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

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RESEARCH

UDOT Keeping Utah Moving
Utah Department of Transportation - Research Division
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DISCLAIMER

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16. Abstract
To improve traffic safety on a section of I-80 (through the mountains east of Salt Lake City) that experiences frequent periods of difficult weather, the Utah Department of Transportation (UDOT) implemented a Variable Speed Limit (VSL) zone (from MP 128.0 to MP 141.0 in both directions) using regulatory hybrid Changeable Message Signs (CMS). Originally, the CMS used white LED digits and black backgrounds. However, it was found that the visibility of those white digits that indicate speed limits has become a problem during inclement weather, especially snowstorms. During the summer season, strong sunlight can also affect the visibility of those white digits. To tackle this problem, UDOT has replaced the original CMS with amber/yellow digits for improved visibility. This research project aims to evaluate the effectiveness of the new CMS and perform a comprehensive before-and-after analysis of VSL system performance. The analysis is done by field trip video recordings, detector data analysis, and crash data examinations. Moreover, this research develops a road safety assessment model that takes occurrence data, road geometric features, and crash records as input. The model can be further used to predict road safety and the speed compliance rate improvement after the implementation of new CMS on other freeway corridors.

17. Key Words Variable Speed Limit, Visibility, Traffic Management, Safety Evaluation, Safety Model, Machine Learning.		18. Distribution Statement Not restricted. Available through: UDOT Research Division 4501 South 2700 West P.O. Box 148410 Salt Lake City, UT 84114-8410 www.udot.utah.gov/go/research		23. Registrant's Seal N/A
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LIST OF ACRONYMS

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

EXECUTIVE SUMMARY

In practice, dynamic traffic management is an effective solution to improve both traffic safety and operational efficiency due to its ability to continuously adapt to changing traffic conditions. For example, some operations strategies, such as variable speed limit (VSL) control, have been recognized as promising control methods since the emergence of Intelligent Transportation Systems (ITS) in the 1990s. Due to exposure to frequent inclement weather in Parley's Canyon, the Utah Department of Transportation (UDOT) implemented a VSL zone (from MP 128.0 to MP 141.0 in both directions) using regulatory hybrid Changeable Message Signs (CMS). At the early stage, the CMS were operated with white digits and black backgrounds. However, during inclement weather, especially snowstorms, it was found that the visibility of those white digits that indicate speed limits has become a problem, when VSL control is particularly needed. Moreoever, during the summer season, strong sunlight can also affect visibility of the white digit speed limits. Since low visibility can invalidate the primary goal of VSL to improve safety, those CMS have been replaced by new ones with amber/yellow digits. The primary objective of this research project is to evaluate the effectiveness of the new CMS by performing a comprehensive before-and-after analysis. Moreover, the previous system that requires traffic engineers to manually change speed limits has been updated to an online-based version with automatic operation. In this research, a detailed study of road safety and operation performance is also conducted to evaluate the new system's performance and efficiency.

In the first stage of this research, multiple field trips for video recordings were made to evaluate the CMS' visibility from the driver's view. Considering that inclement weather such as snowstorms and bright sunlight can affect sign visibility, field trips were made in both summer and winter. Then, by collecting other field data such as traffic flow information, displayed speed limit records, weather index data, and crash rates, road safety performance before and after the implementation of the new VSL system with amber CMS, are compared. Finally, machine learning (ML) models, including Artificial Neural Network (ANN) and Support Vector Machine (SVM), are developed to model crash frequency and severity along the I-80 corridor. Those safety models can help evaluate the road safety improvement for future VSL deployments.

Based on data anlaysis, it was found that the I-80 corridor's average speed and speed variation have been reduced after the implementation of the new CMS. The driver compliance rate, which is the critical indicator of VSL system performance, has also been improved. In addition, the new CMS have resulted in significantly lower crash rates and severity. Crash severity decrease is detected mostly under adverse driving conditions (e.g., icy road survey, low visibility, etc.), which proves the effectiveness of the new CMS in improving traffic safety.

1.0 INTRODUCTION

1.1 Problem Statement

Inclement weather such as snowstorms and fog will change driver behaviors, reduce visibility, and consequently affect road traffic safety. According to existing traffic safety studies, adverse driving conditions have caused many traffic injuries and fatalities in the US during the past decade (Hassan *et al.*, 2012). Moreover, physical road conditions such as grade, altitude, and curvature can also result in various unusual driving conditions. Therefore, providing road information and beforehand notification becomes crucial for safety concerns. In these cases, Changeable Message Signs (CMS) are often implemented with visibility detectors to warn the drivers about incidents and adverse road conditions (Federal Highway Administration, 2009; Hassan and Abdel-Aty, 2011; Hassan, Abdel-Aty and Oloufa, 2011; Hassan *et al.*, 2012). Particularly, variable speed limit (VSL) is one CMS that will dynamically adjust the speed limit. Under low visibility conditions, VSL control has proven to be effective in reducing average traffic speed and speed variations, improving driver compliance with the posted speed limit, and mitigating traffic crash risks (Rämä, 1999; Sisiopiku and Professor, 2001; Bertini, Boice, and Bogenberger, 2006; Gonzales, Fontaine, and Dutta, 2019; Wu *et al.*, 2019). Moreover, besides the improved safety and reduced crash risk, the deployment of VSL also helps save travel time and improve traffic operational efficiency in some cases (Lee, Hellinga, and Saccomanno, 2004; Abdel-Aty, Dilmore, and Dhindsa, 2006a).

To increase safety and operational efficiency on a section of I-80 that experiences frequent periods of difficult weather, the Utah Department of Transportation (UDOT) has implemented a VSL zone (from MP 128.0 to MP 141.0 in both directions) using regulatory hybrid CMS. By MUTCD guidelines, amber/yellow LED digits are commonly used to represent warning notifications and white LED digits are used for traffic control and law enforcement (Federal Highway Administration, 2009). Hence, CMS on the I-80 corridor originally operated with white digits and black backgrounds to display speed limits. However, it was found that the visibility of those white digits decreased during inclement weather (e.g., snowstorms). This problem is compounded by the fact that this is when there will most likely be a need to activate

VSL controls to improve safety. Moreover, during the summer season, strong sunlight can also affect CMS visibility.

To tackle this problem, UDOT started replacing those white digit CMS with new ones with amber digits in 2019. To study the effectiveness of those new CMS in improving sign visibility and roadway safety, this research project performs a comprehensive before-and-after analysis of VSL system performance based on the VSL records, onsite traffic detector information, historical traffic crash data, and field trip videotapes. The outcome of this project will assist UDOT in evaluating whether or not such implementation can indicate a demonstrable improvement of road safety under various weather and traffic conditions.

In addition, the original VSL system required traffic engineers to manually change speed limits (usually started at 2-3 AM) based on the observed traffic speed. Considering tremendous labor is needed to carry out such a task, UDOT's Traffic Operations Center (TOC) further developed an online-based system for automatic operations. To assist UDOT in evaluating the new system's performance, another goal of this project is to analyze I-80 safety performance and the driver compliance rate before and after the new system implementation. Notably, this project will also examine the condition when traffic is too light to provide enough speed data to determine the VSL to be displayed. Then, based on the collected data, machine learning (ML) models, including Artificial Neural Network (ANN) and Support Vector Machine (SVM), are developed to model crash frequency and severity along the I-80 corridor. Those safety models can help evaluate the road safety improvement for future VSL deployments.

1.2 Objectives

The primary objective of this research project is to analyze road safety performance after implementing the amber CMS and the automatic VSL system. For this purpose, multiple field trips for video recordings are made to examine the visibility alteration from the driver's view. Also, various real cases using VSL with amber CMS are reviewed to offer lessons learned regarding the effects of the amber legend on the safety and functionality of transportation networks. Then, using the occurrence data, the corridor's weather index data, displayed speed limits, and historical crash records, a comprehensive evalution of the new VSL system's safety and operational performance is conducted.

Moreover, using ML techniques, two safety models are developed to estimate crash severity and crash frequency. ANN and SVM classification modes are employed to classify the crash frequency level and severity based on road geometric features, traffic flow data, and driving conditions. The two developed models are further applied to study the effectiveness of new signs in road safety.

1.3 Scope

The research scope of this project includes:

1. In the first task, this research performs a literature review of state practices of VSL with amber legend, studies about VSL control, and road safety evaluations.
2. In the second task, this research conducts multiple field trips with video recordings, during both summer and winter seasons, to compare VSL system performance before and after the implementation of CMS with amber digits.
3. In the third task, this research obtains supplementary data such as traffic flow information by highway sensors, historical crash records, VSL log data, and weather index in corresponding times. Those data are collected for Fall 2018 and 2019, and Winter 2019 and 2020 to study the VSL zone's safety.
4. In the last task, this research develops two safety models to estimate crash frequency and severity on the studied I-80 corridor and to confirm the effectiveness of the new system in improving road traffic safety.

2.0 LITERATURE REVIEW

2.1 Overview

In this chapter, existing VSL studies related to control algorithms, the purpose of use, and performance evaluation methods are reviewed. Moreover, state practices from multiple VSL applications are summarized to provide lessons learned. Finally, modeling approaches for road safety evaluation are explored, followed by a summary of the current research gap.

2.2 VSL Guidance and State Practices

When adverse driving conditions are detected, CMS such as speed warnings, regulatory information, and driving guidance are commonly used for improving road safety. A VSL system that dynamically adjusts the displayed speed limit has been recognized as one effective CMS. According to the MUTCD, hybrid CMS for regulatory purposes should be displayed with white LED digits and black backgrounds, while CMS with amber digits are often used for warning and temporary traffic control signs (Federal Highway Administration, 2009). However, the existing regulations may raise safety concerns due to the low visibility of white LED digits under some conditions. Particularly, VSL signs are deployed in many places, include the US and Europe based on different needs and control algorithms. Some VSL systems are used for improving road safety during inclement weather conditions, such as snowstorms, where the visibility of white LED digits could become a problem. Therefore, despite many existing studies showing that traffic safety, congestion, and even pollution have decreased with VSL, the control system's performance could be significantly downgraded when the displayed speed limits are not quite visible.

In many existing VSL applications, weather-related control algorithms first evaluated the road segment visibility based on traffic detector data, friction sensor information, or human observations, and then determined when to activate the VSL control (Chang and Kang, 2008; Katz et al., 2012; Lyu et al., 2017). Depending on the system architecture, a VSL system for weather-related control can consider different variables and can be automated, semi-automated, or manual. According to the Federal Highway Administration (FHWA), the VSL used for wet weather conditions often considered design speed, operating speed, minimum speed, roadway geometrical characteristics, and sight distance from the sensors. The system would check for the road weather condition and use the 85th percentile speed and the road design speed limit to determine the dynamic speed limits to be displayed. In cases where the determined dynamic speed limit is less than the 85th percentile speed, VSL control can be temporarily deactivated and the speed limit regulation for normal conditions would be applied (Katz et al., 2012). In other cases, VSL can be operated to provide advisory speeds for traffic operational efficiency considerations (Texas A&M Transportation Institute, 2017).

In a recent VSL deployment in Wyoming, some modifications to the FHWA suggested algorithm have been made to reduce the crash risk (Lee et al., 2013). Except for the speed data mentioned earlier, the system also took Road Weather Information System (RWIS) data as input. The data were fused with other information to determine the speed limit upperbound. Moreover, the VSL system adopted a multi-stage control algorithm. In the first stage, the obtained 85th percentile traffic speed and vehicle counts were used to suggest a new speed limit. Then, by using some subfilters and a visibility threshold filter in the second stage, the speed limit would be determined by rounding it to the 85th percentile. The difference between the speed limits in these two stages should not be greater than 15 mph. Otherwise, the one from the first stage would be implemented.

2.3 VSL Control for Traffic Safety

VSL was initially designed to reduce speed differences and harmonize traffic flow on hazardous highway segments, lower rear-end collision rates, and improve traffic safety. Most existing studies focus on improving the speed compliance rate and reducing crash severity with VSL control implementations (Piao and McDonald, 2008; Sui and Young, 2013; Abdel-Aty and Wang, 2017; Ding and Gou, 2018). In those studies, road safety improvement is highly correlated to the driver's level of compliance. Also, since the compliance rate becomes critical during irregular situations and congested conditions, the safety improvement by VSL could be more significant in an overcrowded condition (Habtemichael and de Picado Santos, 2013). Using the PARAMICS microsimulation program, Abdel-Aty et al. (2009) found that the implementation of variable speed limits successfully reduced rear-end and lane-change crash risks in low-volume traffic conditions.

Other studies model crash rates based on variables such as geometric design, flow characteristics, and empirical data (Promothes et al., 2006b; Ding and Gou, 2018). Based on their results, traffic flow speed variation and distribution could be effective indicators of VSL's impact on traffic safety. The average speed collected by the detector is an indicator of the driver's response to the speed limit. Besides, the difference in average speed and displayed speed is another parameter to show the drivers' behaviors in response to VSL. Speed variance, 85th percentile speed, travel time, and high-speed rates are other measurements of effectiveness for assessing VSL performances (For et al., 2003; Lyles et al., 2004; Sui and Young, 2013). Particularly, studies have proved that drivers' compliance is the primary measurement directly related to road safety (Hellinga and Mandelzys, 2011). The compliance rate is also relevant to the speed limit shown by VSL, where the compliance rate decreases as the speed increases (Boateng et al., 2019). Moreover, traffic flow information is also used to develop crash level models (Lee, et al., 2006), where most studies show that incident rates will decrease significantly after VSL implementation, especially in severe conditions. Simulation is another approach to predicting the crash rate after VSL implementation and analyzing safety measurements (Piao and McDonald, 2008; Giles, 2004).

Using model-based control logic, Talebpour et al. (2013) proposed a reactive rule-based speed harmonization algorithm to delay or even prevent traffic breakdowns, which improved both safety and efficiency in a microscopic simulation of a hypothetical freeway segment. They assumed that connected vehicle technology was available and able to obtain each vehicle's trajectory to facilitate early detection of shock waves. To reduce crash risk and improve freeway safety, Yang and Lu (2014) developed an optimal VSL control system to smooth speed reduction before traffic reaches work zone bottleneck areas.

2.4 VSL Control for Traffic Operation

Recently, it was discovered that VSL might also have the potential to mitigate traffic congestion and improve traffic operational efficiency in freeway bottleneck sections (Texas

A&M Transportation Institute, 2017; Lu and Shladover, 2014). Through properly displayed and dynamically changed speed limits based on traffic conditions, it is believed that VSL can smooth the flow transition between upstream and downstream segments, preventing shockwaves, and mitigating or at least postponing congestion (Grumert et al., 2018). Hegyi et al. (2005) adopted a model-predictive control approach to determine the optimal speed limit, and observed a nearly 20% travel-time reduction in their simulation experiments. Based on the observed effect of VSL on aggregated traffic flow behavior summarized by Papageorgiou et al. (2008), Carlson et al. (2010) proposed an open-loop, integrated, optimal control framework to coordinate ramp metering with VSL. Their simulation results showed an improvement in total travel time of 15%. And then, Carlson et al. (2011) also extended a 2-loop local feedback controller to decide VSL speed and obtained comparable results in a METANET simulation environment (Messmer and Papageorgiou, 1990), which might face difficulties in practical field implementations. Other researchers, such as Hadiuzzaman and Qiu (2013) and Yang et al. (2015), reported a significant reduction in total travel time with VISSIM simulations.

Unlike the simulation-based evaluation of VSL research, variable speed limit field deployment experiments in the Netherlands (Smulders 1990) and Spain (Soriguera et al., 2015) showed no significant improvement in roadway capacity. However, in a field evaluation on the Dutch A12 Freeway (Hegyi and Hoogendoorn, 2010), VSL was shown to be effective, resolving 80% of solvable shockwaves, but its efficiency improvement in travel time was not significant. Weikl et al. (2013) analyzed data obtained from the German Autobahn A99 Freeway near Munich and concluded that VSL could reduce shockwave speed and balance lane distribution at the cost of slightly reduced capacity. In the United States, Chang et al. (2011) reported successful implementation of an integrated VSL and travel-time information system on the Maryland Route 100 Highway near Coca-Cola Drive (Hanover, Maryland), finding that VSL alone improved travel time by 7.5% and that, paired with a real-time travel-time display, it realized an improvement of 26.4%.

