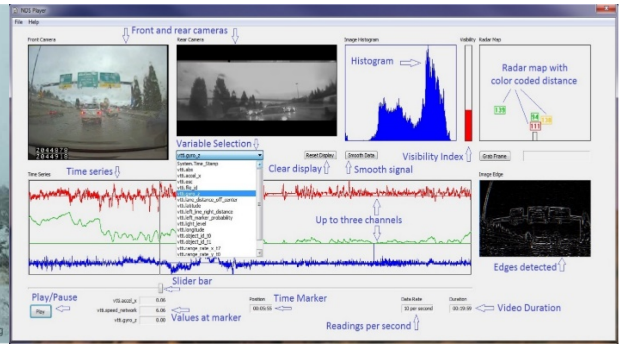
SHRP2 Implementation Assistance Program (IAP)—Round 4

Concept to Countermeasures—Research to Deployment Using the SHRP2 Safety Data



Implementation of SHRP2 Results within the Wyoming Connected Vehicle Variable Speed Limit System

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Phase 2 Early Findings Report and Phase 3 Proposal

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1. Summary of Project Goal and Objective Attainment to Date

Inclement weather conditions such as fog, snow, ground blizzards, slush, rain, and strong winds negatively affect pavement condition, vehicle performance, visibility, and driver behavior. Driver behavior exhibits high variability, and is difficult to quantify, particularly in inclement weather conditions, and it is imperative to understand when describing the influence of adverse weather conditions on roadways. Adverse weather inhibits a driver's ability to perceive their environment, and visibility reductions – caused by adverse weather events – is known to increase the likelihood of crashes. The effects of adverse weather on safe and efficient operation of transportation networks have been extensively researched; however, specific consideration of driver behavior and performance is noticeably absent from these studies.

The Second Strategic Highway Research Program's (SHRP2) Naturalistic Driving Study (NDS) and Roadway Information Database (RID) provide an unprecedented opportunity for researchers to better understand driving behavior. Having identified the potential benefits and value of this unprecedented dataset, the Wyoming Department of Transportation (WYDOT) partnered with the University of Wyoming to evaluate methods by which the data could be used to identify driver behavior and performance characteristics during adverse weather conditions. As part of the SHRP2 Implementation Assistance Program (IAP), the Wyoming research team has completed the first phase of research, and is reporting preliminary results for the second study phase in this report.

In the first phase, the research team focused on drivers' behavior and performance in heavy rain utilizing 50 trips in rain and an additional 100 matching trips in clear weather conditions. Phase 1 concluded that a comprehensive modeling of driver behavior using the SHRP2 data is achievable and will lead to better understanding of driver behavior in adverse weather conditions. In Phase 2, an additional 3,313 NDS trips were extracted (not including additional crash and near-crash data sets) from the SHRP2 states of Indiana, North Carolina, New York, Pennsylvania, Florida, and Washington in different weather conditions including snow, rain, and fog.

The primary objective of the second phase is to model drivers responses to various adverse weather and road conditions (e.g., speed adaptation, lane maintenance, and car following), specifically addressing the defined research questions:

1. Can trips occurring in inclement weather be identified efficiently and effectively using NDS and RID data?
2. Can driver behavior (i.e., speed selection, car following, and lane wandering) during inclement weather conditions be characterized efficiently from the NDS data?
3. What are the best surrogate measures for weather-related crashes that can be identified using the NDS data?
4. What type of analysis can be performed and conclusions be drawn from the resulting dataset?
5. Can the NDS data be extrapolated to provide real-time weather information in the context of the Road Weather Connected Vehicle Applications?

The first goal in transitioning from Phase 1 to Phase 2 was to develop innovative methods to identify trips occurring during adverse weather conditions. The first phase allowed the collection of trips in various levels of precipitation, as the data acquisition method was to collect trips where the drivers activated their windshield wipers. Limitations to this method include: lacking trips occurring in conditions where wipers are not necessary (fog, ice, slush, etc.), as well as missing trips where the windshield wipers activations were not recognized. Therefore, researchers not only expanded the NDS site coverage to include all states, but also introduced two additional data acquisition methods to collect significantly more trips. As a result, a better representation of different adverse weather conditions is included and processing is underway to include all relevant trips into driver behavior models.

Using the experiences derived from the first project phase, the next goal for the research team was to develop a semi-automatic data reduction tool to quickly and efficiently process the NDS trip data. A fully automated data reduction process of time series and video data requires advanced video and image processing, capable of detecting weather, roadway, and traffic conditions automatically. Evaluation and testing of image-processing techniques for this purpose are a priority for the Wyoming research team and are being investigated as part of Phase 2. In the meantime, Phase 2 data reduction was conducted using the semi-automated tool, where the time series and demographics data are automatically processed and aggregated, while observations of the driving environment were completed manually by the research team.

The vital purpose of Phase 2 is to generate models representing driving behavior changes as a function of weather conditions and includes investigation into speed selection, lane changing, and car following models. Speed selection models have been fully developed with a large data sample (212 trips total – 88 in snow, 102 in rain, and 22 in fog) and indicate speed reductions (measured from the posted speed limit) in snow (17.3%), rain (6.3%), and fog (3.9%), which are within to the 2016 Highway Capacity Manual's (HCM) suggestions of a 5% to 64% speed reduction in snow and 1% to 7% speed reduction in rain and similar to other existing literature. As the data reduction process continues through the remainder of the second phase, the speed selection models will be continually updated to increase output confidence. Initial efforts modeling lateral vehicle movements, lane changing and lane wandering indicate heavy rain can significantly increase the standard deviation of lane position, which is a very widely used method for analyzing lane-keeping ability[1]. Data processing tools for identifying automatically identifying car following instances using the on-board radar units have been developed and are currently being evaluated for accuracy. In addition, the research team is collaborating with researchers at the FHWA Turner Fairbank Highway Research Center to exchange and share knowledge related to calibrating the FHWA Driver Model to reflect driving behavior in adverse weather conditions.

The ultimate goal in completing the second phase is to transfer the developed models into tangible and effective countermeasures that will improve the safety and efficiency of roads during adverse weather conditions. The research team is working to translate raw vehicle kinematics, video feeds, roadway characteristics, and driver information into strategies which can be used to support and evaluate Weather Responsive Traffic Management (WRTM) alternatives. One WRTM strategy used in some states that experience severe adverse weather events are Variable Speed Limits (VSLs). VSLs are shown to improve the safety and efficiency of roadways during adverse weather events by slowing speeds and reducing the variation in speeds among drivers with different perceptions of the weather conditions or varying levels of allowable risk [2][3]. The Wyoming DOT was an early adopter of rural VSLs, and since implementation, have been seeking to refine control logic to automatically set speed limits. Existing VSL assignment algorithms were developed using aggregate vehicle and weather data; however, a higher level of precision in both understanding driver behavior and estimating roadway conditions could lead to better driver compliance for these systems, thereby improving the safety and efficiency benefits of VSLs.

The developed Speed Selection model is a key example of a derived mechanism by which the SHRP2 database can be leveraged to improve WRTM strategies directly. The developed car following and lane changing models could then be incorporated with speed selection in a microsimulation environment. Once calibrated to the Wyoming driver population and unique weather and roadway characteristics, the microsimulation model would be capable of illustrating impacts of adverse weather conditions, as well as provide means for examining potential benefits and consequences of proposed countermeasures. In addition to traditional WRTM strategies, the final output of the second phase is expected to provide early insights in data analysis, representative measures of effectiveness, and promising strategies for quantifying benefits essential for successful deployment of the Wyoming Connected Vehicle (CV) Pilot project.

2. Data and Methods Used for Data Analysis

The Phase 2 data analysis goals were to conduct systematic, efficient, and complete analyses of a large number of NDS trips that were collected by newly developed data acquisition strategies. The second phase introduced new acquisition strategies that were not used in the first phase; therefore, a detailed explanation of these strategies are provided.

2.1. Data Acquisition and Preparation

The initial acquisition of data crucial to the success of the second phase, and it presented a unique challenge for researchers to develop creative and unique methods for leveraging the full extent of the provided NDS and RID data. While vehicle's wiper settings give an indication of precipitation intensity, results from the first phase indicated that wiper settings are not consistent between vehicles. The time series wiper setting reported by the NDS vehicle Data Acquisition System (DAS) indicates the position of the wiper switch, rather than wiper swipe rate; moreover, different drivers have different tolerances to precipitation/visibility, and splashes from neighboring vehicles may affect driver choice of the appropriate wiper speed. Finally, the wiper setting was not provided for many trips – likely due to the high percentage of older vehicles (due to higher participation of younger drivers) or errors in the DAS recording. To compensate for these challenges identified from the first phases' data acquisition experiences, three complementary methods to effectively extract NDS trips of interest were developed.

