that were used in this study were Minneapolis-St. Paul International Airport, Seattle-Tacoma International Airport, and the Baltimore-Washington International Airport. The following paragraphs briefly describe visibility and precipitation readings from the ASOS stations.

ASOS visibility measurements were performed at 30-second increments using a forward scatter sensor to compute one-minute average extinction coefficients (sum of the absorption and the scattering coefficients). For this purpose, a photocell that identified the time-of-day (day or night) was used to select the appropriate equation for use in the procedure. The ASOS system computed a one-minute average visibility level that was used to compute a 10-minute moving average (MA) visibility level. This value was then rounded down to the nearest reportable visibility level. ASOS visibility was reported in 0.4-km (0.25-mi) increments up to 3.2 km (2 mi) then at 1.6 km (1 mi) increments to a maximum of 16 km (10 mi). Visibilities greater than 16 km were reported as 16 km and values less than a 0.4 km were recorded as a 0.4 km visibility level.

Four intervals were used to represent different levels of visibility observations: less than 0.8 km (0.5 miles), 0.8 to 1.6 km (0.5 to 1 miles), 1.6 to 4.8 km (1 to 3 miles), and greater than 4.8 km (3 miles).

ASOS used precipitation identification sensors to determine the type of precipitation (rain, snow, or freezing rain). Precipitation intensity was recorded as liquid-equivalent precipitation accumulation measurements using a heated Tipping Bucket (HTB) gauge. The HTB has a resolution of 0.025 cm (0.01 in) and an accuracy of ±0.05 cm (±0.02 in) or 4 percent of the hourly total; whichever is greater.

Rain intensities were divided into three categories: less than 0.025 cm/h (0.01 inch/h), 0.025 to 0.64 cm/h (0.01 to 0.25 inch/h), and greater than 0.64 cm/h (0.25 inch/h). Similarly, snow intensity data were also grouped into three categories: less than 0.13 cm/h (0.05 inch/h), 0.13 to 0.25 cm/h (0.05 to 0.1) inch/h, and greater than 0.25 cm/h (0.1 inch/h). These categories are consistent with previous studies (Agarwal et al. 2005).

Table 4.1 shows the different combinations of visibility and precipitation intensities that were used in this study.

Table 4.1 Precipitation/visibility Combinations Considered

	Visibility (km)			
	<0.8	0.8-1.6	1.6-4.8	>4.8
D: No Precipitation	✓	✓	✓	Base Case
S1: Snow: ≤ 0.127 cm/h	✓	✓	✓	✓
S2: Snow: 0.127-0.254 cm/h	✓	✓	✓	✓
S3: Snow: >0.254 cm/h	✓	✓	✓	✓
R1: Rain: ≤ 0.025 cm/h	✓	✓	✓	✓
R2: Rain: 0.025-0.64 cm/h	✓	✓	✓	✓
R3: Rain: > 0.64 cm/h	✓	✓	✓	✓

Traffic Data

Traffic data were extracted from data reports of study areas' freeway detector systems. Each study area used different data collection technologies and temporal aggregation resolutions, however, at all three locations traffic data were gathered on a lane-by-lane basis. A time interval of five minutes was selected for the analysis in order to be consistent with the ASOS weather data resolution. Four, five, and three detector stations were considered in the Twin Cities, Seattle, and Baltimore areas, respectively. The sites were selected based on the following criteria:

1. The recorded data provided sufficient coverage for all traffic conditions, i.e., uncongested, around capacity, and congested conditions, to allow a full analysis over all traffic regimes.
2. Not within the influence area of merge, diverge, or weaving sections in order to ensure that changes in traffic stream flow were not impacted by lane changing behavior. The influence area of a ramp was considered to be a distance of 400 m (0.25 mi) or less from the ramp.
3. If possible, lanes were neither a shoulder nor median lane because behavior in shoulder lanes are impacted by traffic merge and diverge behavior while traffic stream behavior in median lanes could be associated with High Occupancy Vehicle (HOV) restrictions.
4. Outside the influence of any incidents. This objective was achieved by screening data using incident information obtained from DOTs. The incident information included time of detection, time of clearance, and the location of the incident.
5. As close as possible to ASOS stations.

Twin Cities, Minnesota

Traffic data were available from approximately 4,000 single loop detectors installed on freeway lanes within the Twin Cities area. Each detector recorded the volume and occupancy every 30 seconds. As part of the analysis, the data were aggregated at five-minute time intervals in order to be consistent with the ASOS weather data temporal resolution. The traffic stream variables were computed using equations [3], [4] and [5].

$$q = 3600\frac{n}{T} \qquad [3]$$

$$k = 1000\frac{O}{D \times 100} = 10\frac{O}{D} \qquad [4]$$

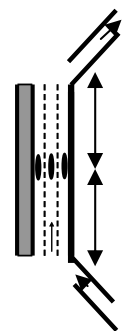
$$u = \frac{q}{k} \qquad [5]$$

where q is the traffic stream flow rate (veh/h/lane), k is traffic stream density (veh/km/lane), u is the space-mean speed (km/h), T is the polling interval (s), n is the number of vehicles observed during a polling interval, O is the detector occupancy during a polling interval (percent), and D is the calibrated detector field length which includes the length of the detection zone plus an average vehicle length (m).

A set of four detectors in the vicinity of the ASOS sites were selected based on the previously described site selection criteria. The closest detector was 5.4 km (3.4 mi) from an ASOS station while the farthest detector was 15 km (9.3 mi) from the weather station. Table 4.2 provides further information on the detectors in the Twin Cities area that were utilized in this study. All selected detectors were located on the middle lane of three-lane sections. Two of the detectors (D2463 and D2390) were in different directions of the same section of freeway.

Table 4.2 Detector Summary Information

Detector	Location	Lane	Detector Type	No. of lanes	Distance to ASOS (km)	d_{down} (km)	d_{up} (km)
D3294	Twin Cities	Middle	Single loop	3	5.4	2.0	1.5
D2390	Twin Cities	Middle	Single loop	3	15	0.4	1.35
D2463	Twin Cities	Middle	Single loop	3	15	1.35	0.4
D2387	Twin Cities	Middle	Single loop	3	14.6	0.9	0.45
042DS_T2	Seattle	Middle	Dual loop	3 + HOV	4.7	1.4	1.3
042DN_T2	Seattle	Middle	Dual loop	3 + HOV	4.7	0.9	1.4
333DN_T2	Seattle	Beside HOV	Dual loop	2 + HOV	7	1.9	1.0
333DS_T2	Seattle	Beside HOV	Dual loop	2 + HOV	7	0.45	2.1
024DN_T2	Seattle	3rd from shoulder	Dual loop	4 + HOV	11.8	1.1	2.6
316008_L2	Baltimore	2nd from median	Microwave	4	18.7	2.4	1.6
403018_L2	Baltimore	2nd from median	Microwave	4	25	0.9	1.5
403023_L2	Baltimore	2nd from median	Microwave	4	15	0.6	1.4



Seattle, Washington

The Washington State Department of Transportation (WSDOT) operates a Traffic Management Center (TMC) in the Seattle metropolitan area that collects and records traffic data on the Seattle freeway network. At the time of the study traffic data were gathered by a network of single and dual loop detectors. The recorded data were publicly available through the Traffic Data Acquisition and Distribution (TDAD) project's web site, which was developed by the University of Washington.

From more than 700 available dual loop detectors, five sites were selected based on the selection criteria described earlier. For some of the detectors, data for multiple lanes were included in the analysis, as summarized in Table 4.2. The distance of the selected sensors from the ASOS stations ranged between 3.2 and 11.8 km (2.0 and 7.3 mi). The frequency of data recording was 20 seconds, and each dual loop detector measured traffic stream time-mean speed and flow at 20-second intervals. The data were then aggregated into five-minute intervals in order to be consistent with the ASOS data collection temporal resolution. The five-minute speed conversion was performed using a flow-weighted harmonic mean of 20-second speed observations in order to compute space-mean speeds (Rakha and Zhang, 2005). The traffic stream density was computed from flow and speed measurements using the fundamental traffic flow relationship (Equation [5]).

Baltimore, Maryland

Baltimore's traffic data were provided by The University of Maryland's Center for Advanced Transportation Technology Laboratory (CATT Lab). The CATT Lab has a high-speed connection with the Maryland State Highway Administration's (SHA) and the Coordinated Highway Action Response Team (CHART). CHART utilizes a network of microwave radar detectors to collect traffic counts and speed measurements on the highway network around Baltimore. The provided traffic data files contained volume and speed measurements at a five-minute temporal resolution.

It was observed that the percentage of missing records in traffic data was relatively high for Baltimore (between 20 to 75 percent missing records versus 1 percent and 2 percent for the Seattle and Twin Cities, respectively). To maintain a good coverage for all the weather and traffic conditions it was decided to discard the recording stations which had more than 40 percent of their records missing. Considering this additional selection condition, only three detector sites were found to satisfy all the selection criteria. Table 4.2 summarizes the characteristics of the three selected detectors in the Baltimore study area. It should be noted that these stations were relatively far from the Baltimore-Washington International ASOS station (15 to 25 km / 9.3 to 15.5 mi).

4.2 Dataset Construction and Data Analysis

After preparing the weather and traffic data separately, the two data sets were merged to form a dataset that contained visibility, precipitation, traffic flow, density, and speed records for each five-minute time interval, as demonstrated in Figure 4.2. This dataset was then used to derive weather adjustment factors for the various parameters.

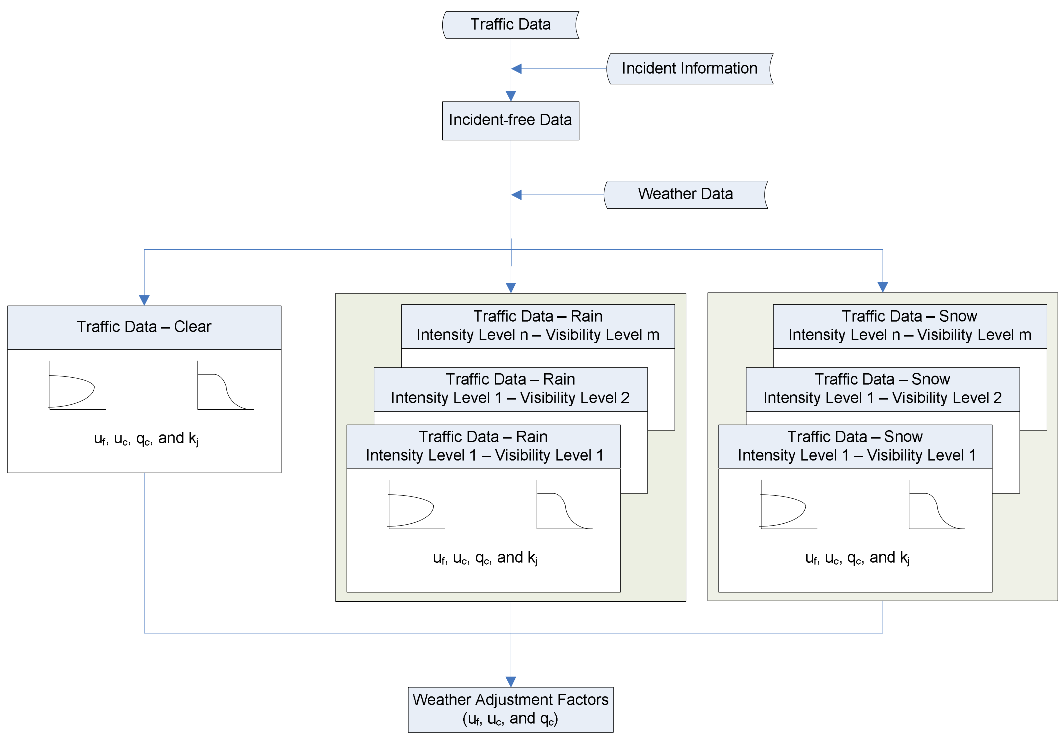
The base case was considered to be the no precipitation condition with a visibility greater than or equal to 4.8 km (3.0 mi), given that this represented the highest visibility scenario within the dataset. The construction of each dataset involved combining data over multiple days until coverage of the uncongested and congested regimes was achieved.

In order to achieve sufficient observations to conduct a statistical analysis, the data corresponding to each cell of Table 4.2 were grouped in a manner to provide as many replications as possible. Each group contained as many days worth of data as necessary to provide a good coverage for all traffic regimes. Consequently, a seven-day period was considered for the initial grouping which was selected to ensure sufficient data coverage for the full-range of traffic conditions. In the event that a seven-day grouping did not provide sufficient data, additional days were included until sufficient data coverage was achieved.