2.5 Road Safety Evaluation Models

In the literature, many studies used system theories and systematic description frameworks to perform a road safety assessment. Those developed models used a logical relation between road features and other factors influencing safety (Goh and Love, 2012; Hughes *et al.*, 2015). Moreover, the impact of the road or human features on crashes was used to set policies and was applied in road designs (Elvik, 2003). Developed numerical safety models typically are based on statistical techniques to predict crash frequency and severity. Road geometric design and its consistency, traffic flow characteristics, and driving conditions were considered in statistical methods (Hauer, 2004; Wang et al., 2011; Zheng et al., 2020). Statistical models, including regression models and multilevel models, have been used to estimate crash frequency in the literature (Lord and Mannering, 2010), and logit and probit models have been used for crash severity estimation (Savolainen *et al.*, 2011).

However, predefined relationships and assumptions in statistical methods may contradict the reality and confine the application of such methods (Silva, Andrade, and Ferreira, 2020). Accordingly, machine learning (ML) methods came in handy which do not need any pre-assumptions. ML-based safety models will be trained and fitted by input data. ML methods evaluate road safety by crash frequency, severity, or a combination of both. Artificial neural network (ANN) is one ML method used for both crash frequency and severity estimations. ANN uses the feature vector, including the variable related to the crash rate, to predict the desired safety factor. The features will be used as an input for each layer (hidden layers) using optimized weight and fitted function to estimate the output (Xie, Lord, and Zhang, 2007; Zeng *et al.*, 2016). Other ML methods such as decision tree, support vector machine (SVM), and nearest neighbor classification (KNN) are also used for crash frequency predictions (Chang, 2005).

To develop a model to estimate crash severity in a road segment, ML methods can be developed in the way of classifying crash severity levels. In the literature, ANN classification models have improved performances using clustering classification (Alikhani et al., 2013). Studies have proved that ML models will perform better compared to statistical methods in safety assessment (Silva et al., 2020). Also, ANN is proved to be the most suitable among all ML models in safety evaluations, which still depend on the data structure and variables available to feed the model (Chang, 2005). Also, the distribution of data correlations and optimization methods to find the best parameters can affect the model's accuracy and fitting (Zeng and Huang, 2014; Pan et al., 2017).

2.6 Summary

This chapter reviewed existing studies and state practices related to VSL control algorithm development, system deployment, and simulation evaluations. VSL signs can be used for various occasions and conveying dynamic information about the road for safer traffic management. Depending on the control objective, VSL control algorithms can be variable and can be presented differently. This chapter also reviewed safety models in the literature and concluded ML models could be a better option for this research.

3.0 VSL SIGNING VISIBILITY STUDY

3.1 Overview

As described in previous chapters, VSL implementation can bring significant road safety benefits by reducing potential crash frequency and severity, especially under adverse driving conditions. Moreover, driver compliance with the posted speed limit can greatly affect the effectiveness and efficiency of the VSL control system. Hence, ensuring the visibility of VSL signs (CMS) to drivers becomes a critical task for improving the compliance rate. Due to frequent inclement weather (e.g., snowstorms) in Parley's Canyon during the winter, the original VSL signs with white LED digits on the I-80 freeway corridor are not quite visible to drivers. Strong sunlight during the summer season can also affect signage visibility. To tackle this problem, UDOT started to replace them with new signs with amber digits starting in Fall 2019. To compare the visibility of original and new signs, this chapter presents some video snippets recorded by vehicle onboard cameras during field trips.

3.2 Field Trip Recordings

Recording road videos using vehicle onboard cameras is the best way to demonstrate the VSL signs' visibility before and after the CMS replacement. Therefore, the research team conducted a few field trips with video recording during both summer and winter seasons. Considering strong sunlight can affect CMS' visibility, the summer field trips were made in June and July. Moreover, in the mornings (8 AM –10 AM) and afternoons (4 PM – 6 PM), due to the sun's position in the sky, the CMS display angle, and drivers' sight height, the sun's reflection is directed to the driver's eyes which makes the VSL indiscernible for drivers. Based on the analysis by SunEarthTools, the sun's position in 2019 is depicted in Figure 3.1. According to the sun's largest angle with Earth, the videos are recorded during both morning and afternoon hours in July, and each period will greatly affect sign visibility in one travel direction. The VSL zone in I-80 towards the east of Salt Lake City aligns with the east-west directions. Hence, it is expected that the visibility along the east/west direction in the morning/afternoon will decrease the most. Besides, the visibility may be also affected by driving lane locations due to the change of sight angle to the CMS.

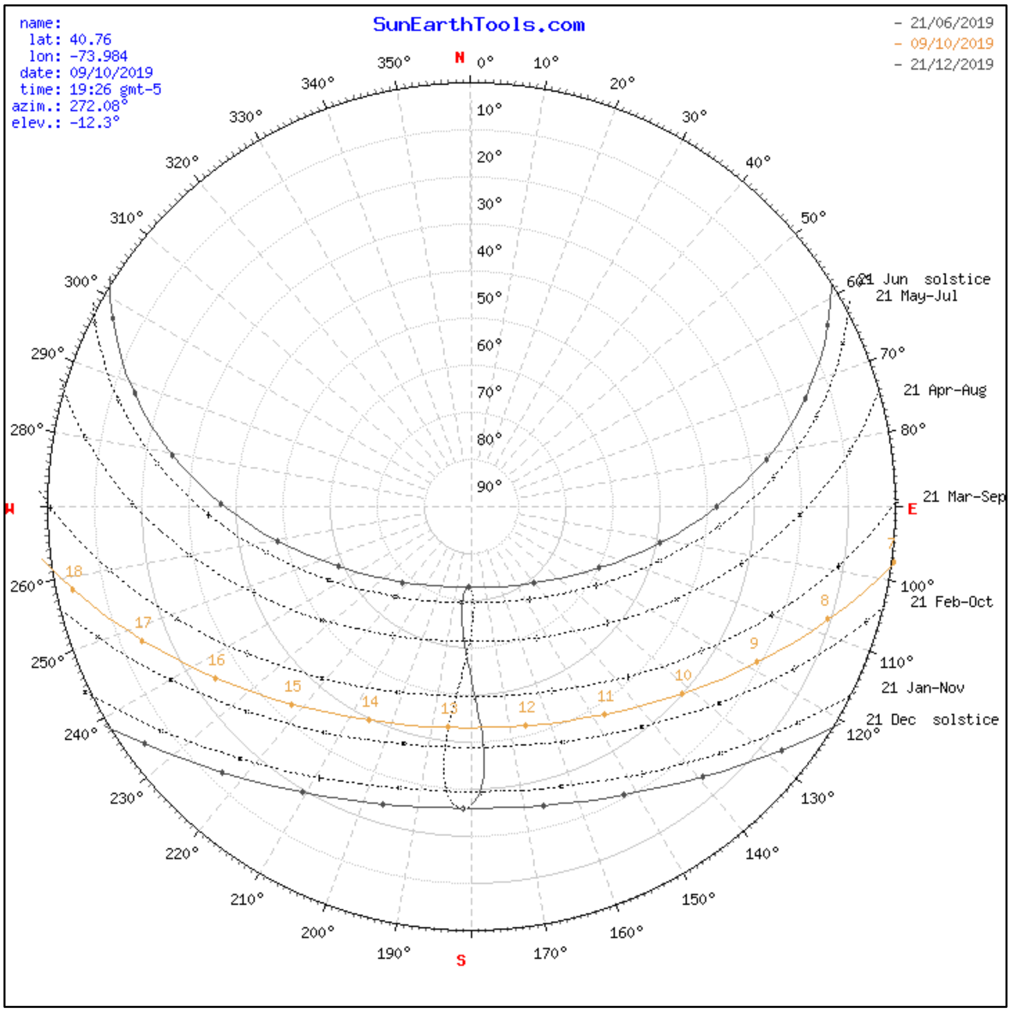

Figure 3.1 The sun position during the year of 2019

Recognizing those impact factors, field trips in both east and west directions, were made from MP 128.0 to MP 141.0 of the I-80 freeway for video recordings. Notably, those videos were taken by driving on all freeway lanes and during both morning and afternoon hours. Some video snippets are presented in the following sections for comparison.

3.2.1 Equipment

For data collections, a Vantrue N2 Pro Dual 1080P Dash Cam placed on a passenger car is used to record front view videos when driving on the studied I-80 corridor. Table 3.1 summarizes the data collection details, including the MP recorded, driving speed, recorded time, and recorded lane. The same data collection strategy is adopted for video recording during both summer and winter seasons. However, it should be noted that the amber CMS were fully installed in September 2019, and the corresponding study of amber sign visibility is only available after that date.

Table 3.1 Data collection features for video recording on 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

3.3 Video Snippets for VSL Sign Visibility Study

3.3.1 Visibility of VSL Affected by Direct Sunlight

On road trips within the I-80 VSL zone, 8 signs in the east direction and 7 VSL signs in the west direction were captured by the vehicle onboard camera. After reviewing the obtained videos and checking their relative visibility, all VSL signs are classified into two groups: VSL with low visibility and VSL with good visibility. Figures 3.2 to 3.13 show the video snippets of each white legend VSL that were collected at different times of day, driving in different lanes, and in different directions during the summer season. The VSL with relatively low visibility are displayed with red tags and those with good visibility are indicated by blue tags. Based on the visibility study, it can be observed that the direct sunlight reflection by the VSL, toward the driver’s sight, can greatly affect the visibility of those VSL with white legends. Also, several VSL signs have very low visibility in all recorded videos due to lack of power or other issues.

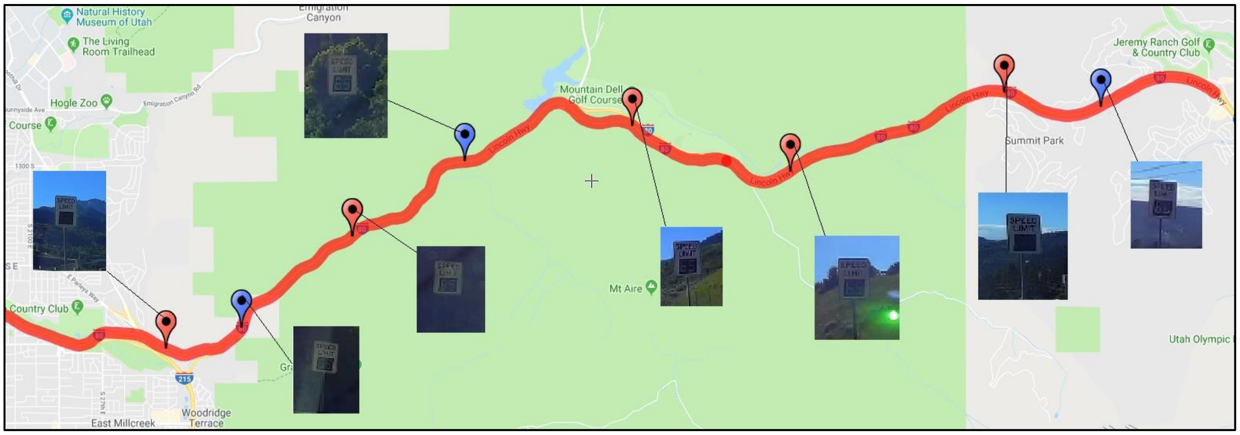

Figure 3.2 Video snippet (east approach, 1st Lane, white legend, morning, summer)

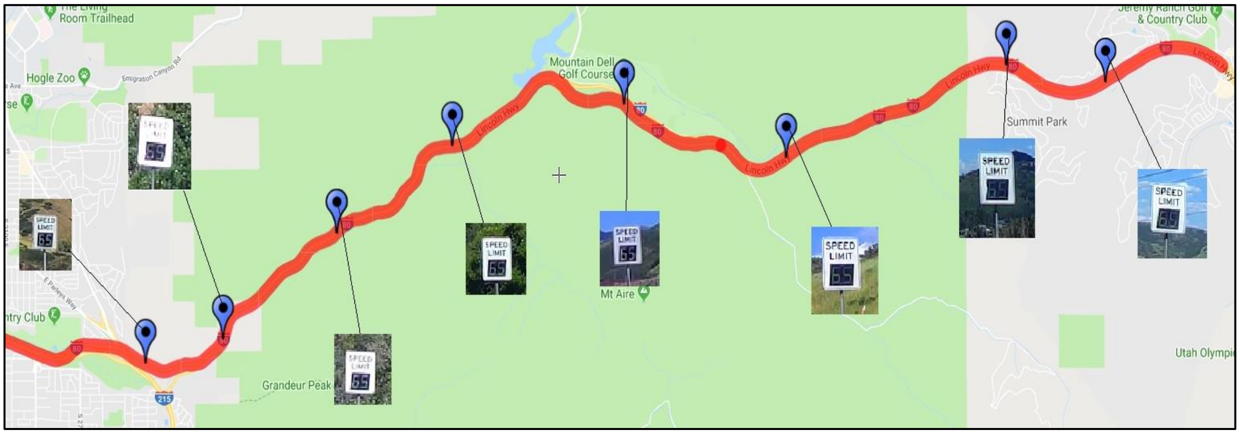

Figure 3.3 Video snippet (east approach, 1st Lane, white legend, afternoon, summer)

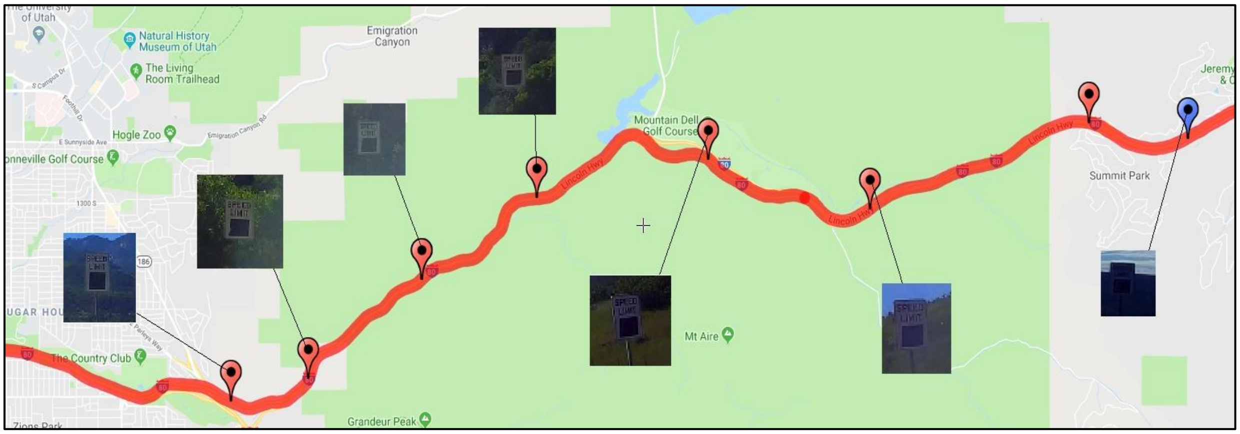

Figure 3.4 Video snippet (east approach, 2nd Lane, white legend, morning, summer)

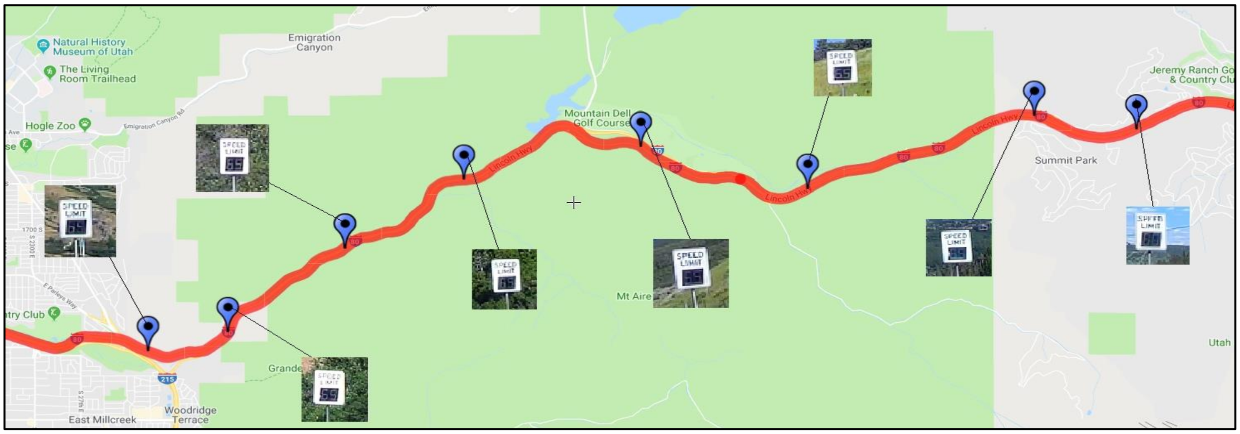

Figure 3.5 Video snippet (east approach, 2nd Lane, white legend, afternoon, summer)

