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working to advance road weather information systems technology

Automating Variable Speed Limits Using Weather, Traffic and Friction Data

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Aurora Project 2022-10

Final Report
September 2025

About Aurora

The Aurora program is a partnership of highway agencies that collaborate on research, development, and deployment of road weather information to improve the efficiency, safety, and reliability of surface transportation. The program is administered by the Center for Weather Impacts on Mobility and Safety (CWIMS), which is housed under the Institute for Transportation at Iowa State University. The mission of Aurora and its members is to seek to implement advanced road weather information systems (RWIS) that fully integrate state-of-the-art roadway and weather forecasting technologies with coordinated, multi-agency weather monitoring infrastructures.

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16. Abstract

Variable speed limits (VSL) are useful in promoting highway safety. According to the Federal Highway Administration (FHWA), "the use of VSLs during inclement weather or other less than ideal conditions can improve safety by decreasing the risks associated with traveling at speeds that are higher than appropriate for the conditions."

The project's research objective was to investigate beneficial ways to recommend VSLs under a variety of adverse weather and road surface conditions. This report presents findings from three key research areas: (1) VSL data analysis and machine learning (ML) model development, (2) VSL physical model development, and (3) a review of VSL requirements and state department of transportation (DOT) rules of practice.

The research team gathered road weather information system (RWIS) and VSL event data covering the winter and early spring seasons from 2021 through 2023 across two study areas in Wyoming and Utah. Due to the timeframes and locations covered by the collected data, the study datasets included significant adverse and impactful weather events. The team used the collected data to develop an analysis methodology and algorithms for issuing VSLs that consider different weather conditions, terrain types, roadway geometries, and road surface conditions using ML and physical models. To understand how state DOTs currently issue VSLs and to guide research efforts, an extensive survey of VSL requirements and DOT rules of practice across multiple state DOTs was conducted, and the findings were summarized. Summary results from each of the three research areas are discussed in the report, followed by conclusions and recommendations for methods and techniques that state DOTs should consider when implementing VSLs or performing future VSL research. Detailed research findings can be found in the appendices.

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AUTOMATING VARIABLE SPEED LIMITS USING WEATHER, TRAFFIC AND FRICTION DATA

Final Report
September 2025

Principal Investigator
Bill Petzke, Software Engineer
NSF National Center for Atmospheric Research (NCAR)

Co-Principal Investigators
Hao Wang, Professor
Rutgers University

Laura Fay, Senior Research Scientist
Western Transportation Institute
Montana State University

Authors
Bill Petzke, Hao Wang, Laura Fay

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A report from
Aurora Program
Iowa State University
2711 South Loop Drive, Suite 4700
Ames, IA 50010-8664
Phone: 515-294-8103 / Fax: 515-294-0467
https://aurora-program.org/

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INTRODUCTION

Variable speed limits (VSL) are useful in promoting highway safety. According to the Federal Highway Administration (FHWA), "the use of VSLs during inclement weather or other less than ideal conditions can improve safety by decreasing the risks associated with traveling at speeds that are higher than appropriate for the conditions."

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The research team gathered road weather information system (RWIS) and VSL event data covering the winter and early spring seasons from 2021 through 2023 across two study areas in Wyoming and Utah. Due to the timeframes and locations covered by the collected data, the study datasets included significant adverse and impactful weather events. The team used the collected data to develop an analysis methodology and algorithms for issuing VSLs that consider different weather conditions, terrain types, roadway geometries, and road surface conditions using ML and physical models. To understand how state DOTs currently issue VSLs and to guide research efforts, an extensive survey of VSL requirements and DOT rules of practice across multiple state DOTs was conducted, and the findings were summarized. Summary results from each of the three research areas are discussed in the report, followed by conclusions and recommendations for methods and techniques that state DOTs should consider when implementing VSLs or performing future VSL research. Detailed research findings can be found in the appendices.

RESEARCH METHODS AND FINDINGS

VSL Data Analysis and ML Model Development

Two distinct study areas were identified for performing ML modeling. These sites were selected based on the availability of VSL signs with substantial winter histories and the availability of spatially and temporally available RWIS. The study areas were as follows:

- Parleys Canyon, Utah, located along I-80, is the first study area. This area includes 4 RWIS stations and 15 VSL signs, with 6 VSL signs collocated or in close proximity to RWIS stations. This area has high winter ski traffic that is frequently impacted by inclement weather, posing safety and mobility concerns.
- The second study area includes sites along I-80, I-25, and I-90 and a few sites along WYO789 in Wyoming. The Wyoming highways wind through some of the harshest environmental conditions in the continental United States and are major shipping and cross-country travel routes.

After RWIS and VSL event data were obtained from the Utah DOT (UDOT) and Wyoming DOT (WYDOT), an extensive quality assurance (QA)/quality control (QC) process was performed on the RWIS data, as experience from other road weather projects has proven that RWIS are sensitive to severe winter conditions found in the remote areas of the mountains and plains. The QA/QC process is summarized as follows:

- For the Parleys Canyon study area, the VSL data were first joined with the nearest RWIS based on spatial and temporal proximity. Then an extensive set of QA/QC algorithms and techniques were applied to produce a high-quality ML training dataset. Procedures included range checks to remove unrealistically high or low observations and stuck value checks to identify values stuck for over 3 hours, followed by the graphic display of data and the subsequent removal of problematic values, such as stations with inoperable air temperature and dewpoint sensors and unrealistically high grip values. An important distinguishing feature of the Utah dataset versus the Wyoming dataset is that Utah's RWIS stations provided friction (grip) measurements, which proved to be a top predictor for VSL speed in some ML models and made these data well suited for the physical modeling efforts. After the QA/QC process was completed, data augmentation was performed to address the highly skewed distribution of VSL speeds and slowdown cases. The dataset was augmented to achieve a more balanced representation of slowdown and non-slowdown data points.
- For the Wyoming study area, the initial dataset included 127 VSL signs collocated with 42 RWIS stations. The initial QC pass performed unit conversion and capping of high visibility values to 2 km. Road state values outside of the 0 to 18 range were fixed, and summer months (May through September) were removed to focus on harsh road conditions. In the second QC pass, range checks were performed, and stuck values were identified and removed. Additional statistical checks were performed. Finally, the RWIS data were merged with the VSL data, and some sites with bad VSL data or sites known to be unreliable were removed.

Appendix A describes the QA/QC process in detail.

Supervised ML modeling was then applied to these Utah and Wyoming study areas for both regression (predicting continuous speed) and classification (predicting binary slowdown/no slowdown or binned speeds). The initial step in the modeling process was to perform statistical analysis and perform predictor identification. Two different types of correlation analysis were performed, along with a permutation testing technique to identify predictors. The most important predictors are generally precipitation, friction, road state, and temperature (particularly road temperature), although other factors such as wind and visibility play a role in setting safe VSL speeds. Finally, ML models were developed using the data from the study areas and the understanding of the predictors. The primary algorithms utilized were eXtreme Gradient Boosting (XGBoost or XGB) and Random Forest (RF), with Cubist also being explored. Model performance was evaluated using root mean square error (RMSE) and mean absolute error (MAE) for regression and the F1 score for classification.

- For Parleys Canyon, Utah, the classification models achieved F1 scores of 0.84 (using meteorological predictors) and 0.82 (using road predictors) for binary slowdown/no slowdown cases. Classification models with F1 scores of 0.82 or above were also possible for binned speed models (e.g., 20 mph bins). Regression models demonstrated high performance, achieving an MAE and RMSE of less than 5 mph on average, with high R^2 scores.
- The ML models for Wyoming exhibited reasonable skill, though their predictive ability was impacted by the absence of grip observations and the high proportion of slowdowns not directly tied to measurable weather or road conditions. The classification models achieved an F1 score of 0.71 with all predictors. However, for specific stations with fewer non-weather-related slowdowns, F1 scores exceeding 0.82 were possible for binary slowdown/no slowdown classification. Regression models for certain stations also achieved MAE errors of less than 5 mph, showing reasonable improvement over simply predicting the average speed.

A significant finding for both datasets was that weather variables held equal or slightly greater importance than non-weather surface variables in reliably predicting VSL speeds.

Appendix B describes the ML modeling process and results in detail.

VSL Physical Model Development

Horizontal curves on roadways are disproportionately associated with a high risk of crashes, particularly single-vehicle roadway departures, which account for a significant percentage of traffic fatalities. This risk is exacerbated by adverse weather conditions such as rain, snow, and ice, which reduces pavement friction and impairs vehicle control. Conventional static speed limits are often inadequate for these variable conditions. While VSL systems are a promising countermeasure, many existing strategies are not sufficiently responsive to real-time changes in road surface friction, a critical factor for maintaining vehicle stability on curves. This project developed a comprehensive methodology to automate VSLs using real-time weather, traffic, and friction data to enhance safety.

This study proposed a physics-based methodology to determine the maximum safe speed of a given curve considering friction demand and friction supply. The maximum safe speed for a given curve and weather condition was identified as the intersection point where the escalating friction demand curve meets the declining friction supply curve.

- **Friction Demand**: The friction required by a vehicle to safely navigate a curve was determined using two approaches: the traditional American Association of State Highway and Transportation Officials (AASHTO) point-mass model and a more sophisticated vehicle dynamics simulation (CarSim). The dynamic simulation proved superior because it incorporates a wider range of variables, including 3D road geometry (horizontal and vertical alignment, superelevation, transition curves), vehicle-specific parameters, and the dynamic load distribution across individual tires during cornering. Analysis showed that passenger cars exhibit the highest friction demand, making them the most critical vehicle type for skidding analysis.
- **Friction Supply**: The available friction on the road surface was derived from real-time data collected by RWIS sensors. Recognizing that RWIS friction is measured as longitudinal (braking) friction and is speed-dependent, the raw data were processed using ASTM International standard formulas to account for the effect of vehicle speed on wet friction. Furthermore, using the tire-force ellipse principle, the longitudinal friction was converted to the maximum available lateral (side) friction, incorporating a safety margin to allow for essential maneuvers.

A road segment of I-80 in Utah, a mountainous route with numerous curves and frequent adverse weather, was selected as a case study. Key findings from the analysis include the following:

- Vehicle dynamics simulation provides a more realistic and critical assessment of friction demand than the point-mass model, especially at higher speeds.
- AASHTO design speeds, while adequate for normal conditions, are often unsafe during snow and ice events, underscoring the necessity of weather-responsive VSLs.
- To enable real-time application, correlation models were developed that directly link RWIS friction values to pre-calculated maximum safe speeds for specific curve geometries.
- A comparison with the existing VSL strategy on I-80 revealed that while the current system is generally conservative, the proposed model offers greater responsiveness to sudden drops in friction.

This research successfully demonstrated a comprehensive and adaptive framework for VSL automation. By integrating real-time RWIS data with advanced vehicle dynamics, the proposed model can generate speed limits that are dynamically tailored to specific road geometries and weather conditions. This approach provides a significant enhancement over static speed limits and less-responsive VSL systems, offering a valuable tool for transportation agencies to proactively reduce crash risk and improve safety on horizontal curves.

Appendix C describes the physical modeling and subsequent results in detail.

VSL Requirements and DOT Rules of Practice for VSL

A survey was used to identify state and local agencies that are using VSLs or variable speed advisories (VSAs) and to capture information on data used, triggers, who is responsible for managing the system, the extent and maturity of deployment, evaluations completed, and design specifications. The key findings from the survey are as follows:

- Of the 26 respondents, 16 indicated that they use VSLs or VSAs in their operations. VSLs and VSAs are most commonly initiated due to roadway conditions, visibility issues, work zones or temporary traffic control scenarios, and traffic volume, with VSLs and VSAs initiated less commonly due to crashes, speed, precipitation, roadway grip, and temperature.
- For most agencies, VSLs are enforceable, but many agencies are using a combination of VSLs and/or VSAs.
- On average, responding agencies indicated that they have been using VSLs or VSAs for 7 years, with a few exceptions. Newer deployments have occurred in Montana and Wyoming, and future deployments are planned in Texas and Nebraska. Respondents provided the locations where VSLs and VSAs have been implemented; all deployments were on state or Interstate highways.
- Roadside changeable speed limit signs and roadside dynamic message signs (DMS) or variable message signs (VMS) are the most commonly used formats to convey messages to the public, followed by news outlets and, less commonly, social media.
- For most agencies, traffic management centers (TMCs) or traffic operations centers (TOCs) support the VSLs and VSAs, with the messages typically triggered manually by a person or by data- or rules-based triggers. RWIS data, meteorological data, and camera images are the most commonly used data to support VSLs and VSAs. For most agencies, the data used to support VSLs and VSAs are retained.
- Just over half of responding agencies indicated that they have evaluated the effectiveness of their VSL/VSA program. Data used in the evaluations have included crash data, driver compliance data, crash severity data, personal experience of survey respondents, and traffic speed sensor data.

Appendix D describes the survey and results in detail.

Follow-up interviews and/or additional information was captured from the Massachusetts DOT, Virginia DOT, and the research team from National Cooperative Highway Research Program (NCHRP) Project 03-142: Evaluating the Impacts of Real-Time Warnings and Variable Speed Limits on Safety and Travel Reliability during Weather Events (publication pending).

Appendix E discusses the results of follow-up interviews.

CONCLUSION AND RECOMMENDATIONS

VSL Data Analysis and ML Model Development

The Parleys Canyon, Utah, dataset, augmented for more uniform speed distribution, proved suitable for both statistical analysis and ML model development, notably providing the friction measurements crucial for physical modeling and the high-quality observations needed for training machine learning models. The Wyoming dataset, despite its larger size, presented data quality challenges due to the lack of grip observations, the study area's harsh environmental conditions, non-weather-related slowdowns, and sensor reliability concerns.

The machine learning models for Parleys Canyon exhibited considerable skill, with the XGBoost and Random Forest algorithms demonstrating superior performance, particularly when leveraging augmented data and other techniques to accommodate highly imbalanced ranges of speeds. The classification models achieved F1 scores exceeding 0.82, and regression models showed RMSE and MAE errors of less than 5 mph. Statistical analysis showed that surface status and friction (grip) appear to be highly correlated with speed and may be important predictors for triggering VSLs. Weather variables, including relative humidity (RH), visibility, precipitation type/intensity, solar radiance, and wind direction, are other important potential predictors for VSL models, as they are associated with winter storm events that lead to a buildup of snow or ice on the pavement and an associated reduction in friction (grip). Correlation and predictor importance analysis showed that grip, surface status, surface temperature, and UDOT's WinterRoadWeatherIndex are variables of high importance for developing ML models for Parleys Canyon.

For Wyoming, the models also exhibited reasonable skill, but their predictive ability was impacted by the lack of grip observations and the high proportion of slowdowns not directly tied to measurable precipitation or road conditions. Despite these limitations, the classification models achieved F1 scores exceeding 0.82 for binary slowdown/no slowdown classification for certain stations, and the regression models achieved MAE errors below 5 mph for certain stations, showing improvement over simply predicting the average speed. Statistical analysis showed that surface status and snow/ice in particular appear to be highly related to speeds and may be important predictors for triggering VSLs. Precipitation variables and visibility were also found to be predictors of note. The combined effect of a high precipitation rate or high RH with cold ambient and road temperatures and/or low visibility likely indicate slower speeds. Correlation analysis showed that road state, precipitation, visibility, and temperature are the observation variables with the strongest potential for predicting VSL speed or indicating yes/no for predicting slowdown/no slowdown. The permutation predictor importance test summarized in Figure B.33 in Appendix B confirmed the importance of these variables and additionally indicated that wind is important.

The data analysis and ML modeling results indicate that weather holds an equivalent or perhaps slightly greater importance than non-weather surface variables in reliably predicting VSL speeds. This is seen in both the Wyoming and Parleys Canyon datasets and ML modeling results.

Future research should focus initially on observation data quality and analysis, as these are critical factors in developing high-performance ML models for reliably predicting VSLs. The XGB algorithm in particular shows great promise for developing state-of-the-art ML models on tabular data such as VSL prediction. XGB should be considered first when trying to push the boundaries of VSL ML model performance. Recent developments in convolutional neural network (CNN) models for predicting weather-impacted road conditions in Wyoming and other states could be harnessed for data QA/QC and to provide additional observational input into VSL prediction algorithms. These observations might be most useful as a QA/QC check when setting VSLs but may be of more limited use as a predictor in an ML VSL model, since they only provide one additional categorical predictor. Reinforcement learning (RL) is another avenue of future research that can be explored if reliable and dynamic or real-time observations become available at a larger scale. RL was not utilized for this ML research effort due to the static and small VSL datasets (on the order of tens of thousands of records) available and the absence of a robust real-time data feed or feedback loop necessary for practical RL application. It is not clear that RL algorithms can provide better performance than supervised learning under these limitations.

VSL Physical Model Development

This study developed a physics-based methodology to determine VSL on curves under varying weather conditions based on vehicle friction demand and friction supply from road surfaces. Various factors affecting friction demand were evaluated, including vehicle type, curve radius, vertical grade, transition curve status, and superelevation. Passenger cars exhibited the highest friction demand, while curve radius, transition curve status, and superelevation significantly impacted demand. Dynamic simulation results were found to be more critical and realistic than point-mass models, as they accounted for a comprehensive whole-vehicle model, tire-road interaction, road geometry, and weather effects on surface friction. On the other hand, adverse weather conditions substantially affect road surface friction characteristics. Real-time data on surface conditions through RWIS and the speed effect on wet friction were used to estimate friction supply. Safety speeds were determined by comparing friction demand and supply curves.

VSL case studies were conducted for selected road segments along I-80 considering different road alignments and surface conditions (wet, snow, ice). During snow and ice conditions, both simulation-derived and point-mass model-derived safety speeds were found to be lower than the static AASHTO design speeds. This finding indicates that AASHTO design speeds may not be sufficient for ensuring safety under severe weather conditions, emphasizing the need for weather-responsive speed limit strategies. By integrating real-time RWIS data with advanced vehicle dynamics, the proposed model can generate speed limits that are dynamically tailored to specific road geometries and weather conditions. This approach provides a significant improvement over static speed limits and less-responsive VSL systems, offering a valuable tool for transportation agencies to proactively reduce crash risk and improve safety on horizontal curves.

The current VSLs are conservative and effective in maintaining additional safety margins under adverse weather conditions, as evidenced by the low fatal crash rate on these highway segments. However, vehicle departure crashes remain a significant life-threatening concern, particularly on curves, where safety must be rigorously ensured. The proposed model, which incorporates real-time road conditions, can serve as a valuable reference for refining current VSL strategies. In scenarios where a significant decrease in friction is observed, the VSLs should be set lower than the simulation-derived safety speeds and provide an additional safety margin. Adapting to real-time road conditions to further mitigate the risk of departure crashes can enhance curve safety.

VSL Requirements and DOT Rules of Practice for VSL

The following summarizes key conclusions and findings from the survey results:

- VSL and/or VSA deployments have been in place for 2 to 27 years, or an average of 7 years for VSL and 5 years for VSA. Newer deployments have occurred in Montana and Wyoming, and future deployments are planned in Texas and Nebraska.
- VSLs and/or VSAs are typically initiated due to roadway conditions, visibility issues, and work zones or temporary traffic control scenarios.
- Most applications of VSLs are enforceable, but many agencies are using a combination of VSLs and/or VSAs.
- All of the reported VSL and/or VSA deployments were on state or Interstate highways.
- Messaging was typically done using roadside changeable speed limit signs or roadside DMS/VMS.
- When messaging for an event, DMS and VMS are the most commonly used formats, followed by news outlets.
- Varying VSLs and/or VSAs for specific vehicle types is not common.
- Most VSLs and/or VSAs are supported by TMCs or TOCs.
- VSLs and/or VSAs are most commonly triggered manually by a person, followed by a data-based or rules-based trigger.
- RWIS data, meteorological data, and camera images are the most commonly used data to support VSLs and/or VSAs.
- Most agencies retain VSL and/or VSA activities and supporting data.
- About half of the agencies surveyed have evaluated the effectiveness of their VSLs and/or VSAs. Data used in the evaluations included crash data, driver compliance data, crash severity data, personal experience by local supervisors and/or superintendents, and traffic speed sensor data.

REFERENCES

[1] Katz, B., C. O'Donnel, K. Donoughe, J. Atkinson, and M. Finley. 2012. *Guidelines for the Use of Variable Speed Limit Systems in Wet Weather*. Federal Highway Administration, Washington, DC.

APPENDIX A. DATA QA/QC

Parleys Canyon, Utah, VSL

RWIS and VSL Dataset Information

The National Center for Atmospheric Research (NCAR) received atmospheric and surface datasets containing road weather information system (RWIS) observations from 4 RWIS sites along Parleys Canyon. The RWIS sites were labeled with the following device IDs: 26, 27, 29, and 157. NCAR also received variable speed limit (VSL) data from 15 VSL signs (Figure A.1) along Parleys Canyon (Figure A.2). Six VSL signs were selected that were very close to the 4 RWIS stations, and the data from those 6 signs were joined in time and space with the associated RWIS data in order to create a dataset with combined VSL and weather information. Quality control (QC) was performed on the RWIS data, but no QC was performed on the VSL speed data. Due to the nature of the VSL data, the NCAR team could not confidently remove any VSL data without additional information. The final paired, QC'd VSL,RWIS dataset for Parleys Canyon, Utah, covers the date range from 20211101 to 20230430 and has 32806 rows of data that can be used for training machine learning (ML) models.

https://www.udot.utah.gov/connect/2014/01/16/variable-speed-limit-signs-now-activated-on-i-80/

Figure A.1. Variable speed limit sign

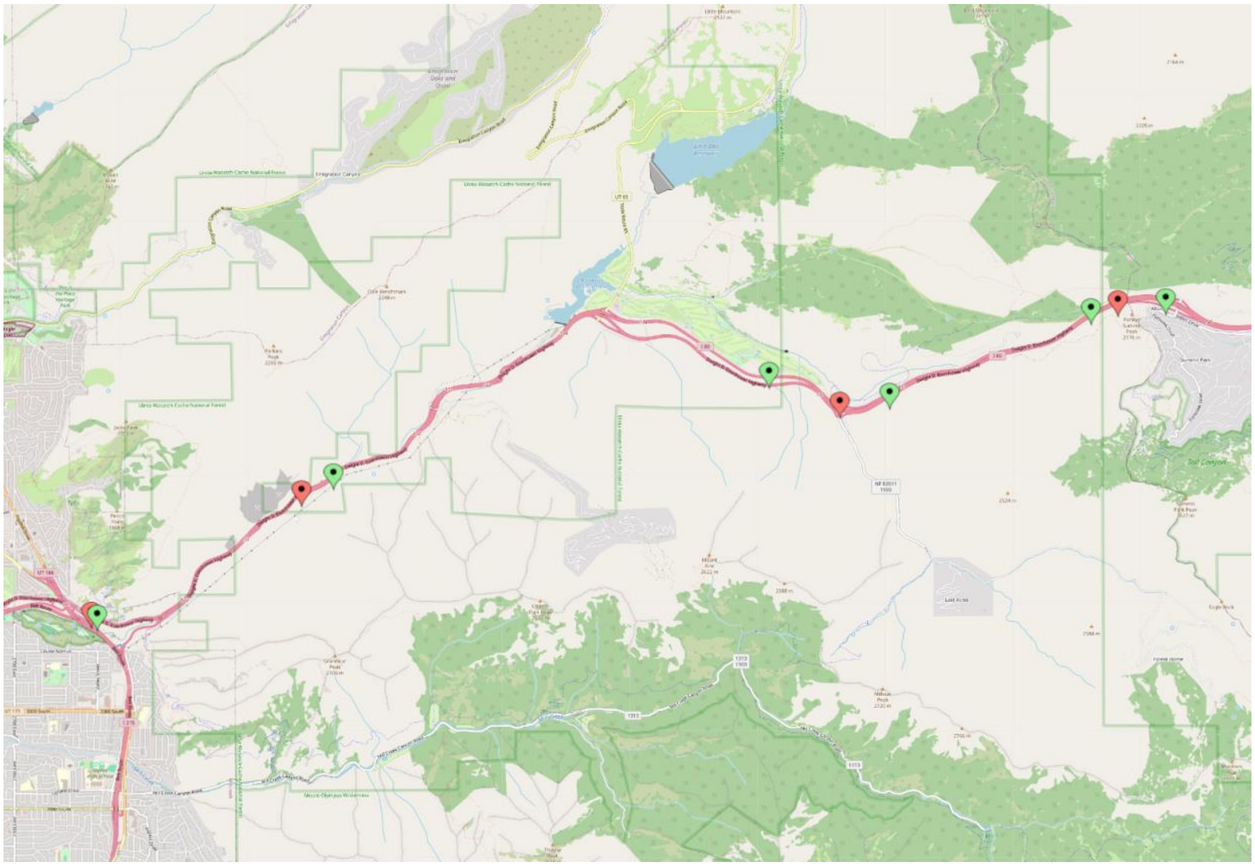

Figure A.2. Map of Parleys Canyon with RWIS (red) and VSL (green) stations used in the machine learning models

RWIS Variables Included in the QC

- AirTemp_Atmos
- RelativeHumidity_Atmos
- DewPoint_Atmos
- WindDirection
- WindSpeedAverage
- WindSpeedGust
- SnowDepth
- SolarRadiation
- Visibility
- WetBulbTemp
- SnowfallRate
- RainTotal
- SurfaceStatus
- SurfaceTemp
- SurfaceWaterDepth
- SubSurfaceTemp

- SurfaceIceDepth
- SurfaceSnowDepth
- AirTemp_Surface
- RelativeHumidity_Surface
- DewPoint_Surface
- SurfaceGrip
- dstRoadTemp
- dscLevelOfGrip

Note that the final QC'd dataset includes a SurfaceGrip field from the RWIS nearest to each VSL sign, which is a useful variable for inclusion in Rutgers physical modeling applications. The final QC'd dataset was provided to them in September 2024.

First QC Pass

- Range checks were performed to remove unrealistically high or low RWIS data
  - Examples include the following:
    - Dew point (deg F): min_value(-20) max_value(80)
    - Relative humidity (percent): min_value(0) max_value(100)
    - Air temperature (deg F): min_value(-20) max_value(120)
- Stuck value checks were performed to remove RWIS data that was stuck at a particular value for more than 3 hours straight.
  - Acceptable "stuck" values were ignored. Examples include (but are not limited to) 0 for snow depth, 0 for water depth, and 10 for visibility.
  - Stuck value checks were *not* performed on the surface status data or the surface grip data due to the fact that these data could have valid "stuck" values.
- Quality assurance (QA)/QC in this pass was performed using NCAR script basic_csv_qc.py with the configuration from Appendix A.1

Second QC Pass

After completing the first QC pass, bad/problematic values were still observed and so a second QC pass was performed to further clean up the data. That pass included the following checks:

- For RWIS ID 26, air temperature values of 0 were removed.
- Dew point values of 58.29 were removed, as this was observed to be a bad value (see the pink line in Figure A.5).
- Surface grip values larger than 0.82 were removed.
- A stuck value was removed for RWIS ID 27 between 2022/01/01 13:00 and 2022/10/03 10:00.
- Surface temperature values of 32 were removed for RWIS ID 26, as this was determined to be a problematic value.

- Surface temperature values of 0 were removed for all sites, as this was also determined to be a problematic value.

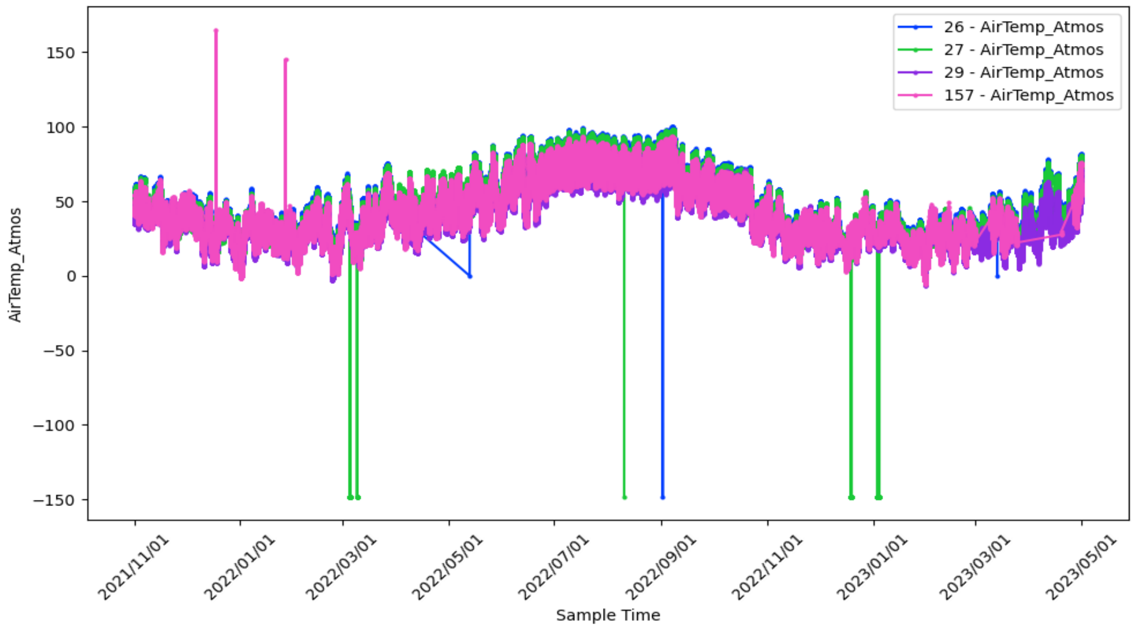

Figure A-3. Example air temperature before QC

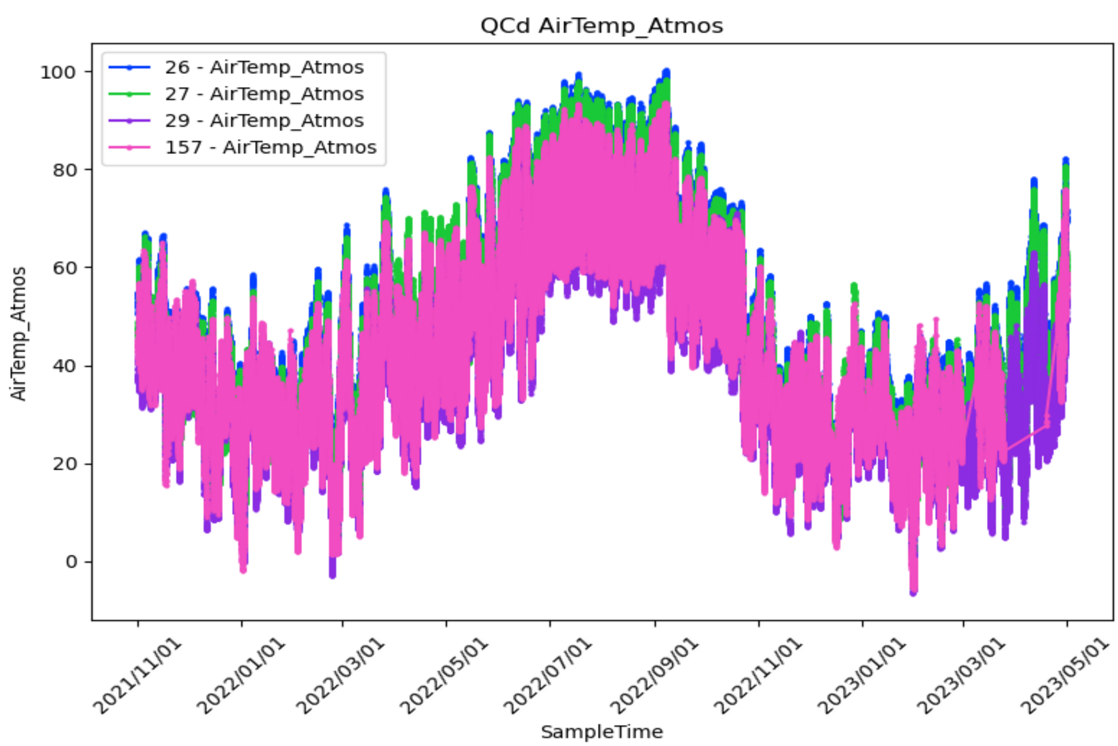

Figure A.4. Example air temperature after QC

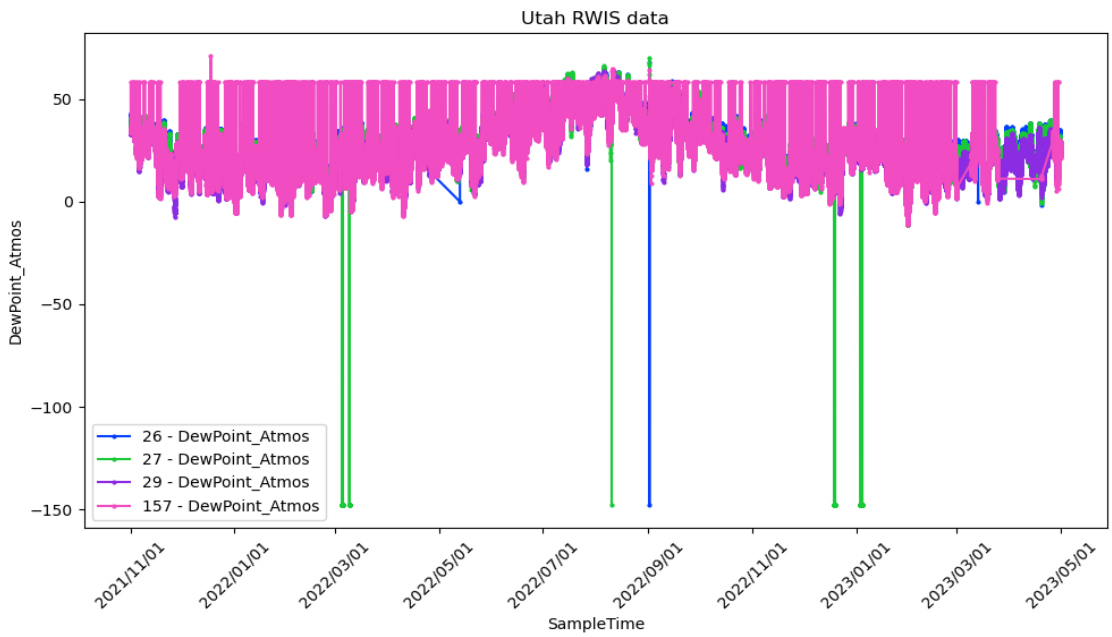

Figure A.5. Example dew point before QC

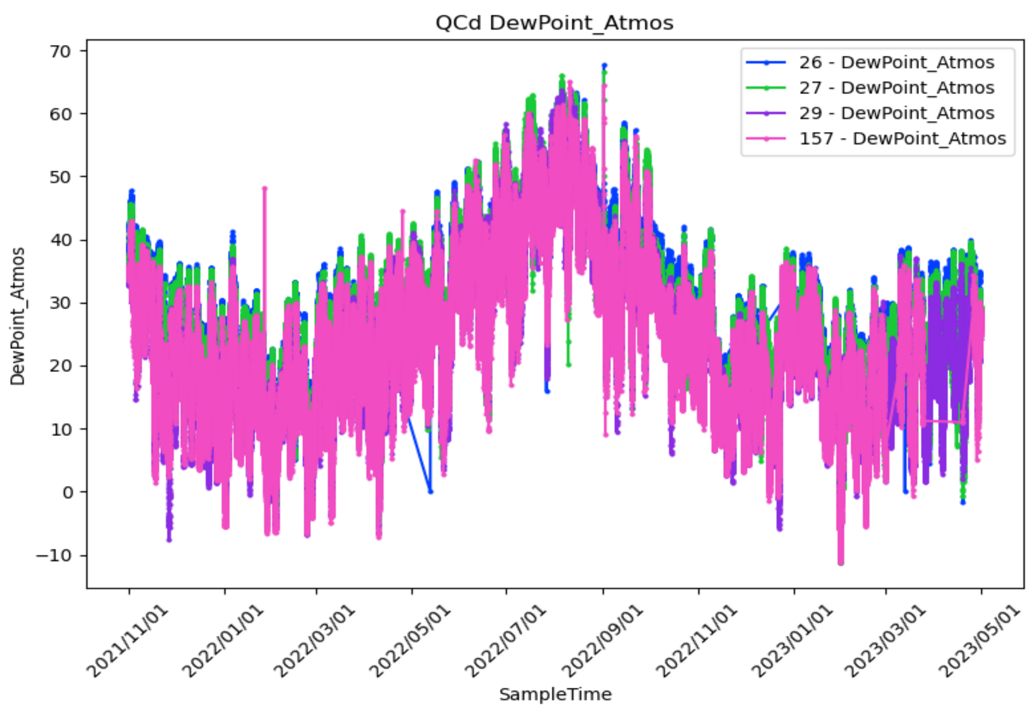

Figure A.6. Example dew point after QC

Derived variables were created as follows:

- Slowdown (Binary) was set to false if the speed was 65 mph, else true.

- Solar azimuth and solar zenith were added for each data point.
- Julian day, day of the week, and hour of the day were added for each data point.
- Precip Intensity was one-hot encoded into binary fields for each intensity category: (“Light,” “Moderate,” “Heavy,” “Fog”).
- Surface Status was one-hot encoded into binary fields for each status category: (“Dry,” “Damp,” “Wet,” “Snow,” “Slushy,” “Ice,” “Frost”).

I-25, I-80, I-90 Wyoming VSL

RWIS and VSL Dataset Information

The RWIS dataset was created from a multi-year archive of real-time RWIS data delivered by the Wyoming Department of Transportation (WYDOT). VSL data was received as a CSV log of recorded VSL events, and their corresponding speeds and device names. When the archived RWIS data was concatenated, the datafiles contained 42 unique RWIS stations and 127 unique VSL signs. These sites were from all across the state but focused mainly on major highway passes along I-80 and I-90. The VSL and RWIS data was combined by joining VSL speed from a specific date and time with the geographically closest RWIS readings within a thirty minute timeframe. Several VSL signs use the same RWIS station reports, as can be seen in the map in Figure A.7. QA/QC was performed on the RWIS data prior to merging with VSL data. Summer months were removed to focus primarily on harsh road conditions and stations/data points with unreliable reports were also removed. This left the final dataset with 38 unique RWIS stations and 115 unique VSL signs. The final paired, QC’d VSL,RWIS dataset for Wyoming covers the date range from 20211201 to 20230428 and has 38634 rows of data that can be used for training machine learning models.

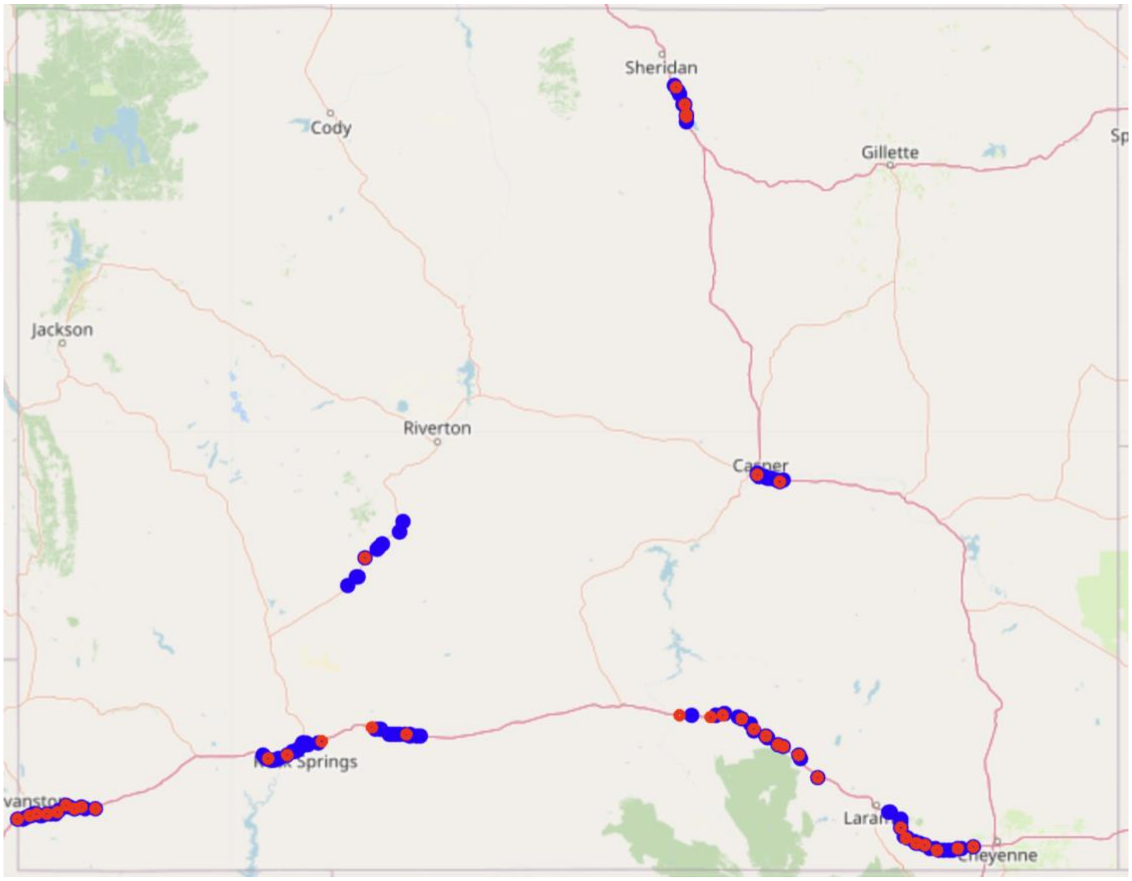

Figure A.7. Plot of colocated RWIS (red) and VSL (blue) along I-80, I-25, I-90 in Wyoming

RWIS Variables Included in the QC

- dewpoint
- precipRate
- relHumidity
- roadTemperature1
- Temperature
- Visibility
- windDir
- windGust
- windSpeed
- roadState1 (See Appendix A.3. Road State Mappings)

Note that the final QC'd dataset does not include friction observations from the RWIS. These are unavailable in Wyoming.

First QC Pass

This pass was performed for specific, static QC meant to prepare the data for later rounds of QA/QC. The specific QA/QC is as follows:

- The visibility variable was converted to meters for all sites after 09/28/2022, as it began being stored as kilometers after that date.
- The visibility variable was fixed such that the max value is 2,000 meters (2 km). Any value greater than this was not removed but simply capped at 2,000 meters.
- The roadState1 variable was fixed by removing any values outside 0-18. Also, values of 0 and 17 were converted to NaN.
- For all stations where the maximum precipRate was 0, all 0 values were changed to NaN so that they would be ignored.
- Data for summer months (May through September) was removed, as weather data from this timeframe would be unnecessary for evaluating weather-impacted roads in Wyoming.

Second (Main) QC Pass

- Range checks were performed to remove unrealistically high or low RWIS data. Examples include the following:
  - Dew point (deg C): min_value(-50) max_value(30)
  - Relative humidity (percent): min_value(0) max_value(100)
  - Temperature (deg C): min_value(-60) max_value(50)
- Stuck value checks were performed to remove RWIS data that was stuck at a particular value for more than 1 day straight.
  - Acceptable "stuck" values were ignored. Examples include (but are not limited to) 0 for precipRate, 1 (dry) for roadState, and 2000 for visibility.
- Outlier checks were performed to remove values considered impossible/erroneous that may interfere with ML training/modeling.
  - The Chebychev_test was performed for both precipRate and windGust, as we were experiencing abnormal outliers in these fields. This test uses a two-phase algorithm developed by Amidan et el. [1] that flags outliers based on Chebychev's limit theorem. The theorem guarantees the proportion of values that are within k standard deviations of the mean for any data distribution.
- QA/QC in this pass was performed using NCAR script basic_csv_qc.py with the configuration from Appendix A.2.

Third QC Pass

This final pass was completed after the RWIS data was merged with the VSL data. The QA/QC in this pass was specified to remove sites whose VSL speed data was unreliable or unideal for our experiments.

- Speed was removed for I-25 SB 187.21 (McKinley Street Interchange).