Due to the variable nature of traffic over a network, the number of datasets for each visibility/precipitation range at each detector site was different, as discussed later in Table 5.2, 5.3, and 5.5.

The next step was to estimate the key traffic flow parameters for each multiday group. For this purpose the SPD_CAL software was utilized for the analysis. The output of each run of the software provided an estimate of the four key traffic flow parameters for each multiday group. Weather adjustment factors were computed for three of the key parameters (u_f, u_c, and q_c) given that jam density (k_j) was found to be insensitive to weather conditions, as would be expected. The weather adjustment factor was computed as the ratio of the key parameter under existing weather conditions relative to the base case key parameter.

Figure 4.2 Data Construction Overview



5.0 Study Results

The research reported in this chapter quantifies the impact of inclement weather on traffic stream behavior by developing weather adjustment factors for key traffic stream parameters. These parameters include the free-flow speed, speed-at-capacity, capacity, and jam-density using data from three different cities in the U.S. The quality of these parameter estimates for a particular condition has a significant impact on the ability to discern changes in this parameter for different conditions. Furthermore, the automation of the parameter extraction process is critical in this situation because of the volume of data involved and the potential bias in manual fits. Consequently, an automated calibration procedure to estimate the key traffic stream parameters is utilized.

Initially, the traffic stream functional form and the calibration procedure are described briefly. Subsequently, the loop detector and weather data are described followed by the results and conclusions of the study.

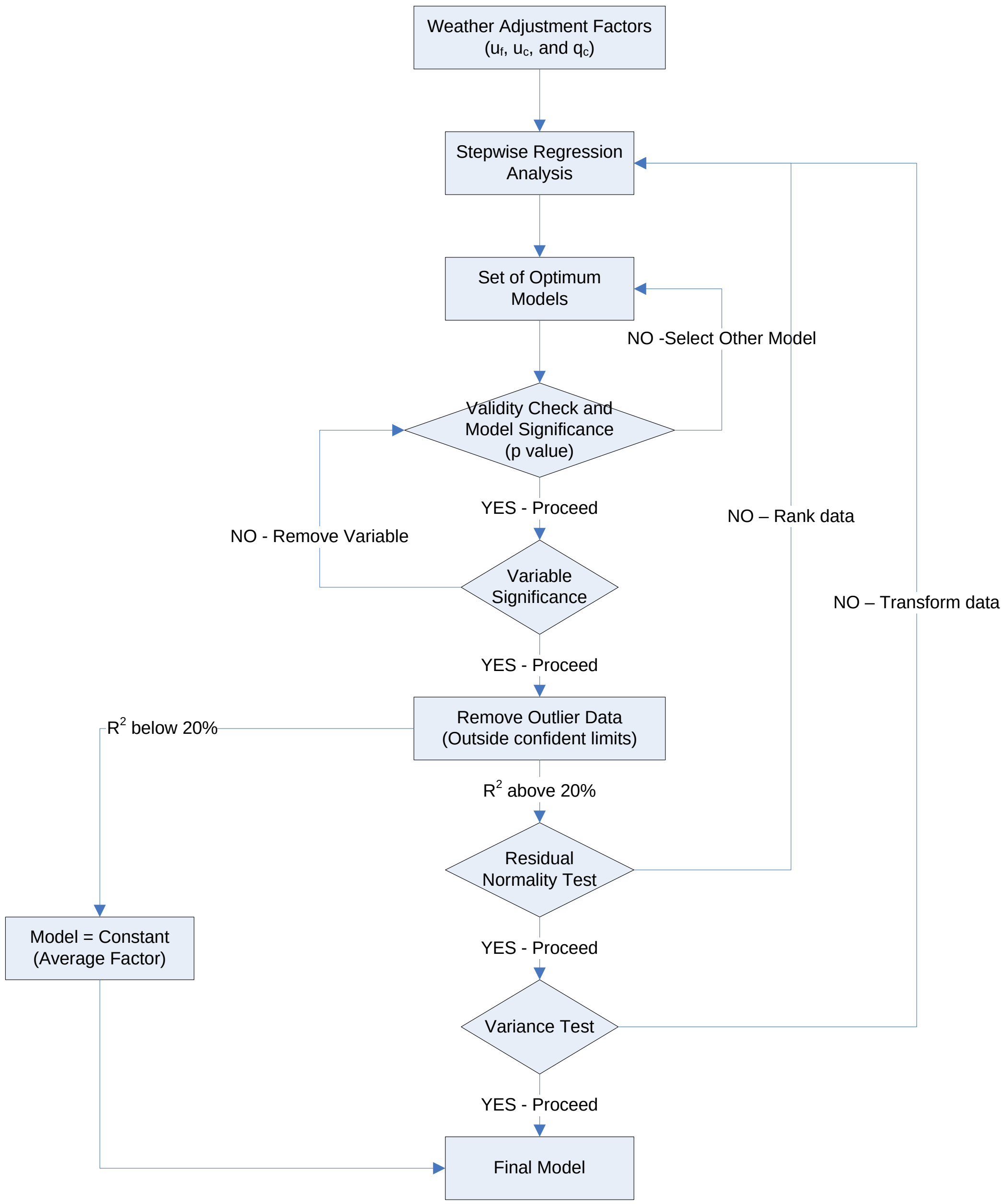
5.1 Study Results

Having computed weather adjustment factors for three key traffic stream parameters (u_f, u_c, and q_c), a regression analysis was utilized to build a model that predicts the weather adjustment factor (WAF) for a given precipitation type (rain and snow), intensity level, and visibility level for each of the three key traffic stream parameters (u_f, u_c, and q_c), as illustrated in Figure 5.1. The general model that was considered was of the form

$$F = c_1 + c_2 \; i + c_3 \; i^2 + c_4 \; v + c_5 \; v^2 + c_6 iv \qquad [6]$$

where F is the WAF, i is the precipitation intensity (cm/h), v is the visibility (km), (vi) is the interaction term between visibility and precipitation intensity, and c_1, c_2, c_3, c_4, c_5 and c_6 are calibrated model coefficients. In all models the interaction term was found to be insignificant and thus is not discussed further in the analysis.

Figure 5.1 Statistical Analysis Overview



The analysis was started by creating the correlation coefficient matrix. This first step along with ANOVA test was performed to assist in the selection of the variables to build the regression model.

A stepwise regression analysis was performed using the Minitab software (MINITAB). Stepwise regression removes and adds variables to the regression model for the purpose of identifying a useful subset of predictors. The coefficients and statistics for the best model for each dataset were generated by running the stepwise regression tool. Recognizing that automatic procedures cannot take into account the specific knowledge the analyst may have about the data, a validity check was made. This validity check ensured that the data did not produce unrealistic trends (e.g., the weather adjustment factors increased as the precipitation intensity increased). While such a model may be the best from a statistical standpoint, that may not be the case from a practical standpoint. In these rare cases, the model was constrained to ensure that it produced realistic trends.

The following step involved a check of both the model and variable significance. The model significance was checked through an Analysis of Variance (ANOVA) test. The null hypothesis (H_0) was that all model parameters were zero (i.e., $c_2 = \ldots = c_n = 0$), where n is the number of model parameters, while the alternative hypothesis (H_1) was that the model parameters were not zero $c_j \neq 0$, for at least one j. Table 5.1 presents the results for the ANOVA test for the Twin Cities free-flow speed model (Rain).

Table 5.1 ANOVA Test Results for Free-Flow Speed (Rain – Twin Cities)

Source of Variation	DF	Sum of Square	Mean Square	F_0	P-value
Regression	1	0.01128	0.01128	52.63	0.000
Error	43	0.00921	0.000214		
Total	44	0.02049			

Since the P-value = 0.000<0.05, it was concluded that at least some of the model parameters ($c_2,\ldots,c_n$) were not equal to zero. It should be noted here that the results of the stepwise regression, in terms of variables that should be included in the model, coincided with those of the previous step.

An imperative part of assessing the adequacy of a regression model is the significance of the individual regression coefficients. This test is important in determining the potential value of each of the independent variables. The null hypothesis that was tested was that the individual regression coefficients (c_j) were zero (H_0: $c_j = 0$ and H_1: $c_j \neq 0$). A P-value greater than α (in this case 0.05) – presented within parenthesis under each coefficient in the table – meant that the null hypothesis could be accepted, implying that the independent variable x_j was insignificant and thus could be deleted from the model. The various models that were developed for the three parameters u_f, u_c, and q_c are summarized in Table 5.2, 5.3, and 5.5, respectively.

Once the model and variable significance was established a screening of outlier data was applied. The screening approach involved removing data outside the 95 percent confidence limits using Minitab's built-in data screening procedures. This data screening only involved the removal of a limited number of observations, which explains the slightly different number of data points for the same weather scenarios within Table 5.2, 5.3, and 5.5.

Table 5.2 Free-Flow Speed Regression Analysis Summary Results

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

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

Table 5.3 Ratio of Speed-at-Capacity to Free-Flow Speed Analysis Summary Results

Precip.	City	n	c_1	c_2	c_3	c_4	c_5	c_6	P-value	R^2_{Adj}	Normality Test A^2	Normality Test P-value	Levene Variance Test
Rain	Baltimore	35	0.936	–	–	–	–	–	–	–	–	–	–
	Twin Cities	53	0.978	–	–	–	–	–	–	–	–	–	–
	Seattle	50	0.940	–	–	–	–	–	–	–	–	–	–
	Aggregate	138		–	–	–	–	–	–	–	–	–	–
Snow	Baltimore	8	1.000	–	–	–	–	–	–	–	–	–	–
	Twin Cities	41	1.000	–	–	–	–	–	–	–	–	–	–
	Aggregate												

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

Table 5.4 Speed-at-Capacity Analysis Summary Results

Precip.	City	*n*	c_1	c_2	c_3	c_4	c_5	c_6	*P*-value	R^2_{Adj}	Normality Test		Levene Variance Test
											A^2	*P*-value	
Rain	Baltimore	35	0.920 (0.000)	-0.0560 (0.003)	–	–	–	–	0.003	0.236	0.581	0.120	0.989
	Twin Cities	53	0.928	–	–	–	–	–	–	–	–	–	–
	Seattle	50	0.906	–	–	–	–	–	–	–	–	–	–
	Aggregate	138	0.909	–	–	–	–	–	–	–	–	–	–
Snow	Baltimore	8	0.956	–	–	–	–	–	–	–	–	–	–
	Twin Cities	41	0.852 (0.000)	–	–	0.0226 (0.000)	–	–	0.000	0.497	–	0.828	0.864
	Aggregate	47	0.816 (0.000)			0.0308 (0.000)			0.000	0.362			0.920

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

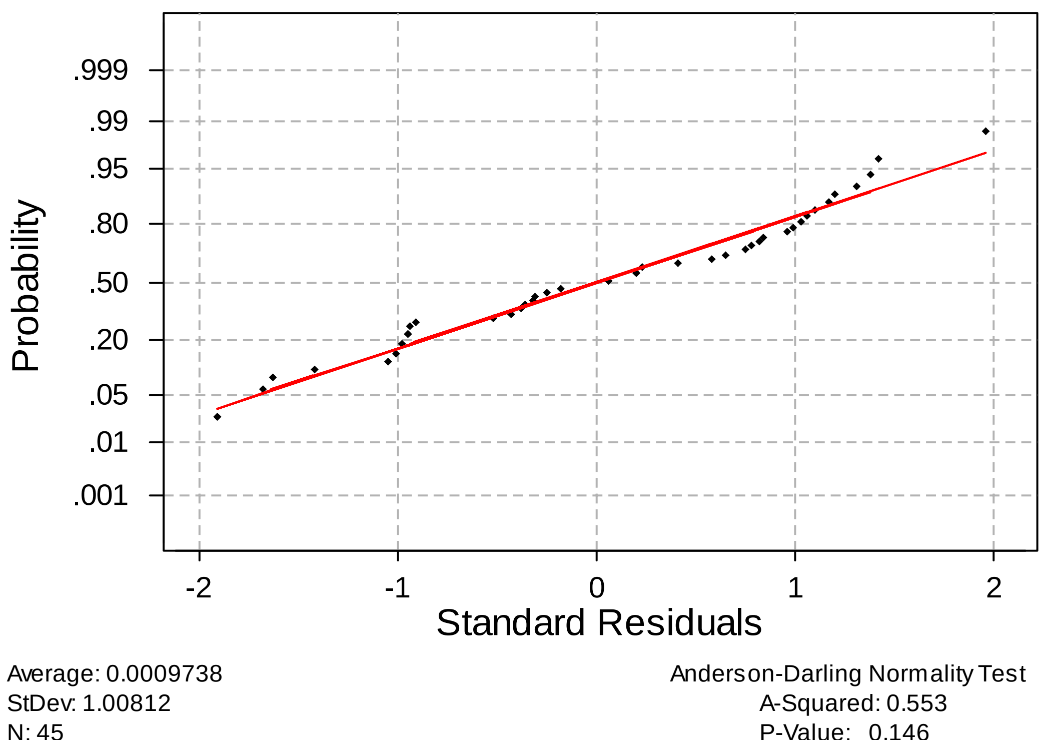
Table 5.5 Capacity Analysis Summary Results

