MOUNTAIN-PLAINS CONSORTIUM

MPC 22-488 | B. Azin and X. Yang

I-80 HYBRID REGULATORY SPEED SIGNING DESIGN AND VSL SYSTEM EVALUATION

A University Transportation Center sponsored by the U.S. Department of Transportation serving the Mountain-Plains Region. Consortium members:

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Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
MPC-610		

4. Title and Subtitle	5. Report Date
I-80 Hybrid Regulatory Speed Limit Signing Design and VSL System Evaluation	September 2022
	6. Performing Organization Code
7. Author(s) Bahar Azin Xianfeng Yang	8. Performing Organization Report No. MPC 22-488
9. Performing Organization Name and Address University of Utah Salt Lake City, UT 84112	10. Work Unit No. (TRAIS) 11. Contract or Grant No.
12. Sponsoring Agency Name and Address Mountain-Plains Consortium North Dakota State University PO Box 6050, Fargo, ND 58108	13. Type of Report and Period Covered Final Report 14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract

A variable speed limit (VSL) is one of the traffic management tools that can maintain network safety performance in the presence of variable road hazards. Road networks plagued by consistent weather or work zones affecting driving conditions are where VSL systems could improve safety. Depending on the road condition and objective of the VSL installation, the system could be advisory or regulatory. In a segment of the I-80 freeway in Parley's Canyon, Utah, due to elevation variation and snowstorms in winter, a variable speed zone is deployed on a segment of the road. Meanwhile, due to harsh weather in the road segment, signs designed with a white legend on a black background have shown to have limited visibility in these environments. Therefore, the Utah Department of Transportation (UDOT) has substituted the sign with an amber legend for improved visibility. This study tries to evaluate the effectiveness of new signs on corridor safety and compare road efficiency with both signs. The analysis is done using field trip recordings, recorded data of various sensors in this corridor, and crash data. Also, a safety evaluation model is developed to assess the traffic operation functionality and safety in response to the VSL system's automation and visibility of the new signs on the road. Driver compliance rate and road safety outcomes by the models determine the impacts of the new system on road safety.

17. Key Word	18. Distribution Statement
Variable Speed Limit, Visibility, Traffic Management, Safety Evaluation, Safety Model, Machine Learning.	Public distribution

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	58	n/a

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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September 2022

Acknowledgments

The authors acknowledge the Utah Department of Transportation (UDOT) for funding this research and the following individuals from UDOT on the Technical Advisory Committee for helping to guide the research:

- Glenn Blackwelder (Operations Engineer)
- Justin Wilstead (Standards and Innovation Manager)
- Tyler Laing (ITS Program Manager)
- John Leonard (Operations Engineer)
- Vincent Liu (Research Project Manager)

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ABSTRACT

A variable speed limit (VSL) is one of the traffic management tools that can maintain network safety performance in the presence of variable road hazards. Road networks plagued by consistent weather or work zones affecting driving conditions are where VSL systems could improve safety. Depending on the road condition and objective of the VSL installation, the system could be advisory or regulatory. In a segment of the I-80 freeway in Parley's Canyon, Utah, due to elevation variation and snowstorms in winter, a variable speed zone is deployed on a segment of the road. Meanwhile, due to harsh weather in the road segment, signs designed with a white legend on a black background have shown to have limited visibility in these environments. Therefore, the Utah Department of Transportation (UDOT) has substituted the sign with an amber legend for improved visibility. This study tries to evaluate the effectiveness of new signs on corridor safety and compare road efficiency with both signs. The analysis is done using field trip recordings, recorded data of various sensors in this corridor, and crash data. Also, a safety evaluation model is developed to assess the traffic operation functionality and safety in response to the VSL system's automation and visibility of the new signs on the road. Driver compliance rate and road safety outcomes by the models determine the impacts of the new system on road safety.

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LIST OF ACRONYMS

ANN	Artificial Neural Network
CMS	Changeable Message Sign
FHWA	Federal Highway Administration
ML	Machine Learning
MP	Mile Post
MUTCD	Manual on Uniform Traffic Control Devices
SVM	Support Vector Machine
TOC	Traffic Operations Center
VSL	Variable Speed Limit
UDOT	Utah Department of Transportation

EXECUTIVE SUMMARY

Due to its ability to adapt to continuously changing conditions, dynamic traffic management can help boost the flow's operational functionality. Road driving conditions are variable in traffic networks and require dynamic control to assure driver safety. One system used in dynamic driving environments is the variable speed limit (VSL), which adjusts the speed limit considering the road conditions. Due to exposure to frequent inclement weather in Parley's canyon, the Utah Department of Transportation (UDOT) has implemented VSL signs on I-80 from MP 128 to 141. Changeable message signs (CMS) are designed to have a white legend on a black background based on the Manual on Uniform Traffic Control Devices (MUTCD). However, signs with a white legend in this corridor are less visible in snowstorms and direct sunlight due to the specific road's landscape. Since the low visibility invalidates VSL's primary goal, which is enhanced safety, these signs are substituted by signs with an amber legend. The manual speed adaption of the system has also changed to automated using real-time traffic data. A detailed evaluation of the road is conducted to find the new system's performance and efficiency, especially corridor safety. Using traffic flow data and machine learning (ML) methods, safety models are developed to predict the road's safety.

The VSL system is used in Europe and many U.S. states to improve road safety. VSLs may have different purposes and each will have a specific algorithm to regulate the speed. VSLs with amber legends are employed on roads in many states due to unusual weather conditions or work zones. However, the purpose of using an amber legend is to improve visibility and alert drivers for unusual driving conditions downstream. Driver's compliance rate and average flow speed are the VSL system's most common performance indicators. Studies have applied driver's reactions and road conditions to evaluate safety. Safety appraisal studies describe the safety qualitatively by either analyzing road design policies or using numerical equations to determine crash rates and their features. Quantitative methods have shown more precise results in road safety areas, and recently, ML methods have outperformed other numerical methods.

In the first stage of this study, multiple road field trips and recording of VSLs have been executed to observe drivers' views from the road and compare the signs' visibilities. The field trips are done in summer for direct sunlight and in winter for limited visibility due to fog and white snow in the background. Next, using traffic flow data, displayed speed limit, weather index data, and crash rates, a road's performance is compared in bi-weekly periods during winter. Finally, ANN and SVM are used to model crash frequency and severity for the corridor, and developed models are used to estimate road safety with the new system.

Based on study results, the corridor's average speed and speed variation are reduced after implementation of new signs. Drivers tend to drive closer to the speed limit; and the compliance rate, which is the critical indicator of the VSL system performance, has improved. The new signs have resulted in significantly lower crash rates and severity. A crash severity decrease is detected mostly during inclement weather, such as icy roads and lower visibility, which proves the effectiveness of the new signs for greater road safety. Also, the safety model shows with high accuracy that road crashes will be reduced using the amber legend for VSL signs.

1. INTRODUCTION

1.1 Problem Statement

Inclement weather, such as snowstorms and fog, will change driver behavior, affect traffic operations and impact visibility. Such conditions, which affect driver behavior and traffic flow situations, have caused many crashes and fatalities in the United States over the past decade (H. M. Hassan, Abdel-Aty, Choi, & Algadhi, 2012). Due to inclement weather on some road segments, road information and timely notifications are needed. Physical road conditions, such as grade, altitude, and curvature, alongside inclement weather will result in various unusual driving conditions. In these cases, changeable message signs (CMS) are implemented using data regarding traffic flow or environmental conditions to warn drivers about upcoming road situations for ensured safety. CMS systems work with visibility detectors to warn drivers about incidents and adverse road circumstances (Federal Highway Administration, 2009; H. Hassan, Abdel-Aty, & Oloufa, 2011; H. M. Hassan & Abdel-Aty, 2011; H. M. Hassan et al., 2012). CMS applications are not limited to the latest conditions, they can be used for lane closures due to incidents, work zones, and wildlife crossings. The choice of variable speed limit over static speed limit signs is for less-than-ideal conditions in which drivers need to be assisted for traffic behavior and environmental changes. In other words, if any conditions adversely affect braking distance or visibility, drivers will require some form of guidance to aid them in navigating variable driving conditions.

The wide range of cases utilizing CMSs has proved they will manage traffic flow according to the road environment and increase safety. A VSL is one of the CMS uses that will justify a speed limit based on the dynamic road situation. A VSL system for low visibility conditions has been proven to result in crash reduction, mean speed decline, improved driver responses to the VSL, and reduced speed variance (Rämä, 1999; Sisiopiku & Professor, 2001). Limited visibility will decrease stopping sight distance, which will increase the risk of rear-end crashes and adapting to the appropriate speed. Downstream road dynamics will improve safety and correlate driver behaviors to the existing conditions (Bertini, Boice, & Bogenberger, 2006; Gonzales, Fontaine, & Dutta, 2019; Wu, Abdel-Aty, Wang, & Rahman, 2019). The benefits of a VSL include not only increased safety and fewer crashes, but it can also help decrease travel times compared with road segments with static speed limit signs (Abdel-Aty, Dilmore, & Dhindsa, 2006a; C. Lee, Hellinga, & Saccomanno, 2004).

Due to the volatile nature of weather fluctuations on a section of I-80 from Salt Lake City to Parley's Canyon, UDOT has applied a VSL zone from MP 128.0 to MP 141.0 on both east and west approaches. According to MUTCD, CMSs should have amber colored legends for warning signs and white on a black background for regulatory signs (Federal Highway Administration, 2009). Yet, during inclement weather in cold seasons or intense sunlight in warm seasons on the I-80 corridor, the signs might be indistinct for drivers. This is counterproductive as the VMS is needed the most during these specific conditions in order to have maximum positive impact on road safety and traffic control. For this issue, UDOT has applied an approach to transform VSL signs with a white legend by an amber legend on the black background.

This report studies the VSL sign legend color's effectiveness from white to amber on the sign's visibility and road safety by analyzing VSL system performance before and after implementation. Another adjustment UDOT has applied to the CMS system is developing an online-based system, which will automatically change the VSL performed by the traffic operation system. To evaluate the system's performance after automatization, another goal of this study is to analyze safety performance and compare driver compliance rates before and after this variation.

1.2 Objectives

This study's main objective is to analyze the road's safety and performance after implementing the amber signs and automation of the VSL system. For this purpose, multiple field recordings of signs are conducted to determine the visibility alteration from the driver's perspective. Also, various cases using VSL with an amber legend are reviewed to comprehend its effects on safety and functionality of the transportation network. Next, using the occurrence data, corridors weather index data, displayed speed limit, and crash records, a thorough review of operationality and safety improvement with the recent transformation is conducted.

Ultimately, using ML models, two safety evaluation models are developed to estimate crash severity and crash frequency. ANN and SVM classification modes are employed to classify crash level and severity based on road geometric design, traffic flow data, and driving conditions. Developed models are applied to study the impact of new signs on road safety.

1.3 Scope

Current research scopes include:

1. VSL implementations with an amber legend in actual cases, studies about VSL systems, and safety evaluation methods are reviewed.
2. Multiple recordings are made after and before the amber legend signs were installed, and video snippets were provided for comparing visibility.
3. For an elaborate study of road operations, supplementary data, such as traffic flow by sensors along the highway, crash records, VSL logs, and weather at corresponding times, are obtained. Recent data are pulled out for fall 2018 and 2019 and winter 2019 and 2020 to include effective variables in VSL zone safety.
4. Lastly, safety evaluation is modeled to estimate crashes and find the outcome of the new system in road performance and safety.

1.4 Outline of the Report

This report presents the findings of the research within the following sections:

- Introduction
- Real-Case Studies and Literature Review
- VSL Zone Records
- Data Analysis
- Safety Evaluation Modeling
- Conclusions and Key Findings

2. LITERATURE REVIEWS

2.1 Overview

In this chapter, studies about VSL systems, their algorithms, purpose of use, and performance evaluations are reviewed. Multiple VSL application reports are summarized. Finally, methods and research about safety evaluations and road safety are explored, and a summary is provided.

2.2 VSL Literature Review

Warning, regulatory, and guidance information are among the CMS applications. Hence, they can be used for areas where there is a need for VSLs. The MUTCD indicated that CMS backgrounds should be black with a white legend for regulatory signs and have an amber legend for warning and temporary traffic control signs (Federal Highway Administration, 2009). While this regulation exists, the need for VSLs due to special events and hazardous situations may raise some expectations in legend regulations. The VSL sign is deployed in some U.S. states and Europe based on different needs and algorithms. These systems utilize traffic variables and road conditions to modify the speed limit. The statistics prove that safety, congestion, and even pollution have decreased with the VSL system. The VSL system may be used for traffic management, hazardous weather fluctuations, and in work zones, and the algorithms employed are related to the scope of the application correspondingly.

The weather-related algorithm might use the visibility of a road segment based on sensor data, friction factor sensor collected data, or manually based on road conditions to set the speed limit (G. Chang & Kang, 2008; Katz et al., 2012). A VSL system for weather use considers several variables for the speed limit and can be operated automated, semi-automated, or manually. The algorithm is based on roadway conditions and visibility. According to the FHWA, the VSL algorithm used for wet weather considers design speed, operating speed, minimum speed, roadway geometrical characteristics, and sight distance from a site study or sensors. It will check for weather conditions on the road and use the minimum 85th percentile of operating speed and design speed for typical situations and the determined speed based on road conditions or design speed in wet weather. In case the determined speed is less than the 85th percentile of operating speed, the speed limit regulation for the normal condition is applied (Katz et al., 2012). In some cases, the VSL is advisory as the preceding vehicle's speed (Texas A&M Transportation Institute, 2017).

In a recent case in Wyoming where the VSL system is deployed, some modification is considered for a speed limit algorithm that has significantly reduced the crash rate and increased safety in the corridor. Except for the speed data mentioned earlier, Road Weather Information System data are captured for the VSL's multi-stage algorithm. The data will be merged and pass two stages for a logical control over the absolute speed limit. First, using the 85th percentile of observed speeds and vehicle count, a new speed limit will be suggested. Next, using sub filters and a visibility threshold filter, the speed limit will be determined by rounding it to the 85th percentile. The variance of these two stages must not be greater than 15 mph; either way, the speed obtained from the first stage will be used (J. Lee, Dailey, Bared, & Park, 2013).

VSL use impacts the safety of roadways by decreasing crashes and emissions in congestion-related deployments. The congestion use of VSL is usually based on real-time volume and speed data, incident data, and queue length (Texas A&M Transportation Institute, 2017). New approaches suggest that, besides VSL system use, the algorithm characteristics should be dynamic to improve the VSL system's output. Accordingly, the new algorithm uses crash data alongside other variables directly in a regression model to specify the speed limit. Another approach is defined based on shockwave theory and to resolve moving shockwaves to determine the speed limit for a corridor. Comparing these algorithms with others using thresholds shows that the control algorithm, application area, incident detection, and implementation duration affect the system (Grumert, Tapani, & Ma, 2018). The VSL system can be useful for both safety and traffic flow improvement. The studies show that the application of VSL in the United States mostly emphasizes safety, while in Europe both parameters are improved significantly. Limitations of sensor measurements and driver behavior variations are considered the main reasons for this difference (Lu & Shladover, 2014).

The system safety evaluation illustrates how the system is performing. Most studies focus on speed compliance rate and crash severity after VSL implementations for safety aspect measurements (Abdel-Aty & Wang, 2017; Ding & Gou, 2018; Piao & McDonald, 2008; Sui & Young, 2013). The network safety improvement and all related parameters are highly correlated with the driver compliance levels. The compliance rate becomes critical during irregular situations and congested traffic flow. Thus, the safety improvement of the VSL system is more significant in an overcrowded condition (Habtemichael & de Picado Santos, 2013).

Most studies model crash rates based on variables such as geometric design, flow characteristics, and empirical data for safety measurements (Abdel-Aty, Dilmore, & Dhindsa, 2006b; Ding & Gou, 2018; Promothes Saha, Mohamed M. Ahmed, & Rhonda Kae Young, n.d.). Traffic flow speed variation and distribution indicate the impact of the VSL system on network safety. Moreover, traffic flow and volume are used to develop crash level models (C. Lee, Hellinga, & Saccomanno, 2006). Nearly all of these models show that incident rates will decrease significantly after VSL implementation, especially in severe conditions. Simulation is another approach to predict the crash rate after VSL implementation and analyze safety measurements (Piao & McDonald, 2008).

Speed distribution and analysis is another safety assessment that can implicate network performance progress. The average speed collected by the detector in the vicinity of a VSL is an indicator of driver response to the speed limit. The difference in average speed and displayed speed is another parameter to show driver behavior regarding VSL. Speed variance, 85th percentile, travel time, and higher speed rates are additional measurements of a VSL's effectiveness and the traffic flow's corresponding characteristics (R W Lyles, Taylor, & Grossklaus, 2003; Richard W Lyles, Taylor, Lavansiri, & Grossklaus, 2004; Sui & Young, 2013). Among the mentioned parameters, studies have proven that driver compliance is relatively the primary measurement directly related to network safety (Hellinga & Mandelzys, 2011). The compliance rate is also relevant to the speed limit shown by the VSL; as the speed increases, the compliance rate decreases (Boateng, Fontaine, & Khattak, 2019).

The safety analysis is influenced by VSL visibility, weather condition, and congestion level (Giles, 2004). Different enforcement levels vary with mentioned factors and affect driver compliance rates (Katz et al., 2017). The visibility and corresponding VSL impact on traffic flow is a means to use amber legend VSLs in the network (R W Lyles et al., 2003; Richard W Lyles et al., 2004). Weather fluctuations can reduce the freeway operational rate, and the VSL system can increase the operational benefits by controlling the traffic flow performance (Habtemichael & de Picado Santos, 2013).

2.3 Safety Evaluation

System theories and systematic description frameworks can perform a road safety assessment. These models use a logical relation between road features and other factors influencing safety to evaluate a strategy or single event analysis, which is not widespread in practice (Goh & Love, 2012; Hughes, Newstead, Anund, Shu, & Falkmer, 2015). However, research that exhibits the impact of road or human features on crashes is used to set policies or applied in road designs (Elvik, 2003). Developed numerical safety models are typically based on statistical techniques to predict crashes and their severity. Road geometry design and its consistency, traffic flow characteristics, and driving conditions are used in statistical methods (Hauer, 2004; Wang, Quddus, & Ison, 2011; Zheng, Sayed, & Mannering, 2020). Statistical models, including regression and multilevel, have been used to estimate crash frequency in the literature (Lord & Mannering, 2010), while logit and probit models are used for the crash severity (Savolainen, Mannering, Lord, & Quddus, 2011).