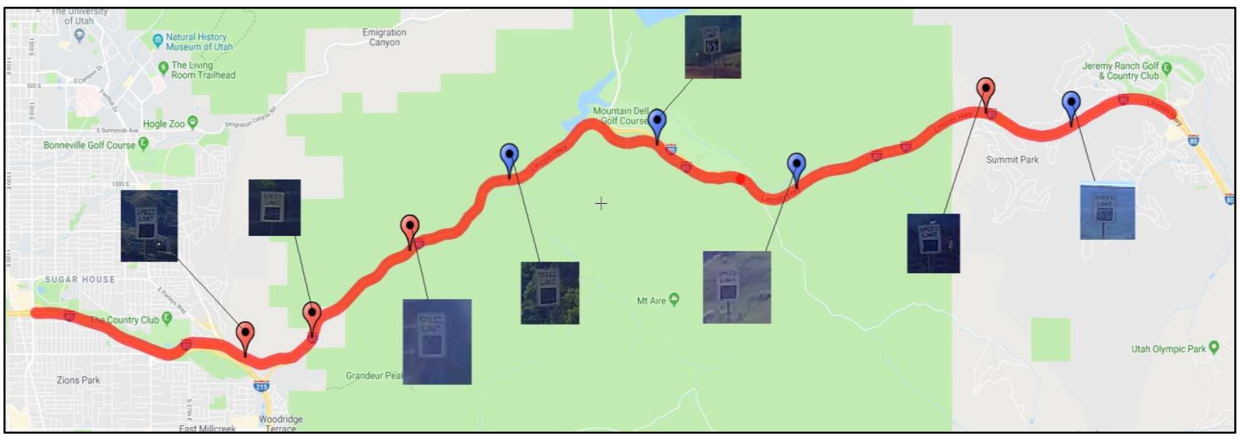

Figure 3.6 Video snippet (east approach, 3rd Lane, white legend, morning, summer)

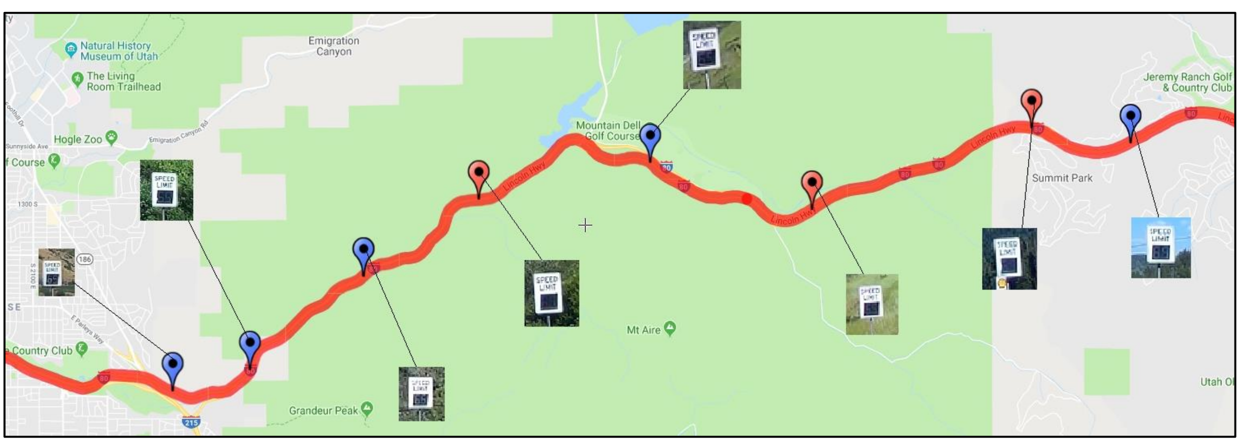

Figure 3.7 Video snippet (east approach, 3rd Lane, white legend, afternoon, summer)

Figure 3.8 Video snippet (west approach, 1st lane, white legend, morning, summer)

Figure 3.9 Video snippet (west approach, 1st lane, white legend, afternoon, summer)

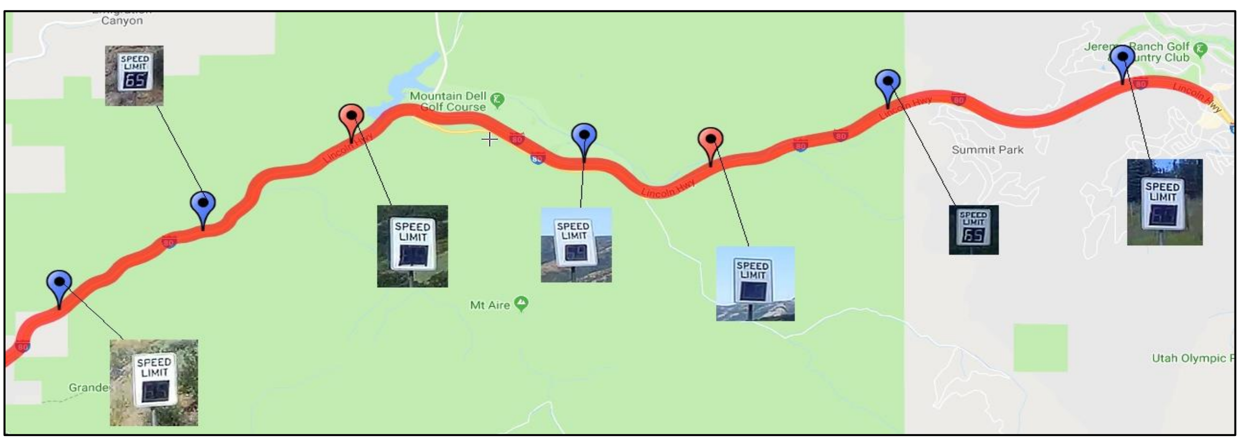

Figure 3.10 Video snippet (west approach, 2nd lane, white legend, morning, summer)

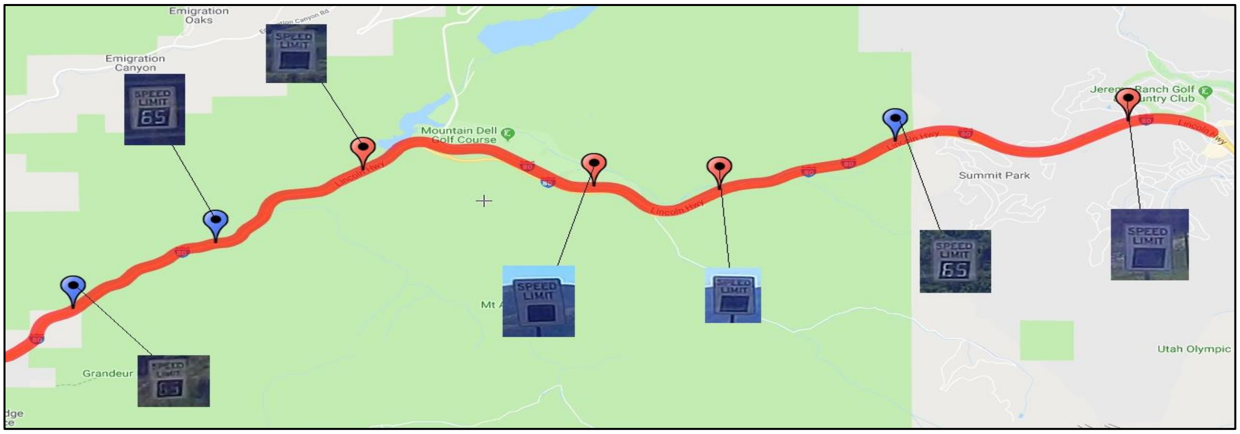

Figure 3.11 Video snippet (west approach, 2nd lane, white legend, afternoon, summer)

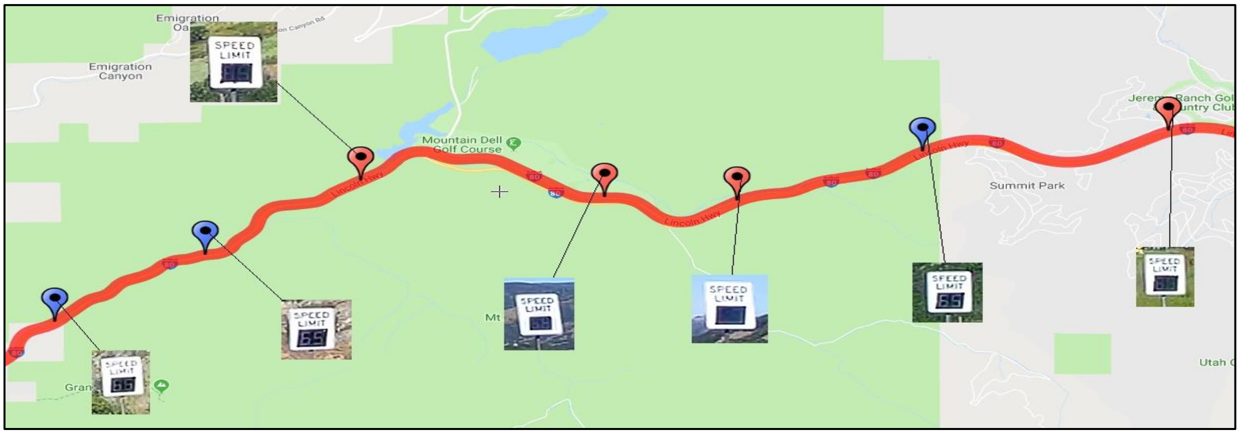

Figure 3.12 Video snippet (west approach, 3rd lane, white legend, morning, summer)

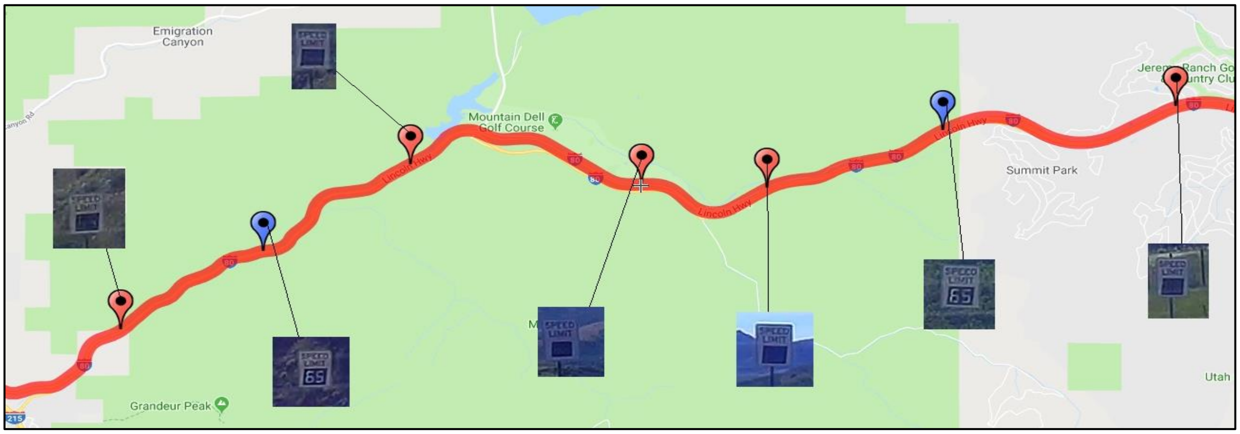

Figure 3.13 Video snippet (west approach, 3rd lane, white legend, afternoon, summer)

More specifically, video shows that sunlight impacts the visibility of the east approach signs more during morning hours while it affects the visibility of the west approach signs more during afternoon hours. To compare the VSL visibility with white and amber legends during the summer, several other field trips were made in summer 2020 for additional video recording. Those field trips were made within the I-80 VSL zone in both east and west directions and in both morning hours (9-11 AM) and afternoon hours (3-5 PM). Figures 3.14 to 3.25 show the video snippets of each VSL. Compared with the snippets in Figures 3.2 – 3.13, the visibility of the new VSL signs with amber legends is significantly improved, which proves the effectiveness of the new system deployed by UDOT.

Figure 3.14 Video snippet (east approach, 1st lane, amber legend, morning, summer)

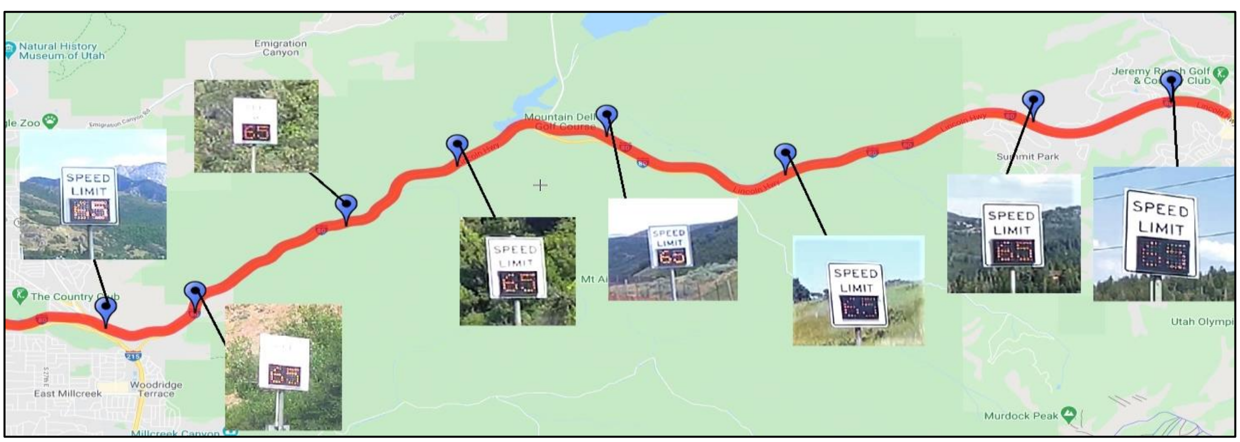

Figure 3.15 Video snippet (east approach, 1st lane, amber legend, afternoon, summer)

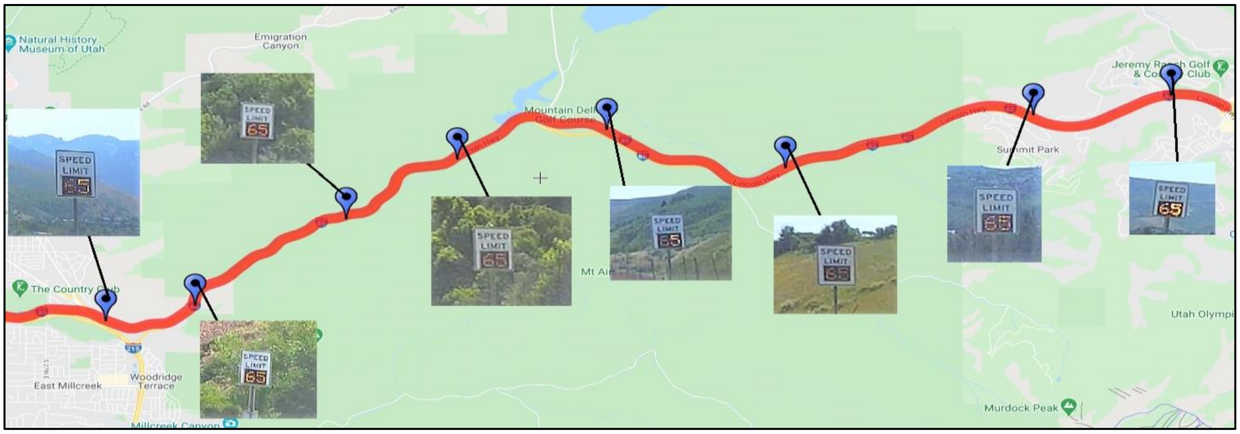

Figure 3.16 Video snippet (east approach, 2nd lane, amber legend, morning, summer)