Precip.	City	*n*	c_1	c_2	c_3	c_4	c_5	c_6	*P*-value	R^2_{Adj}	Normality Test		Levene Variance Test
											A^2	*P*-value	
Rain	Baltimore	35	0.892	–	–	–	–	–	–	–	–	–	–
	Twin Cities	43	0.889	–	–	–	–	–	–	–	–	–	–
	Seattle	49	0.896	–	–	–	–	–	–	–	–	–	–
	Aggregate	137	0.892	–	–	–	–	–	–	–	–	–	–
Snow	Baltimore	6	0.877 (0.000)	–	–	–	–	–	–	–	–	–	–
	Twin Cities	38	0.794 (0.000)	–	–	–	0.00508 (0.000)	–	0.000	0.480	0.318	0.524	0.859
	Aggregate	45	0.792 (0.000)	–	–	–	0.00480 (0.000)	–	0.000	0.503	0.461	0.248	0.627

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

Regression analysis assumes that the residuals are normally and independently distributed with constant variance. Consequently, a normality and equal variance test was conducted on the residuals. The normality test hypothesized that the data were normally distributed (null hypothesis). A *P*-value that was less than the chosen α-value of 0.05 implied that the data might not be normally distributed. Figure 5.2 presents a normal probability plot for the residuals calculated for a sample model, the plot also shows the Anderson-Darling goodness-of-fit test results. The Anderson-Darling statistic is a measure of how far the data points fall from the fitted normal line. The statistic is a weighted squared distance from the plot points to the fitted line with larger weights in the tails of the distribution. A smaller Anderson-Darling statistic indicates that the distribution fits the data better. The Anderson-Darling test's p-value (column before last) (0.553>>0.05) indicates that there was no evidence that the residuals were not normally distributed. As summarized in Table 5.2, 5.3, and 5.5 all data sets provided no evidence that they were not normally distributed.

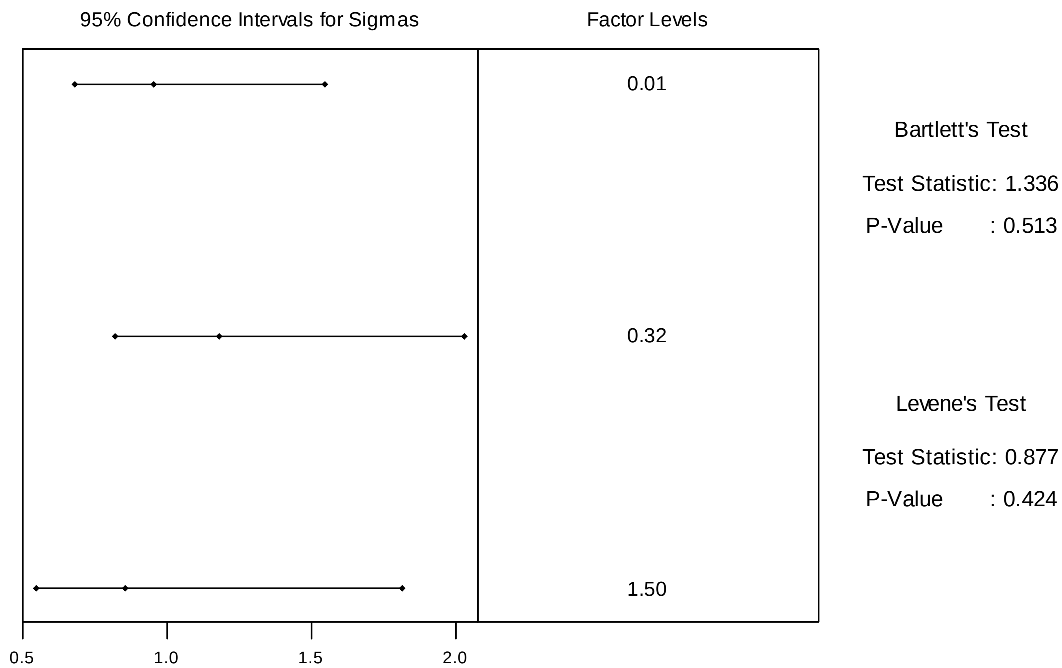
Figure 5.2 Residuals Normality Test for (Rain) Free-Flow Speed Twin Cities, MN



Since the analysis of variance assumes that the samples have equal variances, an equal variance test was conducted on the data. Figure 5.3 illustrates a sample result for the equal variance test considering the free-flow speed WAF under rain precipitation using the Twin Cities data. The *p*-values of 0.424 for Levene's test was greater than α = 0.05, and thus the null hypothesis (H_0) is accepted and the variances are considered to be equal. Again, Table 5.2, 5.3, and 5.5 demonstrate all models passed the equal variance test.

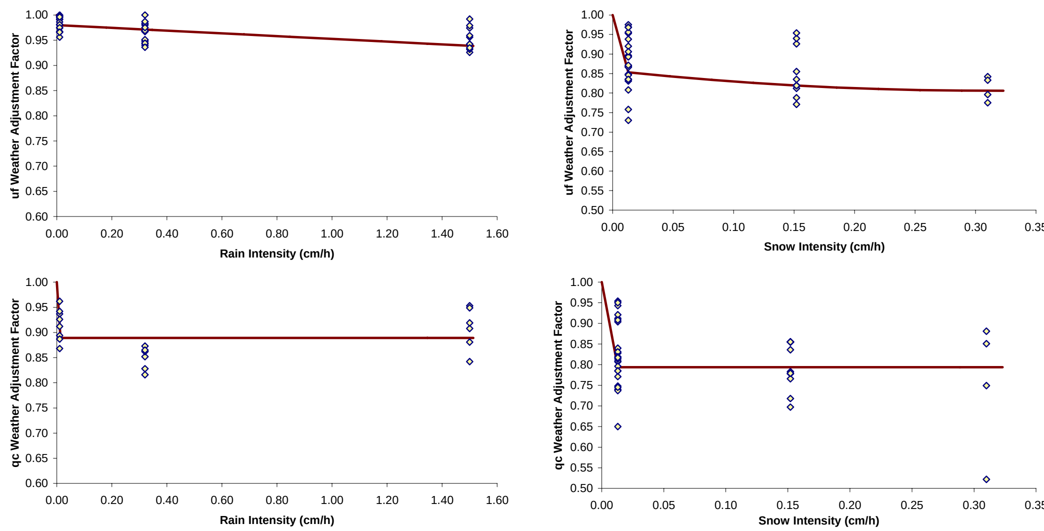
Models that produced an R^2 less than 0.20 were discarded and a constant average WAF was computed for the data. It was felt that an R^2 value less than 0.20 provided very limited explanation for the observed trends that the use of a constant would be sufficient for practical purposes. Overall, the R^2_{adj} values for the various models ranged from 0.30 to 0.83.

Figure 5.3 Results of Residuals Variance Test for the Effect of Rain Intensity on Free-Flow Speed in the Twin Cities, MN



For illustration purposes, the various model fits are plotted against the field observed data considering only different precipitation rates using the Twin Cities data, as illustrated in Figure 5.4. The figures generally demonstrate a good fit to the data except for the capacity WAF at rain intensities of 0.30 cm/h (0.12 in/h). In this case the optimal model was a bowl shaped model, however, this model was not considered because it would indicate an increase in the WAF for rain intensities in the range of 0.30 to 1.50 cm/h (0.12 to 0.59 in/h).

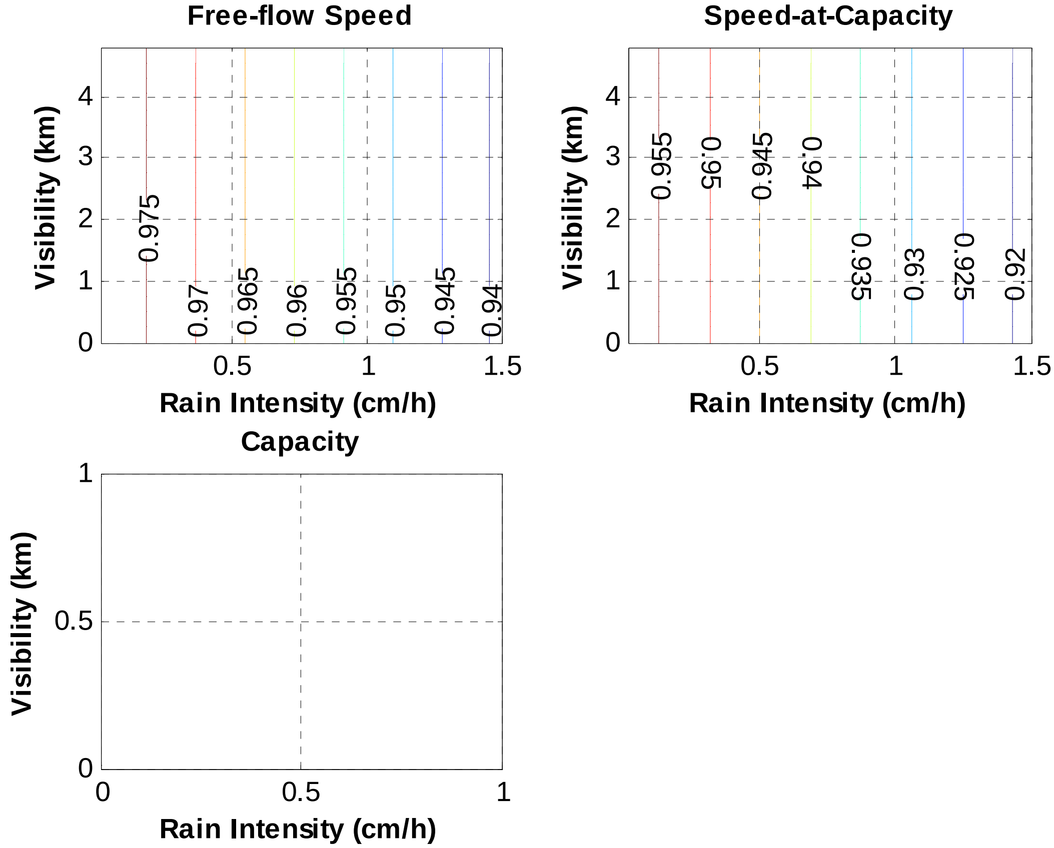
Figure 5.4 Twin Cities Inclement Weather Adjustment Factors



The data fits for the Twin Cities data are also illustrated in a 3-dimensional contour plot for rain and snow precipitation in Figure 5.5 and Figure 5.6, respectively. Figure 5.5 demonstrates that the free-flow speed and speed-at-capacity WAFs are sensitive to the rain intensity and are not impacted by the visibility level, as demonstrated by the vertical contour lines. Alternatively, the capacity WAF is constant and not impacted by the visibility or precipitation level. In the case of snow, Figure 5.6 demonstrates that the free-flow speed and speed-at-capacity WAFs are impacted by both the snow precipitation rate and the visibility level.

Because the proposed procedure hinges on the ability of the SPD_CAL software to estimate the four key traffic stream parameters, the free-flow speed analysis was also conducted using raw data obtained for low density and flow conditions. The free-flow WAF was then computed for the various intensity levels using the raw data and compared against the results obtained using the SPD_CAL parameter estimates. The results demonstrate a high-degree of consistency in the two approaches with errors not exceeding one percent and four percent for the rain and snow precipitation scenarios, respectively, as illustrated in Figure 5.7. This validation exercise demonstrates that the SPD_CAL software provides good estimates of the key traffic stream parameters.