- Speed was removed for I-25 SB 186 (Bryan Stock Trail Interchange).
- Speed was removed for I-25 NB 184.95 (Casper South).
- Speed was removed for I-25 NB 186.05 (Evansville Interchange).
- Speed was removed for I-80 EB 6.94.
- Speed was removed for I-80 EB 101.54 (Interchange Road East).
- Data was removed from any site not along I-80.

Full Data Compilation

Finally, after the first three rounds of QA/QC were completed, derived and engineered variables were added to the dataset as follows:

- Sample time columns (DOW,DOY, Hour) were created using the observation time.
- A slow_down binary column was created using the observed speed versus the max speed for each station.
- A speed shift binary column was created. In this case, a speed shift is defined as any long period of prolonged slowdown due to non-weather-related events like construction. This was also derived using the observed speed versus the max speed for each station but includes the observation time to detect prolonged periods of slowdown. This column allowed filtering before machine learning was performed so that these periods of slowdown could be ignored or adjusted globally.
- Solar zenith and azimuth columns were derived using the observation time and the latitude and longitude.
- The roadState1 variable was one-hot encoded for better ML model interpretation.

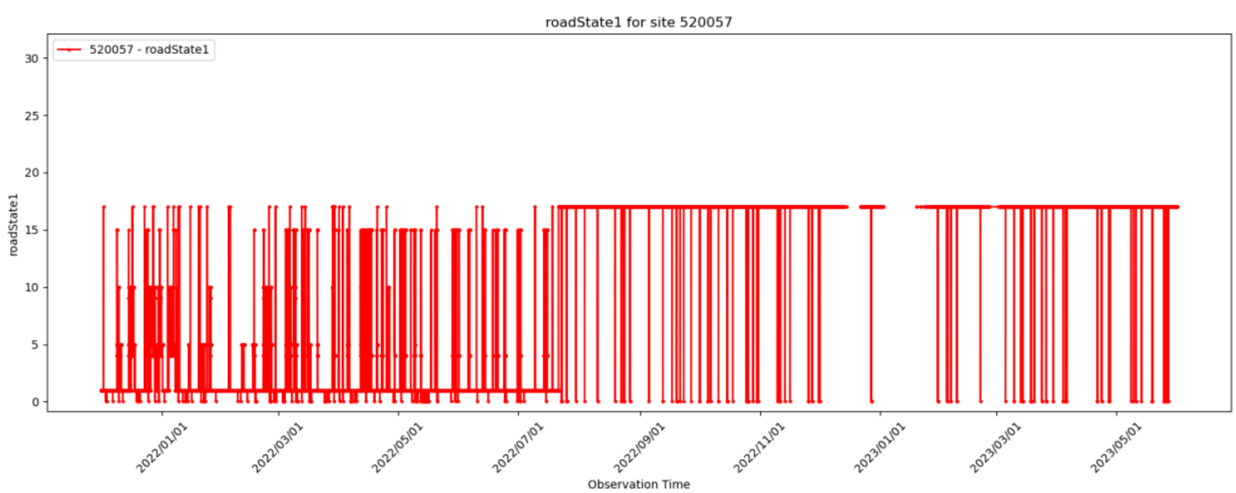

Figure A.8. Example road state variable (site 520057 - I-80 EB 0.06) before QC pass 1 and 2

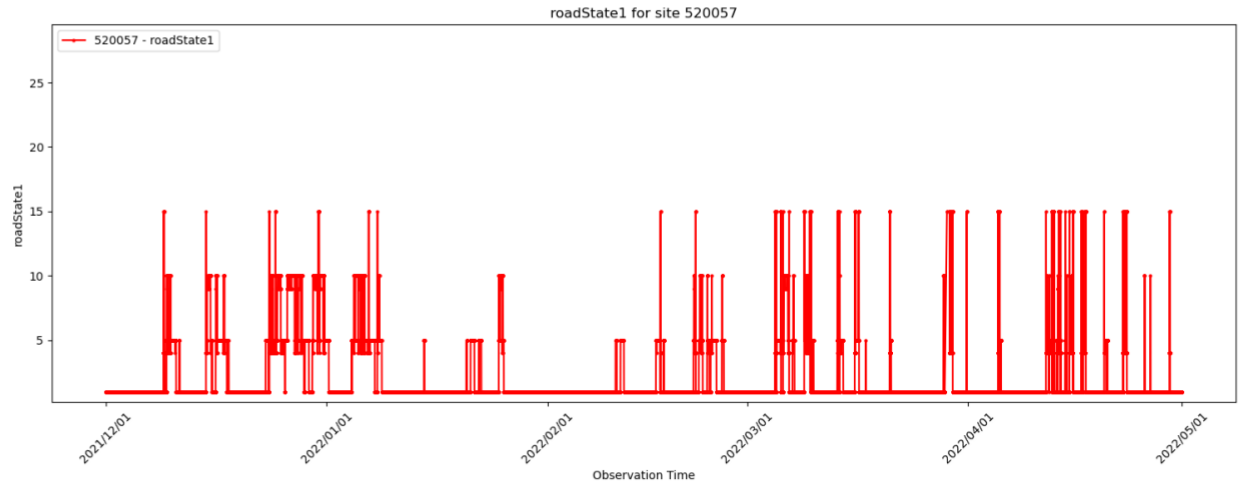

Figure A.9. Example road state variable (site 520057 - I-80 EB 0.06) after QC pass 1 and 2

For details, see Appendix A.3. Road State Mappings.

What was done:

- Stuck values removed (except for 1)
- Values of 17 removed for clarity

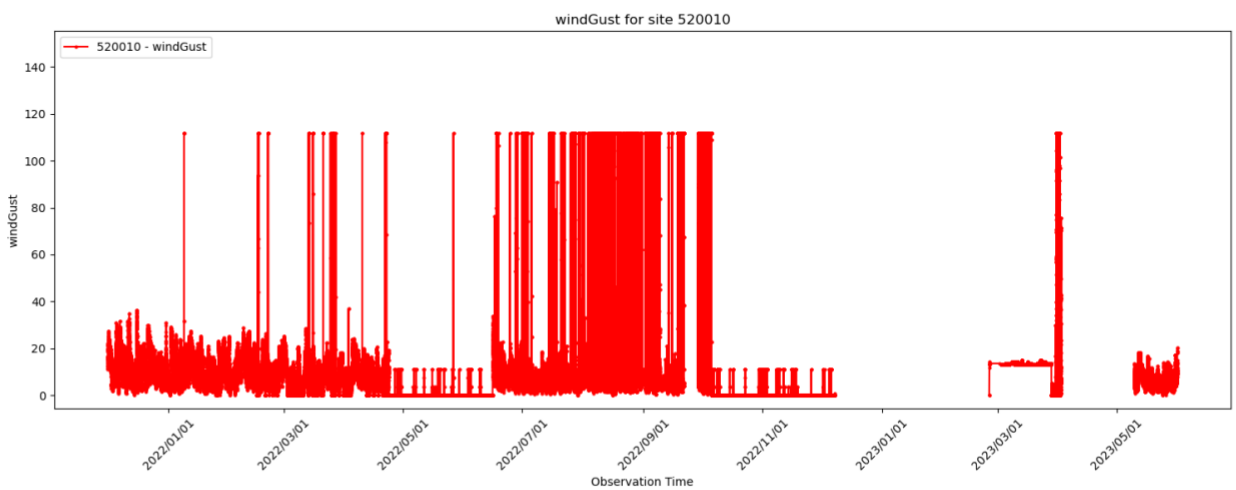

Figure A.10. Example wind gust (site 520010 - I-80 EB 345.9) before QC pass 1 and 2

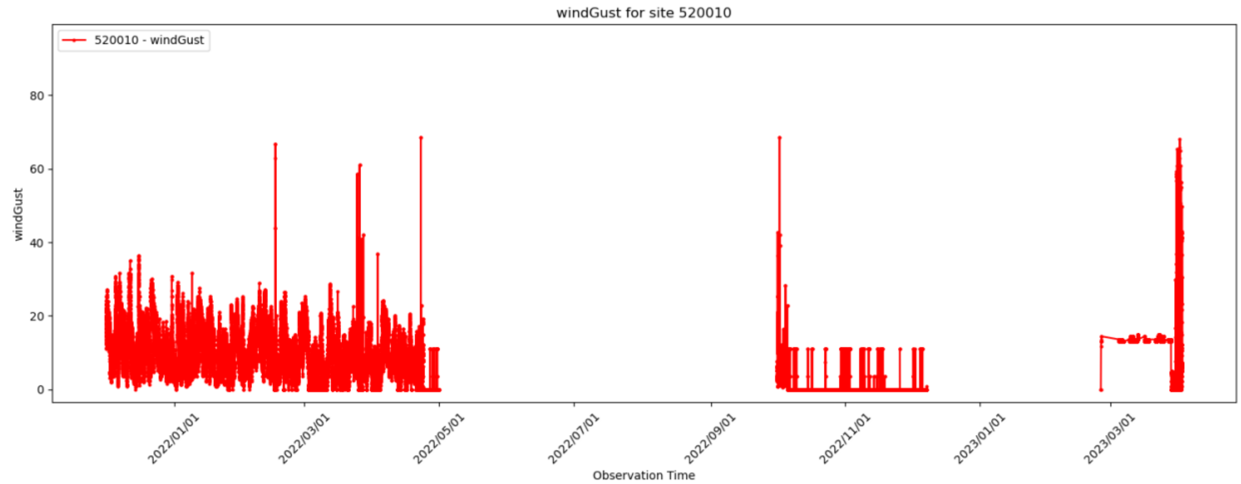

Figure A.11. Example wind gust (site 520010 - I-80 EB 345.9) after QC pass 1 and 2

What was done:

- Stuck values removed
- Extreme outlier removed
- Summer months removed

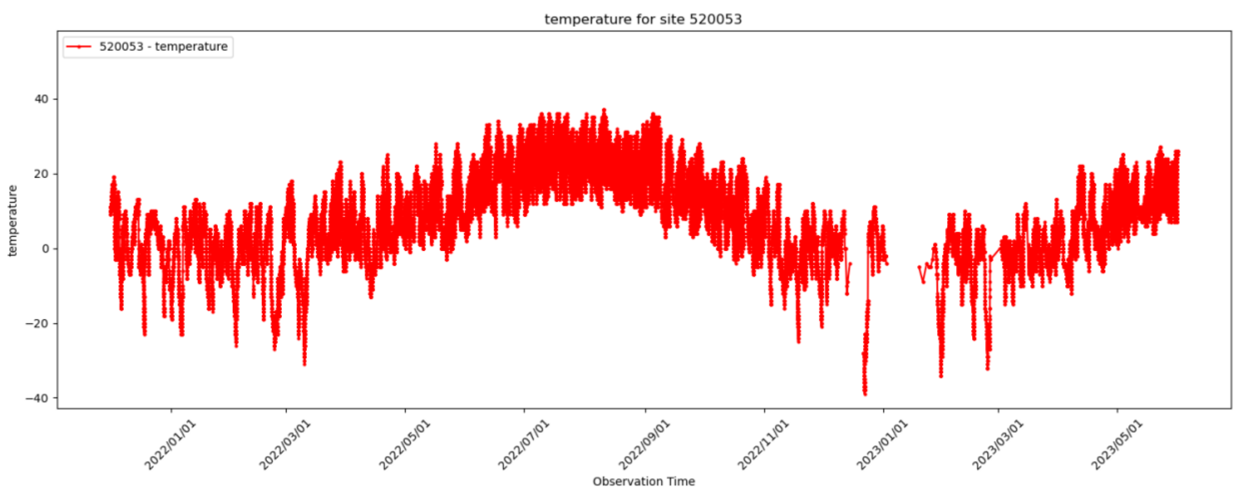

Figure A.12. Example road temperature (520053 - site I-25 NB 180.5) before QC pass 1 and 2

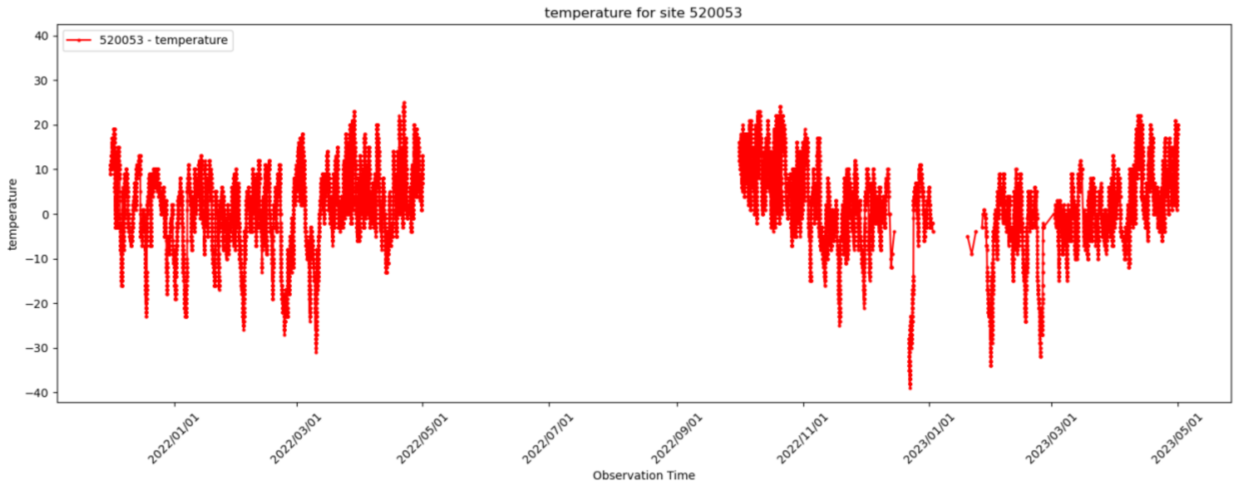

Figure A.13. Example roadTemperature1 (520053 - site I-25 NB 180.5) after QC pass 1 and 2

What was done:

- Summer months removed

Appendix A.1. Parleys Canyon, Utah, QA/QC Configuration Settings


```
{
   "Variables" : [
      {"input_name" : "AirTemp_Atmos",
       "min_bound" : -20,
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      {"input_name" : "RelativeHumidity_Atmos",
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       "max_bound" : 100,
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       "stuck_ignore_values" : []
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      {"input_name" : "DewPoint_Atmos",
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       "max_bound" : 80,
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       "stuck_ignore_values" : [],
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           "second_p": 0.05
       }
       },
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       "min_bound" : 0,
       "max_bound" : 360,
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       "stuck_ignore_values" : []
       },
      {"input_name" : "WindSpeedAverage",
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       "max_bound" : 40,
       "stuck_limit_seconds" : 10800,
       "stuck_ignore_values" : [0]
       },
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       "max_bound" : 90,
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       "stuck_ignore_values" : [0]
       },
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       "max_bound" : 9999,
       "stuck_limit_seconds" : 10800,
       "stuck_ignore_values" : [0]
       },
```

{"input_name" : "SolarRadiation",
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 "max_bound" : 1300,
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 "stuck_ignore_values" : [0]
 },
{"input_name" : "Visibility",
 "min_bound" : 0,
 "max_bound" : 11,
 "stuck_limit_seconds" : 10800,
 "stuck_ignore_values" : [10.00]
 },
{"input_name" : "WetBulbTemp",
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 "max_bound" : 75,
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 },
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 "stuck_ignore_values" : [0]
 },
{"input_name" : "RainTotal",
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 },
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 "max_bound" : 150,
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    "second_p": 0.05}
 },
{"input_name" : "SurfaceWaterDepth",
 "min_bound" : 0,
 "max_bound" : 15,
 "stuck_limit_seconds" : 10800,
 "stuck_ignore_values" : [0]
 },

{"input_name" : "SubSurfaceTemp",
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 "max_bound" : 100,
 "stuck_limit_seconds" : 10800,
 "stuck_ignore_values" : [],
 "chebychev_test": {
    "first_p": 0.10,
    "second_p": 0.05
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 },
{"input_name" : "SurfaceIceDepth",
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 "stuck_ignore_values" : [0]
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    "second_p": 0.05
 }
 },
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 "max_bound" : 100,
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 "stuck_ignore_values" : [],
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 }
 },
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    "second_p": 0.05
 }

```
        },
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        "max_bound" : 150,
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        },
       {"input_name" : "dscLevelOfGrip",
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        "max_bound" : 1,
        "stuck_limit_seconds" : "null",
        "stuck_ignore_values" : [0.82, 0.81, 0.80]
        }
    ]
}
```

Appendix A.2. I-25, I-80, I-90 Wyoming QA/QC Configuration Settings


```
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          {
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         "max_bound": 30,
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         "stuck_ignore_values": []
      },
      {
         "input_name": "precipRate",
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         "max_bound": 130,
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         "stuck_ignore_values": [0],
            "chebychev_test": {"first_p":0.01,"second_p":0.0001}
      },
      {
         "input_name": "relHumidity",
         "min_bound": 0,
         "max_bound": 100,
         "stuck_limit_seconds": 86400,
         "stuck_ignore_values": []
      },
      {
         "input_name": "roadTemperature1",
         "min_bound": -30,
         "max_bound": 80,
         "stuck_limit_seconds": 86400,
         "stuck_ignore_values": []
      },
      {
         "input_name": "roadTemperature2",
         "min_bound": -30,
         "max_bound": 80,
         "stuck_limit_seconds": 86400,
         "stuck_ignore_values": []
      },
      {
         "input_name": "temperature",
         "min_bound": -60,
         "max_bound": 50,
         "stuck_limit_seconds": 86400,
         "stuck_ignore_values": []
      },
      {
         "input_name": "visibility",
         "min_bound": 0,
```

```
          "max_bound": 2000,
          "stuck_limit_seconds": 86400,
          "stuck_ignore_values": [2000]
        },
        {
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          "max_bound": 360,
          "stuck_limit_seconds": 86400,
          "stuck_ignore_values": []
        },
        {
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          "max_bound": 70,
          "stuck_limit_seconds": 86400,
          "stuck_ignore_values": [0],
             "chebychev_test": {"first_p":0.01,"second_p":0.0001}
          },
        {
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          "max_bound": 45,
          "stuck_limit_seconds": 86400,
          "stuck_ignore_values": [0]
        },
          {
          "input_name": "roadState1",
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          "max_bound": 18,
          "stuck_limit_seconds": 86400,
          "stuck_ignore_values": [1]
        }
    ]
}
```

Appendix A.3. Road State Mappings


```
{
  0: "No report",
  1: "Dry",
  2: "Moist",
  3: "Moist and chemically treated",
  4: "Wet",
  5: "Wet and chemically treated",
  6: "Ice",
  7: "Frost",
  8: "Snow",
  9: "Snow/Ice Watch",
  10: "Snow/Ice Warning",
  11: "Wet Above Freezing",
  12: "Wet Below Freezing",
  13: "Absorption",
  14: "Absorption at Dewpoint",
  15: "Dew",
  16: "Black Ice Warning",
  17: "Other",
  18: "Slush",
  MISSING_VALUE : MISSING_CODE
}
```


References

[1] Amidan, B. G., T. A. Ferryman, and S. K. Cooley. 2005. Data outlier detection using the Chebyshev theorem. *2005 IEEE Aerospace Conference*, Big Sky, MT. pp. 3814–3819. https://doi.org/10.1109/AERO.2005.1559688.

APPENDIX B. ML MODELING

Introduction

Research was conducted to automate variable speed limits (VSL) using machine learning (ML) techniques. The primary objective was to develop predictive algorithms for VSL by leveraging comprehensive datasets that included weather conditions and road surface friction measurements.

The study focused on two distinct geographic areas: I-80 through Parleys Canyon in Utah and various locations along I-80, I-25, I-90, and WYO789 in Wyoming. Data collection centered on identifying road weather information system (RWIS) stations situated near VSL signage to enable the acquisition of localized weather and road condition data.

A critical component of the research involved a comprehensive quality assurance/quality control (QA/QC) process. Training datasets were constructed by spatially and temporally aligning VSL speed event records with RWIS observations. This rigorous QA/QC process produced two high-quality datasets suitable for both data analysis and the development of machine learning and physics-based models.

The Parleys Canyon dataset notably included friction (grip) measurements from its RWIS stations, which emerged as important predictors in several ML models. In contrast, the Wyoming dataset lacked friction data, limiting the use of physics-based modeling and potentially influencing ML model performance in that region.

The analysis, methodologies, and algorithm development undertaken in this study are presented in detail, offering insights into data-driven approaches for VSL automation.

Model Training Data

Two study areas with significant VSL and RWIS coverage were selected for ML model development: I-80 through Parleys Canyon, Utah, and locations along I-80, I-25, I-90 and a few sites along WYO789 in Wyoming. Both Utah and Wyoming provided the National Center for Atmospheric Research (NCAR) with VSL speed event data. RWIS stations were identified based on their proximity to VSL sign locations, enabling the collection of weather and road surface condition data from collocated sensors. Training datasets were constructed by joining VSL speed initialization events with RWIS observations based on spatial and temporal proximity. An extensive set of QA/QC algorithms and techniques were then applied to produce two high-quality training datasets suitable for data analysis and the development of machine learning and physical models. Further details on the QA/QC procedures performed can be found in the document *Variable Speed Limits and Weather: Technical Report on Data Quality Control and Organization*. The Parleys Canyon RWIS stations provided friction (grip) measurements, making the Utah training dataset well suited for the physical modeling approaches being developed by the Rutgers team and serving as a top predictor of VSL speed in some ML models. In contrast, the Wyoming RWIS stations did not include friction data, limiting their applicability for such physically based methods and potentially influencing ML model performance for Wyoming.

Parleys Canyon, Utah - VSL

The Parleys Canyon study area includes 4 RWIS stations and 15 VSL signs, 6 of which are collocated or in close proximity to RWIS stations, as shown in Figure B.1. RWIS observations and VSL speed events from these locations were joined in space and time and run through QA/QC algorithms to produce a training dataset consisting of 32,806 records spanning from November 1, 2021, to April 30, 2023.

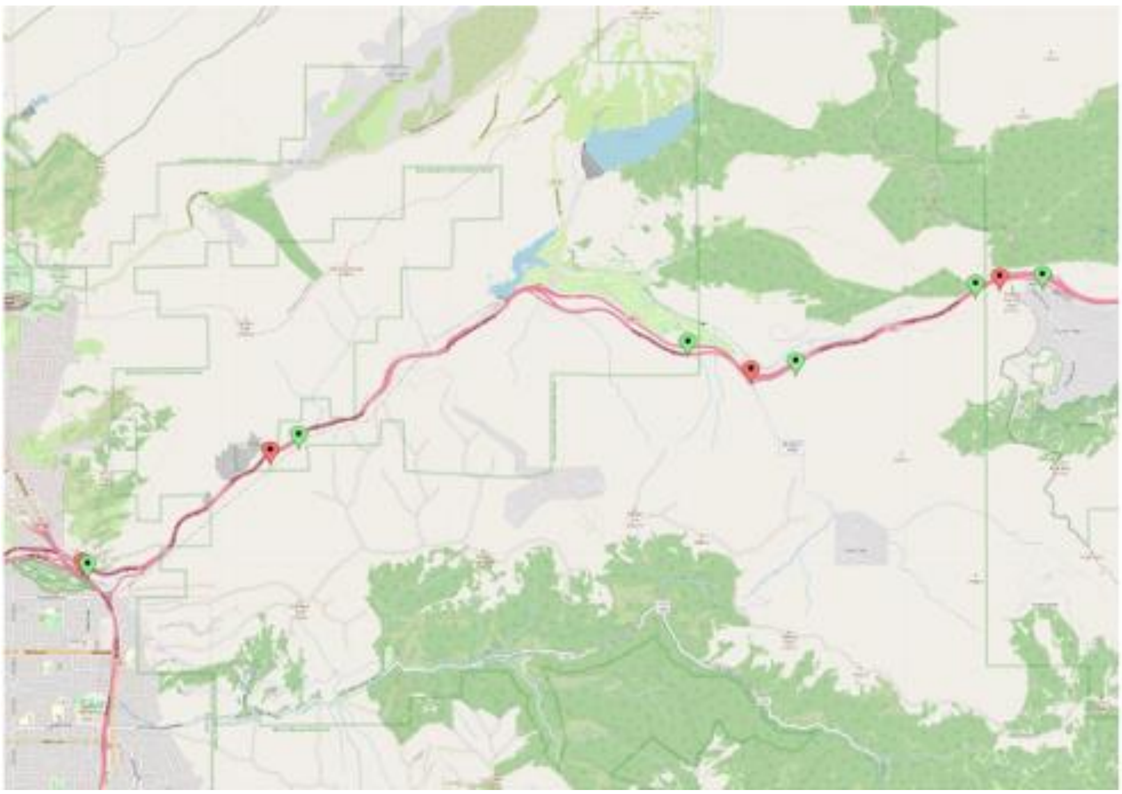


Figure B.1. Map of Parleys Canyon with RWIS (red) and VSL (green) stations used in the machine learning models

Statistics presented later in this report show a highly skewed or imbalance distribution of speeds and slowdown cases across the dataset. Highly skewed datasets are known to negatively affect ML model performance. In order to improve the balance of speeds, and to be able to reliably capture transitions between normal speeds and slow speeds, the training dataset for Utah was augmented based on knowledge of VSL reporting frequency.

Utah's current VSL triggers are determined by rules that consider friction (grip), visibility, snowfall rate, water depth, and wind speed.

Every VSL sign reports every day. A vast majority of the 65 mph (max speed) days had 2 reports or less per device. There are 15 devices that would each report a 65 mph speed about 12 hours apart; therefore, days with less than 31 reports are good candidates for augmentation.

The logic for adding transition data leading into and out of slowdowns is as follows:

1. If number of daily reports > 30, VSL data exists, don't add data for this day.
2. If number of daily reports < 30 *and* the minimum VSL speed != 65, then there was a slowdown this day, so don't add any data.
3. Else (neither above condition is true), look for the previous VSL report for each device. If the previous report != 65, don't add data (to ensure that there wasn't an ongoing slowdown for this day).
4. Finally, add data for this day and device.

Utah RWIS data has a frequency of 10 minutes. We experimented with augmenting data at 30-minute, hourly, and 2-hour intervals. It was determined that adding data at a 2-hour interval was preferable because it led to a nearly even distribution between slowdown and non-slowdown data points.

This dataset was then used to perform statistical analysis and ML model development. The Rutgers VSL team was provided this dataset, which was used to generate physical models.

Wyoming I-80, I-90, I-25 - VSL

Wyoming operates an extensive network of VSL signs and RWIS stations. After spatial and temporal alignment of VSL events with RWIS observations, the resulting training dataset includes 127 VSL signs collocated with 42 RWIS stations across I-80, I-25, and I-90 (Figure B.2). The QA/QC'd dataset contains 38,634 records covering the period from December 1, 2021, to April 28, 2023. Despite the larger VSL and RWIS network available in Wyoming, the data presents more quality challenges due to the harsh environmental conditions encountered during the Wyoming winter and shoulder seasons. Some of the issues observed include sensor malfunctions, leading to stuck or implausible values, prolonged snow and ice cover that make adjusting VSL speeds more difficult, and extended periods of reduced speeds associated with road construction. Wyoming's current rules-based VSL triggers are heavily influenced by surface status, road temperature, relative humidity, visibility and wind speed.

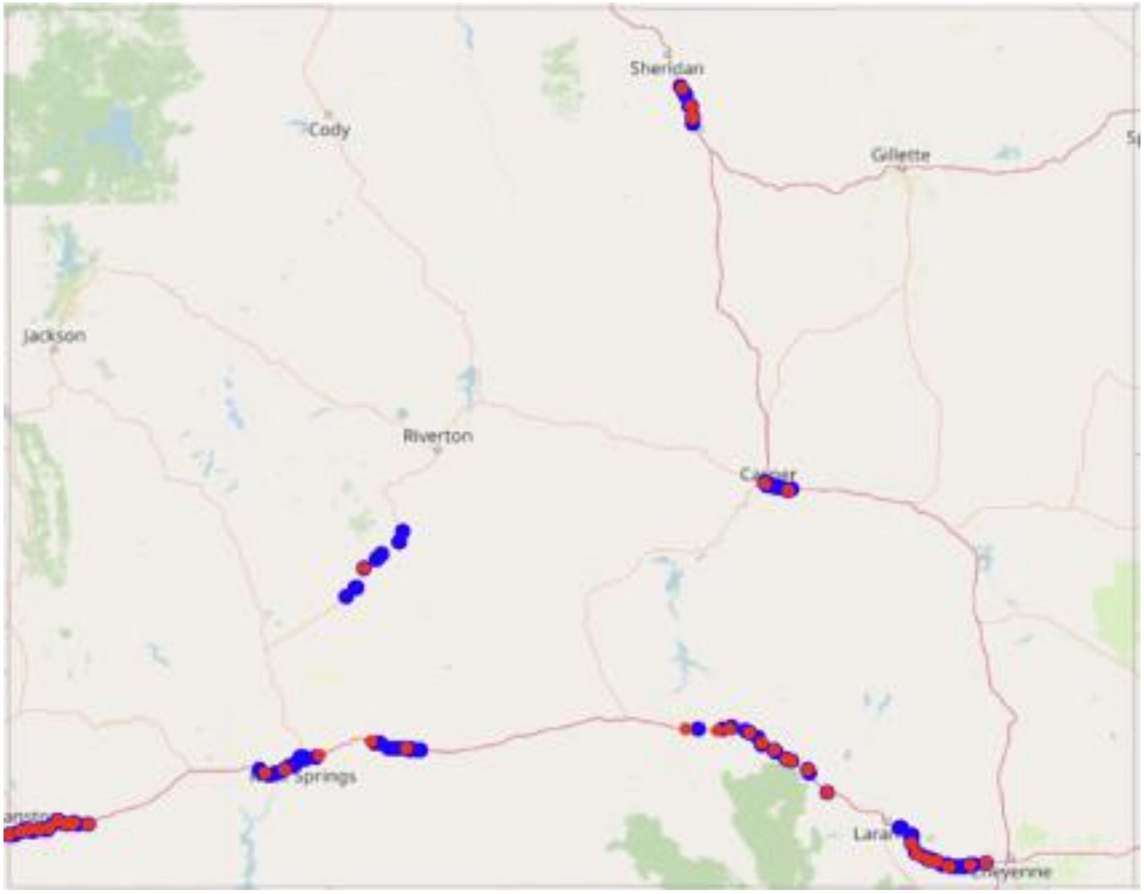


Figure B.2. Plot of collocated RWIS (red) and VSL (blue) along I-80, I-25, and I-90 in Wyoming

Statistical Analysis

Parleys Canyon, Utah

Before starting the ML modeling, statistical analysis was performed on the Parleys Canyon, Utah, training dataset consisting of 32,806 records spanning from November 1, 2021, to April 30, 2023.

As indicated in Figure B.3, the VSL speeds for Parleys canyon were most commonly over 60 mph with a moderate number of reduced speeds and very few low speeds commonly associated with inclement weather or accidents. Accident data are available for Parleys Canyon but are not utilized in the development of training data or Utah ML models due to the infrequency and unreliability of reported incidents time and location. This figure shows the highly skewed nature of the predictand speed data.

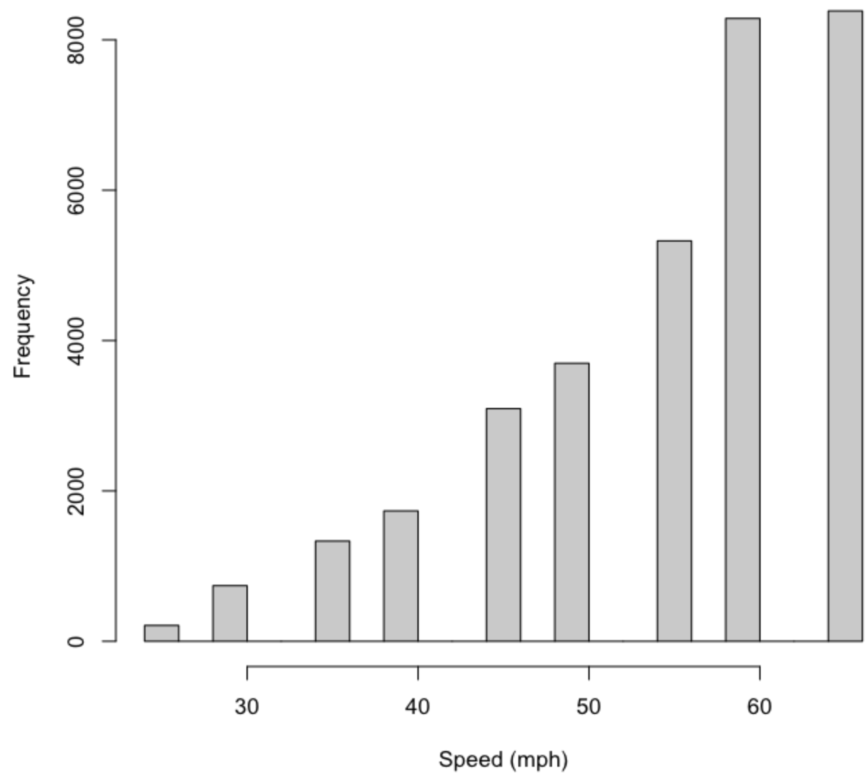


Figure B.3. Parleys Canyon VSL speed distribution

Slower speeds tend to occur under snowy and icy conditions with only a few outliers, although there is more spread with these categories as would be expected based on treatment and severity of the inclement weather.

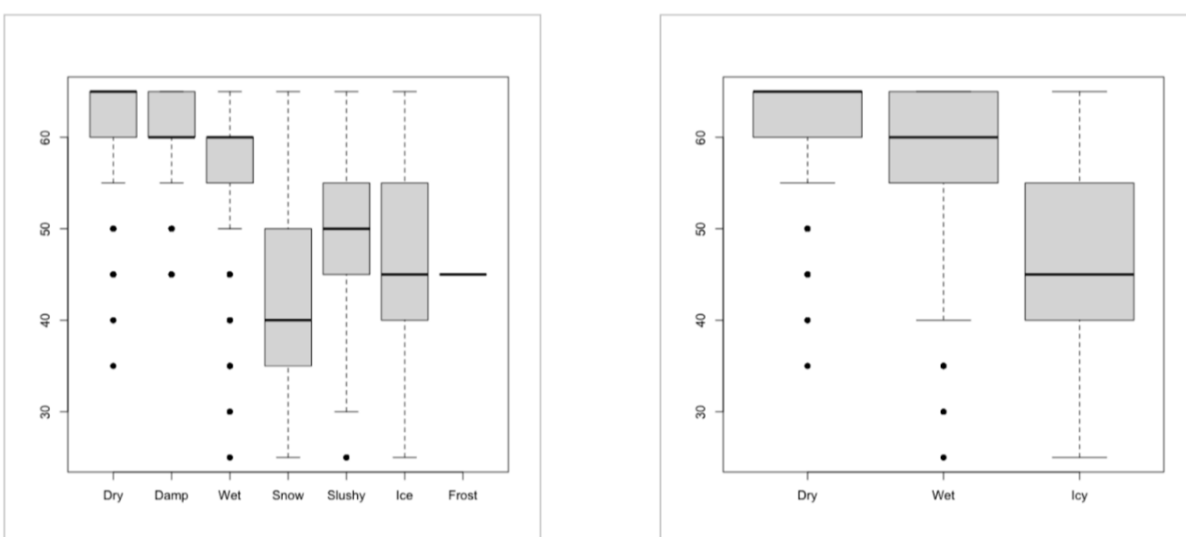


Figure B.4. Speed (mph) distributions by surface status as reported (left) and grouped by like category (right)

With the exception of some outliers, slowdowns tend to occur at lower grip values. Binary slowdown/no slowdown was determined by taking VSL speeds below or above 65 mph respectively.

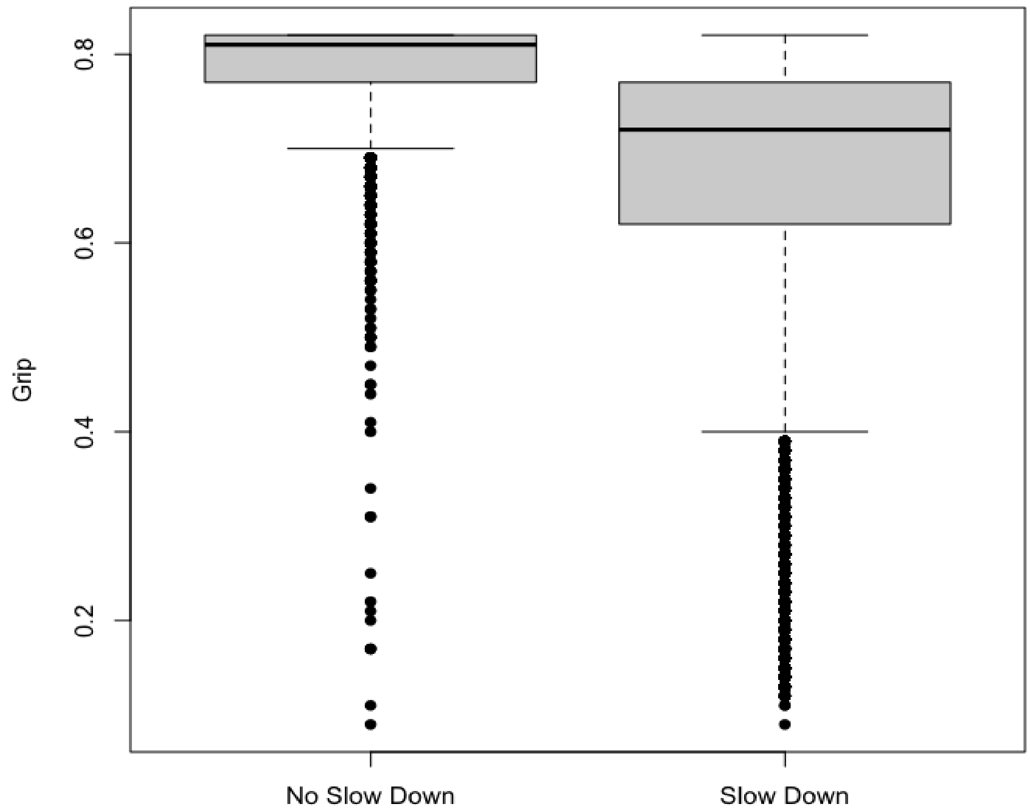
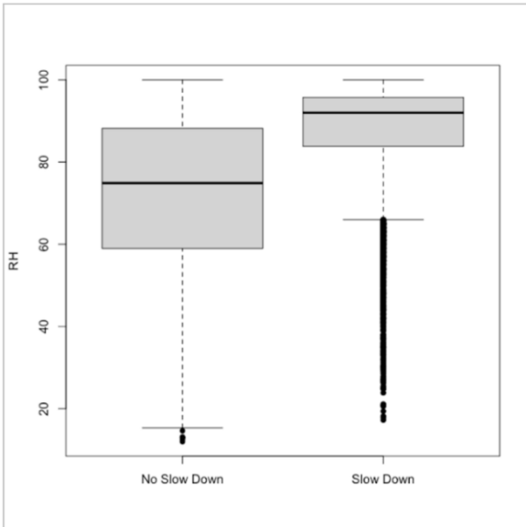


Figure B.5. Binary slowdown/no slowdown distributions of friction (grip)

Figure B.6 shows higher relative humidity with smaller spread during slowdown events and lower VSL speeds during low visibility, likely due to snow events though potentially also fog events



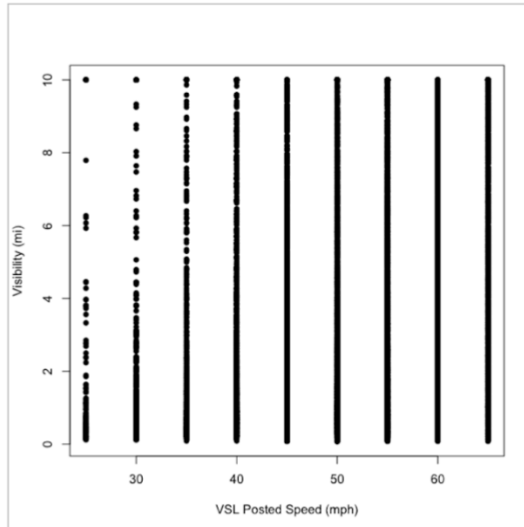
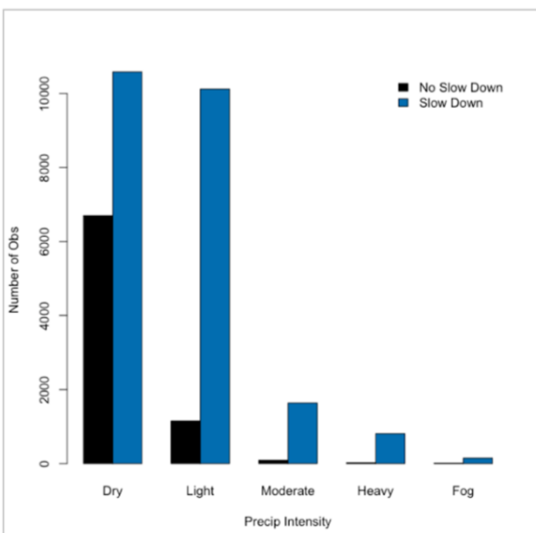


Figure B.6. Relative humidity and visibility distributions

Precipitation is a significant factor in slowdowns as seen in Figure B.7. This figure illustrates the skewed distribution of the non-augmented dataset, which supports the conclusion that precipitation events significantly contribute to weather-related slowdowns within this dataset.



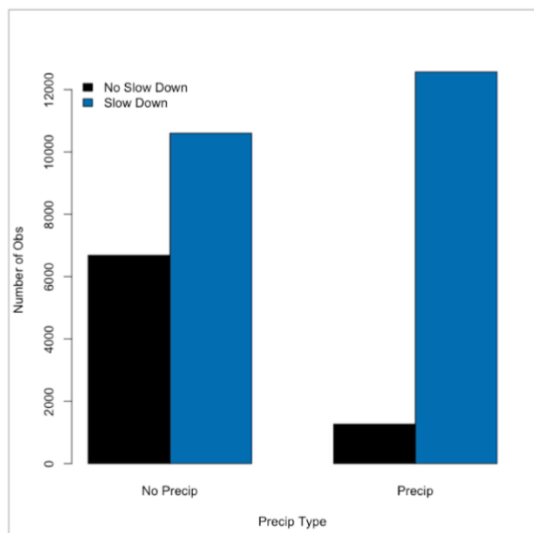


Figure B.7. Distribution of precipitation intensity (left) and events (right)

Figure B.8 shows that higher precipitation rates correspond with lower median speed and greater spread.

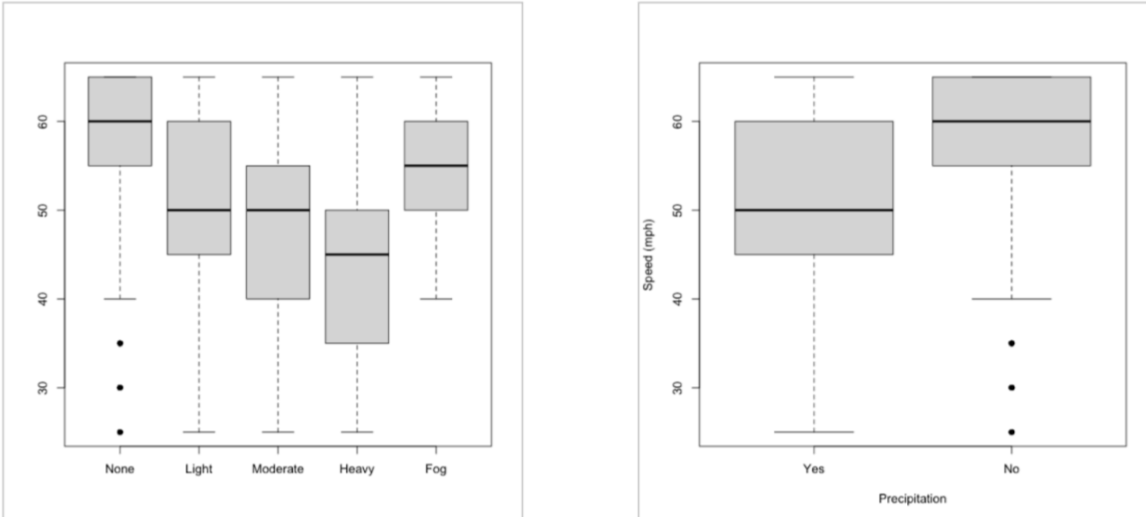


Figure B.8. Speed distributions by precipitation intensity (left) and occurrence (right)

As seen in Figure B.9, there appears to be a higher frequency of slowdowns towards mid-week. This pattern is interesting, but this predictor is static so it doesn't end up providing much useful signal for a weather-dependent ML model.