Figure 3.17 Video snippet (east approach, 2nd lane, amber legend, afternoon, summer)

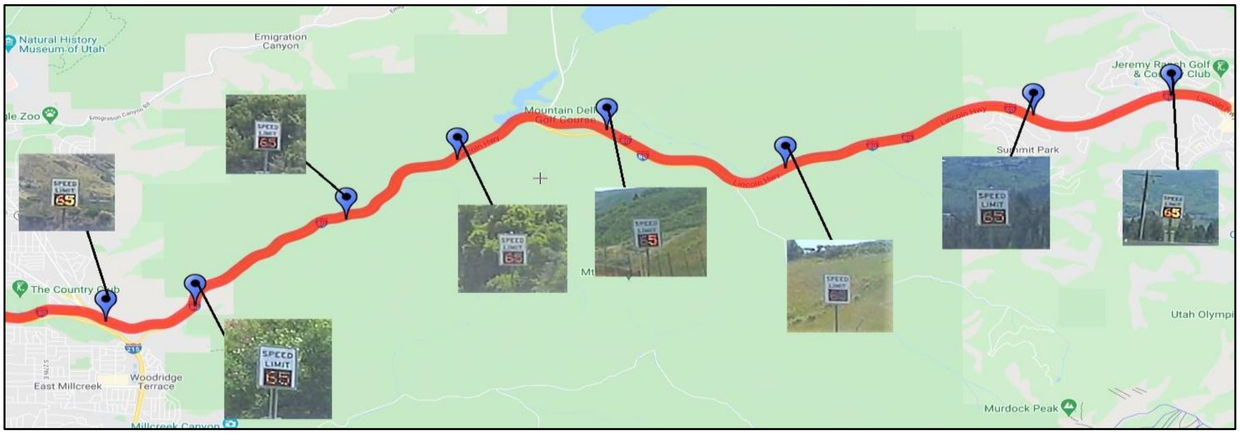

Figure 3.18 Video snippet (east approach, 3rd lane, amber legend, morning, summer)

Figure 3.19 Video snippet (east approach, 3rd lane, amber legend, afternoon, summer)

Figure 3.20 Video snippet (west approach, 1st lane, amber legend, morning, summer)

Figure 3.21 Video snippet (west approach, 1st lane, amber legend, afternoon, summer)

Figure 3.22 Video snippet (west approach, 2nd lane, amber legend, morning, summer)

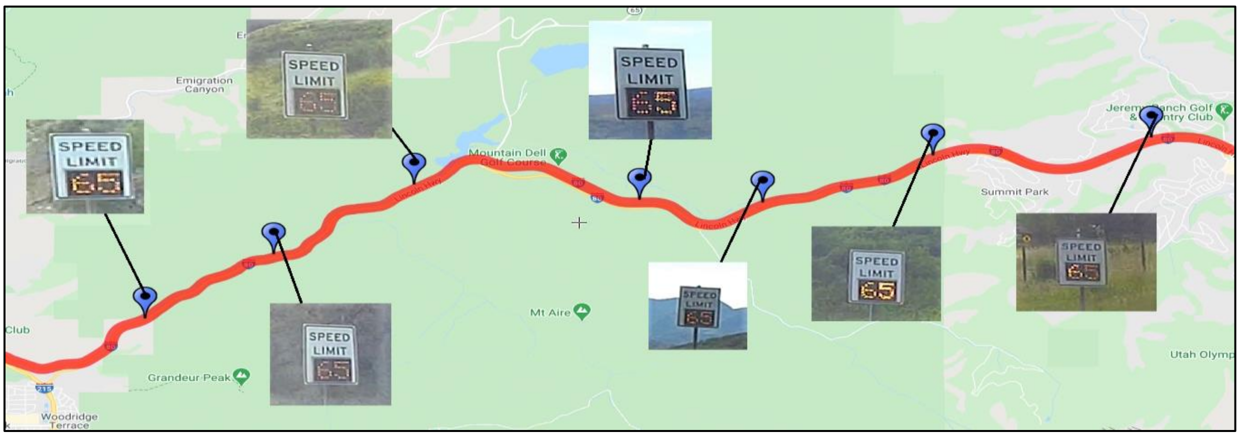

Figure 3.23 Video snippet (west approach, 2nd lane, amber legend, afternoon, summer)

Figure 3.24 Video snippet (west approach, 3rd lane, amber legend, morning, summer)

Figure 3.25 Video snippet (west approach, 3rd lane, amber legend, afternoon, summer)

The snippets of amber legend signs show that visibility has improved significantly in direct sunlight. However, several white legend signs had power issues, which reduced the legend brightness and, correspondingly, the visibility. Hence, a fair comparison is conducted between those fully lighted signs with white and amber legends. The results indicate that signs are more visible to drivers for longer sight distances with the amber legend. During field trips, it was found that the direct sunlight made white LED digits hard to discern, unless at a close distance. Hence, the sight distance has particularly improved with the amber legends, which gives drivers more time to react to the displayed speed limit.

3.3.2 Visibility of VSL after Snowstorms

The same data collection strategy is applied for video recording after a snowstorm within the I-80 VSL zone, for both east and west approaches, and during both morning (9-10 AM) and afternoon (3-5 PM) hours. As shown in Figures 3.26 – 3.37, the visibility of amber legend VSLs is not significantly reduced despite the road's low visibility due to fog and snow. Since the data collections were conducted in foggy weather, the outputs can also prove the necessity of implementing amber LED digits to display speed limits. Notably, as the replacement of VSL signs were completed in the fall of 2018 and this project was started in the late spring of 2019, no field trip has been made to study the visibility of white legend VSLs during the winter season.

Figure 3.26 Video snippet (east approach, 1st lane, amber legend, morning, winter)

Figure 3.27 Video snippet (east approach, 1st lane, amber legend, afternoon, winter)

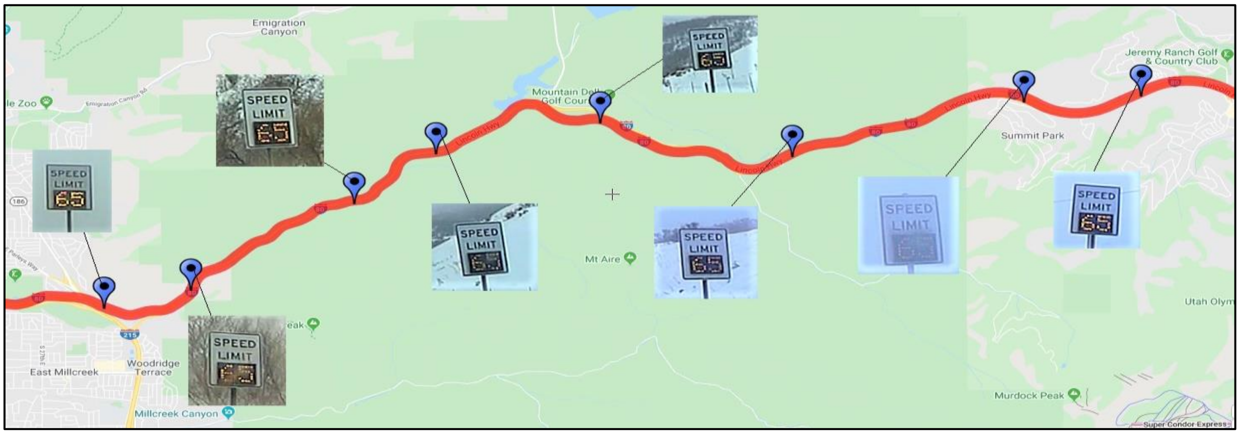

Figure 3.28 Video snippet (east approach, 2nd lane, amber legend, morning, winter)

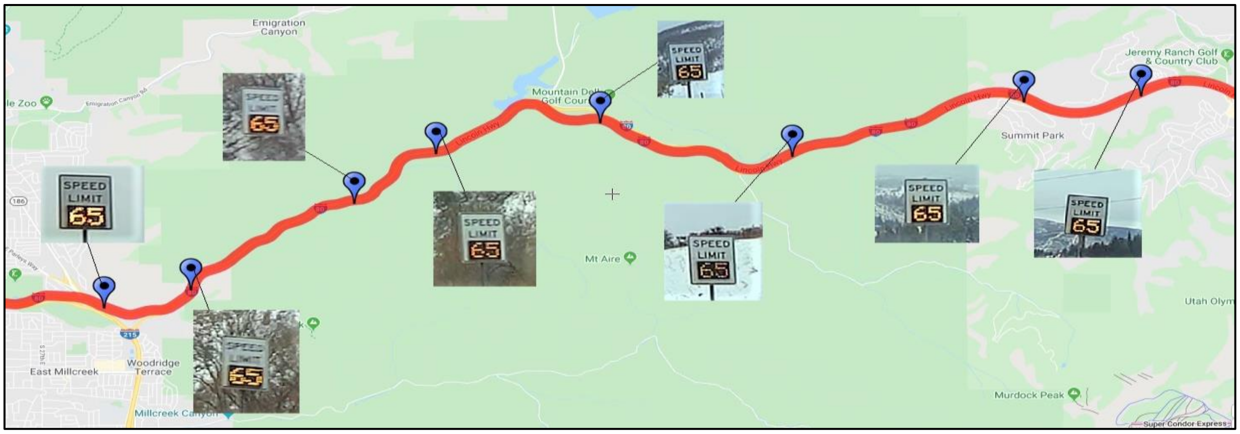

Figure 3.29 Video snippet (east approach, 2nd lane, amber legend, afternoon, winter)

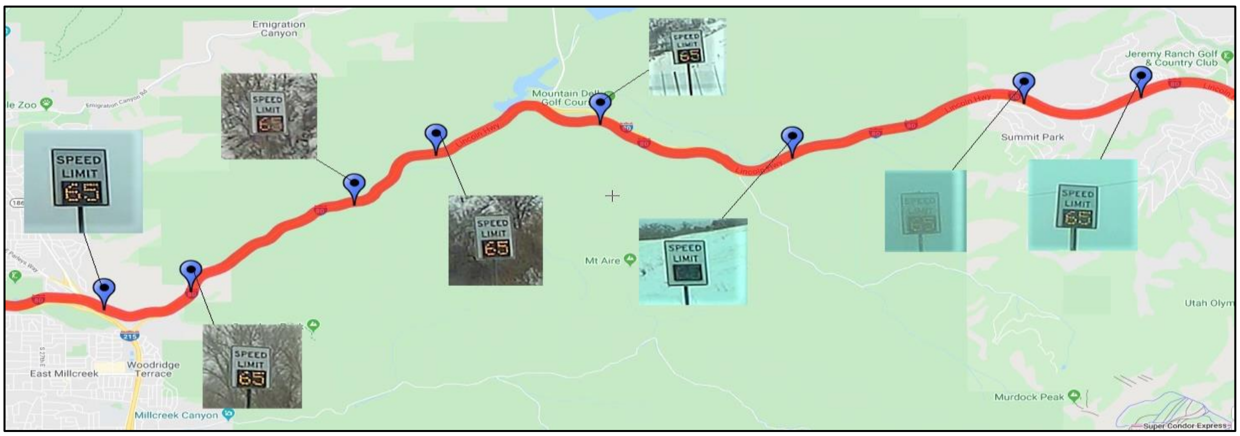

Figure 3.30 Video snippet (east approach, 3rd lane, amber legend, morning, winter)

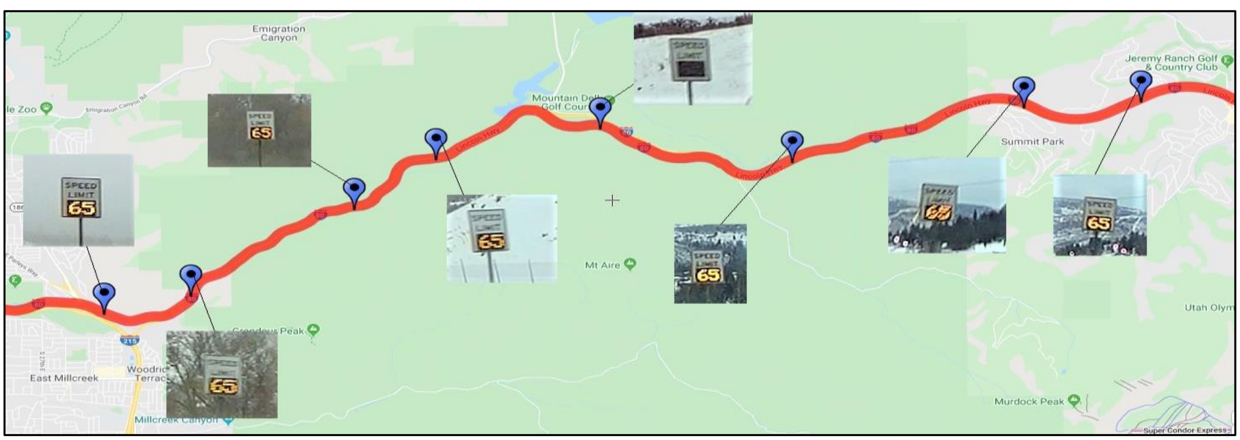

Figure 3.31 Video snippet (east approach, 3rd lane, amber legend, afternoon, winter)

Figure 3.32 Video snippet (west approach, 1st lane, amber legend, morning, winter)

Figure 3.33 Video snippet (west approach, 1st lane, amber legend, afternoon, winter)

Figure 3.34 Video snippet (west approach, 2nd lane, amber legend, morning, winter)

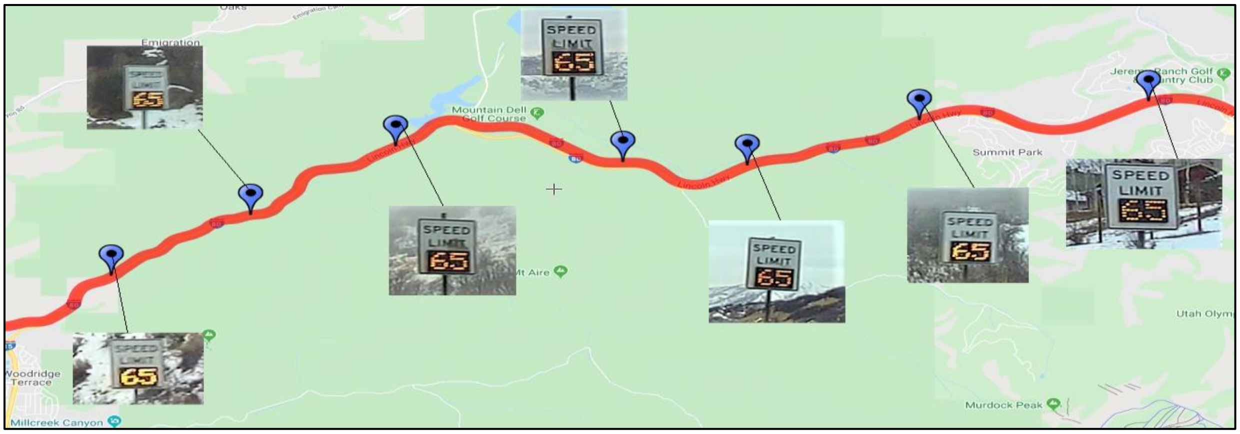

Figure 3.35 Video snippet (west approach, 2nd lane, amber legend, afternoon, winter)

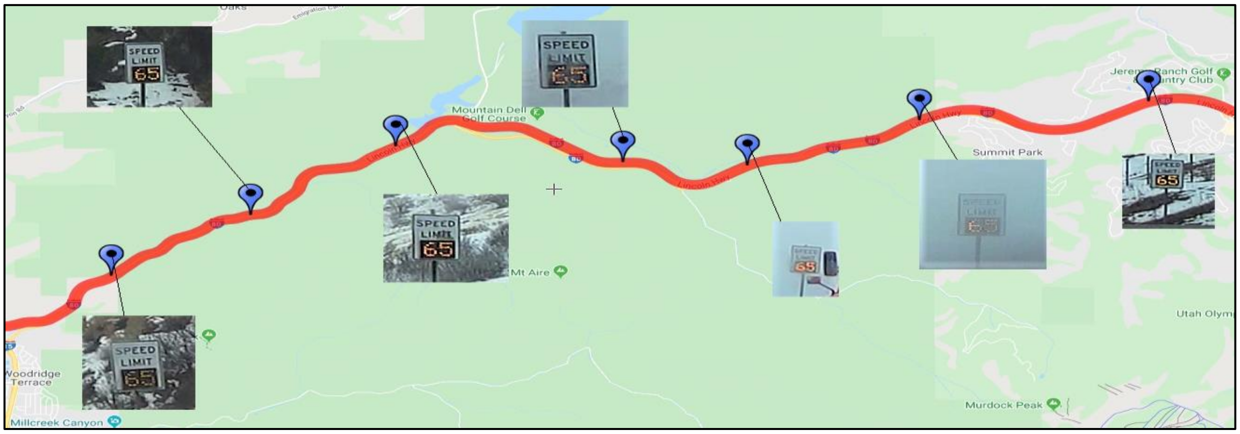

Figure 3.36 Video snippet (west approach, 3rd lane, amber legend, morning, winter)

Figure 3.37 Video snippet (west approach, 3rd lane, amber legend, afternoon, winter)

Based on the review of recorded videos in winter, it can be concluded that amber legend makes the VSL signs much more visible to drivers. The LED digits indicating speed limits are quite visible from a reasonable distance, despite the lower road visibility due to inclement weather. However, it is suggested that CMS alerts about road conditions or flashing amber lights should be added to the system for improving winter road safety (Lee *et al.*, 2013).