Figure 5.5 Variation in Weather Adjustment Factors as a Function of Visibility and Rain Intensity Levels (Twin Cities)



A comparison of the rain and snow free-flow speed, speed-at-capacity, and capacity WAFs demonstrates that snow impacts on traffic stream behavior are more significant than rain impacts (as would be expected), as illustrated in Figure 5.8. Furthermore, the results demonstrate that precipitation appears to produce a constant reduction (independent of the precipitation intensity) for the capacity. Alternatively, the free-flow speed and speed-at-capacity appear to be impacted by the precipitation level.

Figure 5.6 Variation in Weather Adjustment Factors as a Function of Visibility and Snow Intensity Levels (Twin Cities)

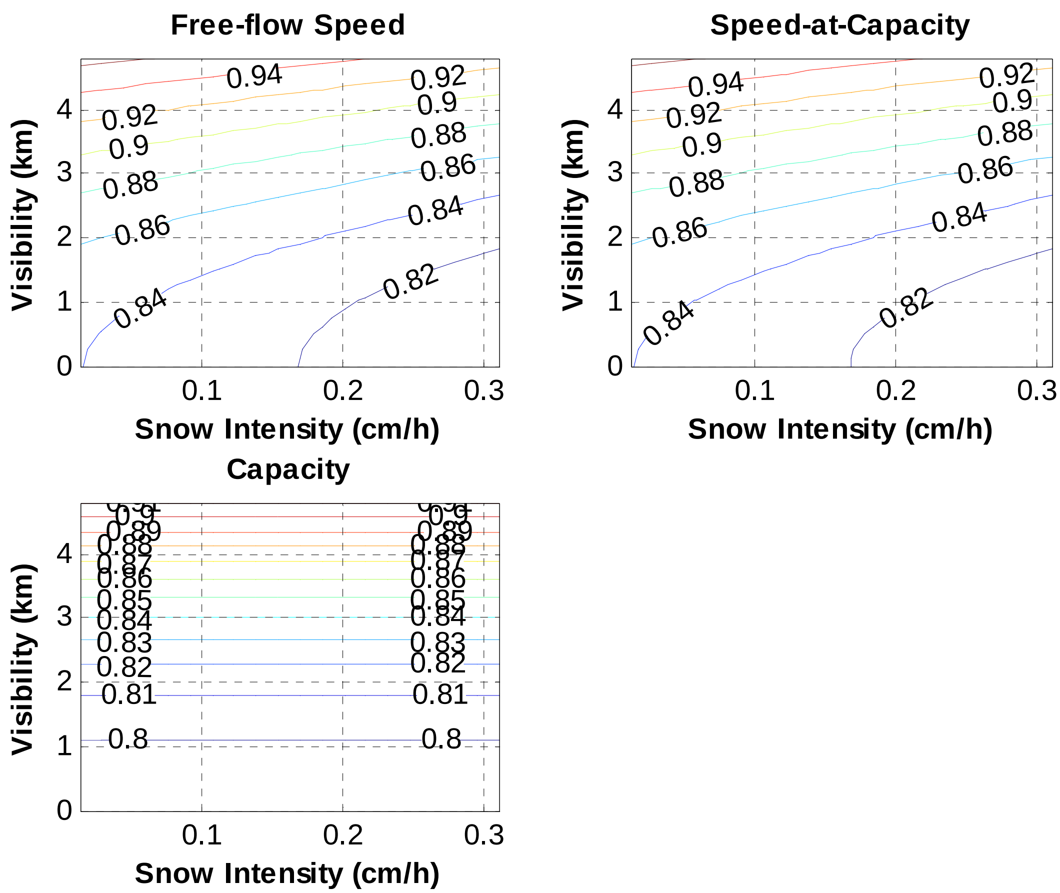


Figure 5.7 Comparison of Raw Data versus SPD_CAL Analysis Results

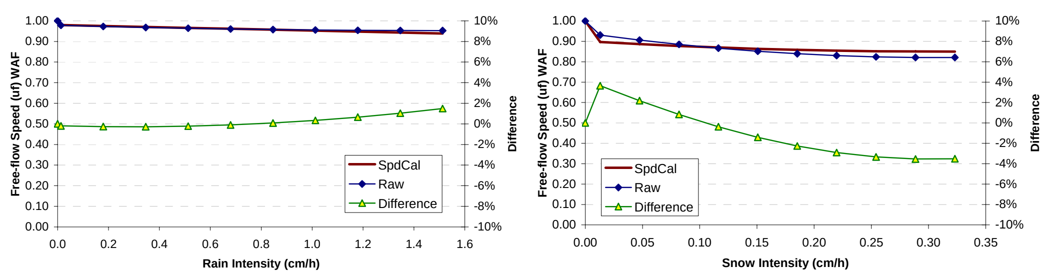
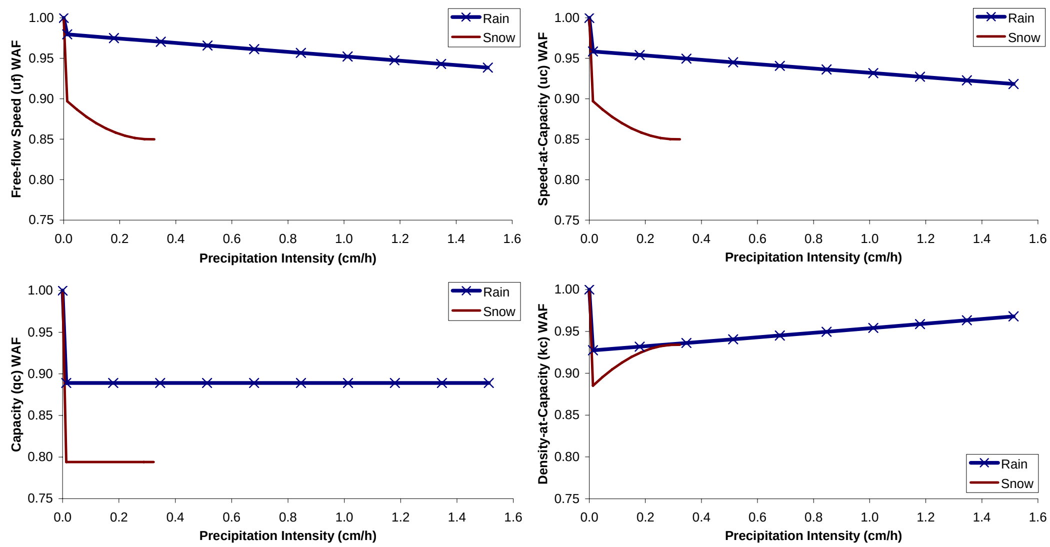
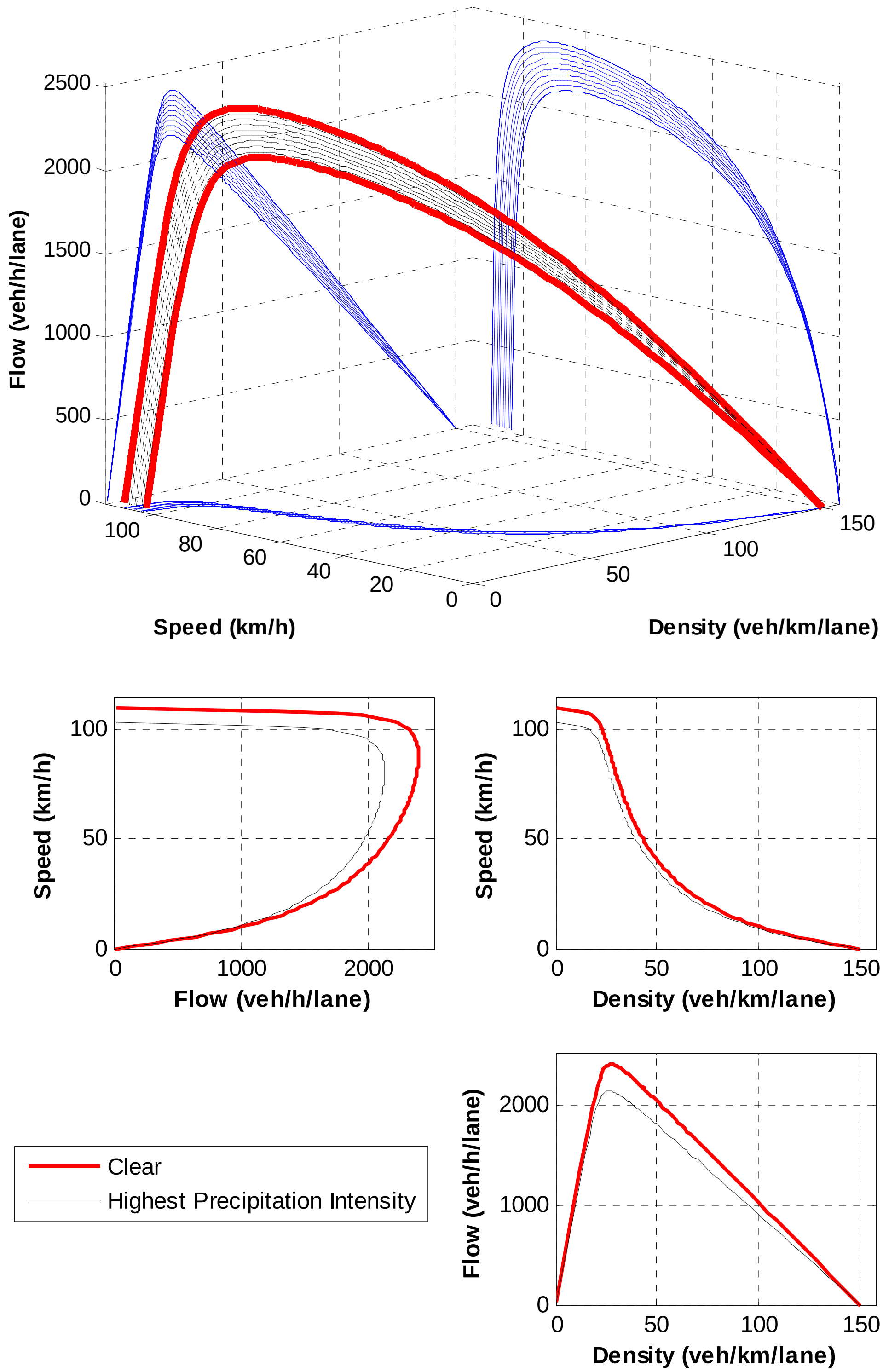


Figure 5.8 Sample Comparison Snow and Rain Weather Adjustment Factors (Twin Cities)



The impact of precipitation intensity on the steady-state speed-flow-density relationship for the Twin Cities data was found to be fairly significant, as illustrated in Figure 5.9. The plot was made for a base case u_f, u_c, q_c, and k_j of 110 km/h, 80 km/h, 2,400 veh/h, and 150 veh/km, respectively. The thick 3-D lines depict the base case (upper thick line) and maximum intensity level case (lower thick line). The thin lines represent different intermediate precipitation/visibility levels between the base (no precipitation) case and the maximum (1.50 cm/h precipitation) case. The projection of the 3-D lines on the speed-flow (u-q) plane, flow-density (q-k) plane, and speed-density (u-k) plane is also illustrated in the figure. The figure demonstrates a high-level of variability in the uncongested regime in the speed-flow and speed-density planes with minimum variability in the flow-density plane. In the congested regime a high-level of variability is only observed in the flow-density plane. In addition, the various 2-D plots illustrate the variation in the traffic stream model on each of the three planes. The thick lines represent clear conditions while the thin lines represent traffic stream behavior at the highest precipitation level. Similarly, Figure 5.10 illustrates the traffic stream behavior as a result of snow precipitation. A comparison of both figures clearly illustrates the more significant impact snow precipitation has on traffic stream behavior.

Figure 5.9 Sample Traffic Stream Model Variation (Twin Cities – Rain)



The next step in the analysis was to investigate the potential for regional differences in weather impacts on traffic stream behavior. The regional differences in free-flow speed, speed-at-capacity, and capacity was conducted using a General Linear Model (GLM) instead of an Analysis of Variance (ANOVA) test because the data were not balanced (different number of observations for different city and intensity combinations), as summarized in Table 5.6. The results demonstrated that in the case of rain precipitation the free-flow speed and ratio of speed-at-capacity to free-flow speed were statistically different, as demonstrated in Table 5.7 and Figure 5.11. A Tukey's comparison demonstrated that these differences occurred between Baltimore and the Twin Cities. Alternatively, differences in the capacity WAFs were not found to be statistically significant. In the case of snow, there was no statistical evidence for differences in the ratio of speed-at-capacity to free-flow-speed, while the free-flow speed and capacity reductions were found to be statistically significant across the various sites, as demonstrated in Table 5.7 and Figure 5.12. Again, this significant difference was only found to occur between Baltimore and the Twin Cities. It is interesting to note here, that the average annual snow precipitation for the Twin Cities was higher than that for Baltimore (7.33 versus 5.57 cm / 2.89 versus 2.19 in). Consequently, one may expect that given the higher annual snow fall rate in the Twin Cities Area, that drivers would be more accustomed to snow and thus would be less impacted by it, however, the results demonstrate the opposite. One interpretation could be that the Twin Cities drivers are more aware of the dangers of driving in snow and thus are more cautious than drivers in the Baltimore Area. However, further analysis is required to investigate the potential causes for these differences in driver behavior.