2.1.1. Approach I

The first approach used the windshield wiper method refined as part of Phase 1, but expanded beyond Florida and Washington to all six NDS states. The process relies on the time series wiper status variable to identify trips where wipers were active at a high speed for an extended length of time along freeway segments; more details about this approach can be found in the Wyoming IAP Phase 1 report [4]. This first approach produced a total of 635 trips (506 rain, 27 snow, and 13 fog on freeways) occurring in adverse weather conditions, plus 1,092 matching trips in clear weather conditions – representing 208 drivers.

2.1.2. Approach II

The second approach took advantage of the crash and near crash dataset developed by VTTI. Trips that contained crash or near crash events in all weather conditions were requested. The second approach produced 37 crashes, 266 near crashes, 606 matched non safety-critical events in all weather conditions, and 1,176 baseline trips. Manual video verification revealed that only 16 crashes occurred on freeways (7 in rain and 9 in clear weather), and 213 trips contained near-crash events (33 in rain or sleet, and 182 in clear weather).

2.1.3. Approach III

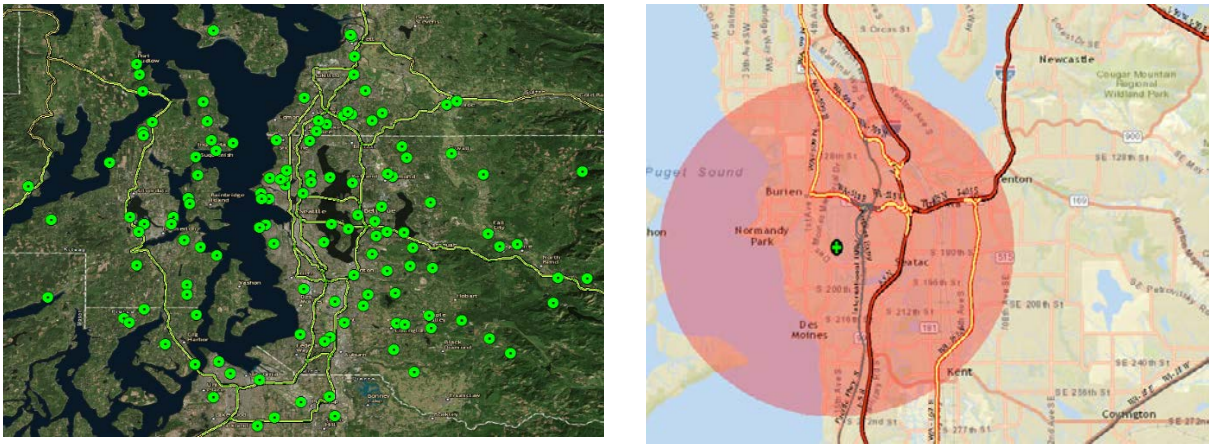
The third approach leveraged external databases (e.g., historical weather and traffic) in efforts to identify NDS trips that overlap with particular adverse weather events. Two methodologies were developed using the weather data extracted from the National Climate Data Center (NCDC) and weather-related crashes from the RID. These data sources allowed researchers to enact a type of perimeter around the sensor or crash location and search for trips that occurred during the same time period. The NCDC archives weather data from various weather stations nationwide, including radar, satellites, airport weather stations, and military weather stations. Among these data sources, the airport weather stations proved to be the most beneficial to identifying adverse weather events. Over 5 GB of weather data from more than 250 weather stations in the NDS states (between 2010 and 2013) were collected from the National Oceanic and Atmospheric Administration (NOAA) - National Climatic Data Center (NCDC) website.

Airports' automated weather stations monitor weather conditions continuously and record the weather parameters according to predefined changes in their values; for that reason, the data do not follow a specific time pattern, but report weather conditions relative to real time weather changes. The weather parameters collected include: visibility, temperature, humidity, wind speed and direction, and precipitation. Among these parameters, visibility is considered one of the most critical factors affecting driver behavior. Visibility can generally be described as the maximum distance that an object can be clearly perceived against the background sky; visibility impairment can be a result of both natural (e.g., fog, mist, haze, snow, rain, windblown dust, etc.) and human induced activities (transportation, agricultural activities, fuel combustion, etc.). The automated weather stations cannot directly measure the visibility, but rather calculate it from a measurement of light extinction, which includes the scattering and absorption of light by particles and gases.

Previous studies concluded that airport weather stations provided spatial-temporal weather conditions for adjacent roadways within five nautical miles and within a two hour time period at 60% to 80% accuracy [5]. In this study, daily weather data were acquired and NDS trips were requested based on the daily weather information to identify all trips impacted by adverse weather events (such as those conducted on ice or slush road surfaces), not only those occurring during active precipitation or fog. Therefore, the date and time for every weather event was superimposed on the NDS trips for freeways within 5 nautical miles.

Figure 1-a shows weather stations used to identify the snow-related trips in Washington and Figure 1-b shows the five nautical mile coverage area used in the NDS trip data acquisition process. In total, 24 GIS-shape files were provided representing rain, snow, fog, and wind conditions for the six NDS states and provided to VTTI to extract NDS trips. Using this approach, the research team received 9,847 weather-related trips and 19,732 matched trips in clear weather conditions. The identified NDS trips involved 1,523 drivers between 16 and 99 years of age with the majority of the drivers in young age group, 16 to 29 years old. Gender representation was balanced in most age groups, with the exception of a slight overrepresentation of female drivers between 20 and 24 years old. The total duration of adverse weather trips plus two matched trips in clear condition represents over 11,205 hours of driving.

Extensive manual video observation and preliminary processing was conducted to screen the received NDS trips and filter trips occurring in clear weather or dry surface conditions. This preliminary screening process was required because of the wide projection of an adverse weather event on an entire day, but allowed for collection of trips that would not have been otherwise identified. Of the received 9,847 trips, 2,682 freeway trips were verified to have adverse weather or roadway surface conditions.



1-a 1-b

Figure 1 (a) Weather Stations Considered in Washington State (b) Five nautical miles buffer and coverage area of freeways for one weather station in Washington State

The same concept was utilized for identifying neighboring weather-related trips from reported weather related crashes. Each weather-related crash was essentially considered as a weather station; a buffer representing five nautical miles influence area was used to provide spatial-temporal segments of freeways as potential locations for trips occurring in adverse weather conditions. At the time of this early progress report, results from Approach III-NCDC are available; however, requests for trips in the temporal and spatial domain of weather-related crashes are still in progress.

2.2. Data Reduction and Analysis Procedures

The extent of required data processing to ascertain actual roadway conditions and derive meaningful driver behavior statistics is an extremely time consuming process. At the end of Phase 1, researchers expected that inclusion of new methodologies for data acquisition would produce a significant larger quantity of NDS trips, and in order to efficiently process these data, a semi-automatic process for reducing the time series and video data would be needed for Phase 2 (the process is shown in Figure 2). The developed semi-automated data reduction process reduces the dimensionality of the data by extracting time series variables identified in the first phase as being pertinent for evaluation of driving behavior in inclement weather. Analyses in Phase 1 revealed high variability in weather conditions within a single trip; therefore, each trip was divided into one-minute segments to create homogeneous segments with similar environmental and traffic conditions. This process of splitting trips into segments is a new analysis protocol introduced in the second phase to expand the capability of the research team to evaluate a significant number of trips, drivers, and conditions in the most efficient and effective manner possible. Observation templates of each trip are automatically created by the data reduction tool, identifying each one-minute segment within the trip, its' corresponding timestamps, and leaves data fields for video reviewers to report observed environmental and traffic conditions for the segment. The process of data reduction is considered semi-automatic because the Wyoming team created an analytic tool that automatically reduces the NDS time series data into statistics, plots, and observation templates; however, manual observation of videos to determine traffic and environmental conditions is still required.