Predefined relationships and assumptions of statistical methods typically contradict actual conditions and available data and confine the application of those methods (Silva, Andrade, & Ferreira, 2020). Accordingly, machine learning (ML) methods, which do not need any pre-assumptions, are useful, and the safety model will be trained and fitted by input data. ML methods evaluate road safety by crash frequency, severity, or a combination of both. An artificial neural network (ANN) is one of the ML methods used for both crash frequency and crash severity estimation. ANN will use the feature vector, including the variable related to the crash rate, and predict the desired safety factor. The features will be used as inputs for each layer (hidden layers) using optimized weight and fitted function to estimate the output (Xie, Lord, & Zhang, 2007; Zeng, Huang, Pei, Wong, & Gao, 2016). Other ML methods such as decision tree, support vector machine (SVM), and nearest neighbor classification (KNN) are also used for crash frequency prediction (L. Y. Chang, 2005).

To develop a model that will estimate the crash severity in a road segment, ML methods can be used for the classification of crash severity levels. An ANN classification model used to evaluate road safety has improved performance using the clustering classification (Alikhani, Nedaie, & Ahmadvand, 2013). Studies have proved that ML models will perform better compared with statistical methods in the safety assessment (Silva et al., 2020). Also, ANN is proven to be the most suitable one among all ML models in safety evaluations, which still depend on the data structure and variables available to feed the model (L. Y. Chang, 2005). Distribution of data attributes correlation and optimization methods to find the best parameters affects the model's accuracy and fitting (Pan, Fu, & Thakali, 2017; Zeng & Huang, 2014).

2.4 Summary

In this chapter, the studies and reports about CMS systems and their applications were reviewed. CMS signs can be used for various occasions and convey dynamic information about the road for safer traffic management. Depending on the CMS's utilization, the algorithms used for the dynamic message can be variable and presented differently. However, the critical effect of the CMS is road safety and performance, which will be evaluated. Safety evaluations can be performed with methods developed by scholars depending on the primary aim of the system.

3. VSL VISIBILITY RECORDS

3.1 Overview

In the following chapter, method recordings are described, and the output of field trip data is presented. Snippets from VSL signs in both summer and winter are compared for visibility in critical conditions with the white and amber legend.

3.2 Field Trip Recordings

In recoding VSL signs, it is required to monitor and analyze the sign's visibility status before and after the legend color has changed from white to amber. Therefore, two field trip videos are conducted in various positions during strong sunlight and snow. The most direct sunlight is during June and July, which will decrease the visibility of VSL signs the most. In the hours of 8–10 a.m. and 4–6 p.m., due to the sun, signs, and driver position, the sun's reflection is directed to the driver's sight and makes the VSL sign indiscernible for the driver. The sun's position in a year is depicted in Figure 3.1 ("Calculation of sun's position in the sky for each location on the earth at any time of day," 2019). According to the sun's largest angle with earth, the videos are recorded during July in both morning and afternoon hours, and each period will affect one approach the most. The VSL zone in I-80 toward the east of Salt Lake City is an east-west approach segment. Accordingly, it is expected that the east approach visibility in the morning hours and the west approach visibility in the afternoon hours will decrease the most. The lane a driver is driving in may alter the VSL's visibility.

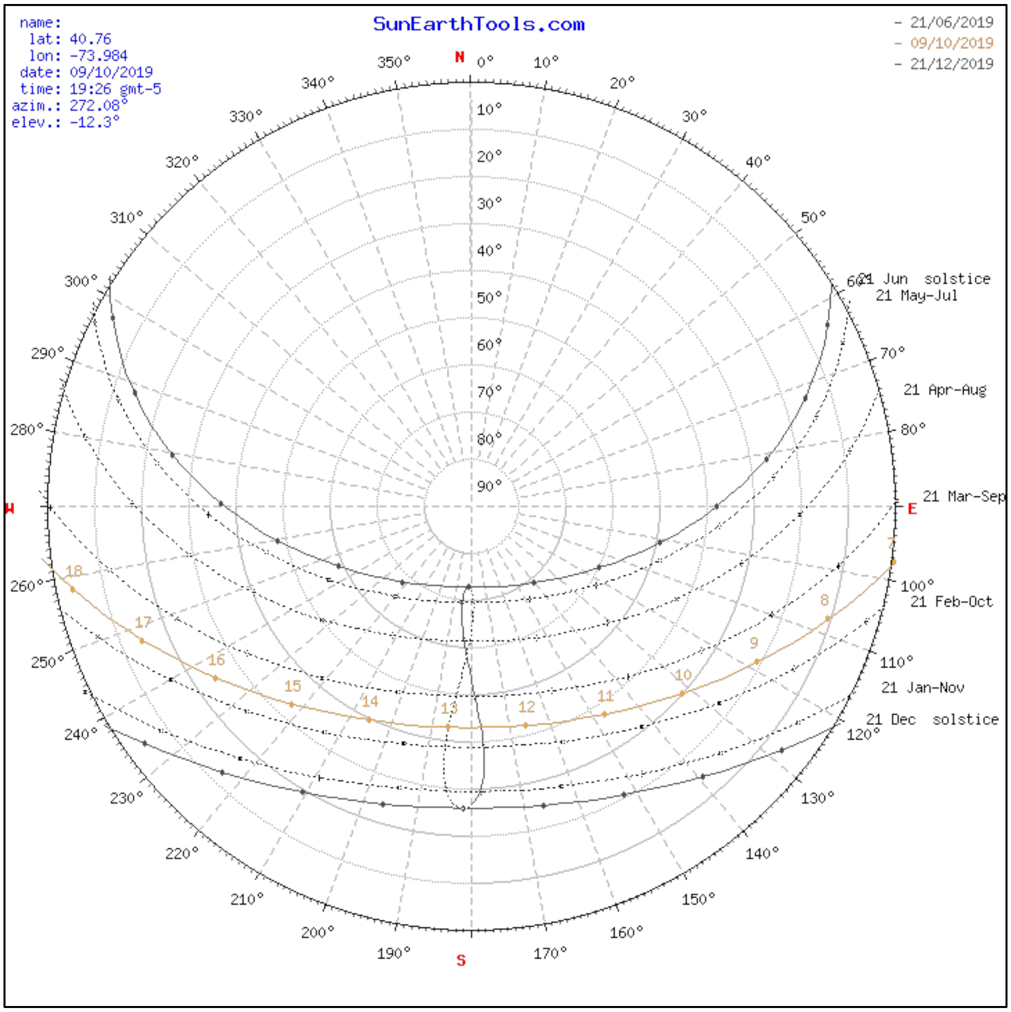

Figure 3.1 The Sun Position During a Year (2019)

Next, field trips of both approaches from MP 128.0 to MP 141.0 are recorded for all lanes during both morning and afternoon hours. The details and the outputs of these recordings are as follows.

3.3 Equipment

Throughout data collection, the goal is to record the VSL sign's visibility during the intense sunlight of summer. To determine the signs' visibility, a Vantrue N2 Pro Dual 1080P dash cam placed on a personal car is used to record the VSL signs located on I-80. Details of the data collection approach are described in Table 3.1. Also, the same timing is used for recording during winter after a snowfall and in low visibility driving conditions. But as the amber signs were installed in September 2019, the signs' recordings are only available with the amber legend.

Table 3.1 Data Collection Features for Recorded Field Trips

Route	I80-W	I80-E
MP Recorded	128-141	128-141
Driving Speed	65 mph	65 mph
Recorded Time	8-10AM/4-6PM	8-10AM/4-6PM
Recorded Lanes	1,2,3	1,2,3

3.4 VSL Snippets

3.4.1 Data Collection of VSL in Direct Sunlight

Based on I-80 VSL zone recordings, eight signs in the east approach and seven VSL signs in the west approach are captured. Some of the signs may have lower visibility due to a reduction in power or other issues. During all periods, the visibility of the corresponding signs was low; most importantly, direct sunlight affects the signs' visibility differently during various times of the day. After inspecting signs and checking their relative visibility, all the signs are classified into two groups: VSL signs with low visibility and VSL signs with normal visibility. The signs' locations and their corresponding visibility, recording timing, and recorded lane are depicted in Figure 3.2 to Figure 3.13. The VSL signs with relatively low visibility are displayed with red tags, while the VSL signs with typical visibility are shown with blue tags.

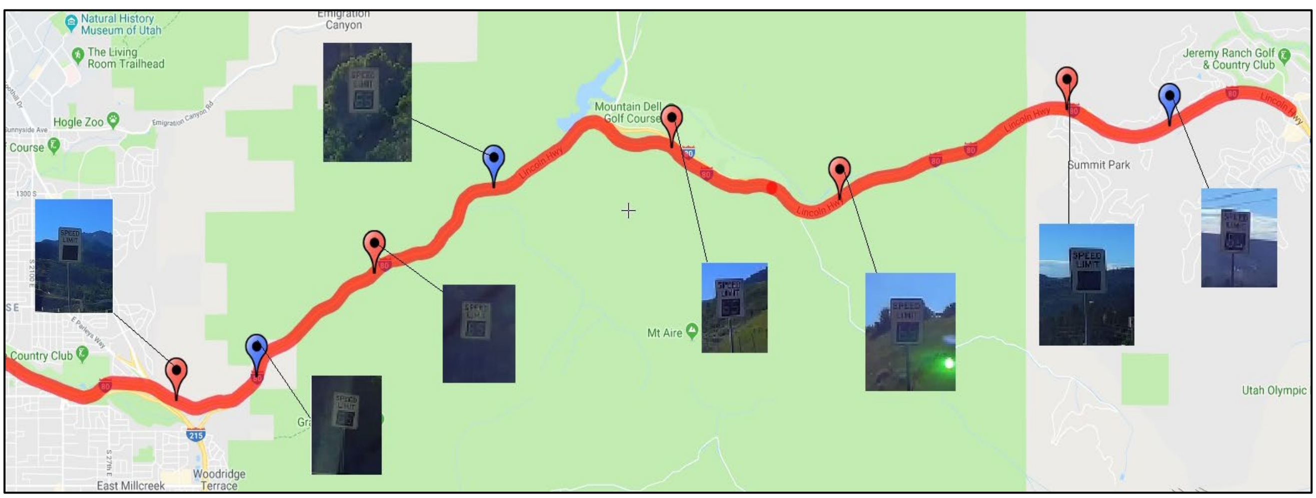

Figure 3.2 East Approach 1st Lane VSL Signs Recorded with White Legend in Morning, Summer

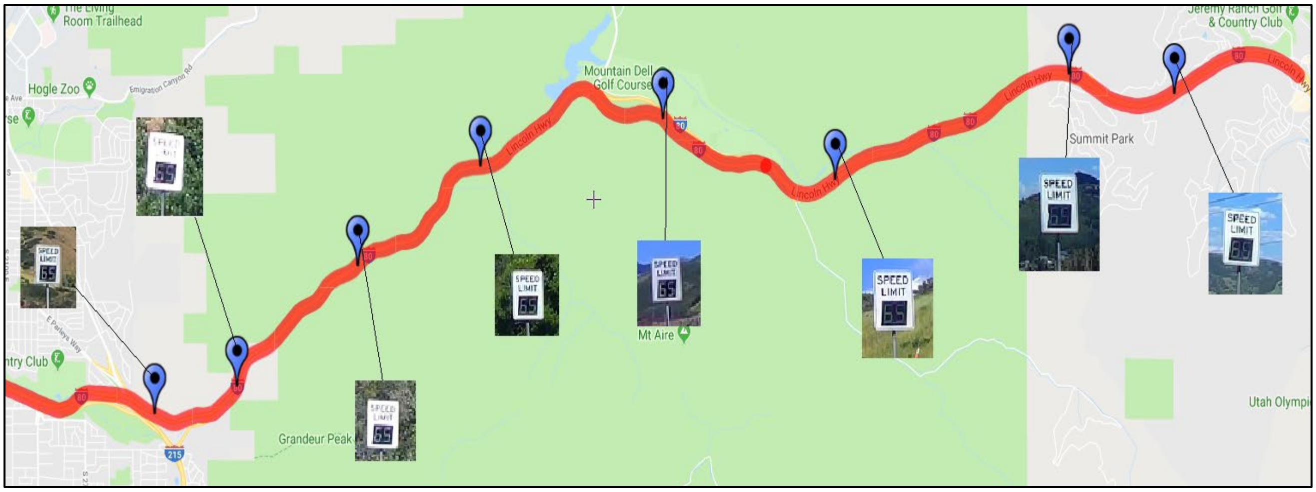

Figure 3.3 East Approach 1st Lane VSL Signs Recorded with White Legend in Evening, Summer

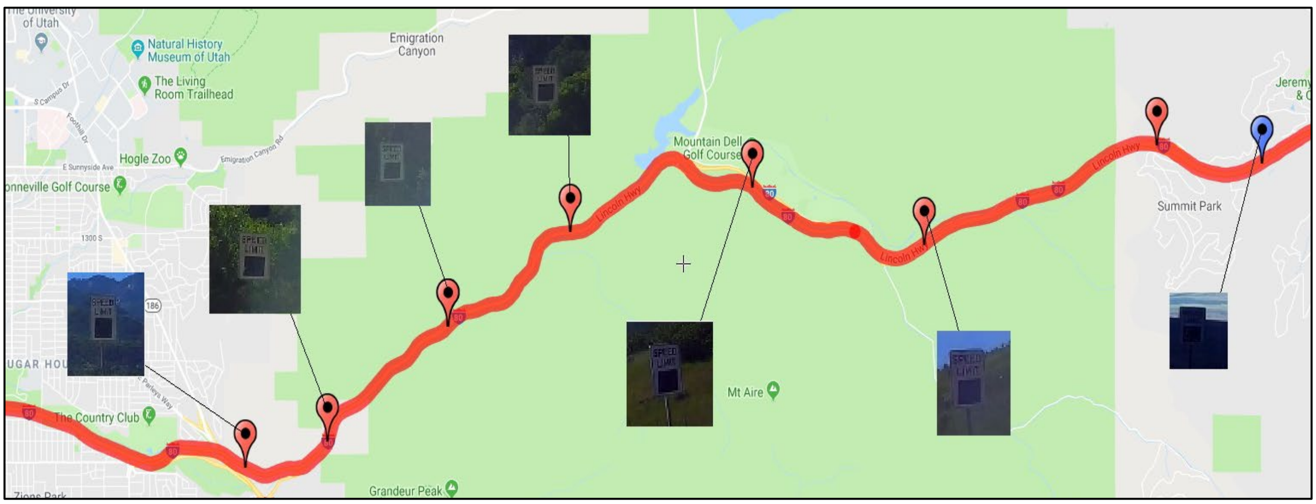

Figure 3.4 East Approach 2nd Lane VSL Signs Recorded with White Legend in Morning, Summer

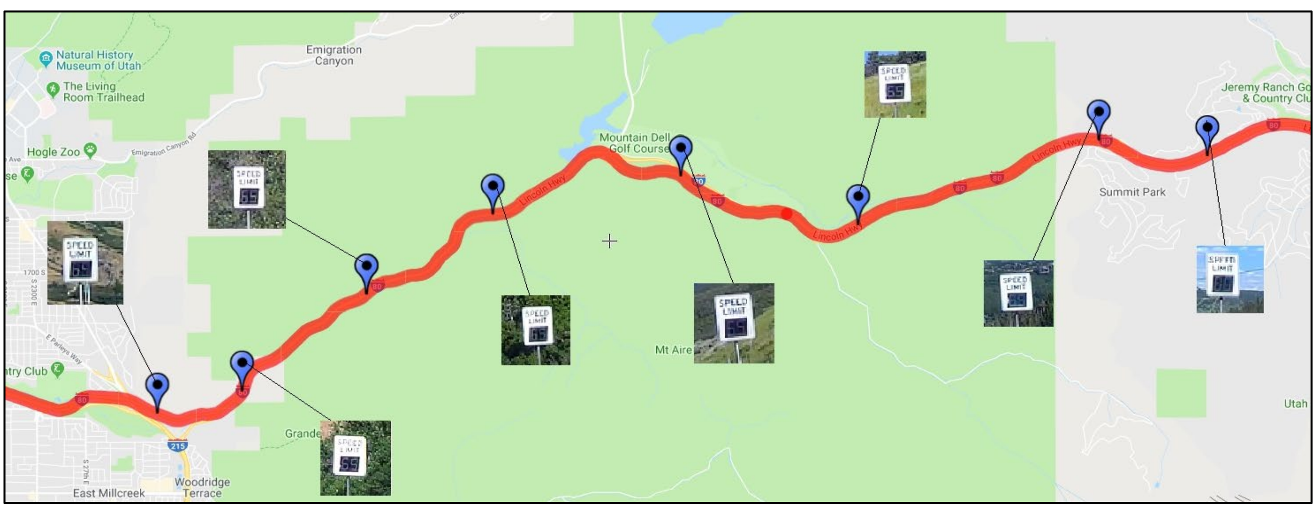

Figure 3.5 East Approach 2nd Lane VSL Signs Recorded with White Legend in Evening, Summer

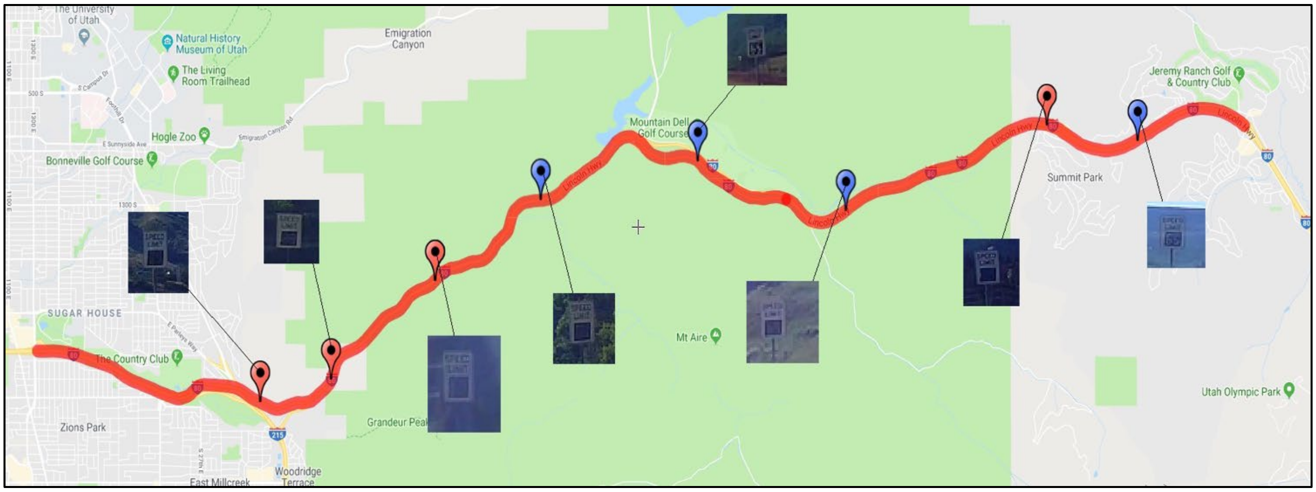

Figure 3.6 East Approach 3rd Lane VSL Signs Recorded with White Legend in Morning, Summer