Figure 5.10 Sample Traffic Stream Model Variation (Twin Cities – Snow)

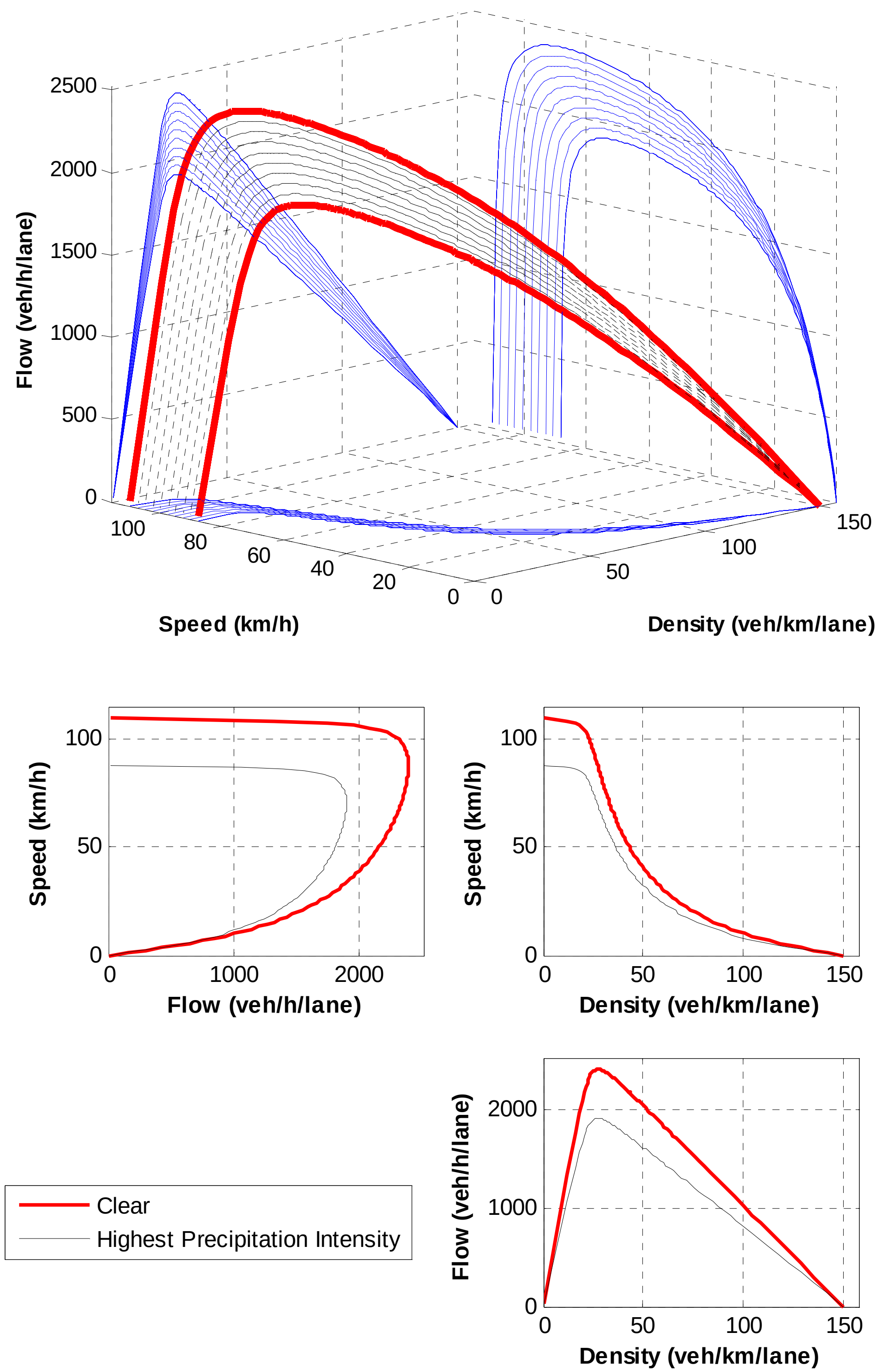


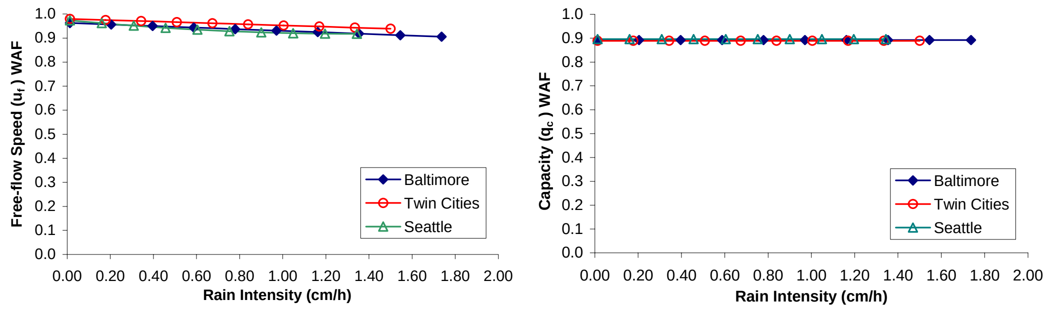
Table 5.6 General Linear Model (GLM) – Analysis of Variance

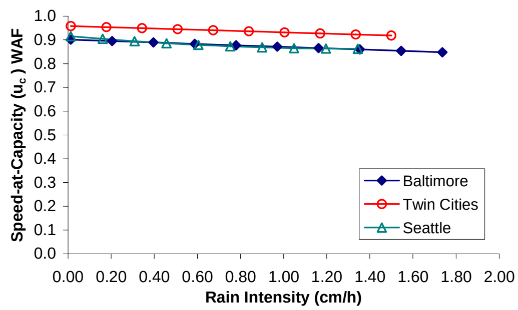
Source	D.F.	Seq SS	Adj SS	Adj MS	F	P
City	2	0.0091430	0.0104431	0.0052215	7.35	0.001
Intensity(City)	11	0.0286104	0.0286104	0.0026009	3.66	0.000
Error	125	0.0888420	0.0888420	0.0007107		
Total	138	0.1265954				

Table 5.7 Analysis of Variance Summary of results

Precipitation Type	Parameter	Factor	*P*-value
Rain	u_f	City	0.001
		Intensity	0.000
	uc/uf	City	0.032
		Intensity	0.025
	qc	City	0.431
		Intensity	0.002
Snow	u_f	City	0.000
		Intensity	0.224
	uc/uf	City	0.882
		Intensity	0.816
	qc	City	0.016
		Intensity	0.579

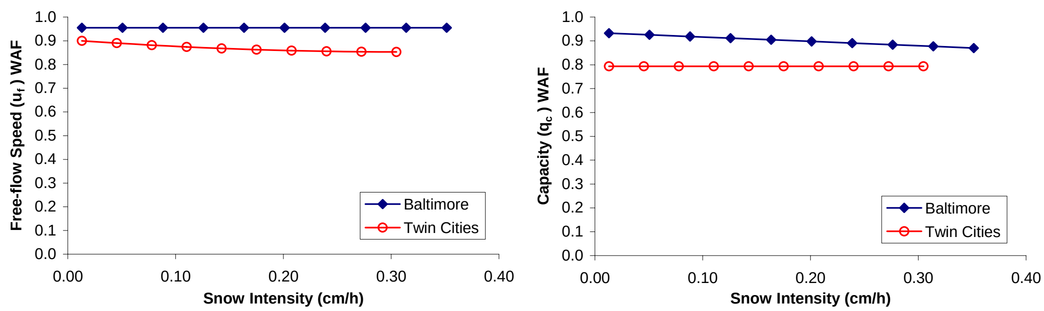
Figure 5.11 Variation in Weather Adjustment Factors as a Function of Rain Intensity

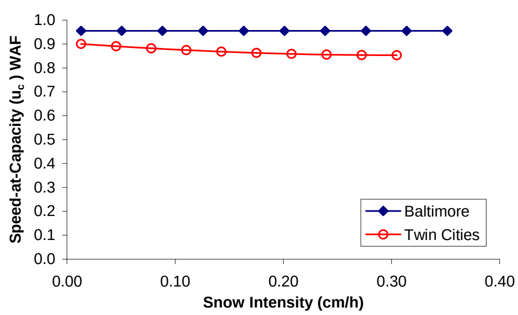




		Baltimore	Seattle	Twin Cities
u_f	c_3	0.000	0.032	0.000
	c_2	-0.033	-0.086	-0.027
	c_1	0.963	0.975	0.980
u_c	c_3	0.000	0.030	0.000
	c_2	-0.031	-0.080	-0.027
	c_1	0.901	0.917	0.958
q_c	c_3	0.000	0.000	0.000
	c_2	0.000	0.000	0.000
	c_1	0.892	0.896	0.889

Figure 5.12 Variation in Weather Adjustment Factors as a Function of Snow Intensity





		Baltimore	Twin Cities
u_f	c_3	0.000	0.534
	c_2	0.000	-0.331
	c_1	0.955	0.851
u_c	c_3	0.000	0.534
	c_2	0.000	-0.331
	c_1	0.955	0.851
q_c	c_3	0.000	0.000
	c_2	-0.184	0.000
	c_1	0.935	0.794

5.2 CONCLUSIONS

The research results reported in this section quantified the impact of inclement weather (precipitation and visibility) on traffic stream behavior and key traffic stream parameters, including free-flow speed, speed-at-capacity, capacity, and jam density. The analysis was conducted using weather data (precipitation and visibility) and loop detector data (speed, flow, and occupancy) obtained from Baltimore, Twin Cities, and Seattle in the USA. The study demonstrated the following:

1. Traffic stream jam density is not impacted by weather conditions.
2. Light rain (0.01 cm/h / 0.0039 in/h) results in reductions in the traffic free-flow speed, speed-at-capacity, and capacity in the range of 2 to 3.6 percent, 8 to 10 percent, and 10 to 11 percent, respectively. These results are consistent with the 2 percent free-flow speed reductions for light rain conditions that were reported in earlier studies (Ibrahim and Hall 1994).
3. Reductions in free-flow speed and speed-at-capacity generally increase with rain intensity. The maximum reductions are in the range of 6 to 9 percent and 8 to 14 percent for free-flow speed and speed-at-capacity, respectively at a rain intensity of approximately 1.6 cm/h (0.63 in/h). Earlier studies had shown reductions in free-flow speed in the range of 4.4 to 8.7 percent (Ibrahim and Hall 1994) in heavy rain. Furthermore, the HCM suggests reductions in free-flow speed in the range of 4.8 to 6.4 percent in heavy rain.
4. Roadway capacity reductions remain constant (10 to 11 percent reductions) and are not affected by the rain intensity in the rain intensity range of 0 to 1.7 cm/h (0 to 0.67 in/h).
5. Snow precipitation results in larger reductions in traffic stream free-flow speed and capacity when compared to rain.
6. Light snow (0.01 cm/h) produces reductions in free-flow speed, speed-at-capacity, and capacity in the range of 5 to 16 percent, 5 to 16 percent, and 12 to 20 percent, respectively.
7. Typically reductions in free-flow speed and speed-at-capacity increase with an increase in the snow intensity. The maximum reductions are in the range of 5 to 19 percent at a snow intensity of approximately 0.3 cm/h (0.12 in/h) (intensity measured in equivalent liquid-equivalent precipitation). Ibrahim and Hall had observed reductions in free-flow speed in the range of 33 to 43 percent in a study conducted in Canada.
8. The study demonstrated that the Twin Cities experienced more significant reductions in the traffic stream free-flow speed and speed-at-capacity under snowy conditions when compared to Baltimore (19 versus 5 percent reductions). This finding might appear to be counter intuitive given that the Twin Cities experience higher annual snow precipitation when compared to Baltimore. A possible explanation for this finding is that drivers who are

more accustomed to snow are more aware of the dangers of snow. This could also explain the higher reductions that were observed in the Canadian study (33 to 43 percent).