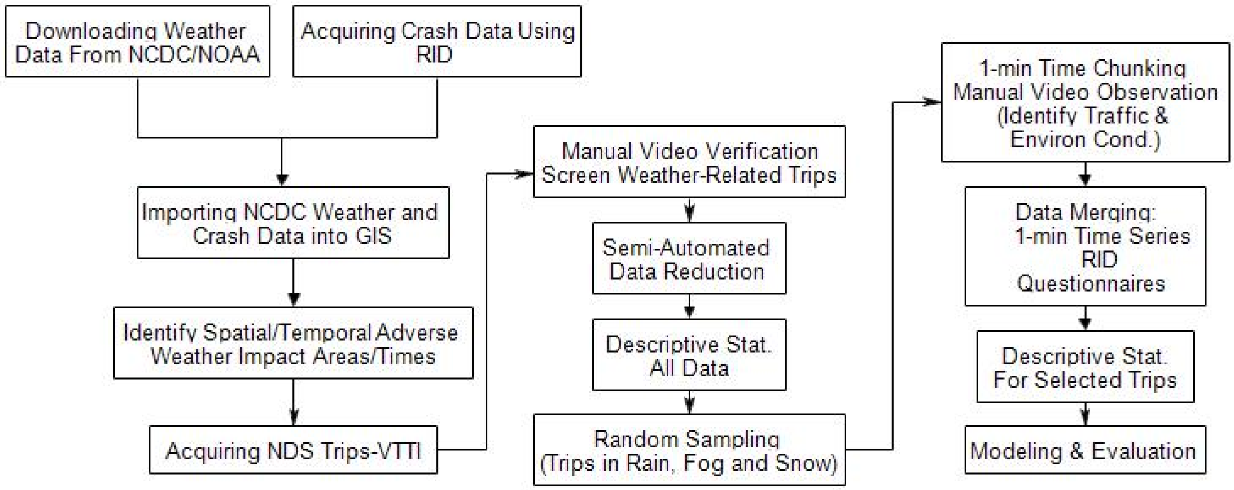


Figure 2 Conceptual Overview of Phase 2 Data Acquisition and Preparation

To eliminate subjectivity and any potential bias in identifying weather, traffic, or roadway conditions, comprehensive training and a detailed description of each condition was provided to hired students before the manual observation began. The video reviewers then leverage the benefits of the University of Wyoming's NDS Visualization and Reduction Tool (developed in Phase 1) to review the video and time series data for each trip. The team is currently exploring possible machine learning and image processing techniques to determine if a mechanism for reliably determining these environmental and traffic conditions automatically is possible. Major hindrances to this effort include the quality of the NDS video and the variation in quality and physical location of the camera/ camera angle between equipped vehicles, please see Section 2.2 for more details.

Once the manual video observation is complete and conditions (i.e., weather, visibility, surface condition, freeway segment type, and traffic density) are reported for a group of trips, summary files describing statistical averages, standard deviations, coefficient of variations, ranges of time series variables (including wind shield wipers, speed, acceleration, braking, yaw rate, headway, etc.), and driver demographics for each one-minute segment were generated automatically. These summary files then serve as the foundation of modeling and representing driver behavior in any weather/traffic condition or by any driver demographic of interest.

As the research team reports their intermediary results for Phase 2, a total of 212 trips in adverse weather conditions identified in approach 1 and 3, including: 22 trips in fog; 102 trips in rain; and 88 trips in snow – plus 424 matching clear weather trips – have been fully processed using the described semi-automatic data reduction procedure. The selected NDS trips involved 145 drivers between 16 and 89 years of age with the majority of the drivers in the young age group (16 to 29 years old). Gender was mainly balanced among age groups, except for a slight overrepresentation of female drivers between 20 and 24, which follows the same distribution that is reported by VTTI for all SHRP2 NDS trips.

As mentioned in Section 2.1, preliminary filtering techniques were required for reducing the quantity of trips acquired through the third acquisition approach (levering weather stations and weather related crashes to identify potentially impacted trips). In addition, only trips occurring on freeways were considered. To date, a total of 14,923 one-minute segments – equivalent to nearly 249 hours of driving time and 18,453 km (Rain: 3582 km, Snow: 1615 km, and Fog: 954 km) plus their matching trips in clear weather conditions – have been processed. Once non-freeway segments were removed, 10,606 one-minute segments were included in preliminary driver behavior models (explained in Section 3). The speed limit data provided in the RID was used to merge speed limits with each one-minute segment. Additional work in the second phase will link additional roadway characteristics (such as geometry) from the RID for additional analyses.

2.3. Visualization and Reduction Tool

Improvements to the Wyoming Visualization and Reduction Tool, initially developed in Phase 1, are currently underway to extend the capabilities to detecting environment conditions from the NDS video feed. The visibility estimation algorithm applies methods that look for object boundaries and edges as a way to assess the existence of objects and their clarity in the image. This technique assumes that an image of an adverse weather conditions is, generally, more blurry than that of a clearer weather. The algorithm calculates the Laplacian filter of the image and estimates the visibility level based on its magnitude. The algorithm is heuristic; therefore, accurate results for all input images are not guaranteed. The accuracy of the visibility estimation algorithm depends on numerous factors including: the training data set, the filter magnitude interpreted, cutoff limits used for different weather conditions, and the input image quality. The visibility index (VI) is the resulting value given to an image to describe its visibility level. The VI is expressed as a percentage and classified in one of three levels: low, medium, or high. Current work is in progress to improve the methods for deriving the VI values, as well as to produce representative ranges of VI values for each classification (i.e., low, medium, high). As the visibility estimation algorithm is still under development and refinement, only experimental accuracies can be defined. Preliminary testing of the algorithm using 19 video files suggests a 79% accuracy (14 trips yielding results consistent with human observation; 2 trips yielding partially consistent results, and 3 trips yielding inconsistent results).

3. Findings to Date

As mentioned in Section 1, the goal of the second phase is to produce models describing various driver behaviors in adverse weather conditions. At this point in the analysis process, researchers have begun modeling using three targeted adverse weather conditions (snow, rain, and fog) and two traffic states (free flow traffic and mixed traffic). In addition, surrogate safety measures detailing crash and near-crash events have been started at this point in phase 2. The speed selection models have produced highly promising results to be directly included in the Wyoming VSL assignment algorithms. Additional behavior modeling are promising for implementation into microsimulation models for evaluation countermeasure effectiveness that will be used in the Wyoming CV Pilot. The section concludes with the next steps for completing the second project phase.

3.1. Driver Behavior (Speed, Acceleration, Lane Keeping)

Figure 3 shows the distribution of average speed in snow, rain, fog, and the matched clear weather in free-flow conditions. Average speed in snow, rain, and fog was found to be 18.35 km/hr (snow), 6.17 km/hr (rain), and 4.25 km/hr (fog), lower than the speed in clear condition, indicating that drivers exhibit greater speed reduction in snow conditions than in rain and fog. The acceleration/deceleration variable was examined, and ± 0.3g acceleration/deceleration rates were set as a threshold to identify aggressive braking/acceleration events. However, all acceleration/deceleration were found to be within the [-0.3g, +0.3g] range, resulting in the recognition of zero aggressive braking events. Preliminary analysis in Table 1 showed that no significant variability in average acceleration were recognized between rain and fog, compared to their respective matched clear-weather trips; however, the average acceleration in snow conditions was found to be higher than matched trips in clear conditions. The average deceleration was lower in rain and fog compared to their matching clear trips, but no significant difference was found in snow conditions. Deceleration variability was found to be higher in rain and fog, compared to their matching clear trips; yet, no significant difference was found for snow conditions.

