SHRP2 Implementation Assistance Program (IAP)—Round 4
Concept to Countermeasures—Research to Deployment Using the SHRP2 Safety Data

Driver Performance and Behavior in Adverse Weather Conditions: An Investigation Using the SHRP2 Naturalistic Driving Study Data

WYDOT Sponsor:
Vince Garcia, P.E., GIS/ITS Program Manager

Principal Investigator:
Mohamed M. Ahmed, Ph.D., P.E.

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A Proposal from
Department of Civil and Architectural Engineering
University of Wyoming
1000 E. University Avenue, Department 3295
Laramie, Wyoming 82071
Telephone: (307) 766-5550
Fax: (307) 766-2221
E-mail: mahmed@uwyo.edu

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1. INTRODUCTION

Inclement weather events such as fog, snow, ground blizzard, slush, rain, and strong wind affect roadways by impacting pavement conditions, vehicle performances, visibility, and drivers' behavior. Road-user characteristics and behavior are among the most important elements influencing the driving task. The ability to see objects that are in motion relative to the eye ("dynamic visual acuity") and the reaction process (e.g., speed choice, lane maintenance, car following, etc.) are of utmost importance for safe driving. Adverse weather conditions can result in a sudden reduction in visibility on roadways, which leads to an increased risk of crashes. Effects of adverse weather conditions on the operations and safety of transportation is considerably researched; however, the primary elements of driver behavior and performance are absent from these studies. According to the U.S. Department of Transportation's Federal Highway Administration (FHWA), weather contributed to more than 24% of the total crashes between 1995 and 2008, based on National Highway Traffic Safety Administration (NHTSA) data. Several studies concluded that crashes increase by 100% or more due to vision obstruction during rainfall (National Traffic Safety Board, 1980; Brodsky and Hakkert, 1988), while others found more moderate, but still statistically significant, increases (Andrey and Olley, 1990; Andreescu and Frost, 1998). Sudden reduction in visibility was found to increase severity level of crashes, and these crashes tend to involve more vehicles compared to other crash types. According to the NHTSA's Fatality Analysis Reporting System (FARS), inclement weather of rain, snow, and fog/smoke resulted in 31,514 fatal crashes between 2000 and 2007. Shankar, Mannering, and Barfield (1995) reported that the crash rates increased for locations with a high number of rainy days per month, maximum rainfall, and maximum snowfall. Ahmed et al. (2012) reported that an additional one inch increase in precipitation elevated the risk of a crash by 169%. The literature shows a variation of crash risk estimates; however, a general trend can be concluded that adverse weather and road conditions can easily elevate the risk of crashes. Drivers' performance and behavior are absent in safety modeling due to lack of driver data. The second Strategic Highway Research Program (SHRP2) has collected the most comprehensive Naturalistic Driving Study (NDS). The unique NDS data will enable researchers to better understand the role of driver performance and behavior under various highway research.

2. PROJECT OBJECTIVES AND RESEARCH QUESTIONS

The Wyoming Department of Transportation (WYDOT) and University of Wyoming have completed a proof-of-concept utilizing a sample NDS data set and Roadway Information Database (RID). The NDS and RID data sets were utilized to better understand how drivers adjust their behaviors to compensate for increased risk due to reduction in visibility. The main goal of this study was to enhance the understanding of how drivers respond to adverse weather and road conditions (e.g., speed adaptation, lane maintenance, car following, etc.). This was conducted by compiling a sample data set from DS data, then extracting and reducing the data for inclement weather events (i.e., heavy rain in Phase 1) on freeways to address the following research questions:

1. Can inclement weather trips be identified effectively using NDS and RID data?
2. Can driver responses (i.e., speed and headway adaptation, and lane wandering) during inclement weather (i.e., reduction in visibility due to heavy rain in Phase 1) be characterized efficiently from NDS data?
3. What are the best surrogate measures for weather-related crashes that can be identified using NDS data?

4. What type of analysis can be performed and conclusions be drawn from the resulting data set?

According to the FHWA, Connected Vehicle (CV), Variable Speed Limits (VSL), and Advanced Traveler Information Systems (ATIS) are considered the next step in tackling U.S. freeway congestion and safety problems. VSL systems have been widely implemented in the U.S. and Europe to help mitigate: 1) recurrent congestion; 2) adverse weather impacts on freeways; 3) traffic injuries and fatalities; and 4) pollution. VSL systems will be an integral part of CV technology.

Because selecting the right speed for the condition is considered one of the most important driving tasks on high speed facilities, and the interaction between the driver and weather condition is not well understood, the objective of this research is to assess the relationship between driver behavior (i.e., speed and headway choice), roadway factors, and environmental factors.

The study will gain insights into drivers' dynamics in regard to choosing speeds and headways for different conditions and what cues are the most effective in providing drivers with a more realistic VSL system. It will also provide valuable information about how drivers interact with changing roadway and weather conditions and the effectiveness of countermeasures. All current VSL systems' algorithms are based solely on weather and traffic conditions. To the knowledge of the principle investigators, no VSL systems considered driver behavior in their algorithms. Current practices in setting speed limits within VSL systems under different traffic and weather conditions are based on traffic simulation, survey questionnaires, and historical crash data. The NDS data will help provide objective insights into what drivers actually do during adverse weather and road conditions.

Wyoming was selected as one of three sites for the Connected Vehicle Pilot Deployment; the project will be conducted on Interstate 80 (I-80) VSL corridors. The research from this study will aid in supporting CV technology. Continuous data collected in real-time from vehicles will be analyzed to examine the usefulness of the NDS data in providing real-time weather information.

Based on the experiences in Phase 1, we propose in Phase 2 addressing a 5th research question:

5. Can the NDS data be extrapolated to provide real-time weather information in the context of Road Weather Connected Vehicle Applications?

The main objective of this research is to examine the feasibility of using NDS and RID data sets to improve our understanding of weather- and visibility-related crashes. The study will help in enhancing suggested speed limits within VSL systems and providing guidance information within ATIS. This study will investigate the applicability of using vehicle time series data to support CV technology during inclement weather. The outcome from this research will help in reducing traffic injuries and fatalities.

3. DATA ACQUISITION AND PREPARATION

Data acquisition and reduction are crucial steps in this study. In Phase 1, NDS data were requested to examine driver response in rain/heavy rain in the states of Florida and Washington. Roadway Information Database (RID) as well as visual inspection of aerial and street view images from Google maps were also utilized. The provided NDS data included forward-facing and rear-facing videos, basic trip characteristics, and selected vehicle time series data. To address the first research question of identifying appropriate trips in rainy conditions, a preliminary criterion for data extraction was identified by the University of Wyoming (UW) research team. To accomplish the study objectives, 50 NDS trips during rain/heavy rain on freeway segments from Florida and

Washington States were requested. Identifying and extracting requested data was a challenging task in this project. The criterion for NDS data extraction is unique for various reasons. Weather information is not readily available in NDS and RID. Although wiper setting could give an indication about rain intensity, wiper setting is not consistent across different vehicles. Wiper setting in NDS data indicates the position of the wiper switch rather than wiper swipe rate; moreover, different drivers have different tolerances to rain/visibility, and splashes from other vehicles may affect driver choice of the appropriate wiper speed. There was another issue encountered during the preliminary investigation on five sample traces provided by VTTI to fine tune the extraction process: the wiper blades of Honda Civic vehicles did not cover the whole windshield in front of the camera. The UW research team had to come up with a strategy to effectively identify NDS trips in rain/heavy rain without introducing biasness to the sample data used in Phase 1. The final NDS extraction steps for trips in rain/heavy rain were as follows:

1) Only trips with multiple wiper settings were targeted; vehicles that did not include the full spectrum of values for the wiper status (0, 1, 2, and 3) were filtered out. Vehicles with on/off wiper settings only would not provide an indication of rain intensity.
2) Months with high rain precipitation in the states of Washington and Florida were used for this task.
3) Only NDS daytime trips in rain on freeways would be used. Nighttime trips were eliminated in Phase 1 due to the low resolution of provided sample video data.
4) Honda Civics were eliminated from the data set because of the lack of wiper blade coverage of the windshield surface in front of the camera.
5) Potential events were tagged with the duration of the trip that different wiper settings of 0, 1, 2, and 3 were active to facilitate data extraction for light/heavy rain conditions.
6) Each identified trip in rain was matched with two trips in clear weather conditions for the same route and subject as much as possible.