9. Reductions in roadway capacity are not impacted by the snow intensity (range between 12 and 20 percent).

10. Visibility seems to have a larger impact on traffic stream parameters for snow precipitation when compared to rain. Reductions in the range of 10 percent are observed for a reduction in visibility from 4.8 to 0.0 km (3.0 to 0 mi).

Finally, the study also developed free-flow speed, speed-at-capacity, and capacity weather adjustment factors that vary as a function of the precipitation type, precipitation intensity, and visibility level. These factors can be implemented within the HCM freeway procedures.

6.0 Recommendations for Next Phase of Study

The study of the impact of inclement weather on traffic flow thus far has provided insight into the limitations of existing data and the resulting analysis and gaps in existing research, as well as a vision for future exploration of the topic. This section will outline the direction for research in the next phase of the study.

6.1 LESSONS LEARNED FROM COMPLETED RESEARCH

High-quality traffic and weather data is critical to accurate analysis of the effects of inclement weather on traffic flow and driver behavior. The data must be accurate, complete and representative of the geographic, functional (i.e., freeways, arterials), and geometric (i.e., grades, curves) areas of interest. In this phase, researchers were limited by the extent of existing traffic and weather data collection. Better, more comprehensive data will result in better modeling and analysis.

In addition, information on roadway surface conditions is critical to an accurate analysis of inclement weather impacts on traffic flow and driver behavior. Consequently, video or roadway sensors are required to gather roadway surface conditions.

In many major metropolitan areas, traffic sensor data are collected and archived. However data quality is not always as high as desired. It is important that the sensors and communications equipment are maintained and data are reviewed regularly for quality control.

Weather data collected by state DOT's and other transportation agencies are typically not as robust as the traffic data. While meteorological concerns are often considered in the siting of Environmental Sensor Stations (ESS), they are most often used for winter maintenance activities, and as a result, are located with those needs in mind. The availability of communications and power are also important considerations and compromises from the ideal location may be necessary. Some agencies are now trying to colocate new ESS with traffic counting stations, but for the most part they are not found in the same locations. One of the major problems with using DOT ESS data in this project was that many ESS only report the presence of precipitation, not the rate. Therefore the data have limited utility

The study has shown that while traffic and weather data sets are often sufficient for day-to-day operations, the combination of the two data sets is lacking for analysis of this detail and sensitivity. Therefore, it is recommended that the current study – evaluating the macroscopic traffic flow parameters – be replicated with better, complimenting, sets of traffic, weather, and roadway surface data.

Enhancement of macroscopic analysis

The macroscopic analysis conducted for this project should be enhanced through a data collection procedure as outlined below:

1. Select sites with dual loop detectors that collect high-quality and robust traffic data elements of volume, speed, and occupancy. The set of locations should provide enough uniformity to have a large data set and enough variety of functional classification or geometric configuration to provide direction for further research.
2. Place ESS near traffic loop detectors. The ESS should have a weather sensors, a roadway surface sensor, and a video detection system to collect atmospheric (temperature, precipitation, visibility, wind) and pavement condition (pavement temperature, surface condition) environmental data. It is important to use roadway surface conditions when evaluating the impact of inclement weather on traffic flow to capture the true conditions of the roadway (e.g., wet, slushy, icy) and consider splash from vehicles.
3. Collect traffic and weather data during dry, rainy, and winter conditions. A potential source of both traffic and weather data is VTTI's Mobile Traffic Laboratory (MTL), a fully self-contained modular laboratory that provides real-time traffic data, such as traffic volume, vehicle speed, lane occupancy, and pedestrian detection. The MTL van is equipped with a weather station that measures wind speed, direction, temperature, relative humidity, and rainfall. In addition, the van is equipped with an Autoscope Solo Pro™ wide-area video vehicle detection system, an Autoscope Image Sensor™ (AIS), a pneumatic mast (13.71-meter maximum raised height) with color pan/tilt/zoom cameras, a computer system, and a videocassette player/recorder. The equipment racks are easily configurable and the MTL has a modular design that allows for extension and enhancement. A mobile collection approach will enable the collection of relevant field data at multiple geographic locations.

Additionally, there were a number of research issues identified in the research synthesis report that were not adequately studied in the current research due to data restrictions:

The impact of precipitation on macroscopic traffic flow indicators on a wide-range of facilities

After a review of existing sources during the development of the data collection plan it did not appear that arterial data could be obtained that meet the criteria above. Most arterial detectors are located at intersections making it difficult to calculate average speeds along a stretch of highway. Speed and volume data are also difficult to obtain on nonurban stretches of arterial roadway. While only freeways will be included in this analysis, different types of freeway facilities will be incorporated into the study. One potential categorization is by function, with the hypothesis that radial and circumferential/crosstown freeways may experience different impacts from adverse weather. More likely is that the size of the facility will result in different traveler responses to weather events. As a result, the study tried to incorporate different freeway capacities into the analysis, including four-lane, six-lane, and eight-lane sections. While there was some variation in the freeways sampled, including both radial and circumferential highways, the number of stations observed was not adequate to identify differences in behavior. A good research goal for the future would also be to analyze adverse weather impacts on different types of roadway geometry. Given the relatively sparse distribution of RWIS in most metropolitan areas this analysis would require collection and analysis of additional observations from a dense network such as the NWS Cooperative Observer program.

Study of regional differences in reaction to precipitation

The limitation of this study to three cities limited the ability to draw conclusions about regional differences in driver response to adverse weather. Given the limited number of cities and detector stations, it was difficult to isolate the impact of weather events from other factors such as roadway geometry, signing and in the case of snow, winter maintenance. A more thorough analysis of regional differences will require a larger sample of cities with more detailed data from each.

Study the macroscopic impacts of reduced visibility

Some of the RWIS stations identified for this study included visibility sensors. The findings related to visibility are documented in Section 5 but conclusions are limited due to the limited number of locations studied and lack of refinement in some of the sensor data. More detailed analysis is needed in the future to separate the impact of fog from other factors. This is clearly an important area of emphasis but it is not clear whether there are adequate data to support this analysis.

6.2 Microscopic and Human Factors Analysis

In addition to refining the macroscopic analysis with better data, future research on weather-sensitive traffic flow modeling should focus on individual driver behavior and resulting vehicle movements under different weather and pavement conditions. Proposed microscopic and human factors analyses are outlined below.

Empirical evidence regarding the microscopic effects of weather on individual drivers is deficient in the literature. Similarly, research into human factors has been limited to vehicle safety investigations, with minimal consideration of traffic flow. These gaps in research provide a need and motivation to study both microscopic parameters (i.e., desired speed, acceleration, minimum gap acceptance, and lane changing) and human factors (i.e., reaction times, demographics, driver workload). The following tasks will focus on enhancing knowledge in this field.

Use of existing naturalistic driving and NGSIM data

The Federal Highway Administration is collecting a significant amount of detailed vehicle trajectory and driver behavior data as part of the Next Generation Simulator (NGSIM) Project. Additionally, previous work in developing driver behavior models has resulted in numerous, detailed vehicle data. Subsets of this data can be extracted and analyzed to characterize driver longitudinal motion in clear, rainy, and snowy weather conditions. The trajectory data should be augmented with historical ASOS weather data. If the dataset includes inclement weather conditions then an analysis of driver behavior during inclement weather conditions could be compared to driver behavior during clear conditions to establish differences in driver behavior.

In addition to the NGSIM data, a number of naturalistic Field Operational Test (FOT) data sets are available. The 100-Car Study was the first instrumented-vehicle study undertaken with the primary purpose of collecting large-scale naturalistic driving data. Drivers were given no special instructions, no experimenter was present, and the data collection instrumentation was unobtrusive. In addition, the majority of the drivers drove their own vehicles (78 out of 100 vehicles). The dataset contains data at 10 HZ for many extreme cases of driving behavior and performance, including severe drowsiness, impairment, judgment error, risk taking, willingness to engage in secondary tasks, aggressive driving, and traffic violation.

The data collection effort resulted in the following dataset contents: a) approximately 2 million vehicle miles of driving, b) almost 43,000 hours of data, c) 241 primary and secondary driver participants, d) 12- to 13-month data collection period for each vehicle; 18-month total data collection period, e) 15 police-reported crashes, f) 67 non-police-reported crashes (some producing no damage), g) 761 near-crashes, h) 8,295 incidents, and i) five channels of video and many vehicle state and kinematics variables.

If the naturalistic driving data are augmented with weather and pavement data, it will be possible to study the effect of inclement weather on driver behavior.

Acceleration, lane changing and gap acceptance models should be evaluated for differences based on varying precipitation and visibility conditions.

Controlled field studies

In addition, vehicle trajectory data and driver behavior/response data should be collected from instrumented vehicles in a controlled field study to model individual decisions drivers make under different weather conditions. We recommend that a combination of controlled field and naturalistic driver studies be conducted as part of the next phase of the project.

The Smart Road, a 3.5 kilometer fully instrumented two-lane road in southwest Virginia, is a joint project of the Virginia Department of Transportation (VDOT), VTTI, and the FHWA. The facility is an operational test-bed for detailed, real-world performance of vehicles in a controlled environment. It is a real roadway environment that has the capability to generate and monitor all types of weather and pavement conditions. Data will be collected on drivers under generated weather conditions of rain, snow, and dense fog. DGPS will be utilized to track exact trajectories of test vehicles and in-vehicle camera systems will be used to record driver reactions. Environmental monitoring stations will record conditions on the roadway. The facility has the following unique capabilities:

- **All-weather testing capability.** The facility is capable of producing rain, snow, and a fog-like-mist over a one-half-mile stretch of roadway. At maximum output, the system produces up to five inches of rain per hour and 10 inches of snow per hour. A 500,000-gallon water tank feeds the system and allows for multiple research events. The all-weather testing towers are automatically controlled and can produce rain and snow at multiple intensities. In addition, water can be sprayed by the towers onto freezing pavement to create icy conditions.

- **Environmental monitoring.** VTTI has installed a permanent visibility sensor and three weather stations to provide direct data for operational conditions to the research staff. Available data includes temperature, humidity, wind speed, wind direction, and visibility measured in miles. These data are used in conjunction with the All Weather Testing section to provide quantitative measurements of test conditions as subjects complete research tasks.

- **On-site data acquisition capabilities.** The roadway has an underground conduit network with manhole access every 60 meters. This network houses a fiber optic data network and interfaces with several on-site data acquisition systems. The facility also has a complement of Road Weather Information Systems (RWIS) stations connected to the data network. The fiber network has an interface with a card that will allow RWIS data to be transmitted via wireless communications.

- **Wet Visibility Section.** VTTI recently constructed a Wet Visibility road section that runs alongside a section of the Smart Road. This roadway section is a "crownless" road: it has no arch in the middle and runs as flat across as is possible. On such a road, water will not drain off onto the sides and will pool in the middle. This section of roadway is being used to test pavement markings in wet-weather conditions. This two-lane road connects with the Smart Road intersection. It joins the intersection on the opposite side of the Smart Road and runs parallel to the Smart Road up to the first turnaround. In addition, 35 portable rain towers were constructed to be used along the wet visibility section.

- **In-house differential GPS system**. Precise vehicle location can be tracked on the road with a military-grade global positioning systems (GPS) base-station. This system can track the location of a vehicle on the road to 2.0-centimeter accuracy at four samples per second, or 5.0-centimeter accuracy at 10 samples per second.

- **Surveillance camera systems.** In 2001, VTTI installed a complete video surveillance system consisting of nine permanently mounted, low-light color cameras. Also on hand are two portable cameras that can be moved to any location on the roadway for project-specific needs. Six of the cameras use dedicated fiber optic links to transmit video and data signals to the control room. The cameras are fed directly to the Smart Road Control Room and monitored by staff. VTTI has the ability to pan/tilt/zoom all of the cameras via custom software on the video wall computer.

- **Variable lighting test bed.** VTTI and Virginia DOT, in conjunction with FHWA, developed a highway lighting test bed on the Smart Road. The system consists of overhead light poles with the following spacing: 40-20-20-40-40-20-20-40-40-20-20 meters. This spacing, combined with wiring the poles on three separate circuits, allows for evaluating lighting systems at 40, 60, or 80 meters. The poles incorporate a modified design to allow for easy height adjustment of the bracket arm. In addition to evaluating spacing and bracket height, various luminaries are available as well, including metal halide and high-pressure sodium. If desired, differing levels of roadway lighting also can be simulated concurrently with the variation in visibility produced by the all-weather testing equipment. This allows a multitude of visibility conditions to be created, on demand, for testing purposes.