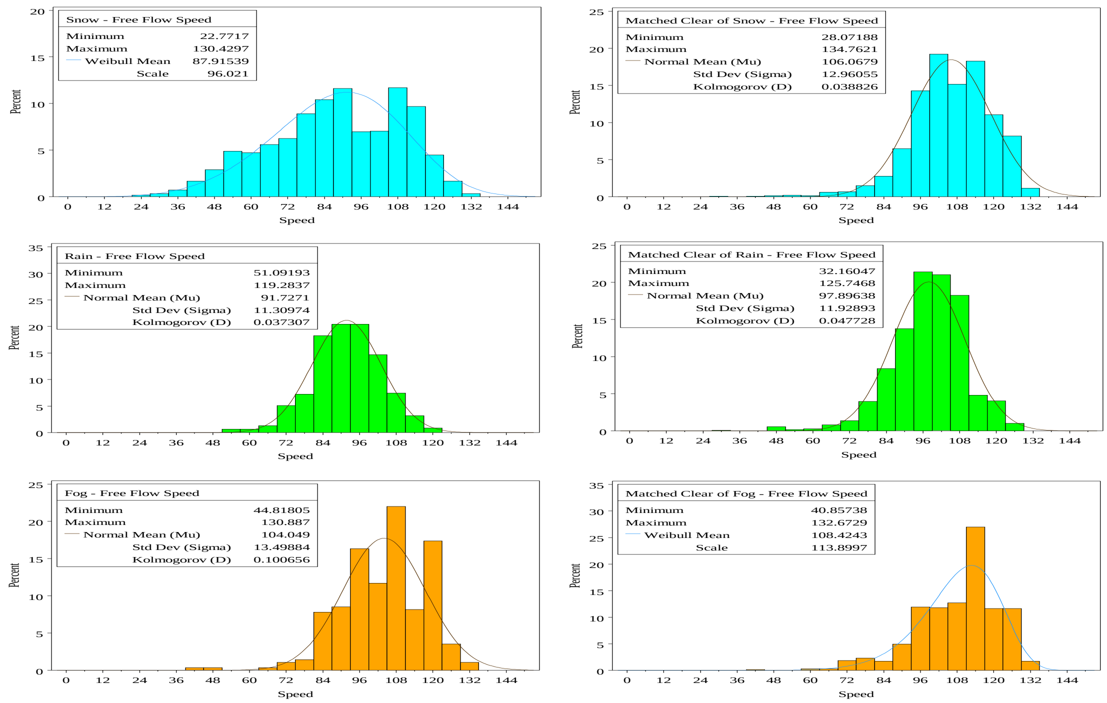


Figure 3 Observed and Fitted Distributions for Speeds during Adverse and Clear Weather under Free-Flow Traffic

3.2. Lateral Vehicle Movements (Lane Change and Lane Wandering)

The reported lane offset variable, provided as part of the time series trip data, is estimated based on machine vision. Lane offset can be considered an indication of intended (lane change) or unintended deviation from the lane. Phase 1 and 2 of this analysis has considered potential techniques for modelling lane change behavior using time series variables, such as: turn signal, steering wheel angle, yaw rate, and lane offset. Investigating drivers' lane changing habits is an integral part of understanding driver behavior in adverse weather. Separating intended lateral movements (lane changes) from unintentional lateral movements (lane wandering or swerving) is also imperative to this analysis.

Thus far, research efforts have focused on separating intentional and unintentional lateral movements using lane offset thresholds of ±0.3 meters to indicate lane wandering and ± 0.3 meters to ± 9.5 meters in a single direction to indicate a full lane change. Phase 2 analysis indicates that the average lane offset is higher in snow and fog conditions, compared to their matching clear trips. However, the average lane offset is lower in rain conditions than matching clear trips. The frequency of lane wandering instances was found to be higher in adverse conditions (snow, rain,

Table 1 Descriptive Statistics for NDS instrumented Vehicles in Snow & Free Flow Traffic

		Snow		Matched Clear		Rain		Matched Clear		Fog		Matched Clear	
		Speed	% Speed Reduction	Speed	% Speed Reduction	Speed	% Speed Reduction	Speed	% Speed Reduction	Speed	% Speed Reduction	Speed	% Speed Reduction
Speed (Kph)	Average	87.723	-10.118	106.068	8.523	91.727	1.074	97.9	6.931	104.049	8.906	108.295	8.201
	SD	21.762	20.32	12.961	13.323	11.31	12.856	11.929	12.329	13.499	26.562	13.559	15.859
	Min.	22.772	-74.268	28.072	-88.64	51.092	-49.458	32.161	-63.658	44.818	-44.291	40.857	-44.308
	Max.	130.43	43.246	134.762	78.02	119.284	76.741	125.7	54.018	130.887	173.12	132.673	150.997
	Median	89.054	-7.752	106.655	8.977	92.046	0.742	98.75	7.185	106.595	5.22	111.402	8.563
	t-test	Avg. speed in Snow is sig. lower in snow				Avg. speed sig. lower in Rain				Avg. speed sig. lower in Fog			
	F-test	Speed variability is higher in Snow				No sig. difference in speed variability				Speed variability is sig. higher in clear			
	Z-test	No sig. difference between the proportion of speeding ≥ 10 km/h				No sign. Sig. between the proportion of speeding ≥ 10 km/h				No sig. difference between the proportion of speeding ≥ 10 km/h			
Acceleration/ Deceleration(g)		Acc.	Dec.	Acc.	Dec.	Acc.	Dec.	Acc.	Dec.	Acc.	Dec.	Acc.	Dec.
	Average	0.017	-0.015	0.016	-0.015	0.021	-0.014	0.022	-0.021	0.02	-0.026	0.021	-0.022
	SD	0.015	0.014	0.014	0.013	0.019	0.015	0.02	0.019	0.017	0.02	0.018	0.018
	Min.	0	-0.08	0	-0.078	0	-0.072	0	-0.105	0	-0.07	0	-0.096
	Max.	0.076	0	0.081	0	0.121	0	0.093	0	0.074	0	0.079	0
	Median	0.012	-0.011	0.012	-0.011	0.015	-0.009	0.016	-0.015	0.014	-0.02	0.016	-0.019
	t-test	Average acceleration is sig. higher in snow				No sig. difference in Avg. Acc.				No sig. difference in Avg. Acc.			
		No sig. difference in average deceleration				Avg. dec. is sig. lower in rain,				Avg. dec. is sig. higher in Fog			
	F-test	Acceleration variability is sig. higher in snow				No sig. difference in Acc. variability				No sig. difference in Acc. variability			
		No sig. difference between deceleration variability in snow and Clear				Dec. variability is higher in clear weather				Dec. variability is higher in fog			
	Z - test	--				No Acc./Dec. were found higher than ±0.3g				No Acc./Dec. were found higher than ±0.3g			
Yaw Rate, negative sign = left rotation (deg./s)		**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**
	Average	0.271	-0.362	0.321	-0.41	0.412	-1.602	0.417	-0.462	0.346	-0.463	0.34	-0.386
	SD	0.335	0.335	0.443	0.427	0.344	2.318	0.445	0.431	0.457	0.348	0.311	0.336
	Min.	0	-2.761	0	-3.965	0.004	-7.631	0.002	-2.578	0.005	-1.969	0.001	-2.183
	Max.	3.681	-0.001	4.74	-0.001	1.651	-0.001	3.773	-0.001	3.2	-0.003	1.482	0
	Median	0.183	-0.261	0.203	-0.287	0.299	-0.485	0.267	-0.322	0.226	-0.403	0.246	-0.297
	t-test	Right rotation in Snow is sig. lower than clear weather				No sig. difference in right rotation,				No sig. difference in right rotation,			
		Left rotation in Snow is sig. lower than Clear Weather				Left rotation is sig. higher in Rain.				Left rotation is sig. higher in Fog.			
	F-test	Right rotation variability is sig. higher in clear weather				Right rotation variability is sig. higher in clear weather				Right rotation variability is sig. higher in Fog			
		Left rotation variability is sig. higher in clear weather				Left rotation variability is sig. higher in rain				No sig. difference in left rotation variability			
Lane Offset (cm)		**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**	**Pos.**	**Neg.**
	Average	32.996	-36.096	20.74	-30.568	15.46	-15.913	19.644	-16.119	19.162	-27.956	14.695	-22.447
	SD	41.074	47.163	29.717	42.838	10.416	22.169	18.234	19.412	17.053	42.499	14.108	25.582
	Min.	0.001	-333.65	0.095	-383.706	0.095	-224.66	0.076	-266.98	0.078	-323.856	0.073	-345.241
	Max.	377.895	-0.004	155.516	-0.071	51.171	-0.308	121.291	-0.049	76.985	-0.192	68.494	-0.225
	Median	19.222	-18.269	12.022	-18.876	14.321	-10.538	15.985	-9.343	15.42	-17.086	10.275	-17.222
	t-test	Lane offset to the right in Snow is sig higher than clear				Avg. lane offset to the right is lower in rain				Avg. lane offset to the right and left from lane center is sig. higher in Fog			
		Lane offset to the left in Snow is sig. higher than clear				No sig. difference in lane offset to the right							
	F-test	Lane offset to the right variability is sig. higher in Snow				Lane offset to the right variability is sig. higher in clear weather				Lane offset to the right variability and left variability is sig. higher in Fog			
		Lane offset to the left variability in sig. higher in Snow				Lane offset to the left variability is sig. higher in rain							

fog), while lane change frequency was found to be higher in clear conditions. The video observations indicated that in adverse conditions drivers chose to reduce their speed behind a slower vehicle more frequently than they would have in clear conditions, contributing to the reduction in lane change maneuvers.