An additional 100 matching NDS trips during clear weather on the same segments and subjects in Florida and Washington States were requested. About 147 useful traces with requested characteristics in rain/heavy rain, and their matching clear weather traces, were provided. Some of the provided trips in rain did not have matching trips in clear weather and thus were excluded from the analysis. Although most of the trips in inclement weather conditions were matched with two trips in clear weather conditions, only a matching rate of 1:1 was achieved in Phase 1 due to data limitation. Matching is important to control for sundry factors such as driver population, roadway geometry, etc. It is worth mentioning that real-time traffic data are not available in the NDS data. To isolate the impact of adverse weather conditions on driver behavior, trips in free-flow traffic were identified. Classifying the NDS data into two different traffic states (free-flow and mixed traffic) resulted in a total of 56 trips that were considered for further analysis. Travel times were used to broadly identify trips in free-flow/light traffic; the presence and distance to other vehicles identified by the front radar and the estimated headway times were also a good indicators of traffic conditions. NDS video data were manually analyzed to verify and validate results. Table 1 shows summary statistics for the number of trips, route names and length of routes, total travel times, and percentages of wiper use at different settings along with their matching clear weather trips. After screening provided data for surrogates for crashes/near crashes, only three trips were identified as events, two of which occurred in rain. All corresponding RID data were identified and linked to the provided NDS data. The 56 NDS trips constituted a total of about 1,775 interstate kilometers traveled over 21.94 hours on six interstate routes in Florida and Washington States. These trips occurred mostly on I-4, I-75, and I-275 in Florida, and on I-5, I-90, and I-405 in Washington.

Table 1: Summary Statistics of NDS Trips Considered in Phase 1

Traffic Condition	Weather Condition		Heavy Rain	Matched Clear	Light Rain	Matched Clear	Total
Free-Flow Condition	Number of Trips		**7**	**7**	**9**	**9**	**32 trips**
	% Wiper Setting	0	6.1%	99.5%	0.0%	96.6%	
		1	0.0%	0.0%	60%	3.4%	
		2	0.0%	0.0%	22%	0.0%	
		3	93.9%	0.5%	18%	0.0%	
	Total Duration (hr)		3.26	2.80	1.42	1.37	**8.85 hr**
	Total Length (km)		308.67	308.67	172.76	172.76	**962.86 km**
Heavy/ Mixed Traffic	Number of Trips		**3**	**3**	**9**	**9**	**24 trips**
	% Wiper Setting	0	0.0%	99.9%	6%	91.2%	
		1	10%	0.0%	50%	8.8%	
		2	14%	0.0%	26%	0.0%	
		3	75.2%	0.1%	18%	0.0%	
	Total Duration (hr)		1.34	1.64	5.44	4.67	**13.09 hr**
	Total Length (km)		95.3	95.3	309.64	312.05	**812.29 km**
Total Number of Trips			**10**	**10**	**18**	**18**	**56**

4. DATA VISUALIZATION AND REDUCTION

Dealing with the NDS data could be challenging for various reasons: the size and complexity of the data, the continuous nature of the data, the difficulty of identifying events of interests, processing and reducing video data, identifying weather conditions and visibility limits, linking NDS data with RID data, identifying surrogates for different crash types, and defining baselines in normal driving conditions.

To efficiently characterize driver responses (i.e., speed and headway adaptation, and lane wandering) during inclement weather (i.e., reduction in visibility due to rain/heavy rain in Phase 1), an interactive visualization and reduction software was developed. The software is developed in C++ under the Microsoft Visual Studio 2013 environment. It runs on Windows workstations and uses multimedia libraries that allow the playback and manipulation of video files. The software synchronizes the two video files for the front and rear NDS cameras, as well as the time series data file. This allows users to relate various time series variables to the front and rear videos. In addition, time series could be smoothed using a moving average technique and extracted for further analysis.

5. MACHINE VISION VISIBILITY ESTIMATION

The software is also under development to provide the level of visibility exhibited during driving conditions as recorded in the video. The UW research team is investigating various image processing techniques. One approach to gauge the level of visibility is by measuring the amount of blur in the image. If an image is sharp, one can assume that the visibility is rather high. Conversely, a low visibility level would cause the image to loose sharpness and become blurred. The problem of determining the visibility level is heuristic. In other words, it requires computational algorithms that may not guarantee a correct solution for every case. They can have a good level of accuracy, but they are not 100% foolproof.

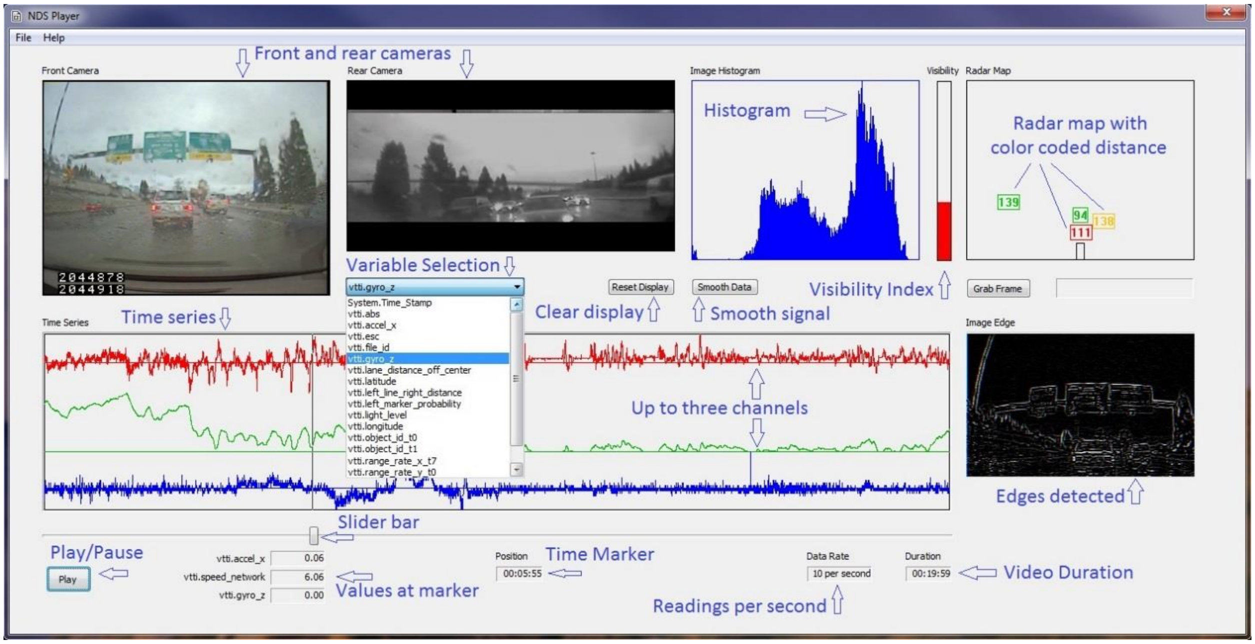


Figure 1: NDS Visualization and Reduction Software

Current challenges with the NDS videos include the fact that they span a wide range of driving and weather conditions. These conditions, among others, include varying levels of brightness and ambient light, sceneries, distances to other vehicles and obstacles, headlights and/or taillights of cars ahead, reflections from the road and other objects, street lights, and rain. These conditions, when aggregated together in different combinations, can trick the algorithm into making inaccurate assumptions, and eventually providing less than optimal results.

The algorithm may work with a certain level of confidence on some images, but behaves poorly on others. It is also difficult to teach the algorithm to know when it is providing inaccurate results. This is typically the nature of the heuristic algorithm development cycle where calibration is applied to pertinent factors and conditions to improve the performance. The algorithm is then retested, and the cycle is repeated in an iterative manner. The effort is currently focused on improving the accuracy and performance of the visibility algorithm. The goal is to maximize the detection accuracy by minimizing false positives and false negatives. The research team is attempting other image processing techniques. One of the techniques aims at detecting lane markings and other objects, such as road signs and light poles, to estimate the visibility level. It also takes into account an estimate of the object distance from the camera as correlated with the object location in the video frame. The visibility index is estimated based on the object clarity and its estimated distance from the camera. It should be noted that the NDS utilizes a single camera, though a stereo camera system usually provides a higher accuracy for distance estimation.

6. PRELIMINARY ANALYSIS AND DESCRIPTIVE STATISTICS

As mentioned earlier, trips in rainy conditions were identified by extracting trips with a high number of minutes of wipers used at different speed settings. NDS video data were manually analyzed for 14 randomly selected trips to verify and validate results. The verification and validation process revealed that some trips had mixed light rain and heavy rain, and clear weather conditions. Also, traffic conditions were characterized using presence and distance to other vehicles, and average headway times. Trips were classified into six categories based on visibility and traffic condition: light rain, heavy rain, and clear weather in free-flow and heavy traffic.