Figure 6.1 Image of Smart Road Weather Making Capabilities

These data will be used to estimate differences in microscopic models in varying weather conditions, especially different precipitation and visibility combinations.

Pretrip driver decisions

A survey should be developed and conducted to determine how weather events and forecasts impact driver's pretrip decisions, including departure time, route choice, expected travel time, and aggressiveness. There are several options for conducting such a survey. One is a traditional telephone survey that would identify regular commuters and ask them about their use of pretrip information. A survey conducted by Cambridge Systematics for Michigan DOT asked commuters in the Detroit region whether they used pretrip information to change their time of departure or route of travel. The survey found bad weather to be one of the major factors in the decision to change departure time but much less of a factor in changing route choice. It also indicated that the sensitivity to weather information is much greater during the a.m. peak commute than the p.m. peak commute. This is an expected result since weather is less likely to vary by route than traffic conditions.

Table 6.1 Reasons for Changing Routes
West Sector (Washtenaw, Livingston and Western Wayne Counties, Michigan)

Reasons for Changing Routes	a.m. Commute	p.m. Commute
Traffic Accident or Incident	57%	51%
Roadway Construction	38%	40%
Normal Traffic Congestion	23%	27%
Bad Weather	4%	2%
Business or Personal Reasons	2%	5%
Don't Know/No Reason	–	2%

Source: Michigan ITS Predeployment Study: West Sector Report, prepared by Cambridge Systematics and Kimley-Horn Associates for Michigan DOT, 2003.

Table 6.2 Reasons for Changing Departure Time
West Sector (Washtenaw, Livingston and Western Wayne Counties, Michigan)

Reasons for Changing Departure Time	a.m. Commute	p.m. Commute
Traffic Accident or Incident	51%	35%
Roadway Construction	22%	35%
Normal Traffic Congestion	29%	39%
Bad Weather	24%	8%
Business or Personal Reasons	10%	4%
Don't Know/No Reason	2%	4%

Source: Michigan ITS Predeployment Study: West Sector Report, prepared by Cambridge Systematics and Kimley-Horn Associates for Michigan DOT, 2003.

This survey was focused on general uses of ITS and also obtained information on how commuters might value different types of emerging technology and new information sources. The following table, for example, summarized commuters' ranking of various technologies and information sources on a scale of 1 to 10.

Table 6.3 Stated Importance
Total Sample (Oakland, Genessee, Washtenaw, Livingston, Monroe, Western Wayne and southern Wayne Counties, Michigan) and West Sector (Washtenaw, Livingston and Western Wayne Counties, Michigan) Results

	Total Sample	West Sector
Obtaining traffic information from a variety of sources, like the radio and TV	8.3	8.3
Obtaining information about alternate routes as a result of accidents, congestion or weather	8.3	8.5
Having a device in your vehicle to automatically call an emergency number during an accident	8.1	7.7
Providing continuous traffic advisory information on a dedicated radio station	8.0	7.9
Having immediate access to traffic information in your vehicle	7.8	7.9
Using electronic highway message signs to obtain traffic information	7.5	7.4
Having immediate access to traffic information at home	7.3	7.1
Having a collision avoidance device in your vehicle	7.2	7.1
Providing automatic traffic and accident reports on a device in your vehicle	6.9	7.0
Having a device in your vehicle that gives maps and directions	6.8	6.9
Obtaining information on public transportation at home or at work	6.2	6.0
Using a toll-free mobile phone to obtain traffic information	5.8	5.4
Offering a customized paging service that gives traffic information about routes you take	5.6	5.2
Accessing traffic information on the Internet	4.4	4.2

Source: Michigan ITS Predeployment Study: West Sector Report, prepared by Cambridge Systematics and Kimley-Horn Associates for Michigan DOT, 2003.

This chart indicates the importance of alternate route information to commuters and also indicates that it is the information that is important, not the technology that delivers it.

A survey focused on weather response would expand on some of these questions and use some of the questions used in previous studies that are documented in the literature search in Section 2. In particular, the survey effort should attempt to obtain more detail on what type of weather phenomena impact pretrip decisions and what level of detailed information is desired. For example, do commuters respond to generalized regional forecasts or are they more likely to respond to maps showing estimated snowfall totals around the region? What is the best way to express the impact of weather on road conditions? One method may be to read a weather forecast or road weather information scenario to the respondent and ask them whether they would modify their trip based on that forecast. This method could be used in a focus group setting as well as a phone survey.

It is important to note that other methods are now available for collecting data on traveler pretrip preferences. While most of them would not achieve the statistical validity found in a survey sample, they could be less expensive and still provide strong insight into customer preferences:

- **Web site surveys –** Volunteers may be solicited from regular users of traveler information web sites. They would be asked to report any changes in their trip patterns based on weather and traffic information. The data could provided directly over the Internet.
- **E-mail surveys –** A preselected group of commuters could be e-mailed on a daily basis to obtain information on their use of pretrip information and their travel habits.
- **In-vehicle devices –** Volunteers could be solicited among subscribers to in-vehicle information and navigation services. They could report their trip patterns, such as time of departure on a daily basis, and this could be matched against weather data for that time period.

Another important consideration is the geographic scope of such surveys. They may be more effective if concentrated in a small number of cities that represent a range of climates. While this study may be location-specific, it also may identify some overlying trends in how weather impacts driver behavior prior to entering the vehicle.

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A. Literature Classification and Summary

Table A.1 Literature and Research on Studies Using Secondary Data

Reference	Authors	Year	Comment
Calibrating Traffic Simulation Models to Inclement Weather Travel Conditions with Application to Arterial Coordinated Signal Systems	S.J. Abolosu-Amison and A.W. Sadek, University of Vermont	Ongoing	Measuring changes in arterial traffic flow during adverse weather and developing microsimulation adjustment factors. Second stage will use model to develop weather-dependent arterial timing plans
Driver Response to Rainfall on an Urban Expressway	Jean C. Andrey and Daniel Unrau, University of Waterloo	2006	Modeled the impact of light rain on urban expressway conditions. Looked at several traffic variables under dry and wet conditions and addressed the safety implications of driver adjustment to rain during night and day conditions.
Effective Message Design for DMS	Conrad Dudek, Brooke Ulman, Nada Trout, Melisa Finley and Gerald Ullman, Texas Transportation Institute	2006	Focus groups and human factors studies were used to help improve the effectiveness of DMS messages under different situations, including inclement weather. The methodology can provide a useful model, or could be built upon, to help identify driver response to inclement weather.
Evacuation Planning, Human Factors, and Traffic Engineering	Reuben Goldblatt and Kevin Weinisch, KLD Associates	2005	The case study dealt with a simulated evacuation of an area impacted by a nuclear power plant emergency. This case study addressed pretrip behavior and some of the methods may be adaptable to pretrip decisions related to adverse weather.
Minimizing Truck-Car Conflicts on Highways	S. Peeta and W. Zhou, Purdue University and Indiana DOT	2004	This study developed a simulation model that focused on the behavior of nontruck drivers when encountering trucks. Behavior during adverse weather was one of the factors evaluated. Experiments used data from the Borman Expressway data and from stated-preference surveys of nontruck drivers.
Benefit Assessment of Implementing Weather-Specific Signal Timing Plans by Using CORSIM	Henry C. Lieu and Shiow-Min Lin, Turner-Fairbank Highway Research Center, FHWA	2004	The purpose of this study was to use CORSIM to illustrate a procedure for assessing the benefits of retiming traffic signals in adverse weather.
Methodology for Measuring Recurrent and Nonrecurrent Traffic Congestion	Richard Dowling and Michael Carroll (Dowling Associates), Alexander Skabardonis (UC Berkeley Institute of Transportation Studies, Wang Zhongren (Caltrans)	2004	A methodology is presented for estimating and predicting the total annual traffic congestion attributable to recurrent and nonrecurrent congestion. Weather delays are estimated based on frequency of occurrence and capacity reductions during adverse weather.

Table A.1 Literature and Research on Studies Using Secondary Data

Reference	Authors	Year	Comment
Synthesis of the Effects of Wet Conditions on Highway Speed and Capacity	Panos D. Prevedouros, Ph.D., University of Hawaii at Manoa	2003	This study included a review and synthesis of research conducted on the impact of wet conditions on speed and capacity over approximately 30 years. The report compared HCM factors for adverse weather to those found in the synthesized studies.
Dynamic Speed Adaptation in Adverse Conditions: A System Proposal	A. Varhelyi	2002	This research looked at potential design and use of an in-car system that would adaptive speed controls to guide driver behavior under adverse weather conditions. The report focused on system design considerations and further research required.
Measuring the Effect of Traffic Safety Improvement Measures Using ITS	K. Sasaki, T. Tamuro and K. Saito	2002	The objective of the paper was to evaluate users' willingness to pay for traffic safety information, primarily regarding fixed point road safety information such as safe curve speed. The methodology could be applied to pretrip information related to weather.
Changes in Flow-Density Relationship due to Environmental, Vehicle and Driver Characteristics	K. M. Kockelman	1998	This study modeled flow-density relationships over roadway segments in adverse weather. Some disaggregation of various markets was tested.
Commuters' Normal and Shift Decisions in Unexpected Congestion: Pretrip Response to Advanced Traveler Information Systems (ATIS)	Asad Khattak (PATH Program, UC Berkeley), Moshe Ben-Akiva and Amalia Polydoropoulou (MIT Center for Transportation Studies)	1996	This study used stated-preference and behavioral surveys to test traveler response to pretrip information on congestion. The results showed prescriptive pretrip information does increase the likelihood that travelers will modify their route or time of departure.
Effect of Adverse Weather Conditions on Speed-Flow-Occupancy Relationships	A.T. Ibrahim and F. L. Hall	1994	This study used Freeway TMS data and weather data from Ontario's Queen Elizabeth Way to look at the effect of adverse weather on flow-occupancy and speed-flow relationships. Results indicated that the speed-flow function shifted downward during adverse conditions and that maximum observed flow rates were also reduced.
Effect of Weather on the Relationship between Flow and Occupancy on the Freeways	F.L. Hall and D. Barrow	1988	This study looked at the relationship between flow rates and roadway occupancies on freeways. This study also noted that the slope of the line relating flow to occupancy decreases as weather conditions deteriorate. The paper also noted the importance of developing flow-occupancy relationships on

Table A.2 Literature and Research on Studies Using Primary Data

Reference	Authors	Year	Comment
Inclement Weather and Traffic Flow at Signalized Intersections: Case Study from Northern New England	S.J. Abolosu-Amison, A.W. Sadek, and W. Elessouki, University of Vermont	2004	This study involved collection of data over a three month period via videotape from a signalized intersection in Burlington, VT. The study looked at the feasibility of developing special timing plans for adverse weather conditions. The study showed that saturation headways are impacted by adverse weather but start-up times are not. The implementation of special plans did appear to be beneficial.
Effects of Weather-Controlled Variable Message Signing on Driver Behaviour	Pirkko Rama, Technical Research Centre of Finland	2001	The study looked at the effects of using VMS to provide motorists with updated and local weather and road condition information. Different sign configurations and technologies were studied. Signs were used to lower speed limits and suggest greater headways. Motorists responded positively to these efforts.
Effect of Weather on Free-Flow Speed	M. Kyte, Z. Khatib, P. Shannon, E. Kitchener	2001	The impact of poor weather conditions on free-flow speed on a rural Interstate was evaluated. It was found that pavement condition, visibility and wind all had an impact on free flow speed.
Mobility and Safety Impacts of Winter Storm Events in a Freeway Environment	Keith Knapp, Dennis Kroeger and Karen Glese, Iowa State University Center for Transportation Research and Education	2000	The primary focus of this extensive study was to estimate the impacts of winter storm events on traffic volume, speed and crash rates on a rural Interstate highway. An initial study was conducted using secondary, archived data. This was followed by a second phase that involved field collection of weather and traffic data using both manual methods and video detection equipment. Significant speed reductions were estimated and the results were similar during both phases of the study.
Effects of Variable Speed Limit Signs on Driver Behavior During Inclement Weather	J. Perrin, University of Utah	2000	This paper presents results of the ADVISE system, which uses DMS to recommend speeds to drivers during periods of low visibility. It was found that the system reduced variability since faster drivers slowed down and overly cautious drivers reacted to a recommendation that they could go faster.
Adverse Weather Signal Timing	Pamela J Maki, SEH Consultants	1999	This study used both secondary and primary data to look at the feasibility of implementing traffic signal timing plans to address adverse weather conditions in the Twin Cities of Minnesota. Weather and traffic data were both collected at the site and a Synchro analysis was conducted to determine whether alternative timing plans could reduce delay under adverse conditions.
The Effect of Rainfall on Freeway Speeds	DJ Holdener	1998	Wet and dry speed data were collected along I-290 in Houston and analyzed using ANOVA. Speeds were measured at different times of day and significant differences were found between wet and dry conditions.
Effects of Rain on Daily Traffic Volume and on Driving Behaviour	JH Hogema, Delft Hydraulics Laboratory	1996	This study investigated the effects of rain on traffic volume and behavior in Holland. Rain did not impact volumes but did result in reduced speeds and longer headways.