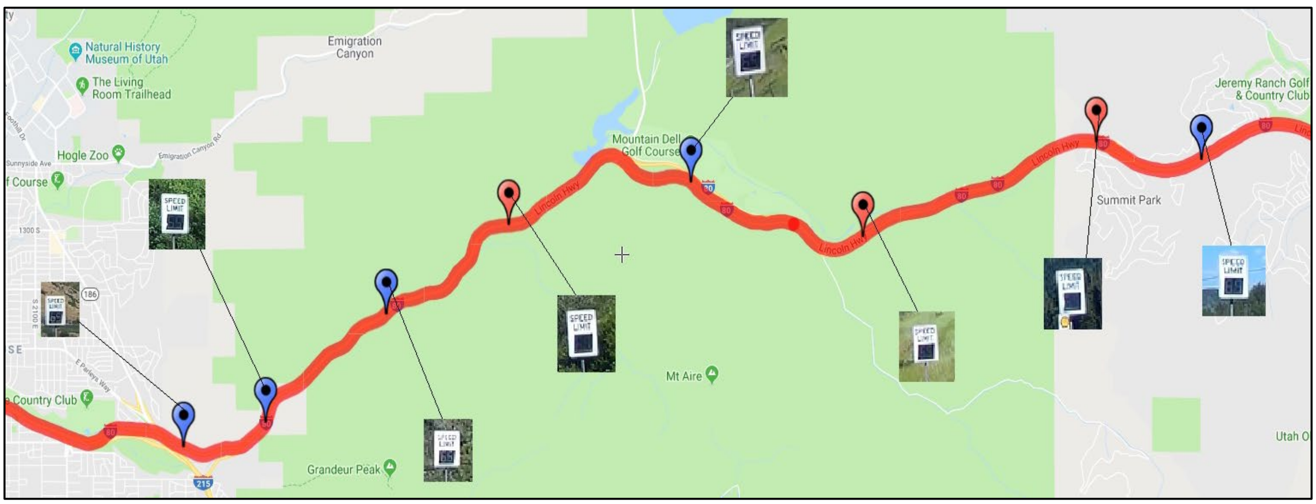

Figure 3.7 East Approach 3rd Lane VSL Signs Recorded with White Legend in Evening, Summer

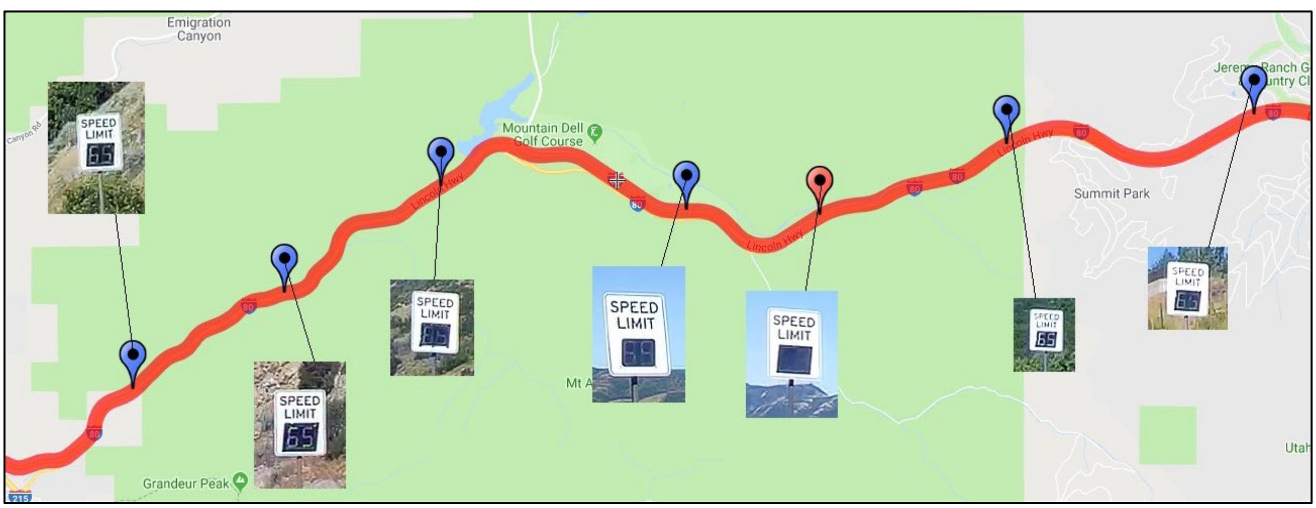

Figure 3.8 West Approach 1st Lane VSL Signs Recorded with White Legend in Morning, Summer

Figure 3.9 West Approach 1st Lane VSL Signs Recorded with White Legend in Evening, Summer

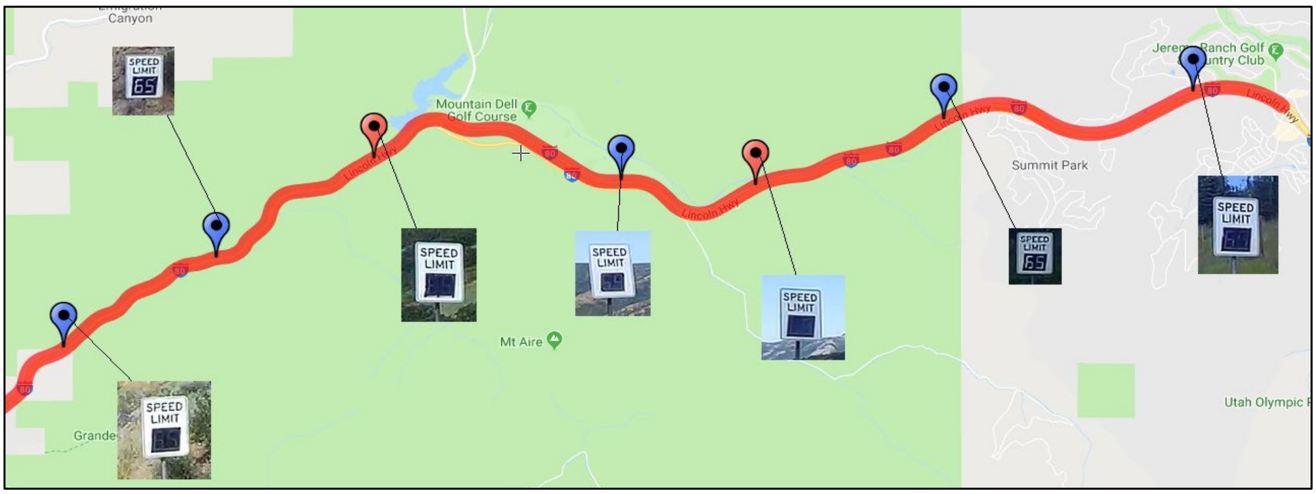

Figure 3.10 West Approach 2nd Lane VSL Signs Recorded with White Legend in Morning, Summer

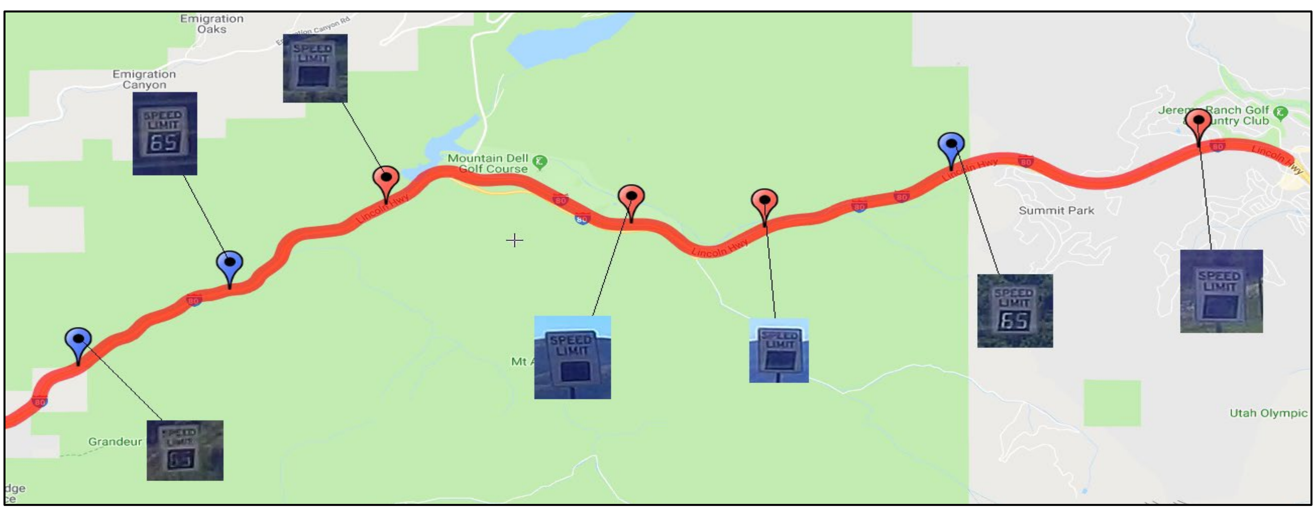

Figure 3.11 West Approach 2nd Lane VSL Signs Recorded with White Legend in Evening, Summer

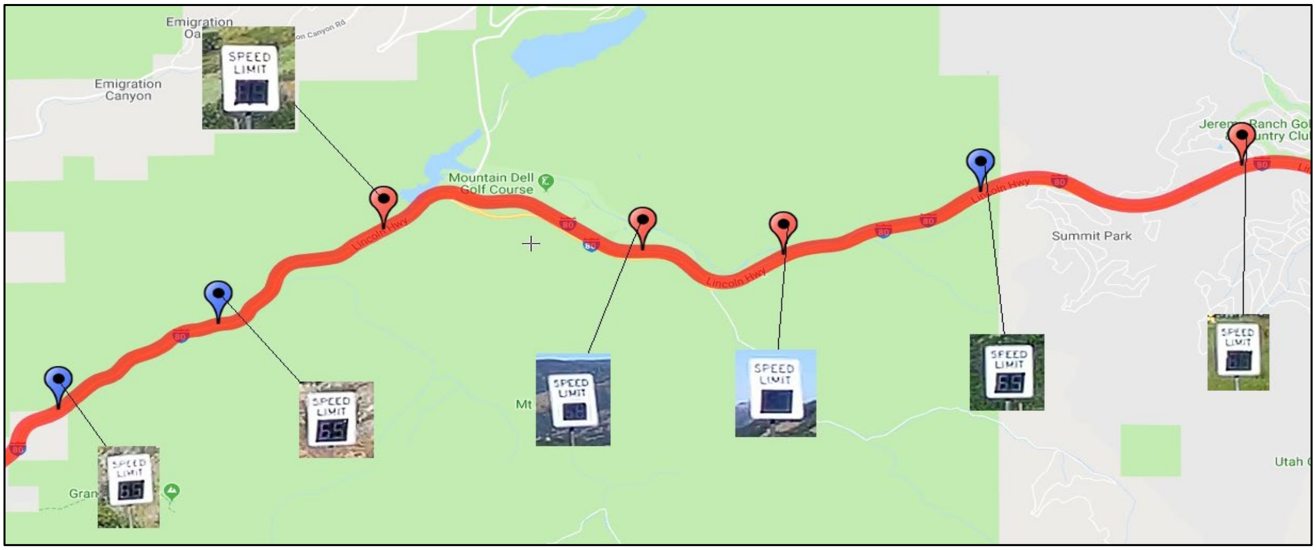

Figure 3.12 West Approach 3rd Lane VSL Signs Recorded with White Legend in Morning, Summer

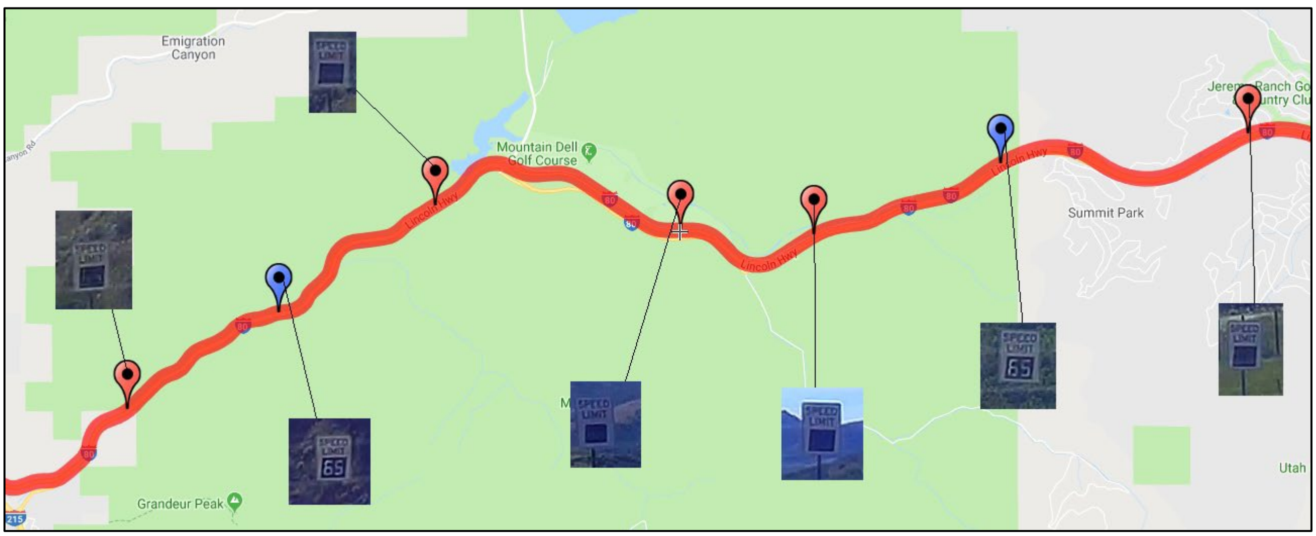

Figure 3.13 West Approach 3rd Lane VSL Signs Recorded with White Legend in Evening, Summer

Based on the VSL signs' visibility condition, it is concluded that morning hours of sunlight will impact the east approach signs more, while evening hours of sunlight will affect the west approach signs more. An extension of data collection was done in the summer of 2020 to compare with the records of VSL sign visibility from the summer of 2019. VSL visibility is recorded on I-80 for both approaches in the morning (from 9-11 a.m.) and afternoon hours (3-5 p.m.). Based on snippets from the latest recordings, the visibility of all VSL signs has improved by the legend color transition. The visual visibility of recordings with the amber legend compared with the white legend recordings is convincing evidence to demonstrate improved visibility of signs by the legend color transition. Snippets of the latest recordings are shown in Figure 3.14 to Figure 3.25.

Figure 3.14 East Approach 1st Lane VSL Signs Recorded with Amber Legend in Morning, Summer

Figure 3.15 East Approach 1st Lane VSL Signs Recorded with Amber Legend in Evening, Summer

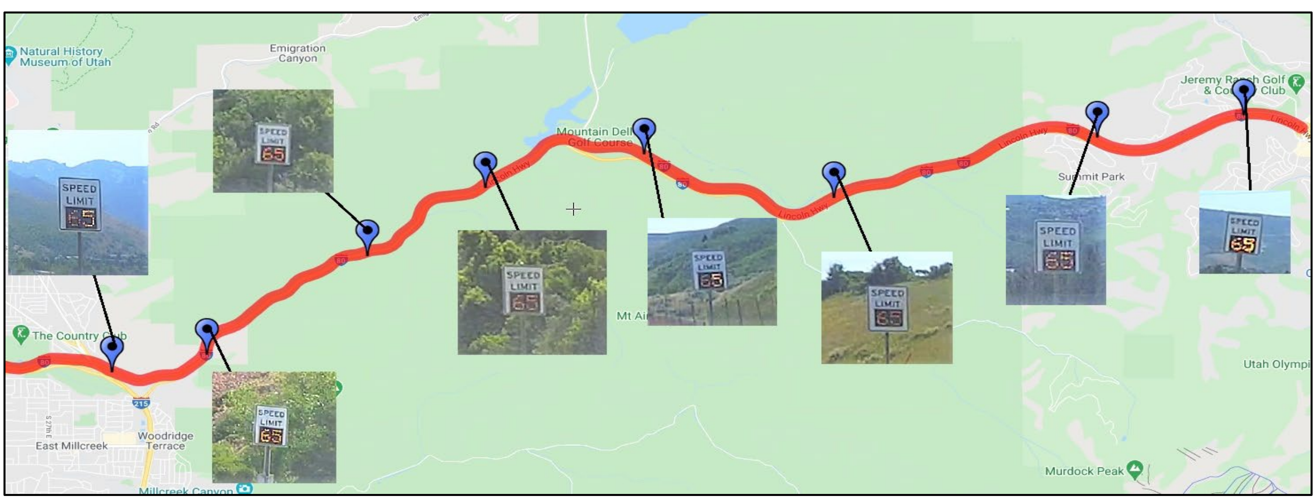

Figure 3.16 East Approach 2nd Lane VSL Signs Recorded with Amber Legend in Morning, Summer

Figure 3.17 East Approach 2nd Lane VSL Signs Recorded with Amber Legend in Evening, Summer

Figure 3.18 East Approach 3rd Lane VSL Signs Recorded with Amber Legend in Morning, Summer

Figure 3.19 East Approach 3rd Lane VSL Signs Recorded with Amber Legend in Evening, Summer

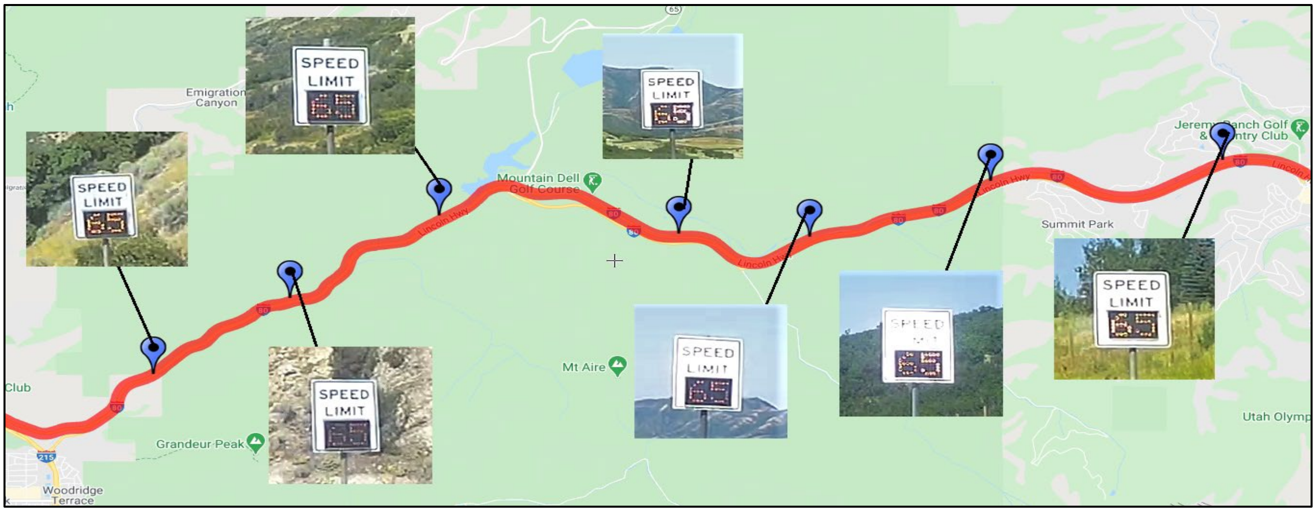

Figure 3.20 West Approach 1st Lane VSL Signs Recorded with Amber Legend in Morning, Summer