For automatic identification of trips in rain, other basic trip characteristics such as number of brake activations, high variability in headway times and distances, electronic stability control, roadway departures, low coefficient-of-friction, number of Anti-Lock Braking System (ABS) activations, and number of traction control activations were examined in Phase 1. A preliminary analysis on trips in rain/heavy rain indicated that there were no ABS, traction control, or electronic stability control activations in any of the trips. This could be explained due to the fact that these variables are not available in NDS data for all vehicles; moreover, the activation of these safety features is not common in rain on freeway segments. As mentioned earlier, 147 NDS total trips were acquired, but only 56 were considered for further analysis when matching is needed. The total 147 acquired trips were utilized in the Ordered Probit model. Results from the preliminary analysis and descriptive statistics were as expected in most of the cases. The following sections provide discussions about speed, acceleration, lane maintenance (yaw rate), lane change, and headway during heavy rain contrasted to clear weather condition in free-flow and heavy traffic. Table 2 shows descriptive statistics and various statistical tests for the main time series variables of interest for heavy rain/clear weather in free-flow and heavy traffic. Also, descriptive statistics are shown for trips that included heavy rain and clear weather conditions within the same trips.

6.1. Driver Behavior (Speed, Acceleration, Lane Maintenance/Change, and Headway)

This proof-of-concept phase investigated the distribution and variation of speeds between clear and adverse weather conditions in various traffic conditions. Six possible scenarios were considered and compared: light rain, heavy rain, and clear weather in light and heavy traffic. Characterization of traffic flow became very important for various reasons: realistic traffic conditions and the appropriate distributions are needed for the calibration of the simulation models, and predictability of traffic conditions in various weather conditions is needed for an effective and realistic VSL system. Characterization of traffic conditions and speed in different weather conditions, moreover, will help in applications such as CV technology. If unusual traffic patterns are detected, these geospatial locations could be flagged for a possible and timely mitigation strategy. From the NDS sample data, it was concluded that speeds have a Weibull distribution in heavy rain under free-flow condition while the speeds were normally distributed in clear weather for the matching data set as shown in Figure 2. Speed in free-flow condition is important for VSL application because the speed choice here is not affected by the interaction with traffic. A t-test indicated that the average speed in heavy rain under free-flow traffic condition was significantly (16.32km/hr) lower than in clear condition and free-flow traffic. It was also found that speeds have higher variability during heavy rain compared to clear condition under free-flow traffic.

Other speed distributions for other scenarios were examined, but they were not included in this report for brevity. Examining drivers' selection of speed during traffic congestion is also important. This could help determine whether drivers take higher risks during adverse weather conditions to make up for delays encountered because of congestion. Speed distribution during heavy rain in congestion (mixed/heavy traffic) did not fit a specific distribution, which may indicate higher speed variability. The speeds during clear weather conditions in mixed/heavy traffic volumes on the same routes and subjects fitted two normal distributions, which is common during congestion on freeways. There was no significant difference in the distribution of speeds during light rain.

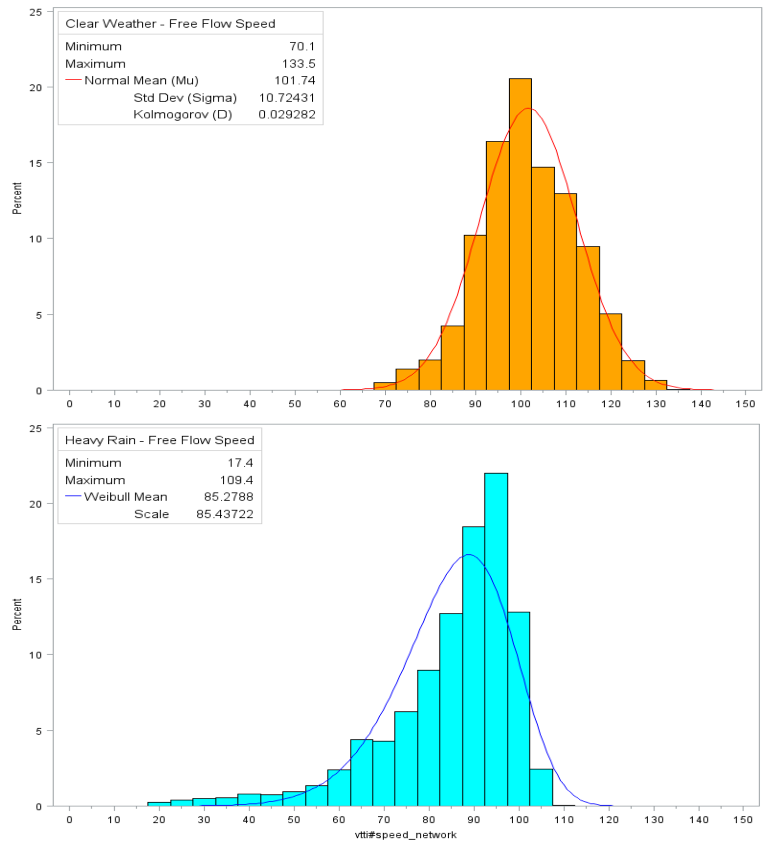


Figure 2: Observed and Fitted Distributions for Speeds during Heavy Rain and Clear Weather under Free-Flow Traffic

Although matching technique may control for sundry factors (among them roadway geometry, traffic condition, and driver population) supplementary traffic-flow parameters may be needed to fully isolate driver behavior of speed selection due to the environment. Loop detector and Automatic Vehicle Identification (AVI) traffic-flow data will be collected on the NDS routes during the same time duration from local agencies in Phase 2.

The acceleration/deceleration variable was examined, and ±0.3g acceleration/deceleration rates were set as a threshold to identify aggressive braking/acceleration events. The preliminary analysis showed that while heavy rain has a wider range of acceleration and statistically has a higher average, the average deceleration was found to be statistically higher in the matching clear weather conditions. The variability of acceleration and deceleration and the proportions of deceleration lower than -0.3g were found to be greater in clear weather conditions. These findings coupled with the observed reduction in speed during heavy rain indicate that drivers compensate for the slippery surface conditions by not decelerating by rates greater than -0.3g.

The lane offset variable in the NDS data is estimated using machine vision techniques. Lane offset is an indication of either a lane change or a deviation from the lane. Lane change is defined as an intended and substantial lateral shift of a vehicle (Chovan et al., 1994). Lane change could be modeled using multiple variables: turn signal, steering angle, yaw rate, and machine vision lane offset. Although lane change is not the main focus of this study, distinguishing lane change from lane wandering is important to understand driver behavior in adverse weather conditions. Utilizing time series and video data, lane changes were separated from lane wandering.

Table 2: Descriptive Statistics for the NDS Instrumented Vehicles

	Statistical Tests	Free-Flow Traffic (Matched Trips)				Comparison within Trips			
		Heavy Rain		**Matched Clear**		**Heavy Rain**		**Clear Weather**	
Speed (kph)	Average	85.07		101.39		91.8		106.36	
	SD	14.69		10.72		14.65		6.53	
	Min.	17.4		70.1		35.09		53	
	Max.	109.4		133.5		125.5		125.9	
	Median	87.5		101		94.19		106	
	t-Test	Avg. Speed is significantly lower in Heavy Rain				Avg. Speed is significantly lower in Heavy Rain			
	F-Test	Speed variability is higher in Heavy Rain				Speed variability is higher in Heavy Rain			
	Z-Test	Proportion of violation ≥ 10 km/h above the speed limit is significantly higher in Clear Weather				Proportion of violation ≥ 10 km/h above the speed limit is significantly higher in Clear Weather			
Acceleration/ Deceleration (g) (Positive columns= Acceleration)	Average	0.0263	-0.0266	0.0253	-0.0276	0.0213	-0.0282	0.0158	-0.0162
	SD	0.0181	0.0214	0.0184	0.0225	0.0157	0.0245	0.0160	0.0185
	Min.	0.0029	-0.3132	0.0015	-0.4321	0.0015	-0.2842	0.0029	-0.2610
	Max.	0.2059	-0.0029	0.1769	-0.0015	0.1769	-0.0015	0.1624	-0.0029
	Median	0.0232	-0.0232	0.0203	-0.0232	0.0174	-0.0218	0.0116	-0.0087
	t-Test	Average Acc. is significantly higher in Heavy Rain and avg. Dec. is higher in Clear Weather				Average Acc./Dec. is significantly higher in Heavy Rain			
	F-Test	Acc./Dec. variability is higher in Clear Weather				Acc./Dec. variability is higher in Clear Weather			
	Z-Test	Proportions of Dec. lower than -0.3g is significantly greater in Clear Weather. No Acc. were found higher than +0.3g				No Acc./ Dec. were found higher/lower than ±0.3g			
Yaw Rate (deg/s) (negative sign=left rotation)	Average	0.84	-0.97	0.89	-0.8	1.01	-0.97	0.64	-0.61
	SD	0.73	0.65	0.71	0.59	0.88	0.86	0.41	0.46
	Min.	0.33	-8.78	0.33	-3.9	0.16	-8.78	0.16	-4.55
	Max.	6.83	-0.33	5.85	-0.33	10.08	-0.16	3.25	-0.16
	Median	0.65	-0.65	0.65	-0.65	0.65	-0.65	0.49	-0.33
	t-Test	Yaw rate (right rotation) is significantly higher in Clear Weather—no significant difference in left rotation				Yaw rate is significantly higher in Heavy Rain			
	F-Test	Yaw rate variability is higher in Heavy Rain				Yaw rate variability is higher in Heavy Rain			
Lane Offset (cm)	Average	24.4	-23.04	62.26	-71.92	39.55	-45.99	34.56	-43.39
	SD	22.55	26.87	130.79	135.39	76.44	83.33	65.58	75.06
	Max	964.95	0	999.86	-0.01	838.83	-0.01	955.04	-999.59
	Min	0	-590.8	0.05	-999.12	0.05	-998.61	0.05	-0.04
	Median	20.32	-17.02	18.66	-29.08	16.85	-26.94	15.54	-26.88
	t-Test	Avg. lane offset to the right and left from the lane center is significantly higher in Clear Weather				Avg. lane offset to the right and left from the lane center is significantly higher in Heavy Rain			
	F-Test	Lane offset to the right and left variability is higher in Clear Weather				Lane offset variability is higher in Heavy Rain			
Headway(sec)	Average	2.17		2.01		1.98		2.02	
	SD	1.00		1.12		1.16		1.14	
	Max	7.84		6.65		7.58		6.68	
	Min	0.16		0.08		0.12		0.15	
	Median	2.10		1.99		1.83		1.81	
	t-Test	Headway is significantly higher in Heavy Rain				No significant difference			
	F-Test	Headway variability is higher in Clear Weather				No significant difference			