3.3. Speed Selection

Table 2 indicates that speed reduction is more likely to occur in adverse weather (snow, rain, fog) conditions in comparison with the matched trips in clear weather conditions. The odds ratios of driving below the speed limit, were 7, 2.7, and 2 times more likely to be in snow, rain, and fog, respectively, than their matching trips in clear weather conditions.

Table 2. Odds Ratios for Speed Behavior in Snow, Rain, and Fog

	Driving below Speed Limit	Driving above Speed Limit	Odds Ratio	Confidence Interval	Significance level
Snow	773	441	6.93	5.89 to 8.14	P < 0.0001
Matched Clear of Snow	386	1525			
Rain	220	251	2.67	2.13 to 3.35	P < 0.0001
Matched Clear of Rain	268	816			
Fog	91	191	2.1	1.53 to 2.89	P < 0.0001
Matched Clear of Fog	119	531			

Additional analyses were conducted to compare speed reduction in each NDS state during free flow speed conditions. Findings indicate that the speed reduction was not similar in each state. For instance, in New York one-minute segments in snow had a speed reduction of about 18% being the highest among all NDS states. Important sample size considerations note that 74% of the identified snow segments were from New York. Whereas in Pennsylvania with only 7% of snow-related segments, the speed reduction was about 9% being the lowest. In addition, in rainy weather conditions, trips in Indiana had the highest speed reduction of about 33%. Among the considered segments in rain, 1% was travelled in Indiana while Washington had 44% with the lowest speed reduction of about 3%. In fog, the highest speed reduction was 6% in Florida with 37% of fog-related trips and the lowest speed reduction was in Washington with 14% of fog-related segments, where the NDS drivers reduced their speed by nearly 2%. These differences are certainly a function of the distribution and sample size of snow, rain, and fog events in each state; nonetheless, the finding indicates that driving behavior in adverse weather conditions must be calibrated based on local driver populations and their familiarity with the weather condition.

Direct comparisons between clear weather in free flow speed and driving in adverse weather/ traffic conditions are imperative to identify critical traffic and environmental conditions. GIS was used to illustrate driver speed behavior under various weather conditions. Figures 4-6 illustrate a significant speed reduction due to whiteout condition on a traversed route in New York, using data from a sample trip and a matching trip. The average speed during the whiteout condition was about 35 kph (22 mph) less than the matched trip in clear weather conditions. Figure 5 represents the driver performance on roadways considering the risk of crashes. Two heat-maps representing crash-prone zones using the three years of crashes (2011-2013) on I-190 and I-290 were developed.

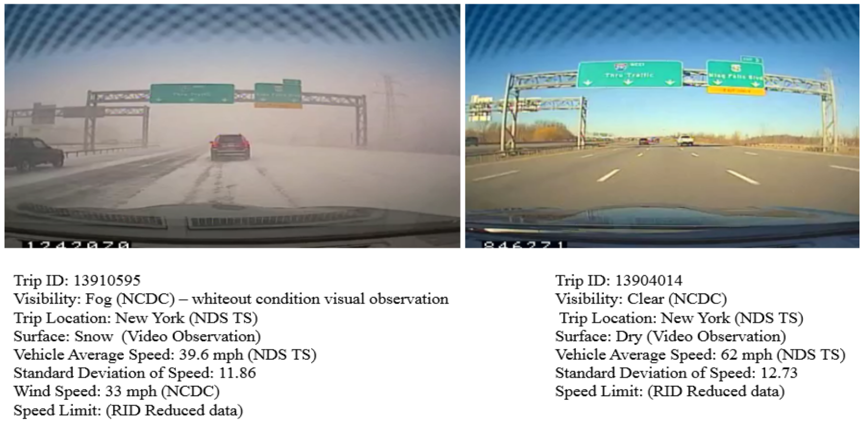


Figure 4 Illustration of a Trip in Fog and Whiteout Condition (I-290 New York)

Speed reduction percentages along the travelled routes are shown in a range of colors from green (low crash rate) to red (high crash rate). In addition, a separate color scale along the interstate route represents the speed reduction (compared to the posted speed limit) realized for the trip in whiteout conditions and the matching clear. These maps indicate speed reduction was much greater in whiteout conditions compared to the matched clear weather conditions. The potential benefit of visualizing continuous driver performance data (here speed reduction percentage) and crash-prone locations heat-map is in VSL/VMS application. This information can be utilized in updating VSL/VMS in real-time. More clearly, using this representing GIS maps can highlight not only the crash hotspots but also the possible driver role in crash occurrence. This work will be expanded using more NDS drivers in different weather conditions. In addition, the same concept could be implemented on Phase 3 I-80 VSL corridor.

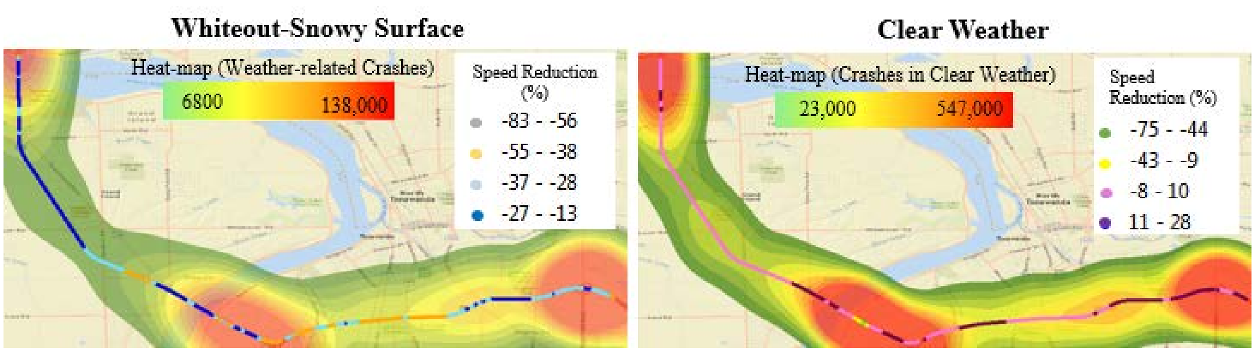


Figure 5 Speed behavior-GIS Representation

Direct comparisons between clear weather in free flow speed and driving in adverse weather/ traffic conditions are imperative to identify critical traffic and environmental conditions. GIS was used to illustrate driver speed behavior under various weather conditions. Figures 4-6 illustrate a significant speed reduction due to whiteout condition on a traversed route in New York, using data from a sample trip and a matching trip. The average speed during the whiteout condition was about 35 kph (22 mph) less than the matched trip in clear weather conditions. Figure 6 shows the drivers' speed and lane keeping behavior in both the clear and whiteout conditions, indicating lower travel speeds and difficulty in maintaining his/her lane in whiteout condition.

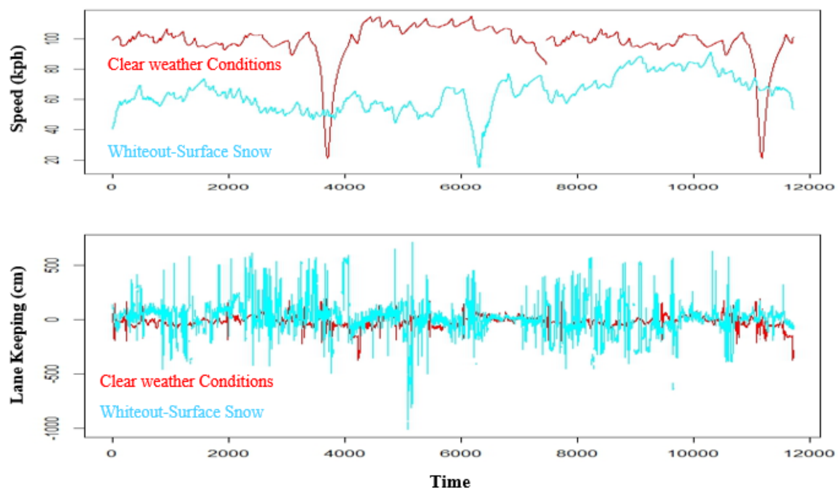


Figure 6 Time-Series Speed and Lane keeping Performance in Clear and Whiteout- Snowy Surface Condition

3.3.2. Modeling Speed Selection

Factors affecting driver speed selection can be identified using both parametric and nonparametric models. Each modeling technique has its own advantages and disadvantages. A parametric ordered logistic regression model could provide the relationship between a response variable and predictors. One of the advantages of parametric models is the feasibility of interpreting the risk factors' marginal effects [6] [7]. However, literature showed that nonparametric models have better accuracy than parametric models. Risk factors can also exhibit various exposure effects in different circumstances in parametric models (hidden effects problem). These shortcomings cannot be addressed using common parametric models such as logistic and probit models [8][9]. One of the major solutions to address the hidden effects problem is to split the full sample data into several sub-datasets. This method might be an effective way to see the effects of risk factors' hidden exposure in different situations. In comparison, non-parametric models such as classification and regression tree models (CART), artificial neural networks, stochastic gradient boosting, and genetic algorithm (GA) are becoming more popular in transportation safety analysis [10] [11] [12] [13] [8]. Machine learning techniques are advantageous because of their superior classification performance and minimal data preparation requirements, and their promising application in real-time risk assessment [8].