Figure 3.21 West Approach 1st Lane VSL Signs Recorded with Amber Legend in Evening, Summer

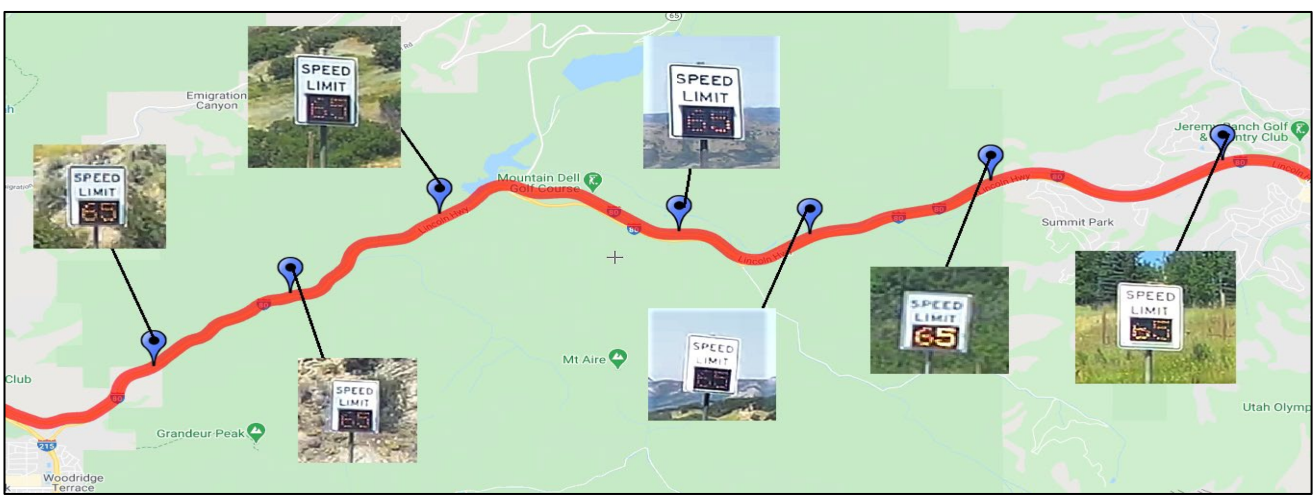

Figure 3.22 West Approach 2nd Lane VSL Signs Recorded with Amber Legend in Morning, Summer

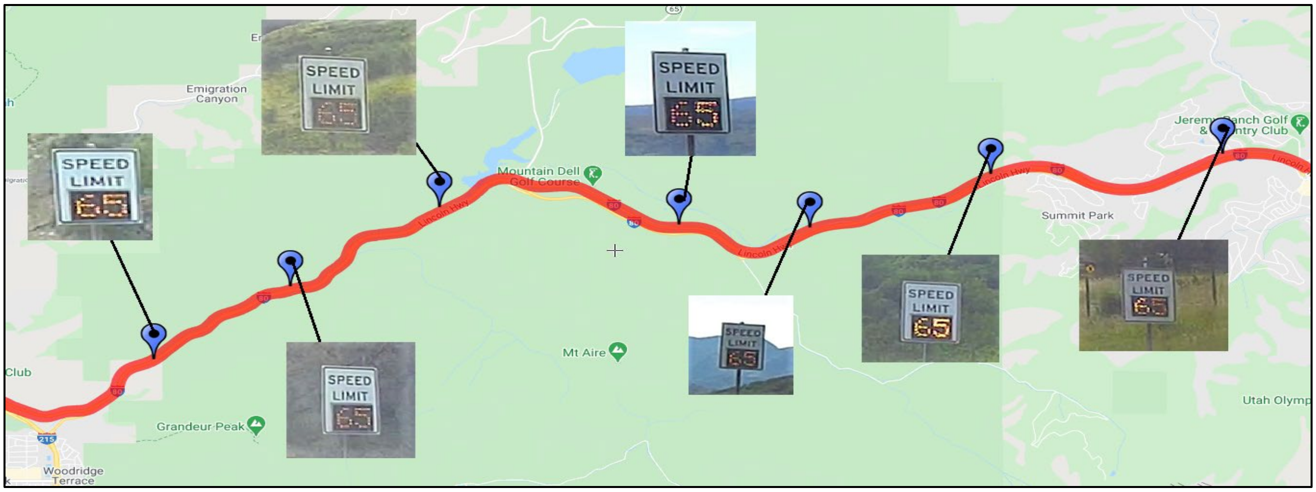

Figure 3.23 West Approach 2nd Lane VSL Signs Recorded with Amber Legend in Evening, Summer

Figure 3.24 West Approach 3rd Lane VSL Signs Recorded with Amber Legend in Morning, Summer

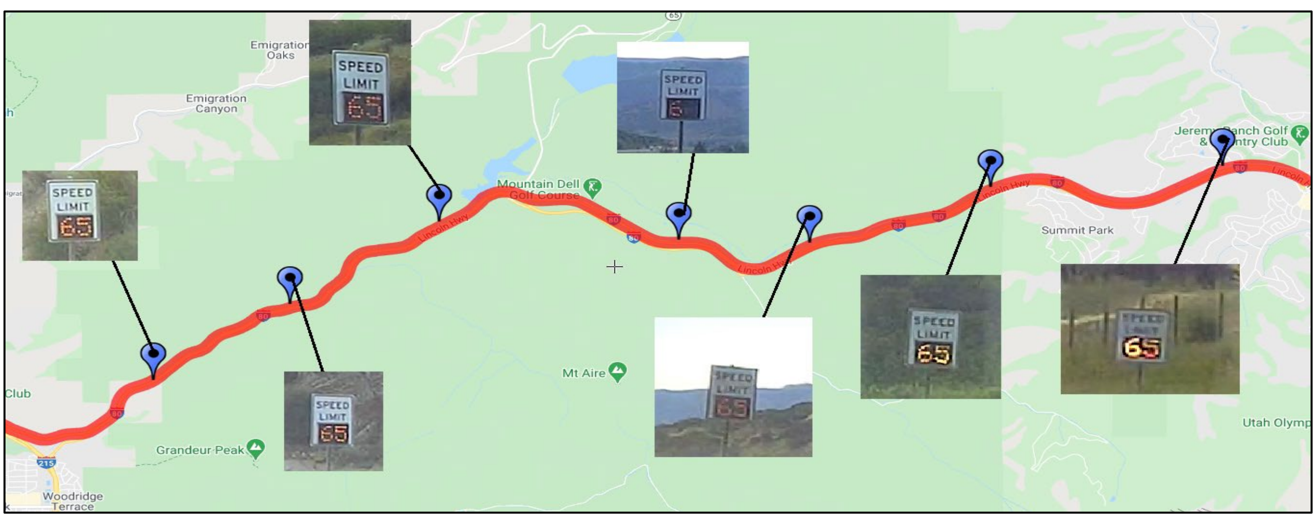

Figure 3.25 West Approach 3rd Lane VSL Signs Recorded with Amber Legend in Evening, Summer

The snippets of the signs with amber legend show that visibility has improved significantly in direct sunlight. However, a few signs had power issues, which reduced the legend brightness and, correspondingly, the visibility. In comparing fully lighted signs with white and amber legends, it is observed that signs are more visible to drivers for longer sight distances with amber legends. During field trips, it was noted that the combination of direct sunlight and a white legend makes the numbers perceptible at closer distance but harder to discern. Overall, sight distance has particularly improved with the amber legend, which gives drivers more time to decide and reduce their speed if necessary.

3.4.2 Data Collection of VSL with Snowstorms

The same VSL data collection is conducted after a snowstorm on I-80 for both approaches in the morning (9-10 a.m.) and afternoon (3-5 p.m.). As shown in the figures, signs are visible despite the road's low visibility due to fog and snow. Since the data collection was done in foggy weather, the outputs can be an inference to consider the VSL for inclement weather as a warning sign and use the amber legend.

Figure 3.26 East Approach 1st Lane VSL Signs Recorded with Amber Legend in Morning, Winter

Figure 3.27 East Approach 1st Lane VSL Signs Recorded with Amber Legend in Evening, Winter

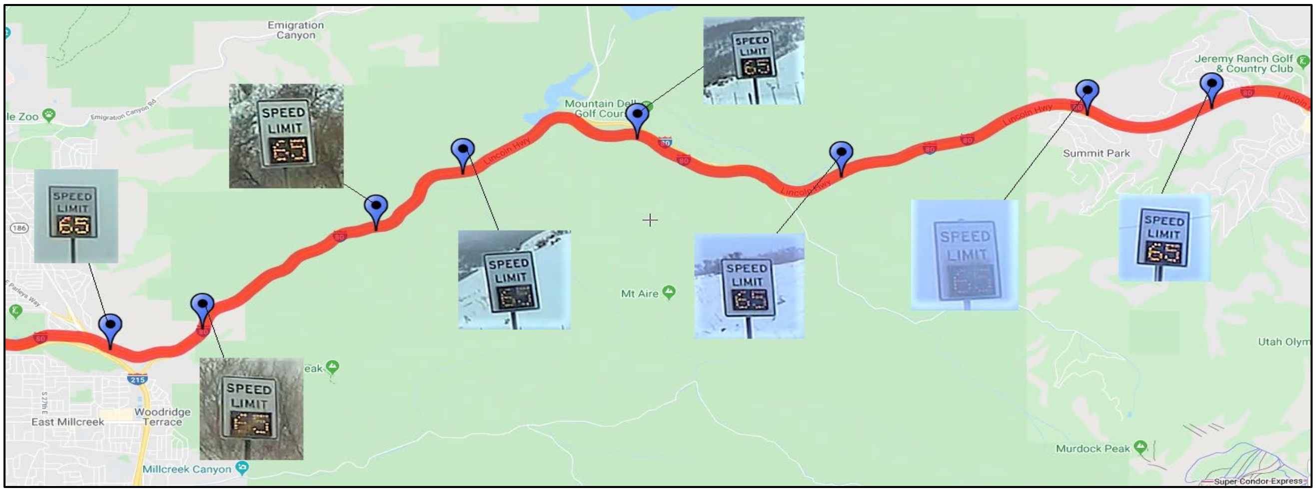

Figure 3.28 East Approach 2nd Lane VSL Signs Recorded with Amber Legend in Morning, Winter

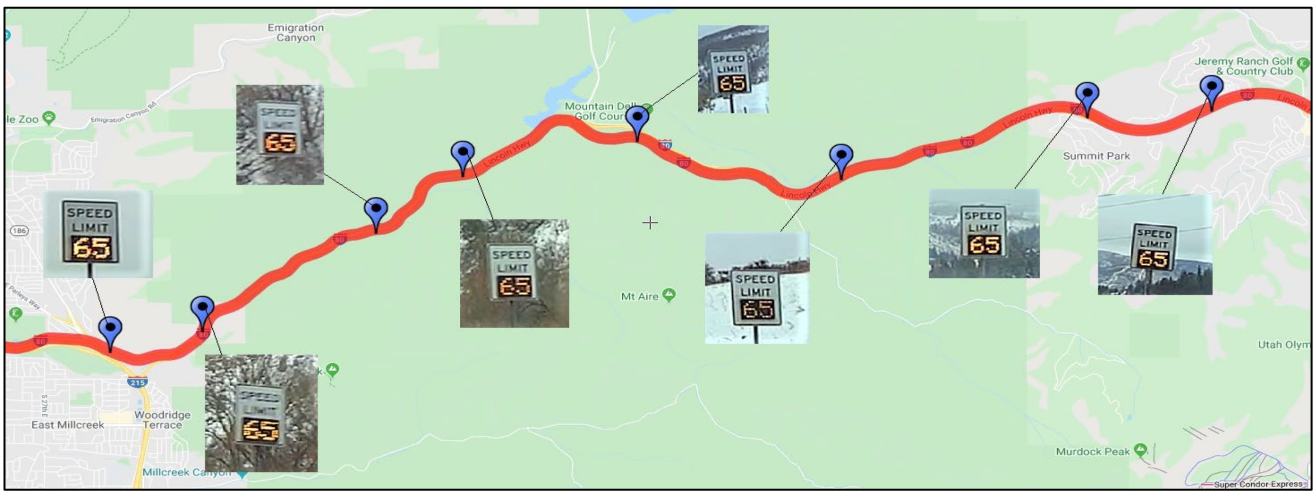

Figure 3.29 East Approach 2nd Lane VSL Signs Recorded with Amber Legend in Evening, Winter

Figure 3.30 East Approach 3rd Lane VSL Signs Recorded with Amber Legend in Morning, Winter

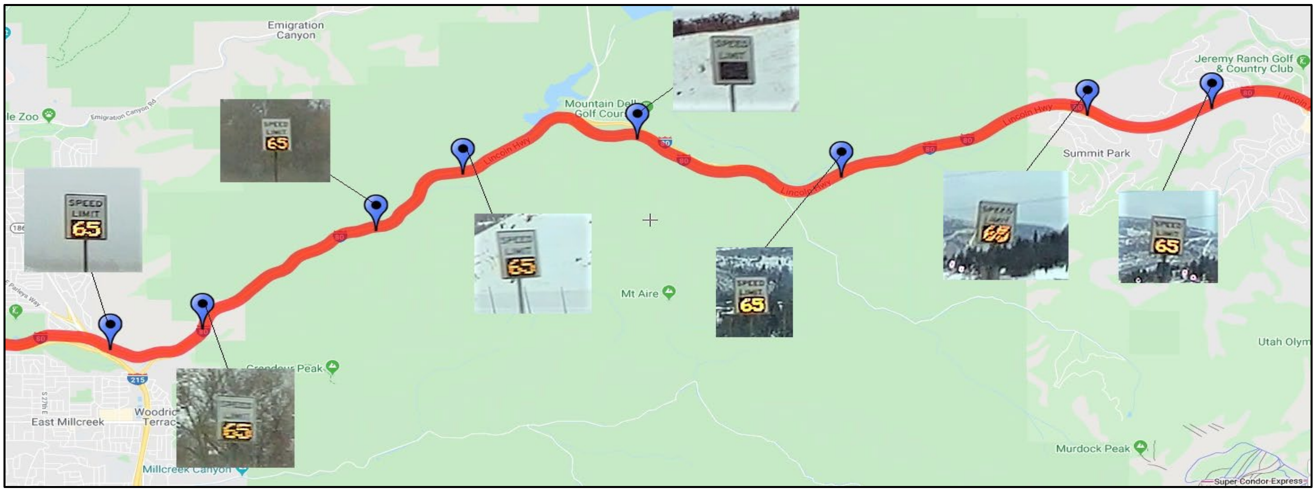

Figure 3.31 East Approach 3rd Lane VSL Signs Recorded with Amber Legend in Morning, Winter

Figure 3.32 West Approach 1st Lane VSL Signs Recorded with Amber Legend in Morning, Winter

Figure 3.33 West Approach 1st Lane VSL Signs Recorded with Amber Legend in Evening, Winter

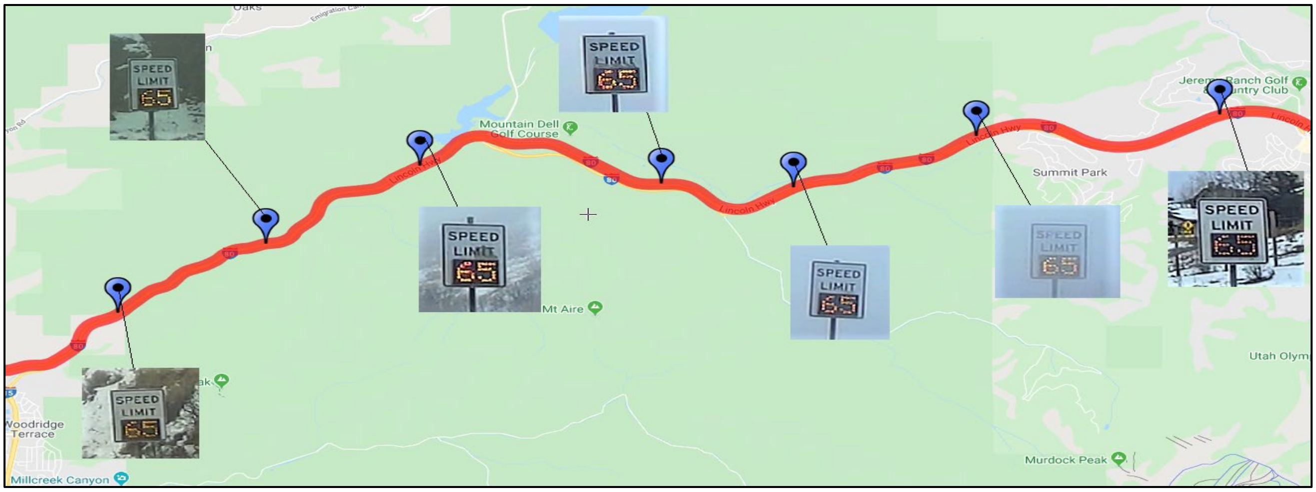

Figure 3.34 West Approach 2nd Lane VSL Signs Recorded with Amber Legend in Morning, Winter

Figure 3.35 West Approach 2nd Lane VSL Signs Recorded with Amber Legend in Evening, Winter