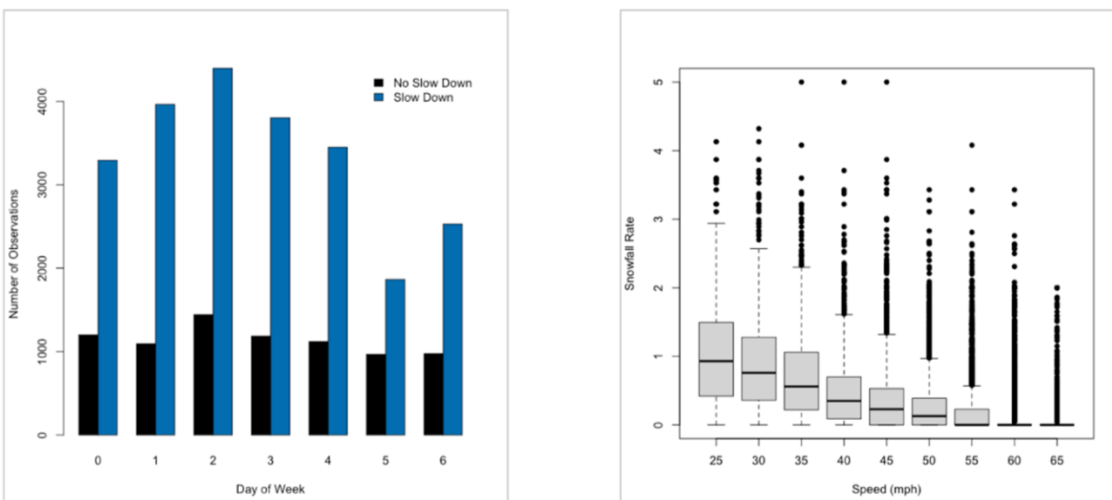


Figure B.9. Observed slowdowns by day of the week

There is an inverse relationship between speed and snowfall rate, although there is significant overlap of IQR bands (Figure B.10). This is consistent with the categorical precipitation intensity analysis (Figures B.7 and B.8).

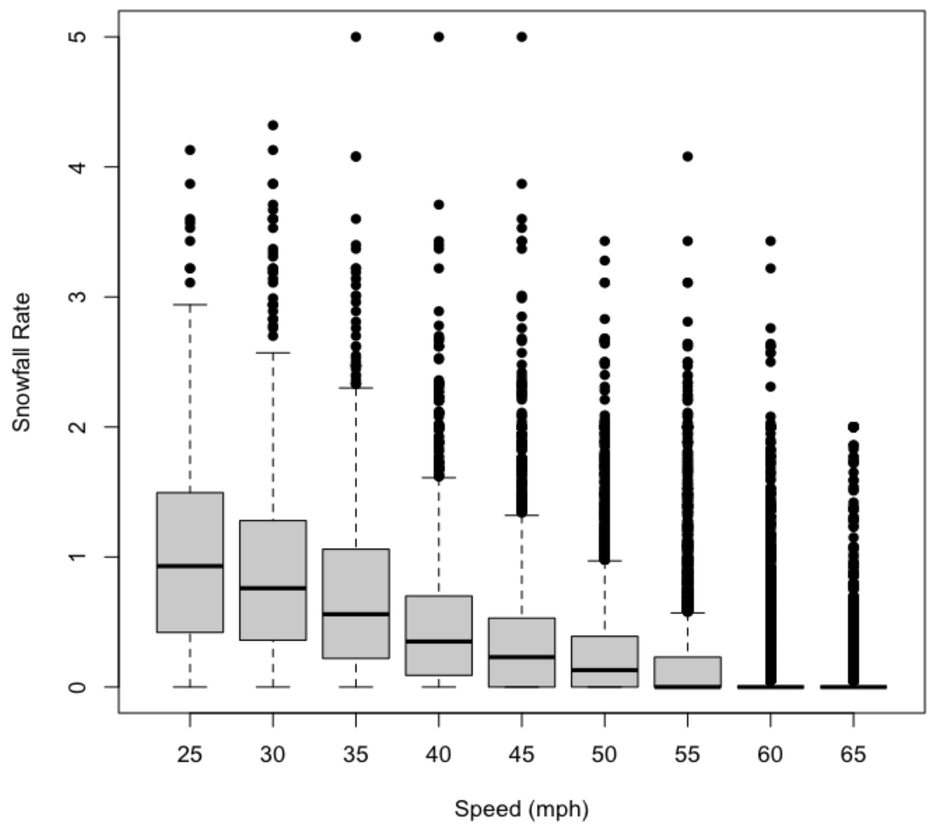


Figure B.10. Snowfall rate distribution by speed

Typically, there are lower speeds at lower solar radiance observations (Figure B.11). This is likely due to clouds and precipitation during storm events given the speed dependence on precipitation intensity.

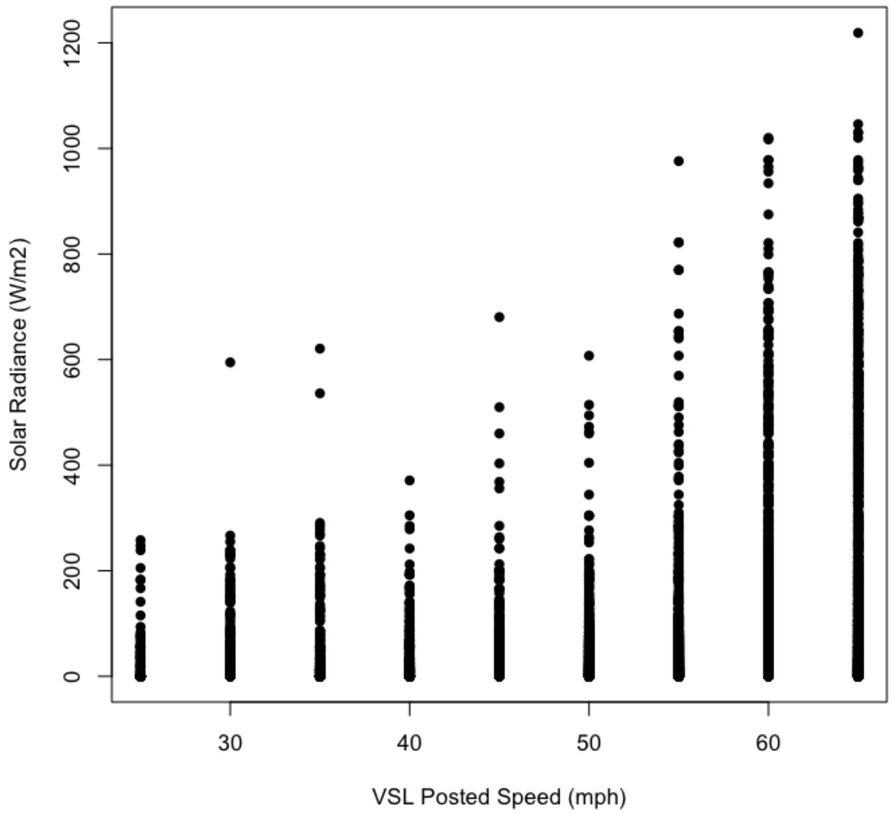


Figure B.11. VSL speed versus solar radiance

Figure B.12 shows that the wind direction is clustered around westerly/northwesterly values for slower speeds. This may be the dominant wind direction during winter storm events, as northwesterly winds are typically expected after the passage of a cold front and on the backside of a passing low pressure system or in a northwest flow pattern, all of which are associated with winter storms.

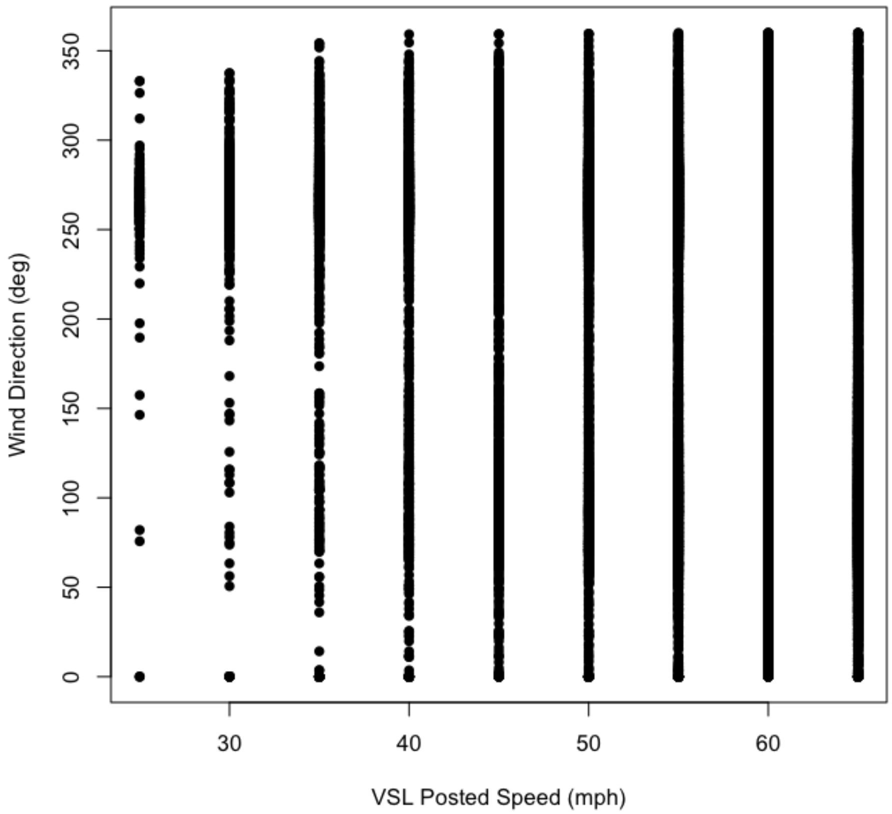


Figure B.12. Speed versus wind direction

Summary

Surface status and friction (grip) appear to be highly correlated with speed and may be important predictors for triggering VSL. Weather variables including relative humidity, visibility, precipitation type/intensity, solar radiance and wind direction are other important potential predictors for VSL models, as they are associated with winter storm events that lead to a buildup of snow or ice on the pavement and associated reduction in friction (grip).

Wyoming I-80

Similar analysis was performed for the Wyoming training dataset consisting of 38,634 records covering the period from December 1, 2021, to April 28, 2023.

As indicated in Figure B.13, the Wyoming VSL speeds were most commonly over 60 mph with a moderate number of reduced speeds and very few low speeds commonly associated with inclement weather or accidents. Accident data were not utilized in the development of Wyoming training data or ML models. Like the distribution for Parleys Canyon in Figure B.3, Figure B.13 shows the highly skewed nature of the predictand speed data.

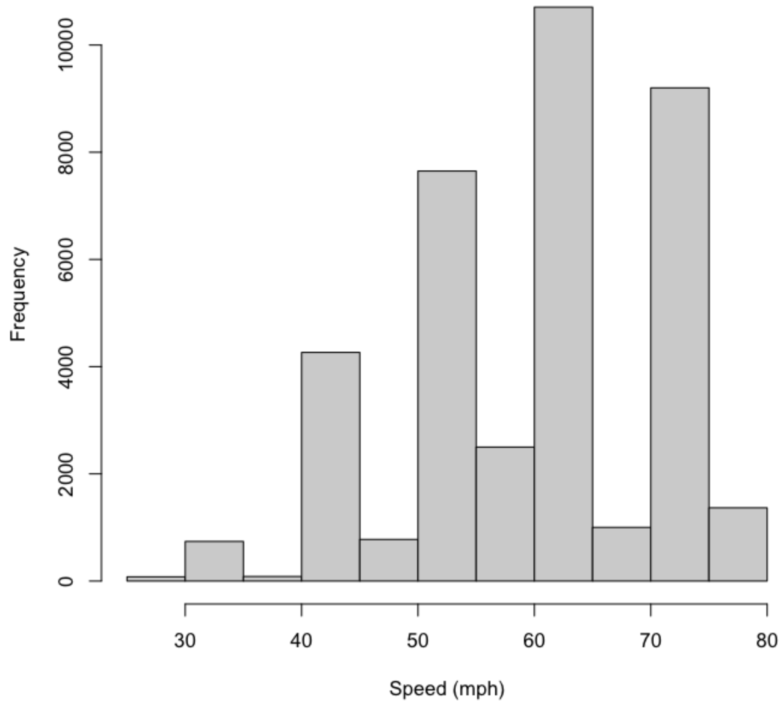


Figure B.13. Wyoming VSL speed distribution

Under icy conditions, slower speeds are commonly seen with less spread than other categories, although the speeds under wet conditions also include some greatly reduced speeds and a large spread (Figure B.14).

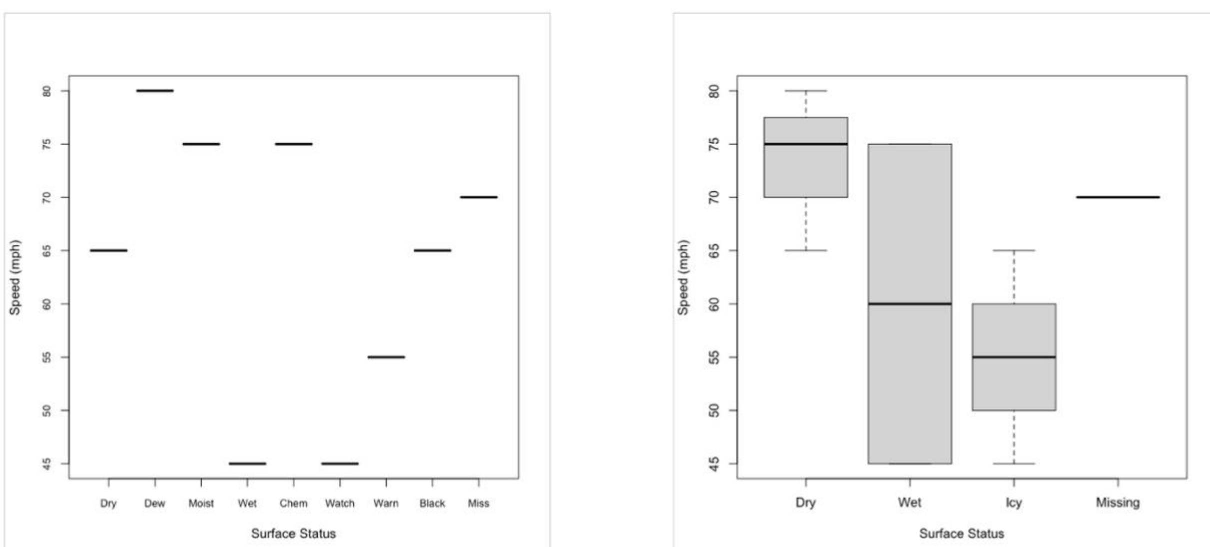


Figure B.14. Speed (mph) distributions by surface status

The dataset contains more icy conditions with slow speeds or slowdowns, and there are fewer wet and dry conditions (Figure B.15).

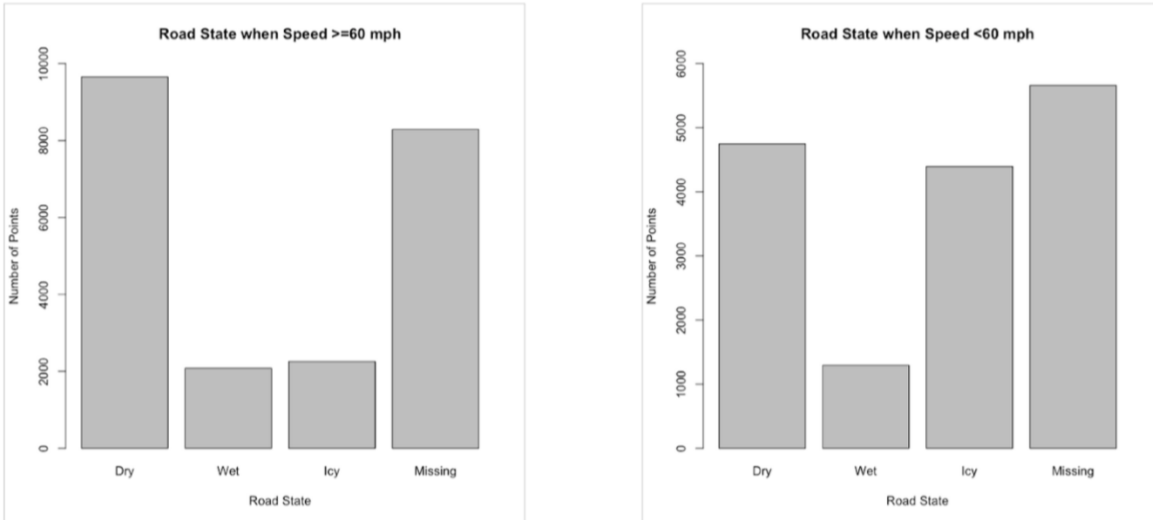


Figure B.15. Number of surface status observations by normal speed (≥60 mph) or reduced speed (<60 mph)

Figure B.16 shows that slower speeds are associated with high relative humidity (RH), likely due to precipitation and cold temperatures. Slower speeds are associated with a wider spread of visibilities with median and first quartile speeds being lower than normal speeds in general. The low visibility observations are likely due to snow or fog conditions.

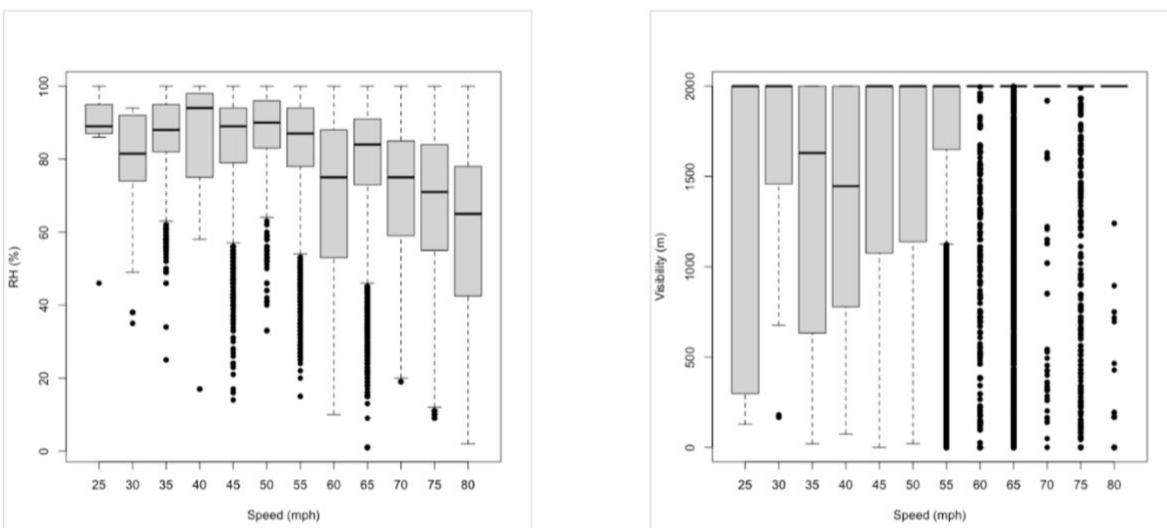


Figure B.16. Relative humidity (left) and visibility (right) distributions by speed limit

A binary slowdown/no slowdown variable was calculated for each VSL sign by assigning speeds below the max speed as a slowdown, otherwise no slowdown. Figure B.17 shows that slowdowns are associated with higher relative humidity, consistent with Figure B.16.

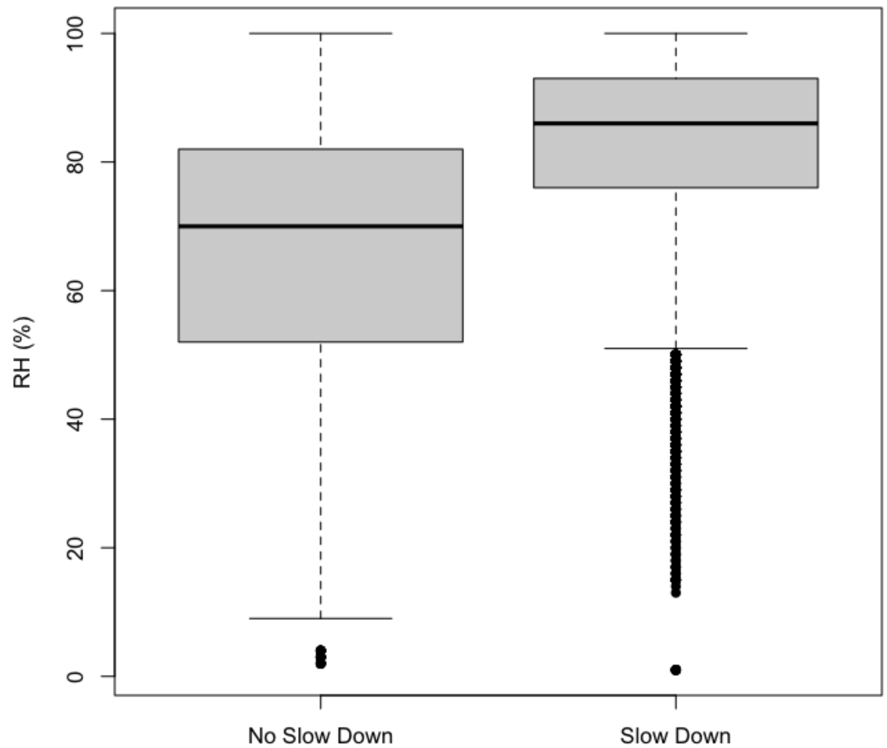


Figure B.17. Relative humidity distributions by slowdown and no slowdown

Although there is some relationship between lower speeds and higher precipitation rate, there are many outliers. Figure B.18 is an indication that the Wyoming VSL speeds are not as strongly correlated to weather conditions as Utah's VSL. This may be due to the nature of the adverse weather experienced on I-80 in Wyoming, or it may be due to the RWIS stations' inability to accurately measure precipitation rate in high winds, which are typical in this area, given the type of precipitation instrumentation available.

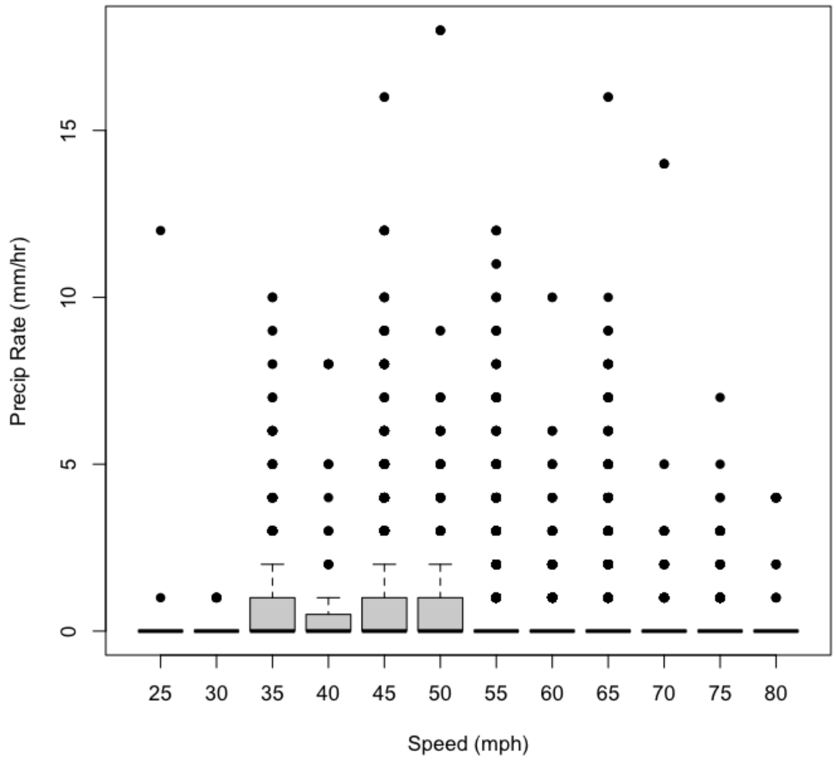


Figure B.18. Speed distributions by precipitation rate (mm/hr)

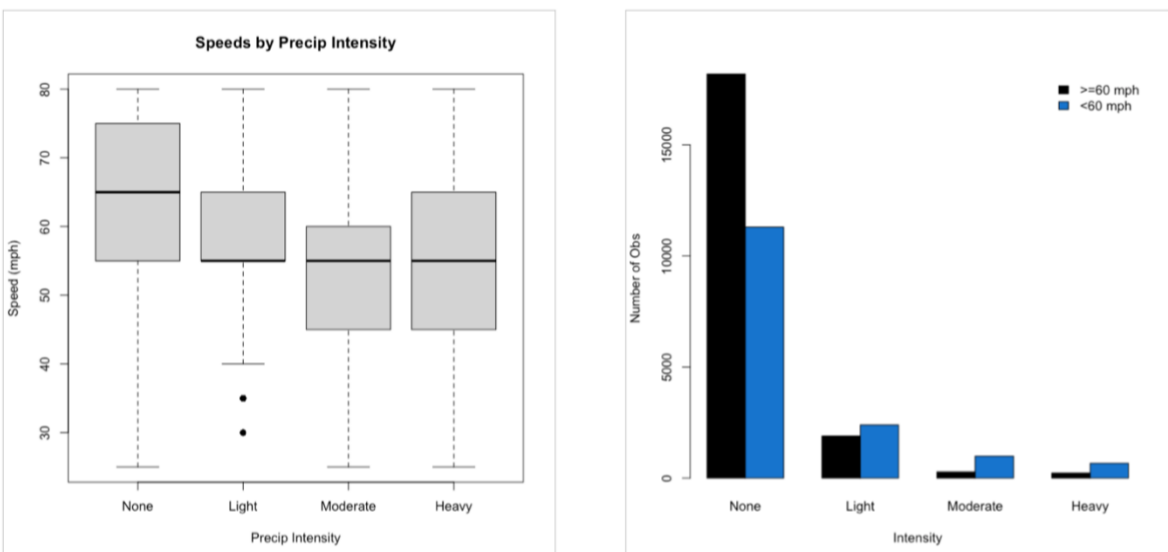


Figure B.19. Speed distributions by precipitation intensity (left) and precipitation intensity observation counts (right)

The precipitation intensity is calculated as follows:

$$
\begin{aligned}
&If\ T_a > 1^oC\ then \\
&\qquad Precip_{rate} \leq 0.25\ cm/hr,\ intensity = "light" \\
&\qquad Precip_{rate} > 0.25\ cm/hr\ \&\ \leq 0.76\ cm/hr\ ,\ intensity = "moderate" \\
&\qquad Precip_{rate} > 0.76\ cm/hr,\ intensity = "heavy" \\
&else \\
&\qquad Visibility \geq 1000\ m,\ intensity = "light" \\
&\qquad Visibility > 500\ m\ \&\ < 1000\ m,\ intensity = "moderate" \\
&\qquad Visibility \leq 500\ m,\ intensity = "heavy"
\end{aligned}
$$

where T_a is the ambient air temperature and $Precip_{rate}$ is the precipitation rate measured at the RWIS station. Temperatures above 1°C were assumed to be rain and intensity set according to the AMS glossary definition at https://glossary.ametsoc.org/wiki/Rain. Colder temperatures were assumed to be snow and intensity set according to the AMS glossy definition at https://glossary.ametsoc.org/wiki/Snow. Note that all air temperatures above 1°C fell into the "light" intensity category.

In Figure B.19, there are more slow speeds associated with no precipitation than there are slow speeds associated with precipitation; however, there are more slow speeds than not when there is precipitation. As the observed precipitation rate was used for the intensity calculations, the same caveats with high wind impacts to the observed precipitation rate apply here as in Figure B.18.

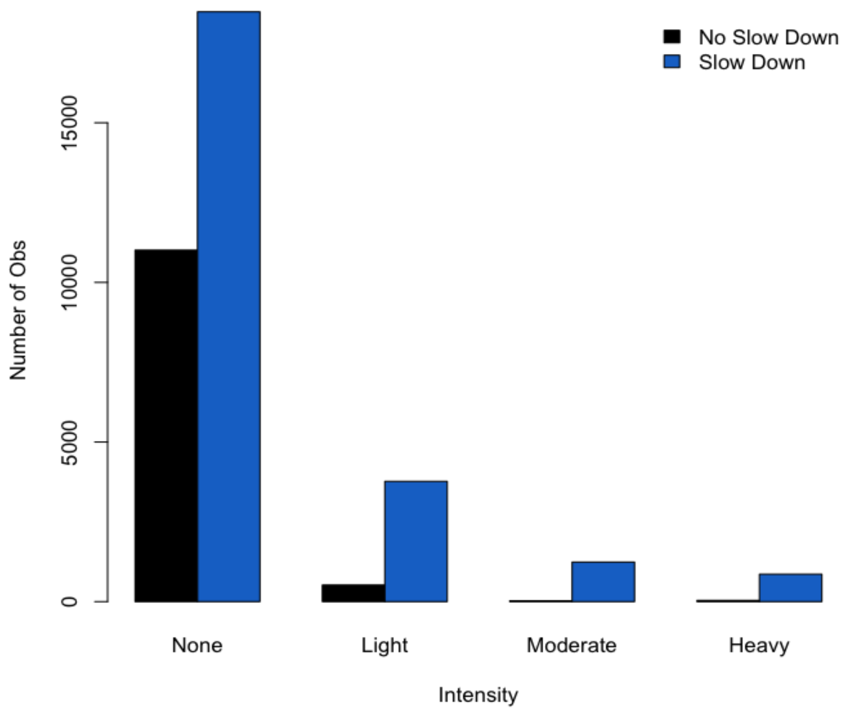


Figure B.20. Observation count for precipitation intensity in slowdown and no slowdown cases

When using the slowdown/no slowdown variable, there are more slowdowns in all precipitation intensity categories and there are fewer normal speeds in all of the active precipitation categories (Figure B.20).

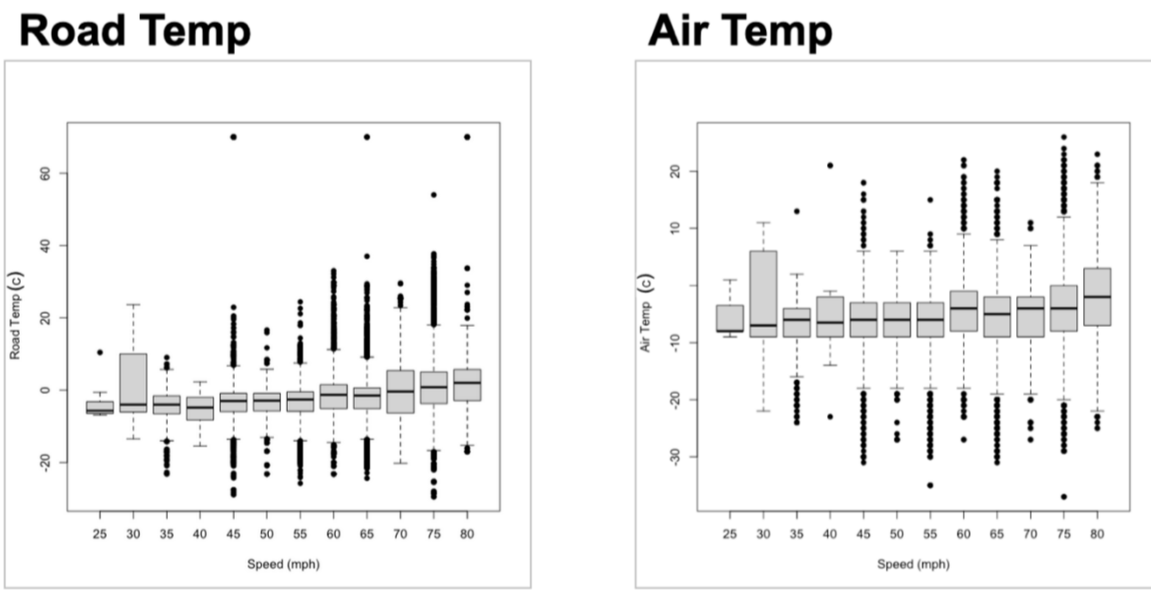


Figure B.21. Road temperature (left) and air temperature (right) distributions in Celsius at different speeds

The data shows a very slight relationship between speed and temperature (Figure B.21), likely reflecting the impact of snow and ice on the roadways

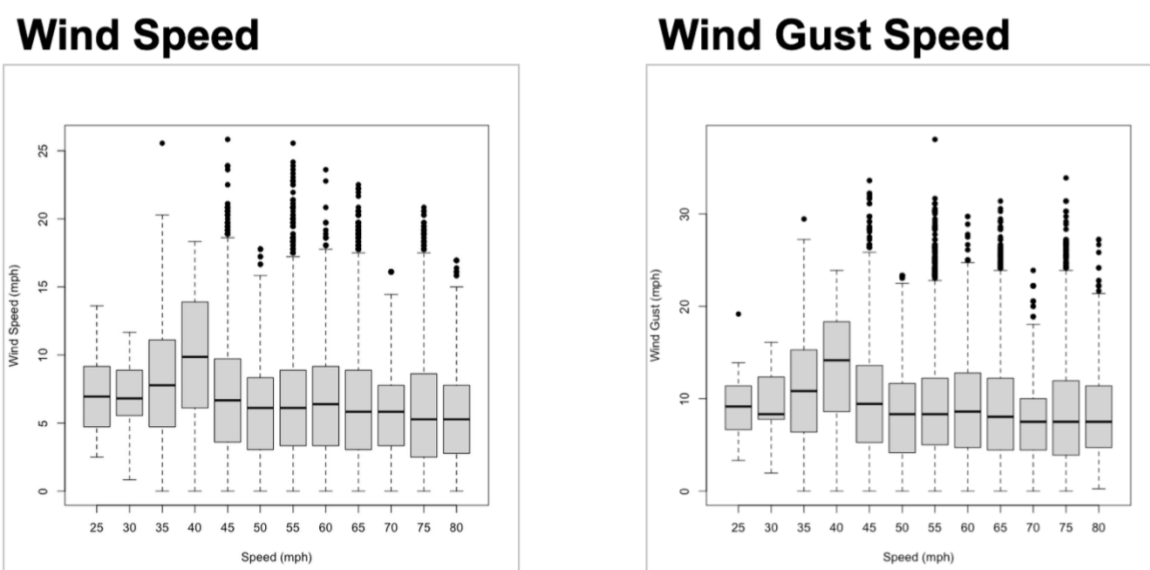


Figure B.22. Wind speeds (left) and gust speeds (right) in mph distributions at different VSL speeds (mph)

WYDOT does not set their VSL based on wind gusts; however, some of the larger range of wind speeds (bounds of whiskers) and wind gusts do occur at slower highway speeds. This could be due to the co-occurrence of high winds during many winter weather events in the region.

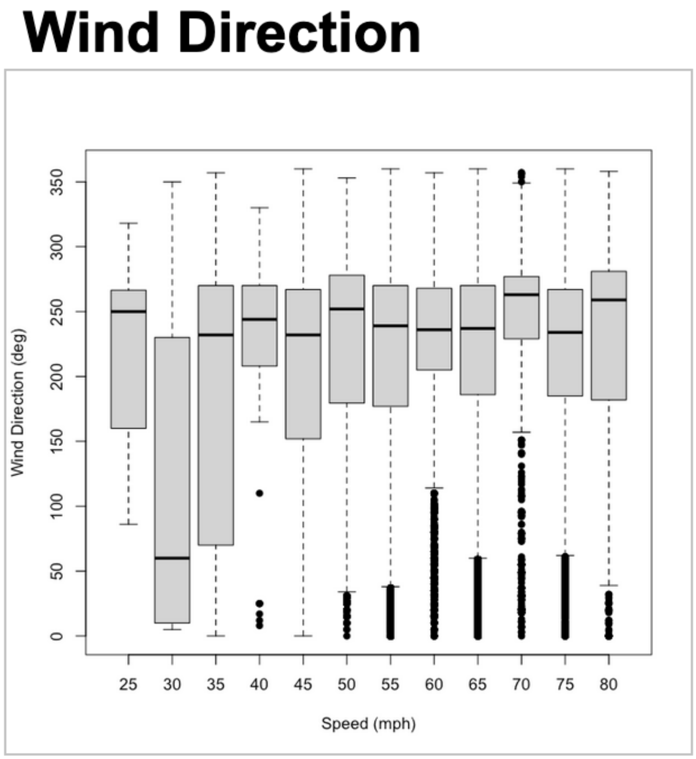


Figure B.23. Wind direction (deg) distributions by speed (mph)

The data show VSL has no significant relationship with wind direction, but there may be some indication of more easterly winds with slower speeds (Figure B.23). This is possibly indicative of an upslope condition, which leads to higher snowfall rates and totals due to the terrain-induced lift provided during upslope events.

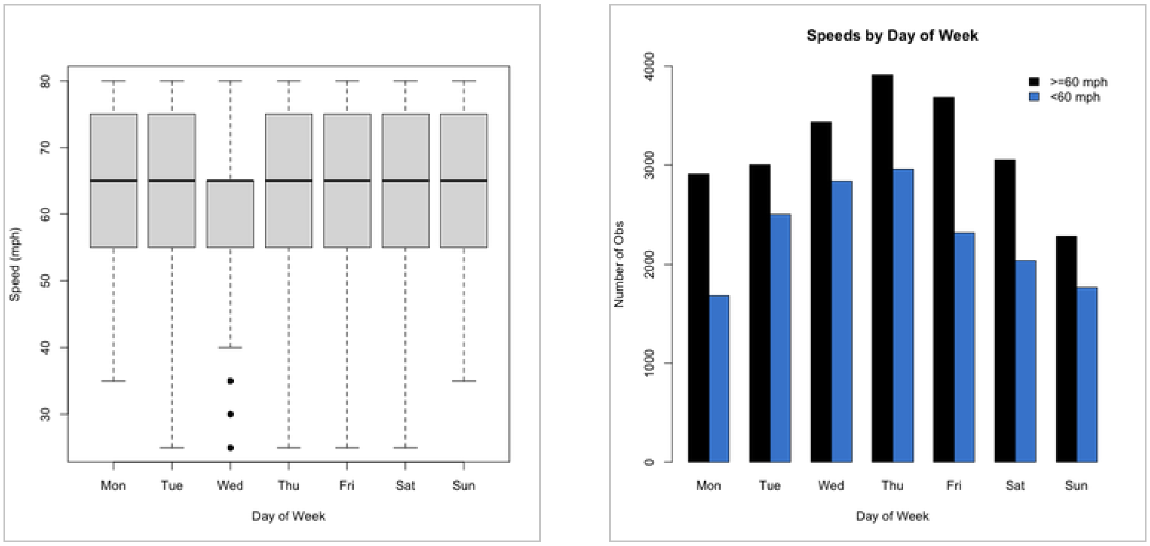


Figure B.24. Speed limit distributions by day of week (left) and day of the week reduced speed frequency (right)

Although there seem to be more low speeds set on Wed-Fri, there are no definitive patterns (Figure B.24).

Summary

Surface status and snow/ice in particular appear to be highly related to speeds and may be important predictors for triggering VSL. Precipitation variables and visibility are also predictors of note. The combined effect of a high precipitation rate or high RH with cold ambient and road temperatures and/or low visibility likely indicate slower speeds.

Identification of Important Predictors

Parleys Canyon, Utah

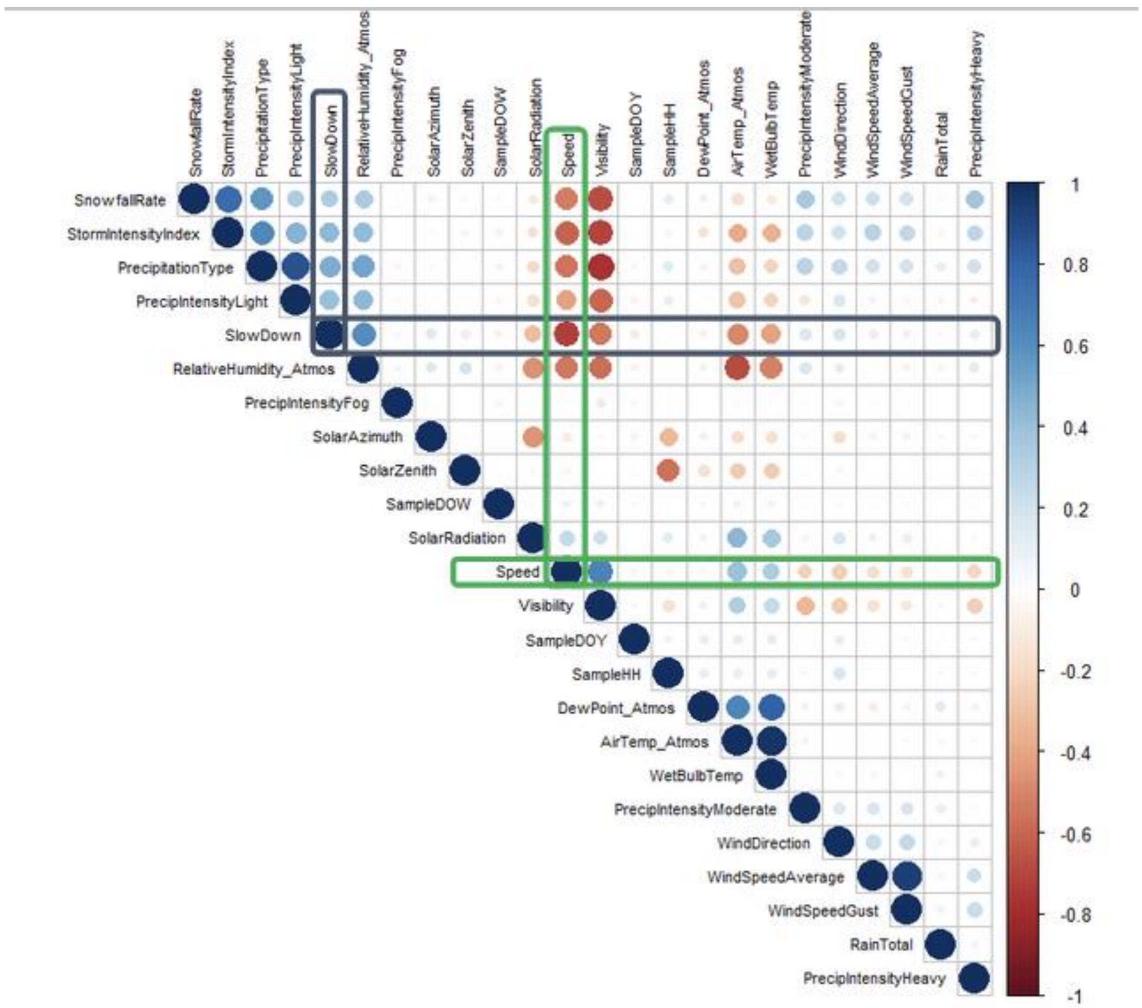


Figure B.25. Correlations between speed or slowdown and various meteorological variables

The identification of relationships between predictor variables (features) and the predictand (target variable) is an important step in the ML modeling process. The Spearman correlation coefficient measures monotonic (linear) dependence between predictors and a predictand. For Parleys Canyon, Utah, and Wyoming correlation coefficients were calculated to determine the relationship between meteorological and road condition observations and VSL speed ("Speed" in the figures). Additionally correlations were calculated for a derived binary SlowDown predictand where a slowdown is defined as speeds below 65 mph in Parleys Canyon. Figure B.25 shows strong relationships between precipitation/visibility variables and Speed and weaker relationships between temperature observations and Speed. Relationships between meteorological predictors and the binary SlowDown predictand are similar to those identified for the VSL speed.