B. Model Formulation

The functional form that is utilized in this study is the Van Aerde nonlinear functional form that was proposed by Van Aerde (Van Aerde 1995) and Van Aerde and Rakha (Van Aerde and Rakha 1995), which is formulated as:

$$h_n = c_1 + c_3 u_n + \frac{c_2}{u_f - u_n}. \qquad [7]$$

As was demonstrated by Rakha and Crowther (2002) this functional form amalgamates the Greenshields and Pipes car-following models where h_n is the spacing or distance headway (km) between vehicle *n* and vehicle *n-1* in the same lane, u_n is the speed of vehicle *n* (km/h), u_f is the facility free-flow speed (km/h), c_1 is a fixed distance headway constant (km), c_2 is a variable headway constant (km^2/h), and c_3 is a variable distance headway constant (h^{-1}). This combination provides a linear increase in vehicle speed as the distance headway increases with a smooth transition from the congested to the uncongested regime. This combination provides a functional form with four degrees of freedom by allowing the speed-at-capacity (u_c) to differ from the free-flow speed (u_f), which is a common assumption in a number of models, including the Pipes and Gipps model, or half the free-flow speed, as is the case with Greenshields model. Specifically, the first two parameters of Equation [7] provide the linear increase in the vehicle speed as a function of the distance headway, while the third parameter introduces curvature to the model and imposes a constraint on the vehicle's speed to ensure that it does not exceed the facility free-flow speed through the use of a continuous function. Demarchi (2002) demonstrates that by considering three boundary conditions the model constants can be computed as

$$c_1 = \frac{u_f}{k_j u_c^2}\left(2u_c - u_f\right); \quad c_2 = \frac{u_f}{k_j u_c^2}\left(u_f - u_c\right)^2; \quad c_3 = \frac{1}{q_c} - \frac{u_f}{k_j u_c^2}. \qquad [8]$$

Ignoring differences in vehicle speeds and headways within a traffic stream and considering the relationship between traffic stream density and traffic spacing, the speed-density relationship can be derived as

$$[9]\, k = \frac{1}{c_1 + \frac{c_2}{u_f - u} + c_3 u}, \qquad [9]$$

where *k* is the traffic stream density (veh/km) and *u* is the traffic stream space-mean speed (km/h) assuming that all vehicles are traveling at the same average speed (by definition given that the traffic stream is in steady-state). A more detailed description of the mathematical properties of this functional form can be found in the literature (Rakha and Crowther 2002; Van Aerde and Rakha 1995), as can a discussion of the rationale for its structure.

Of interest is the fact that Equation [9] reverts to Greenshields' linear model, when the speed-at-capacity and density-at-capacity are both set equal to half the free-speed and jam density, respectively (i.e., $u_c=u_f/2$ and $k_c=k_j/2$). Alternatively, setting the speed-at-capacity to the free-speed ($u_c=u_f$) results in the linear Pipes model given that

$$c_1 = \frac{1}{k_j} = h_j; \quad c_2 = 0; \quad c_3 = \frac{1}{q_c} - \frac{1}{k_j u_f}.$$

The wave speed at jam density (denoted as w_j) can be computed by differentiating the speed-density relationship with respect to density at jam density, to be

$$w_j = k_j \left.\frac{du}{dk}\right|_{k_j} = -h_j \left.\frac{du}{dh}\right|_{h_j}. \qquad [10]$$

By applying Equation [10] to [9] we derive

$$w_j = -h_j \left.\frac{1}{\frac{dh}{du}}\right|_{u=0} = -\frac{h_j}{c_3 + \frac{c_2}{u_f^2}} = -\frac{u_f}{k_j\left(c_3 u_f^2 + c_2\right)} = -\left[k_j\left(\frac{k_j}{q_c} - \frac{u_f}{u_c^2}\right) + \frac{\left(u_f - u_c\right)^2}{u_f u_c^2}\right]^{-1}. \qquad [11]$$

Considering, a typical lane capacity of 2,400 veh/h, a free-flow speed of 110 km/h (which is typical of U.S. highways), and a jam density of 140 veh/km/lane, the wave velocity at jam density ranges between approximately -11.5 to -20.3 km/h, when the speed-at-capacity is varied from 80 to 100 percent the free-flow speed (which is typical on North American freeways).

As was demonstrated earlier, the Van Aerde model reverts to the Pipes linear model when the speed-at-capacity is set equal to the free-flow speed. Consequently, it can be demonstrated that under this condition the wave speed of [11] reverts to

$$w = -\frac{q_c u_f}{k_j u_f - q_c}, \qquad [12]$$

which is the speed of the linear model. Furthermore, when $u_c=u_f/2$ and $k_c=k_j/2$ the wave speed at jam density is consistent with the Greenshields model estimates and is computed as

$$w_j = -u_f. \qquad [13]$$

If we consider the Van Aerde functional form the optimization model can be formulated as

$$\text{Min} \quad E = \sum_i \left\{ \left(\frac{u_i - \hat{u}_i}{\tilde{u}}\right)^2 + \left(\frac{q_i - \hat{q}_i}{\tilde{q}}\right)^2 + \left(\frac{k_i - \hat{k}_i}{\tilde{k}}\right)^2 \right\}. \qquad [14]$$

S.T.

$$\hat{k}_i = \frac{1}{c_1 + \dfrac{c_2}{u_f - \hat{u}_i} + c_3 \hat{u}_i} \quad \forall i$$

$$\hat{q}_i = \hat{k}_i \times \hat{u}_i \quad \forall i$$

$$\hat{q}_i, \hat{k}_i, \hat{u}_i \geq 0 \quad \forall i$$

$$\hat{u}_i < u_f \quad \forall i$$

$$0.5u_f \leq u_c \leq u_f; \quad q_c \leq \frac{k_j u_f u_c}{2u_f - u_c} \qquad [15]$$

$$c_1 = \frac{u_f}{k_j u_c^2}\left(2u_c - u_f\right); \quad c_2 = \frac{u_f}{k_j u_c^2}\left(u_f - u_c\right)^2; \quad c_3 = \frac{1}{q_c} - \frac{u_f}{k_j u_c^2}$$

$$u_f^{\min} \leq u_f \leq u_f^{\max}; \; u_c^{\min} \leq u_c \leq u_c^{\max}; \; q_c^{\min} \leq q_c \leq q_c^{\max}; \; k_j^{\min} \leq k_j \leq k_j^{\max}$$

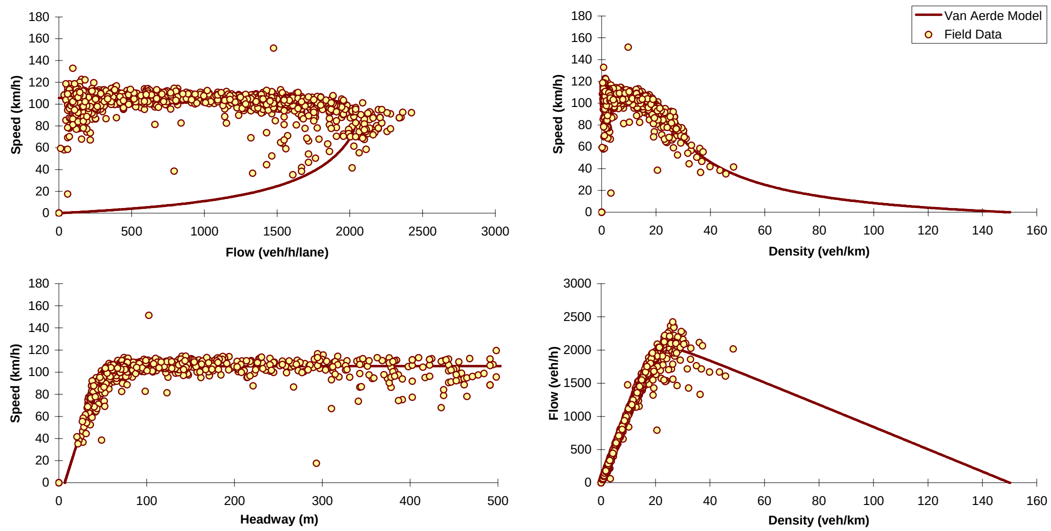
Where u_i, k_i, and q_i are the field observed space-mean speed, density, and flow measurements, respectively. The speed, density, and flow variables with hats (^) are estimated speeds, densities, and flows while the tilde variables (~) are the maximum field observed speed, density, and flow measurements. All other variables are defined as was done earlier in describing the Van Aerde functional form.

The objective function ensures that the formulation minimizes the orthogonal error between the field observations and the functional relationship – in this case the Van Aerde functional form. The distances are normalized in order to ensure that the objective function is unitless in order to minimize an objective function over different domains. The initial set of constraints, which is nonlinear, ensures that the Van Aerde functional form is maintained, while the second set of constraints is added to constrain the third dimension, namely the flow rate. The third and forth set of constraints guarantees that the results of the minimization formulation are feasible. The fifth set of constraints, ensures that the four parameters that are selected do not result in any inflection points in the speed-density relationship (i.e., it ensures that the density at any point is less than or equal to the jam density). A detailed derivation of the final constraint is provided elsewhere (Rakha 2006). The sixth set of equations provides estimates for the three model constants based on the roadway's *mean* free-flow speed (u_f), speed-at-capacity (u_c), capacity (q_c), and jam density (k_j). The final set of constraints provides a valid search range for the four traffic stream parameters that are being optimized (u_f, u_c, q_c, and k_j).

A heuristic tool was developed (SPD_CAL) and described elsewhere to calibrate traffic stream models. The procedure can be summarized briefly as follows:

1. Aggregate the raw data based on traffic stream density bins in order to reduce the computational space.
2. Initialize the four traffic stream parameters u_f, u_c, q_c, and k_j, and call them u_f^0, u_c^0, q_c^0, and k_j^0.
3. Construct the model functional form and move along the functional form at increments of Δk to compute the objective function. The accuracy of the objective function computation and the computational speed will depend on the size of the Δk variable.
4. Vary the four parameters u_f^i, u_c^i, q_c^i, and k_j^i at iteration i from u_f^{min}, u_c^{min}, q_c^{min}, and k_j^{min} to u_f^{max}, u_c^{max}, q_c^{max}, and k_j^{max} at increments of u_f^{inc}, u_c^{inc}, q_c^{inc}, and k_j^{inc}.
5. Construct the model functional form for each parameter combination and move along the function form at increments of $\Delta k/i$ to compute the objective function. Note that the computational accuracy increases as the iteration number increases.
6. Compute the set of parameters u_f^i, u_c^i, q_c^i, and k_j^i that minimize the objective function.
7. Reduce the search window by a factor of 1/i and compute u_f^{min}, u_c^{min}, q_c^{min}, and k_j^{min} to u_f^{max}, u_c^{max}, q_c^{max}, and k_j^{max} at increments of u_f^{inc}, u_c^{inc}, q_c^{inc}, and k_j^{inc}.
8. Go to step 3 and continue until either the number of iterations is satisfied or the minimum change in objective function is satisfied.

Figure B.1 Van Aerde Model Fit to Freeway Data (Twin Cities, USA)



Free-Speed:	106 km/h
Capacity:	2041 veh/h/lane
Speed-at-Capacity:	85 km/h
Jam Density:	150 veh/km/lane
Wave Speed (wj):	-17.0 km/h

The fit to five-minute data from the Twin Cities, Minnesota, demonstrates that the calibration tool is able to capture the functional form of the data. The figure clearly demonstrates the effectiveness of the proposed calibration tool together with the Van Aerde functional form to reflect steady-state traffic stream behavior on this facility over multiple regimes.

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