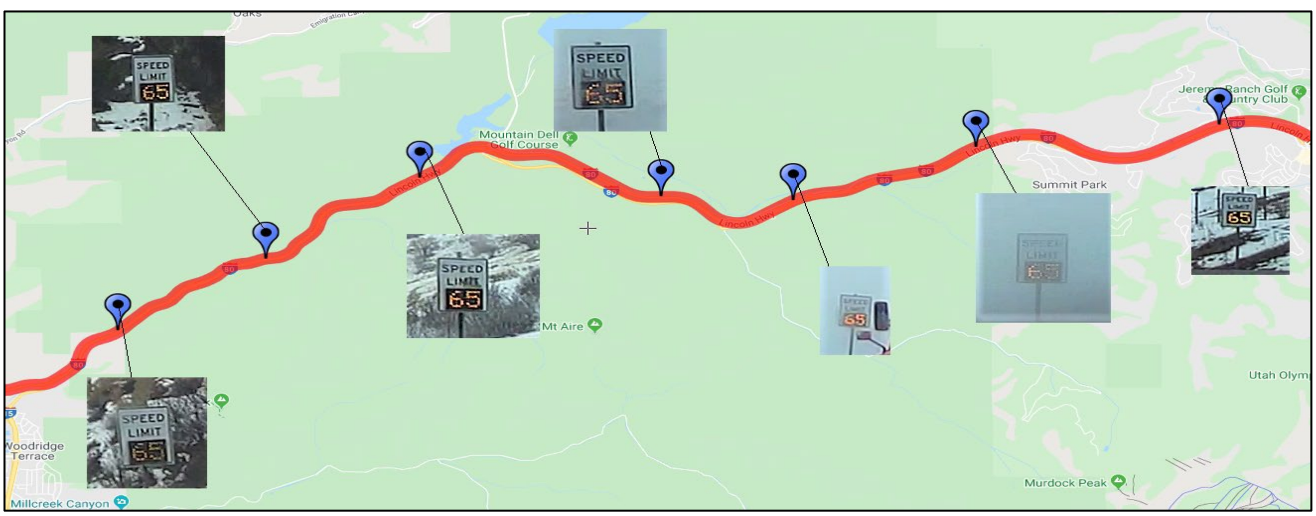

Figure 3.36 West Approach 3rd Lane VSL Signs Recorded with Amber Legend in Morning, Winter

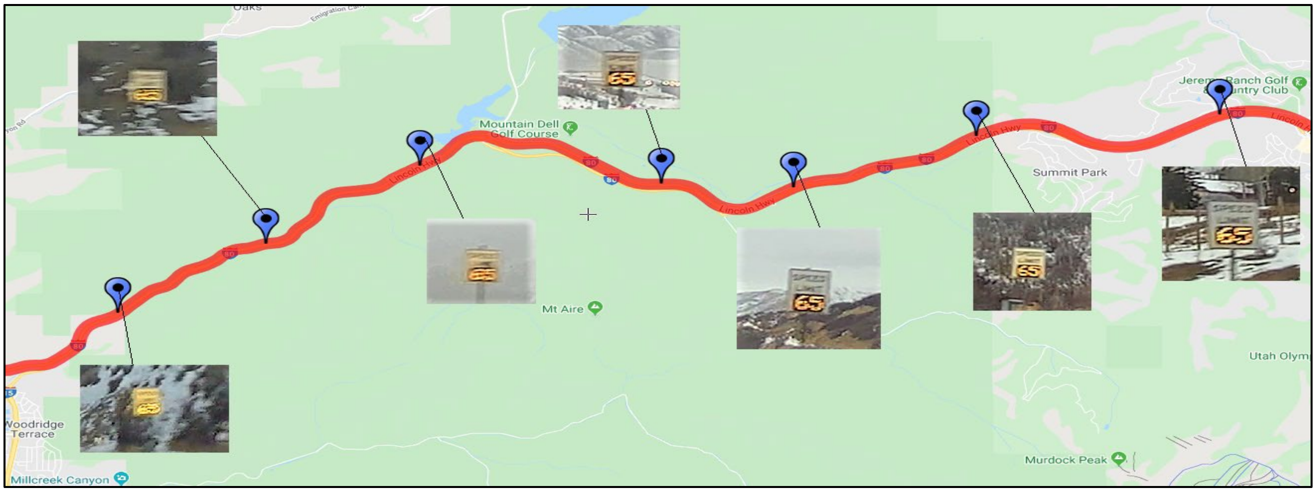

Figure 3.37 West Approach 3rd Lane VSL Signs Recorded with Amber Legend in Evening, Winter

Based on VSL sign visibility in winter and with low visibility driving conditions, it can be concluded that the amber legend makes the sign detectable for drivers. The numbers are readable from a reasonable distance considering the lower distance of visibility on the road. However, it is suggested that a CMS showing road conditions or a flashing amber light be added to the system for critical driving conditions in winter. The latest approach has been implemented in multiple states for VSL signs during low visibility conditions (J. Lee et al., 2013).

3.5 Summary

This chapter provided the field trip recordings of VSL signs conducted before and after new signs were installed. Based on recorded snippets, it was shown that a sign's visibility is enhanced in summer, and numbers are more discernable from a further distance. Also, for low visibility driving conditions in winter, the signs are visible from a safe distance.

4. DATA ANALYSIS

4.1 Overview

Snippets of the signs showed that visibility has improved from the driver's perspective; however, a more comprehensive study of corridor behavior needs to be considered. For this purpose, the corridor's traffic flow data are analyzed, and the driver's compliance is determined. Moreover, crash data comparisons for both signs are studied in this chapter. The results of the following chapter illustrate the effect of the amber legend on the road's performance.

4.2 Data Description

Considering the primary purpose of new VSL signs, the measurements representing safety and traffic flow characteristics are analyzed before and after the VSL sign legend color change. The studied data include historical traffic flow data by detectors, displayed speed limit of VSL signs, the corridor's weather index data, and crash data. Collected data have a biweekly range in fall (October 2018 and 2019) and winter (January 2019 and 2020) before and after installing new signs. The drivers' response and safety are evaluated by analyzing the time series mean speed profile versus the displayed speed limit. Traffic flow response to the VSL signs indicates how visibility improvement has affected the flow's safety and performance. Moreover, the road condition and weather impact the road's safety aspects, which for a more distinct comparison of crash rates are surveyed.

4.3 Road Data Analysis and Evaluation

Safety measurements of the speed log data for the fall and winter seasons before and after implementation of the new VSL signs are analyzed in this section. The trends indicate that drivers tend to drive closer to displayed speed limits, especially in lower speed limits, which might be due to lower visibility, high-risk weather conditions, and crashes in the downstream flow. The compliance rate is measured by the ratio of drivers who drive no more than 10 mph of the freeway's displayed speed limit. The compliance rates for all sensors are examined to represent driver behavior toward the higher visibility of displayed speed. Although the drivers' adoption rate did not change significantly in October, when road conditions are more stable, the average speed flow is closer to the speed limit in January, when there are more snowstorms and lower visibility. The increase in wintertime compliance rate is shown in Table 4.1 and Table 4.2. When visibility is affected the most in the wintertime, the compliance rate is enhanced by 9% on average. New compliance rates have also increased by more than 20% at the sensor 100616 location. Meanwhile, the drivers' compliance has not changed significantly in the fall when driving is safer than in winter.

Table 4.1 Drivers' Compliance Rate Comparison for Legend Colors for Eastbound Sensors

Legend Color	White	Amber	White	Amber
Sensor ID \ Date	**January 19**	**January 20**	**October 18**	**October 19**
100389	0.96	0.95	0.98	0.97
100619	0.80	0.91	0.88	0.78
100599	0.91	0.94	0.98	0.94
100616	0.70	0.85	0.66	0.67
100430	0.91	0.95	0.94	0.89

Table 4.2 Drivers' Compliance Rate Comparison for Legend Colors for Westbound Sensors

Legend Color	White	Amber	White	Amber
Sensor ID \ Date	**January 19**	**January 20**	**October 18**	**October 19**
100619	0.80	0.91	0.88	0.78
100599	0.91	0.95	0.98	0.94
100616	0.70	0.86	0.66	0.67
100618	0.82	0.93	0.84	0.85
100430	0.91	0.94	0.92	0.92

The flow throughput of the road segment can also impact the traffic compliance rate. In congested conditions, the flow will not precisely follow the speed limits and drivers drive less than the displayed speed limit. To keep track of flow behavior in free flow conditions, the compliance rate for uncongested flow for each station is measured as well. The slight decrease in compliance rate in stations relates to drivers' tendency to drive over the speed limit when there is no barrier in the network. The rates are displayed in Table 4.3 and Table 4.4.

Table 4.3 Drivers' Compliance Rate Comparison for Legend Colors for Eastbound Sensors for Uncongested Flow

Legend Color	White	Amber	White	Amber
Sensor ID \ Date	**January 19**	**January 20**	**October 18**	**October 19**
100389	0.95	0.92	0.66	0.89
100619	0.60	0.53	0.57	0.54
100599	0.63	0.60	0.64	0.55
100616	0.55	0.53	0.56	0.53
100430	0.95	0.92	0.66	0.89

Table 4.4 Drivers' Compliance Rate Comparison for Legend Colors for Westbound Sensors for Uncongested Flow

Legend Color	White	Amber	White	Amber
Sensor ID \ Date	**January 19**	**January 20**	**October 18**	**October 19**
100619	0.60	0.53	0.56	0.55
100599	0.63	0.60	0.63	0.56
100616	0.55	0.53	0.55	0.55
100618	0.62	0.58	0.60	0.57
100430	0.60	0.61	0.63	0.57

Speed fluctuation over time demonstrates the precise traffic flow pattern by the displayed speed limit. Time series data of average speed are depicted for available sensors in the vicinity of VSL sign data after and before installation to illustrate how this transition has affected the traffic pattern. Figure 4.1 to Figure 4.8 show these trends for both fall and winter for recorded data. At a glance, the speed profiles with blue lines, which are after the installation of new VSL signs, demonstrate that average traffic flow speed is closer to the displayed speed limit, significantly when the speed limit is dropped. Altogether, the trends show how the average speed follows the speed limit as the signs' visibility improves.

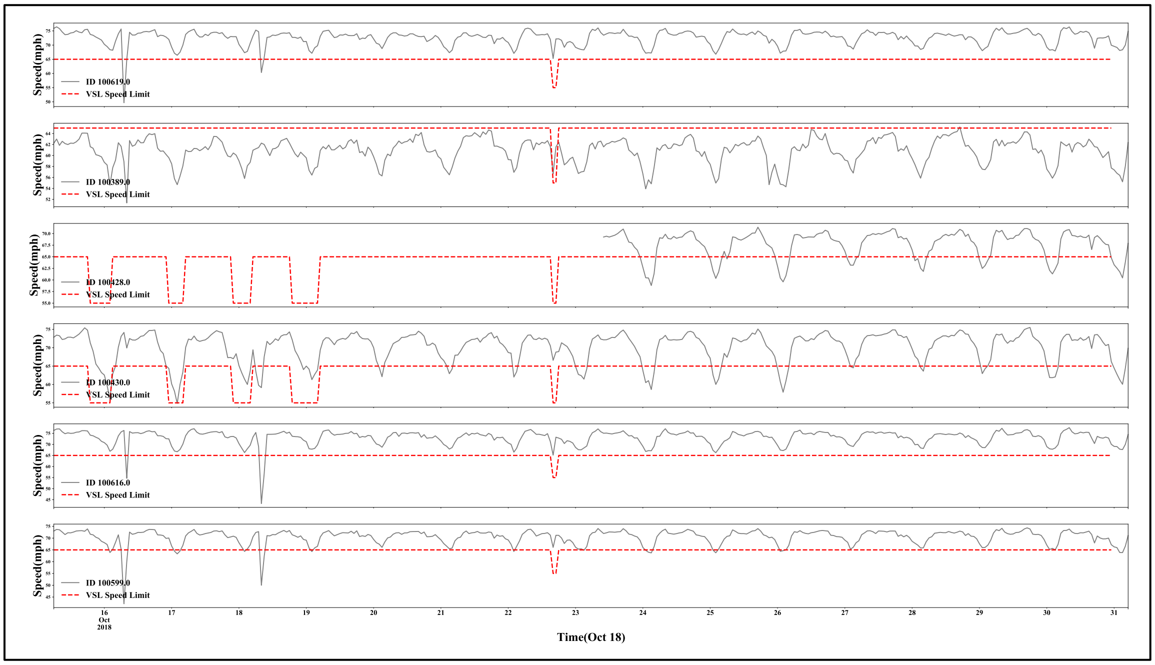

Figure 4.1 Hourly Average Speed of Sensors with Displayed VSL Speed Limit in I-80 Eastbound (Fall 2018)

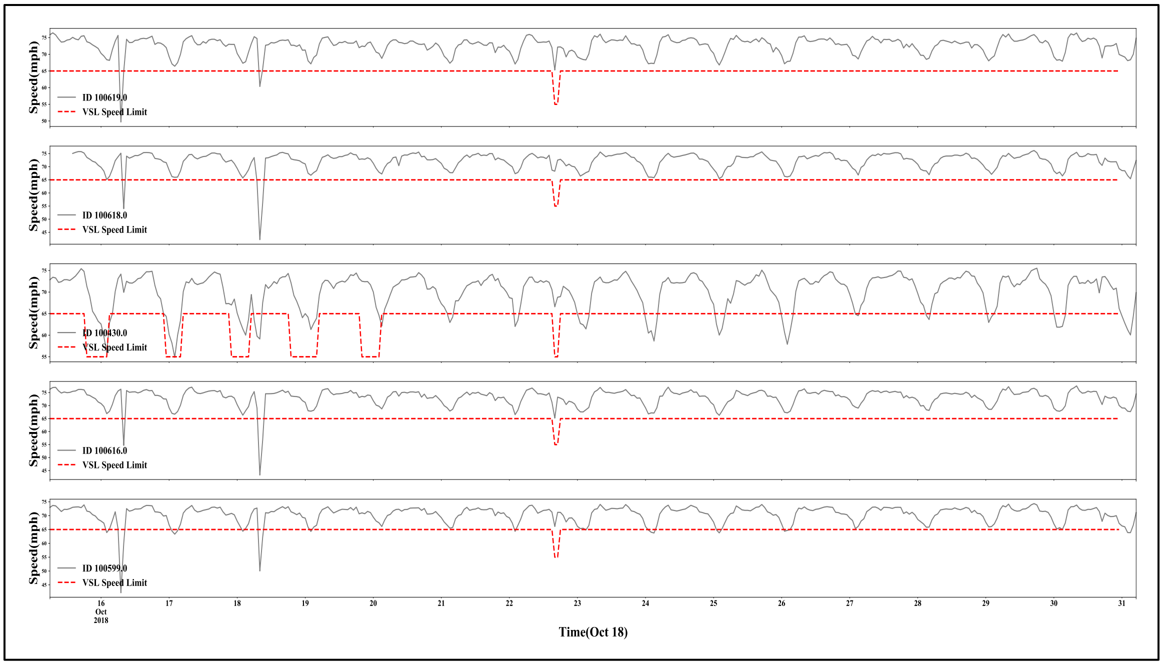

Figure 4.2 Hourly Average Speed of Sensors with Displayed VSL Speed Limit in I-80 Westbound (Fall 2018)

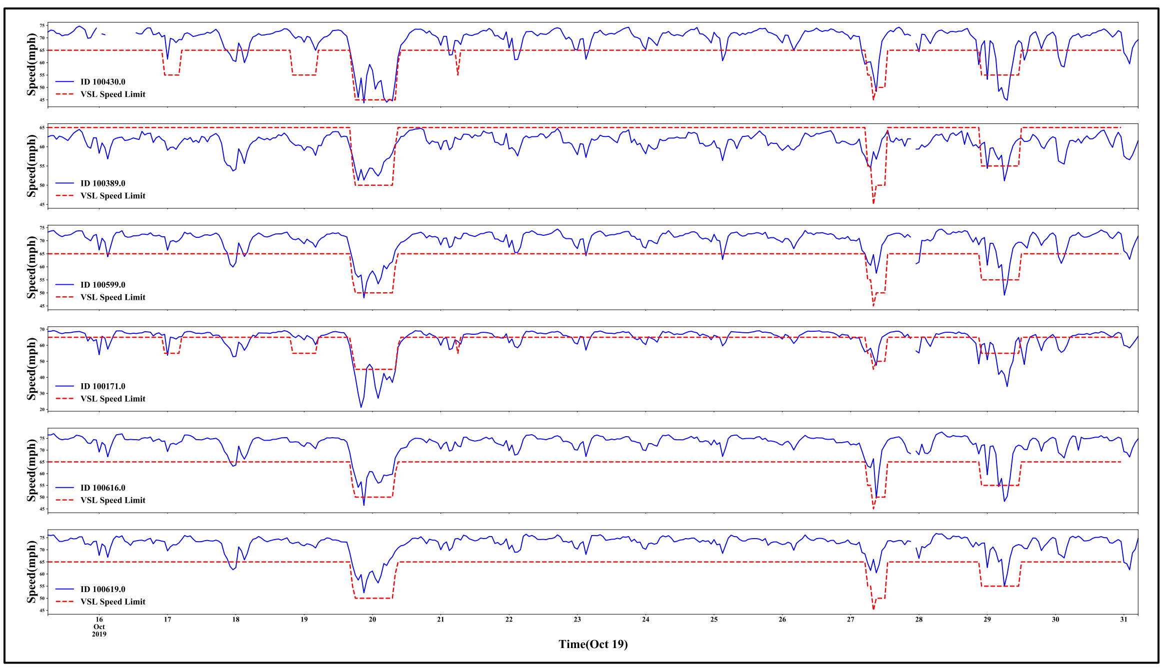

Figure 4.3 Hourly Average Speed of Sensors with Displayed VSL Speed Limit in I-80 Eastbound (Fall 2019)

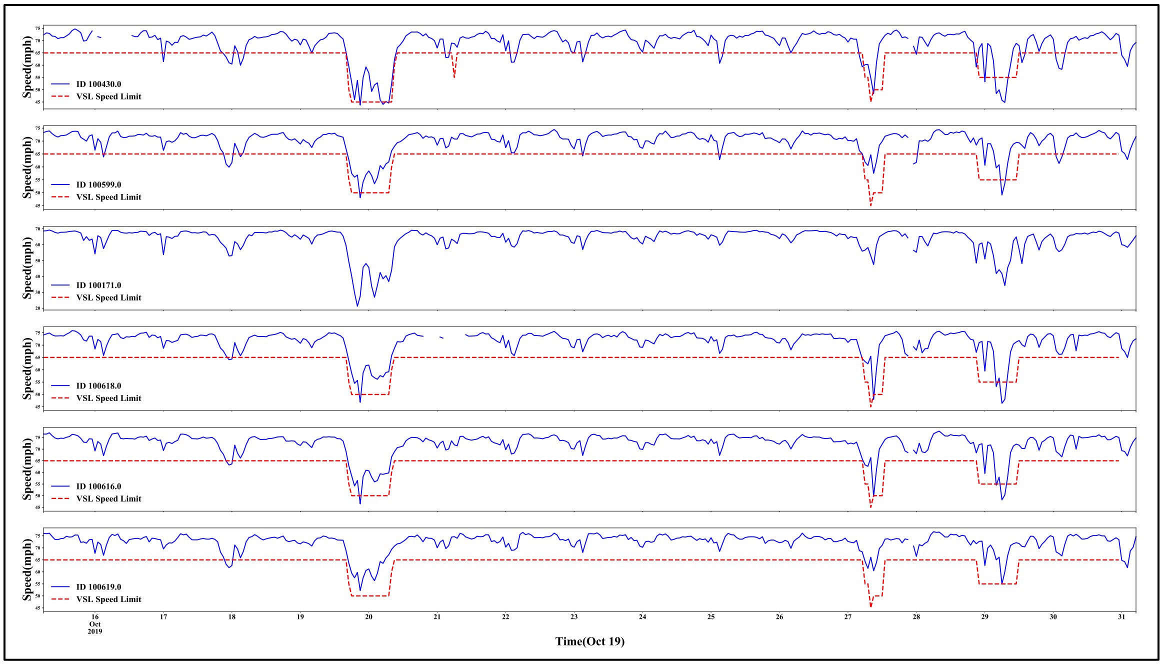

Figure 4.4 Hourly Average Speed of Sensors with Displayed VSL Speed Limit in I-80 Westbound (Fall 2019)