In this study, both a parametric ordered logit model and a nonparametric classification tree were used to analyze the contributing factors affecting driver speed selection in different weather conditions. The dependent variable in the model is the Percent Speed Reduction (PSR), and the explanatory variables are the environmental, traffic, roadway, and driver characteristics.

3.3.2.1. Ordered Logit Model

The ordered logit model was calibrated using all available data at the time of the preliminary report; representing a dataset of 10,606 one-minute segments of drivers' speed selections occurring in various weather and traffic conditions (matching is not required). The model was developed for four speed intervals based on the median of the Percent Speed Reduction above or below the speed limit ($\frac{(Speed - Speed\ Limit)}{Speed\ Limit}$). The four-quantile intervals were defined as: 1) more than 14% Speed reduction percentage, 2) Speed reduction percentage between 0 to 14%, 3) 0-10% increase in speed, and 4) more than 10% increase in speed. These intervals were used to achieve a sufficient sample size in each category of speed reduction. The remaining variables are exploratory variables, consisting of information extracted from questionnaires including driver demographics (age, marital status, gender, education) and driver experience, roadway factors, and observed environmental and traffic conditions.

To confirm the suitability and fitness of the model, the Log Likelihood Ratio (LR) was used. Table 3 shows the results of the model. The Multi-collinearity was assessed by calculating the Variance Inflation Factor (VIF) for each predictor, which indicates how much the variance of an estimated regression coefficient increases if the predictors are correlated. A VIF between 5 and 10 shows high correlation between predictors and VIF greater than 10 indicates that the regression coefficients are poorly estimated due to multi-collinearity [14]. The explanatory variables introduced to the model produced VIF values between 1.03 and 1.40, excluding any concerning multi-collinearity. Only statistically significant variables were retained in the final models.

Table 3 Estimation of Ordered Logit Model for Speed Selection in Different Weather Conditions

Analysis of Maximum Likelihood Estimates									
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Odds Ratio	Confidence Interval	
Intercept	4	1	-2.57	0.09	800.41	<.0001	-	-	-
Intercept	3	1	-1.3	0.09	218.23	<.0001	-	-	-
Intercept	2	1	0.32	0.09	13.93	0.0002	-	-	-
Weather Cond.	Rain	1	0.44	0.09	25.35	<.0001	1.55	1.31	1.83
Weather Cond.	Snow	1	2.23	0.06	1612.52	<.0001	9.29	8.33	10.36
Weather Cond.	Fog	1	0.26	0.09	7.61	0.0058	1.29	1.08	1.55
Visibility	Affected	1	0.56	0.09	35.24	<.0001	1.75	1.45	2.1
Traffic Cond.	C-F	1	1.28	0.04	995.02	<.0001	3.6	3.32	3.89
Gender	Female	1	0.09	0.04	5	0.0254	1.09	1.01	1.18
Age	>40	1	0.2	0.05	18.24	<.0001	1.23	1.12	1.35
Marital Status	Divorced	1	0.81	0.09	86.57	<.0001	2.25	1.9	2.67
Marital Status	Widow(er)	1	1.2	0.11	121.33	<.0001	3.31	2.68	4.1
Marital Status	Unmrid-partnrs	1	-0.94	0.1	88.74	<.0001	0.39	0.32	0.48
Marital Status	Married	1	0.34	0.05	45.09	<.0001	1.4	1.27	1.55
Mileage Last Year	10,000 to 20,000	1	-0.5	0.05	122.3	<.0001	0.61	0.56	0.66
Mileage Last Year	>20,000	1	-0.58	0.06	92.33	<.0001	0.56	0.5	0.63

Adverse weather conditions – snow, rain, and fog – were found to have a significant effect on speed selection. Results showed that the odds of a driver reducing their speed were 9.29, 1.55, and 1.29 times higher for drivers travelling in rain, snow, and fog conditions, respectively, in comparison with drivers who were driving in clear weather conditions. Findings related to visibility indicated that the odds of a driver reducing their speed were 1.75 times greater for drivers who were driving in affected visibility conditions versus those driving in good visibility conditions. As expected, traffic conditions indicated a significant negative effect in speed selection. More clearly, the odds of having more speed reduction percentage were 3.6 times greater for drivers who were driving in higher traffic density compared to free flow speed (level of service A and B). Considering drivers' gender, findings indicated that the odds of a female driver reducing her speeds greater than male drivers was 1.09.

3.3.2.2. Classification Tree Model

Classification can be defined as a procedure for predicting the class of an object – considering the object's features [15]. Classification models are built from a training dataset in which trends of predictor and target variables are identified and used to predict the value of the target variable for a new datasets [16]. The two main components of decision trees are the "root node" and the "leaf node". The "root node" is the node located at the top of the tree, which contains all ingested data and the "leaf node" refers to the termination node, which has the lowest impurity.

The root node is divided into two child nodes, based on the independent variable (splitter) that creates the best homogeneity. This procedure of partitioning the target variable recursively is repeated until all the data in each node reach their highest homogeneity. At that point, tree growth stops, and the node(s) that do not have any branches are the resulting "leaf node(s)". Each path from the top of the tree (root node) to the bottom/termination of the tree (leaf node) can be considered a rule. Following this sequence, the data in each child node is purer (more homogenous) than the data in the upper parent node [17].

In order to identify possible splits among all variables, a splitting criterion is generated. The splitting criterion is the main design component of a decision tree [18]. In a decision tree learning algorithm, the splitting criterion's role is to measure the quality of each possible split among all variables. Two common tests used to generate splitting criteria are: 1) chi-square and 2) Gini reduction. In this study, Gini splitting criterion is used to select which variable and split pattern is to be used to best split the node. Gini impurity indicates the data purity; specifically, it shows the probability of incorrect classification for a randomly chosen record from the specific node in the subset. Figure 7 shows the decision tree diagram for the drivers' speed selection in different weather conditions based on the training data described in the previous section. In the node boxes, the node number and the percentage of data in each category are provided.

One beneficial characteristic of a decision tree, compared to other modeling methods, is that it gives decision makers rules to address ''if-then'' questions efficiently. The dataset introduced to this model included 10,606 one-minute segments with time series vehicle data, weather conditions, driver demographics, and roadway characteristics data. The dataset contains four categories of drivers' speed selection behavior as mentioned before. Of the 10,606 one-minute segments, 60% were considered for training dataset, 20% were considered for validation, and the remaining 20% were used to test the model.

The misclassification rate, based on the training and validation datasets, indicated that the best tree could be obtained with 15 terminal nodes. More clearly, with 15 terminal nodes, the misclassification rate for the model reaches a minimum value of 0.42 and remains fairly steady. Node 3, on the right side, shows the data related to driving in snowy conditions. On the right branch of the tree, there are four terminal nodes (nodes 7, 13, 24, and 25). In three of these terminal nodes, the drivers were predicted to reduce their speed more than 14% (Class Label 1), which implies that, if a driver is travelling in snowy conditions, he/she will more likely reduce their speed, regardless of any other variables.