3.4 Summary

This chapter studied the visibility of VSL before and after the installation of amber signs by reviewing the recorded road videos during both summer and winter seasons. Based on the comparison of the video snippets, it can be found that original white legend VSLs have reduced visibility in direct sunlight during the summer. The new amber legend VSLs have much improved visibility in the summer. Moreover, the visibility of amber legend is not significantly affected by inclement weather, such as fog and snow, in the winter.

4.0 COMPREHENSIVE DATA ANALYSIS

4.1 Overview

Through field investigation with video recordings, the last chapter shows that the visibility of the new amber VSL signs is significantly improved. Hence, it is expected that the driver compliance rate to VSL and the associated road safety performance will also be improved. To prove such a hypothesis, this chapter aims to obtain additional numerical data, including road sensor information, historical VSL log (i.e., displayed speed limits), and crash records, to conduct a more comprehensive analysis. Particularly, a comparison will be conducted to evaluate both road safety and efficiency before and after the VSL sign replacements.

4.2 Data Description

As the primary purpose of using VSLs on the studied I-80 corridor is to alert drivers to drive slower during inclement weather, it is critical to study whether the driver compliance rate improved after the implementation of amber legend VSLs. To satisfy this need, the first collected dataset includes roadside stationary detector data (i.e., speeds and flows). Moreover, another direct measurement of effectiveness (MOE) for VSL is the resulting crash frequency and severity. Hence, this research also obtained historical crash data on the I-80 corridor. Considering weather conditions could play a key role in affecting both the VSL compliance rate and road safety performance, weather index data during the study period were also collected.

More specifically, this research collected biweekly data in four months, October 2018, October 2019, January 2019, and January 2020, which spans the periods before and after the deployment of new VSL signs. Driver compliance rates to VSL can be calculated by comparing the time-dependent mean speed profile to displayed speed limits. Hence, an analysis is conducted to examine whether improved sign visibility can result in improved compliance rates. In terms of road safety evaluation, the crash records are studied with consideration given to weather impacts.

4.3 Traffic Data Analysis

By collecting road traffic detector data and historical VSL log data, this section focuses on the traffic performance analysis. As aforementioned, the driver compliance rate to VSL has been recognized as a useful MOE for VSL. In this research, the compliance rate is measured by the ratio of drivers who drive no more than 10 mph over displayed speed limits. This is because the majority of Utah drivers tend to drive faster (e.g., 5-10 mph) than the speed limit, based on our analysis of the general speed profile for the Utah freeway network. Based on the compliance rate definition, Tables 4.1 – 4.2 present the calculated driver compliance rates by VSL systems with different legend colors during different times of the year. Based on the results, it can be observed that compliance rates haven't improved significantly in October after the deployment of the new amber signs. The reason might be that traffic speed is quite steady when the driving condition is good in October and the low visibility of several VSL signs could have little impact on driver behaviors. However, when visibility is affected most (e.g., in wintertime), the compliance rate, with the amber signs, has improved by 9% on average. The improvement is more than 20% at the location of sensor 100616.

Table 4.1 Driver compliance rate comparision for eastbound flows

Legend Color	**White**	**Amber**	**White**	**Amber**
Date / Sensor ID	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 Driver compliance rate comparision for westbound flows

Legend Color	White	Amber	White	Amber
Date / Sensor ID	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

In the process of data analysis, this research found that driver compliance rates are much higher under congested traffic conditions. This is because the high density and slow speed traffic pattern can prevent vehicles from driving too fast. Moreover, from the road safety perspective, crash frequency and severity have been significantly decreased in those cases as well. Considering the primary objective of implementing VSL on the I-80 corridor is to slow down traffic, it is more critical to study driver compliance rates under uncongested conditions. To satisfy such a need, Table 4.3 and Table 4.4 summarize the compliance rate for both eastbound and westbound uncongested flows. Compared with the results shown in Table 4.1 and Table 4.2, it can be observed that compliance rates under uncongested conditions are smaller than the average value of the study period.

Table 4.3 Driver compliance rate comparision for eastbound uncongested flows

Legend Color	White	Amber	White	Amber
Date / Sensor ID	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 Driver compliance rate comparision for westbound uncongested flows

Legend Color	White	Amber	White	Amber
Date / Sensor ID	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

Besides the examination of driver compliance rates, analyzing the profile of average traffic speeds against the displayed speed limits can also help study drivers' responses to the VSL. This is due to the driver compliance rate being defined as the proportion of vehicles that speed no more than 10 mph over the displayed speed. Average traffic performance in response to the VSL would not be fully captured by the compliance rate study.

Therefore, Figures 4.1 – 4.9 present the time-dependent traffic mean speeds and displayed speed limits over the study periods. Notably, red dash lines in all figures indicate the change of speed limit over time, based on the VSL log data at UDOT's TOC. Gray lines show the time-dependent average traffic speed when white legend VSLs were used and blue lines represent the average speed profile after the amber legend VSLs were deployed. Based on the results, it can be observed that the average traffic speed lines are closer to the VSL lines after the installation of new VSL signs, especially when the speed limits dropped. Hence, it can be concluded that more traffic is following the VSL after sign visibility is improved.

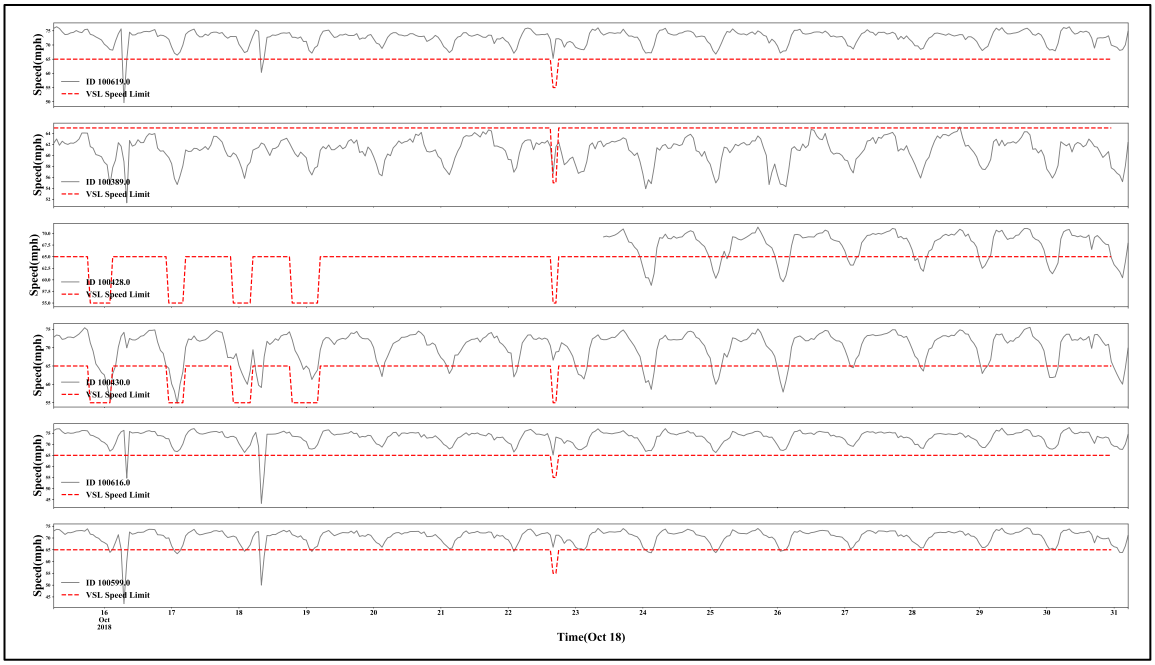

Figure 4.1 Hourly average speed vs. displayed speed limit on I-80 eastbound (Fall 2018)

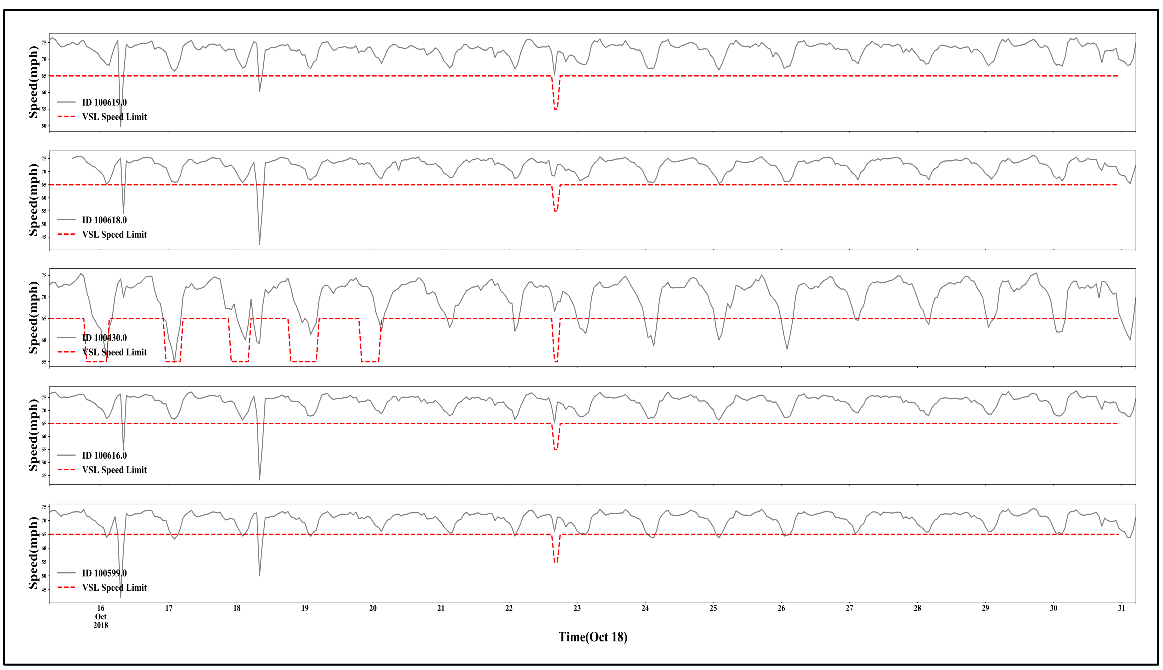

Figure 4.2 Hourly average speed vs. displayed speed limit on I-80 Westbound (Fall 2018)

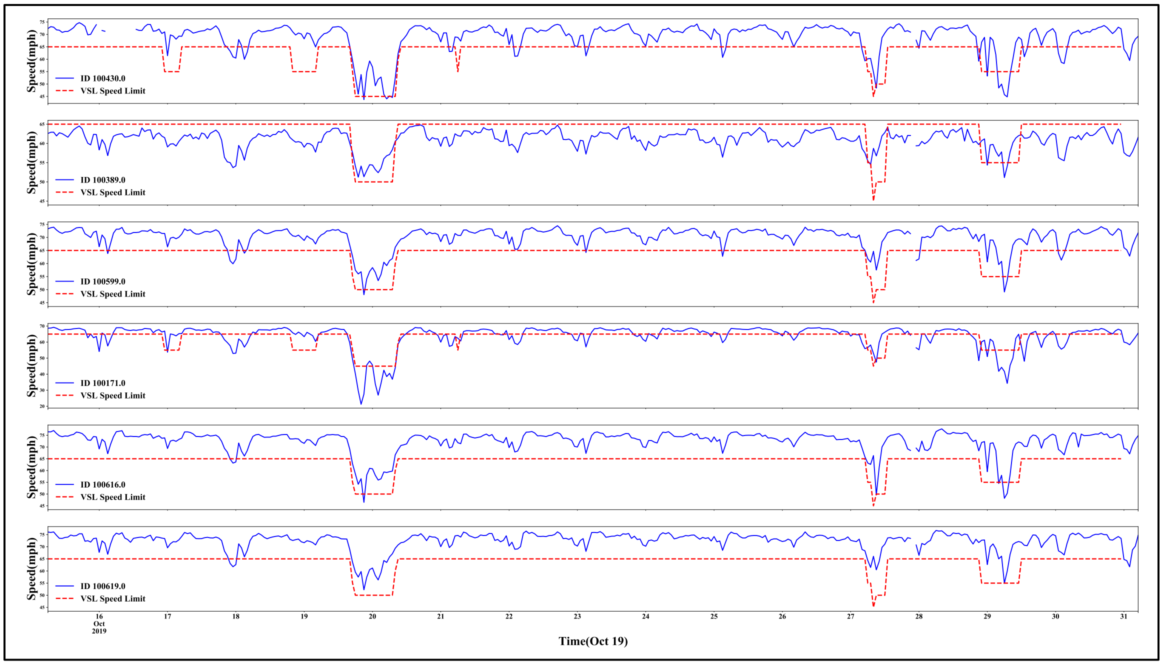

Figure 4.3 Hourly average speed vs. displayed speed limit on I-80 eastbound (Fall 2019)

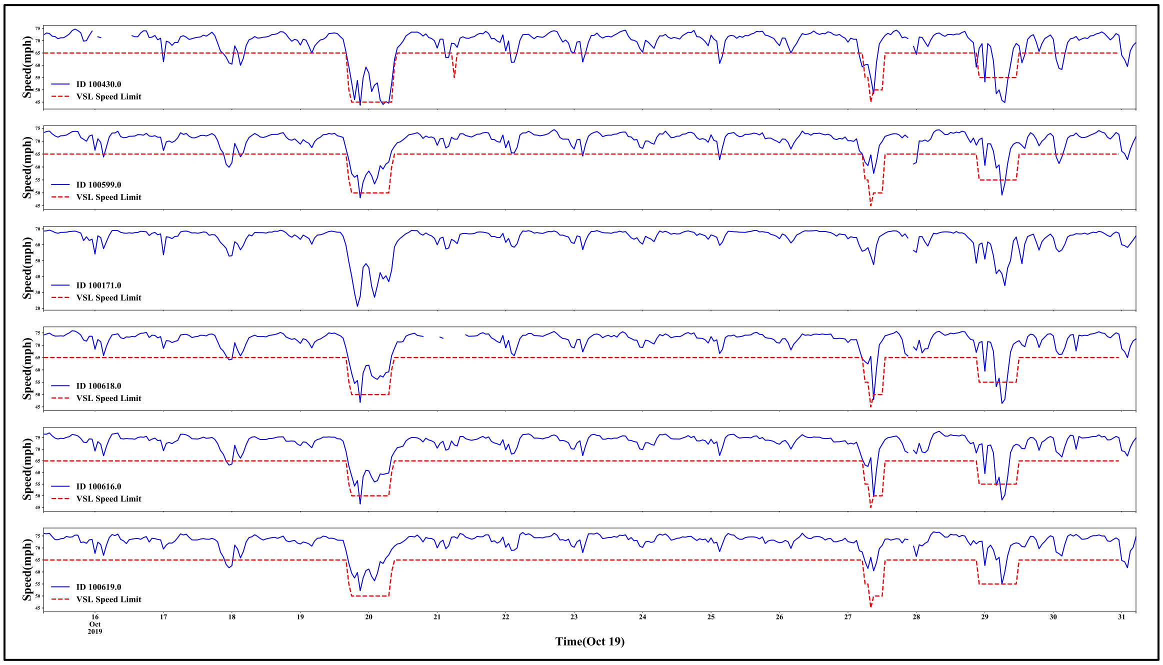

Figure 4.4 Hourly average speed vs. displayed speed limit on I-80 westbound (Fall 2019)