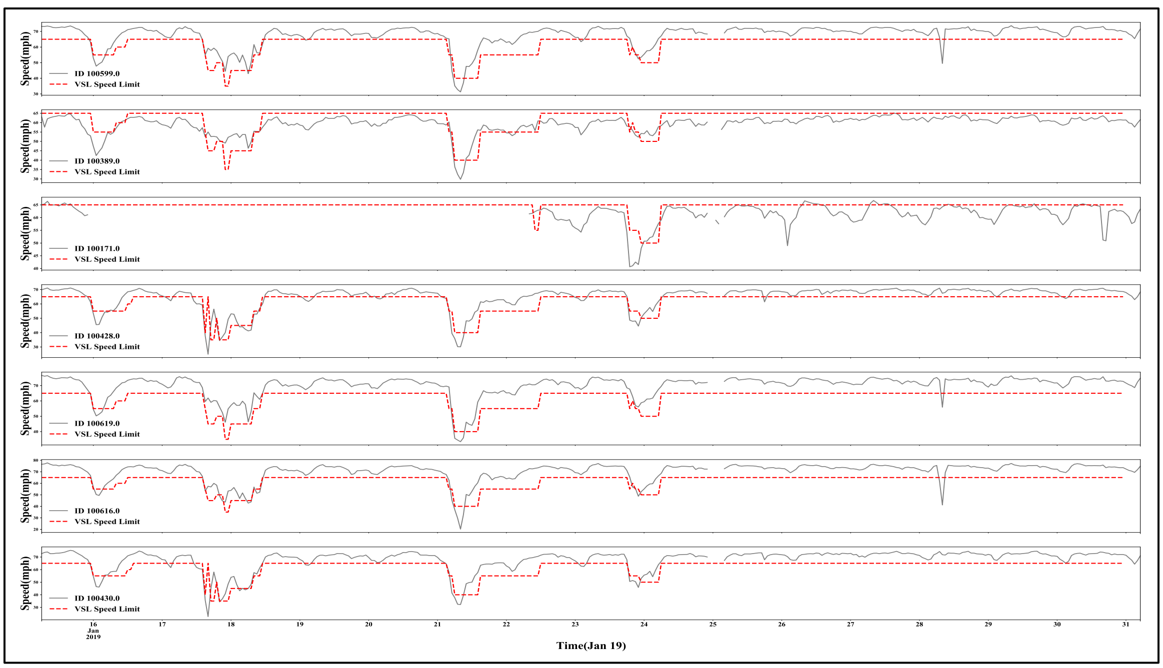

Figure 4.5 Hourly Average Speed of Sensors with Displayed VSL Speed Limit in I-80 Eastbound (Winter 2019)

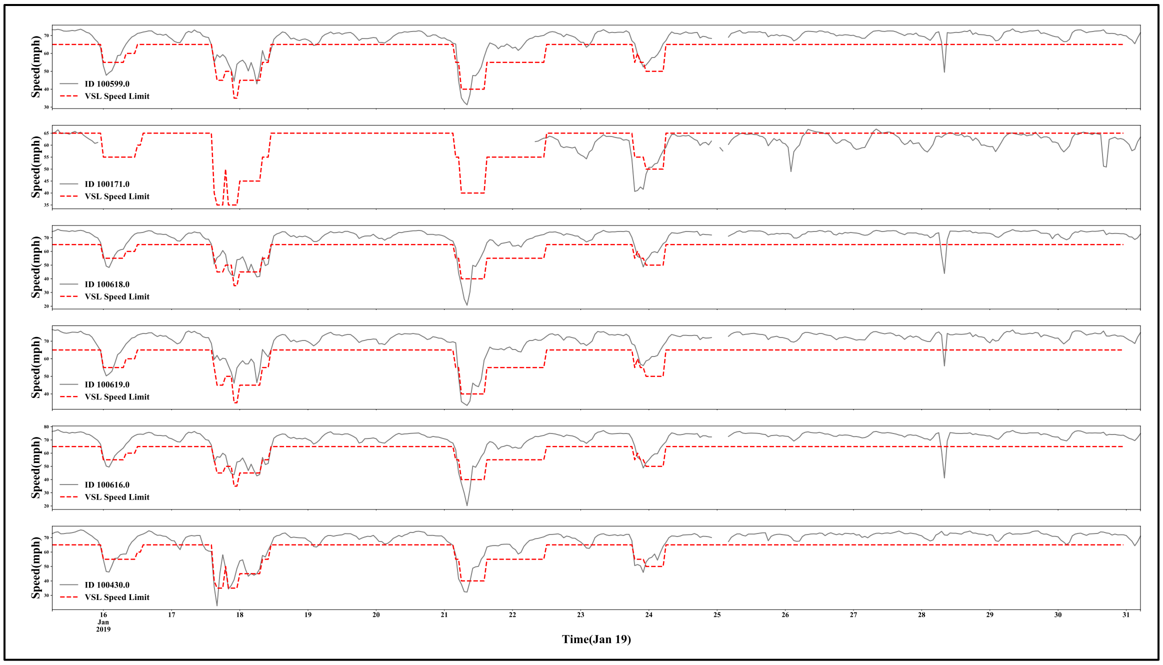

Figure 4.6 Hourly Average Speed of Sensors with Displayed VSL Speed Limit in I-80 Westbound (Winter 2019)

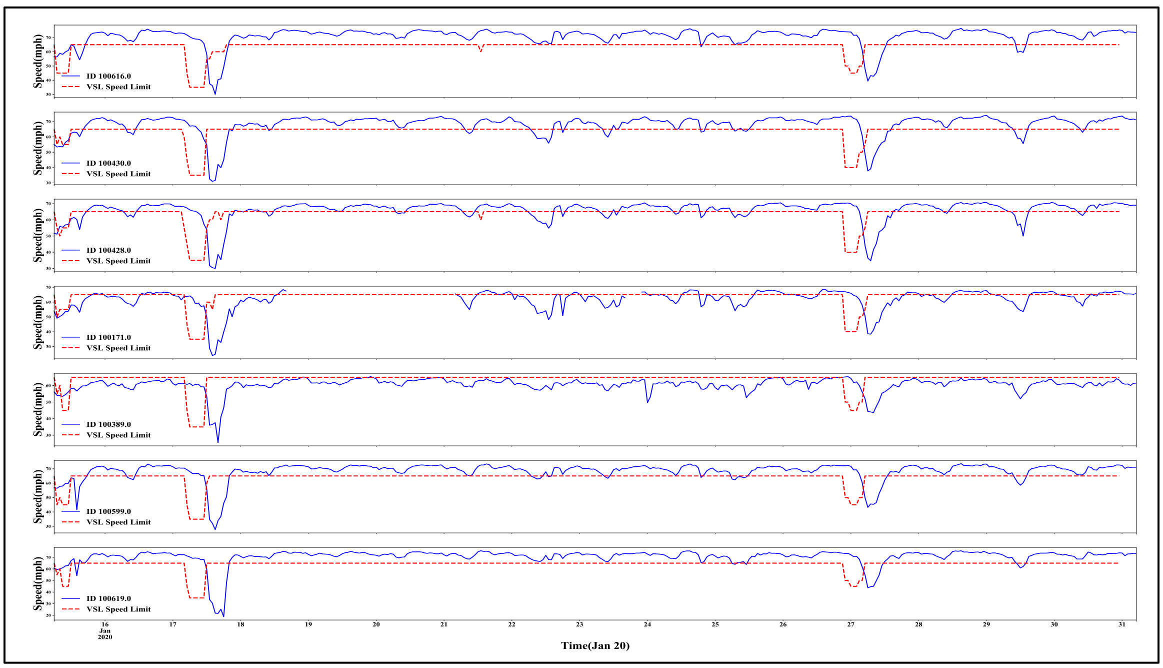

Figure 4.7 Hourly Average Speed of Sensors with Displayed VSL Speed Limit in I-80 Eastbound (Winter 2020)

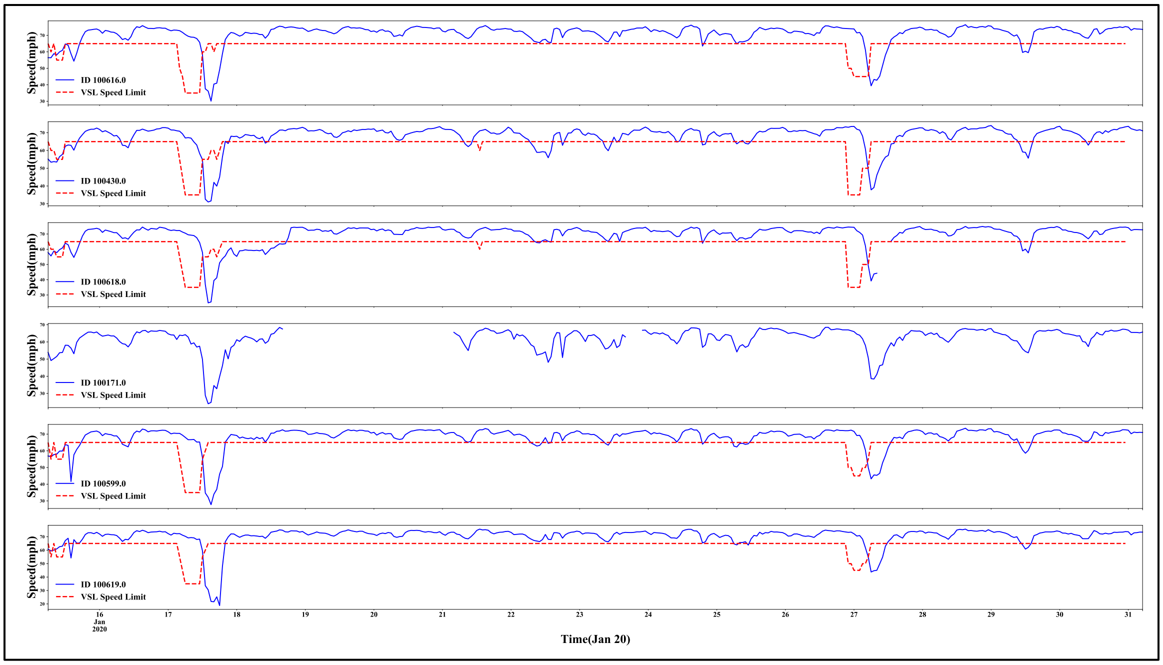

Figure 4.8 Hourly Average Speed of Sensors with Displayed VSL Speed Limit in I-80 Westbound (Winter 2020)

The second parameter shows that the safety impact of signs with higher visibility is the number of crashes in the VSL zone on I-80. Crash rates have been reviewed for both legend colors to determine if the amber legend positively impacts the network. Based on recorded crashes on the I-80 corridor, there is about a 50% decrease in incident numbers after installing new VSL signs. The number of recorded crashes is depicted in Figure 4.9.

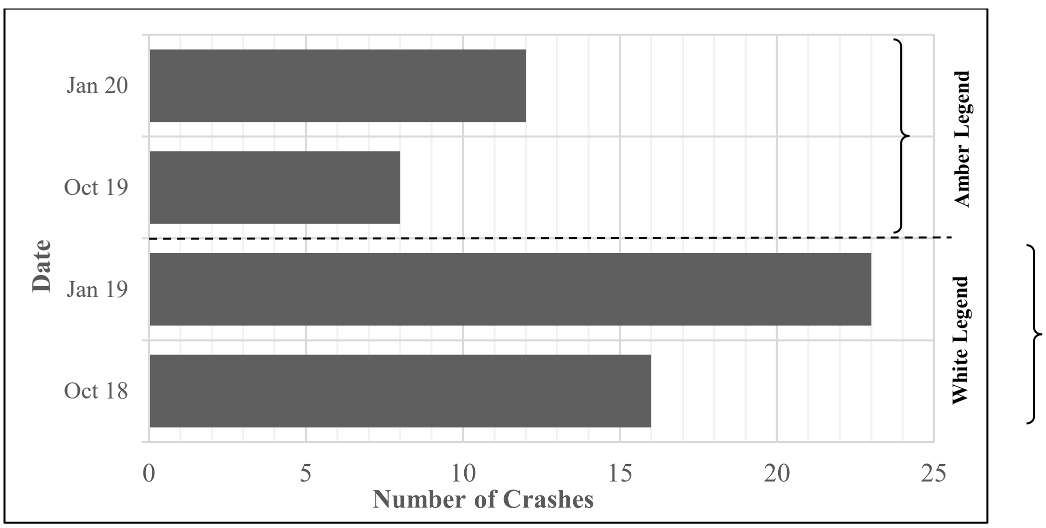

Figure 4.9 Crash Rate of I-80 Corridor Before and After the new VSL Sign Installation

Road conditions, visibility, and inclement weather are factors that affect crashes. To see how the road environment has influenced the number of crashes, the corridor crash records are analyzed for the recorded crashes. The results indicate that in both periods the road setting and driving conditions were at high risk, which proves that the reduction in incidents results from improved safety due to more visible signs. The road impact analysis on crash rates is presented in Figure 4.10 and Figure 4.11.

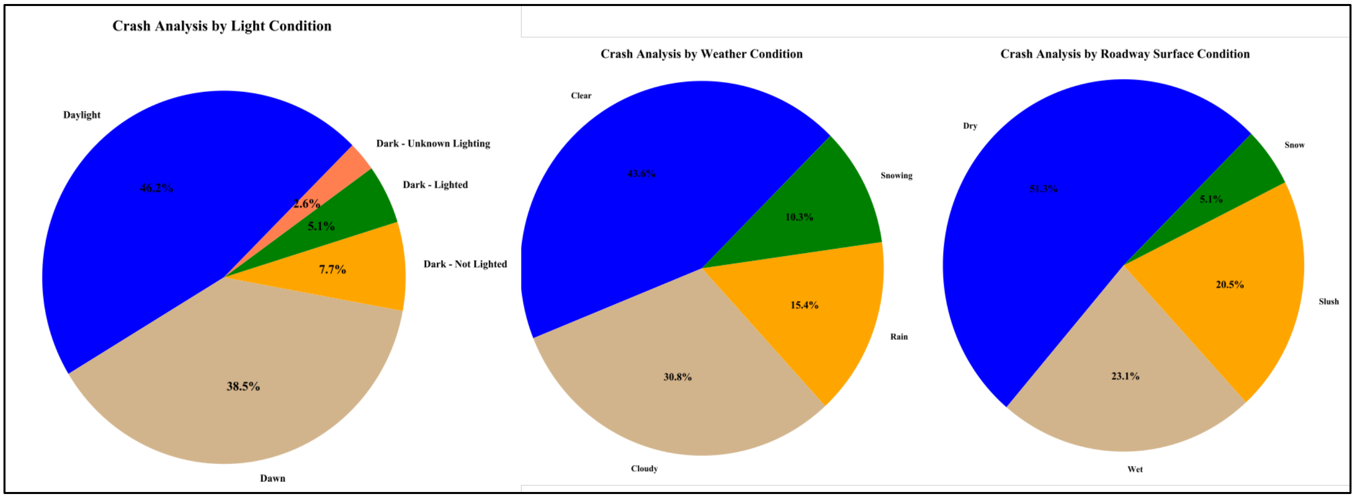

Figure 4.10 Crash Rate Analysis for Road Condition with VSL Signs with White Legend

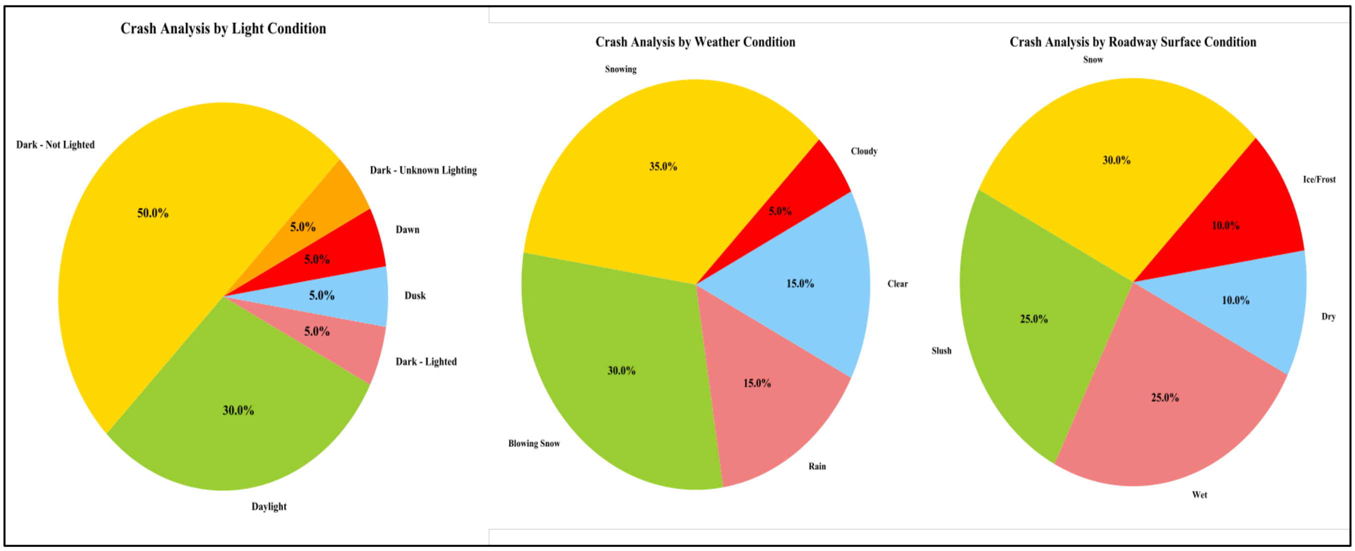

Figure 4.11 Crash Rate Analysis for Road Condition with VSL Signs with Amber Legend

A more detailed speed profile of the recorded data for dropped speed limit is evaluated to analyze driver behavior with the reduced speed limit. As in the wintertime, the I-80 corridor experiences multiple snowstorms and lower visibility conditions; safety assurance is needed for drivers and traffic flow. By investigating the weather index of the corridor in January 2019 and 2020, it is found that most crashes occurred due to reduced visibility and wet road surface conditions. The weather condition of the corridor is demonstrated. The weather road index indicates the driving status of the road segment, and as it gets below zero, the driving situation is riskier. The plots in Figure 4.12 and Figure 4.13 show there are multiple occasions in winter where road conditions become precarious. Yet, the lower visibility at the same time worsens driving conditions for drivers.