A criterion for lane offset values within ±0.3 meters was set to flag lane wandering events, especially when these events vary to the right and left over a short duration of time. Continuous and steady lane offset within a threshold greater than ±0.3 meters to ±9.5 meters in one direction was considered as a full lane change. A past NDS study indicated that using a threshold of ±0.1 meters resulted in a higher than expected number of lane departures (Hallmark et al., 2015). Preliminary analysis indicated that the number of lane changes is higher in clear weather conditions while lane wandering was found to be significantly higher in adverse weather conditions (heavy rain). Analyzing the NDS time series data in conjunction with video data revealed that the estimated NDS machine vision lane offset is too noisy in adverse weather conditions and where there are multiple marking lines near merge and diverge sections. The min/max values for the lane offset also revealed a very interesting finding: drivers tend to change multiple lanes (2–3 lanes) during clear weather conditions versus a single lane change in heavy rain conditions. Controlling for entry and exit of the freeway maneuvers, lane changes occurred in heavy rain were mostly evasive maneuvers to mitigate an increased risk. From video observations, it was found that drivers opted out of speed reduction behind a slower vehicle more often than changing lanes. Yaw rate and steering angle are additional variables that could be used to analyze lane maintenance. Unfortunately, steering wheel position was only available for a fraction of vehicles (only two trips included steering angle data). Yaw rates were analyzed for events with lane offset within ±0.3 meters where there were no lane changes. Yaw rates were significantly higher in heavy rain, which, as mentioned earlier, might indicate frequent evasive maneuvers to mitigate an increased risk.

On the one hand, average headways were found to be significantly higher in heavy rain compared to clear weather condition under free-flow traffic. On the other hand, the variability of headways was found to be significantly higher in clear conditions. This could be explained by the fact that drivers tend to compensate for the increased risk due to the limitation in visibility by maintaining longer headway times.

Additional analyses were conducted on an individual (no matching) seven NDS traces that were identified to have both clear and heavy rain conditions within the same trip. All seven trips were in free-flow traffic condition. There was an agreement across the seven trips that speeds were reduced significantly with a higher standard deviation in heavy rain than in clear condition. Also, the acceleration/deceleration and lane change/maintenance were affected. Number of brakings, decelerations, and accelerations were significantly higher in heavy rain than in the clear portion of the trips. There were 44 and 22 braking events in heavy rain and clear weather conditions, respectively. High variability in yaw rate might indicate either too many lane changes or poor lane maintenance. Although the number of lane changes was very limited in heavy rain compared to clear conditions, the high variability in yaw rate during heavy rain suggested worse lane maintenance capabilities than in the clear condition.

Figure 3 shows a continuous speed profile, yaw rate, and acceleration data for one of the seven trips with both clear and adverse weather conditions in free-flow condition. The driver reduced the speed by more than 20 km/hr at the onset of the heavy rain; speed varied significantly afterword. It was also noted that a higher yaw rate and acceleration/deceleration rates were encountered during the heavy rain duration. It is worth mentioning that the results from trips that included clear and heavy rain were not consistent with the matched trips for obvious reasons. Number of accelerations, decelerations, and lane changes due to exit, entry, and weaving maneuvers, among other variables, are controlled for in the matching approach.

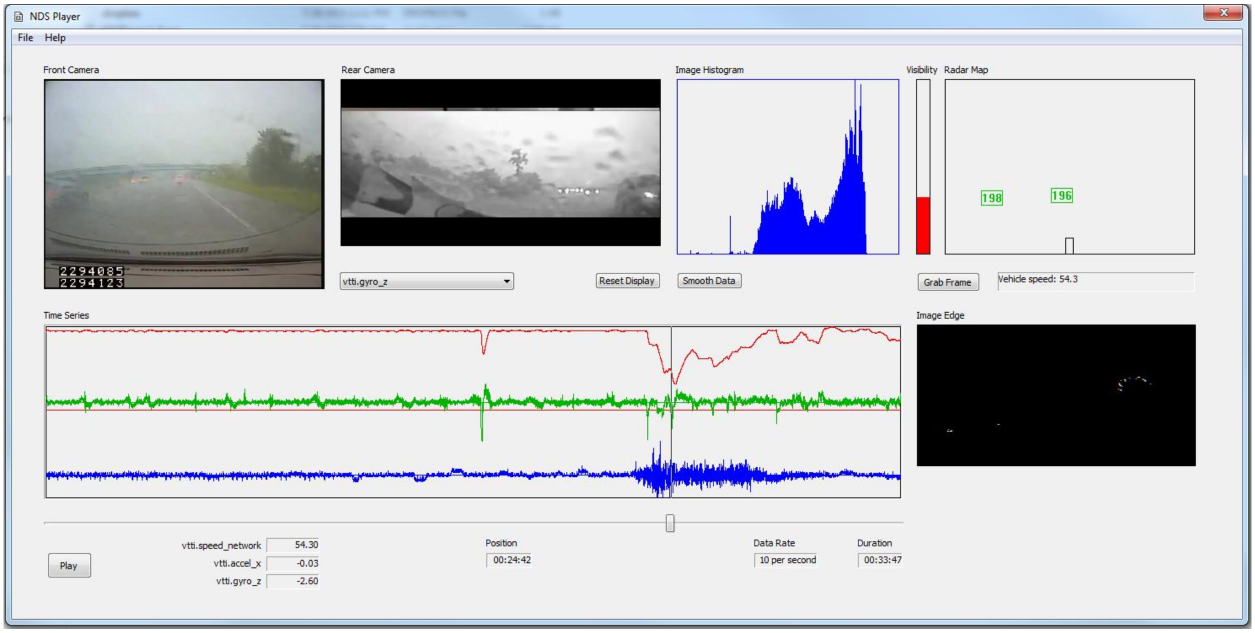


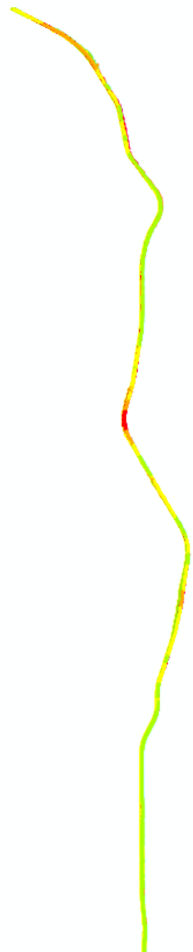
Figure 3: Illustration of Sudden Reduction in Visibility Impact on Driver's Performance

6.2. Speed Selection: GIS Analysis and Odds Ratios

Table 3 and Figure 4 show speed behavior in clear and adverse weather conditions. Twelve NDS trips were linked to the RID via ArcGIS software. The main objectives of linking the NDS continuous data and RID were to: 1) compare the NDS speed to the speed limit along a defined route, and 2) provide a visual representation of speed selection in ArcGIS environment. Three sets of trips in heavy rain, light rain, and clear weather conditions were identified on the same 18.19-km route (Interstate 405) in Washington. A new layer was added in the ArcGIS to indicate the speed selection in both clear and rainy traces along the same route. Odds ratios were used to examine the impact of rain on speed behavior. A Z-test was utilized to test the statistical significance of the difference between the proportion of speeds in clear and adverse weather conditions. Table 3 shows that speed reduction was more likely to occur in heavy rain than the corresponding matched trip in clear weather condition. For instance, the NDS drivers drove below the speed limit in approximately 37% of their trips in clear weather. In comparison, about 85% of the trips in heavy rain were driven with speeds less than the limit. Table 3 indicates that speed reduction was more likely to be in light and heavy rain conditions in comparison with the matched trips in clear weather condition. The odds ratios of driving below the speed limit, in general, were 10 and 3 times more likely to be in heavy and light rain, respectively, than matching trips in clear weather conditions. On the same I-405 route in Washington, 37% of the speeds were under the posted speed limit. This was reduced to more than 85% during heavy rain events.