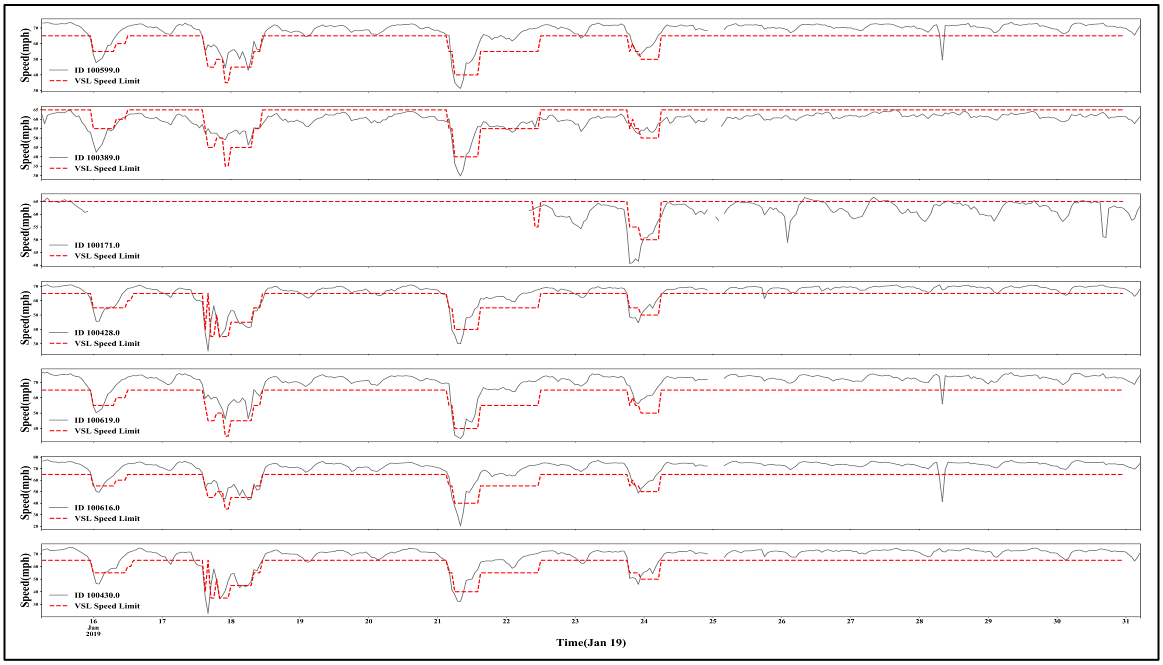

Figure 4.5 Hourly average speed vs. displayed speed limit on I-80 eastbound (Winter 2019)

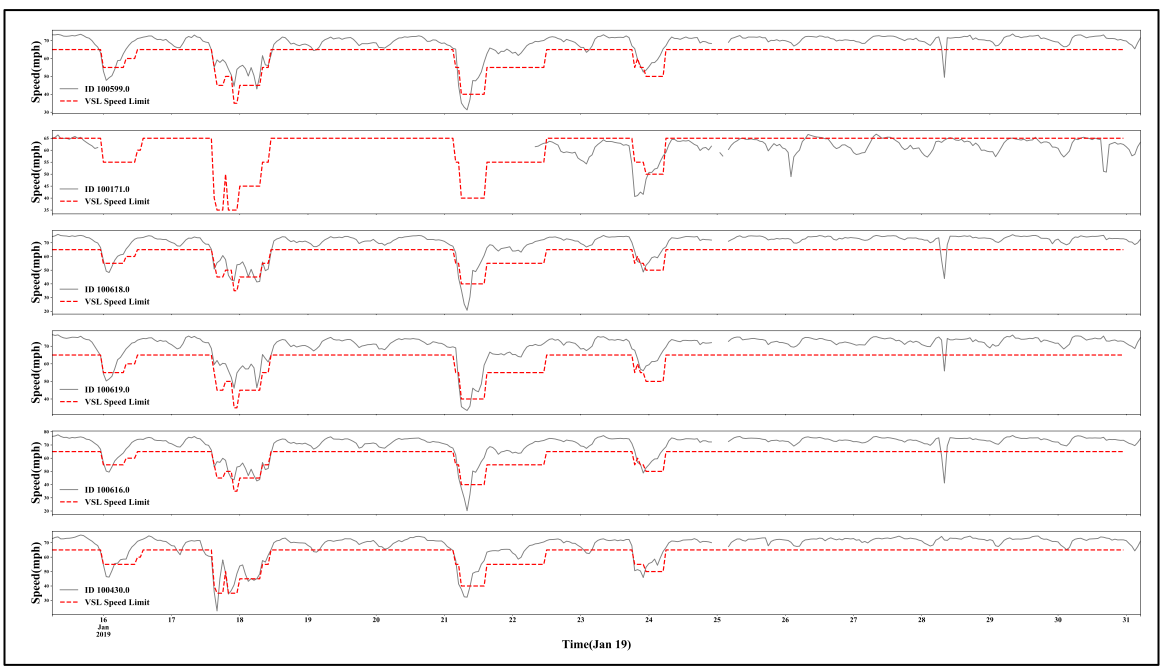

Figure 4.6 Hourly average speed vs. displayed speed limit on I-80 westbound (Winter 2019)

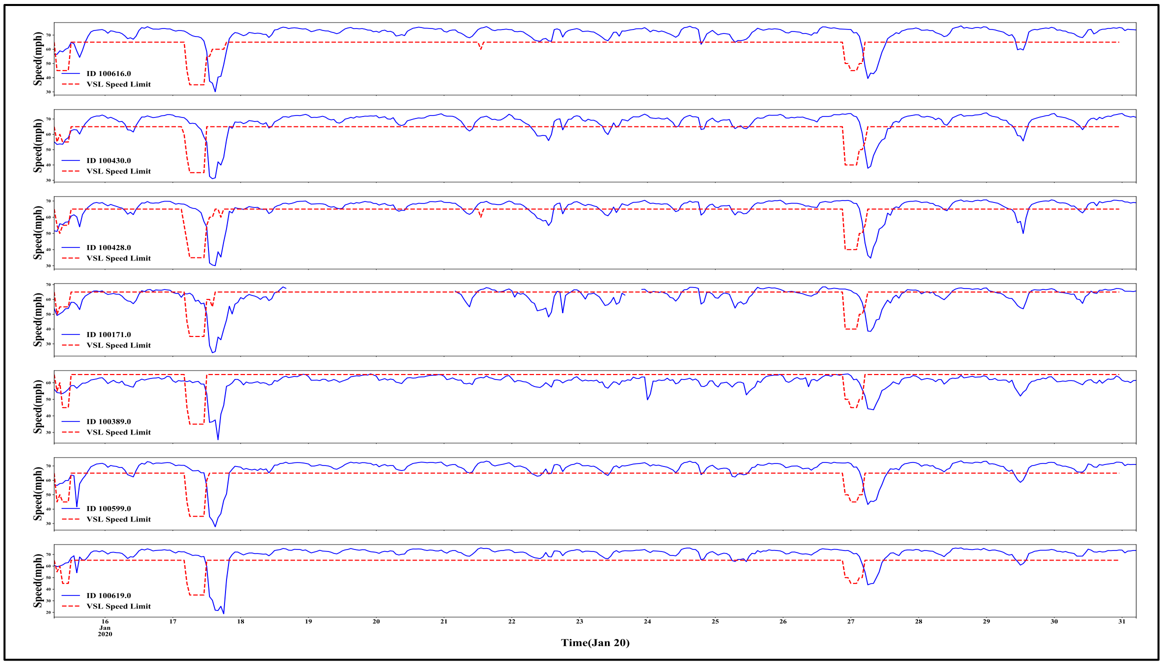

Figure 4.7 Hourly average speed vs. displayed speed limit on I-80 eastbound (Winter 2020)

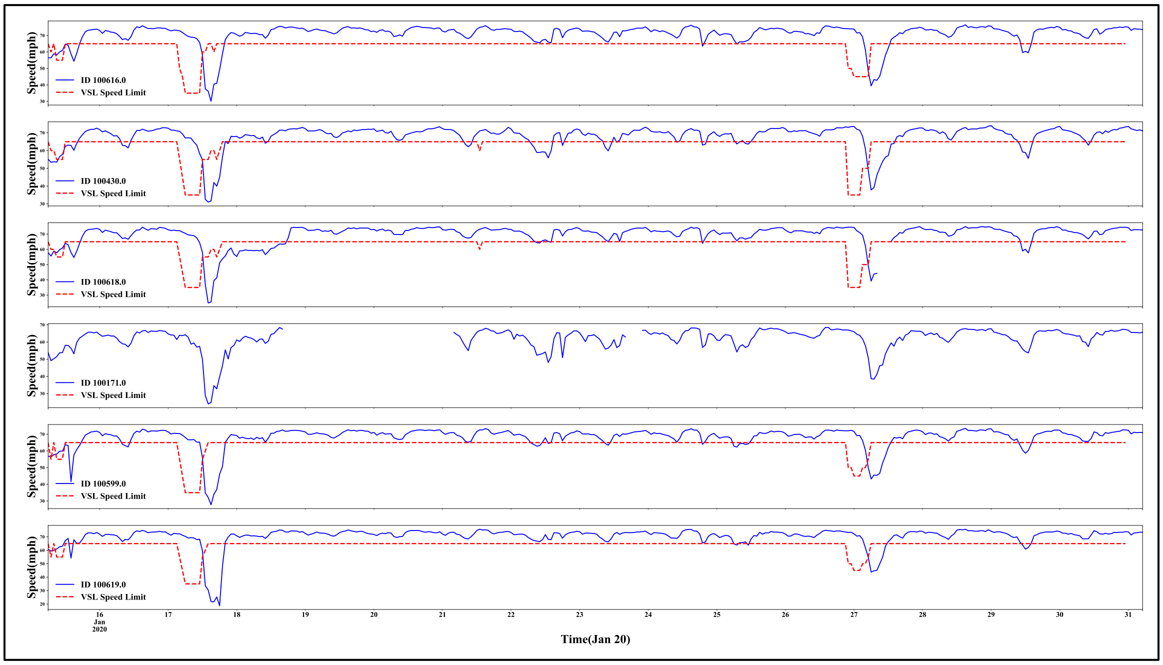

Figure 4.8 Hourly average speed vs. displayed speed limit on I-80 westbound (Winter 2020)

4.4 Safety Data Analysis

The second type of data that can help evaluate the impact of VSL signs with higher visibility is the crash record. In this research, crash rates within the I-80 VSL zone have been reviewed before and after the VSL sign replacement to determine whether the amber legend could positively impact road safety. Based on crash data analysis, there is about a 50 percent decrease in crash numbers after installing the new VSL signs. The numbers of recorded crash incidents over different months are depicted in Figure 4.9, where data collected in October 2018 and January 2019 are related to white VSL legends, and the data obtained in October 2019 and January 2020 are impacted by amber VSL legends.

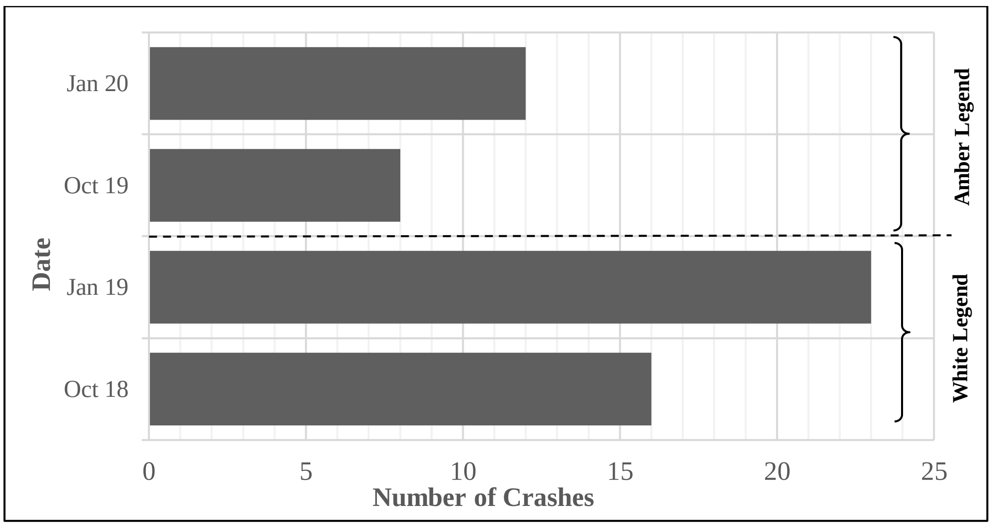

Figure 4.9 Crash rate of I-80 corridor before and after the new VSL installation

Road conditions, sign visibility, and inclement weather are also factors that can greatly affect road safety performance. This includes the light condition, weather condition, and road surface condition, as shown in Figures 4.11 - 4.12. The results indicate that in both periods, road setting and driving conditions were at high risk, which proves that the reduction in incidents results from improved sign visibility.

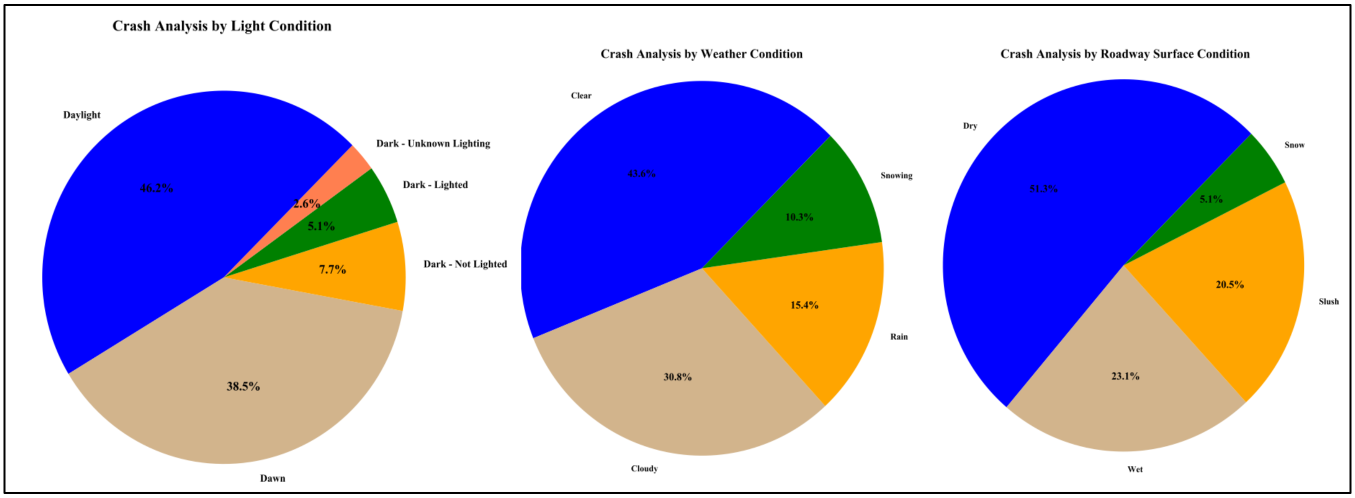

Figure 4.10 Crash rate analysis by road conditions (white legend)