Speed Feature	Correlation	Slow Down Feature	Correlation
SlowDown	-0.72	Speed	-0.72
Visibility	0.66	RH	0.62
StormIntensityIndex	-0.61	Visibility	-0.55
PrecipitationType	-0.56	PrecipitationType	0.48
RH	-0.54	StormIntensityIndex	0.44
SnowfallRate	-0.52	PrecipIntensityLight	0.40
PrecipIntensityLight	-0.42	AirTemp_Atmos	-0.49
WetBulbTemp	0.33	WetBulbTemp	-0.42
AirTemp_Atmos	0.40	SnowfallRate	0.33
WindDirection	-0.25	SolarRadiation	-0.31

Figure B.26. Correlations between meteorological predictors ≥ ±0.25 and Speed or SlowDown

Figure B.26 shows the strongest relationships (≥ ±0.25) between meteorological variables and VSL Speed or SlowDown. As anticipated, the correlations are similar however the ranking shifts slightly depending on the predictand. The importance of precipitation and visibility can be clearly seen in this table.

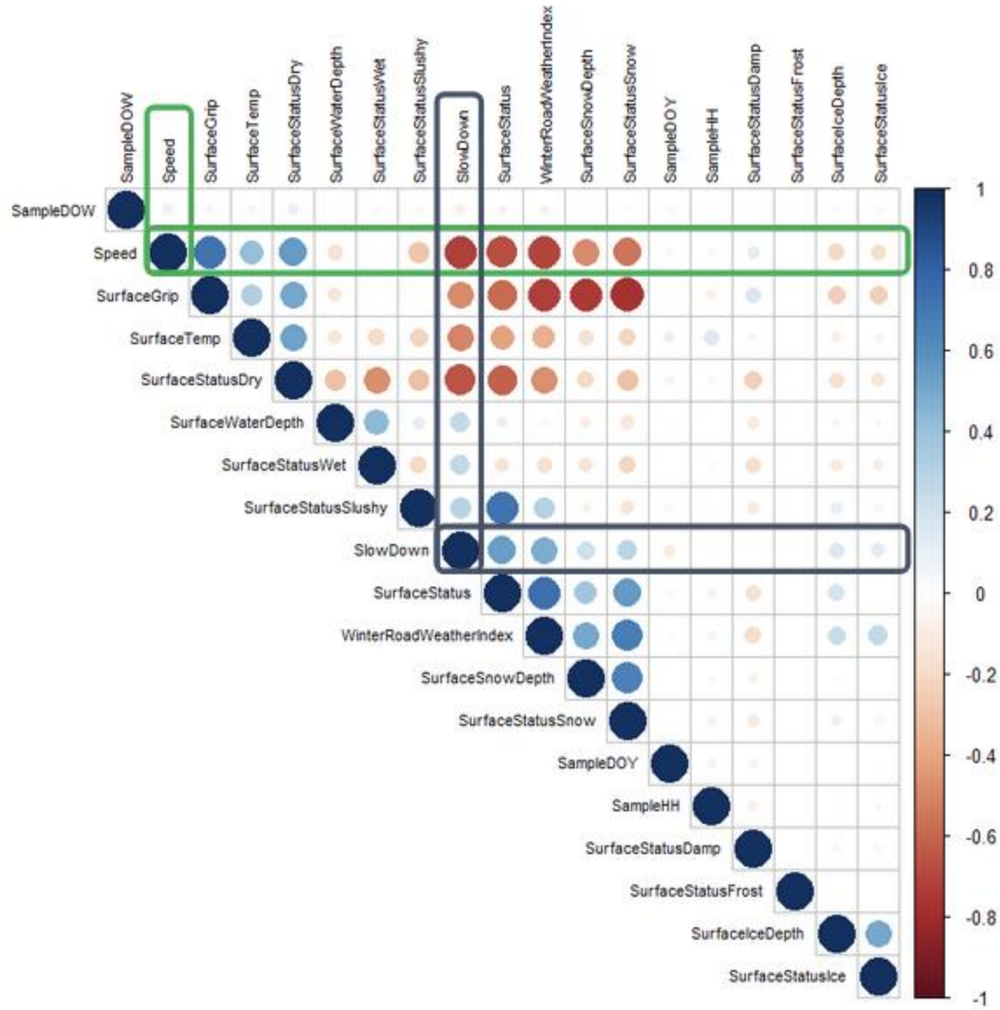


Figure B.27. Correlations between speed or slowdown and road condition variables

Similar correlation analysis was performed to discover the relationship between road condition variables and Speed or SlowDown. Strong relationships can be seen between several surface status variables and grip with Speed or SlowDown.

Speed Feature	Correlation	Slow Down Feature	Correlation
SlowDown	-0.72	Speed	-0.72
SurfaceGrip	0.72	SurfaceStatusDry	-0.65
WinterRoadWeatherIndex	-0.71	SurfaceStatus	0.54
SurfaceStatus	-0.68	SurfaceTemp	-0.51
SurfaceStatusDry	0.56	SurfaceGrip	-0.48
SurfaceStatusSnow	-0.55	WinterRoadWeatherIndex	0.48
SurfaceSnowDepth	-0.49	SurfaceStatusSlushy	0.30
SurfaceTemp	0.41	SurfaceStatusSnow	0.28
SurfaceStatusSlushy	-0.29	SurfaceWaterDepth	0.25
		SurfaceStatusWet	0.25

Figure B.28. Correlations among road predictors ≥ ±0.25

Grip, surface statuses, surface temperature and the WinterRoadWeatherIndex are variables with a strong relationship to Speed and SlowDown. The importance of grip underscores its potential usefulness for the physical modeling efforts by the Rutgers VSL team that are part of this project.

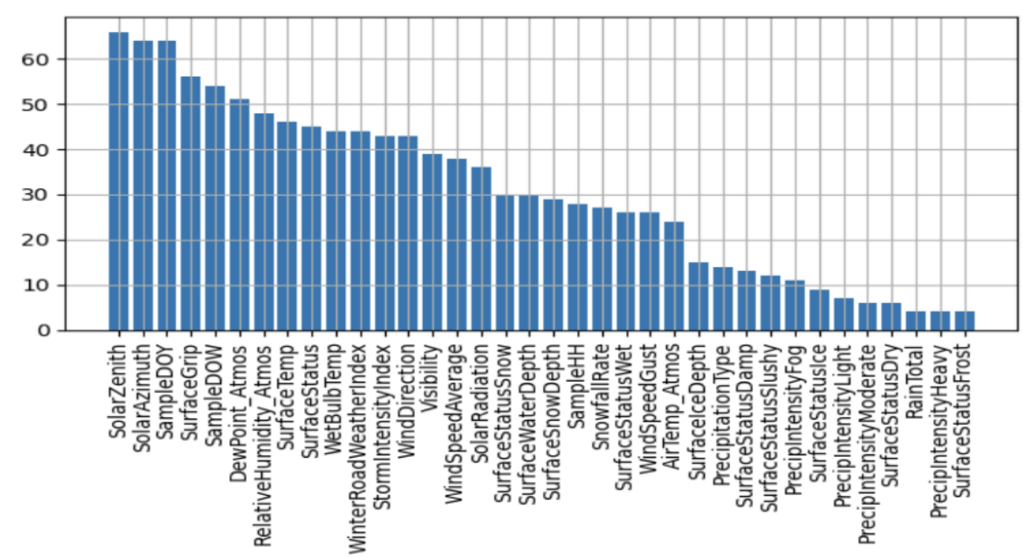


Figure B.29. Permutation test predictor importance results from 75 XGB and Cubist models with MAE < 3.00

In the permutation test algorithm, a baseline (Extreme Gradient Boosting [XGB] or Cubist) model performance is calculated and then at each iteration the rows of one predictor column are permuted and the model is restrained and tested. This breaks the dependence of the predictand on the permuted variable. The importance is calculated as [permuted score - baseline score] for each variable. Larger differences indicate more important predictors. It can be seen that the grip, precipitation, temperature, weather indices, and surface variables are considered the most important predictors to the model.

One downside of the Spearman's correlation coefficient is that it is most effective when identifying symmetric, monotonic (linear) relationships. In many real world problems, relationships are asymmetric, highly non-linear, and non-monotonic. Because of these facts correlation provides one view of the relationship between predictor and predictand but it may not properly identify non-monotonic or non-linear relationships. The Xi Correlation by Chatterjee [1] promises to provide a better metric for measuring relationships, especially data with many outliers and those that are oscillatory or non-monotonic in nature. Appendix B includes a correlogram of the Xi correlation coefficient between predictors for Parleys Canyon and the predictand Speed. Values of 0 can be interpreted under Xi to be independent and those with a correlation of 1 indicate Speed is a measurable function of a predictor [1]. In this correlogram the last red row of all 1 values for SurfaceStatusFrost can be ignored and is likely due to insufficient positive samples in the dataset which cause the calculations in the Python xicorr library to fail.

Summary

The results of the correlation analysis identify that precipitation, visibility and temperature are the meteorological variables with the strongest predictive potential for predicting VSL speed or indicating yes/no for predicting slowdown/no slowdown. The permutation predictor importance test of Figure B.29 confirms the importance of these variables and additionally indicates that wind and the depth of snow/surface water are important.

The correlation analysis shows that grip, surface statuses, surface temperature and the WinterRoadWeatherIndex [2] are variables of importance for developing ML models. The permutation predictor importance test of Figure B.29 confirms the importance of these variables and additionally indicates the importance of the StormIntensityIndex [2].

One interesting conclusion of this study is that weather holds an equal or slightly greater importance than surface variables for predicting VSL speeds in Parleys Canyon.

Wyoming I-80, I-90, I-25

Correlation analysis was performed to discover the relationship between meteorological variables, road condition variables and Speed or SlowDown. Since Wyoming observation data was obtained from I-80, I-90, and I-25, and a few sites along WYO789, as seen in Figure B.2, a slowdown for Wyoming indicates a deviation from the max speed set for each individual VSL sign, which varies across the state. Additionally, many Wyoming VSL signs were located along highway segments where construction was being performed. These were identified and excluded from the analysis where possible. Strong relationships can be seen between road state, precipitation, visibility, and temperature with Speed or SlowDown. It should be noted that Wyoming RWIS do not collect grip, so these data offer limited utility for physical friction-based modeling.

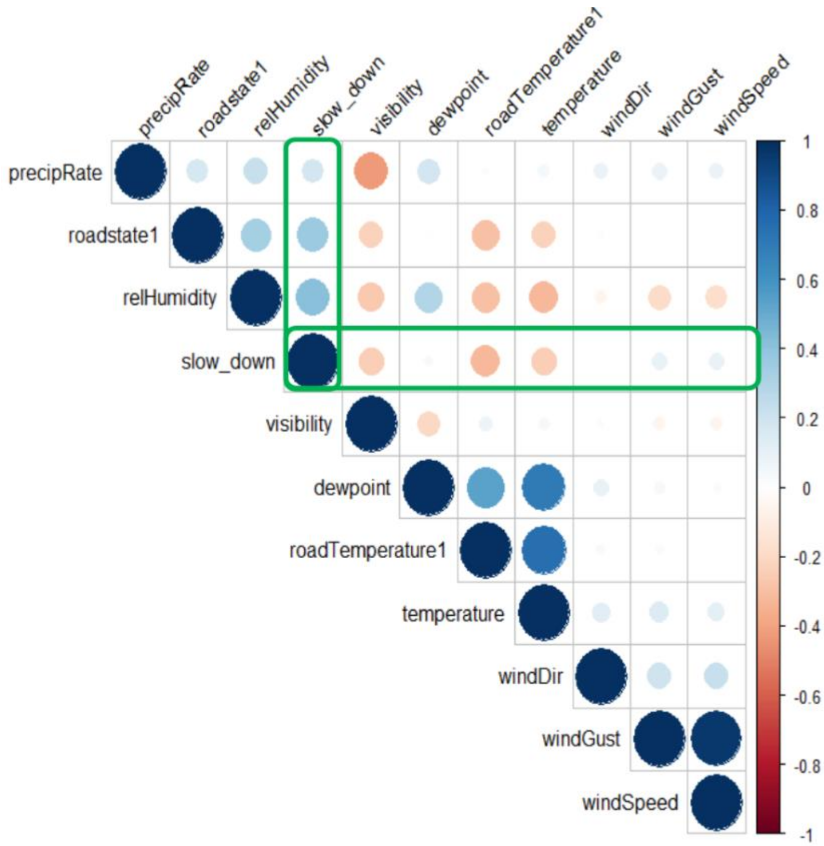


Figure B.30. Correlations between slowdown and various meteorological and road condition variables

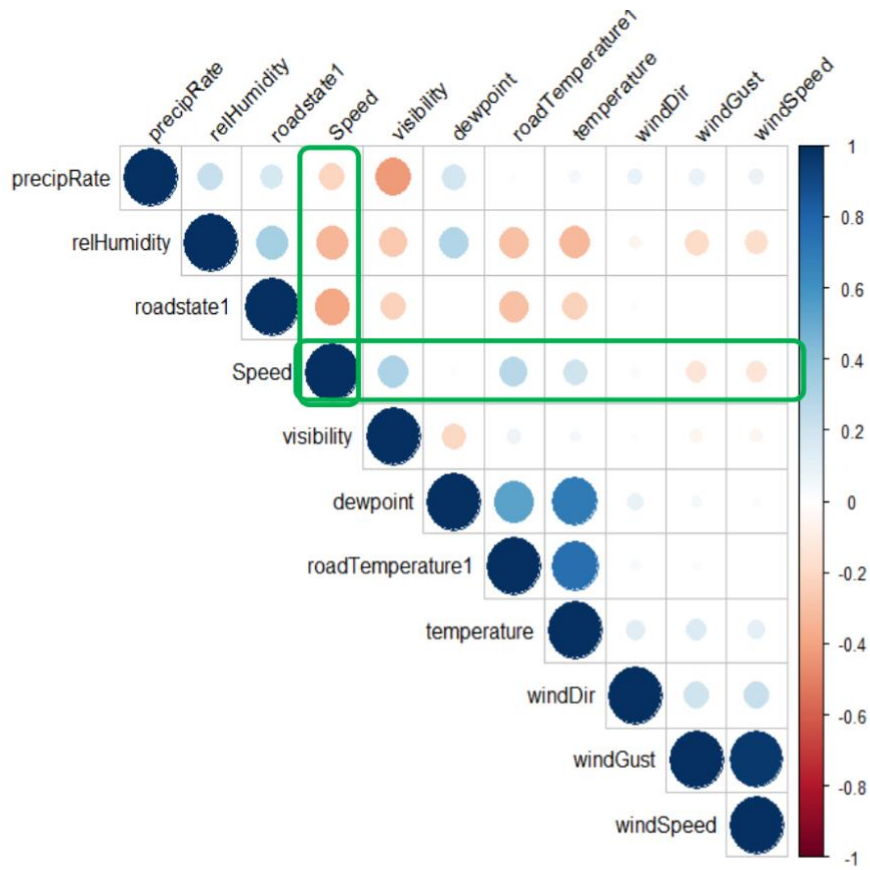


Figure B.31. Correlations between absolute VSL speed and various meteorological and road condition variables

Speed Feature	Correlation	Slow Down Feature	Correlation
Road State	-0.36	Relative Humidity (RH)	0.42
Relative Humidity (RH)	-0.34	Road State	0.34
Visibility	0.30	Road Temp	-0.28
Road Temp	0.25	Visibility	-0.23
Precip Rate	-0.22	Temp	-0.21

Figure B.32. Correlations among road predictors ≥ ±0.20

Figure B.33 shows the results of running a predictor permutation algorithm on the Wyoming VSL training dataset using a RF base model. It can be seen that the temperature, precipitation, road condition, and visibility are considered the most important predictors to the model.

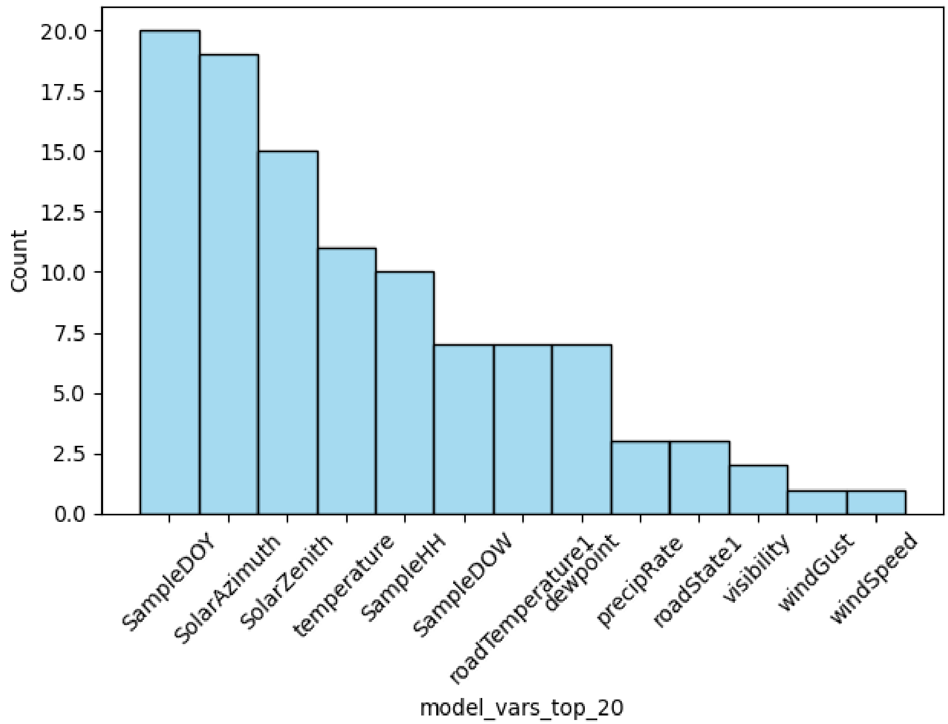


Figure B.33. Permutation test predictor importance results

Summary

The results of the correlation analysis identify that road state, precipitation, visibility and temperature are the observation variables with the strongest potential for predicting VSL speed or indicating yes/no for predicting slowdown/no slowdown. The permutation predictor importance test of Figure B.33 confirms the importance of these variables and additionally indicates that wind is important.

The Wyoming predictor analysis also points to the fact that weather holds an equal or slightly greater importance than surface variables for predicting VSL speeds. In analyzing Wyoming's predictors, it was observed that weather conditions are as, or slightly more significant than surface variables in predicting VSL speeds.

Machine Learning Modeling

Several supervised ML modeling techniques and algorithms were applied to the Parleys Canyon, Utah, data. Approaches can be categorized based on the type of predictand: continuous (floating point) or categorical (mapped to integer). Regression models were trained to predict a continuous variable Speed that is an actual speed. Classification models were used to predict binary slowdown/no slowdown or speeds binned into 20 mph categories. This approach may be valuable for advisory or warning signs, alerting drivers to hazardous road conditions.

Several different ML algorithms were used to train models for predicting VSL and/or SlowDown/No SlowDown. Testing several algorithms and problem representations through cross validations is an important part of the ML modeling process, since the No Free Lunch Theorem in ML states that no single ML algorithm is the best across the universe of all problems. The algorithms utilized in this research are briefly discussed below, with a high-level description of their steps provided in Appendix A.

Random Forest (RF) is an ensemble approach that uses multiple decision trees trained with random selection of predictors and input predictor data, resulting in higher accuracy and lower variance.

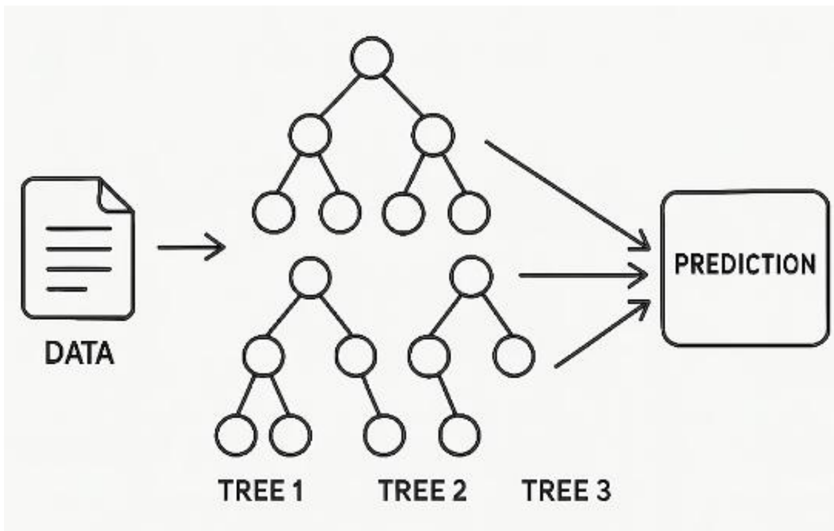


Figure B.34. Random Forest algorithm

The gradient boosted trees (GBT) algorithm builds an ensemble of decision trees sequentially, where each new tree is trained to minimize the loss function by correcting the residual errors (gradients) of the previous ensemble. The eXtreme Gradient Boosting (XGBoost or XGB) library is a highly optimized implementation of the GBT algorithm that is known to exceed the performance of many other ML algorithms when producing models for tabular data, such as these VSL datasets. XGBoost was used extensively for this research.

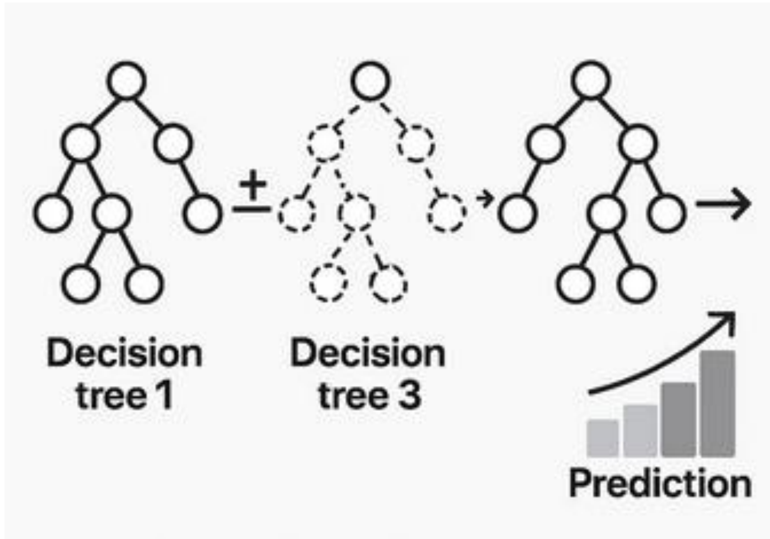


Figure B.35. Gradient boosted tree (GBT) algorithm

The Cubist algorithm has been shown to perform well in other atmospheric research projects. This algorithm combines a decision tree algorithm with linear regression at the final leaf decision nodes. One advantage of this algorithm is that it can produce sets of if - then - else if - else rules. Initially, the hope was that these rules might provide a simple set of conditional rules that could be implemented in Python for DOTs, but the rule trees produced are fairly complex and interpretability is not as strong as desired.

In many cases, k-fold cross validation was used to confirm results. The k-fold cross validation approach involves breaking the data up into k partitions or folds. On each iteration of the k training/testing cycles, one fold is chosen as the test partition to be held out. The other k-1 partitions are used to train the model. Finally, the test fold is passed to the trained model for inference, and performance statistics are gathered. Statistics are aggregated across iterations, which helps to verify model consistency across slightly varied training/test distributions.

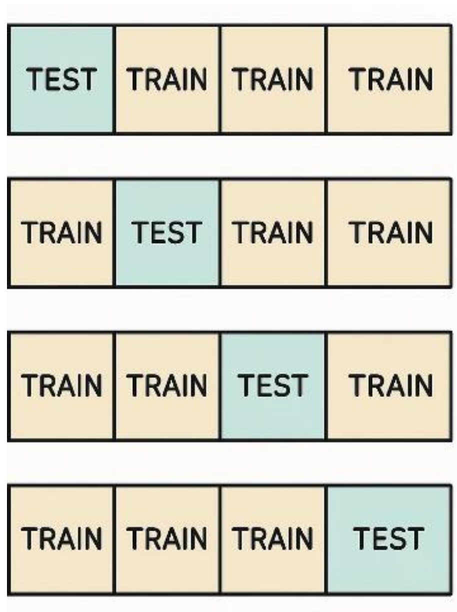


Figure B.36. Four-fold cross validation

In other cases, an 80/20 training/test split was applied to the data, which is a common cross validation split for ML modeling.

Root mean square error (RMSE) and mean absolute error (MAE) serve as the key performance metrics for regression modeling. The F1 score, illustrated in Figure B.37, serves as the main performance metric for classification modeling, representing the harmonic mean of precision and recall.

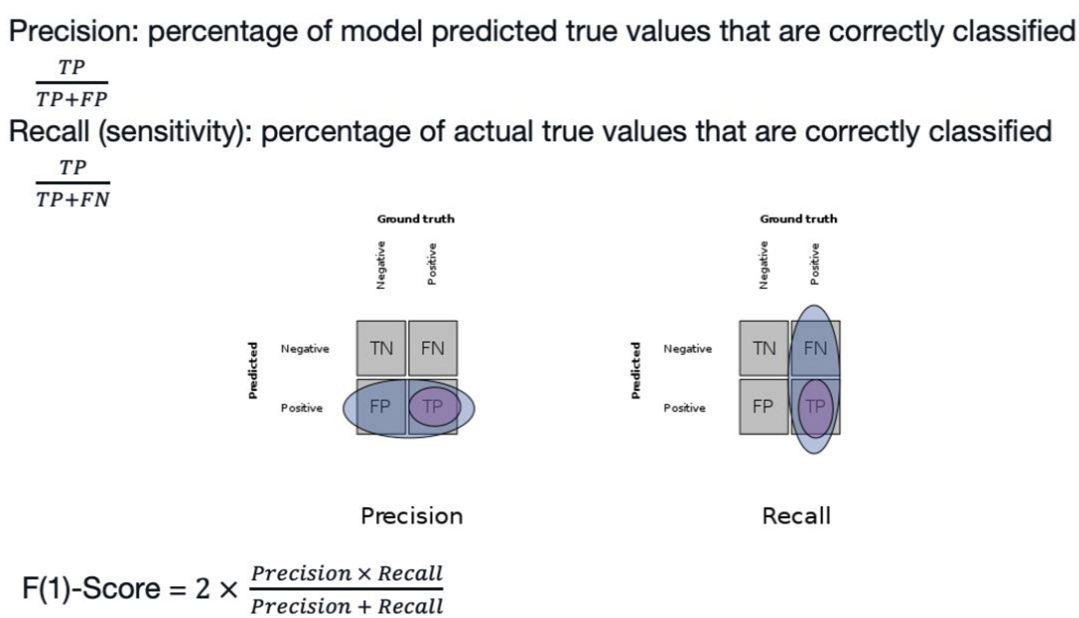


Figure B.37. Definition of the F1 statistic

Parleys Canyon, Utah

As discussed in the Model Training Data section above and showcased in the statistics, the VSL data has large imbalances of slow speeds (or slowdowns) versus normal highway speeds. This poses challenges for ML modeling, with the primary solutions being data augmentation and numerically weighing underrepresented speeds more heavily in training. Both approaches were attempted when modeling the Parleys Canyon VSL data.

The RF model used to create Figure B.38 has an observed classification F1 score of 0.84 when using 10-fold cross validation across 27,464 samples of the balanced (augmented) Parleys Canyon training data. This model was created using meteorological predictors only. Rows with missing meteorological values were removed before training.

	Observed	
Predicted	No SlowDown	SlowDown
No SlowDown	2,584	521
SlowDown	489	3,272

Figure B.38. SlowDown/No SlowDown classification confusion matrix for meteorological predictors only

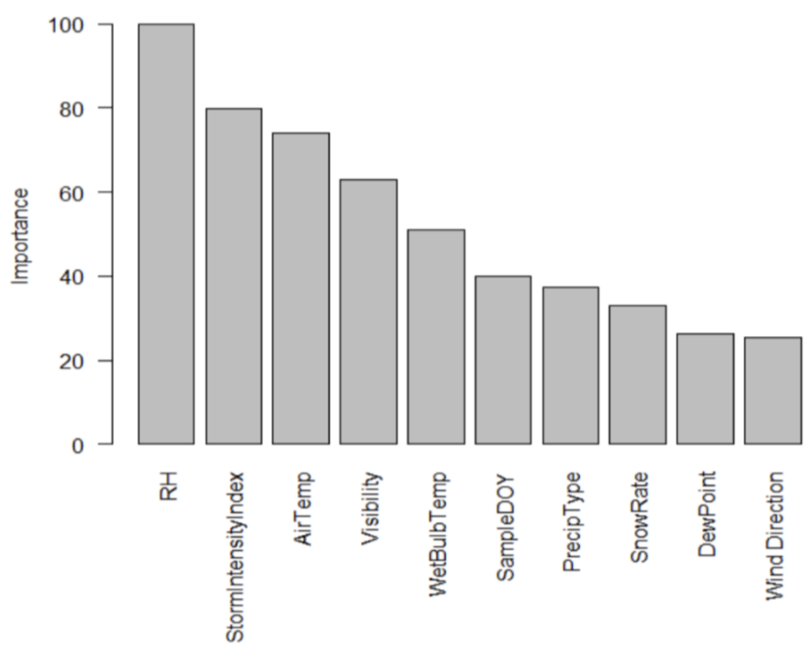


Figure B.39. Random Forest predictor importance scores from the model trained using only meteorological predictors

Figure B.40 shows an observed classification F1 score of 0.82 when using 10-fold cross validation across 33,236 samples of the balanced (augmented) Parleys Canyon training data. This model was created using road predictors only. Rows with missing road values were removed before training.

Predicted	Observed	
	No SlowDown	SlowDown
No SlowDown	2,933	433
SlowDown	835	4,108

Figure B.40. SlowDown/No SlowDown classification confusion matrix for road predictors only

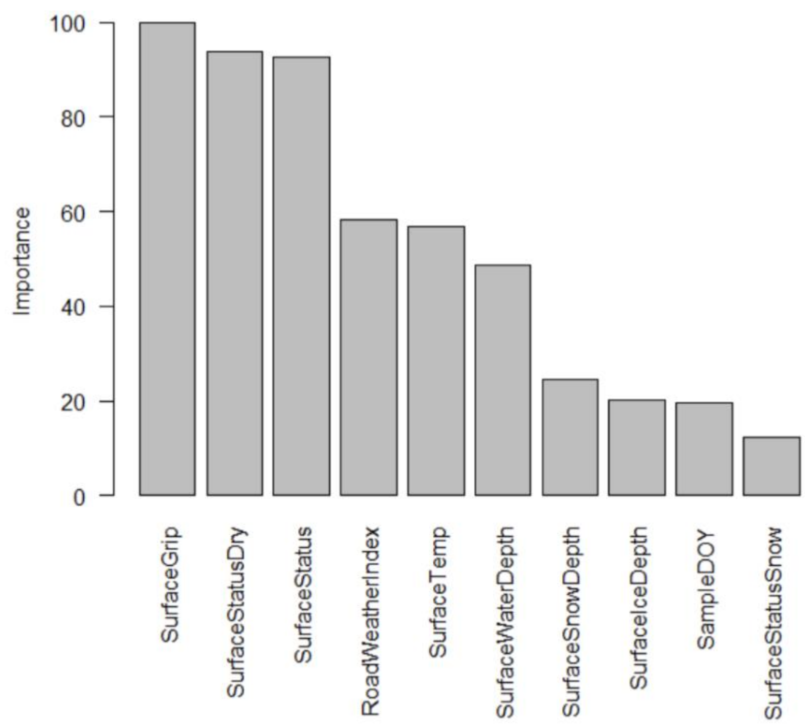


Figure B.41. Random Forest predictor importance scores from the model trained using road predictors only

Figure B.42 shows six different regression model tests. V1 is a highly correlated set of variables, and V2 a list of variables that were chosen based on a custom forward/backward predictor elimination process. The forward/backward predictor elimination process starts with four random variables; data for those variables are then shuffled one-by-one to determine which variable has the least impact on performance. Once the variable with the least impact on performance is determined, this variable is dropped and two new variables are added. This process is repeated with all available variables. When the list of variables rises above a certain threshold (20 variables), additional variables are dropped (based on the same logic) to keep the number of total predictors below 20. These tests show low MAE and RMSE, particularly for the XGB V2 test.

V1 = Highly correlated list of variables
V2 = list of variables selected by forward selection / backwards elimination process

H1 = Binned Hit rate (Regression model rounded to nearest 5, Hit: prediction == speed)
H2 = Loose Binned Hit Rate (Hit : Prediction +- 5 == Speed)

Model Type	Variable List	Scores
Cubist	V1	**MAE, RMSE, BIAS, R2, H1, H2** 4.51, 6.29, -2.09, 0.39, 38%, 83%
Cubist	V2	**MAE, RMSE, BIAS, R2, H1, H2** 4.47, 6.26, -2.34, 0.40, 38%, 83%
XGB	V1	**MAE, RMSE, BIAS, R2, H1, H2** 4.50, 6.23, -1.70, 0.40, 38%, 83%
XGB	V2	**MAE, RMSE, BIAS, R2, H1, H2** 4.37, 5.97, -2.10, 0.45, 38%, 83%
Random Forest	V1	**MAE, RMSE, BIAS, R2, H1, H2** 4.44, 6.14, -1.93, 0.41, 38%, 83%
Random Forest	V2	**MAE, RMSE, BIAS, R2, H1, H2** 4.34, 5.95, -2.09, 0.45, 38%, 83%

Figure B.42. Models trained on data from 2021/11/01 to 2023/04/29, then tested on data from 2023/11/-01 to 2024/04/30

Figure B.43 shows the F1 scores (fscore) and a confusion matrix for an XGB classification model trained with data separated into 20 mph bins. An 80/20 train/test split was used. The counts of samples from each of bins (20,40), (40,60), (60,80) can be seen under the column labeled *support*. The class imbalance is significant, as the higher speed sample count dwarfs the slower speed cases. Experiments were performed to break the bins into smaller intervals, including 10 mph and 5 mph. However, the smaller the bin size, the lower the sample size in bins with reduced speeds, which leads to worse class imbalances and performance. For future research, these problems may be addressed by using a larger VSL/RWIS dataset and possibly by supplementing with synthetic data generated from interpolation techniques like SMOTE: Synthetic Minority Over-sampling Technique [3] or ADASYN: Adaptive Synthetic Sampling Approach for Imbalance Learning [4].

```
-------------------------
Global F1: 0.827953643929377
-------------------------
    precision    recall    fscore  support
40   0.710588  0.459665  0.558226      657
60   0.752577  0.710117  0.730731     4112
80   0.867984  0.917779  0.892188     8088
-------------------------
```

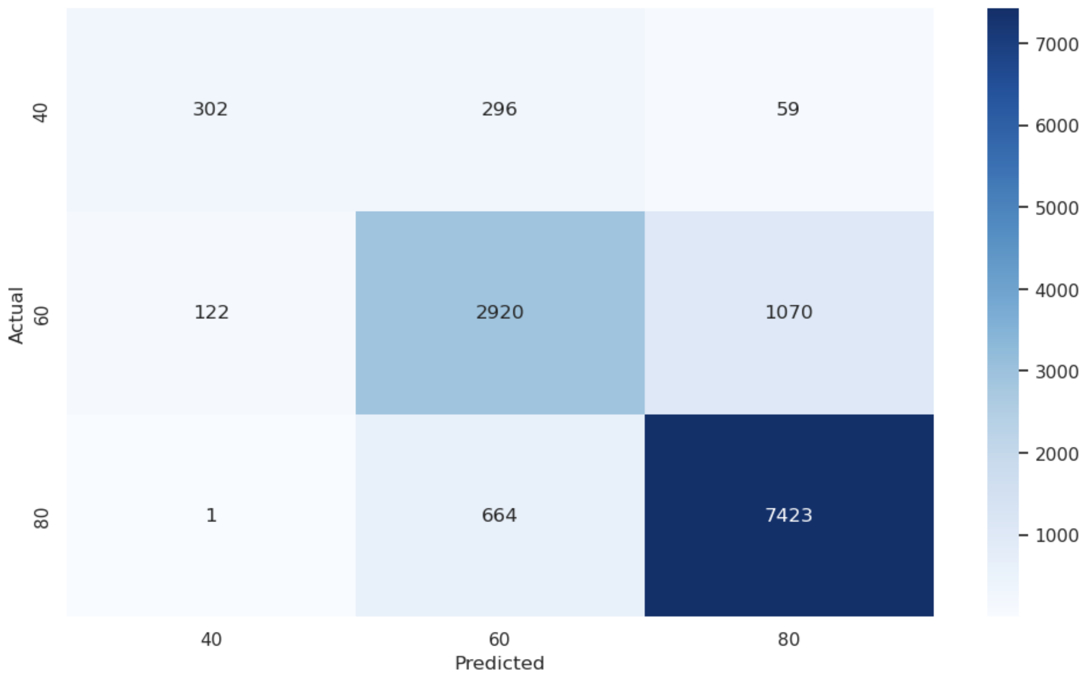


Figure B.43. Confusion matrix and F1 scores for a Parleys Canyon XGB classification model using 20 mph bins with an 80/20 train/test split

The best regression results found across all VSL regression models for Parleys Canyon are shown in Figure B.44. This model was able to predict VSL speed with average error of 5 mph or less, and it exhibits a high R^2.

All Stations Regression (80/20 - train/test split)
Model RMSE: 4.95
Model MAE: 3.54
Model R2 Score: 0.71

All Stations Regression Non-Stratified 8-Fold Cross Validation
CV RMSE mean: 5.90, std +/-: 0.07
CV MAE mean: 4.40, std +/-: 0.05

feature_columns_best = [
'AirTemp_Atmos', 'RelativeHumidity_Atmos','SnowfallRate', 'SolarRadiation',
'StormIntensityIndex', 'SurfaceGrip', 'SurfaceIceDepth', 'SurfaceSnowDepth',
'SurfaceWaterDepth','SurfaceStatus', 'SurfaceTemp', 'Visibility',
'WetBulbTemp', 'WindSpeedAverage', 'WindSpeedGust','WindDirection',
'WinterRoadWeatherIndex', 'PrecipitationType', 'PrecipIntensityLight', 'PrecipIntensityModerate',
'PrecipIntensityHeavy', 'PrecipIntensityFog', 'SurfaceStatusDry','SurfaceStatusSnow',
'SurfaceStatusSlushy', 'SurfaceStatusIce']

Figure B.44. XGB regression model statistics from an 80/20 train/test split and 8-fold cross validation using the best predictor variables listed

Summary

Research models developed for predicting VSL speed and slowdown conditions in Parleys Canyon exhibit significant skill. The best models were produced using the XGB and RF algorithms with augmented data to capture the transition from normal road conditions to slowdowns occurring during inclement weather. Tests show that classification models with F1 scores of 0.82 or higher are possible for a variety of binary or multiple class binned speed models. Regression models show that RMSE and MAE errors of less than 5 mph are possible.

Wyoming I-80, I-90, I-25

Figure B.45 shows an observed classification F1 score of 0.71 when using 10-fold cross validation across 9,344 samples of the Wyoming training data. Rows with missing values were removed before training. Figure B.46 shows that temperature, RH, road state, and wind were major contributors to the model.

	Observed	
Predicted	**No SlowDown**	**SlowDown**
No SlowDown	**575**	**186**
SlowDown	**278**	**1297**

Figure B.45. SlowDown/No SlowDown classification model confusion matrix using all predictors from VSL,RWIS pairing along I-80, I-90, and I-25 in Wyoming

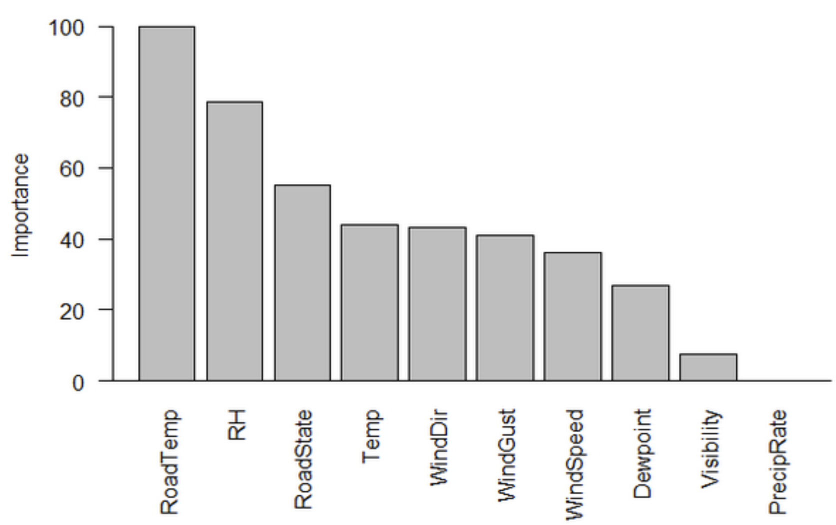


Figure B.46. Random Forest predictor importance scores from the Wyoming classification model trained using all predictors (Figure B.45).

Figure B.47 shows RMSE and MAE from an RF regression model trained using 9,344 samples of the Wyoming training data and tested using 10-fold cross validation. Rows with missing values were removed before training. Figure B.48 shows that temperature, RH, road state, and wind were major contributors to the model.