Table 3: Odds Ratios for Speed Behavior on I-405 (Heavy/Light Rain vs. Clear)

	Driving below Speed Limit	Driving above Speed Limit	Odds ratio	Confidence Intervals	Z-statistic	Significance level
Light Rain	1,797	958	3.19	2.86 to 3.57	20.43	P < 0.0001
Clear Weather	968	1,651				
Heavy Rain	2,621	454	9.85	8.67 to 11.18	35.19	P < 0.0001

Heavy Rain				**Rain**				**Clear**			
Trip ID:643,653,657, and 672				Trip ID: 646,656,660, and 667				Trip ID:642,654,652, and 669			
Total trips duration: 52:36				Total trips duration: 46:13				Total trips duration: 44:30			
Speed Groups				Speed Groups				Speed Groups			
>5 Below SL	(0-5) Below SL	(0-5) Above SL	>5 Above SL	>5 Below SL	(0-5) Below SL	(0-5) Above SL	>5 Above SL	>5 Below SL	(0-5) Below SL	(0-5) Above SL	>5 Above SL
64%	21%	13%	2%	38%	27%	22%	13%	19%	18%	31%	32%
											

Route: Interstate 405,Washington, Length: 11.3 miles (18.19 km), Start: Mile Marker 27
Speed limit source: Roadway Information Database (RID) and Street View in Google Map

- **>5 km/hr below the speed limit**
- **0-5 km/hr below the speed limit**
- **0-5 km/hr above the speed limit**
- **>5 km/hr above the speed limit**

Figure 4: Speed Behavior in Clear, Light-Rain, and Heavy-Rain on I-405, Washington (Mile-Marker 27 to Mile-Marker 38.3)

7. MODELING SPEED SELECTION: ORDERED PROBIT LOGIT MODEL

To model speed selection, an ordered probit model was calibrated utilizing all the 147 trips occurring in various weather and traffic conditions (matching is not required). The model was developed for four speed intervals: more than 5 kph below the speed limit (base case), 0–5 kph below the speed limit, 0–5 kph above the speed limit, and more than 5 kph above the speed limit. Table 4 shows the selected variables for developing the "speed behavior" model in weather conditions. The dependent variable is speed selection behavior considering four levels. Generally, explanatory variables can be considered as driver's demographics, vehicle characteristics, roadway factors, and traffic and environmental conditions. Due to the lack of drivers' and vehicle characteristics data in Phase 1, only environmental and traffic variables were considered. This analysis will be extended with more driver demographics, vehicle characteristics, roadway geometry, and test data variables in Phase 2.

Table 4: Data Description

Variable	Description	Type	Levels
Response Variable			
Speed Behavior	Speed selection in various weather conditions	Ordinal	More than 5 kph below the speed limit
			0–5 kph below the speed limit
			0–5 kph above the speed limit
			More than 5 kph above the speed limit
Explanatory Variables			
Traffic	Traffic Condition	Binary	0= Free-flow
			1= Traffic
Speed Limit	Posted Speed Limit	Categorical	0= below 90 kph
			1= above 90 kph
Surface Condition	Road surface condition extracted from video data	Binary	Dry
			Wet
Weather	Type of severe weather condition	Categorical	Clear
			Light Rain
			Heavy Rain

7.1. Model Evaluation and Results

To confirm the suitability and fitness of the model, the log likelihood ratio and the pseudo R^2 were used. Table 5 shows the results of the model; the Likelihood Ratio (LR) test statistic falls into the rejection area (p-value < 0.05), which means that the overall explanatory variables of the model have significant influence on the response at a statistical significance level of 95%. Only statistically significant variables were retained in the final models.

Three factors were found to be significant: weather, speed limit, and traffic condition. Among these, weather and traffic have the highest effect on speed behavior. This indicates that reduction in visibility significantly impacts drivers' behavior of selecting speed when compared to light rain or clear weather conditions. Drivers are likely to select significantly lower speed during heavy rain. Traffic has a negative coefficient as expected. Controlling for all other variables, drivers are limited to lower speeds in poorer levels of service. Interestingly, speed limit was significant with a negative coefficient, which might imply that NDS drivers tend to comply more to the speed limits on freeway segments with higher speed limits. Headway was also used as a crash surrogate under various weather and traffic conditions. The results from the headway model yielded expected outcomes and were consistent with the preliminary analysis. Drivers tend to have higher average headway times during heavy rain compared to light rain and clear weather conditions. More driver demographics such as age, gender, taking risks, etc., and vehicle characteristics might be needed to fully reveal driver behavior with respect to speed and headway selection. It is worth mentioning that for VSL application in the U.S., speed levels should be modeled within 5 mph intervals. In this analysis, there were no trips with 10 mph (16 km/hr) higher than the speed limit, and hence speed in km/hr was used.

Table 5: Ordered Probit Model for Speed Behavior in Different Weather Conditions

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	**4**	1	9.5048	3.8032	6.2458	0.0124
Intercept	**3**	1	10.7118	3.8058	7.9219	0.0049
Intercept	**2**	1	12.5218	3.8504	10.5760	0.0011
Weather	**Clear**	1	-	-	-	-
	Light Rain	1	-1.1883	0.6594	3.2476	0.0715
	Heavy Rain	1	-1.6786	0.6414	6.8492	0.0089
Speed Limit	**Below 90kph**	1	-	-	-	-
	Above 90kph	1	-0.1204	0.0391	9.5040	0.0021
Traffic	**Free-Flow**	1	-	-	-	-
	Traffic	1	-2.5873	0.4704	30.2481	<.0001

8. NATURALISTIC DRIVING STUDY EVENTS ANALYSIS

Although crashes and near crashes are available now for various weather conditions in the NDS database, no crashes or near crashes were provided in the sample NDS data received in Phase 1. Analysis of crash surrogates is important for various reasons; among them is the fact that the Connected Vehicle Initiative proposed using vehicles to communicate roadway conditions in inclement weather conditions. The objective of analyzing crash surrogates is to provide insights into CV weather applications. Real time vehicle dynamics could indicate adverse weather conditions. An increased risk because of adverse weather condition could be flagged in real-time for a mitigation strategy via VSL systems and CV technologies. Manual observations of the forward-facing video and time series data indicated that there are only three trips with events. Two events were a rear-end conflict, while one event involved swerving to the shoulder in a slippery-surface condition. All events were analyzed as a learning sample to investigate different screening procedures to automate the identification of weather-related crash surrogates. The swerving event is explained in detail in this report.

The swerving incident occurred within 30 seconds due to an abrupt change in speed of downstream traffic (the leading vehicle had to reduce its speed rapidly). Examining the video reveals no obvious reason for the abrupt speed reduction (it seemed like a phantom shockwave phenomena). Due to the slippery surface, the following vehicle could not stop on time behind the leading vehicle in the same lane. The following vehicle swerved to the right shoulder to avoid a collision with the leading vehicle. Figure 5 shows a time line for the event video as sequential snapshots (headway distance extracted from the forward radar is indicated). To address question 3, driver behavior of the instrumented vehicle (i.e., the following vehicle), the leading vehicle, and the surrounding vehicles were characterized before and during the swerving event. The analysis was conducted through detailed modeling of the trajectories of the following, leading, and surrounding vehicles utilizing the forward radar, speed, headway, yaw rate, and acceleration time series NDS data.