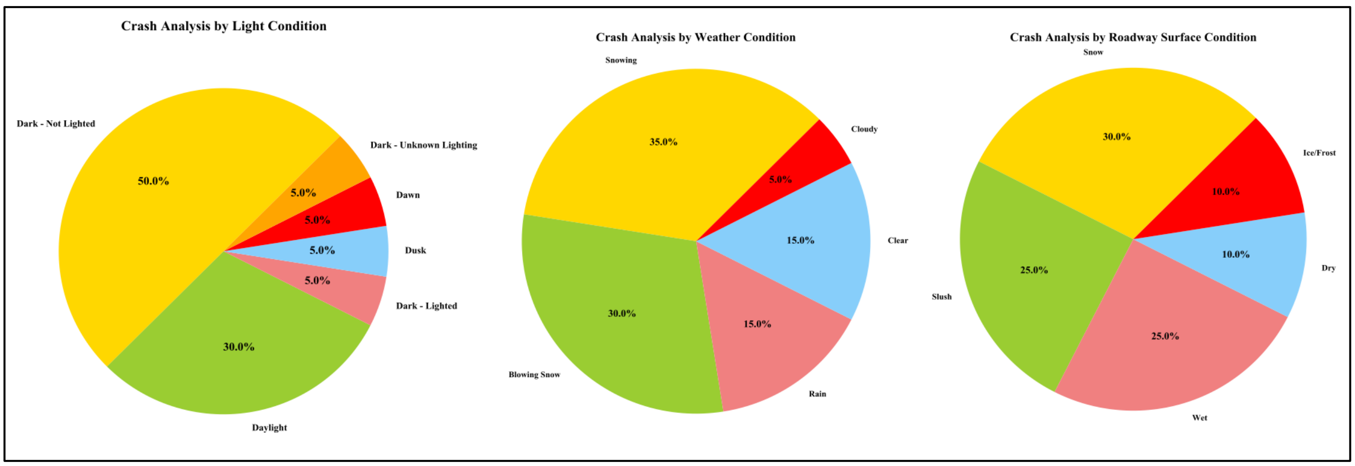

Figure 4.11 Crash rate analysis by road conditions (amber legend)

More detailed speed profiles under adverse driving conditions are evaluated to study drives' behaviors in response to reduced speed limits. Because the I-80 corridor experiences multiple snowstorms and lower visibility issues in the wintertime, safety-oriented speed guidance is needed for drivers. By investigating the weather index of the corridor in January 2019 and 2020, it is found that most traffic crashes were caused by reduced visibility and wet road surface conditions. Figure 4.13 and Figure 4.14 demonstrate the distribution of the weather conditions. The weather road (WF) index indicates the driving status of the road segment, and as it gets below zero, the driving situation is riskier. The results show that there are multiple occasions in winter where road conditions becoms precarious. Yet, lower visibility at the same time worsens the driving conditions for drivers.

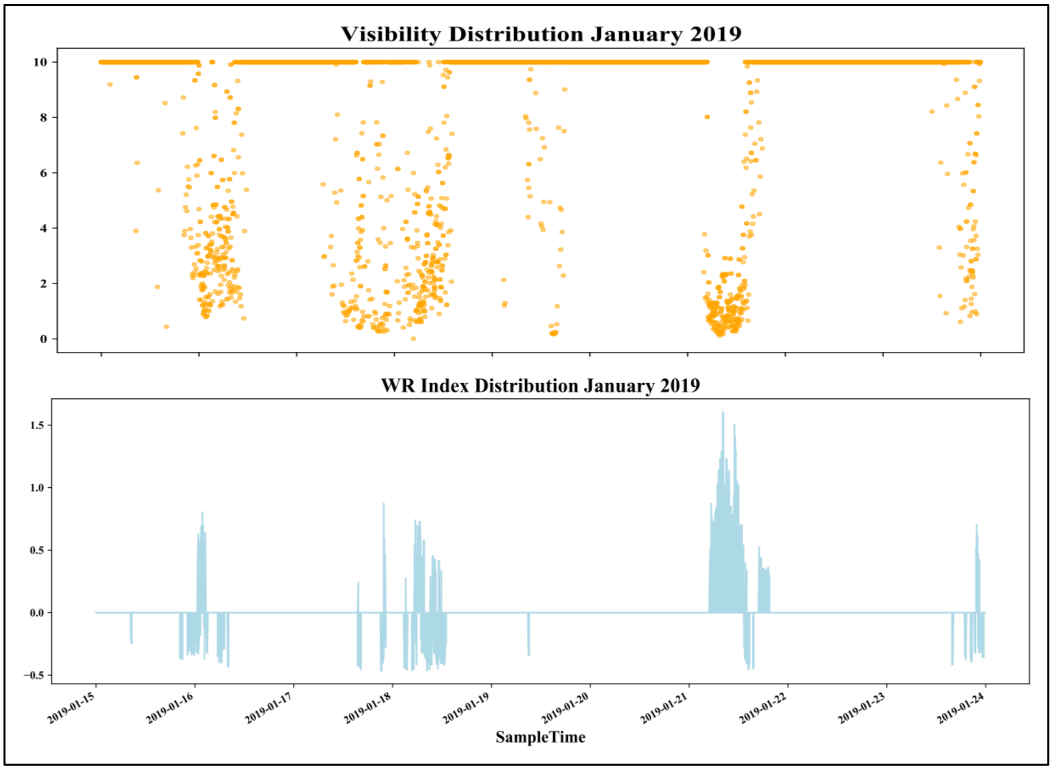

Figure 4.12 Weather condition of the I-80 corridor in January 2019

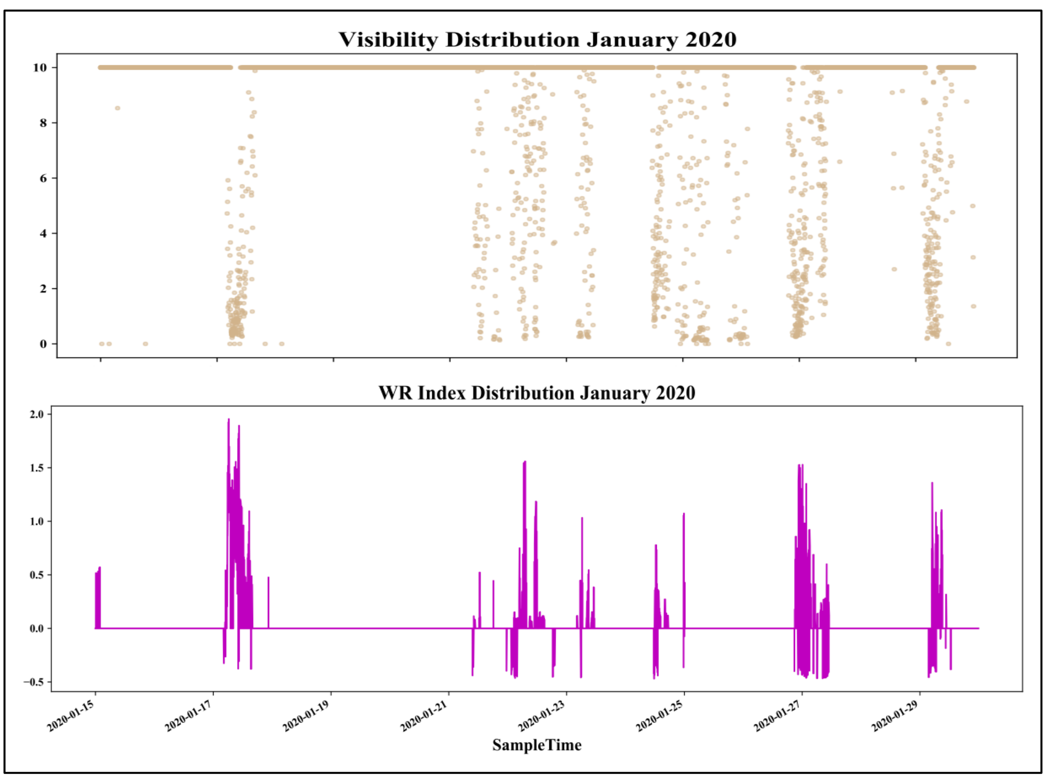

Figure 4.13 Weather condition of the I-80 corridor in January 2020

The driver compliance rate study implies that the new VSL system has improved the effectiveness of speed limit enforcement in insecure conditions. A more detailed speed profile of the road, as shown in Figure 4.14 and Figure 4.15, further proves this fact. Hence, the reduced speed numbers demonstrate the safety performance of the corridor.

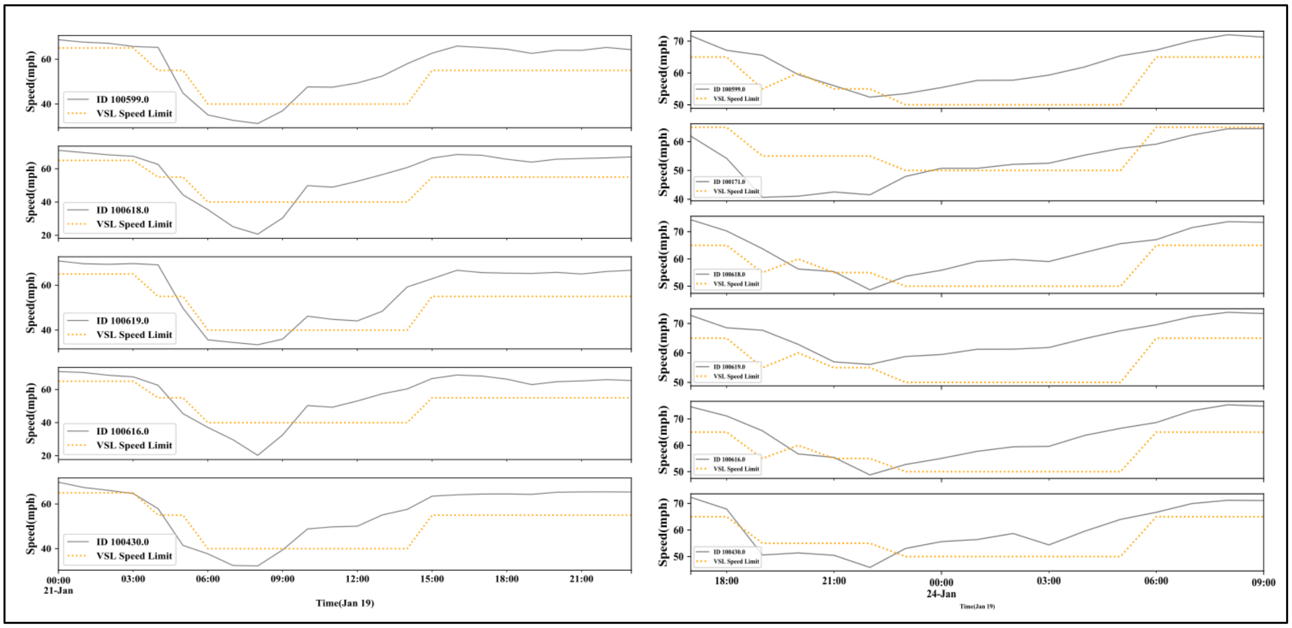

Figure 4.14 Detailed sample of speed profile with inclement weather (white legend)

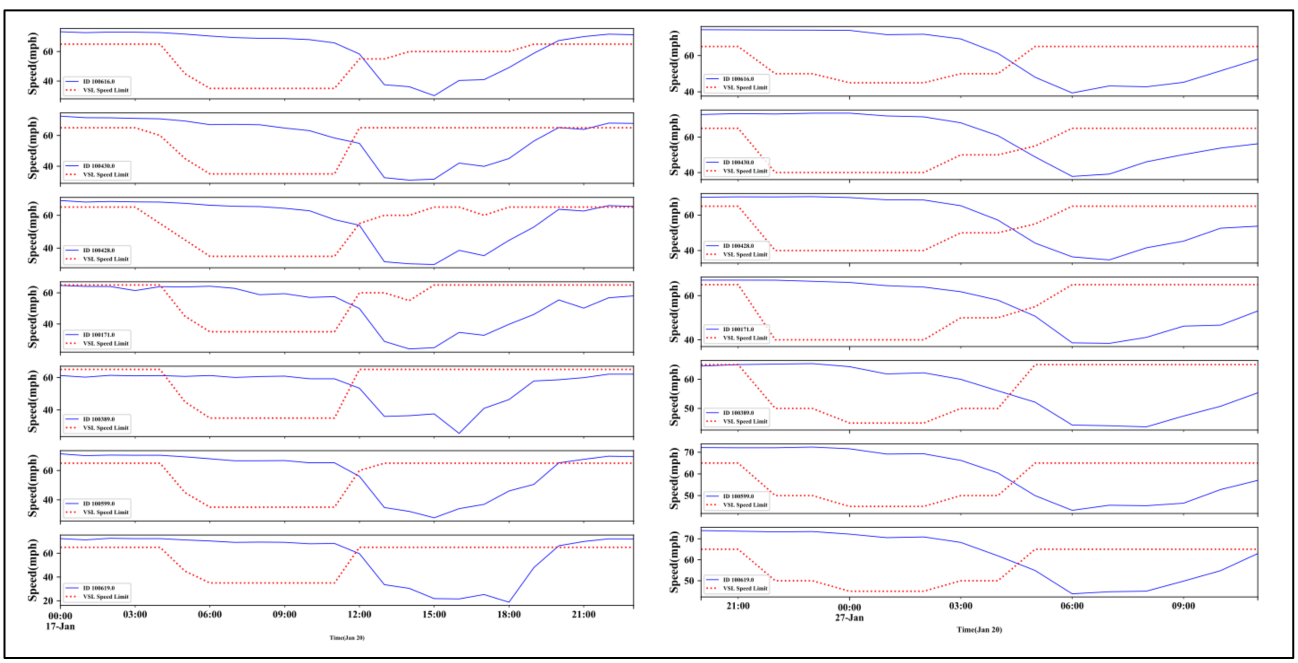

Figure 4.15 Detailed sample of speed profile with inclement weather (amber legend)

Based on the analysis of the recorded data, it can be concluded that safety and driver compliance rates have been enhanced due to the improved visibility of the new VSL signs. The conversion from white to amber LED legends has had a notable positive impact on visibility and traffic flow compliance. The decrease in traffic flow average speed and the increase of drivers' tendency to follow the speed limit can be attributed primarily to the change of the VSL legend color from white to amber. Furthermore, in winter, when higher precipitation results in a slick road surface and reduced visibility, the driver compliance rates were increased. The reduction in crash rates also indicated improved VSL visibility directly mitigates the adverse effects of the 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 to the improved visibility of the amber legends.

4.5 Summary

This chapter focused on evaluating the impact of amber legend VSLs on road traffic speed profile and safety performance. For evaluation of traffic speeds in response to VSL, environmental data, VSL log historical data, and crash records were examined. First, driver compliance rates were calculated to study drivers' reactions to new VSL signs. The results demonstrated that average speeds have decreased, and speed variations from displayed speed limits have lowered. Moreover, the hourly average speeds are depicted versus the speed, which further proved the improved compliance rates. Finally, the analysis of crash records showed that new signs can improve safety as crash frequency decreased and became less severe under adverse driving conditions. In conclusion, the new signs have increased the road safety of the studied I-80 corridor.

5.0 SAFETY EVALUATION MODEL

5.1 Overview

Safety models are developed in this chapter to evaluate crash frequency and severity on the I-80 corridor using the occurrence data, weather index, and crash records. ML technique is leveraged to train model parameters based on features that contribute to the road safety level. By adding the variable of VSL legend color to the model, the safety model results can show the impact of improved visibility on crash severity.

5.2 Training Data

The studied data include recorded traffic flow data by detectors, displayed speed limits of VSL, weather index data, and historical crash records. Two weeks of data were collected in one month of 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 congestion level will influence road safety, these variables have been used as an input in the safety evaluation model. Since this study aims to study the impact of the improved visibility of VSL on road safety, the VSL legend color is also considered a feature for safety assessment.

In this study, some explanatory variables are transformed into binary variables. For example, in terms of the VSL legend color, the white legend is represented by “0” and the amber legend is represented by “1”. All traffic state information, including flows and speeds, is aggregated hourly for the 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 the collected datasets

Feature	Mean	SD	Min	Max
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 determine which variables should be considered as the model development input, the correlation between attributes needs to be analyzed. Using the Pearson correlation analysis method, the correlation of each variable pair is evaluated and the obtained correlation coefficients are presented in Table 5.2. Notably, even though there is a low correlation between crash severity and VSL legend color, the negative coefficient demonstrates that amber legend has decreased the severity.