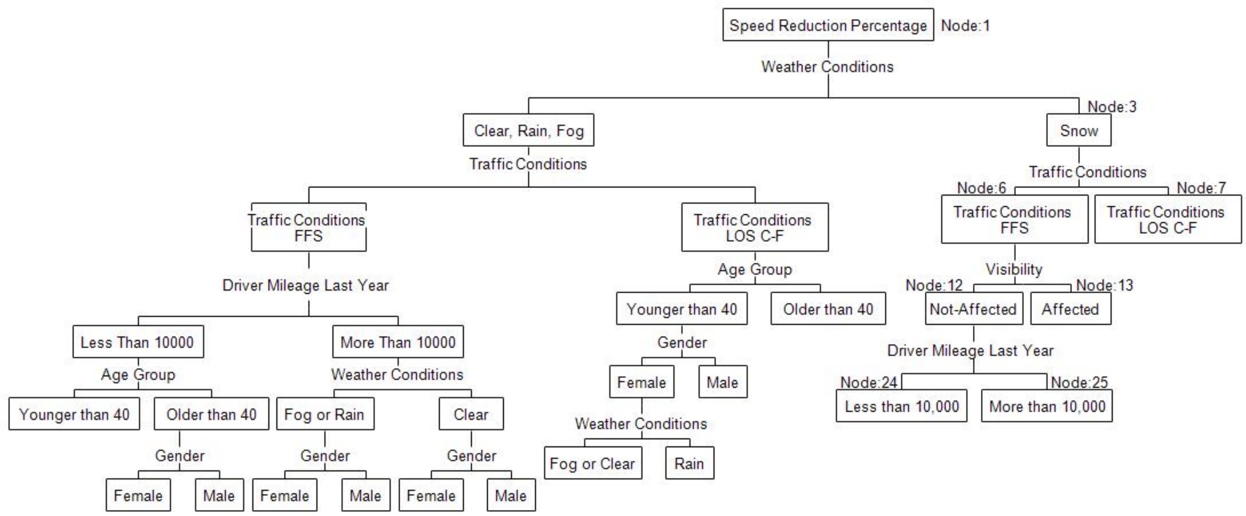


Figure 7 Classification tree diagram for Speed Selection Model

As a function of traffic conditions, node 3 is split into node 6 and terminal node 7; terminal node 7 shows that when a driver travels in any level of traffic congestions (not a free flow speed) during snow covered road surface conditions, there is an 86% probability that the driver will reduces their speed more than 14%. Node 6 is further split into node 12 and terminal node 13 based on visibility conditions. Node 13 shows that drivers are 56% likely to reduce their speed more than 14% in snowy surface conditions, free flow traffic, and reduced visibility. Node 12 is split into node 24 and 25, based on driver mileage last year. Lastly, node 24 shows that if a driver, drove less than 20,000 miles last year, they were 59% more likely to reduce their speed more than 14%.

3.4. Analysis of Safety-Critical Events in Adverse Weather

With the influx of second-by-second kinematic vehicle data in a connected vehicle (CV) environment, identification of the deviation from normal driving (i.e., safety-critical events) will be feasible. These data will be beneficial in a wide range of safety applications. Among these applications, real-time hotspot network screening and emergency response are promising to reduce fatalities and injuries. Moreover, the USDOT CV Initiative proposed using vehicles to communicate roadway and weather conditions in real time. The National Highway Traffic Safety Administration (NHTSA) has recently mandated vehicular on-board equipment; vehicles sold or imported in the U.S. must come equipped with Dedicated Short Range Communication devices by 2018.

Phase 2 identified 16 crashes, 213 near-crashes, and 1176 baseline trips on freeways in the 6 NDS states. The objective of acquiring these data was to examine suitable Surrogate Measures of Safety (SMoS). The analysis focused on distinguishing between (SMoS) in reduced visibility compared to clear weather conditions. Driver behavior of the ego-vehicle (i.e., the NDS vehicle) and the leading vehicle were analyzed. Manual observations of the forward-facing video and time series data, as well as modeled trajectories of the ego- and following vehicles provided useful insights into safety-critical events. SMoS considered in this phase were Time-to-Collison (TTC), Perception Reaction Time (PRT), headway, longitudinal acceleration, lateral acceleration, and yaw rate. Preliminary analysis indicated a great variation in these measures. TTC was found to range between 1.2 to 5.2 seconds for speeds ranged between 30 to 105 kph without a clear trend. However, acceleration and yaw rate showed distinct patterns.

In addition, the project team is seeking insights into the identification of inclement weather conditions using kinematic vehicle data. The average of decelerations for near-crashes in light and heavy rain was found to be significantly less than their clear weather counterparts. Based on the preliminary results from manual video observations, visualization of trajectories, and descriptive statistics, next steps involve the development of a regression model to determine threshold values for safety-critical event indicators, specifically for events occurring during adverse weather conditions. Moreover, a logistic regression model will be calibrated to identify safety-critical events based on SMoS, roadway, environmental and traffic conditions.

3.5. Next Steps for Phase 2

The research team recognizes the importance of understanding all forms of driver behavior, including speed selection, car following, lane changing, and safety critical/ evasive maneuver behaviors. For that reason, in addition to increasing confidence in the current models, the Wyoming research team is coordinating research efforts with the Federal Highway Administration (FHWA) to determine the capability of using SHRP2 NDS data to calibrate existing car following models. FHWA's Driver Model Software is a platform that was originally developed as a psycho physical car following model representing work zones [19]. As part of the ongoing development of the FHWA Driver Model Software, FHWA collaborated with Wyoming to attain access to Wyoming's NDS dataset. FHWA plans to use these data as a case study to evaluate the usability of the NDS trips to calibrate and validate their Driver Model Software to represent driving behavior in adverse weather conditions and share these information with Wyoming. Coordination in data cleansing and manual video observation have been shared between both research groups.

In addition to working with FHWA, the Wyoming research team is investigating other mechanisms of calibrating and validating common car following models, such as Wiedemann models, used in PTV VISSIM. Preliminary efforts to automatically capture car following instances using the NDS datasets have been developed and are under investigation to ensure that adequate detection reliability can be realized, without manual detection of car following instances. By the conclusion of Phase 2, potential calibration procedures will be developed and initial calibration efforts will be presented.

This early research findings report indicates that an understanding of driver behavior is achievable using the developed methods and extracted NDS data. Next steps for completing the second phase include using the all received data for snow and fog and increase the sample size of trip segments representing rain conditions. Not only will a greater sample size be evaluated, but additional time series and demographic data (including responses to physical, psychological, and cognitive surveys completed by most SHRP2 NDS participants) will be modeled and evaluated by the completion of the second phase. Factor analysis methods will be used specifically to address relevant survey questionnaire responses. Additional data mining techniques, including Multivariate Adaptive Regression Splines (MARS) will be used to better understand driver behavior in different environmental and traffic conditions. Advantages of using MARS include the capacity to intake continuous response variables, promising predictive power, and overcoming the black-box limitations. Once Phase 2 is completed, it is expected that the reliability of these preliminary results will be updated by a robust sample size and additional available data fields.

4. Comparison of Phase 2 Findings with Existing Literature

Many studies analyzed the impact of adverse weather conditions on freeway traffic speed at the macroscopic and microscopic levels. Studies that have examined the impacts of adverse weather on traffic operations at the microscopic level are rare compared to their macroscopic counterparts. For the microscopic level, very limited sample size was used in previous studies including either probe vehicles, EZ-Pass equipped vehicles, or GPS/ Bluetooth tracked vehicles. These studies were conducted on very limited routes and using few subjects. Table 4 shows the comparison between the results from this study and other literature illustrating of speed selection in different adverse weather conditions.

As mentioned, Phase 2 recognize speed reductions of 17.3% in snow, 6.3% in rain, and 3.9% in fog, which is close to the speed reduction mentioned in various literature. For instance, FHWA reported 55% to 40%, 3% to 13% and 3% to 16% reduction due to snow, light rain, and heavy rain respectively[20]. The study of Agrawal et al. (2006) concluded 3%-5%, 7%-9%, 8%-10% and 11%-15% free flow speed reduction for trace, light, moderate and heavy snow respectively[21]. In addition, they concluded that during the trace (none), light rain and heavy rain, the free flow speed reduced by 1%-2%, 2%-4%, and 4%-7% respectively. In another study, Rakha et al. (2012) found snow and rain can reduce free flow speed up to 19% and 9%, respectively [22].

Table 2 NDS Speed Reductions in Adverse Weather VS. Literature

SHRP2 NDS		Literature	
Weather Conditions	**Speed Reduction**	**Speed Reduction**	**Reference**
Snow	18.35 kph 17.30%	5% - 64% for heavy snow	Highway Capacity Manual 2000, 2010, and 2016 [23]
		11% - 15% for heavy snow	Agarwal et al. [21]
		5% - 19%	Rakha et al.[22]
		13%	Jr et al[24]
		16.4 kph	Kyte, et al.[25]
Rain	6.17 kph 6.30%	1% - 7%	Highway Capacity Manual 2000, 2010, and 2016[23]
		2% - 9%	Rakha et al.[22]
		2% - 17%	FHWA[26][20]
		5% - 6.5%	Smith et al.[27]
		2kph - 5kph	Ibrahim and Hall[28]
Fog	4.25 kph 3.90%	8kph -10 kph	Hogema and van der Horst[29]
		8kph	Liang et al.[30]

5. Plans for Phase 3

5.1. Implications of Findings for Countermeasure Implementation

According to the Federal Highway Administration (FHWA), Active Traffic Management, 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 recurrent congestion, adverse weather impacts on freeways, traffic injuries and fatalities, and pollution.