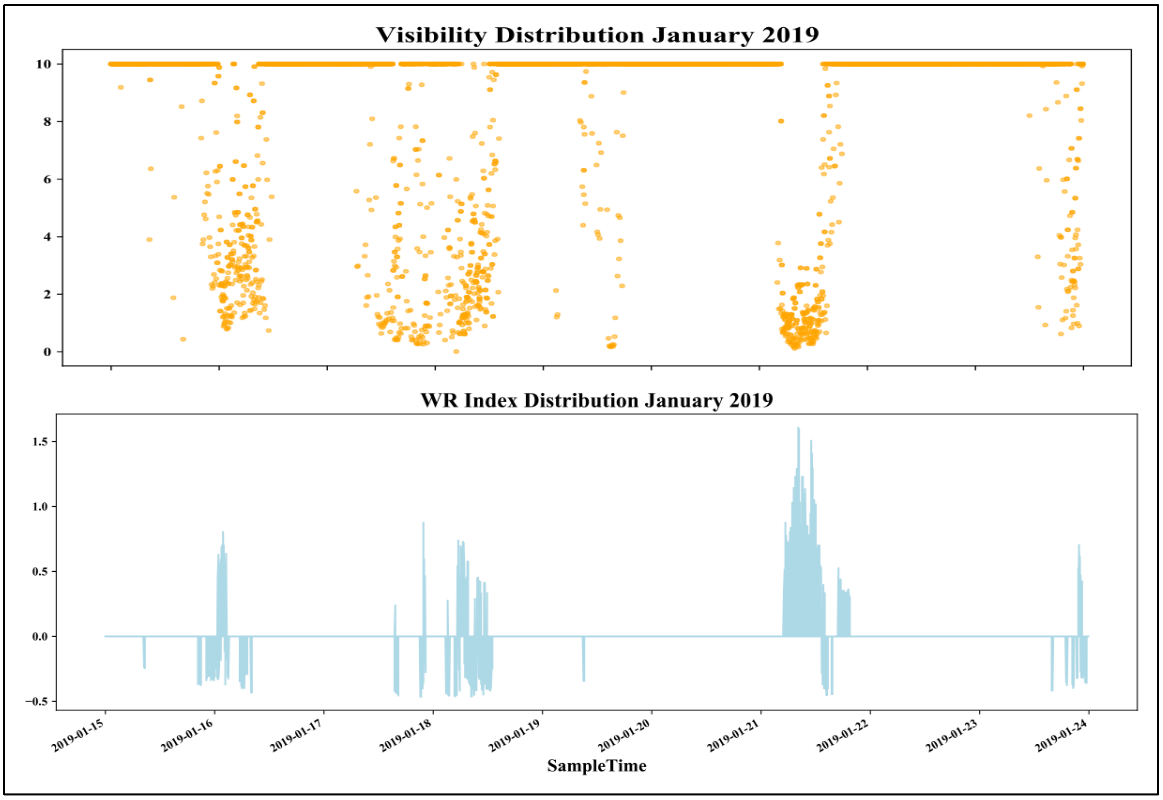

Figure 4.12 Weather Condition of Corridor in January 2019

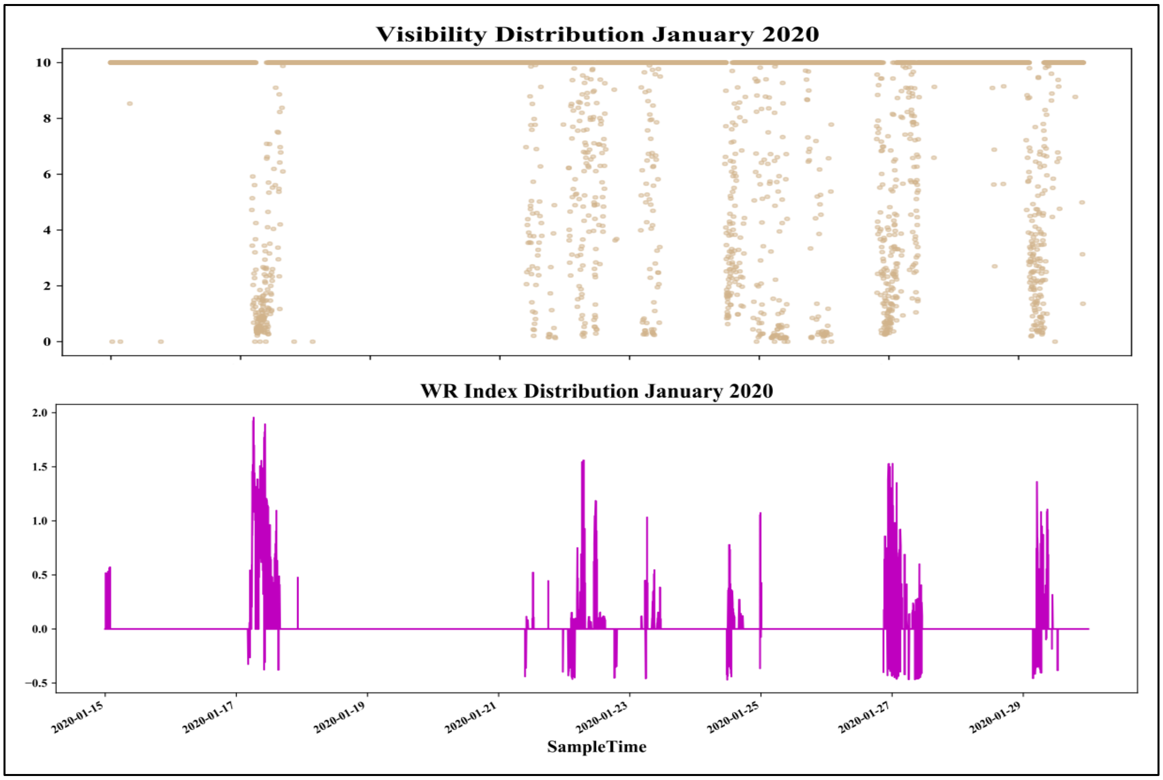

Figure 4.13 Weather Condition of Corridor in January 2020

The drivers' compliance implies that the new VSL system has improved and enhanced driver performance in insecure conditions. A more detailed speed profile of the road in Figure 4.14 and Figure 4.15 verify this recent finding. Still, the reduced speed demonstrates the safety performance of the corridor.

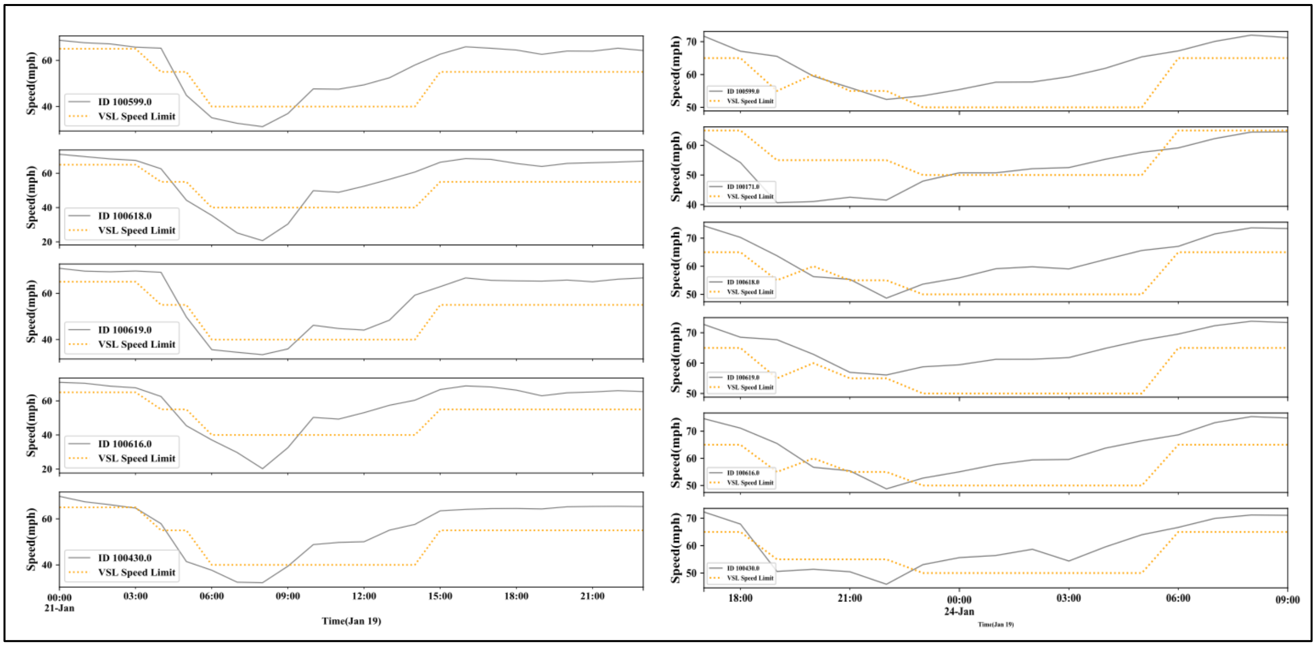

Figure 4.14 Detailed Sample of Speed Profile in Inclement Weather with White Legend VSL Signs

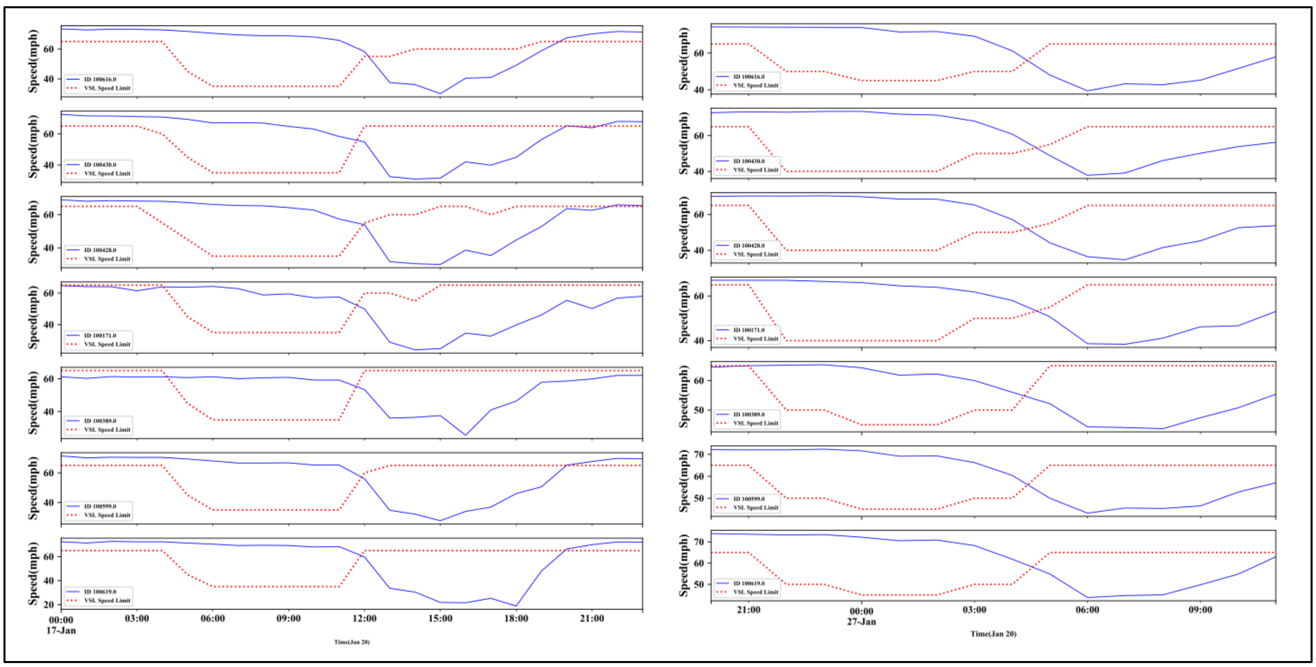

Figure 4.15 Detailed Sample of Speed Profile in Inclement Weather with Amber Legend VSL Signs

Based on the analysis performed on recorded data, it can be concluded that safety and compliance rates have been enhanced due to the improved visibility of the new VSL signs. The conversion of the VSL from an advisory sign to a regulatory sign has had a notable positive impact on visibility and traffic flow compliance. The decrease in average traffic flow speed and drivers' tendency to drive closer to the speed limit can be attributed primarily to the VSL sign legend's transition from white to amber. Furthermore, in winter, when higher precipitation results in slick road surfaces and reduced visibility, the driver compliance rate increases. The reduction in crash rates also indicates that improved VSL sign visibility directly impacts dampening the adverse effects of a road's low visibility and unusual weather conditions. The detailed description of crash data showed that most crashes occur due to poor lighting conditions or slushy road surfaces in this corridor. The former conditions also hold for crashes that occurred in the winter before and after the new VSL sign installations. Keeping in mind that comparisons were made with similar road conditions and months, the decline in crash numbers can be positively correlated with the improved visibility of the amber legends.

4.4 Summary

The data evaluation chapter focused on amber legend signs' impact on road performance and safety. For an evaluation of flow operation speed records, environmental data, VSL log historical data, and crash records were examined. First, the compliance rate was determined to evaluate drivers' reactions to new signs. New values demonstrate that average speed has decreased and variation from speed limits has lowered. Next, the hourly average speed was depicted versus the speed limit to evaluate the flow's behavior toward the new VSL, which shows coordination between the variables. The crash analysis proved that new signs can improve safety as the crash quantity decreased and became less severe in unusual conditions. In conclusion, the new signs have boosted flow operation and increased the safety of the corridor.

5. SAFETY EVALUATION MODEL

5.1 Overview

A safety model is developed in this chapter to evaluate the corridor's crash severity using the occurrence data, weather index, and crash records to analyze the system's safety. the developed models are ML models, which are trained based on features that contribute to road safety levels. By adding the VSL color legend's transition to the model, results show the impact of improved visibility on crash severity.

5.2 Training Data

The studied data include traffic flow data recorded by detectors, VSLs' displayed speed limits, weather index data, and crash data. Collected data have a biweekly range in fall (October 2018 and 2019), summer (July 2019), and winter (January 2019 and 2020) before and after the implementation of new signs. As the road condition, environment condition, and traffic flow state will influence road safety, these variables have been used as inputs in the safety evaluation model. However, before developing the safety model, these variables need to be analyzed and their correlation with safety must be evaluated. Since this study aims to study the impact of improved visibility of VSL signs on road safety, the VSL sign color legend is also considered a feature for safety assessment.

The hybrid VSL signs with yellow legend were set up in September 2019. Therefore, the crash records for the obtained traffic data were studied, and the frequency of crashes for each VSL setting was compared. Based on recorded crashes in the I-80 corridor, there was a reduction in incident numbers after installing new VSL signs for the same seasons. The number of recorded crashes is depicted in Figure 5.1.

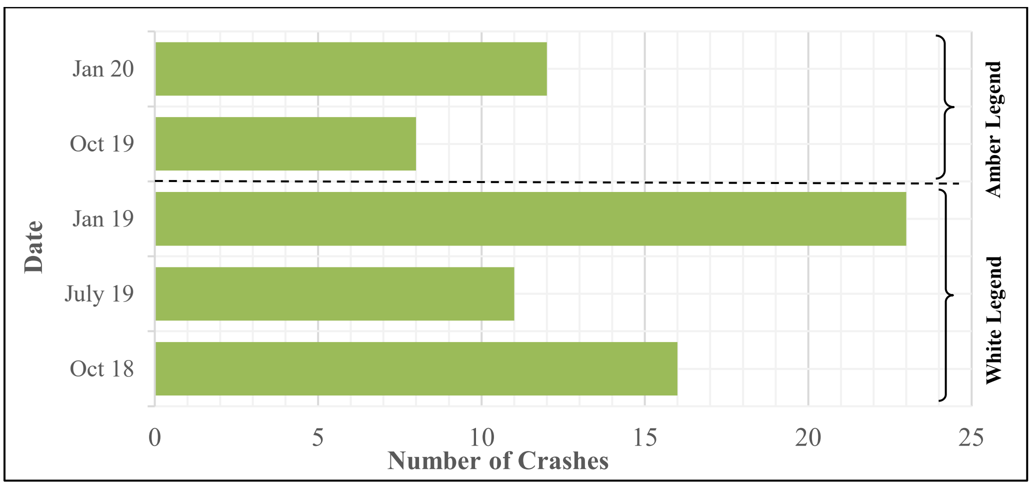

Figure 5.1 Crash Rate of I-80 Corridor Before and After the new VSL Sign Installation

Variables used in model development contain data collected by detectors in the VSL zone, weather index data collected by sensors, and crash records. This study tried to develop a safety model that will predict crash severity classifications. Therefore, some explanatory variables like VSL sign legend color are transformed into a binary variable in which a white legend equals zero and a yellow legend is shown by 1. The average hourly data are used as the dataset for model development. A summary of the dataset and statistic distribution of each variable is provided in Table 5.1.

Table 5.1 Statistical Summary of Dataset

Feature	Count	Mean	SD	Min	Max
	9755				
Speed		63.61	7.23	10.16	78.36
Speed Limit		64.15	3.74	35	65
Postmile				127.39	141.28
Visibility		9.51	1.73	0.14	10
WRWI		0.01	0.12	-0.41	1.6
Surface Status		1.32	1.34	1	12
Surface Grip		0.8	0.07	0.18	0.82
Crash Severity		0.01	0.12	0	4
Frequency		0.01	0.09	0	3
# Vehicles		0.01	0.15	0	4
VSL Legend Color				0	1
No Lanes		2.74	0.76	2	4

To feed the inputs to the model, the correlation between attributes needs to be analyzed. Using Pearson correlation, the correlation of a pair of variables are evaluated, and these values are presented in Table 5.2. Based on the values in Table 5.2, there is a low correlation between crash severity and legend color, but the negative values demonstrate that the yellow legend has decreased the severity.

Table 5.2 Pearson Correlation Value between Input Variables for Safety Model

Variable	Severity	Frequency	# Vehicles	Legend
Speed	-0.043	-0.044	-0.026	-0.068
Speed Limit	-0.063	-0.060	-0.056	-0.044
Postmile	-0.002	-0.010	-0.001	0.002
Frequency	-0.061	-0.054	-0.048	-0.150
# Vehicles	0.070	0.058	0.057	0.067
Visibility	0.139	0.148	0.117	0.107
WRWI	-0.065	-0.064	-0.058	-0.124
Legend		0.846	0.866	-0.048
Surface	0.846		0.876	-0.049
Lanes	0.866	0.876		-0.055

Among the datasets used to develop the model, only 69 crashes are recorded, and their severity is divided into four classifications. Crash severities in order of severity levels are no injury (the lowest level), possible injury, suspected minor injury, and suspected serious injury. Crash severity rate for each level is demonstrated in Figure 5.2. Even though the dataset is big enough, higher crash severity frequency is relatively low, affecting the model's accuracy in classifying more severe crashes.