Table 5.2 Pearson correlation value between variables

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 dataset used to develop the model, only 69 crashes are recorded and the crash severity is divided into four classifications, including no injury, possible injury, suspected minor injury, and suspected serious injury. The crash severity rate of each level is demonstrated in Figure 5.1. Because the crash dataset is not big enough, the frequencies of higher crash severity levels are relatively low, which can affect the model's accuracy in classifying more severe crashes.

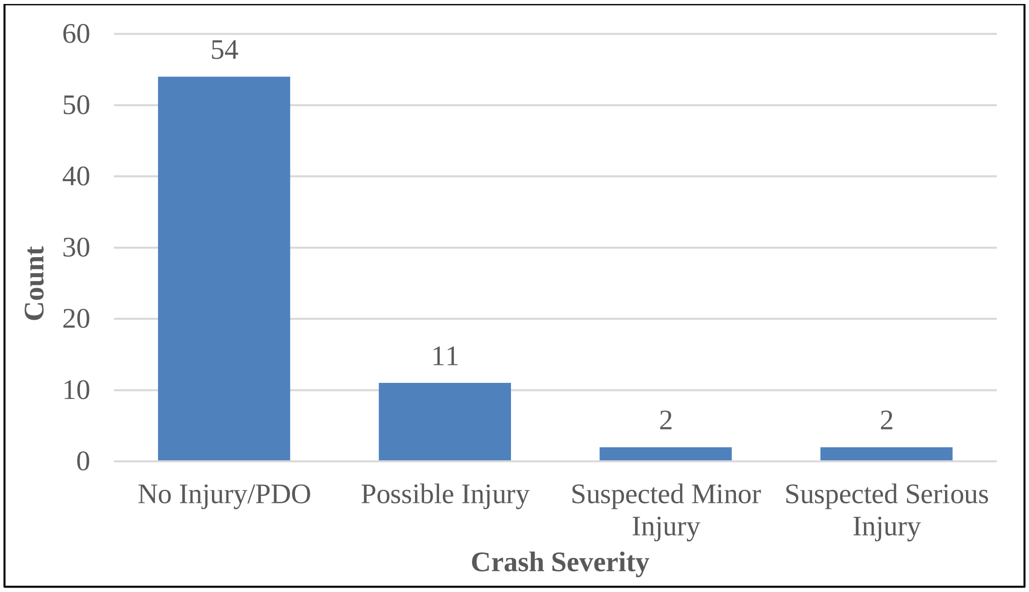

Figure 5.1 Crash frequency by severity levels

5.3 Safety Model Development

To evaluate the I-80 corridor's safety performance, the SVM and ANN classification methods are used to predict the crash frequency and severity, respectively, using road and environment data. Since crash variables are with discrete classification values, classification multilayer perception (MLP) is used in this research. Then, the SVM classifier will predict the number of crashes per hour (e.g., 0, 1, etc.) and the ANN model will estimate the corresponding crash severity from level 1 (no injury) to the highest level (level 4). Notably, level 0 is also created to represent the hours without crashes.

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 and Cheriet, 2009) to find the best function to classify the inputs. Depending on the number of features and input dimension, the hyperplane will be created with different complication levels.

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 ANN framework is depicted in Figure 5.2, schematically.

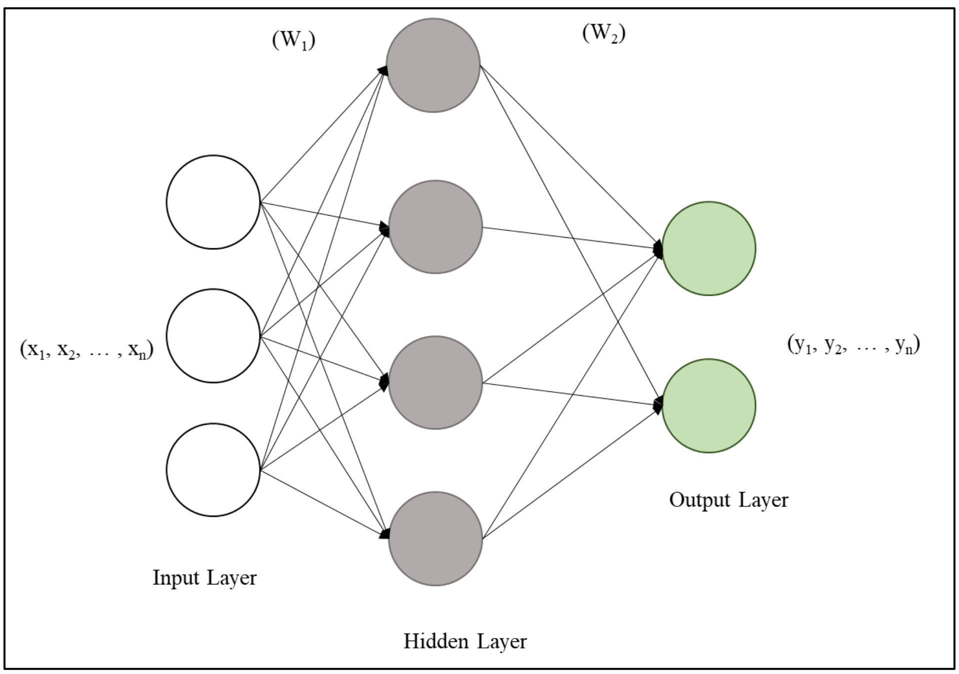

Figure 5.2 Schematic framework of ANN

The original data are divided into a training set, testing set, and cross-validation set to train, evaluate, and validate the model. The ratios of the training set to the testing set and the cross-validation set are 3 and 2, respectively. After training the model based on input data and tuning the parameters, the best results are made by an SVM with radial basis function fore crash frequency prediction and a 4-layer ANN with 50 and 40 nodes in hidden layers for crash severity prediction. For the SVM model, occurrence data, weather index, and speed limit data are used for training. And for the ANN model, crash records features are used. 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. Other results are presented 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 ANN 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

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

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 VSL legend color, the developed models are used to predict the number of crashes and crash severities under both conditions. Based on the model's results tested on a set of data, both SVM and ANN models show a 0.99 accuracy and a low mean square error (i.e., 0.005 and 0.001). The heat maps of both models predicting the crash frequency and severity are depicted in Figure 5.3 and Figure 5.4.

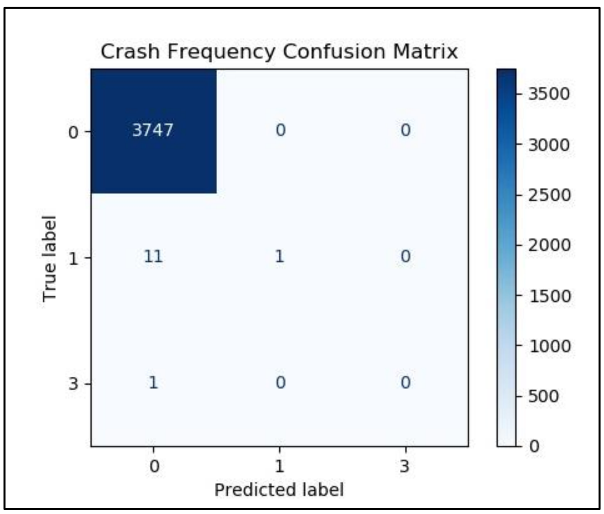

Figure 5.3 Heat map of crash frequency model

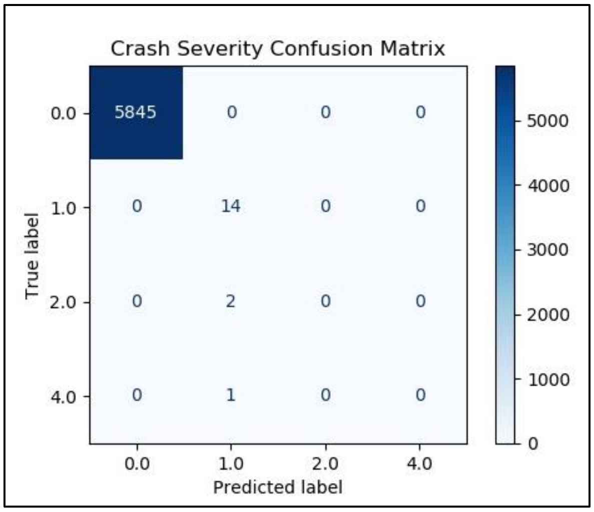

Figure 5.4 Heat map of crash severity model

With the completion of the training and testing processes, this research further implements the two ML models to predict crash frequency and severity with different VSL legend colors. Results shown in Figure 5.5 show that with the new amber legend VSL, the number of crashes will be decreased by 80% and crash severity will be reduced by 8.26%. Such results further confirm the effectiveness of the amber legend VSLs in reducing both crash frequency and severity, with the improved visibility.

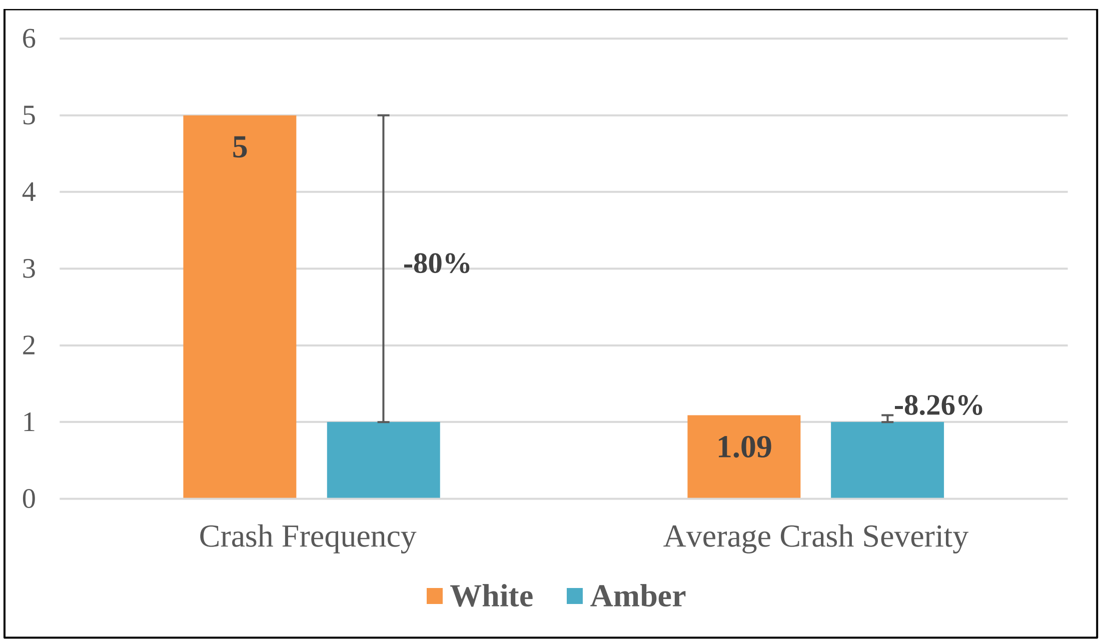

Figure 5.5 Safety model estimation with both VSL legend colors

5.4 Summary

In this chapter, I-80 VSL zone safety is modeled using traffic data and crash records. Leveraging ML techniques, the developed models can predict crash frequency and severity with high accuracy performances. Although the lack of sufficient severe crash records may result in lower prediction accuracy for higher severity crashes, the developed models can perform precisely for other classes. In addition, using the amber legend as a variable helps to study the relationship between safety and VSL sign visibility. Model results show a decline in both crash severity and frequency after installing VSLs with amber legends.

6.0 CONCLUSIONS

6.1 Summary

The objective of this research is to scrutinize the impact of changing VSL signs from white legend to amber legend on the I-80 corridor of the Parley's Canyon area. To achieve this purpose, this research is started by reviewing VSL control algorithms and case applications. Information from existing studies helps identify the potential benefits of VSLs and highlight exceptional cases from the MUTCD. Thereafter, by investigating the historical traffic data and road condition data, driver compliance rates to VSL and the average traffic speed profiles before and after the installation of the new system are evaluated. Finally, by developing safety models, the crash data help create a framework that can appraise road safety considering the changes in VSL signs.

6.2 Findings

VSL signs have been used increasingly in North America based on variable traffic and weather conditions. VSL's objective is to manage traffic with speed fluctuations by providing drivers with information and cautions concerning downstream status. A change in regular road geometry or flow patterns increases the need for precautionary signs such as VSLs to improve safety performance. Displayed speed limit by signs is regulated by the embedded algorithm in the system that considers the average flow's speed, driving condition impacts, and road geometry. Recorded data by weather and visibility detectors installed on the road will also adjust the advised speed limit for enhanced safety when the VSL is implemented in corridors with severe climate. The dynamic speed limit assists drivers in adapting 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 installed originally. Reduced visibility in snowstorms during winter and strong sunlight during summer were motives to have the legend color changed from white legend to amber. This transformation aims to increase the visibility of these signs to improve safety by enhancing driver adaptability to upcoming flow. This study collects onsite traffic detector data, weather radar data, and crash data to evaluate VSL system performance and its results in traffic operation before and after implementation of new signs. In the following sections, the conclusions of each task are provided.

6.2.1 Literature and Case Studies

By exploring the studies and research done on VSL applications, this research summarized the commonly adopted VSL algorithms. Also, VSL implementation cases have shown that an additional advisory system about driving conditions can enhance driving safety. Although the MUTCD states that VSL signs should have a white legend on a black background for regulatory signs, VSL signs have been used with the amber legend in corridors with low visibility due to recurring adverse conditions or work zones. Besides, safety evaluation literature is reviewed, which utilizes various safety models to assess road safety. Among developed methods, this research picked the ML models that can outperform other models in prediction accuracy.

6.2.2 Visibility Based on Sign Recordings

Since the start of the project, three rounds of field trips were conducted to record road videos in the VSL zone. Judging from the driver’s view, the amber legend makes drivers more alert about the speed limit, especially under lower visibility driving conditions. Another critical finding was the sight distance with an amber legend has increased, which provides drivers more time to respond to the speed limit.

6.2.3 Corridor’s Operation Performance

Based on the analysis performed on the recorded data, it can be concluded that safety and driver compliance rates have been enhanced due to the improved visibility of the new VSL signs. The decrease in traffic average speed and the increase of drivers’ tendency to follow the speed limit can be primarily attributed to the VSL legend’s change from white to amber. Furthermore, in winter, when higher precipitation results in a slippery road surface and reduced visibility, the driver compliance rate was increased. The reduction in crash rates also indicates improved VSL visibility directly mitigates the adverse effects of poor road and weather conditions. The detailed description of crash data showed that most crashes occurred due to poor lighting conditions or slushy road surfaces in this corridor. The former conditions also hold for crashes that occurred in 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.

6.2.4 Safety Evaluation Using ML

To develop the safety models, traffic occurrence data, driving condition, and crash data were collected for model training. The correlation of input data demonstrated that safety factors are positively related to road and driving conditions. The transition from white legend VSLs to amber legend VSLs, as an input variable, can help study the impact of the improved sign visibility on traffic safety. Based on this relation, safety models were developed using the SVM and ANN classification methods. Performance evaluation of the models demonstrated high model accuracy in safety prediction. However, due to the limited number of records for higher crash severity, it does not show the same accuracy at those levels, although, the results of models in both conditions demonstrated lower crash records with the amber legend. Outcomes of safety models indicated that the new legend color improved the safety of the corridor by reducing crash frequency and severity.

6.3 Limitations and Challenges

Since this project started in Spring 2019 and the new signs were installed in Summer 2019, the research team did not have a chance to record videos with white legend signs during cold seasons. However, before-and-after videos in summer were compared and VSL visibility was examined in winter. In addition, due to the project's timeline, the summer data for the VSL zone with the amber legend were not pulled for further analysis and assessment. Despite most crashes occurring in cold seasons, 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 when developing the safety model. Most literature studies used at least 2 to 3 years of data for reliable model development. Furthermore, this research suggests expanding a survey for drivers on the I-80 corridor to investigate the VSL's visibility from a broader range of users.

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