Model Performance Metrics	Metric Value
RMSE	8.17
MAE	6.56

Figure B.47. RMSE and MAE for a Wyoming VSL regression model

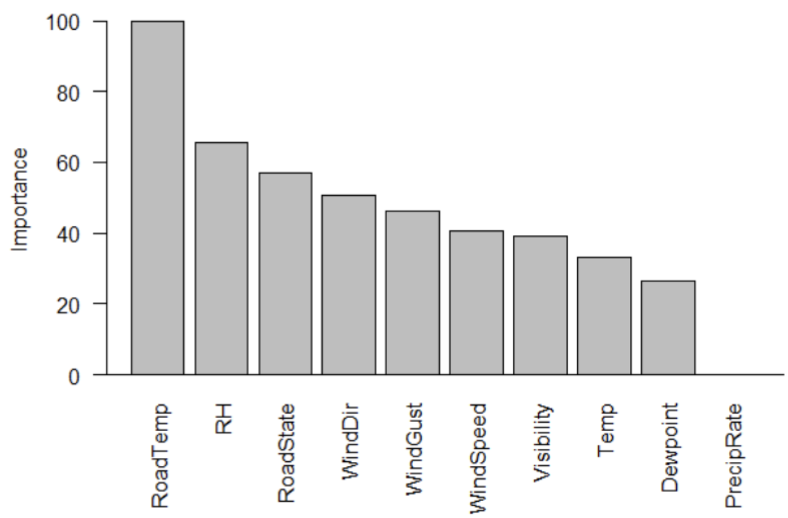


Figure B.48. Random Forest predictor importance scores from the Wyoming regression model (Figure B.47) trained using all predictors from VSL,RWIS pairing along I-80, I-90, and I-25 in Wyoming

Figure B.49 shows the F1 scores and a confusion matrix for an XGB classification model trained with data separated into 20 mph bins. An 80/20 train/test split was used. The counts of samples from each of bins [40,60), [60,80] can be seen under the column labeled *support*. The sample count is small since many slower speeds from Wyoming stations were triggered by other causes such as accident/incident, road closure, or construction. Fully two-thirds of all WYDOT VSL,RWIS paired events occurred when the precipitation was zero and the road state was dry.

```
--------------------------
Model Accuracy: 0.825688
--------------------------
--------------------------
Global F1: 0.8256880733944955
--------------------------
    precision    recall    fscore  support
60   0.838384  0.790476  0.813725      105
80   0.815126  0.858407  0.836207      113
--------------------------
```

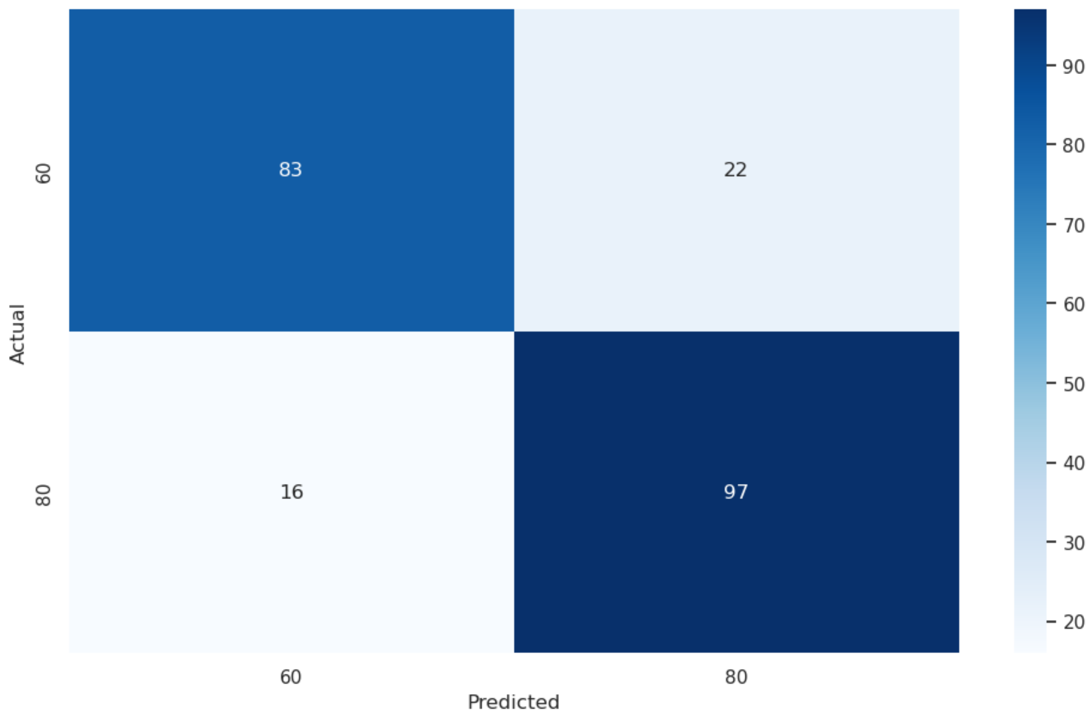


Figure B.49. XGB model confusion matrix for Wyoming slowdown [40,60) and no slowdown [60,80)

Figure B.50 lists the station names for the RWIS spatially and temporally nearest to VSL signs with 10 or fewer non-weather-related slowdowns. These were stations used to train the XGB model in Figure B.49 and may be good stations to focus on in future Wyoming VSL research.

Device Name
I-25 NB 187.92 (McKinley Street Interchange)
I-80 EB 88.86 (West of Green River)
I-25 SB 187.92 (Center Street Interchange)
I-80 EB 90.45 (East of Tunnel)
I-80 EB 14.59 (Divide Interchange)
I-80 EB 345.9 (Warren Interchange)
I-80 EB 21.05
I-80 EB 143.14 (Bitter Creek Rest Area East)
I-80 EB 8.45 (East Evanston Interchange)
I-25 SB 190.14 (N Casper SB Section)
I-90 WB 36.5 (Prairie Dog)
I-90 WB 47.13 (Shell Creek)
I-80 WB 90.45 (Green River East Interchange)
I-80 EB 24.56 (Leroy Interchange)
I-25 SB 188.44 (N Casper SB Section)
I-80 WB 5.75
I-80 EB 140.09 (Red Hill Interchange East)
I-25 SB 188.52 (Poplar Street Interchange)

Figure B.50. Wyoming RWIS stations (and adjacent VSLs) with ≤ 10 non-weather-related slowdowns

Figure B.51 shows the results from two regression models tested using 8-fold cross validation. The MAE scores exhibit reasonable predictive skill. The MAE of the speed versus average speeds is 8.4 mph, showing reasonable improvement of the ML models over a predicted average.

8 Fold Cross Validation - Filtered Data 9,771 data points
CV MAE mean: 6.67

8 Fold Cross Validation - All Data 20,079 data points
CV MAE mean: 4.02

```
target = ['Speed']
feature_columns_best = ['roadTemperature1', 'windDir',
'relHumidity', 'visibility', 'windGust', 'roadState1',
'windSpeed', 'temperature','dewpoint', 'precipRate']
```

Figure B.51. Wyoming regression model with best MAE scores

Summary

ML models developed for predicting VSL speed and slowdown conditions across I-80, I-90, and I-25 across Wyoming exhibit reasonable skill. The predictive skill of the models is impacted by the lack of grip observations collected at RWIS and the fact that two-thirds of slowdown cases do not coincide with measurable precipitation or impacted road state. This may be due to very short duration weather events that impact conditions but do not exceed the measurement fidelity of the instruments. Also, Wyoming has more significant slowdowns caused by high wind events, closures, and road construction. The best models were produced using the XGB and RF algorithms. Tests show that classification models with F1 scores of 0.82 or higher are possible for a binary slowdown/no slowdown data representation of certain stations, but data limitations make more granular binned classification models less feasible. Regression models show that MAE errors of under 5 mph are possible for certain stations.

Conclusions

The Parleys Canyon, Utah, dataset, augmented for more uniform speed distribution, proved suitable for both statistical analysis and ML model development, notably providing the friction measurements crucial for physical modeling and the high-quality observations needed for training machine learning models. The Wyoming dataset, despite its larger size, presented data quality challenges due to the lack of grip observations, the study area’s harsh environmental conditions, non-weather-related slowdowns, and sensor reliability concerns.

The machine learning models for Parleys Canyon exhibited considerable skill, with the XGBoost and Random Forest algorithms demonstrating superior performance, particularly when leveraging augmented data and other techniques to accommodate highly imbalanced ranges of speeds. The classification models achieved F1 scores exceeding 0.82, and the regression models showed RMSE and MAE errors of less than 5 mph. Statistical analysis showed that surface status and friction (grip) appear to be highly correlated with speed and may be important predictors for triggering VSLs. Weather variables, including relative humidity, visibility, precipitation type/intensity, solar radiance, and wind direction, are other important potential predictors for VSL models, as they are associated with winter storm events that lead to a buildup of snow or ice on the pavement and an associated reduction in friction (grip). Correlation and predictor importance analysis showed that grip, surface status, surface temperature, and the WinterRoadWeatherIndex [2] are variables of high importance for developing ML models for Parleys Canyon.

For Wyoming, the models also exhibited reasonable skill, but their predictive ability was impacted by the lack of grip observations and the high proportion of slowdowns not directly tied to measurable precipitation or road conditions. Despite these limitations, the classification models achieved F1 scores exceeding 0.82 for binary slowdown/no slowdown classification for certain stations, and the regression models achieved MAE errors below 5 mph for certain stations, showing improvement over simply predicting the average speed. Statistical analysis showed that surface status and snow/ice in particular appear to be highly related to speeds and may be important predictors for triggering VSLs. Precipitation variables and visibility were also found to be predictors of note. The combined effect of a high precipitation rate or high RH with cold ambient and road temperatures and/or low visibility likely indicate slower speeds. The results of the correlation analysis showed that road state, precipitation, visibility, and temperature are the observation variables with the strongest potential for predicting VSL speed or indicating yes/no for predicting slowdown/no slowdown. The permutation predictor importance test summarized in Figure B.33 confirmed the importance of these variables and additionally indicated that wind is important.

The data analysis and ML modeling results indicate that weather holds an equivalent or perhaps slightly greater importance than non-weather surface variables in reliably predicting VSL speeds. This is seen in both the Wyoming and Parleys Canyon datasets and ML modeling results.

Future research should focus initially on observation data quality and analysis, as these are critical factors in developing high-performance ML models for reliably predicting VSLs. The XGB algorithm in particular shows great promise for developing state-of-the-art ML models on tabular data such as VSL prediction. XGB should be considered first when trying to push the boundaries of VSL ML model performance. Recent developments in convolutional neural network (CNN) models for predicting weather-impacted road conditions in Wyoming and other states could be harnessed for data QA/QC and to provide additional observational input into VSL prediction algorithms. These observations might be most useful as a QA/QC check when setting VSLs but may be of more limited use as a predictor in an ML VSL model, since they only provide one additional categorical predictor. Reinforcement learning (RL) is another avenue of future research that can be explored if reliable and dynamic or real-time observations become available at a larger scale. RL was not utilized for this ML research effort due to the static and small VSL datasets (on the order of tens of thousands of records) available and the absence of a robust real-time data feed or feedback loop necessary for practical RL application. It is not clear that RL algorithms can provide better performance than supervised learning under these limitations.

Appendix B.1. Machine Learning Algorithms

Random Forest

1. **Ensemble of Decision Trees**:
   A Random Forest creates many decision trees, each trained on a different random subset of the data.
2. **Bootstrap Sampling (Bagging)**:
   Each tree is trained on a bootstrapped sample of the dataset (i.e., sampling with replacement). This helps reduce overfitting.
3. **Random Feature Selection**:
   When splitting a node in a tree, only a random subset of features is considered. This decorrelates the trees and improves generalization.
4. **Voting or Averaging**:
   - For **classification**, each tree votes for a class label, and the majority vote is the final prediction.
   - For **regression**, the predictions from all trees are averaged.
5. **Robustness and Accuracy**:
   By aggregating the outputs of many diverse trees, the Random Forest reduces variance and improves predictive accuracy.

Gradient Boosted Tree

1. **Ensemble of Trees, Built Sequentially**:
   Unlike Random Forests (which build trees in parallel), Gradient Boosted Trees build trees **one at a time**, each trying to correct the errors of the previous trees.
2. **Boosting via Gradients:**
   At each step, the algorithm fits a new tree to the **gradient of the loss function**—that is, it learns how to adjust the prediction to reduce the error.
3. **Loss Minimization:**
   The model is trained to **minimize a specific loss function** (e.g., mean squared error for regression, log loss for classification) by following the direction of the steepest descent—hence the name "gradient boosting."
4. **Small, Weak Trees**:
   Each tree is shallow (often called a "decision stump") and is trained to fix the residual errors made by the ensemble so far.
5. **Weighted Combination**:
   The final prediction is a **weighted sum** of all the weak learners, where each tree contributes a small amount (controlled by a **learning rate**).

Cubist

1. **Grow a Tree with Linear Models**
   Cubist builds a decision tree, but instead of predicting a constant at each leaf, it fits a **linear regression model**.
2. **Create Rules from Tree Paths**
   Each path from the root to a leaf becomes a **rule**, and each rule includes a linear model.
3. **Smooth the Predictions**
   To avoid sudden changes between regions, Cubist blends predictions from the leaf with predictions from higher levels of the tree.
4. **Optional Committees**
   Multiple trees (called **committees**) can be trained and averaged to improve accuracy.
5. **Optional Nearest Neighbors Adjustment**
   Cubist can also look at the **nearest training examples** to fine-tune the prediction.

Appendix B.2. Xi Correlation

Parleys Canyon (Speed)

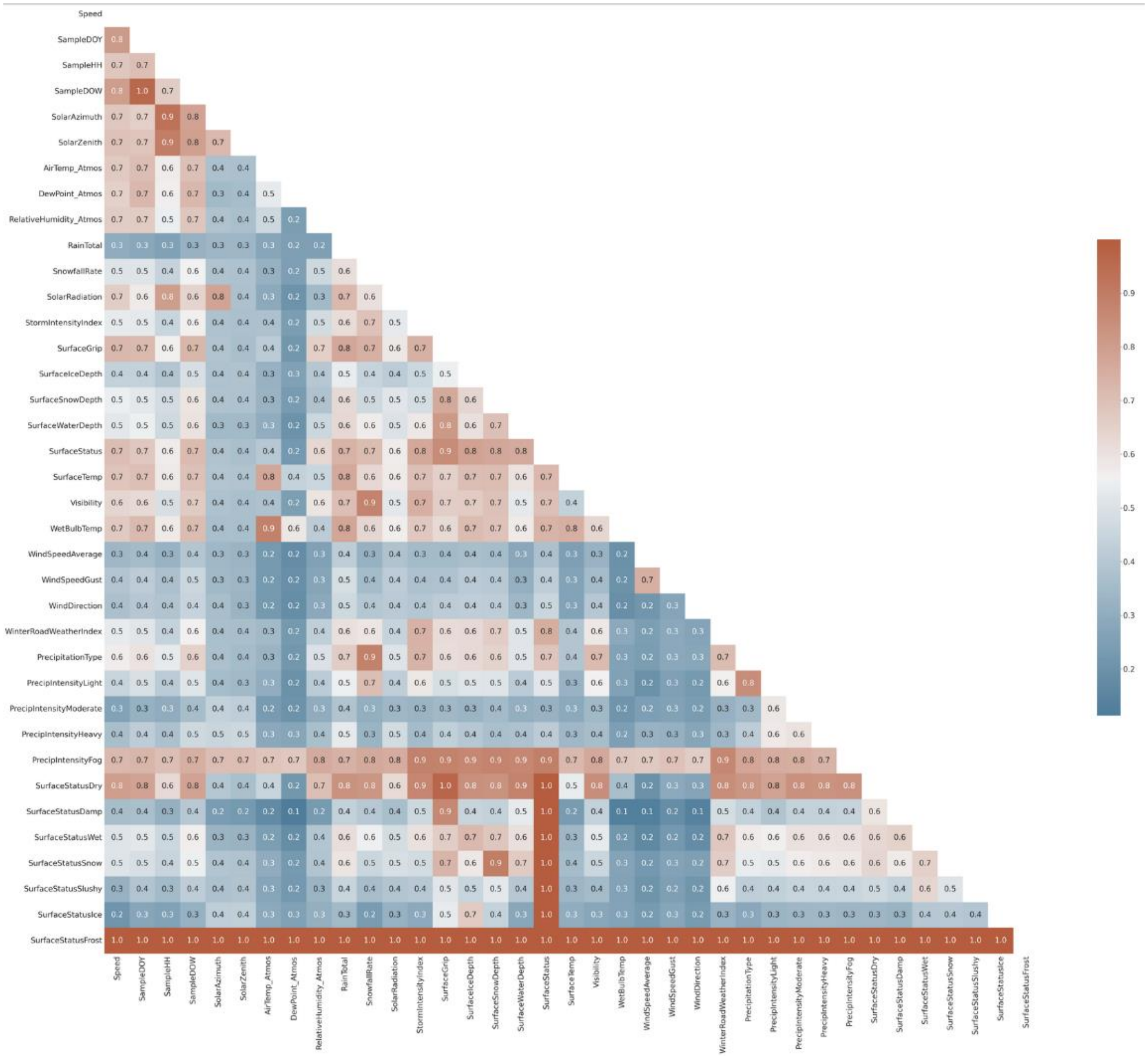


Figure B.52. Parleys Canyon speed

References

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[2] Williams, J. 2025. UDOT Weather Operations: Road Weather Index/Performance Metric. Utah Department of Transportation. https://transops.s3.amazonaws.com/uploaded_files/UDOT%20Winter%20Maintenance%20Performance%20Metric.pdf.

[3] Chawla, N. V., K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. 2002. SMOTE: Synthetic Minority Over-sampling Technique. *J. Artificial Intelligence Research*, Vol. 16, pp. 321–357. https://doi.org/10.1613/jair.953.
[4] He, H., Y. Bai, E. A. Garcia, and S. Li. 2008. ADASYN: Adaptive synthetic sampling approach for imbalanced learning. *Proceedings of the 2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, IEEE. pp. 1322–1328.

APPENDIX C. VSL PHYSICAL MODELING

Introduction

Traffic Safety on Curves

Horizontal curves are associated with a significantly higher risk of crashes compared to straight segments. Departure crashes—defined as incidents where a vehicle crosses an edge line, crosses the centerline, or leaves the traveled way—are particularly prevalent on curved sections of roads. According to statistics, there were an estimated 5.93 million police-reported traffic crashes in the United States in 2022, resulting in 42,514 fatalities and approximately 2.38 million injuries on highways and streets. Notably, approximately 76% of the curve-related fatal crashes involve single vehicles leaving the roadway and striking trees, utility poles, rocks, or other fixed objects, or overturning, highlighting the elevated risks associated with horizontal curves [1].

It has been found that the average crash rate along horizontal curve sections of two-lane rural highways is three times higher than on tangent roadway sections. Moreover, more than 25% of fatal crashes are associated with horizontal curves [2]. About 50% of curve accidents were found to be due to wet or icy road conditions, even though vehicle mileage driven under these conditions is far lower than that on dry pavements. Additionally, about 65% of accidents on curves were single-vehicle accidents, mostly run-off-road incidents. Most run-off-road accidents are caused by inappropriate maneuvering under unexpected situations, such as skidding caused by panic braking on curves [3]. *A Guide for Reducing Collisions on Horizontal Curves* further illustrates the problem associated with roadway departure crashes along horizontal curves. One of the main objectives of this guide is to reduce the likelihood of vehicles leaving their lane to improve safety along horizontal curves [4]. The strategies include providing advanced warning of unexpected changes in horizontal alignment, enhancing delineation along the curve, providing skid-resistant pavement surfaces (reducing wet-road accidents by as much as 50%), etc.

Therefore, countermeasures are needed to mitigate roadway departure crashes along horizontal curves. There are many strategies that could be implemented individually or in combination to reduce roadway departure crashes on horizontal curves, such as pavement markings, speed signs, roadway surface countermeasures, roadside countermeasures, and intersection treatments [5].

Current Practice of VSL

Variable speed limits (VSLs) have the potential to further enhance driver safety under adverse weather conditions and can reduce the number of crashes during the winter [6]. A report from the Federal Highway Administration (FHWA) safety program on VSL usage guidelines [7] states, "The purpose of any speed limit sign is to inform drivers of the maximum acceptable and safe speed for normal travel conditions. However, if roadway conditions are less than ideal, such as during wet weather, conventional static speed limit signs may not display an appropriate, reasonable, and/or safe speed limit for those conditions."

To determine the VSL, agencies consider various conditions such as traffic volume, operating speeds, weather information, sight distance, and roadway surface conditions when posting speed limits. The guidelines calculate the speed limit based on the sight distance to preserve enough space for braking, which can reduce up to 65% of highway rear-end crashes [8]. The implementation of VSL strategies from Washington State Department of Transportation (WSDOT) is shown in Table C.1.

Table C.1. VSL strategies from WSDOT

Weather Conditions	Pavement Conditions	Control Strategies
• Light to moderate rain • Visibility distance greater than 0.5 mi. (0.80 km)	• Dry • Wet	• Speed limit remains at 65 mph (104.5 km/h) • No tire regulations
• Heavy rain • Fog • Visibility distance less than 0.2 mi. (0.32 km)	• Slushy • Icy	• Speed limit reduced to 55 mph (88.4 km/h) • Traction tires advised
• Heavy rain or snow • Blowing snow • Visibility distance less than 0.1 mi. (0.16 km)	• Shallow standing water • Compacted snow/ice • Deep slush	• Speed limit reduced to 45 mph (72.4 km/h) • Traction tires required
• Freezing rain • Heavy rain or snow • Blowing snow • Visibility distance less than 0.1 mi. (0.16 km)	• Deep standing water • Deep snow/slush	• Speed limit reduced to 35 mph (56.3 km/h) • Tire chains required

VSLs are typically installed on interstate highways or high-speed arterials. They are used for three primary functions to improve safety and operations: (1) reducing congestion, (2) reducing speeds during inclement weather, and (3) managing speeds during traffic events such as work zones and incidents. VSLs provide many benefits for improving roadway safety and operations. Using VSL systems to manage speed during inclement weather or other challenging driving conditions can improve safety by decreasing the risks associated with traffic moving at higher speeds than appropriate for the conditions [9].

However, many existing VSL strategies may not adequately address safety speeds on curves, particularly for departure crashes. Most agencies implement a hybrid approach, where VSL adjustments are automated but can be manually overridden by agency personnel when necessary. For example, a regulatory hybrid VSL system on I-4 in Florida uses real-time traffic data to recommend speed limits, which can then be accepted or modified by operators. Similarly, the manual VSL system on the New Jersey Turnpike considers both congestion and weather (primarily visibility) in determining speed limits. The advisory VSL system on Oregon Route 217 is fully automated and accounts for both congestion and current weather conditions. This weather-responsive system incorporates multiple variables (e.g., visibility, surface grip, and pavement conditions) to determine the appropriate warning messages for drivers. Thus, the ability to automatically recommend safe speeds for different weather conditions on roadway curves in real time is crucial for enhancing road safety.

Literature Review

Many evaluation methodologies and computer-based techniques have been developed in recent years to evaluate and analyze lateral stability on horizontal curves, considering different factors. Point-mass models are widely used by simplifying the vehicle as a point mass cornering on a horizontal curve, in which centrifugal force needs to be balanced to avoid skidding. In the American Association of State Highway and Transportation Officials (AASHTO) curve design guide, the design speed is determined by side friction factors based on the driver's comfort [10]. Objective measures of comfort typically include lateral acceleration, longitudinal acceleration, and the rate of change of lateral acceleration [11]. Based on the point mass model, side friction demand at different operating speeds can be computed, and a side friction coefficient (friction supply) can be measured from a dynamic friction tester. Donnell [12] assessed the differences between friction demand and supply to evaluate side safety.

Finite element modeling has also been used to generate friction demand, which takes water film thickness into account, which is further compared to the friction demand curve from the point-mass model to determine safe speed limits [13–15]. In these models, only tire behavior was considered, and thus they cannot accurately reflect the real vehicle dynamics during cornering, especially the different behavior of the front/rear or left/right tires, and the complexity of road alignment is ignored.

Dynamic vehicle simulations, which contain full-vehicle models (car body, powertrain, front/rear suspension, front/rear tire, brake system, and steering, etc.), 3D road models, and tire-road interaction models, can estimate realistic vehicle performance and analyze real-time responses of vehicles on the roadway. This approach can consider both longitudinal and lateral friction forces during vehicle braking and/or cornering. Li and He [16] established an integrated model of vehicle, road, and control systems in Adams/Car and MATLAB/Simulink. The safe speed was assessed by comparing the lateral forces acting at the center of the vehicle and the lateral tire friction forces. The effects of radius, speed, superelevation, and right/left wheel path friction coefficient were considered. Alrejjal and Ksaibati [17] considered the combined effects of roadway alignment and adverse weather on lateral skidding on curves with a high crash rate. The demand for side friction was defined as the ratio of lateral force to vertical force on a tire, while the friction supply was generated from field tests [18]. In those simulations, vehicle dynamic responses can be simulated and evaluated under approximately real conditions. However, the friction coefficient of different weather conditions is estimated from the value of the experiment and does not meet the real-time need of a VSL system.

There is a notable lack of research incorporating roadway geometry and available roadway friction into determining VSLs. To effectively implement variable speed limits during adverse weather conditions, the analysis should account for the integrated effects of road alignment and reduced road friction caused by weather. Additionally, the entire vehicle's dynamic performance should be considered to ensure comprehensive and accurate outcomes.

Objectives

Considering the increased crash risk on horizontal curves, single-vehicle departure crashes are particularly common, especially under adverse weather conditions. To mitigate these crashes, the VSL strategy must prioritize vehicle stability on curves, which largely depends on vehicle speeds and driver behavior. Ensuring good driver compliance is essential, requiring that the underlying VSL algorithm effectively accounts for adverse weather conditions.

The primary objective of this research was to develop and validate a methodology for automating VSLs on horizontal curves to enhance traffic safety during adverse weather conditions. This project addressed the high incidence of roadway departure crashes on curves by focusing on real-time vehicle stability. The specific aims were as follows:

1. To establish a robust method for determining maximum safe speeds by dynamically balancing vehicle friction demand with available road surface friction supply.
2. To leverage real-time data from road weather information systems (RWIS), including surface friction, and integrate it into a responsive VSL algorithm.
3. To utilize advanced vehicle dynamics simulation to accurately model friction demand, accounting for critical factors such as roadway geometry (radius, superelevation, vertical grade), vehicle type, and load distribution, providing a more realistic assessment than traditional point-mass models.

Ultimately, this research sought to provide a framework for a more adaptive and effective VSL strategy that can significantly mitigate the risks associated with driving on horizontal curves under inclement weather conditions like rain, snow, and ice.

Proposed Methodology

This project aimed to develop VSLs tailored to different weather conditions based on real-time road and weather data. Adverse weather, such as rain and snow, significantly impacts vehicle safety and mobility by reducing road friction and impairing visibility. In analyzing safety speed limits on curves, the impact of weather is represented as a reduction in the side friction factor. Under wet or icy road conditions, friction supply decreases as speed increases while friction demand escalates. Consequently, the safety speed limit is determined by balancing lateral forces, which compares the vehicle's friction demand with the available friction supply.

To determine the appropriate friction demand, this study employed vehicle dynamic simulations and the point-mass model. Simulation inputs included road alignment, friction supply, vehicle speed, and driving behavior, while outputs measured lateral and vertical forces and their ratios, defined as friction demand. The friction demand derived from the point-mass model was also calculated for comparison. Friction supply data, recorded by the RWIS, were processed to incorporate weather effects and account for the speed effect on friction. When friction demand approaches or exceeds friction supply, the vehicle may lose traction and fail to maintain its trajectory around the curve, resulting in skidding and potential departure crashes. The speed at which this imbalance occurs is identified as the limit of safe speed. At this point, lateral force equilibrium is disrupted, leading to unstable vehicle dynamics. A detailed flowchart illustrating the study methodology is provided in Figure C.1.

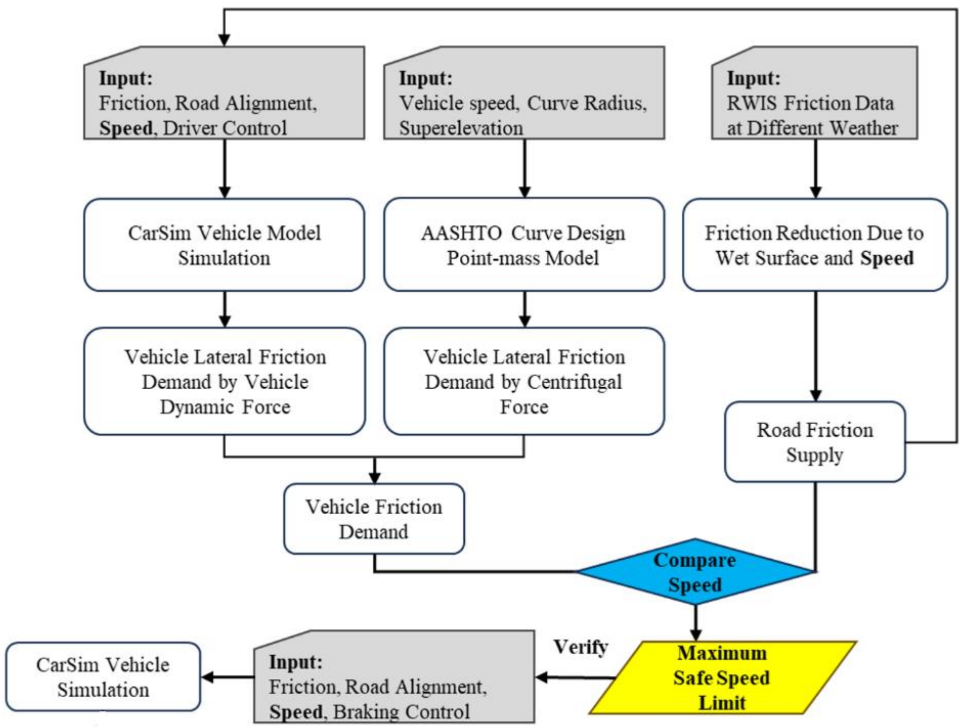


Figure C.1. Flowchart determining speed limits on horizontal curves

Case Studies for VSL

Road alignment has a significant effect on side vehicle stability [17]. The project identified roadway segments suitable for VSL implementation. It was determined that these segments should frequently experience adverse weather conditions (e.g., snow, rain, fog, high winds), high traffic volumes, or elevated safety risks. Real-time weather and traffic data collection were used to support the analysis, targeting the road sections where crash rates are higher than average.

According to Utah Crash Facts 2022, there were 58,992 crashes in 2022, resulting in 25,325 injuries and 319 fatalities [19]. The crash types of fatalities from 2018 to 2022 are summarized in Table C.2. Among all crashes, the most common contributing factors were “Failure to Yield” (20%) and “Following Too Closely” (19%). However, for fatal crashes, the leading factors, aside from speeding (35%), were “Failure to Keep in the Proper Lane” (31%), “Running Off-Road” (12%), and “Over-Correcting/Over-Steering” (8%), all of which are strongly associated with horizontal curves. Additionally, turning left or right accounted for nearly half of the top five pre-crash movements (excluding traveling straight ahead).

These statistics underscore the severity of roadway departure crashes linked to improper behavior on curves, emphasizing the critical need to establish safe speed limits that ensure vehicle stability on curves.

Table C.2. Utah fatalities by crash type

Crash Type	2018	2019	2020	2021	2022
Total Fatalities (All Crashes) *	260	248	276	332	319
(1) Single Vehicle	138	139	152	170	186
(2) Involving a Large Truck	37	43	40	67	51
(3) Involving Speeding	71	67	72	109	112
(4) Involving a Rollover	88	73	87	94	92
(5) Involving a Roadway Departure	130	113	135	161	167
(6) Involving an Intersection (or Intersection Related)	64	51	82	84	88

The I-80 highway, spanning from Canyon Rim to Summit Park with a 65 mph speed limit, is a mountain route characterized by numerous horizontal curves and steep vertical grades. These features inherently increase the risk of lateral slippage and run-off-road crashes. This segment is equipped with real-time RWIS sensors to monitor weather conditions and VSLs to regulate speeds during adverse weather. Between 2020 and 2022, there were three fatal crashes along this stretch, with the locations illustrated in Figure C.2. Although this may seem like a low crash rate, it can likely be attributed to the effectiveness of the existing VSL system.

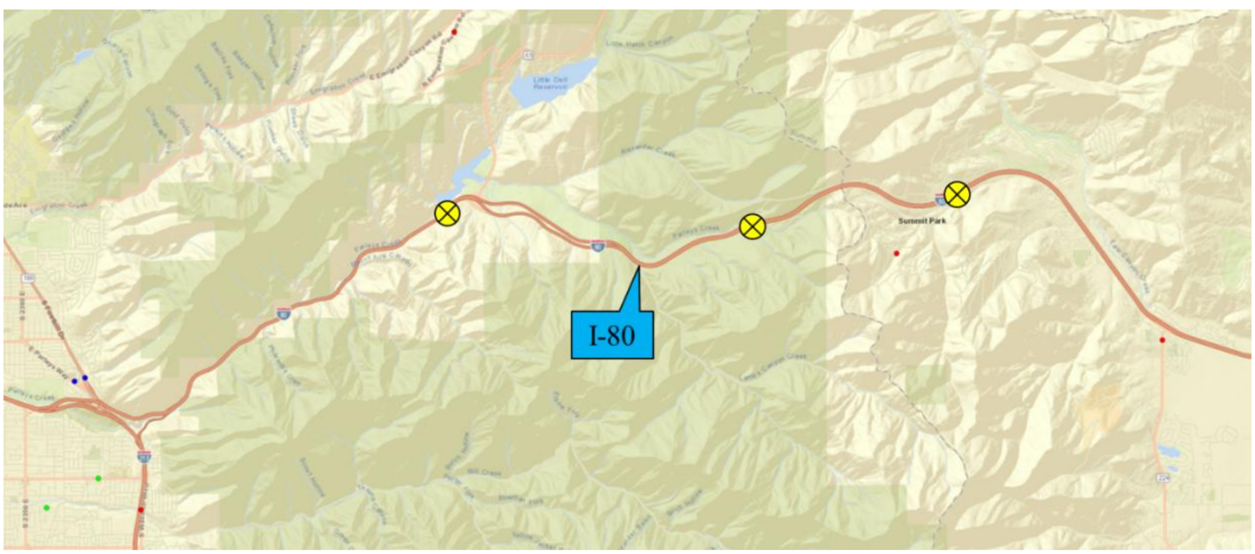


Figure C.2. Fatal crash location in this highway segment

From a weather perspective, RWIS data indicate that during winter, approximately 42% of days exhibited adverse conditions, including wet, snowy, or icy road surfaces. This high frequency of adverse weather underscores the necessity of speed management in such areas. Considering the crash history and frequent adverse weather, this segment of I-80 is a good candidate for further refinement and enhancement of VSL strategies to improve roadway safety.

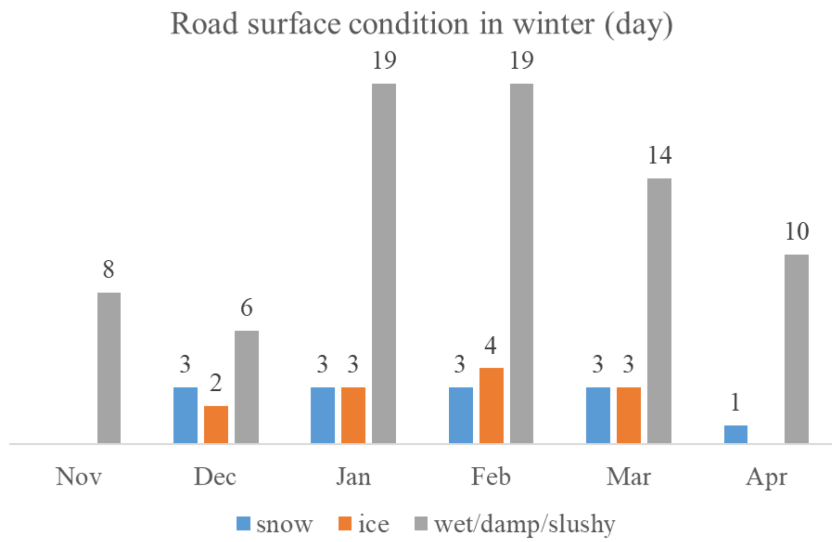


Figure C.3. Adverse road surface conditions during winter

In this project, the curves located on four road segments accompanied by RWIS and VSL (dynamic message signs) were selected for analysis, providing a real-world case for analyzing VSLs during adverse weather conditions. Figure C.4 illustrates the alignment of one segment along with the locations of RWIS and VSL.

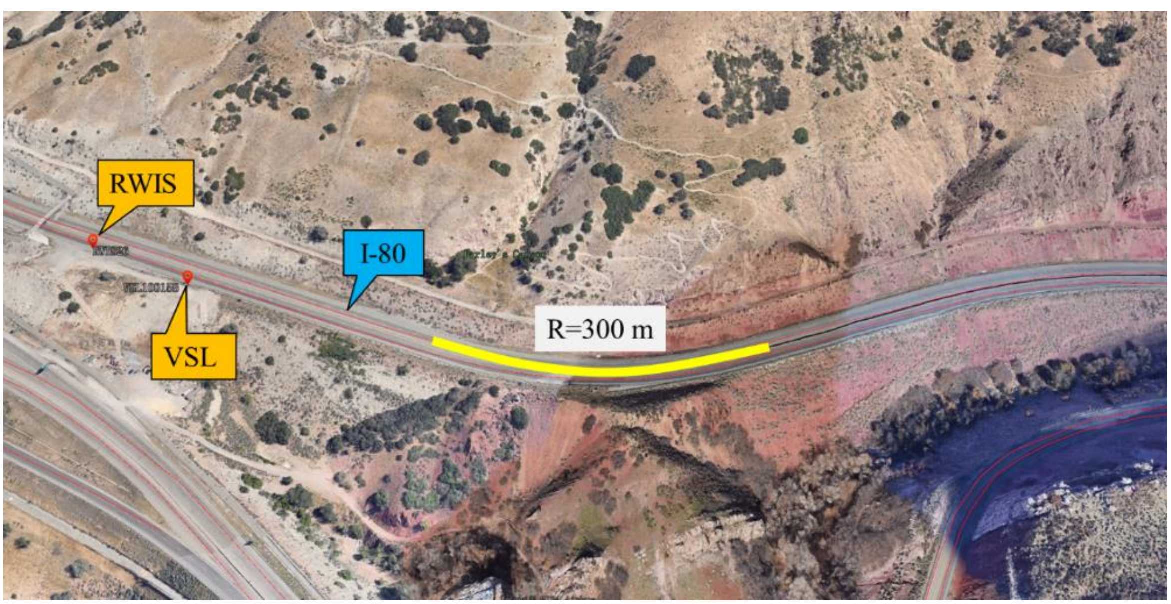
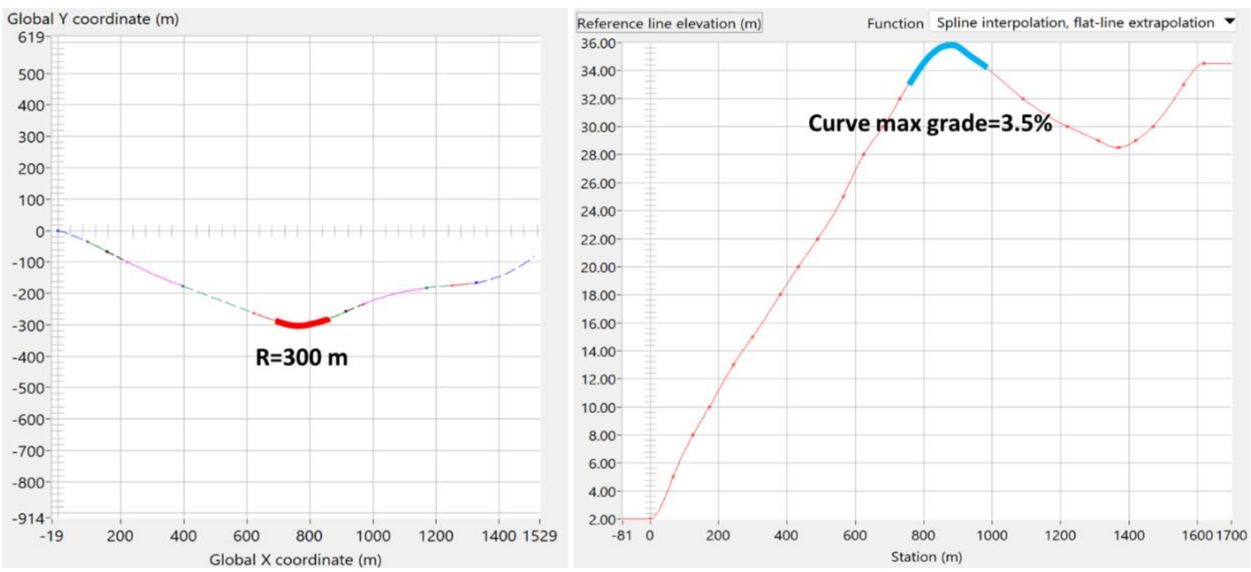
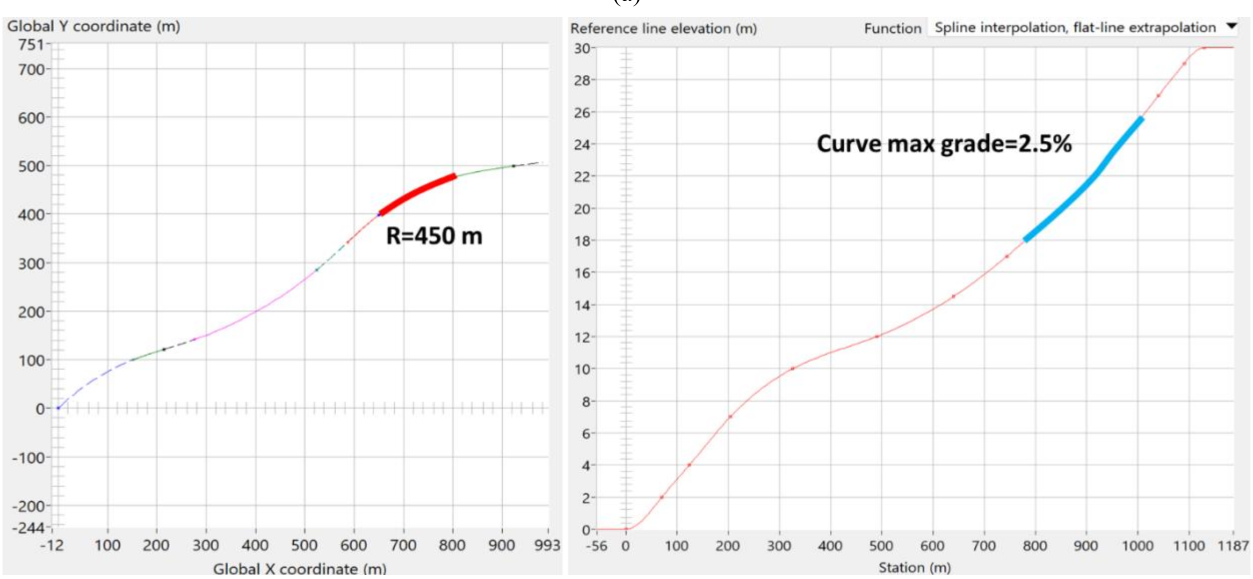


Figure C.4. One of four I-80 segments with RWIS and VSL locations

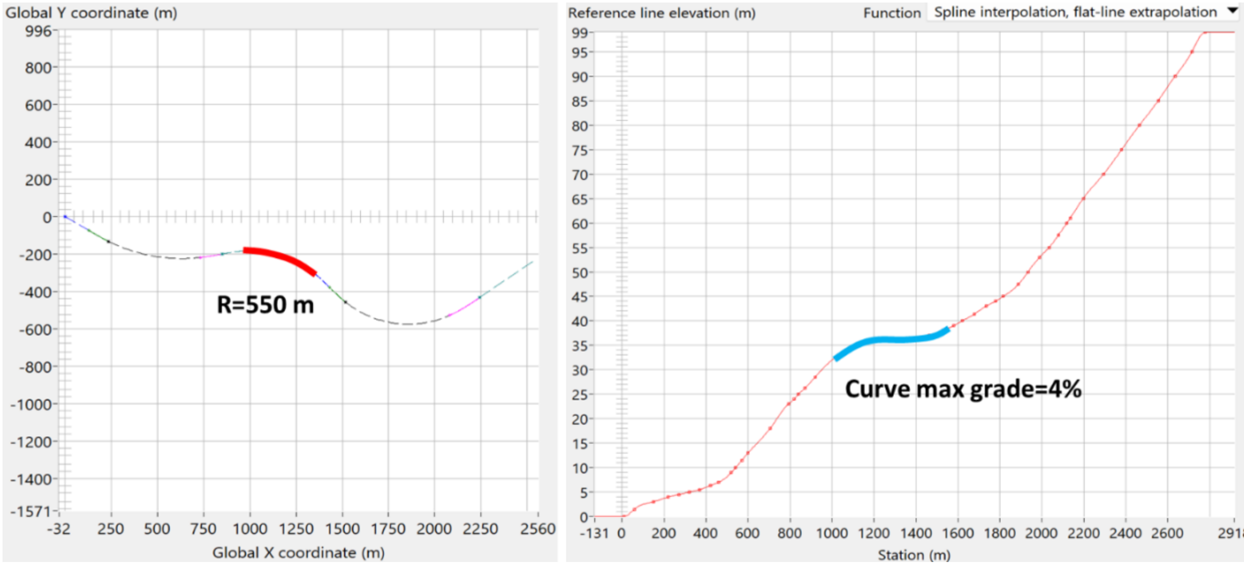
To simulate the real driving environment accurately, curve geometry features such as grade, superelevation, and clothoid were sourced from different sources. The horizontal alignment details were extracted from the geographic information systems (GIS) database of the Utah Department of Transportation (UDOT) and subsequently modeled in AutoCAD to derive the horizontal curve parameters. Vertical alignment information was gathered from the vertical profile available on Google Earth. Superelevation data were also sourced from the GIS data by selecting the maximum value of superelevation recorded. These integrated alignment features were then used to build a 3D road surface for simulation, as shown in Figure C.5; the information on those features is listed in Table C.3. The need for friction demand increases with the decrease in curve radius. Among the road segments monitored by RWIS and selected in this study, the most critical curve segment is depicted in Figure C.5 (a), which features R=300 m with 6% superelevation.