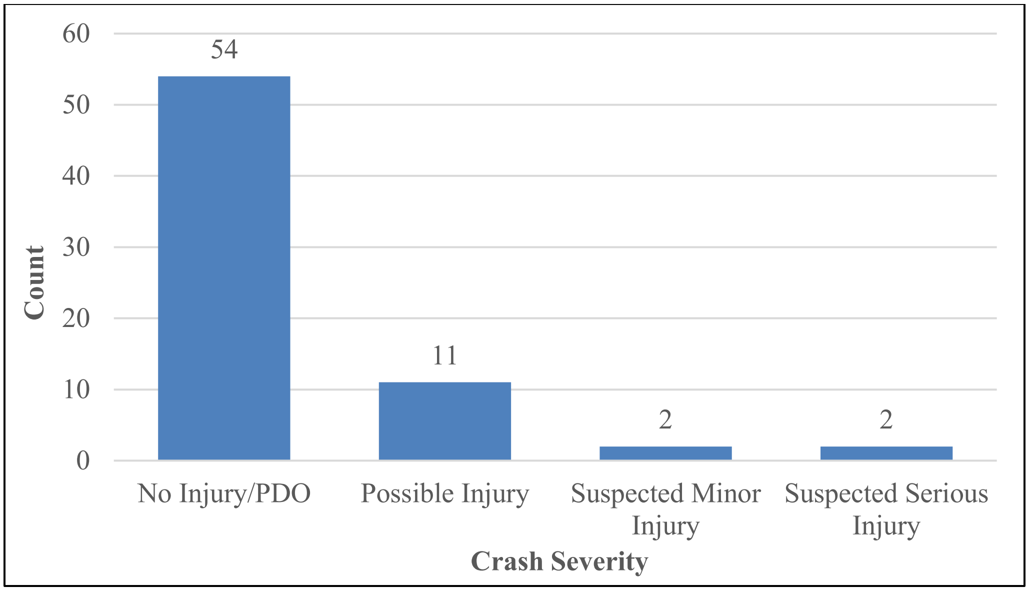

Figure 5.2 Crash Severity Frequency in Dataset

5.3 Safety Model Development

To evaluate the corridor's safety, the SVM and ANN classification methods are used to predict crash frequency and severity correspondingly in the corridor per hour using the road and environment data. Since the crash variables are discrete classification values, classification multilayer perception (MLP) is used. The SVM classifier will predict the number of crashes per hour (0,1,..). The ANN model will also estimate crash severity from level 1 (no injury) to the highest level (level 4) and level zero for when there is no crash.

SVM is constructed from a set of hyperplanes that will classify the data. These hyperplanes can be linear or any other higher dimension functions. The most suitable hyperplane is the one that will maximize the distance from the closest data point in each class, which means the generalization error is minimized. Line classifiers are based on the margin maximization principle (Adankon & Cheriet, 2009) to find the best function to classify the inputs. Depending on the number of features and input dimension, the hyperplane will get more complicated.

On the other hand, ANN is a framework created out of multiple layers, including the input layer, hidden layers, and output layers. The attributes are taken as input and fed to the next layers (hidden layers) with their corresponding weight and activation function in this approach. Then using the actual labels, the weights are adjusted. The weights and parameters of the function will be optimized using gradient descent optimization. The framework is depicted in Figure 5.3, schematically.

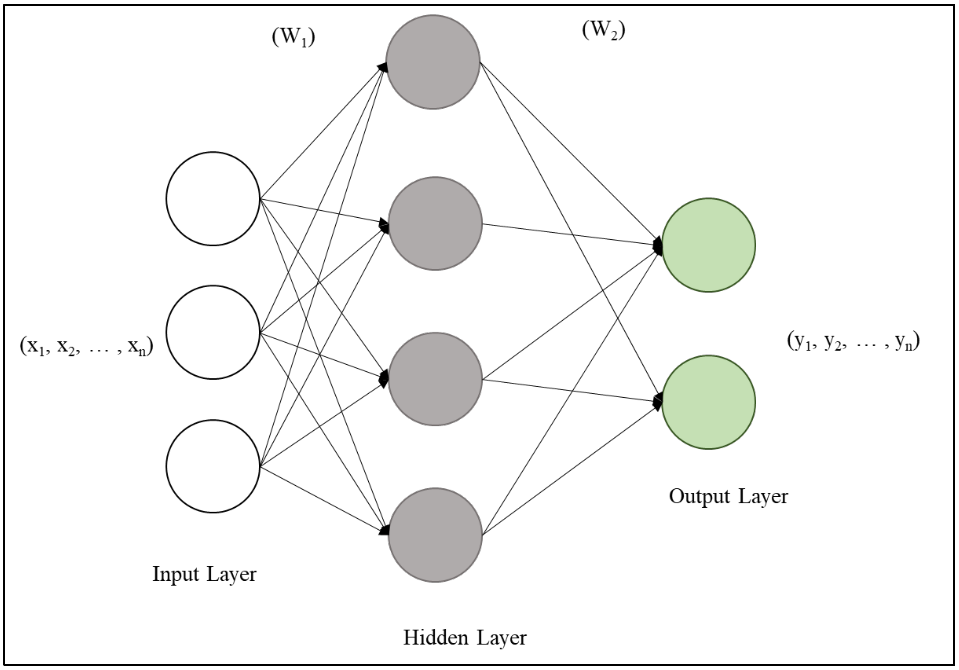

Figure 5.3 Schematic Work-frame of ANN

The original data are divided into a training set, testing set, and cross-validation set to develop and train the model. The ratio of the training set to testing set and cross-validation site is 3 to 2. After training the model based on input data and tuning in the parameters, the best result is made by an SVM with radial basis function to predict the crash frequency and a 4-layer ANN with 50 and 40 nodes in hidden layers for crash severity. To predict the crash frequency, occurrence data, weather index, and speed limit data are used, while for crash severity, crash records features are used to train the model. Fitted model results show a regression score function (r-squared) of 0.14 and 0.65 and the root of the mean square (RSME) of 0.087 and 0.083 for the SVM and ANN model, respectively. The results are shown in Table 5.3 and Table 5.4.

Table 5.3 SVM Model Safety Evaluation Performance Metrics

Frequency/Hr	Precision	Recall	F1-score	Support
0	0.99	1	1	3877
1	0.83	0.22	0.34	23
2	0	0	0	3

Table 5.4 MLP Safety Evaluation Performance Metrics

Class	Precision	Recall	F1-score	Support
Level 0	1	1	1	3877
Level 1	0.69	1	0.82	18
Level 2	0	0	0	5
Level 3	0	0	0	1
Level 4	0	0	0	2

Precision and recall in Table 5.3 and Table 5.4 show the model's ability not to label the negative values as positive and label all the positive values correctly. In this case, a positive value means one that belongs to a specific class and a negative one that does not. Also, F1-score is the average of precision and recall, and support is the sample size available in the set for each class.

Since the MLP model can be affected by random state and data split set, 5-fold cross-validation is also done, producing the following results. Performance metrics for each iteration are shown below. Cross-validation will divide the dataset into 'k' subsets and train the model each time to remove the bias values in training the model.

Table 5.5 SVM Cross-Validation Performance Results

Iteration	Accuracy	MSE	MAD	R^2
1	0.993	0	0	0.044
2	0.996	0	0	0.42
3	0.995	0.16	0.16	0.138
4	0.995	0	0	0.137
5	0.994	0.02	0.21	0
Average	0.9946	0.036	0.074	0.1478

Table 5.6 ANN Cross-Validation Performance Results

Iteration	Accuracy	MSE	MAD	R^2
1	0.995	0	0.0059	0.44
2	0.998	0	0.0017	0.81
3	0.996	0.028	0.0034	0.59
4	0.999	0	0.008	0.89
5	1	0.002	0	1
Average	0.9976	0.006	0.0038	0.746

To show the effect of changing the VSL sign's color legend, the developed models are used to predict the number of crashes and crash severities in both conditions. Based on the models' test results on a set of data, both models show a 0.99 accuracy and mean square error of 0.005 and 0.001 for the SVM and ANN model, respectively. The heat map of both models predicting the crash frequency and severity is depicted in Figure 5.4 and Figure 5.5.

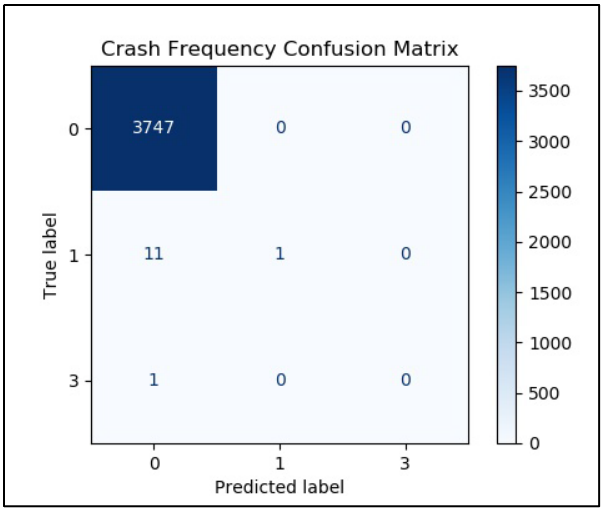

Figure 5.4 Heatmap of Crash Frequency Model

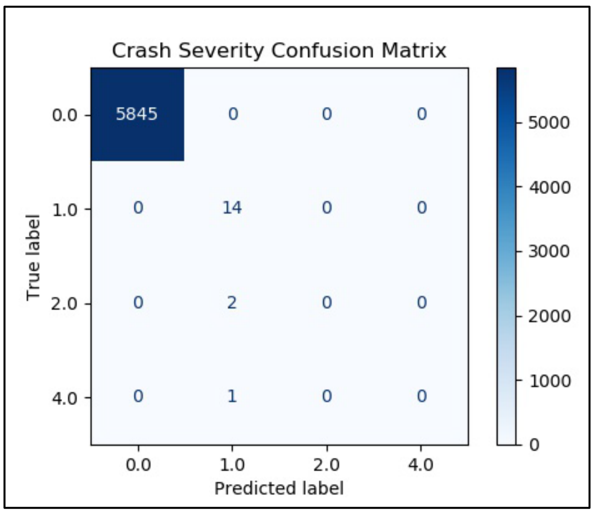

Figure 5.5 Heatmap of Crash Severity Model

The models' estimation shows that with the new VSL sign's color legend, crash frequency will decrease up to 80% and crash severity to almost 10%. Sample datasets based on multiple implementation models are shown in Figure 5.6. The new VSL sign color legend shows that safety has improved due to fewer and less severe crashes.

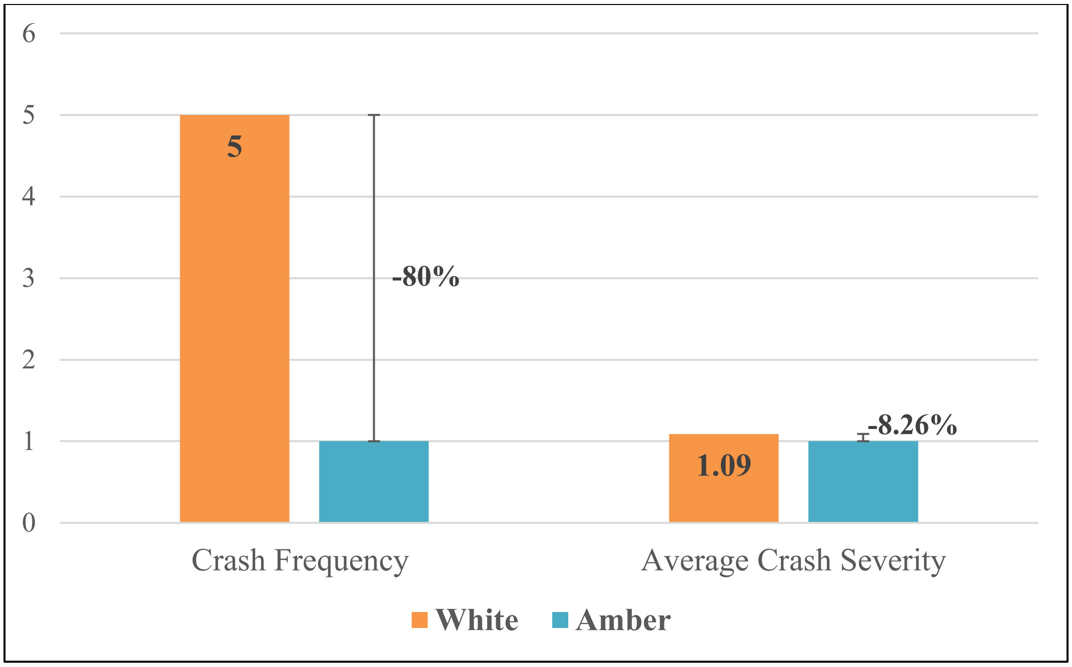

Figure 5.6 Safety Model Estimation with Both VSL Sign Color Legends

5.4 Summary

In this chapter, VSL zone safety was modeled using traffic data and crash records. Using ML models, the developed models will predict crash frequency and severity with high accuracy. Although lack of sufficient severe crash records may result in lower accuracy for higher severity crashes, the models can perform precisely for other classes. In addition, using the amber legend as a variable helps study the relationship between safety and sign legend. Model results show a decline in both crash severity and frequency after installing signs with the amber legend.

6. CONCLUSIONS

6.1 Summary

The purpose of this study was to scrutinize the transition of VSL signs from white legend to the amber legend on I-80 in Parley's Canyon area. To achieve this, we started by studying the VSL system literature and case applications. The literature review information helped identify the adoption of a road's performance to system and exception cases from MUTCD. Thereafter, by investigating the historical traffic and road data, traffic flow performance and drivers' compatibility with the new system were evaluated. Finally, by developing safety models, the crash data are estimated to create a framework that can appraise road safety considering the changes in VSL signs. The project outcomes help apprise planners and authorities about the effects of the new VSL system on road function and safety.

6.2 Findings

VSL signs have been used increasingly in North America based on variable traffic and weather conditions. VSL signs' objective is to manage traffic at flow fluctuations by providing drivers with information and alerts regarding downstream status. A change in regular road geometry or flow patterns increases the need for precautionary signs such as VSLs to improve safety performance. The speed limit displayed on signs is regulated by the embedded algorithm in the system that considers average flow speeds, driving condition impacts, and road geometry. When a VSL sign is implemented in corridors with severe climates, data recorded by weather and visibility detectors installed on the road will also adjust the advised speed limit for enhanced safety. The dynamic speed limit helps drivers adapt to changing road conditions while maintaining road safety.

In a section of the I-80 freeway in Parley's Canyon, Utah, VSL signs have been mounted as a response to reduced visibility from a harsh climate during cold seasons. As these signs are categorized as regulatory devices by MUTCD guidelines, hybrid signs with a white legend on a black background were originally installed. Reduced visibility in snowstorms during winter and strong sunlight during summer were motives to change signs from a white legend to an amber legend. This transformation initially aimed to increase the visibility of these signs to improve safety by enhancing driver adaptability to upcoming flows. This study focused on on-site traffic detector data, weather radar data, and crash data to evaluate VSL system performance and its results in traffic operation before and after the implementation of new signs. The conclusions of each task are provided in the following chapter.

6.2.1 Literature and Case Studies

By exploring the studies and research done on CMS applications, we became more familiar with the CMS system and VSL algorithms. Also, the VSL implementation cases have shown that an additional advisory system about driving conditions can enhance driving safety. Based on the MUTCD, VSL signs might have a white on black background for regulatory signs; however, VSL signs have been used with the amber legend in corridors with low visibility due to recurring adverse conditions or work zones. The safety evaluation literature we reviewed utilizes various safety models to assess road safety. Among the developed methods, we picked the ML models, which are proven to outperform other models in accuracy and speed.

6.2.2 Visibility Based on Sign Recordings

Since the start of the project, three rounds of field trips were conducted to record signs in the VSL zone. Judging from the driver's view and sign's sight, the amber legend is more noticeable, especially in low visibility conditions, making drivers more alert about the speed limit. Another significant improvement was that sight distance with the amber legend increased, providing drivers with more decision-making time.

6.2.3 Corridor's Operation Performance

Based on the analysis performed on recorded data, it can be concluded that safety and compliance rates have been enhanced due to improved visibility of the new VSL signs. The conversion of the VSL sign from advisory sign to regulatory has had a notable positive impact on visibility and traffic flow compliance. The decrease in average traffic flow speed and drivers' tendency to drive with speeds closer to the speed limit can be primarily attributed to the VSL sign legend's change from white to amber. Furthermore, in winter, when higher precipitation results in slick road surfaces and reduced visibility, driver compliance rates increased. The reduction in crash rates also indicates that improved VSL sign visibility directly impacts dampening the adverse effects of poor road and weather conditions. The detailed crash data descriptions showed that most crashes occur due to poor lighting conditions or slushy road surfaces in this corridor. The former conditions also hold true for crashes that occurred in the winter before and after the new VSL sign installations. Keeping in mind that comparisons were made with similar road conditions over a period of months, the decline in crash numbers can be positively correlated with the improved visibility of the amber legends.

6.2.4 Safety Evaluation Using ML

Traffic occurrence data, driving conditions, and crash data were used to evaluate the safety model. The correlation of input data demonstrated that safety factors are positively related to road and driving conditions. The transition from a white to amber legend, as used as an input variable, positively impacted visibility; the correlation of crash variables and color legend proved this. Based on this relation, a safety model was developed using the SVM and ANN classification methods. Performance evaluation of the models demonstrated the high accuracy of the model for safety evaluation. However, due to the limited number of records for higher crash severity, it did not show the same accuracy for those levels. Results of the models in both conditions demonstrate lower crash records with the amber legend, indicating the safety improvement. Outcomes of safety models indicate that the new legend color improved the safety of the corridor by reducing crashes and their severity.

6.3 Limitations and Challenges

Since this project started in spring 2019 and the new signs were installed in summer 2019, we did not have a chance to record the white legend signs during cold seasons. Even though corresponding data for cold seasons are analyzed before and after, the signs' visibility comparison was confined to summer. Also, due to the project's timeline, summer data of the VSL zone with the amber legend are not pulled for further analysis and assessment. However, most crashes have occurred in cold seasons, but summer data evaluation will provide a more comprehensive overview of the road's performance.

A broader range of data will improve the model's precision for all levels of severity and frequency for developing the safety model. Most literature studies use at least a two-to-three-year data range for reliable model development. Furthermore, we suggest expanding the survey from drivers in the I-80 corridor to investigate the VSL signs' visibility from a broader range of users. Recent experiments help officials get a sense of driver perspectives regarding the new VSL system.

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