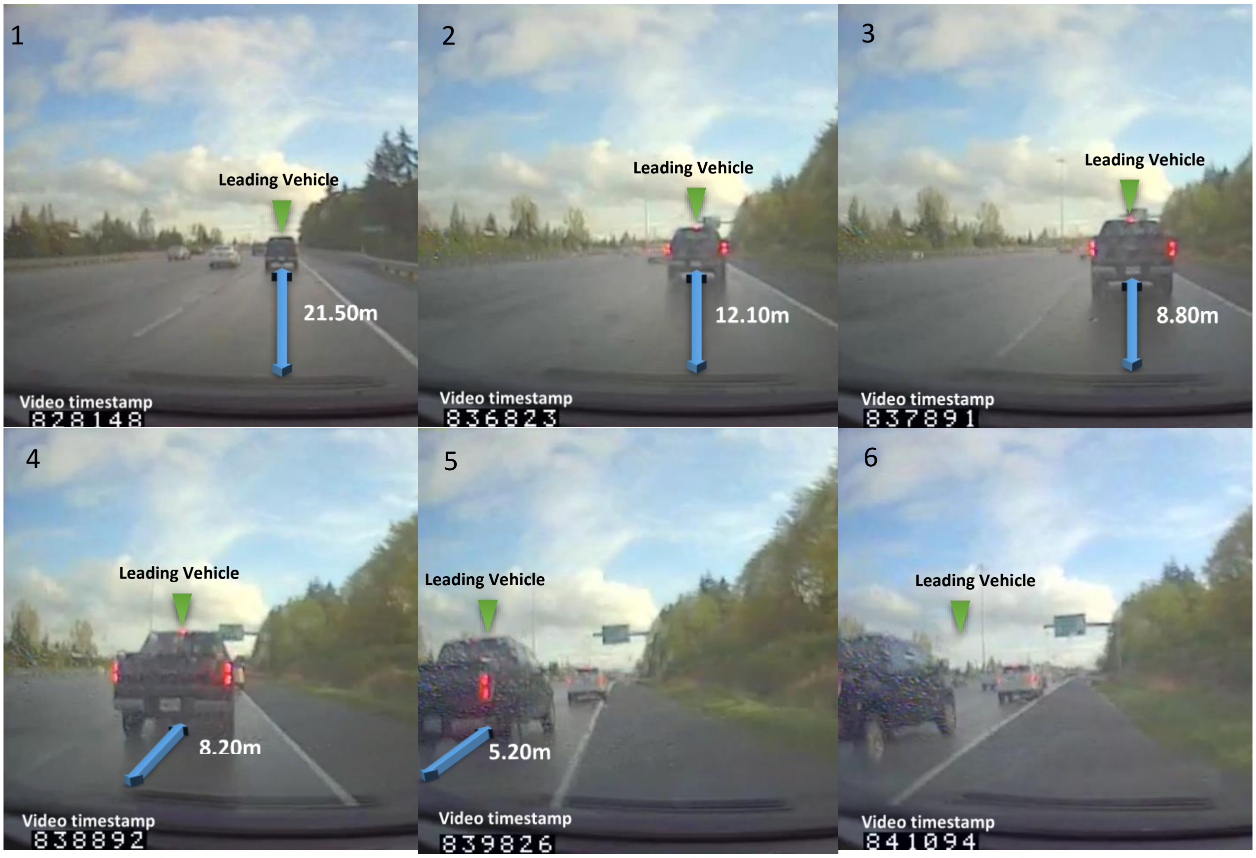


Figure 5: Timeline Snapshots for Incident in Third Case

Figure 6 illustrates the acceleration and yaw rate for following vehicle synchronized with the trajectories of the following, leading, and surrounding vehicles for the swerving event in Figure 5. For the first 12 seconds, the acceleration and the yaw rate were nearly constant. Also, the leading and following vehicles had a constant headway distance as shown in the trajectory part. Starting from the 12th second, an increase in the deceleration was associated with an increase in the yaw rate. The deceleration reached -0.66 m/s^2, and the yaw rate reached 12.7 deg/s. Additionally, the trajectories of the two vehicles intersected, which indicates a near crash if the following vehicle continued in the same path/ lane. That event is a clear example of having a near crash that could be geospatially flagged in real-time for a proper intervention. The vehicle trajectories show that if the driver in the following vehicle continued in the same lane without turning to the right shoulder, a crash would have taken place. Acceleration and the yaw rate indicated that the driver made a hard brake in combination with a sudden right turn to avoid hitting the leading vehicle.

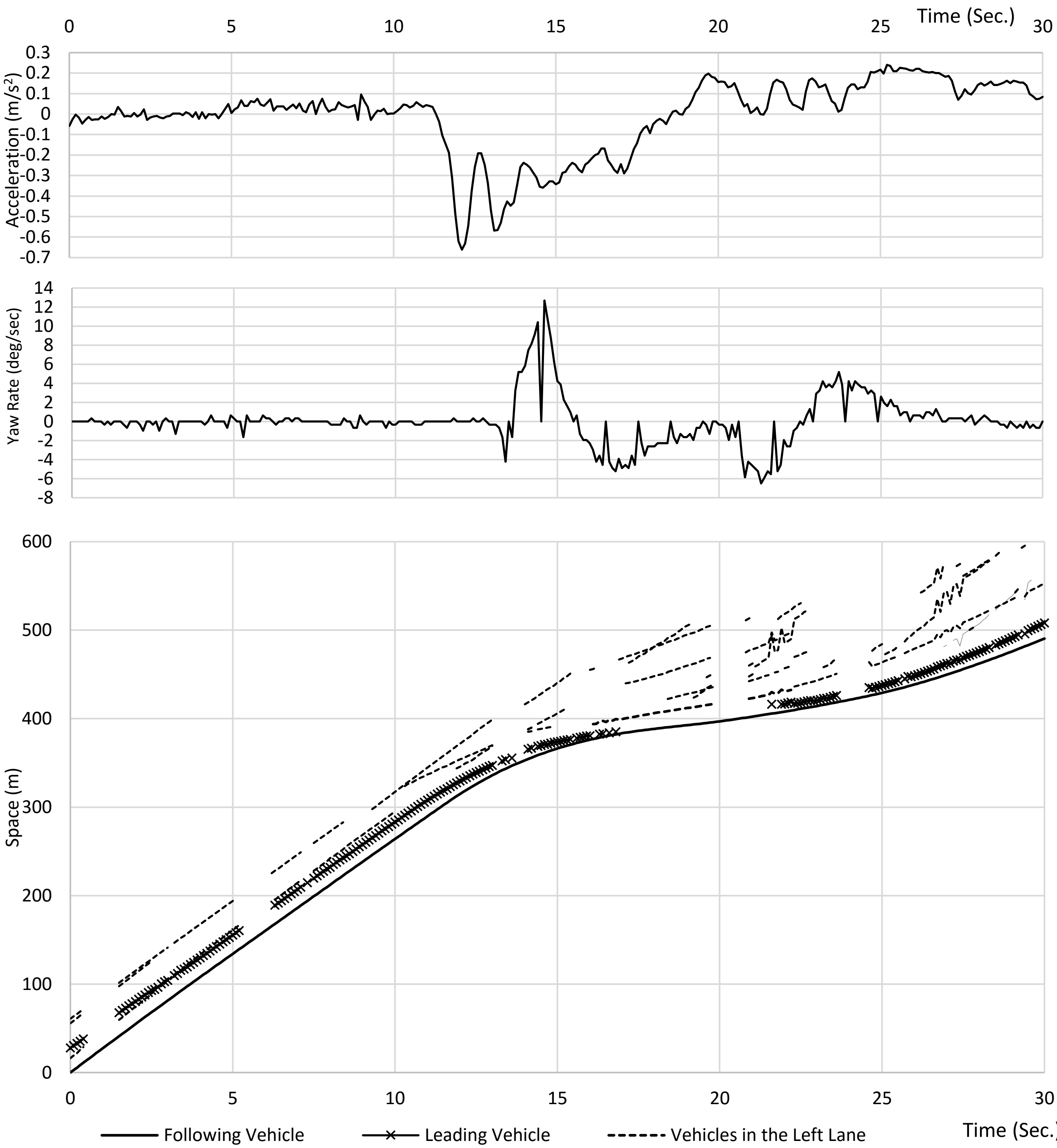


Figure 6: Acceleration and Yaw Rate for Following Vehicle Synchronized with Trajectories of Following, Leading, and Surrounding Vehicles for Swerving Event

Although an automated process of weather-related events could be constructed, three events (two of which are rear-end conflict) might not be enough to verify the result. More events will be investigated in Phase 2 for various adverse weather conditions. About 500 crashes, near crashes, and conflict events that occurred in rain, fog/smoke, snow, sleet, and hail as well as an additional

1,844 balanced-sampled baseline events will be acquired in Phase 2. Analysis of crash precursors is also important to understand the different contributing factors to weather-related crashes.

9. CONCLUSIONS FROM PHASE 1

Behavior and road-user characteristics are among the very important elements influencing the driving task. A driver's reaction process to speed choice, lane maintenance, and car following, etc., along with his or her ability to see objects that are in motion relative to the eye ("dynamic visual acuity") are critically important factors for safe driving. Though much research has focused on highway safety in relation to adverse weather and road conditions, driver behavior and performance are absent from these studies. The NDS and RID datasets utilized in Phase 1 revealed that modeling drivers' behavior in adverse weather conditions using vehicle time series data is realizable. All research questions proposed in Phase 1 were adequately addressed. Heavy and light rain trips were identified effectively using the NDS data. A visualization and reduction software was developed; the driving variables such as speed selection, acceleration/deceleration, lane change/keeping, and headway were efficiently characterized. The preliminary analysis showed significant behavior and performance differences between driving in adverse (i.e., heavy rain) and clear weather conditions under free-flow and heavy traffic conditions. An analysis for the trajectories and time series vehicle data indicated that surrogate measures for weather-related crashes could be identified using the NDS data. Preliminary analysis and ordered probit logistic regression models were useful to help in understanding driver behavior under various rain and traffic conditions. Phase 2 is aiming at using a larger NDS data set from the six locations and analyzing various adverse weather conditions.