(a)



(b)



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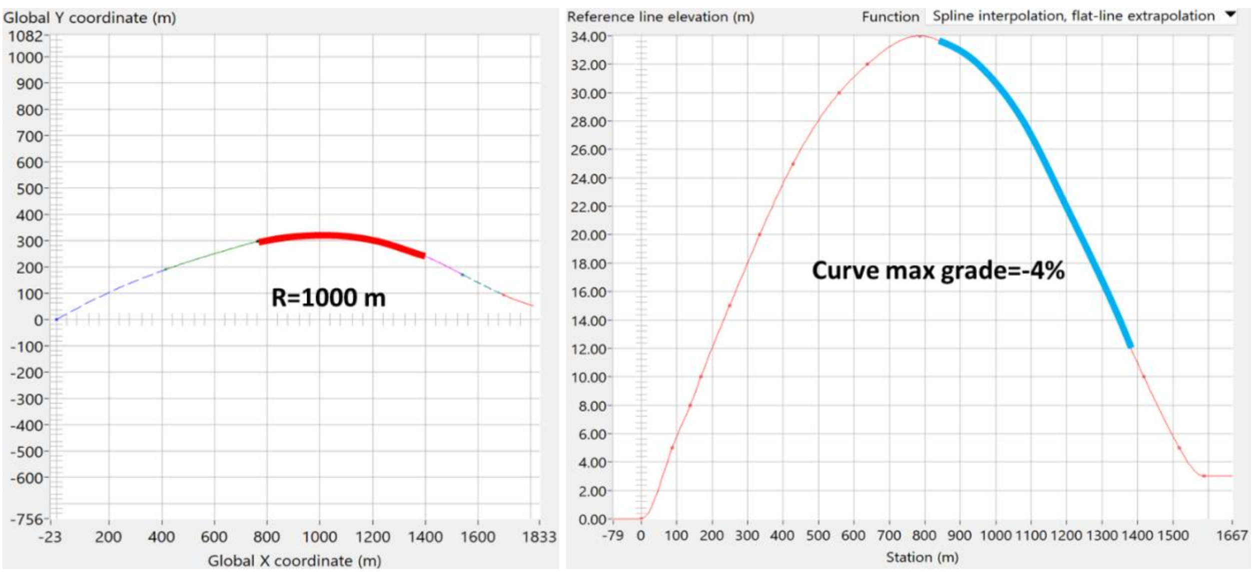


(d)

Figure C.5. Road horizontal profile for the four selected segments on I-80

Table C.3. Alignment features on I-80 segments

Segment	Min Radius(m)	Max Grade at Min Radius (%)	Superelevation (%)
1	300	3.5	6
2	450	2.5	6
3	550	4	6
4	1000	-4	6

Determination of Friction Demand

Point-Mass Model

In the AASHTO horizontal curve design policy, the point-mass model is employed to determine the curve radius [20]. Figure C.6 illustrates a point-mass navigating a curve, where the point experiences a centripetal force (perceived as a centrifugal force C). This force must be counterbalanced by gravity due to the road superelevation and the lateral friction force resulting from tire-road interaction.

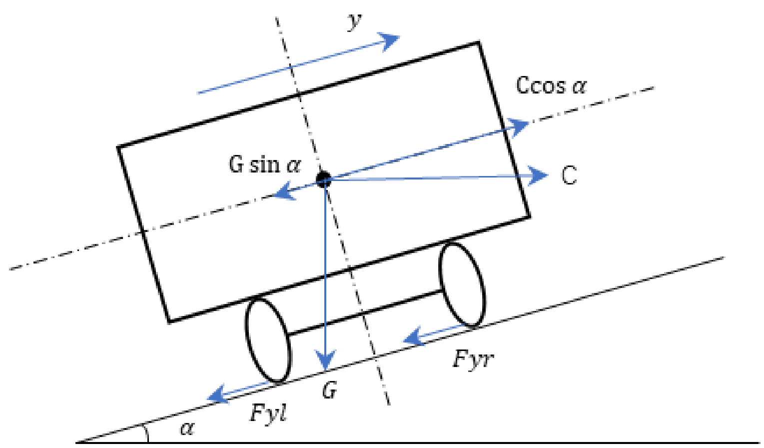


Figure C.6. Point-mass model during cornering

The minimum curvature radius is defined according to the AASHTO guidelines as a function of the designated design speed, roadway superelevation, and the maximum side friction factor. This relationship is presented in the simplified formula shown in equation (1), where *f* is termed the side friction factor, quantifying the lateral force not counteracted by the gravity component due to superelevation. It is important to note that the side friction factor employed in the geometric design of highways and streets is a demand value primarily based on thresholds of driver comfort, which typically ranges between 0.10 and 0.20, rather than the actual side friction coefficient of the tire-pavement interaction.

$$R = \left(\frac{V^2}{g \cdot (f + 0.01e)}\right) \tag{1}$$

The side friction factor represents the friction demand required when a vehicle navigates a horizontal curve. From the demand perspective, when the curve radius, speed, and superelevation of an existing curve are specified, the side friction factor can also be derived using the equation. This is detailed in equation (2). The tire-road friction supply must exceed this demand to ensure vehicle stability and prevent skidding.

$$f = \frac{V^2}{g \cdot R} - 0.01e \tag{2}$$

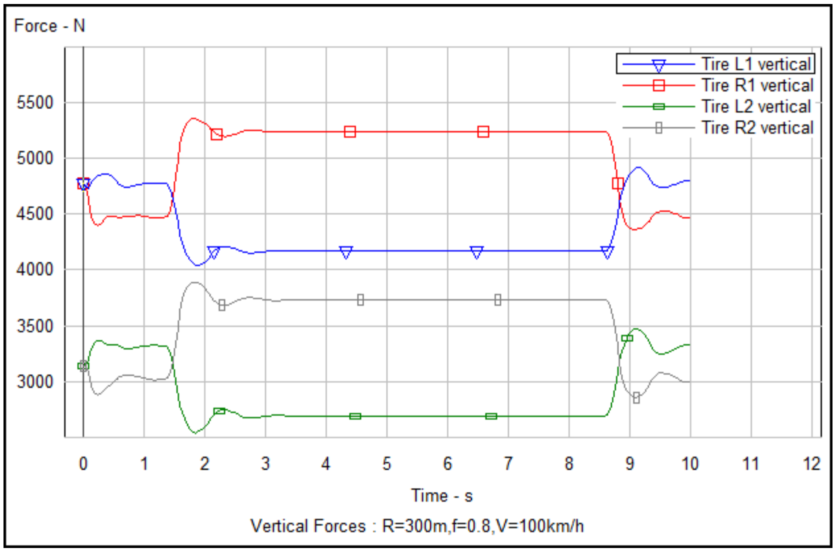
where

R = minimum curve radius,
V = design speed,
f = side friction factor, and
e = superelevation.

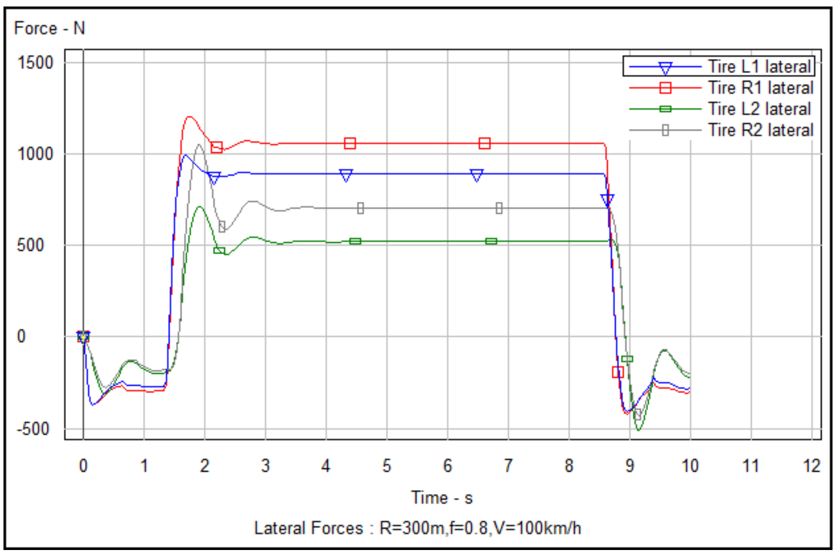
Vehicle Dynamics Simulation

The major limitation of a point-mass model is its simple calculation and inability to accurately reflect the dynamic behavior of the entire vehicle along with different tires during cornering. In this study, specialized software developed by Mechanical Simulation Corporation, CarSim, was utilized for vehicle dynamics simulation during cornering for its ability to comprehensively account for the entire vehicle, individual tires, road alignment, road friction, and the interactions among these components. It is an integrated dynamic simulation software package that can receive inputs reflecting real-world scenarios like driver behavior, vehicle parameters, road alignments, and environmental parameters. The corresponding dynamic outputs can be generated through the simulation process to reflect the force and status of the vehicle. The simulation outcomes of CarSim have been validated by several studies and have been proven consistent with experimental results [18, 21].

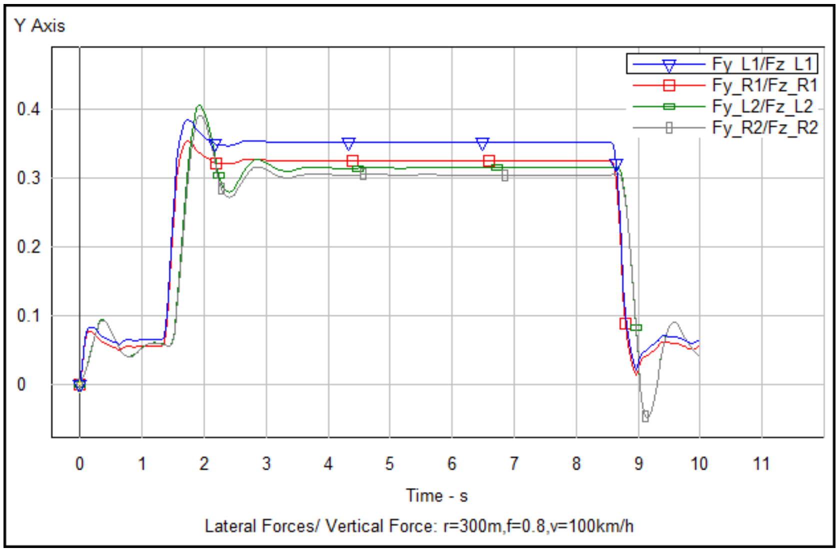
An example of tire forces during cornering from vehicle dynamics simulation is shown in Figure C.7, based on the simulation of full vehicle behavior for a D-class sedan car. The simulation conditions are set with R = 300 m, e = 6%, and V = 100 km/h. During the cornering maneuver, the weight transfer and varying slip angles across different tires result in disparate vertical loads and lateral forces on each tire, leading to variation in friction demand (the ratio of lateral force and vertical force) across the four tires. This is different from the results of a point-mass model, which can only reflect one value of friction demand from the whole vehicle (as a point). Therefore, it is necessary to compare the friction demand results derived from vehicle dynamics simulation and the point-mass model to determine the most appropriate friction demand for ensuring vehicle safety and performance.


Force - N
Tire L1 vertical
Tire R1 vertical
Tire L2 vertical
Tire R2 vertical
5500
5000
4500
4000
3500
3000
0
1
2
3
4
5
6
7
8
9
10
11
12
Time - s
Vertical Forces : R=300m,f=0.8,V=100km/h

(a)


Force - N
Tire L1 lateral
Tire R1 lateral
Tire L2 lateral
Tire R2 lateral
1500
1000
500
0
-500
0
1
2
3
4
5
6
7
8
9
10
11
12
Time - s
Lateral Forces : R=300m,f=0.8,V=100km/h

(b)



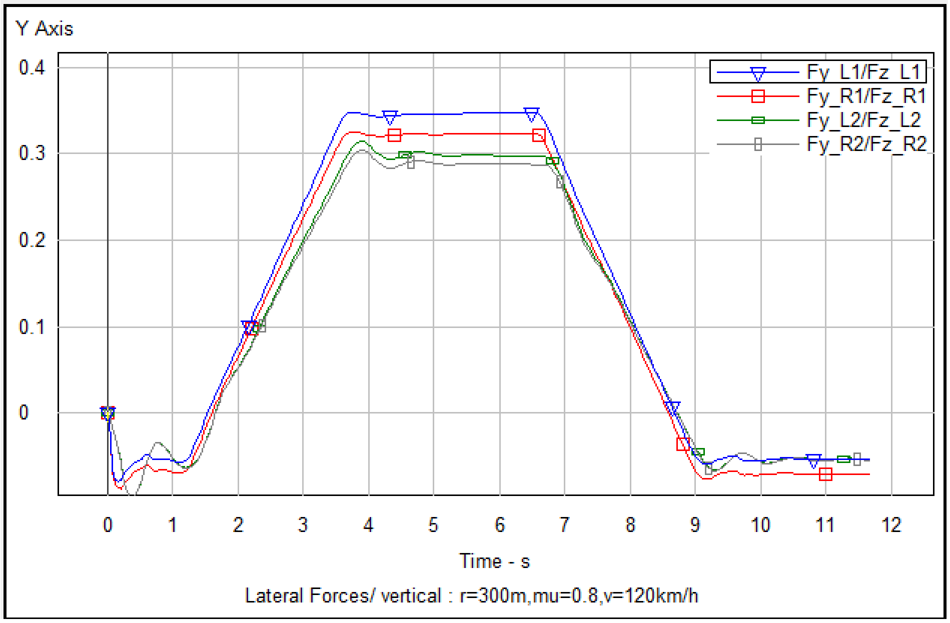
(c)

Figure C.7. Tire forces during cornering: (a) vertical force, (b) lateral force, (c) ratio of lateral force and vertical force

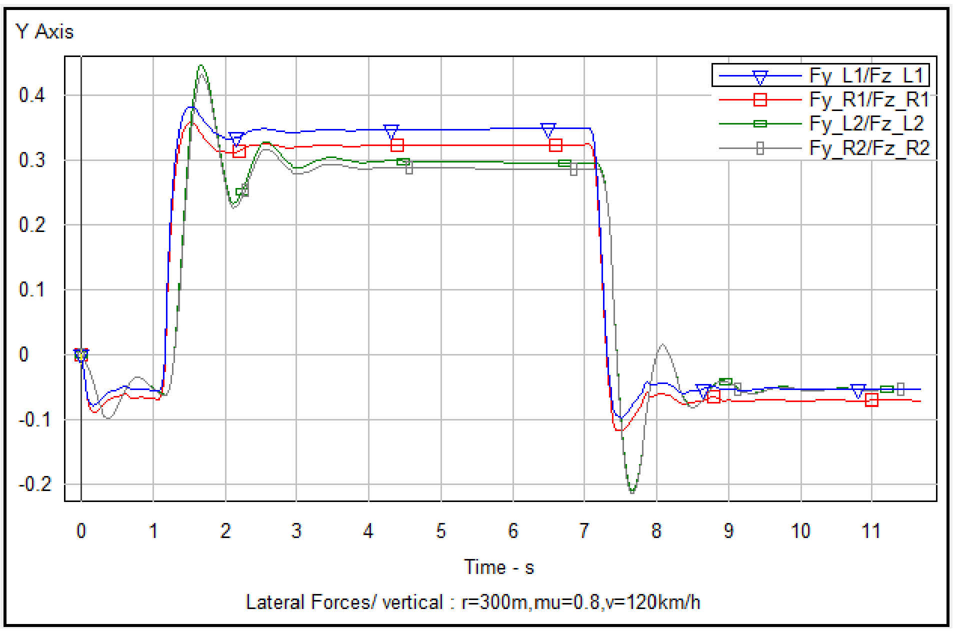
Factors Influencing Friction Demand Simulation

Many factors influence the dynamic response of vehicles during cornering, including vehicle type, curve radius, vertical grade, transition curve, superelevation, etc. [22]. This section examines these factors through vehicle dynamics simulations conducted using CarSim. The curve had a radius of 300 m with 0% vertical grade, and the vehicle traveled at a speed of 120 km/h for the simulations.

The first critical factor examined was the presence of a transition curve on horizontal curves, which significantly affects a vehicle's dynamic performance. Figure C.8 illustrates the vehicle's friction demand when cornering to the left on a 300 m curve (zero grade) with and without a transition curve. The results reveal that the highest friction demand on a curve without a transition curve is substantially higher and appears at different tires compared to the case with a transition curve. This discrepancy is due to sudden changes in the vehicle's steering angle when cornering without a transition curve, causing a shift in the vehicle's mass center toward the outer side of the curve. Consequently, over 55% of the lateral and vertical forces act on the right tire, leading to increased instability (Figure C.9) [23]. In contrast, when a transition curve is present, the steering angle changes smoothly to the target angle, allowing the friction demand to gradually stabilize at the level required for the curve segment. Typically, 55% to 60% of the passenger car's gravity load acts on the front axle, while 40% to 45% acts on the rear axle [24]. As a result, the left front tire becomes the most critical tire for navigating the curve. Given its importance in ensuring stability and reducing friction demand, the transition curve is indispensable in horizontal curve design. To simulate real-world conditions, all curves in subsequent simulations included a transition curve.

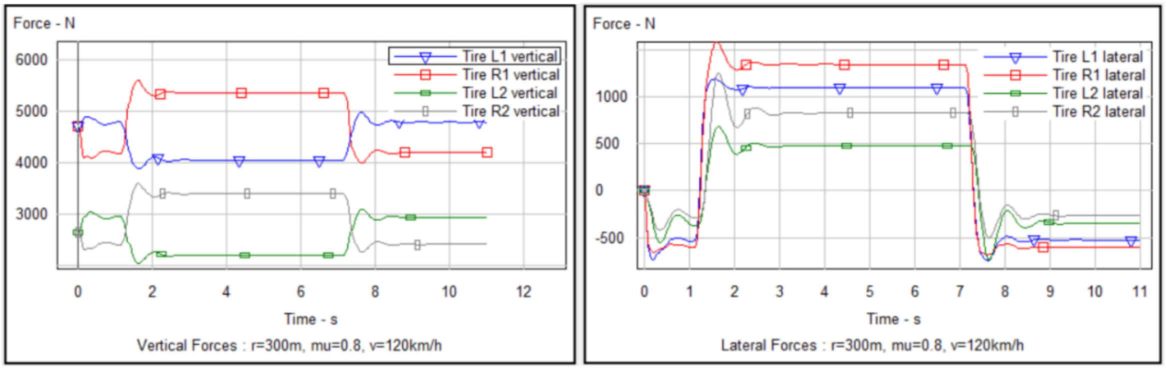


(a)



(b)

Figure C.8. Vehicle friction demands when cornering to the left on a curve (a) with and (b) without a transition curve



(a) (b)

Figure C.9. Vehicle vertical and lateral forces when cornering on a curve without a transition curve

The friction demand of three vehicle types on a 300 m curve (zero grade) was compared. Figure C.10 illustrates that passenger cars exhibited the highest side friction demand compared to other vehicle types. This increased friction demand can be primarily attributed to their low center of gravity [22]. In contrast, sport-utility vehicles (SUVs) and trucks, which are heavier, generate higher vertical forces. This is because the side friction factor is the ratio of lateral to vertical forces; the greater weight of the SUV and truck creates a larger vertical force, resulting in a lower overall friction factor demand compared to the lighter sedan at high speeds [24]. Consequently, passenger cars are at a higher risk of skidding and were the model for simulation, and the vehicle parameters are shown in Figure C.11.

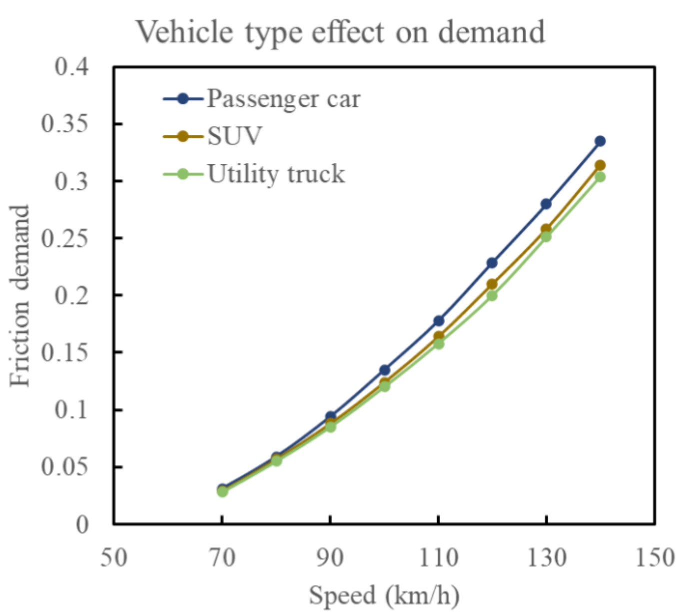


Figure C.10. Friction demand of different vehicle types

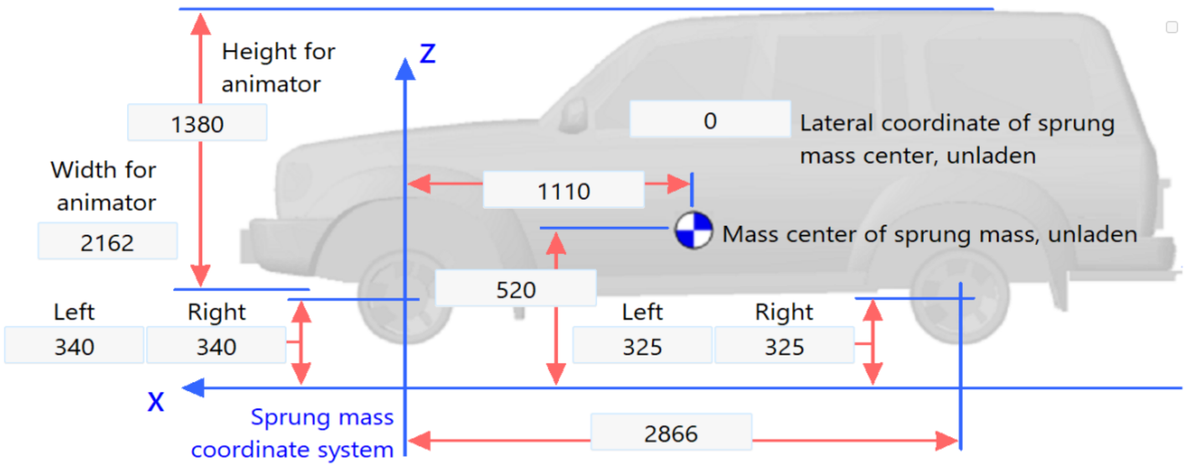
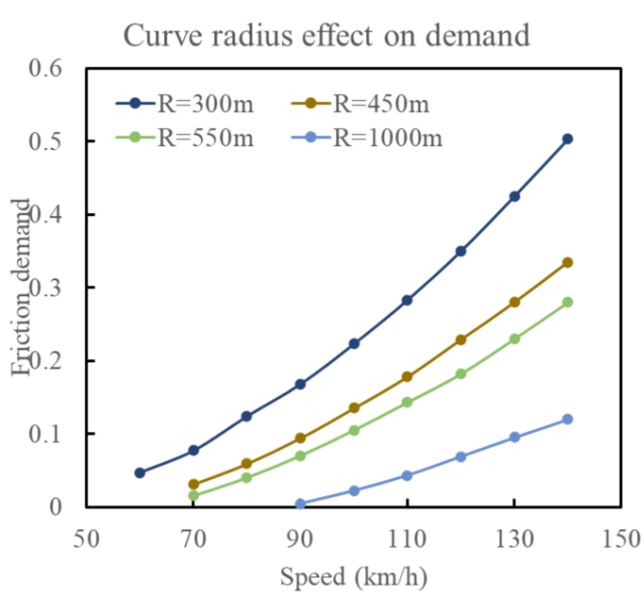
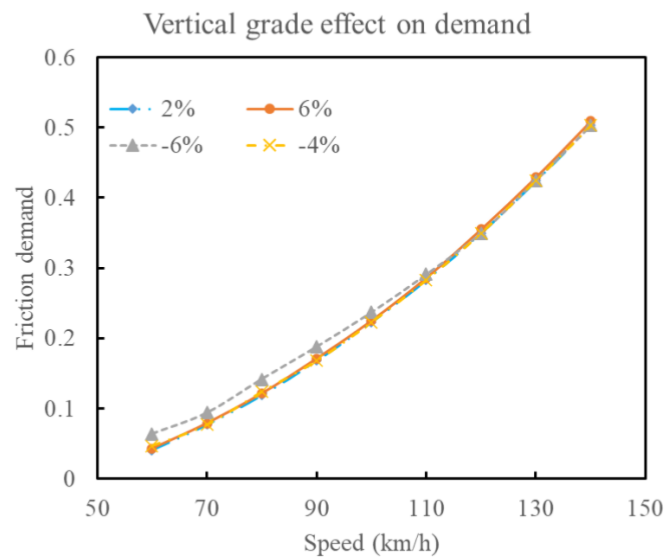


Figure C.11. Passenger car parameters (mm)

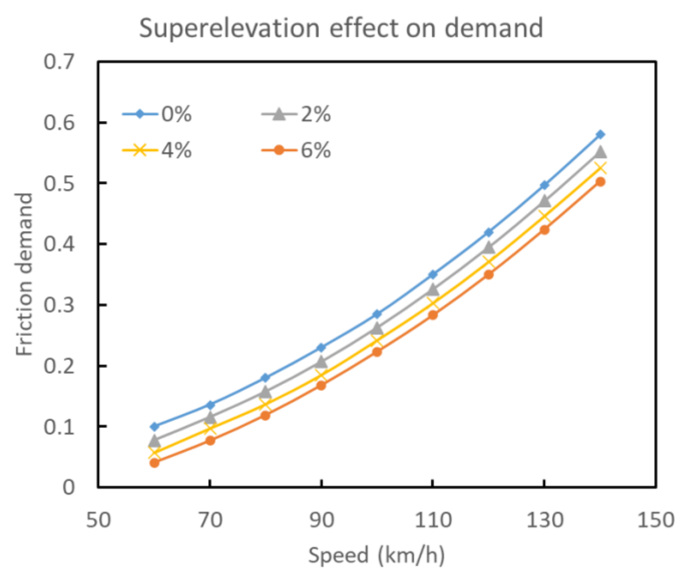
Figure C.12 illustrates the effects of horizontal curve radius, vertical grade, and superelevation on friction demand. The results reveal that both the radius of curvature and superelevation significantly influence friction demand, as they directly affect the balance of tire lateral forces, aligning with the predictions of the point-mass model. The friction demand for the R = 1000 m curve at the same speed is lower compared to those for the R = 300, 450, and 500 m curves, reflecting the lower demand for friction as the curve becomes less sharp. Meanwhile, the vertical grade at the curve did not have considerable impact on side friction demand during cornering. However, the influence of steep downhill conditions cannot be overlooked. The additional force from gravity increases friction demand for braking, making vertical gradient a factor that warrants attention in specific cases [25].



(a)



(b)



(c)

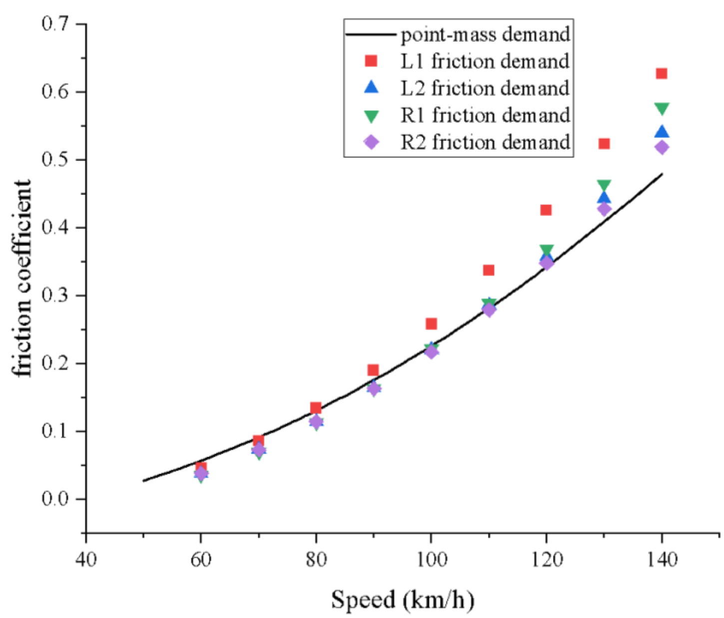
Figure C.12. Effects of road alignment-related factors on friction demand: (a) curve radius, (b) vertical grade, (c) superelevation

Vehicle dynamics simulation provides a much more robust analysis than the simple point-mass model [24]. While the point-mass model calculates lateral balance using only curve radius and superelevation, dynamics simulation incorporates additional critical elements like vertical grade, transition curves, load distribution, and specific vehicle dynamics. This comprehensive approach allows for a more accurate and realistic assessment of friction demand and vehicle stability under a wide range of conditions.

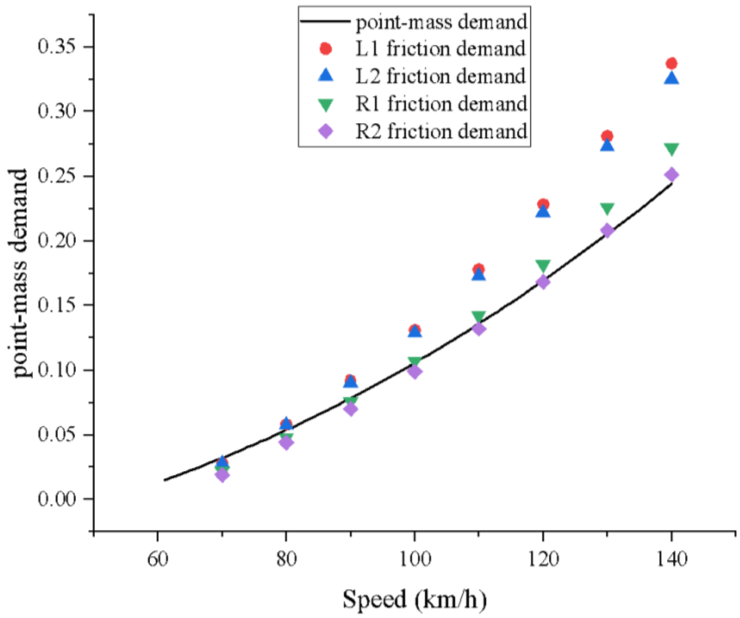
Friction Demand Comparison between Two Methods

The two methods of friction demand calculation, the point-mass model and dynamic simulation, differ in complexity and accuracy, and their respective outputs were compared to determine the most reasonable friction demand values for different scenarios. In the analysis of the curve cases, the friction demand for both methods was calculated at varying vehicle speeds to generate the escalating trend of friction demand with speed.

Figure C.13 presents the calculated friction demands on two curves from the point-mass model and vehicle dynamics simulation where the friction supply is sufficient. The friction demand from dynamic vehicle simulation varies for each of the four tires, L1 (left front tire), L2 (left rear tire), R1 (right front tire), R2 (right rear tire), and yields an overall friction demand curve derived from the point-mass model. The graph shows significant variability in the friction demand of each tire, with the left front tire (L1) consistently exhibiting the highest demand. The results between the vehicle simulation and the point-mass model are similar at lower speeds. However, as the speed increases, notable discrepancies arise. For example, the friction demand difference reaches up to 0.15 between the two models at 140 km/h, suggesting that the point-mass model cannot accurately predict vehicle dynamics in higher-speed scenarios.



(a)



(b)

Figure C.13. Friction demand of point-mass model and dynamic simulation on two curves: (a) R = 300 m, (b) R = 550 m

The divergence between the results from dynamic vehicle simulation and the point-mass model at higher speeds (Figure C.14) indicates the point-mass model's limitations in accounting for dynamic factors such as load transfer and slip angles, which underscore the need for employing dynamic simulations for accurate safety and stability assessments, especially in high-speed driving scenarios. Consequently, the maximum tire friction demand value from vehicle dynamics simulation is recommended as the most suitable metric for determining vehicle friction demand, ensuring a more reliable and safe assessment of vehicle performance, especially during critical maneuvering or adverse conditions.

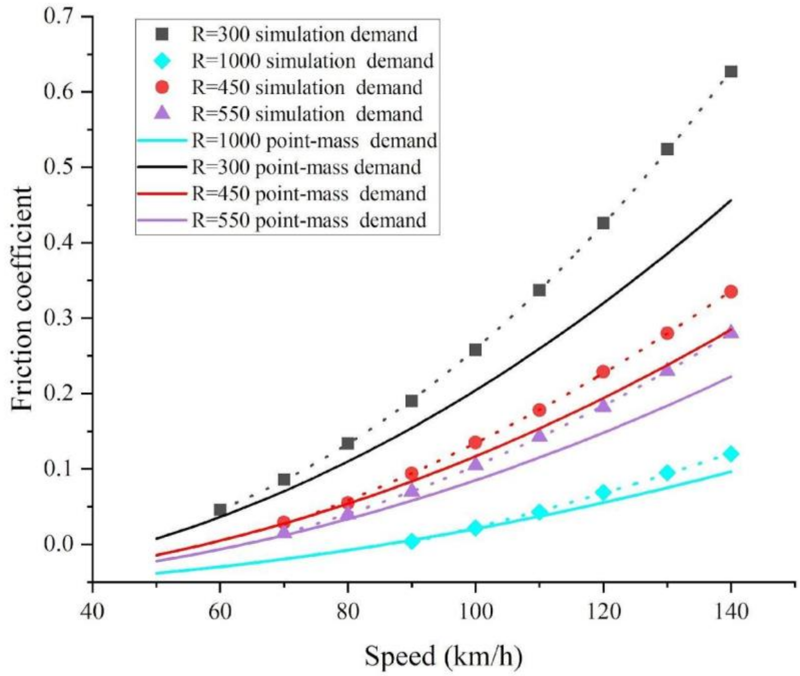


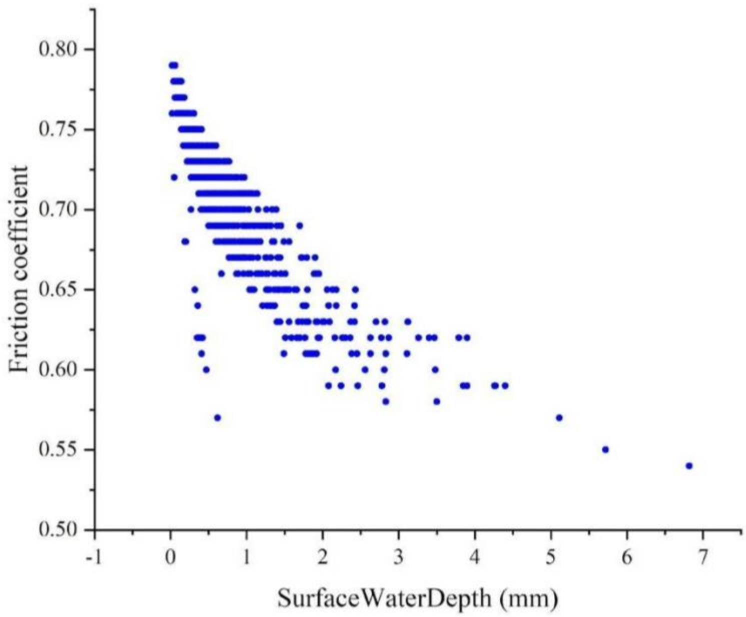
Figure C.14. Comparison of friction demand from vehicle dynamics simulation and point-mass model

Determination of Friction Supply from RWIS data

RWIS Friction versus Water/Snow/Ice Depth

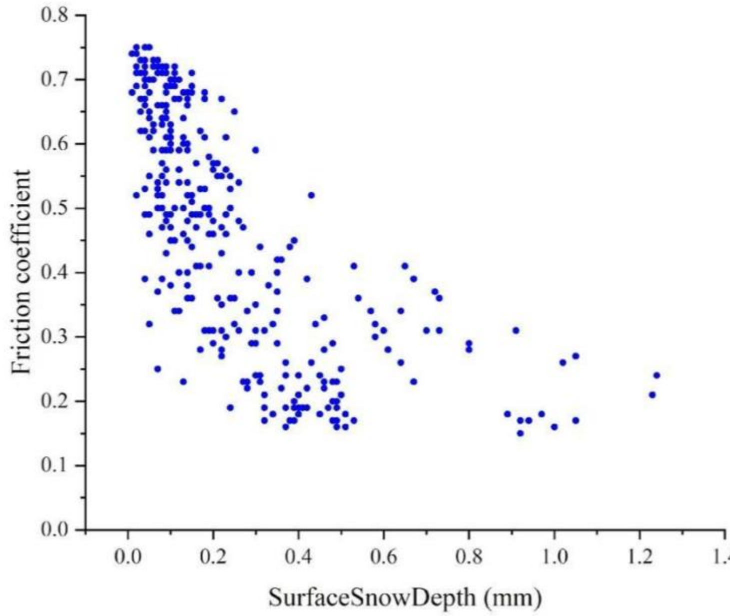
Friction supply is the maximum friction force (coefficient) that originates from tire-pavement interaction and provides the lateral balance (side friction) or sufficient braking force (longitudinal friction). During adverse weather conditions, pavement surfaces are frequently covered by water, snow, or ice. Previous studies [26–28] typically characterized friction supply as a constant value across different vehicle speeds. However, it is well known that with increasing speeds, a significant reduction in friction occurs on wet surfaces [12]. Additionally, as the water depth and speed increase, the hydrodynamic lift force rises and reduces the tire-road contact area and, consequently, diminishes friction [29].

RWIS stations, which monitor surface grip (friction) along with wind speed, road surface temperature, water/snow/ice depth, etc., are commonly used for winter roadway maintenance. In RWIS data, the effect of water/snow/ice accumulation on friction is represented as a reduction value derived from the weather and surface conditions recorded by sensors. The RWIS data recorded on I-80 between 2021 and 2024 are plotted in Figure C.15. The figure shows that water/snow depth significantly impacts friction values, while the effect is less clear for ice depth because less data is available on icy surfaces and ice is always accompanied by water and snow.



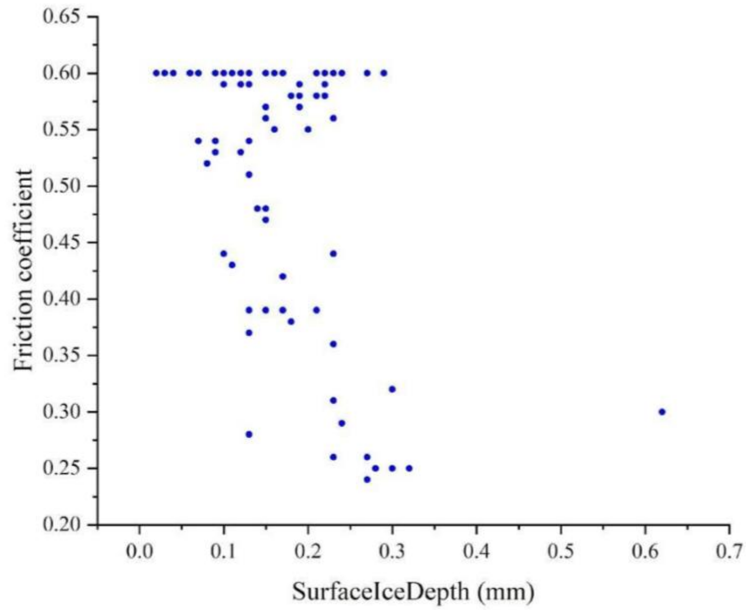
Friction coefficient
0.80
0.75
0.70
0.65
0.60
0.55
0.50
-1
0
1
2
3
4
5
6
7
SurfaceWaterDepth (mm)

(a)



Friction coefficient
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
SurfaceSnowDepth (mm)

(b)



(c)

Figure C.15. Correlation between RWIS friction value and (a) water, (b) snow, (c) ice depth

RWIS Friction versus Speed

The friction from RWIS data should not be regarded as a straightforward representation of friction supply without accounting for the speed effect. Previous work has found that RWIS friction values exhibit a strong linear correlation with the friction values measured during braking of a vehicle at 60 km/h, as shown in Figure C.16 [30, 31]. Based on this correlation, an assumption was made that the RWIS friction data are equivalent to the reading of a braking friction meter at 60 km/h.

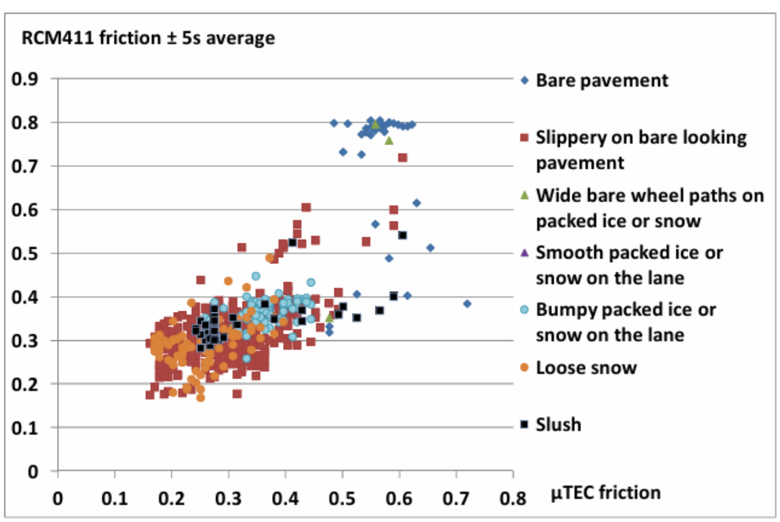


Figure C.16. Comparison between RCM411 (RWIS sensor) and µTEC (friction meter) friction [30]

Consequently, this equivalence facilitates the conversion process to consider the speed effect. The conversion and standardization of friction measurements at different speeds were guided by the recommended practices in ASTM E1960-07, as shown in equations (3) through (5). It is noted that the speed effect on wet friction is directly influenced by the mean profile depth (MPD) of the pavement surface.

$$Sp = 14.2 + 89.7MPD \tag{3}$$

$$FS = F60 \cdot \exp\left[\frac{(60 - S)}{S_p}\right] \tag{4}$$

where

S_p = speed constant of wet pavement friction,
MPD = mean profile depth (mm),
F60 = friction value from RWIS at 60km/h,
FS = friction at another slip speed, S.

As shown in Figure C.17, the pavement surface with the higher MPD values maintains greater skid resistance at higher speeds.

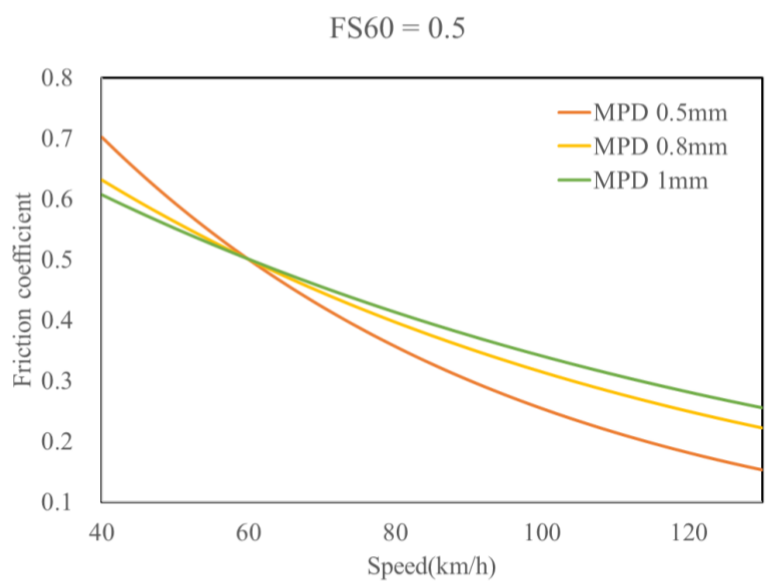


Figure C.17. MPD effect on wet friction with speed

Longitudinal Friction versus Lateral Friction

Braking friction meters measure the friction during braking on a straight roadway, meaning that the RWIS friction can be used to represent the longitudinal friction. However, the relationship between lateral and longitudinal forces needs to be considered for vehicle dynamics simulation. When a vehicle travels on a curve with lateral friction, longitudinal friction is needed for acceleration and deceleration. When a vehicle experiences a combined slip condition due to braking and cornering, the lateral and longitudinal forces generated by tire-road interaction can be represented using an ellipse formula [32]. As shown in Figure C.18, the combined friction value must remain within the boundaries of this friction ellipse. This relationship is critical for accurately assessing vehicle stability under combined braking and cornering scenarios.