Selecting the right speed for the condition is considered one of the most important driving tasks on high-speed facilities. Because the interaction between the driver and weather conditions is not well understood, the continuation of this research is highly likely to result in an improved Connected Human-in-the-Loop VSL system which is aligned with the SHRP2 Task Force's focus areas. An important component of driver-weather interaction is the characterization of traffic flow because driving behavior and behavior variations in adverse weather conditions are not consistent across traffic flow conditions and congestion levels. Modeling variation in driver behavior with adverse weather conditions and traffic flow states is crucial to assigning effective Variable Speed Limits, as these algorithms must consider the impact of both weather and traffic conditions when suggesting the safest and most efficient speeds. Additional benefit from these developed models could be seen in CV applications, where the VSL system could be expanded to incorporate mobile vehicle data as input and to export to VSL data to in-vehicle units. The in-vehicle units could provide speed advisories, regulatory speeds, or other related advisories, such as, “turn off cruise control” in real-time to more effectively regulate driving speed and preserve a safe flow of traffic. If unusual traffic patterns are detected or inclement weather events are forecasted or experienced, these geospatial locations could be flagged for implementation of an appropriate and timely mitigation strategy.

The objective of Phase 3 is to improve the existing weather-based VSL system on the 402-mile I-80 corridor in Wyoming by integrating Phase 2 results into the existing VSL logic utilized by WYDOT. Significant challenges faced by the Wyoming I-80 corridor include severe weather events, high crash rates, frequent road closures, and lack of alternative routes. The winter crash rates were found to be 3 to 5 times as high as crash rates in the summer. For example in April 2015, two major crashes occurred within days of each other. The first was on April 16 involving around 50 vehicles and it occurred to the east of Laramie. No fatalities resulted and over 20 injuries were reported. The second pileup crash occurred just four days later (April 20, 2015) to the west of Laramie involving 64 vehicles and resulting in 2 fatalities and over 20 injuries. The interstate was closed for 2 days because of the first crash and for approximately 32 hours for the second crash. Both of these crashes occurred during winter weather conditions with highly reduced visibility. The first crash occurred within a VSL corridor and analysis of speeds at the time of the crash showed that vehicles had reduced their speed but visibility and roadway geometrics were such that the vehicles were not aware of the crash in front of them. The second crash has similar conditions but was located about one mile prior to a VSL corridor so speeds at the time of the crash were higher than the earlier crash, likely contributing the increased severity of the second crash.

Figure 8 Map of Wyoming I-80 Variable Speed Limit Corridors

The integration of the research results will help in providing drivers with a more realistic VSL in adverse weather conditions encountered in Wyoming. 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. Results from this research helped in objectively acquiring better understanding into what drivers are actually doing during adverse weather and road conditions. Early results showed that NDS data are very useful in understanding driver behavior in light and heavy rain, snow, and fog compared to clear weather driving. This human factors integration within the VSL system will help achieving the Vision Zero goal of no fatalities or serious injuries. To the knowledge of the principle investigators, there are no VSL systems that considered driver behavior in their algorithms.

Moreover, Phase 2 early results are very promising to support CV Pilot Deployment in Wyoming conducted on the same I-80 VSL corridor. 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 Wyoming 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, CVs could be used to collect weather information in real-time and to reduce the cost of deploying more RWIS, as well as to potential reduce the ongoing maintenance costs associated with existing

RWIS sensors. CV weather information could provide better weather data than RWIS for the following reasons; 1) RWIS sensors are usually mounted at higher vertical distances above the roadway for communication and maintenance reasons, while CV data reflect the road-level conditions experienced by drivers, and 2) continuous weather information collected from CV reflect actual vehicle performance along the length of the roadway as opposed to the spot observations of RWIS.

As mentioned earlier, NDS data has several advantages over existing non-naturalistic data. Driver behavior information prior to crashes or near-crashes, and during various circumstances were 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 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.

5.2. Management Approach and Risk Mitigation

Phase 2 early results attained to date are very promising for a more effective Variable Speed Limit System. However, transferability of the SHRP2 NDS results will be examined. While many studies including this study concluded that adverse weather conditions have a tremendous impacts on traffic operations, all studies reported that these results are site-specific and speed and car-following behaviors may be different at other locations based on varying driver experience and roadway characteristics. In most of the studies in the literature, driver characteristics are missing. The SHRP2 NDS data provided comprehensive insights into driver characteristics. This will enable better transferability to other sites if driver population is known. While the SHRP2 NDS data can account for most of the confounding factors such as roadway and driver characteristics, the transferability of the results to I-80 corridor will be inspected. Wyoming DOT is collecting comprehensive traffic and weather data as part of the CV Pilot deployment, these data may be used to examine the applicability of Phase 2 results. Speed data from CV Pilot in Wyoming will be used to adjust factors identified in Phase 2.

Task 1. Collect Wyoming VSL Baseline Data: Collect baseline data on current WYDOT TMC's VSL operations including traffic speed and volume, weather, and VSL sign data to quantify measures of system performance, such as traffic flow speed deviations, vehicle headways and speed compliance during different weather event categories.

Task 2. Add Connected Vehicle Speeds to VSL Algorithm: Add Connected Vehicle data to the existing software developed to monitor real-time individual speed and speed deviations from the existing roadside speed radar sensors. Update microscopic traffic and driver parameters associated with speed selection in microsimulation models for Wyoming based on driver behavior models calibrated in Phase 2. The inclusion of connected vehicle data would allow for insight into the road conditions between RWIS sites so that the speeds reflect the entire speed segment and not just the conditions at a spot location near the RWIS site. The Phase 2 models provide insight into translating driver behavior into road conditions.

Task 3. TMC VSL Protocol Comparison: Compare Current TMC VSL Protocol Comparison with the Automatic Logic developed by UW in previous research, which utilized a self-learning regression tree analytic model. Currently WYDOT TMC operators apply components of the developed control logic manually. Full deployment of the control logic would set targets for speed compliance and speed deviations and would learn from each storm event based on success of each storm event speed strategy.

Task 4. Integrate SHRP2 NDS Study Results: Update the VSL logic using results from the NDS Phase 2 study. Identify and model Deviation from Normal Driving. Calibrate models to identify Critical-Safety Events based on I-80 roadway characteristics. Account for variation between NDS and CV data in identifying Safety-Critical Events. Different techniques could be used to identify CSE including modeling drivers' acceleration preferences (no need for radar data), modeling changes in velocity and headway between an ego-vehicle and its leader (radar data or Basic Safety Message from CV technology are needed), and modeling deviation of vehicle dynamics and roadway geometry.

Task 5. Update VSL Logic: Add VSL logic to the real-time speed software to develop recommendations for both VSL Speeds and non-VSL Advisory Speeds. The current VSL logic only applies to the ~ 145 miles of VSL-controlled roadway in the four VSL corridors. These VSL corridors have VSL signs spaced on average between 5 and 7 miles and have speed radar and RWIS equipment installed at each VSL sign location. For the proposed system, the CV data would be used to supplement the sensors in the non-VSL corridors in order to recommend non-regulatory speed advisories in the ~255 miles of non-VLS segments. The non-VSL corridors have far greater spacing between speed radar and RWIS installations.

Task 6. VSL System Testing and Evaluation: Run the system in the TMC environment spring and summer of 2018 to test and debug. The performance of the updated VSL system will be examined and compared to the baseline system.

Task 7. IRIS Integration: Integrate the system into the TMC's IRIS software for winter of 2018-2019.

It is envisioned that total time required for Phase 3 including the submission of the final report would be 28 months, starting August 2017-Decmber 2019. This lines up perfectly with the deployment of the CV Pilot. Detailed timeline for milestones is provided in Table 1 in the Appendix.

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
	2017					**2018**												**2019**						
	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J
Task 1																								
Collect Baseline VSL Data																								
Task 2																								
Add CV Speeds to VSL																								
Task 3																								
TMC VSL Comparison																								
Task 4																								
SHRP2 NDS Integration																								
Task 5																								
Update VSL Logic																								
Task 6																								
VSL System Testing																								
Task 7																								
IRIS Integration																								
Documentation and Deliverables Schedule																								

Quarterly Reports Final Report Preparation Final Report /Presentation to FHWA

ACKNOWLEDGMENT

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