10. FUTURE DIRECTION: PHASE 2

According to the Federal Highway Administration (FHWA), Variable Speed Limits (VSL) and Advanced Traveler Information Systems (ATIS) are considered the next steps in tackling U.S. freeway congestion and safety problems. VSL systems have been widely implemented in the U.S. and Europe to help mitigate: 1) recurrent congestion; 2) adverse weather impacts on freeways; 3) traffic injuries and fatalities; and 4) pollution.

Because selecting the right speed for the condition is considered one of the most important driving tasks on high speed facilities, and the interaction between the driver and weather condition is not well understood, the objective of Phase 2 is to extend the analysis performed in Phase 1 to better assess the relationship between driver behavior (i.e., speed and headway choice), roadway factors, and various environmental factors. In Phase 2, it is envisioned that about 2,000 to 3,000 NDS traces will be acquired from six states (Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington) in various weather conditions (i.e., heavy rain, fog, snow, ice, etc.). The study will gain insights into drivers' behavior in regard to choosing speeds and headways for different conditions. The results will help in identifying cues that are the most effective in providing drivers with a more realistic VSL system. It will also provide valuable information about how drivers interact with roadway and weather and the impact on the effectiveness of countermeasures. The algorithms of current VSL systems are based solely on weather and traffic conditions. To the knowledge of the principle investigators, there are no VSL systems that considered driver behavior in their algorithms.

Current practices in setting speed limits within VSL systems under different traffic and weather conditions are based on traffic simulation, survey questionnaires, and historical crash data. The NDS data will help in objectively acquiring better understanding into what drivers are actually doing during adverse weather and road conditions.

While it was proven in Phase 1 that NDS data are very useful in understanding driver behavior in light and heavy rain, these data have a great potential in other adverse weather conditions such as snow, ice, fog, etc. More NDS data from different states will be used in Phase 2 to analyze drivers' behavior not only in rainy condition, but also in other adverse weather conditions including snow, fog, hail, etc.

Moreover, NDS could be used to support CV technology. One aspect of CV technology is to collect data from vehicles in real-time. Once an adverse weather condition is detected on a particular roadway segment, these data could be communicated to the appropriate traffic management center (TMC) and useful information could be disseminated to drivers in real-time to mitigate the increased risk. While Road Weather Information Systems' (RWIS) stations are needed to support VSL systems, Connected Vehicle could be a better system to collect weather information in real-time and reduce the cost of deploying more RWIS on our roadways. CV weather information could be better than RWIS for the following reasons: 1) RWIS stations are usually mounted at higher elevations for better communication and less maintenance, 2) continuous weather information collected from CV is better to reflect actual vehicle performance, and 3) severe weather conditions could be disseminated in real-time to the TMC to help determine if the road should be closed.

Wyoming has been selected as one of the three sites for the CV Pilot Deployment. The corridor selected for this deployment is equipped with a VSL system. The results from Phase 2 will provide insights to improve the algorithms of the weather-based VSL system in Wyoming.

As mentioned earlier, the NDS data has several advantages over existing non-naturalistic data. Driver behavior information prior to crashes, prior to near crashes, and during various circumstances could be extracted from the NDS data. Aggregate traffic and weather parameters (e.g., average speed, headways, and global weather information) were used in previous studies. These studies utilized traffic and weather data collected from inductive Loop Detectors (iLD), Automatic Vehicle Identification (AVI) systems, and Roadway Weather Information Systems (RWIS) to separate 'crash prone' conditions from 'normal' conditions. Although the approach is novel, the aggregation level of traffic and weather information might have limitations. In this study, we will have the opportunity to look into continuous speed profiles collected from the vehicle itself, trajectories of speeds, accelerations, and decelerations of the following and leading vehicles, and driver performance and behavior related to different types of crashes and near crashes in various weather conditions. There are more than 3,500 weather-related events recorded in the InSight Data Access Website (https://insight.shrp2nds.us/). Among these events, there are 500 crashes, near crashes, and conflict events that occurred in rain, fog/smoke, snow, sleet, and hail. In Phase 2, the 500 weather-related events as well as an additional 1,844 balanced-sampled baseline events will be acquired.

Countermeasures are being proactively implemented by many states to improve safety and mobility on highways and freeways; however, the safety effectiveness of such countermeasures is not well quantified. The results from this study (Phase 2) will provide more information about drivers' perspective and behavior in choosing safe speeds. The results will help in understanding what drivers are actually doing during adverse weather and road conditions and will help suggest reasonable speed limits and warning messages within VSL and ATIS systems for implementation in Phase 3.

10.1. Management Approach and Risk Mitigation

Consistent with previous data, analyses conducted in Phase 1 suggest that SHRP2 motorists alter driving-related behaviors in response to inclement weather; however, the extent to which individual driver characteristics influence the occurrence and/or extent of these changes remains largely unexplored. Inferences drawn from the studies that have taken into account the impact of person-level variables in response to adverse weather conditions are generally limited by the reliance on retrospective, self-report methods. Data extracted from SHRP provide a unique opportunity to evaluate the relation of trait-level driver characteristics on response to inclement weather in real-time. It is likely that identifiable motorist variables including experience (e.g., age, annual kilometers driven), risk behavior (e.g., accident history, low-knowledge), and other psychological variables (e.g., impulsivity, risk perceptions) to date account for important variability in driver behavior across studies. Isolation of relevant variables promise to inform targets for driver training, real-time data monitoring needed for Connected Vehicle technology, and optimization of VSL algorithms.

Once the notice of approval for Phase 2 is received, the research team will initiate the process for the required data-sharing agreement with the Center for Data Reduction and Analysis Support at VTTI. To expedite the process, the required Institutional Review Board approval from the University of Wyoming has been submitted for Phase 2. In addition, the Statement of Work for the data needed in Phase 2 has been finalized with the director of the Center for Data Reduction and Analysis Support at VTTI. The expected tasks and their timeline for completing this research study are as follows:

Task 1. Literature Review: Conduct a critical review of the literature related to the Naturalistic Driving Study and lessons learned from recently published SHRP2 safety research. This is expected to take 12 months.

Task 2. Data Acquisition: Data requirements have been updated based on the experience from Phase 1. The research team has already discussed various approaches to collect more data needed to expand the study. As outlined previously, three-pronged approaches will be used for data acquisition in Phase 2:

- Approach I: Use the approach refined as part of the Phase 1 process, extending it to vehicles beyond the Florida and Washington test sites. The process relied on the wiper status variable to identify cases where wipers were active at a high speed for an extended length of time along freeway environments. It is expected that this approach will yield about 300 trips to examine.
- Approach II: Use the InSight event table to filter out trips that contained crashes, near crashes, or baselines and during which heavy rain and some additional adverse weather event was observed. The trips will be filtered to exclude those with short-duration (e.g., less than 15 minutes). It is expected that this approach will yield about 200 trips to examine.
- Approach III: Leverage external databases (e.g., historical weather, traffic) and attempt to find NDS trips that overlap with particular adverse weather events. It is expected that this approach will yield about 1,500 to 2,500 trips to examine. The processing capabilities of the VTTI data warehouse will probably be leveraged in this effort so that the locations and times specified by the historical databases can be crossed with all trips in the database to obtain trips of interest.

Additional trips in clear conditions will be acquired to compare a matched "control group" condition against driving epochs occurring in adverse weather conditions. The results from Phase 1 indicated that a ratio of 4:1 would be recommended to cover different traffic states (level of service).

To protect subjects' privacy, the segments of trips selected will not occur near the beginning or end of the trip (defined as a pre-determined distance from trip origin or destination; the distance contains a limited random noise element to further anonymize the trip). Once the segments are identified and vetted, time series data for each different trip segment will be exported to include various time series data. These data will include DAS Timestamp, FILE_ID, network speed, Global Positioning System (GPS) speed, acceleration in x, acceleration in y, ABS activation, traction control state, Electronic Stability Control, radar data, estimated headway, estimated lane offset, marker probability, ambient light level, yaw rate, wiper status, latitude, longitude, light level, steering angle, turn signal, head position, day of week, month, and eye glance location. In addition, for drivers represented in the overall sample, specific items from the following questionnaires will be acquired: Driver Demographics, Driver History, Driver Knowledge, Visual and Cognitive Tests, Conners' Continuous Performance Test, Barkley's Attention Deficit Hyperactivity Disorder, Screening Test, Risk Perception, Risk Taking, Sensation Seeking, and Driving Behavior. According to VTTI, these data will be delivered as one or more Excel spreadsheets, and linked to the rest of the data by the Participant ID.