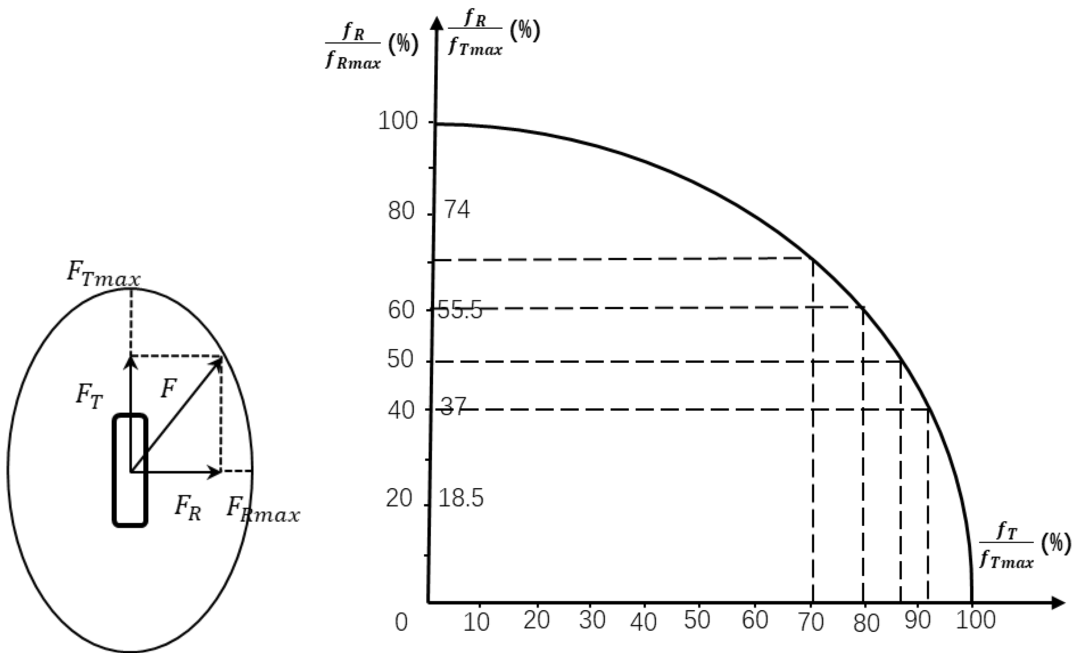


Figure C.18. Ellipse correlation between longitudinal and lateral friction (*fT* is longitudinal friction and f_R is lateral friction) [33]

Because designers cannot use 100% of the available friction and still maintain a margin of safety, this relationship requires them to select an appropriate utilization ratio (n). Therefore, a critical question arises: What range should be used for the utilization ratio of the maximum permissible side friction factor to ensure stability? Lamm et al. [34] observed that the maximum lateral friction was approximately 92.5% of the maximum longitudinal friction, and this ratio also varied depending on tire conditions. International practices suggest that *n* typically ranges between 40% and 50% for rural roads. Based on Figure C.18, this indicates that 92% and 87% of lateral friction remains available for acceleration or deceleration or for evasive maneuvers when driving through curves. However, recent research has shown that utilization ratios of n = 40% and n = 50% may be overly conservative for a universally valid safety evaluation [34]. To ensure that 80% of lateral friction remains available for essential maneuvers while navigating curves, a utilization ratio of n = 60% is recommended. The general equation for determining the maximum permissible side friction factor, shown in equation (5), incorporates this utilization ratio (n) to account for the safety margin.

$$f_R = n \times 0.925 \times f_{Tperm} \quad (5)$$

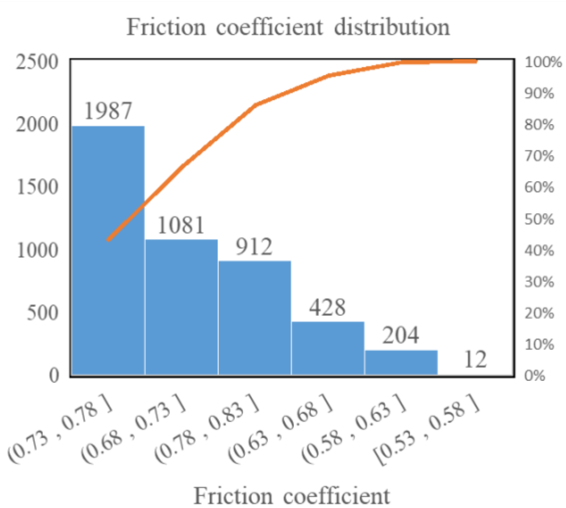
where f_R is the maximum permissible side friction factor, f_{Tperm} is the maximum permissible tangential(longitudinal) friction factor, n is the utilization ratio from longitudinal to lateral factor.

Lateral Friction for Different Surface Conditions

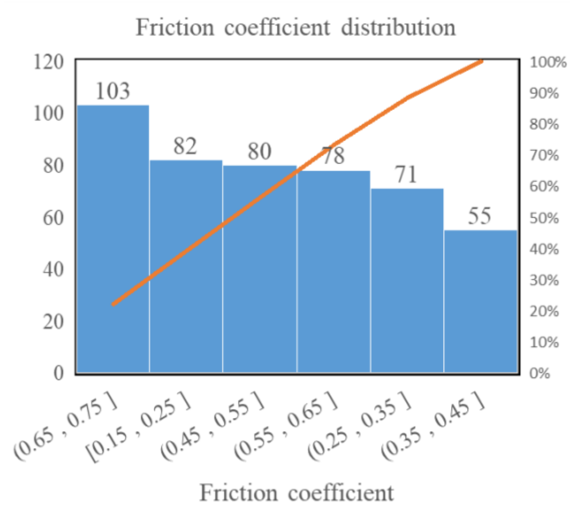
To estimate the lateral friction under adverse weather conditions, the friction data from RWIS that were collected from 2021 to 2023 were analyzed. The friction ranges in various weather and road surface conditions are shown in Table C.4. The table shows that the friction values vary with water/snow/ice depth and surface temperature and have a relatively large range under the same surface conditions. The distributions of friction values for each condition are shown in Figure C.19. To represent the relatively severe friction values for each condition, the 95th percentile friction values were selected, which were determined to be 0.62 for wet surfaces, 0.26 for ice, and 0.18 for snow.

Table C.4 Friction range of different weather and road surface conditions

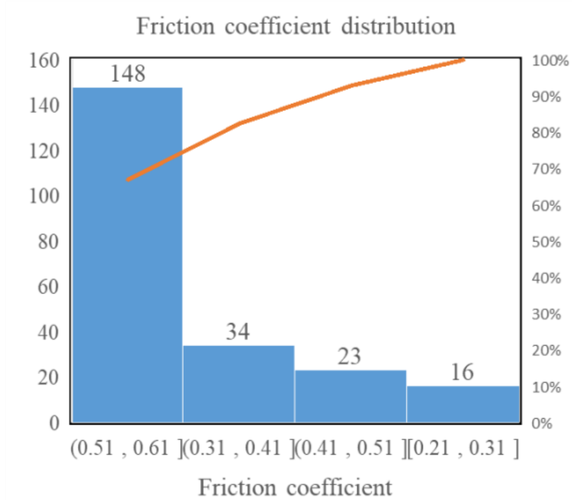
Surface Condition	Dry	Wet	Snow	Ice
Friction coefficient range	0.8–0.83	0.54–0.8	0.16–0.46	0.24–0.5



(a)



(b)



(c)

Figure C.19. Friction distribution of different surface conditions: (a) wet, (b) snow, (c) ice

According to the procedure, equations 3 and 4 were employed to establish the relationship between longitudinal friction and speed. The utilization ratio (n) was then applied to translate longitudinal friction into lateral friction. While no measured MPD data were available for the selected road segments, the common MPD values of dense-graded asphalt pavement surfaces range from 0.3 mm to 1.2 mm [35]. Considering the impact of the tire polishing effect on MPD over time, a conservative MPD value of 0.8 mm was adopted for this study. The results of this conversion, shown in Figure C.20, reveal a significant reduction in friction as speed increases from 50 km/h to 120 km/h under wet conditions. This sharp decline in friction substantially increases the risk of side skidding, highlighting the importance of accounting for speed and surface condition when setting safety parameters for curves.

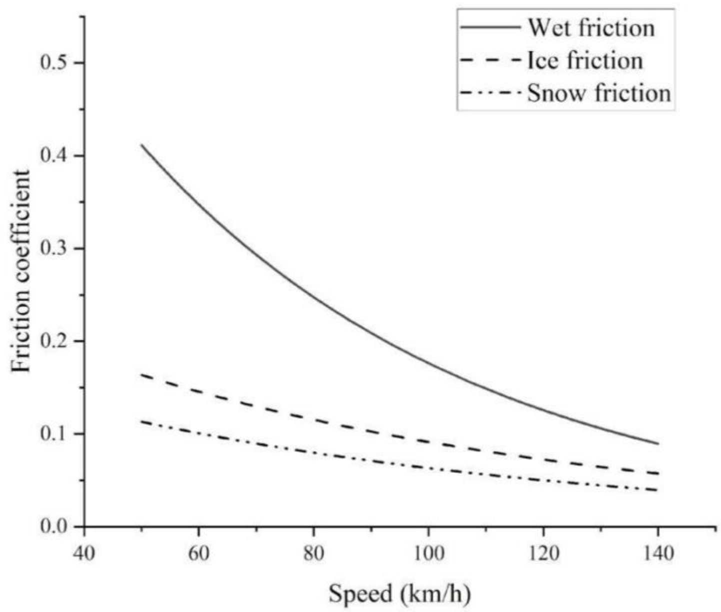


Figure C.20. RWIS friction conversion results

Safety Speed on Horizontal Curves

Safety Speed under Adverse Weather Conditions

Based on the simulation results of CarSim and RWIS data, Figure C.21 displays curves of maximum friction demand against friction supply for different surface conditions. When a vehicle navigates a curve, both friction demand and supply are functions of vehicle speed, showing opposite trends. Skidding would occur when the maximum friction demand surpasses the available friction supply. The intersection point between friction demand and supply indicates the maximum safe speed for the specific curve and surface condition. As expected, a curve with a larger radius allows for higher safe speeds in the same road surface conditions. Consequently, the intersection point, representing the maximum safe speed—is substantially lower for both sharper curves and adverse road conditions like snow or ice.

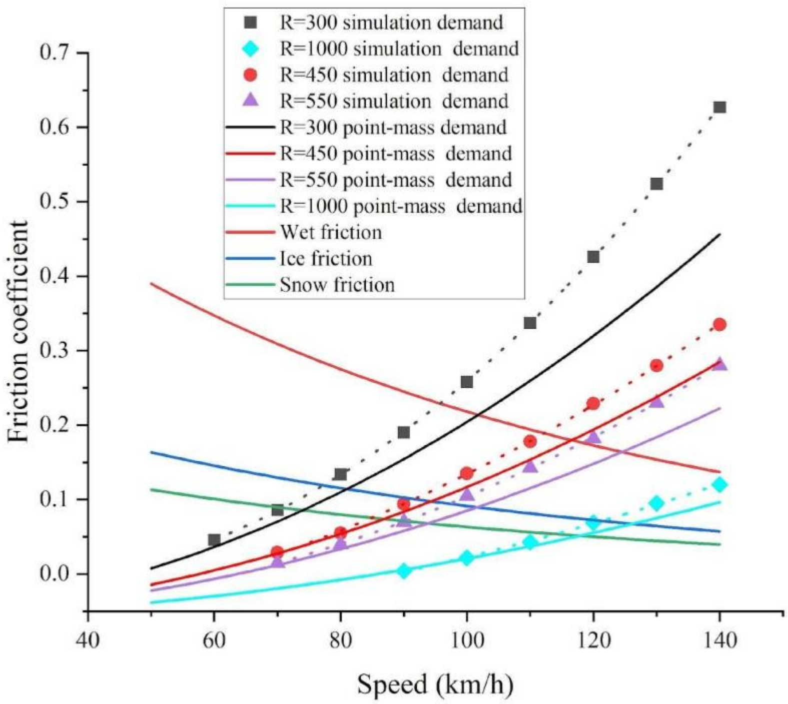


Figure C.21. Intersection points of friction demand and supply curves

Table C.5 compares the design speeds recommended by AASHTO design standard with the maximum speed limits determined through vehicle dynamics simulation and the point-mass model under adverse weather conditions. The AASHTO design speed is calculated using the point-mass model equation, with side friction factors of 0.14, 0.12, 0.11, and 0.10 for curve radii of 300 m, 450 m, 550 m, and 1000 m, respectively. The comparison reveals that AASHTO design speeds are insufficient for adverse conditions such as snow and ice.

Table C.5. Comparison of AASHTO design speed and simulation results

Curve Radius (m)	e (%)	AASHTO design speed (km/h)	Maximum speed from vehicle dynamics simulation (km/h)			Maximum speed from point-mass model (km/h)		
			Wet (f=0.62)	Snow (f=0.18)	Ice (f=0.26)	Wet (f=0.62)	Snow (f=0.18)	Ice (f=0.26)
300	6	89	96	70	77	101	74	81
450	6	102	112	84	91	117	87	94
550	6	110	119	90	97	125	94	102
1000	6	>117	>140	114	120	>140	118	126

This finding underscores the necessity of implementing VSLs that account for weather-related road surface conditions. Moreover, the safe speeds derived from vehicle dynamics simulation are consistently lower than those from the point-mass model, demonstrating the conservative nature of vehicle dynamics simulations and their potential for enhancing safety assessments. While the AASHTO design speeds adhere to established engineering and safety standards for normal conditions, they may not suffice during adverse weather. When the determined safe speeds fall below the design speeds under such conditions, implementing VSLs becomes essential to enhance roadway safety and ensure that traffic operations are responsive to real-time conditions.

Real-Time Recommendation for Speed Limit

RWIS makes real-time monitoring of road surface conditions possible, providing friction supply data for determining VSLs. Integrating RWIS data into a VSL framework ensures that speed recommendations are both responsive and effective in mitigating the risks associated with changing surface conditions. Vehicle dynamics simulation can capture realistic driving scenarios and predict friction demand. However, setting up and running simulations requires a certain amount of time, making it unsuitable for real-time determination of VSLs.

To enable real-time recommendations of safe speeds under adverse conditions, the friction coefficients from RWIS were assumed to be in the range of 0.1 to 0.7 to determine maximum safe speeds for four specific roadway segments, as illustrated in Figure C.22. After that, the correlation between maximum safe speeds and friction coefficients was established, as shown in Figure C.23. Using these correlation models, real-time RWIS friction data can be input to determine the appropriate speed limit for a given segment, which allows for real-time recommendations for VSLs.

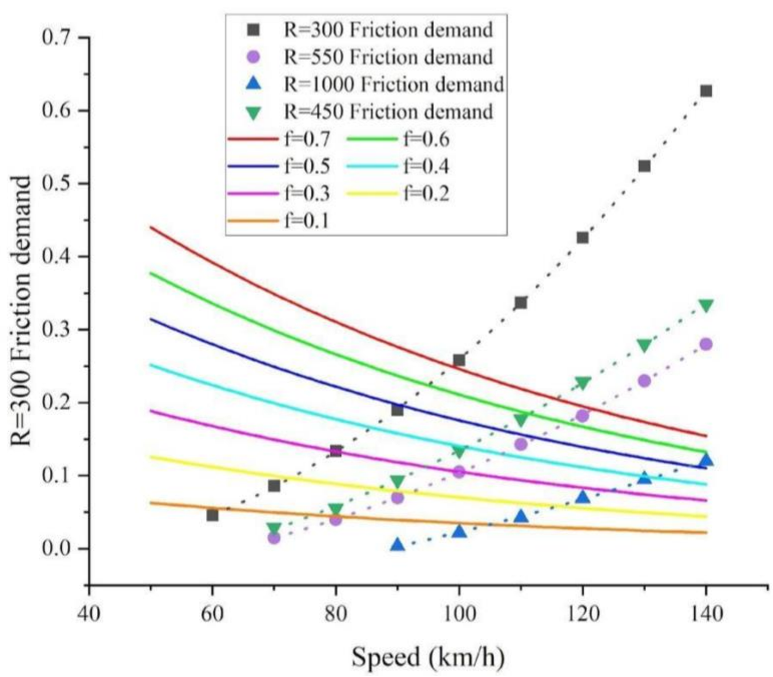


Figure C.22. Determining the intersection points of friction demand and supply curves

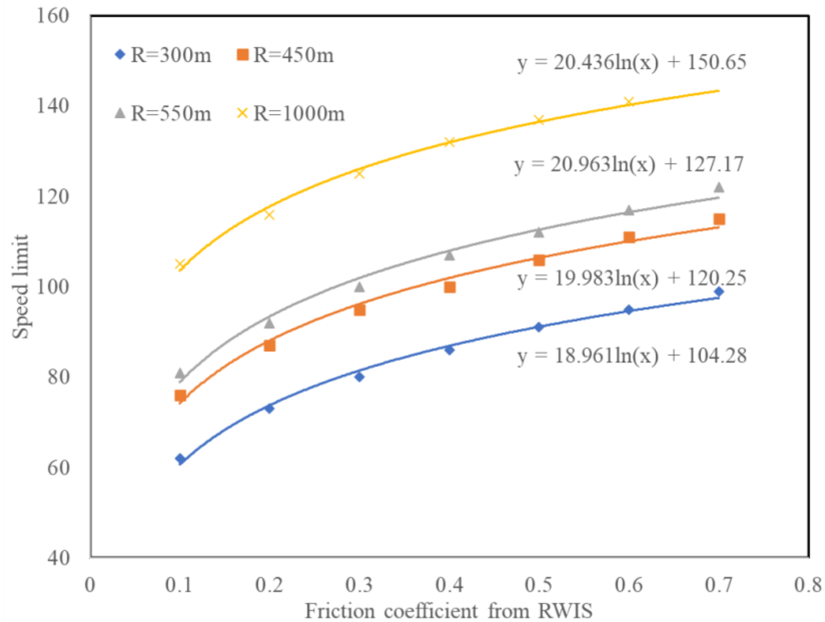


Figure C.23. Examples of speed limits at different RWIS friction values

This method aims to address the limitations of vehicle dynamic simulation for real-time control. By conducting vehicle dynamics simulation considering different vehicle types, curve radii, vertical grades, surface conditions, and superelevation values, the correlation model can quickly provide maximum safe speeds using real-time RWIS data to enable an efficient safety management system.

Comparison with the Current VSL Strategy

The current I-80 segments are equipped with both RWIS and VSL systems installed in proximity along the roadway. However, the existing VSL strategy does not utilize real-time RWIS data to calculate speed limits. Instead, the current VSLs are mainly determined based on the operating speeds of vehicles, which primarily reflects driving behavior and traffic flow under current roadway and weather conditions. Therefore, the simulation results from this study were compared with the current VSL strategy to evaluate its effectiveness in addressing safety concerns. The intent was to help determine whether the current VSLs adequately account for adverse weather and road conditions and identify the areas for improvement to enhance roadway safety.

A case analysis was conducted for a snowy day, in which the time-varying RWIS friction data were input to determine the maximum safe speed. Figure C.24 demonstrates that the simulation results and the current VSL strategy exhibit similar trends but have different values. In most cases, the current VSLs are conservative, providing an additional safety margin that reduces the likelihood of oversteering and loss of control during adverse weather. However, during sudden friction changes, the current VSL strategy may not respond immediately, potentially increasing the risk of side slips and crashes. This highlights the need for real-time and adaptive VSLs that can quickly adjust to rapid changes in road surface conditions to enhance safety.

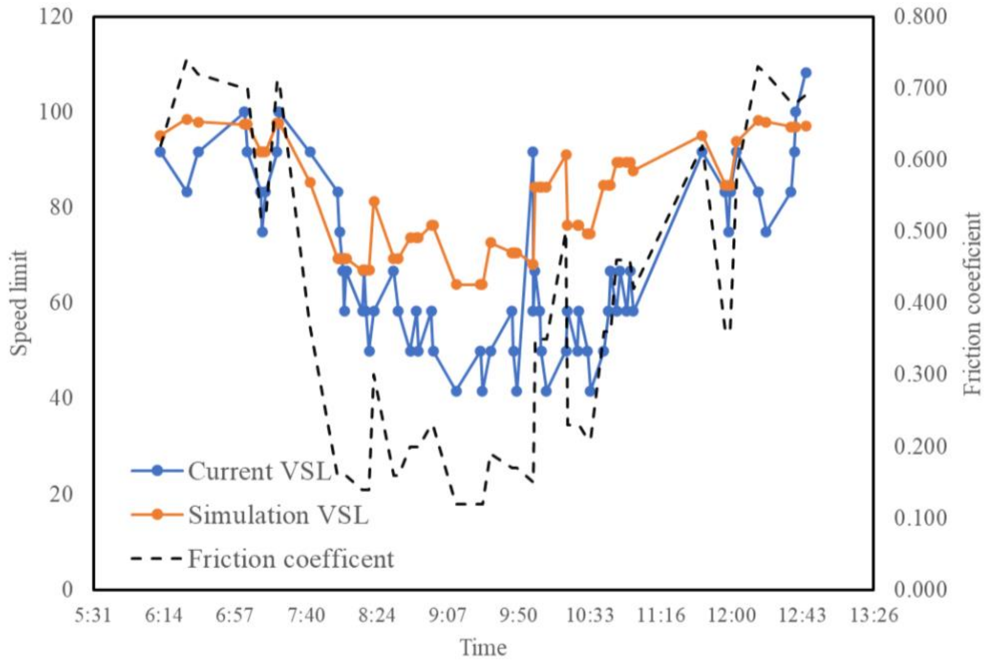


Figure C.24. Simulation VSL and current VSL under snowy weather conditions

Adverse weather conditions introduce significant variability, reducing available friction and complicating the prediction of skidding potential on curves. A vehicle that is safe at a given speed under normal conditions may become unsafe under severe weather. These dynamic conditions highlight the critical need for VSLs that can adapt in real time to current weather and road conditions. Implementing such VSLs has proven effective in reducing the risk of skidding and minimizing accidents during adverse weather. By dynamically adjusting speed limits, traffic management systems can ensure both safety and mobility.

Conclusions and Recommendations

This study developed a physics-based methodology to determine VSLs on curves under varying weather conditions based on vehicle friction demand and friction supply from road surfaces. Various factors affecting friction demand were evaluated, including vehicle type, curve radius, vertical grade, transition curve status, and superelevation. Passenger cars exhibited the highest friction demand, while curve radius, transition curve status, and superelevation significantly impacted demand. Dynamic simulation results were found to be more critical and realistic than point-mass models, as they accounted for a comprehensive whole-vehicle model, tire-road interaction, road geometry, and weather effects on surface friction. On the other hand, adverse weather conditions substantially affect road surface friction characteristics. Real-time data on surface conditions through RWIS and the speed effect on wet friction were used to estimate friction supply. Safety speeds were determined by comparing friction demand and supply curves.

VSL case studies were conducted for selected road segments along I-80 considering different road alignments and surface conditions (wet, snow, ice). During snow and ice conditions, both simulation-derived and point-mass model-derived safety speeds were found to be lower than the static AASHTO design speeds. This finding indicates that AASHTO design speeds may not be sufficient for ensuring safety under severe weather conditions, emphasizing the need for weather-responsive speed limit strategies. By integrating real-time RWIS data with advanced vehicle dynamics, the proposed model can generate speed limits that are dynamically tailored to specific road geometries and weather conditions. This approach provides a significant improvement over static speed limits and less-responsive VSL systems, offering a valuable tool for transportation agencies to proactively reduce crash risk and improve safety on horizontal curves.

The current VSLs are conservative and effective in maintaining additional safety margins under adverse weather conditions, as evidenced by the low fatal crash rate on these highway segments. However, vehicle departure crashes remain a significant life-threatening concern, particularly on curves, where safety must be rigorously ensured. The proposed model, which incorporates real-time road conditions, can serve as a valuable reference for refining current VSL strategies. In scenarios where a significant decrease in friction is observed, the VSLs should be set lower than the simulation-derived safety speeds and provide an additional safety margin. Adapting to real-time road conditions to further mitigate the risk of departure crashes can enhance curve safety.

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APPENDIX D. VSL SURVEY RESULTS

Introduction

The research objective was to investigate beneficial ways to recommend variable speed limits (VSLs) under a variety of adverse weather conditions. The team utilized collected data and developed an analysis methodology for establishing VSL algorithms that consider different terrain types, roadway geometries, and weather conditions (e.g., rainfall, snow, ice, fog). The team explored the use of machine learning (ML) algorithms and other approaches for establishing VSLs. The VSLs were set to satisfy drivers' visibility and stopping sight distance requirements and to prevent lateral slippage at curved sections considering the loss of friction due to inclement weather conditions.

In this task, a survey was used to identify state and local agencies that are using VSLs or variable speed advisories (VSAs) (applied when laws do not allow for VSLs) and to capture information on data used, triggers, who is responsible for managing the system, the extent and maturity of deployment, evaluations completed, and design specifications.

Methods

The VSL and VSA survey was developed and tested by the research team and the Aurora project panel. The survey was distributed via Qualtrics, a web-based tool, and as a PDF from December 11 through 26, 2023. The survey was sent to Aurora project panel members, Aurora pooled funded states and organizations, and Clear Roads member states and posted to the Snow and Ice List-Serv.

Results

There were 26 complete responses to the survey. Sixteen respondents indicated that they use VSLs or VSAs at their agency or organization, and 10 indicated that they do not (Figure D.1). A list of respondents who indicated that their agency does use VSLs or VSAs, the respondents' job titles, and the agencies that provided their contact information are provided in Table D.1.

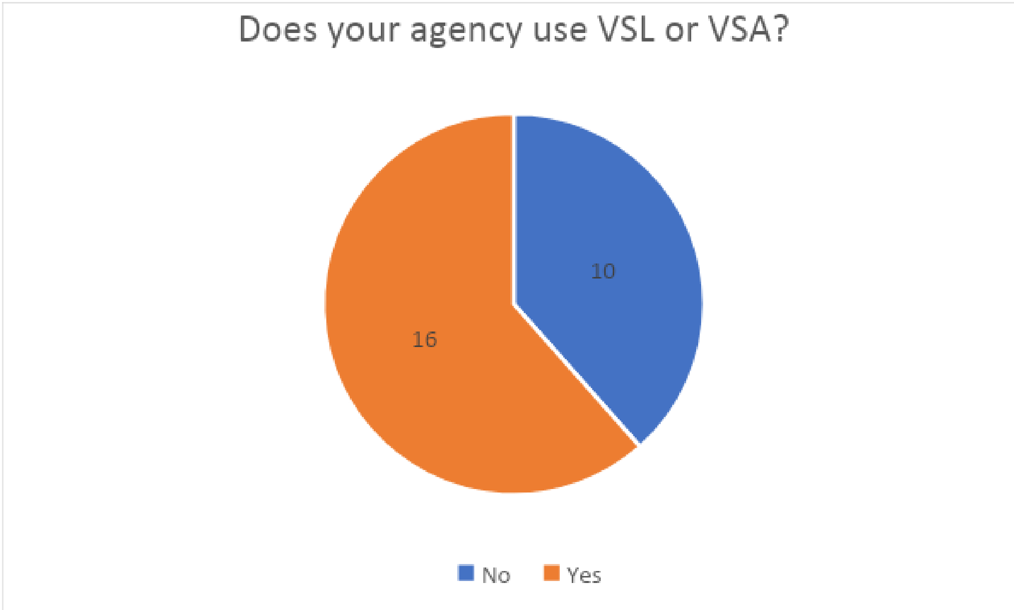

Figure D.1. Does your agency use VSLs or VSAs?

Table D.1. Responding agencies that use VSLs and/or VSAs

Job Title	Agency/Organization
Technical Engineer	Idaho Transportation Department (ITD)
ITS Engineer	Maine Department of Transportation (DOT)
Lead Statewide Snow and Ice Engineer	Massachusetts DOT
Communications Bureau	Montana (MDT)
TSMO Engineer	Nebraska (DOT)
Winter Maintenance Program Specialist	New Hampshire (DOT)
Traffic Management Administrator	Ohio DOT
ITS Engineer	Oregon DOT
Research Engineer	Texas A&M Transportation Institute (TTI)
-	Washington State DOT
TMC Program Manager	Wyoming DOT

Note that two email responses were received from the Missouri Department of Transportation (MoDOT) and Texas Department of Transportation (TxDOT) that stated the following:

- **MoDOT**: "We experimented with variable speed limits on I-270, but our application was pretty limited and was not very successful, so they were ultimately removed." This agency did not fill out the PDF or online survey.
- **TxDOT**: "TxDOT is currently looking to implement VSLs. At this stage there is still some unknown[s], so I just responded with no use of VSLs and VSAs."

Respondents were asked why VSLs and/or VSAs are initiated, and the responses show that roadway condition is the most common, followed by visibility, work zone or temporary traffic control, and traffic volume (Figure D.2). VSLs and VSAs were less often initiated due to crashes, speed, precipitation, roadway grip or friction, and temperature (air or pavement).

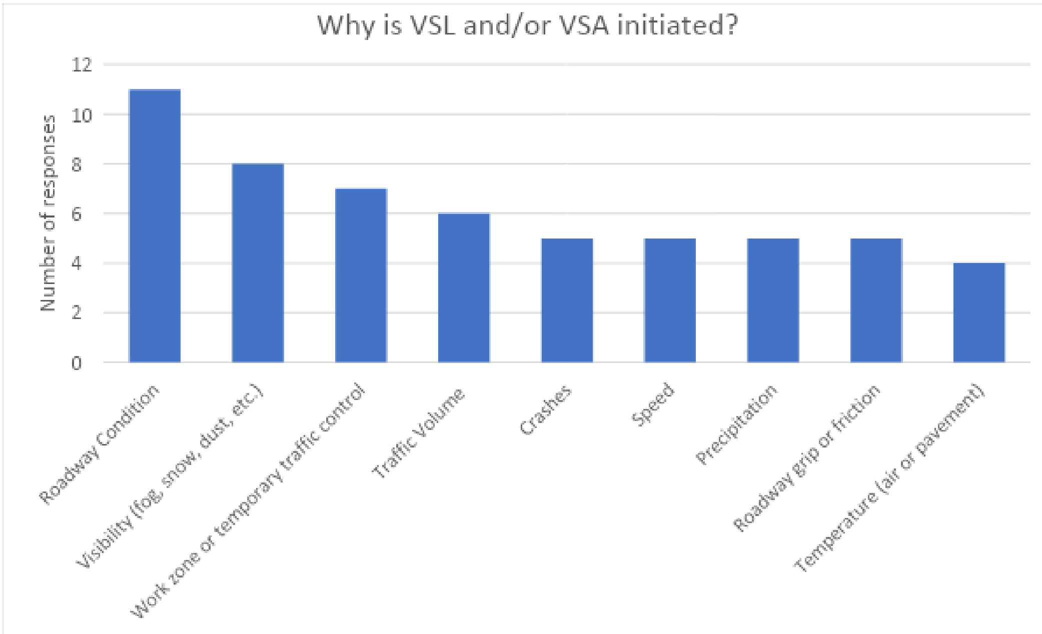

Figure D.2. Why is VSL/VSA initiated?

Four respondents indicated "Other" and stated the following:

- VSLs and/or VSAs are initiated due to congestion at a National Park entrance.
- VSLs and/or VSAs are initiated due to high winds.
- Texas is now looking into this technology.
- Temperature by itself would not precipitate a VSL or VSA, but if roads become slick, particularly due to wintery precipitation, VSAs or VSLs may be implemented.

Respondents were asked if the VSLs are enforceable or advisory, and the majority are enforceable, with equal numbers using advisory VSLs or having VSLs vary by location (Figure D.3).

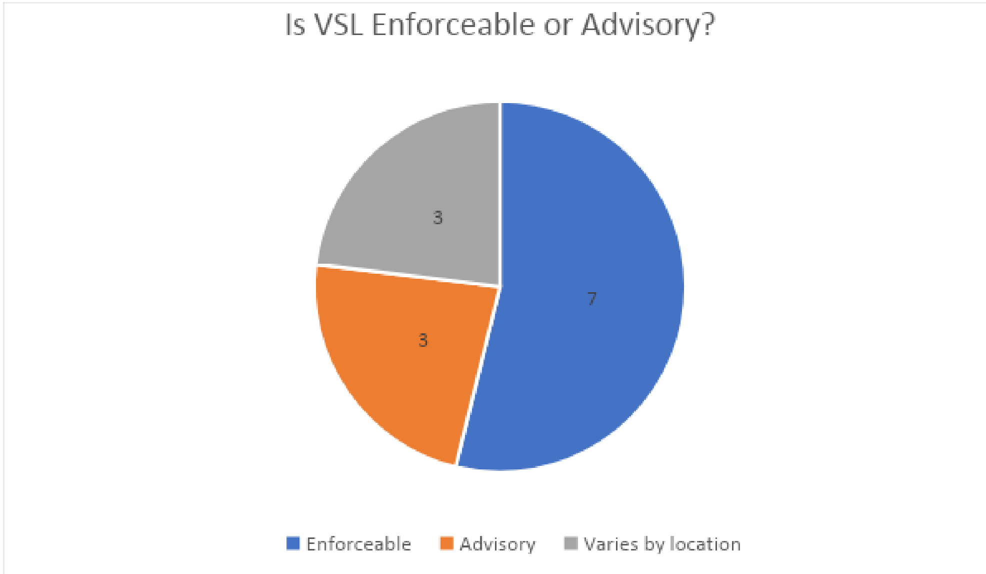

Figure D.3. Is VSL enforceable or advisory?

Respondents were asked how many years they have used VSLs and/or VSAs, with an average of seven years of use and a range of 0 years (not yet deployed) to 27 years (Figure D.4). One agency (Texas) responded that it plans to deploy both VSLs and VSAs this year (2025).

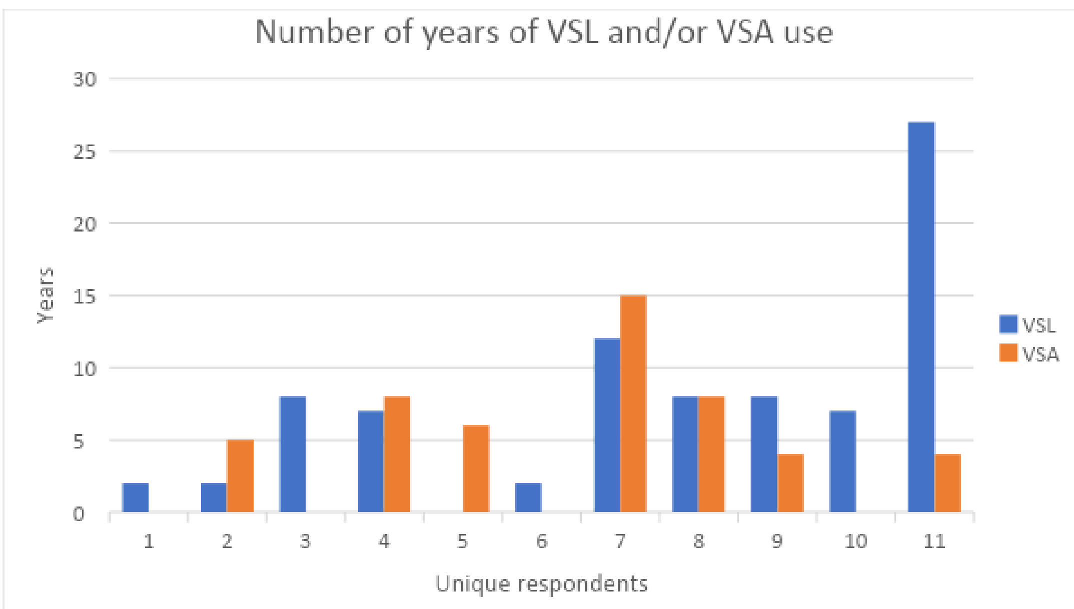

Figure D.4. Years of VSL and/or VSA use

Respondents were asked where they use VSLs and/or VSAs, with detailed responses provided in Table D.2. The most common use of VSLs and/or VSAs is on Interstate corridors, with no deployments on local roadways.

Table D.2. Locations where agencies use VSLs and/or VSAs

Agency	Road Type	Specific Location
Idaho (ITD)	Interstate Corridors	I-15 in Idaho, from 1.303 S OF CTR MCCARY RD to 0.137 N OF CTR MCCARTY RD. This was implemented due to dust storm[s] in the area. Have recently implemented variable speed in [a] work zone on I-84 in the Boise Metro area.
Maine DOT	Interstate Corridors	After every on ramp
Massachusetts DOT	US Highways	VSAs only. Not enforceable, but drivers may still be ticketed for driving too fast for conditions.
Massachusetts DOT	Interstate Corridors	VSAs and VSLs. VSLs enforceable in and of themselves only on I-90, Massachusetts Turnpike.
Montana (MDT)	US Highway	U.S. Hwy 2 at West Glacier entrance to Glacier National Park
Nebraska DOT	Interstate Corridors	I-80 and I-76 west state border to Overton, Nebraska.
New Hampshire DOT	Interstate Corridors	Not provided
Not Provided	Interstate Corridors	Not provided
Ohio DOT	Interstate Corridors	We have two locations, one is an urban interstate in Columbus that is in conjunction with hard shoulder running. The other is a rural interstate in NE Ohio off of the lake that is mainly to lower speeds due to lake effect snow storms/squalls.
Oregon DOT	State Roadways	Greater Portland Area - 6 highways with congestion and weather based VSA.
Oregon DOT	US Highways	US 97 Mile Point 143-153 - Weather Based VSL System
Oregon DOT	Interstate Corridors	I-5 Mile Point 3-12 - Weather Based VSL System. I-84 Mile Point 277-306 - Weather Based VSL System.
TTI (Texas)	State roadways, US Highways, and Interstate corridors	Planned deployment in 2024
Washington State DOT	Interstate Corridors	I-90 Snoqualmie Pass, I-5 metro area.
Wyoming DOT	State Roadways	Hwy 28 South Pass
Wyoming DOT	US Highways	US 87/I-25 Casper Marginal, I-90/US14, and 87 Bighorn Mountains and I-80/US 30
Wyoming DOT	Interstate Corridors	I-80/, I-25 and I-90 mostly Mt. passes (3 sisters, Elk Mountain, Arlington and Laramie-Cheyenne Summit)

Respondents were asked what type of signage is used to display the VSL and/or VSA to motorists (Figure D.5). Overall, roadside changeable speed limit signs and roadside dynamic message signs (DMS) and variable message signs (VMS) are most commonly used. Of the four options, overhead changeable speed limit signs were the least common display type used. Most respondents indicated that they use more than one method of signage but never more than three methods. A comment from a responding agency that uses overhead changeable speed limit signs stated that no speeds are used on overhead DMS.

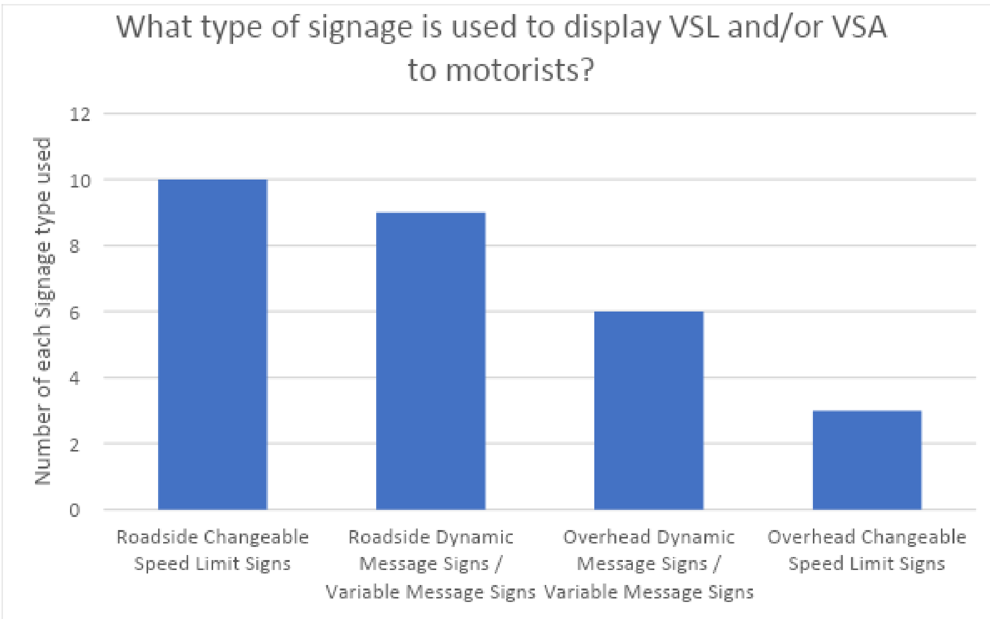

Figure D.5. What type of signage is used to display VSLs and/or VSAs to motorists?

Respondents were asked which messaging formats are used by their agency (Figure D.6). VMS and DMS were reported as the most frequently used, with news outlets reported as the second most frequently used. Social media was the least utilized messaging format. Comments from respondents indicated that among agencies where DMS and VMS are always used, internal agency notifications are provided to maintenance, and for the Massachusetts Department of Transportation (MassDOT), Mass511.com is used.

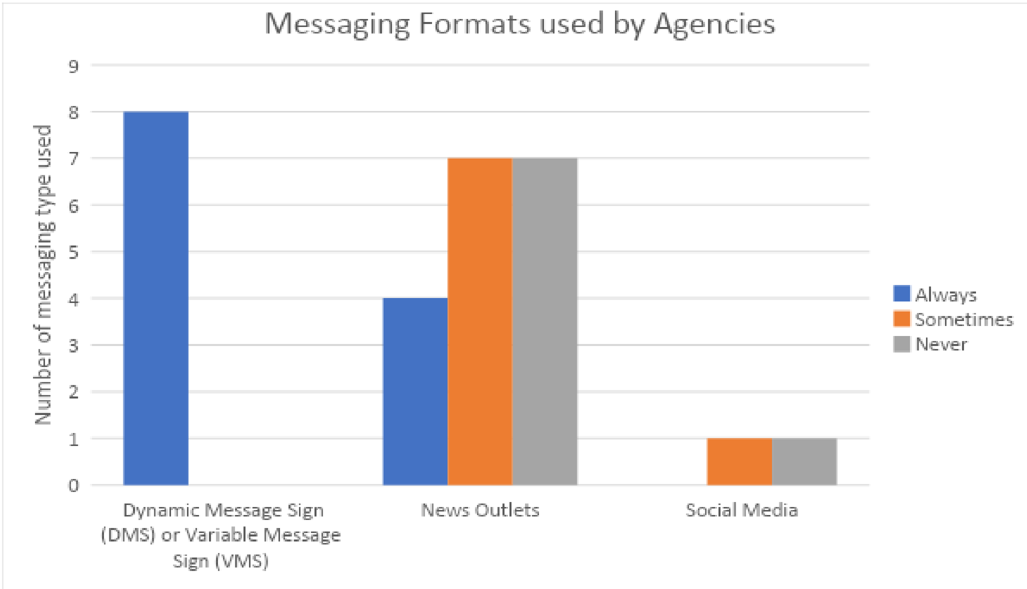

Figure D.6. Messaging formats used by agencies

Respondents were asked if VSL and/or VSA speed restrictions are specific to vehicle type. The majority, 92% (n = 11), stated no, and 8% (n = 1) stated yes. A related comment stated, "We have separate speed limits for trucks that are reduced in addition to the main speed limit reductions."

Respondents were asked which department or group within their agency supports the VSL and/or VSA (Figure D.7). While traffic management centers (TMCs) are most commonly used to support VSLs and/or VSAs at agencies, the following responses were included within "Other":

- TMC makes scheduled [speed] limit changes, Traffic Operations [Center] (TOC) determines speed limits.
- The VSL/VSA system is automated, but the TOC is able to reduce the speed limits via override if there is a sensor failure or speed limits do not match conditions.
- District field staff and leadership.
- TxDOT Safety Division.
- Traffic Operations [Center] (TOC), and Construction if it's in a work zone.

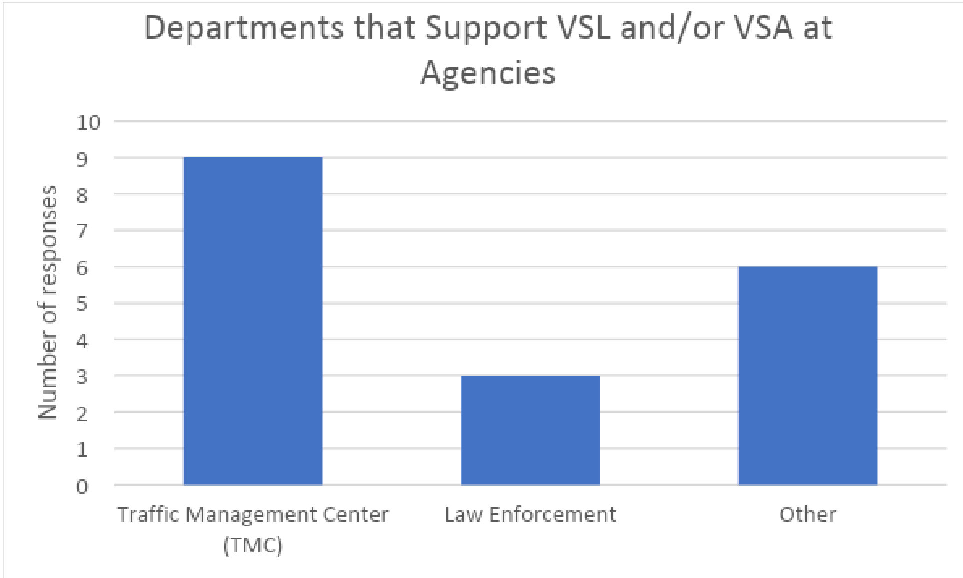

Figure D.7. Departments that support VSL and/or VSA at agencies

Respondents were asked how VSLs and/or VSAs are initiated (Figure D.8). VSLs and/or VSAs are most commonly initiated manually, but many also use a data-based or rules-based trigger. Only two responding agencies indicated that they use both a manual and a data-based or rules-based trigger. Agencies that responded "Other" provided the following additional information:

- The responding agency indicated that it manually triggers a VSL/VSA and that the VSL/VSA is manually set by a person, based on speed and activation times that were previously determined.
- The responding agency indicated that VSLs/VSAs can be triggered manually, by a data-based or rules-based trigger, or by other means and stated that they can be manually triggered by maintenance, patrol, or TMC personnel.
- The responding agency indicated that a VSL/VSA is triggered by other means and added that a VSL/VSA is usually triggered due to a state police request for certain roadways, defined by mile markers.

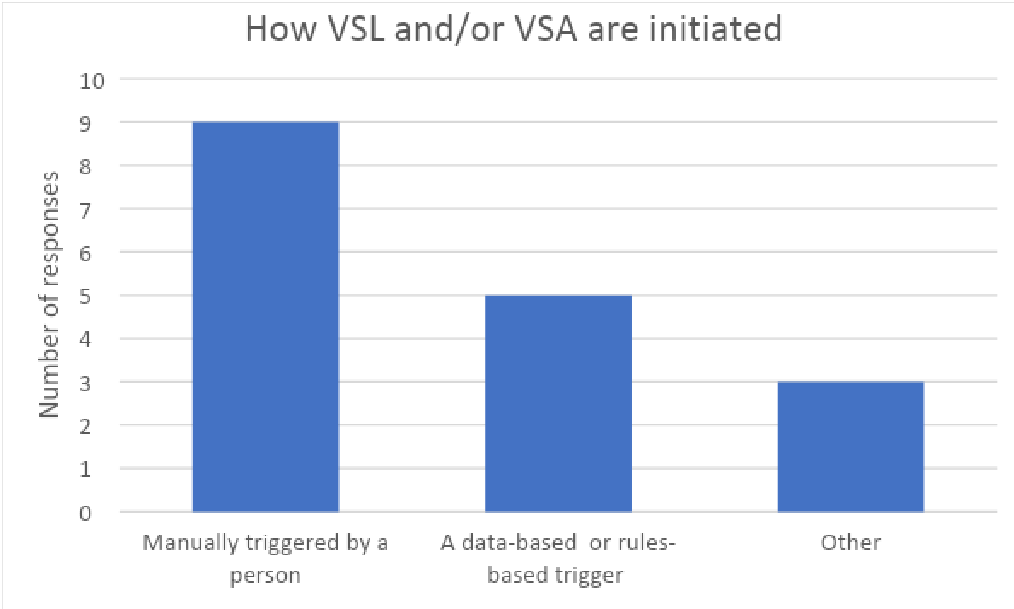

Figure D.8. How VSLs and/or VSAs are initiated by agencies

Respondents were asked what data are used to support VSLs and/or VSAs (Figure D.9). Many agencies use a combination of data sources, with cameras and RWIS or meteorological data being the most commonly used and Waze or INRIX being the least commonly used. Additional information provided by agencies on the data sources used can be found in Table D.3.

	MDT	ITD	NA	WY DOT	Oregon DOT	NH DOT	Nebraska DOT	TTI (future deployment)	WS DOT	Maine DOT	Ohio DOT	Mass DOT
RWIS or Meteorological Data			x	x	x	x			x	x	x	x
Waze or INRIX			x					x			x	
Cameras			x	x		x	x	x	x	x	x	x
Traffic Sensors				x	x			x	x		x	
Other	x	x					x					

Figure D.9. Data used to support VSLs and/or VSAs

Table D.3. Data sources used by agencies to support VSLs and/or VSAs

Agency	Data/Information Source	Detailed comments
ITD (Idaho)	Other	Weather related device that collect[s] dust information for the variable speed zone based on dust. For work zone, it is supposedly just based on time of day or when workers are present.
Maine DOT	RWIS or Meteorological Data	Pavement temperature and grip factor.
Massachusetts DOT (MassDOT)	RWIS or Meteorological Data	Rate of precipitation, roadway grip, surface conditions, prevalence of crashes.
MDT (Montana)	Other	Engineering speed zone study.
Nebraska DOT	Other	We are in the process of creating a correction factor off of the Federal Highway Administration (FHWA) equation. We use tables of friction factors based on pavement condition i.e., wet, dry, packed snow etc., with reported visibility based on number of visible delineator posts which are spaced at a rate of 20 per mile.
Ohio DOT	RWIS or Meteorological Data	The I-90 corridor is triggered mainly by warnings/advisories from the National Weather Service (NWS).
Ohio DOT	Waze or INRIX	We use this to check speeds as well.
Ohio DOT	Traffic Sensors	Our hard shoulder running corridor has separate traffic sensors for speeds.
Oregon DOT	Traffic Sensors	Wavetronix HD sensors are used to measure the volume, occupancy, and speed to determine congestion that reduces the speed limit.
TTI (future deployment)	Waze or INRIX	INRIX
TTI (future deployment)	Traffic Sensors	Bluetooth devices
Wyoming DOT (WYDOT)	Traffic Sensors	Pace speed sensor on VSL

Respondents were asked if data on VSL and/or VSA activations and supporting data are retained by their agency, with 75% (n = 9) indicating that the data are retained by their agency and 25% (n = 3) responding that the data are not retained by their agency.

VSL and/or VSA design documents were requested and provided by the Oregon Department of Transportation (ODOT) and Texas Transportation Institute (TTI). TTI provided the following news item: New Texas law allows TxDOT engineers to introduce variable speed limits (kltv.com). ODOT provided the Oregon Statewide Variable Speed Concept of Operations V2 (2017).

Respondents were asked if they have evaluated the effectiveness of their VSLs and/or VSAs and, if so, which metrics were used in the evaluation. Just under 60% (58%, n = 7) indicated that they have evaluated their VSLs and/or VSAs, and 42% (n = 5) said that they had not. For those who have evaluated the effectiveness of their VSLs and/or VSAs, crash data (n = 4), driver compliance data, crash severity data, personal experience by local supervisors and/or superintendents, and traffic speed sensor data were reported as being used for the evaluation. Additionally, the following information was referenced: "The maximum speed limit for the corridor is 70 mph, while the lowest speed limit, 30 mph, is reserved for high-impact incidents such as a long-term lane closure. The speed limit of the road is reduced in 10-mph increments as conditions warrant." Reports that evaluated VSLs and/or VSAs were provided by ODOT, *OR 217 Active Transportation Management Project: Weather-Responsive Variable Advisory Speed System Evaluation* (2017), and by TTI, *Evaluation of TxDOT Variable Speed Limit Pilot Projects* (2015).

Finally, the respondents were asked if they have made any changes to their VSL and/or VSA messaging or criteria over time. Responses received are presented in Table D.4.

Table D.4. Changes made by agencies to VSL/VSA messaging or criteria

Agency	Response
ITD	Not yet.
Maine DOT	Speed limit display signs have been phased out for message boards.
Mass DOT	VSLs have been used for almost 3 decades, but VSAs have been used for only a few years.
MDT	Yes, the VSL operation is seasonal (NP entrance), and its need has been reevaluated at the start of the park tourist season.
Nebraska DOT	No, we are deploying this year.
Ohio DOT	Not many changes, but we currently have a research project to look at VSL criteria.
Oregon DOT	Sign technology changes, and weather-based reductions have numerous changes to improve accuracy.
WS DOT	Additional messages have been added as per policy changes.
WYDOT	VSL's have become more automated by using sensors and new algorithms.

Conclusions and Key Takeaways

The following summarizes key conclusions and findings from the survey results:

- VSL and/or VSA deployments have been in place for 2 to 27 years, or an average of 7 years for VSL and 5 years for VSA. Newer deployments have occurred in Montana and Wyoming, and future deployments are planned in Texas and Nebraska.
- VSLs and/or VSAs are typically initiated due to roadway conditions, visibility issues, and work zones or temporary traffic control scenarios.

- Most applications of VSLs are enforceable, but many agencies are using a combination of VSLs and/or VSAs.
- All of the reported VSL and/or VSA deployments were on state or Interstate highways.
- Messaging was typically done using roadside changeable speed limit signs or roadside DMS/VMS.
- When messaging for an event, DMS and VMS are the most commonly used formats, followed by news outlets.
- Varying VSLs and/or VSAs for specific vehicle types is not common.
- Most VSLs and/or VSAs are supported by TMCs or TOCs.
- VSLs and/or VSAs are most commonly triggered manually by a person, followed by a data-based or rules-based trigger.
- RWIS data, meteorological data, and camera images are the most commonly used data to support VSLs and/or VSAs.
- Most agencies retain VSL and/or VSA activities and supporting data.
- About half of the agencies surveyed have evaluated the effectiveness of their VSLs and/or VSAs. Data used in the evaluations have included crash data, driver compliance data, crash severity data, personal experience by local supervisors and/or superintendents, and traffic speed sensor data.

Appendix D.1. Survey Questionnaire

The text version of the survey questionnaire is provided below.

Variable Speed Limit (VSL) and Variable Speed Advisory (VSA) Use Survey

This survey has been created to help support Aurora (https://aurora-program.org/) and its member states in their understanding of how and where Variable Speed Limits (VSLs) and Variable Speed Advisories (VSAs) are used and what information is used to support them. Information gathered in the survey will be summarized in a report documenting this project effort (https://aurora-program.org/research/in-progress/automating-variable-speed-limits-using-weather-traffic-and-friction-data/).

Participation in this survey is voluntary and you may skip any question you do not want to answer and/or you can stop at any time. Proceeding with this survey indicates your consent to participate. The survey may take up to 10 minutes. Any questions or comments can be directed to Laura Fay of WTI/MSU at laura.fay1@montana.edu. Thank you for your time.

To participate in this survey, please fill out this survey form and email it back to laura.fay1@montana.edu. Or you can complete the survey online using the QR code or the link here: https://montana.qualtrics.com/jfe/form/SV_0ifyvim8MDXw31Y

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1. Does your agency use Variable Speed Limits (VSLs) or Variable Speed Advisories (VSAs)?

- Yes
- No (If you responded no, you do not need to answer any more questions. Thank you for your time.)

2. Why is VSL or VSA initiated? (Check all that apply)

- Crashes
- Speed
- Traffic Volume
- Visibility (fog, snow, dust, etc.)
- Precipitation
- Roadway condition
- Temperature (air or pavement)
- Roadway grip or friction
- Work zone or temporary traffic control
- Other, please explain ____

3. Are your VSLs enforceable or advisory?

- Enforceable
- Advisory
- Varies by location
- Other, please explain ____

4. How long has your agency used VSLs or VSAs?

    Years of VSL Use: __________________

    Years of VSA Use:__________________

5. Where do you use VSLs/VSAs? Please provide specific corridors or generally describe the locations for both VSLs or VSAs as applies.

- State roadways ____
- US Highways ____
- Interstate corridors ____
- Rural roadways (not interstate or state roadways) _________________________
- Other, please explain____

6. What type of signage is used to display the VSL/VSA to motorists? (Check all that apply.)

- Roadside Changeable Speed Limit Signs
- Overhead Changeable Speed Limit sign
- Overhead Dynamic Message Sign/Variable Message Sign
- Other, please explain____

7. Which of the following messaging formats are used by your agency in cooperation with changes in VSL/VSA to convey additional information (e.g., Speed Limit 55, Crash Ahead)?

Dynamic Message Sign (DMS) or Variable Message Sign (VMS)	● Never	● Sometimes	● Always
News Outlets	● Never	● Sometimes	● Always
Social Media	● Never	● Sometimes	● Always
Other, please explain	● Never	● Sometimes	● Always

8. Are VSL/VSA speed restrictions specific to a vehicle type (E.g., trucks)?

- Yes, please explain ____
- No

9. Which department or group within your agency supports the VSL/VSA? (check all that apply)

- Traffic Management Center (TMC)
- State Police
- Other, please explain____

10. How are VSLs/VSAs initiated?

- A data-based (e.g., traffic speed) or rules-based trigger (e.g., traffic speed reduced by 25 mph or roadway temperature below 32°F)
- Manually triggered by a person
- More complex statistical or artificial intelligence (AI) approach
- Other, please explain____

11. What data is used to initiate the VSLs/VSAs?

- RWIS or Meteorological Data, please describe data used ________________
- Waze or INRIX, please describe data used ___________________________
- Cameras
- Other, please explain ____

12. Is VSL/VSA activation data retained by your agency?

- Yes
- No

13. If available, please email VSL/VSA design document(s) to laura.fay1@montana.edu

14. Has your agency evaluated the effectiveness of your VSL/VSA?

- Yes
- No

15. What metrics and statistics were used in the VSL/VSA evaluation? (please describe) or email the VSL/VSA evaluation report to laura.fay1@montana.edu

____
____
____
____

16. Have any changes been made to your VSL/VSA messaging or criteria over time? Please explain.

____
____
____
____

17. May we follow up to clarify a response as is needed?

- Yes
- No (If you responded no, you do not need to answer any more questions. Thank you for your time.)

If yes, please provide your contact information.

Name ____

Title ____

Organization ____

Email ____

Phone ____

Thank you for your participation in this research effort!

APPENDIX E. VSL SURVEY FOLLOW-UP INTERVIEWS FOR KEY STATES

Utah Department of Transportation

NCHRP 03-142 Survey Summary

There were two responses from the Utah Department of Transportation (UDOT) for the National Cooperative Highway Research Program (NCHRP) 03-142 survey. The following information was provided by (1) Jeff Williams, Weather Program Manager, and (2) Ryan Ferrin, Statewide Maintenance Engineer.

Utah uses both real-time weather (RTW) and variable speed limits (VSL). They use both of these technologies to reduce crashes, improve travel time, severe thunderstorm, tornado, flash flood, dense fog, and high wind warnings; freezing rain, winter storm warning, blizzard warnings, and snow fall. Roadway types for RTW and VSL varied by response (Table E.1). We may want to clarify where VSL is used.

Table E.1. Use of RTW and VSL for various roadway types

Response	Freeway	Major Arterial	Minor Arterial	Collectors
1	RTW, VSL	RTW	RTW	RTW
2	RTW, VSL	RTW, VSL	RTW, VSL	

They indicated they use both RTW and VSL in rural (n = 2) and urban (n = 1) areas. May want to clarify if VSL is used in urban areas.

They communicate RTW using dynamic or variable message signs (DMS/VMS), public media, smartphone apps, navigation services, such as Waze, other (no explanation provided). They communicate VSL using dynamic or variable speed limit sign, dynamic or variable message sign.

RTW is communicated one or more days before an event is expected, a few hours before an event, and during an event, whereas VSL is used only during an event.

Location of RTW and VSL are based on adverse weather-related crash history, general crash history, history of localized adverse weather conditions, and history of traffic congestion delay. (Note that responses varied.)

Adverse weather related RTW is delivered ad hoc processes, automated, custom message for the adverse weather event, using standard message templates combined with custom messages for the same event. Adverse weather related VSL is delivered using ad hoc processes, automated, and standard message templates. Messages provided by the traffic control room manager.

Timing of RTW and VSL messaging depends on the expected intensity of the adverse weather event and depends on the type of adverse weather event. Each response was unique here. Maybe seek clarification.

Data available: Traffic data - volume and speed, travel times, time increments, frequency (continuous or durational), archives of VSL and RTW messaging for adverse weather, archives of weather and road surface condition, availability of probe data (e.g., Waze, Wejo, Streetlight)

Pre-storm messaging was listed as very effective if provided adequately in advance of the event.

Greatest challenge when implementing adverse weather-related messages RTW and VSL noted was to not to provide obvious blanket messaging when the storm is widespread i.e., snowing statewide, do not need to place snowy condition messaging on [all] signs, rather [use] signs for impacts that may be more spot oriented.

UDOT conducted an in house assessment of the success of adverse weather-related RTW and/or VSL systems on the use of dynamic or variable message signs (DMS/VMS). The assessment considered a few days in a county or region (rural areas). Data collection included: traffic volumes, traffic speeds or travel times, weather conditions, road surface conditions. Data was collected by agency personnel or equipment. They assessed the following outcomes: reduction in weather-related crashes, reduction in crashes generally, reduction in vehicle speeds. They assessment found: significant reduction in weather-related crashes, significant reduction in crashes generally, significant reduction in vehicle speeds. Follow up with UDOT to get this assessment.

Narwhal VSL Report Summary

In 2013 the VSL decision support software was launched at the UDOT Traffic Operations Center enabling operators, decision makers, and information providers to request, approve, and notify individuals of changes to VSL signs. The programs allowed for changes to VSL to be requested, made, and then tracked. The process of automating changes to VSL began in 2019 and considered traffic near VSL. This was later improved upon allowing for UDOT weather station data input into the automated VSL system. This project specifically worked to bring the weather station data into the VSL system.

Weather events included data from snowfall rate, solar radiation, soil temperature, road grip, water depth, visibility, relative humidity, and wind gust. The weather event used most current data and the one previously collected. A time limit was put on the data collection variable to eliminate old data from being used. The following scenarios can trigger an event – snow fall rate, standing water, low visibility, and wind gust/high winds. If conditions are met for any of these scenarios, the VSL automation will trigger a weather event (Figure E.1). For example, to generate an event based on snow fall rate, soil temperature and snowfall rate are considered, such that colder soil temperatures require less snow fall to trigger the event. To generate a low visibility event, visibility must decrease to less than 0.20 and relative humidity must be greater than 75, and to trigger a wind gust/high wind event wind gust must be greater than 45 (Figure E.2). To generate a winter driving condition (road grip) event grip must be decreasing from 0.82 and snow fall must be detected, and to trigger a standing water event water depth must be increasing and greater than 0.25 (Figure E.3). Or the VSL can be manually triggered from the VSL dashboard/UI.

For active weather events, the VSL automation will manage speed limit changes at all VSL signs in the corridor affected. If data is missing this is flagged for later QA/QC and moves onto the next criteria. The speed limit ceiling only applies in automated mode, not manual or hybrid modes. The VSL is grouped corridor (considers chain laws (12,000+GVW trucks) and all vehicles), then zone group (speed differential between groups and manual weather event expiration time), then zone levels (weather stations, threshold values, end of event criteria). There is a built in VSL zone group and difference in speeds that is considered so that if you are entering or leaving a VSL zone, the speed differential will be considered. There is a traction device event that if occurring in a VSL zone, this will override the system.

When a VSL event is triggered, an event is created in the system is not already active and the weather event speed limit ceiling is initiated in the automated process, updating the VSL dashboard/UI. The VSL event will continue monitoring weather parameters until event completion conditions are met, or the weather event is manually terminated. When a VSL weather event is terminated, the VSL automation is notified, the weather event speed limit ceiling is removed, and the VSL dashboard/UI is updated.

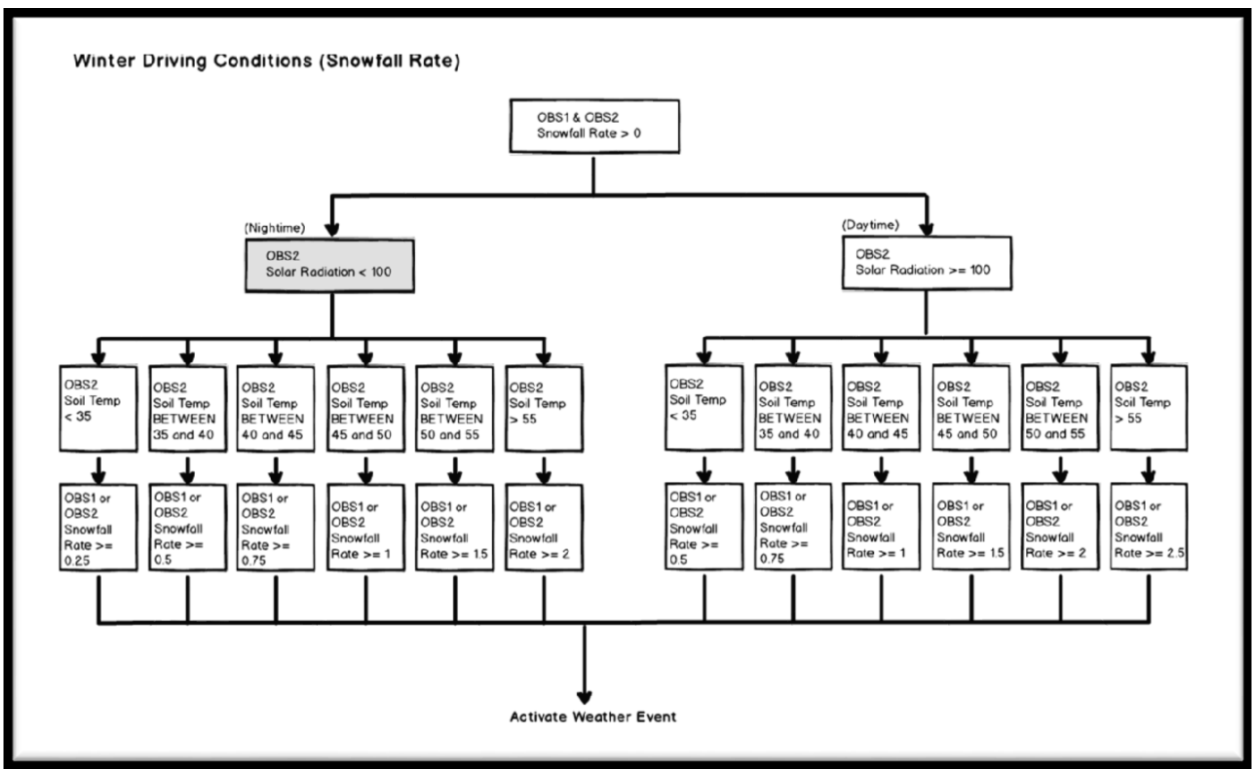

Figure E.1. Snow fall event VSL triggers (taken from Narwhal report)

RWIS data are collected every 5 minutes.

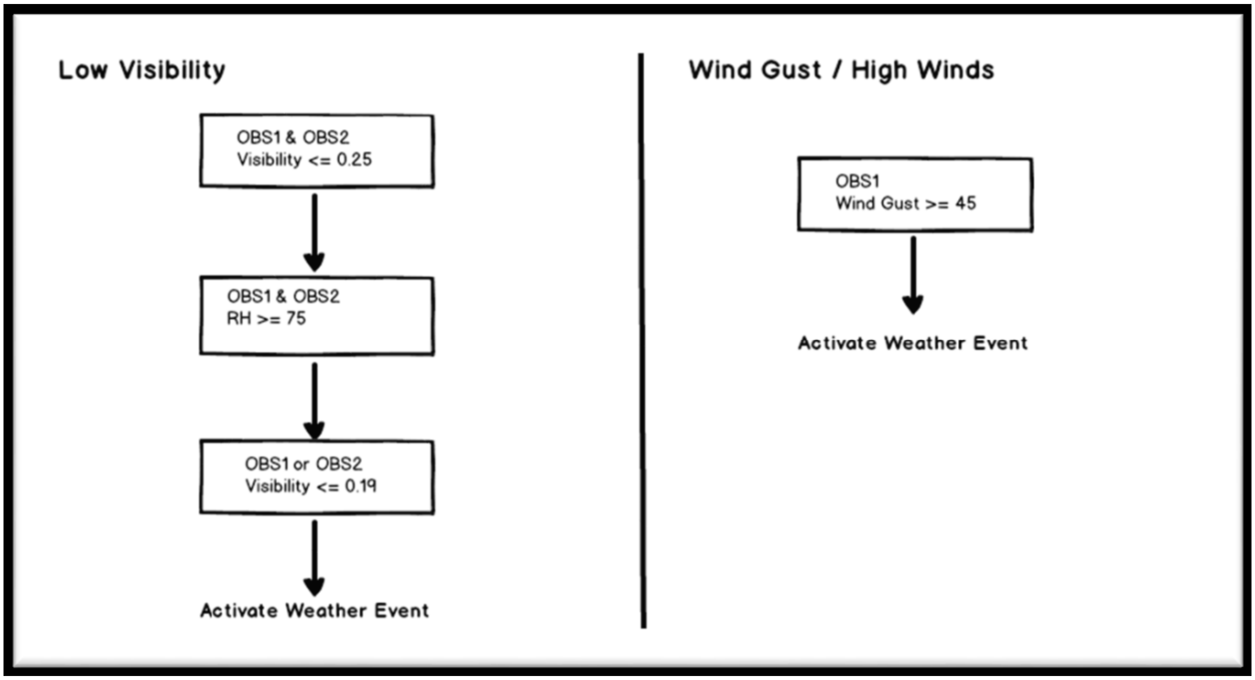

Figure E.2. Low visibility and wind gust/high wind event VSL triggers (taken from Narwhal report)

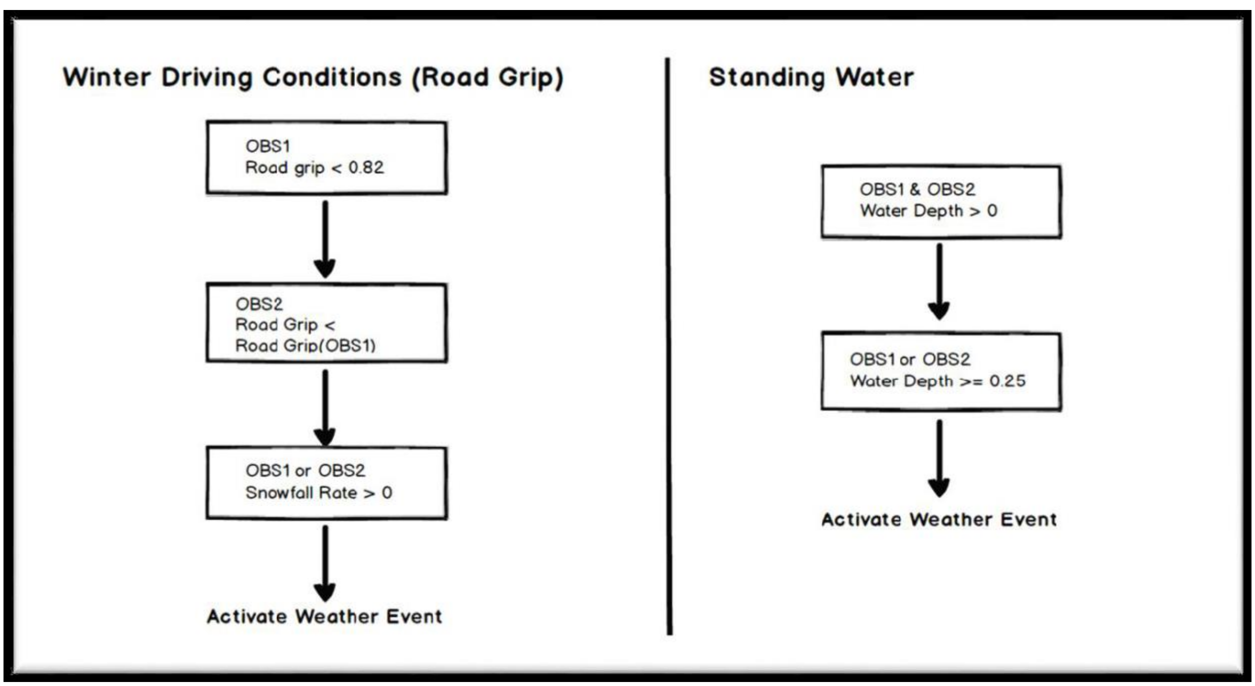

Figure E.3. Winter driving conditions (road grip) and standing water event VSL triggers (taken from Narwhal report)

Use of VSL in Construction Zones (Kimley Horn 2015)

This 2015 project investigated the use of portable VSL (PVSL) in work zones to reduce regulatory speed limits in active construction work zones to improve safety for construction personnel and the traveling public.

Specifically, about VSL in Utah:

> UDOT has a permanent variable speed zone installed in Parleys Canyon, which is a mountainous portion of Interstate 80 (I-80) east of Salt Lake City. The stretch of highway frequently experiences moderate to heavy traffic and significant elevation differences, which is compounded by frequent poor weather and low visibility. A total of fifteen permanent VSL signs are in place in both the eastbound and westbound directions within Parleys Canyon.
>
> The speed limits that are displayed are divided into four zones based on varying elevations and geography and may range from 35 mph to 65 mph. At the beginning of the variable speed limit zone, drivers are warned about the possibility of variable speed limits by a RS2-14a static sign. The posted speed limit for the roadway can differ by zone, although all speeds within a single zone are the same. Speed limits for a zone are adjusted by the traffic operations center (TOC) when it is determined to be necessary by a Traffic Engineer based on traffic and weather input from the TOC as well as input from the Utah Highway Patrol (UHP). The posted speed limits on all signs are regulatory and can be enforced by UHP. (Kimley Horn, 2015, pg. 10)

Note that this is a ConOps plan and includes options for the VSL signage, speeds, and confirmation, but does not provide data on the field deployment.

What appears to be follow-up work on this Van Jura et al. (2018) describes the implementation of the PVSL in Utah (Van Jura, J., Haines, D., and Gemperline, A. (2018). Use of Portable and Dynamic Variable Speed Limits in Construction Zones. *Transportation Research Record*, *2672*(16), 35-45. https://doi.org/10.1177/0361198118794284)

Abstract: The Utah Department of Transportation (UDOT) implemented dynamic management of portable variable speed limit (PVSL) technology to reduce regulatory speed limits through an active work space (AWS). UDOT also developed and tested an intelligent system approach to alter speed limits in construction work zones. The goal of the PVSL system was to provide a portable and dynamic system that was easy for construction personnel to use to prudently reduce speeds within an AWS and make construction work zones safer for workers and the traveling public, while limiting the need to reduce speed throughout the AWS, rather than the entire construction work zone. This was achieved through temporary regulatory reductions in driver speeds within the immediate boundary of an AWS when workers were on site and exposed to the danger of errant vehicles during active construction. The system also raises speed limits when workers were not present. This PVSL system used a dynamic variable speed limit (VSL) algorithm to raise and lower the regulatory speed limits. The PVSL system also provided a queue warning algorithm that operated independent of the VSL algorithm to control messages posted on the portable variable message sign (PVMS) trailers to disseminate dynamic information to drivers. UDOT has completed 2 years of PVSL system deployment testing in four separate construction work zones to evaluate the effectiveness of the system. This paper highlights key elements that guided development of the PVSL system, along with the successful results from deployment of the system.

I-80 Hybrid Regulatory Speed Signing Design and VSL System Evaluation

Work by Azin and Yang (2022) evaluated the use of VSL on I-80 along Parleys Canyon in Utah. UDOT noted visibility issues with the white VSL signs during inclement weather and switched them to amber signs. This effort evaluated the effectiveness of the amber signs on safety and road efficiency. The visibility of the signs was improved and the numbers were visible from a greater distance during summer and during low visibility (winter) conditions the signs were visible from a safe distance. The found the amber signs boosted flow operations and increased safety of the corridor through decreased average speed. The safety model showed a decline in both crash severity and frequency after installation of the amber signs.

Other links, new articles, reports:

- https://www.udot.utah.gov/connect/2014/01/16/variable-speed-limit-signs-now-activated-on-i-80/
- https://www.arcgis.com/home/item.html?id=815ead7b87bb4d09872707495205445c#!
- https://www.itskrs.its.dot.gov/node/209879
- https://udotinput.utah.gov/l6727
- Presentation on VSL in Parleys Canyon

Pennsylvania Department of Transportation

NCHRP 03-142 Survey Summary

There were two responses from the Pennsylvania Department of Transportation (PennDOT) for the NCHRP 03-142 survey. The following information was provided by (1) Bill Blayon Jennueh, Civil Engineer, and (2) Daniel Farley, Director of Traffic Operations and Winter Management Programs. Note that there are differences between responses within many of the questions, and these are noted below.

Pennsylvania uses both real-time weather (RTW) and variable speed limits (VSL), with a goal for both to reduce crashes, improve travel time; with the following indicated for both or only RTW (varied by respondent): severe thunderstorm warning (RTW only), tornado warning (RTW only), flash flood warning, dense fog warning, high wind warning, freezing rain, winter storm warning, blizzard warning, snowfall, and vehicle and speed restrictions due to weather.

RTW and VSLs are used on freeways and major arterials.

They communicate RTW to drivers using dynamic or variable message signs (DMS/VMS), public media, highway advisory radio (HAR), smartphone apps, navigation services, such as Waze, 511PA website and mobile application. They communicate VSL to drivers using dynamic or variable speed limit sign, dynamic or variable message sign.

RTW and VSL messages are used in rural and urban areas. Messaging for RTW is typically used provided one day before an event, a few hours before, and during the event. Whereas VSL is typically provided a few hours before, and during the event. RTW and VSL locations were selected based on adverse weather-related crash history, general crash history, history of localized adverse weather, and RTW only for history of traffic congestion/delay.

VSL messages are delivered on an ad-hoc and using standard templates. Whereas RTW messages are delivered on ad-hoc, automated, using standard templates, custom messages for adverse weather events, and using combinations of standard message templates and custom messages for the same event. Traffic management center supervisors are responsible for messaging with policy directions on types and what messages can be reported. Also have a priority message based on the type of information being displayed to the public.

Timing of RTW and VSL for blizzards or significant storm events follows a plan and active messaging based on as needed and as conditions change. Winter VSL policy is in its first season. RTW policy has been operating for several years and works with the state Vehicle and Speed Ban Framework as well during adverse weather conditions.

Data available: Traffic data - volume and speed, travel times, time increments, frequency (continuous or durational), archives of VSL and RTW messaging for adverse weather.

PennDOT has found great success with RTW and VSL by keeping traffic flowing with no closures during adverse conditions regardless of travel time reliability is more critical to return to normal. We have been very aggressive with vehicle and speed restrictions with trucks in the right lane only with success in reducing full closures during winter events. The greatest challenge with RTW and VSL is the balance of driver acceptance along with staff understanding the balance of data driven messaging versus safety messaging at the right time.

PennDOT conducted an in-house assessment of the success of RTW and/or VSL systems looking at the dynamic or variable message signs (DMS/VMS), public media over winter season and looking at major events. The assessment was statewide, county or region (rural areas), and site-specific. Data used in the assessment included: traffic volumes, traffic speeds or travel times, crash occurrence, weather conditions, road surface conditions, and AVL response with location and application approach. Data was collected through agency personnel or equipment, crowdsource or probe data (e.g., Streetlight, Wejo, etc.). Outcomes assessed included reduction in weather-related crashes, reduction in crashes generally, and they found significant reduction in weather-related crashes, significant reduction in crashes generally.

Wyoming Department of Transportation

NCHRP 03-142 Survey Summary

There was one response from the Wyoming Department of Transportation (WYDOT) for the NCHRP 03-142 survey, from Vince Garcia, GIS/ITS/TMC Program Manager who leads the group that is responsible for messaging for traffic ops and safety.

WYDOT uses both RTW and VSL, with the goal of reducing crashes, improving travel time, dense fog warning, winter storm warning, blizzard warning, snowfall, black ice, limited visibility for any reason, slick roads, etc. RTW only is used for thunderstorms, tornados, flash floods, and high wind warnings.

RTW and VSL are used on freeways, whereas only RTW is used on major and minor arterials. Adverse weather related messaging using VSL are provided in Rural and Urban environments, whereas RTW is only provided in rural areas.

RTW messages are communicated to drivers using dynamic or variable message signs (DMS/VMS), Public media, Highway advisory radio (HAR), and smartphone apps. VSL messages are communicated to drivers using dynamic or variable speed limit sign.

RTW messages are provided one or more days before the expected weather conditions and during the event, whereas VSL is only provided during events. The timing of messaging depends on the type of adverse weather event.

The location of RTW and VSL are based on Adverse weather-related crash history, General crash history, and History of localized adverse weather conditions.

VSL messages are conveyed using automated processes and custom messages for adverse weather events. RTW messages are conveyed using ad-hoc, standard message templates, and Standard message templates combined with custom messages for the same event. When messaging WYDOT tries their best to deliver the problem, location and recommended action (PLA) for any event on the highways. Our TMC is responsible for developing the messages but field personnel have a great deal of input. As much as possible, we attempt to use standard templates but some situations require custom messages.

Data available: Traffic data - volume and speed, travel times, time increments, frequency (continuous or durational), Archives of VSL and RTW messaging for adverse weather, archives of weather and road surface condition.

Successful strategies include Our VSL strategy is focused on reducing the speed distribution in a traffic stream. If we can get all cars moving through a corridor like a train, we reduce the number of conflicts. The biggest challenge is raising VSLs after a weather event has passed has been our greatest challenge. We are working on this with a semi-automation process.

WYDOT had an outside agency/organization assess their VSL, dynamic or variable message signs (DMS/VMS), public media, highway advisory radio (HAR), smartphone apps, and other systems. This was a statewide assessment completed a few years back. Data collected included public acceptance of systems by outside contractors. They did an evaluation of crashes, vehicle speeds, speed variability with VSLs and found significant reduction in crashes generally, significant reduction in vehicle speeds, significant reduction in speed variability.

Colorado Department of Transportation and E-470 Toll Way in Colorado

NCHRP 03-142 Survey Summary

There were three responses from the Colorado Department of Transportation (CDOT) and one from the E-470 tollway in Colorado for the NCHRP 03-142 survey. The following CDOT respondents provided information: (1) John Lorme, Director of Maintenance and Operations, (2) Ben Acimovic, Traffic Engineer in Traffic Operations, and (3) Negar Karimi, Operations Engineer. The respondent from the E-470 tollway was Christopher Ricks, TMC and Safety Patrol Manager. Note that there are differences in responses within many of the questions, and these are noted below.

Note that E-470 only uses RTW which will be summarized here. RTW is communicated to drivers dynamic or variable message signs (DMS/VMS), public media, smartphone apps, navigation services such as Waze. This is done in urban and rural environments. RTW is used one day, a few hours, and during weather events. The location of the RTW was selected based on adverse weather-related crash history, general crash history, history of localized adverse weather conditions, history of traffic congestion/delay, and roadway weather sensors. RTW messages are done ad-hoc, automated processes, standard message templates, custom messages for the adverse weather event, and combination of these. Essentially, they use pre-canned messages and real-time specific messages due to road conditions. General templates are used for advanced notice and alter as road conditions change. Messaging is done by the admin services supervisor (see VSM policy doc). The timing of messaging depends on the expected intensity of the adverse weather event. Data available: traffic data - volume and speed, travel times, time increments, frequency (continuous or durational), archives of VSL and RTW messaging for adverse weather, archives of weather and road surface condition. They have seen success in social media and VMS messages, with the greatest challenge being high speeds of our road (75 mph posted speed). They did an in-house assessment of dynamic or variable message signs (DMS/VMS), public media, and smartphone apps a few years ago for county or region (rural areas), city or metropolitan areas (urbanized areas). In the assessment they used traffic volumes, traffic speeds or travel times, crash occurrence, weather conditions, road surface conditions using data collected by agency personnel. Outcomes assessed included reduction in weather-related crashes, reduction in vehicle speeds and they found significant reduction in weather-related crashes, significant reduction in crashes generally, significant reduction in vehicle speeds.

Note that one CDOT employee indicated that they use VSL only, while two others indicated that they use both RTW and VSL. A summary of these responses is provided here. CDOT hopes to reduce crashes. We hope to improve travel time reliability, specifically to reduce crashes, improve travel time, severe thunderstorm warnings, dense fog, high wind, freezing rain, winter storm, blizzard warning, snowfall. Specifically for RTW tornado, flash flood, high wind warning and most any event that affects traffic and safety.

RTW and VSL are used on both freeways and major arterials, with RTW only on minor arterials, in rural and urban areas.

RTW messaging is conveyed to drivers using dynamic or variable message signs (DMS/VMS), public media, highway advisory radio (HAR), smartphone apps, navigation services, such as Waze. VSL messaging is conveyed to drivers using dynamic or variable speed limit sign, dynamic or variable message sign. RTW messaging is conveyed one day before, a few hours before and during storm events, whereas VSL messaging is conveyed a few hours before and during storm events. RTW messaging is done on an ad-hoc basis, using automated processes, standard message templates, custom messages for the adverse weather event, and a combination of these. VSL messaging is done using ad-hoc, automated processes, and standard message templates. We developed a variable message sign operations SOP. The real-time operations team and PIO Office is responsible for messaging. The timing of messaging The timing depends on the type of adverse weather event and is based on the state winter operations plan. We use an algorithm for all VSL corridors.

RTW locations are selected based on adverse weather-related crash history, history of localized adverse weather conditions, and history of traffic congestion/delay. Whereas VSL locations are selected based on adverse weather-related crash history, general crash history, history of localized adverse weather conditions, and history of traffic congestion/delay.

Data available: traffic data - volume and speed, travel times, time increments, frequency (continuous or durational), archives of VSL and RTW messaging for adverse weather, archives of weather and road surface condition, availability of probe data (e.g., Waze, Wejo, Streetlight).

Successful practices include advanced warning and real-time ops, but they have had challenges with testing and integration.

One of the three respondents indicated an outside organization assessed dynamic or variable message signs (DMS/VMS) over a few months at site-specific locations. Data used in the assessment include traffic volumes, traffic speeds or travel times, crash occurrence, and weather conditions that were collected by agency personnel. They assessed reduction in vehicle speeds, and found significant reduction in vehicle speeds. Another respondent indicated - we are working on the evaluation as we deploy VSL algorithms.

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