According to VTTI, it is expected that Approach I will require one month, Approach II an additional month, and Approach III three months; however, if all three approaches are selected and can be performed concurrently, the overall period of performance is expected to be four months. Five months are allocated for data acquisition based on the experience in Phase 1. Other tasks will be concurrently performed once the first set of data are received.

Task 3. Data Preparation: The acquired NDS video data will be processed and reduced; the data will be checked for missing values and inaccuracies. The NDS data will be linked to RID data. Weather-related events will be verified, and video data will be processed and reduced. The NDS video data will be manually analyzed for a few number of random trips to verify and validate the results, especially for other weather conditions such as fog, snow, etc. The verification and validation process will be automated using the learning sample. This task is expected to be completed in five months.

Task 4. Machine Vision Visibility Estimation: The visualization and reduction software will be updated to provide an accurate estimation of visibility in various weather conditions. More reduction capabilities will be added as necessary to help with data preparation and analysis. Eight months are planned for this task.

Task 5. Exploratory Analysis: Descriptive statistics and preliminary analysis will be performed. Data will be classified according to weather and traffic conditions. This step will facilitate advanced modeling and analysis. This task is planned to be completed in four months.

Task 6. Data Modeling and Analysis: Once trips are identified and data reduced, a manual examination of the video for trips occurred in various weather conditions will be performed. Speeds, headways, acceleration, and deceleration of the leading and following vehicles will be analyzed during adverse weather events from the NDS video data. Time series analysis will be used to compare driver response during adverse and normal driving conditions. This procedure will be automated through modeling of the leader and follower trajectories collected from the NDS speedometer, radars, and GPS speed time series data. A multivariate logistic regression and an ordered probit logit regression will be used to model the probability of different visibility levels affecting driver performance. Other statistical techniques will be utilized to address the third and fifth research questions. Among the techniques will be classical frequentist classification approaches to explain the relationship between an event occurring at a given time (crashes and near crashes) and a set of risk factors, Bayesian statistics with hierarchical structure, and recent data mining and machine learning techniques.

This task will include analysis of weather-related events. The task will be focused on quantifying driver characteristics, behavior, and performance preceding crashes and near crashes in adverse weather conditions to investigate the suitability of vehicle weather data in CV applications. This task is scheduled to be accomplished in eight months.
Task 7. Recommendations and Proposal for Phase 3: Summarize conclusions for Phase 2 and provide recommendations for Phase 3. The findings from Phase 2 will be utilized to improve the only weather-based VSL corridor in the U.S. This task is scheduled to be completed in two months.

Although many of the driver variables proposed for use in Phase 2 contain no direct identifying information (e.g., gender; age; number of annual kilometers traveled; aggregate indices of driver knowledge, attention, risk perception), it is possible that data necessary for the identification of relevant driving events (e.g., dates, times, routes) could compromise participant anonymity. As such, a number of mechanisms will be established to address potential risks' confidentiality. First, trips/events relevant for analyses in Phase 2 will be identified exclusively by VTTI staff given criteria mentioned earlier. Individuals with trips meeting the necessary qualifications will be identified by a unique participation code along with summary scores for driver-level characteristics. Aggregate data for the project will be uploaded to a restricted, confidential scholar website maintained by VTTI staff for access by the lead principle investigator (PI) and approved graduate students. Data utilized for presentation or publication will contain no identifying information.
Phase 2 data made available to the PI will be maintained exclusively on a password-protected computer stored in a locked laboratory on the University of Wyoming campus. The lead PI, graduate students, and one of the co-investigators are the sole individuals with access to the laboratory and relevant computer passwords. Raw data utilized for Phase 2 will be retained by the PI for five years following completion of the study, after which they will be destroyed.

11. TIMELINE

It is envisioned that total time required for Phase 2 including the submission of the final report would be 24 months as shown in Table 1 in the Appendix. The review of the literature will be carried out over the first 18 months to ensure up-to-date information of all recently published SHRP2 safety research.

12. BUDGET

As shown in Table 2 of the Appendix, the overall cost of Phase 2 study is $292,674. Of this total cost, $142,674 is requested from FHWA, while WYDOT will provide a hard match in the amount of $150,000. The requested funding will be used to support three faculty members at UW, one computer science consultant, and two graduate students. In addition, a subcontract will be executed with VTTI in the amount of $37,980 to secure the required data of this study. This subcontract amount was obtained after contacting the director of the Center for Data Reduction and Analysis Support. The budget also includes money for one of the PIs to travel to Virginia to secure the data if needed. In addition, there is money for one of the PIs to travel to Washington, D.C., to present the final report of the study. Table 3 of the Appendix summarizes the anticipated number of hours by the research team for each one of the seven tasks proposed in this study. There might be a need to shift some of the hours among the various PI, senior personnel, and consultants as the project progresses but the overall cost should not change.

APPENDIX

TIMELINE TABLE

Table 1: Work Plan Schedule

	Month																							
Research Task	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Task 1																								
Literature Review																								
Task 2																								
Data Acquisition																								
Task 3																								
Data Preparation																								
Task 4																								
Visibility Estimation																								
Task 5																								
Exploratory Analysis																								
Task 6																								
Data Modeling																								
Task 7																								
Recommendations and Proposal for Phase 3																								
Task 8																								
Analysis/ Comparison to Wyoming Conditions																								
Documentation and Deliverables Schedule																								

Quarter Reports Final Report and Presentation to FHWA Final Report to WYDOT

BUDGET TABLES

Table 2: Proposal Budget Summary

LABOR (Prime)	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Cost
Salary/Wages	$6,410	$13,305	$20,175	$15,760	$21,070	$23,177	$11,315	$111,212
Fringe Benefits	$3,086	$6,415	$9,401	$7,639	$9,847	$11,007	$5,422	$52,817
Other								
subtotal labor	$9,496	$19,720	$29,576	$23,399	$30,917	$34,184	$16,737	$164,029
CONSULTANTS								
Hesham Eldeeb	$600	$600	$3,600	$14,400	$0	$0	$1,200	$20,400
subtotal consultants	$600	$600	$3,600	$14,400	$0	$0	$1,200	$20,400
SUBCONTRACTORS								
*Center for Data Reduction/Analysis Support	$0	$37,980	$0	$0	$0	$0	$0	$37,980
(*exempt from indirect)								
subtotal subcontractors	$0	$37,980	$0	$0	$0	$0	$0	$37,980
OTHER DIRECT COSTS (Prime)								
Travel/Meeting Costs	$0	$2,500	$550	$3,000	$1,500	$550	$3,000	$11,100
Materials & Supplies	$500	$2,500	$1,000	$1,000	$500	$800	$500	$6,800
Postage & Shipping							$1,000	$1,000
*Student Tuition (*exempt from indirect)	$1,400	$1,400	$1,400	$1,400	$2,000	$1,700	$1,400	$10,700
subtotal ODCs	$1,900	$6,400	$2,950	$5,400	$4,000	$3,050	$5,900	$29,600
INDIRECT COSTS (Prime)								
Overhead	$2,119	$5,064	$6,945	$8,360	$6,583	$7,107	$4,487	$40,666
G&A								
subtotal indirect costs	$2,119	$5,064	$6,945	$8,360	$6,583	$7,107	$4,487	$40,666
FEE (not to exceed 7%) if applicable	$	$	$	$	$	$	$	$
TOTAL PROJECT COSTS	**$14,116**	**$69,764**	**$43,071**	**$51,558**	**$41,500**	**$44,341**	**$28,324**	**$292,674**
TOTAL PROJECT HOURS	200	360	605	570	600	688	320	3343

Table 3: Effort by Tasks (Hours and Cost)

Names of Principal Staff Members*	Role in Study	Time (%) Over Contract Period**	Hours								Hourly Rate ($)	Cost ($)
			Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Total		
Mohamed Ahmed	Principal Investigator Overall Project Management	23%	30	125	120	120	130	130	100	755	49	$36,995
Khaled Ksaibati	Senior Personnel	2%	5	10	10	10	10	10	5	60	72	$4,320
Rhonda Young	Senior Personnel	4%	5	10	30	10	30	25	10	120	53	$6,360
Joshua Clapp	Senior Personnel	4%	5	10	30	10	30	25	10	120	53	$6,360
	Graduate Assistants/ Postdoc	63%	150	200	385	300	400	498	185	2118	27	$57,177
Hesham Eldeeb	Consultant	5%	5	5	30	120	0	0	10	170	120	$20,400
Totals			200	360	605	570	600	688	320	3343		$131,612
	* Include Subcontractors and Consultants											
	** Total Hours ÷ 174 hours/month ÷ contract months											

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