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16. ABSTRACT

This report investigates factors contributing to injury severity in work zone crashes, addressing the urgent need for improved safety on aging U. S. highways. Using crash records from California (2018–2021), the research integrates datasets from Caltrans and the Highway Safety Information System to build a comprehensive database of over 30 variables, including work zone characteristics, roadway attributes, environmental conditions, and crash specifics. Feature selection via the Boruta algorithm identified significant predictors of injury severity, which were modeled using multinomial logit approaches. Separate models for northern and southern California revealed regional differences, supporting the need for tailored safety strategies.In the second phase, the study evaluates Dynamic Speed Feedback Signs (DSFS) as a speed management tool in work zones. Drone-collected speed data showed DSFS moderately reduced mean speeds and speed limit violations among cars but had limited impact on heavy vehicles. The findings highlight DSFS's limitations as a standalone measure and emphasize the necessity for additional enforcement and targeted interventions, especially for heavy vehicles. The report recommends expanding systematic data collection, exploring alternative speed control strategies, and integrating conflict-based safety assessment methods to enhance work zone safety across California

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# DISCLAIMER STATEMENT

# Task ID 4125 (65A1029): ENHANCING WORK ZONE SAFETY THROUGH WZSLR)

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# Contents

# ABSTRACT

Due to aging U.S. highways, increasing maintenance and construction activities are expected, making improvements in work zone safety a high priority for transportation planners. Therefore, it is crucial to understand the factors contributing to injury severity in work zone crashes. In Phase I of this research, we obtained datasets from the California Department of Transportation (Caltrans) and the Highway Safety Information System (HSIS), matching them with California work zone crash records from 2018 to 2021. This enabled the creation of a comprehensive dataset with over 30 relevant variables, including work zone characteristics, roadway attributes, environmental conditions, and crash specifics. We used the Boruta algorithm for feature selection, identifying significant variables influencing crash injury severity. These variables were then utilized in multinomial logit models to provide interpretable insights for policymakers, helping them understand the relationships between different factors and injury severity levels. Additionally, separate models were developed for northern and southern California, and statistical analyses were performed to determine whether distinct regional models were necessary.

In Phase II, recognizing that speeding significantly contributes to crash occurrence and severity in work zones, we assessed the effectiveness of Dynamic Speed Feedback Signs (DSFS) in reducing vehicle speeds. Although initial datasets provided by Caltrans lacked essential details on work zone configurations and speed management practices, we supplemented our study by collecting high-resolution vehicle speed data using drones at selected work zones. The analysis considered mean speed reduction, speed variance, and compliance with speed limits separately for cars and heavy vehicles. Our results indicated that DSFS moderately reduced mean speeds and decreased speed limit violations among cars, but had limited effectiveness on heavy vehicles, with many vehicles still exceeding posted limits. These findings highlight the limitations of DSFS as a standalone measure and underscore the necessity of additional enforcement, supplementary speed management strategies, and targeted measures for heavy vehicles. Future research should prioritize expanding detailed data collection, evaluating alternative speed control interventions, and integrating conflict-based safety assessment methods for a more comprehensive understanding of work zone crash risks.

# REPORT OVERVIEW

Sections 1.1 to 1.5 present the work conducted during the first phase of the project. Section 1.1 provides an introduction highlighting the importance of safety in work zones, followed by a literature review in Section 1.2 that examines how various work zone, roadway, and environmental characteristics influence crash injury severity. Section 1.3 outlines the methodology used for crash data preparation and the development of multinomial logit models. The results are presented in Section 1.4, with particular attention to the spatial variation in model performance. These findings indicate that the factors affecting injury severity vary between southern and northern California, supporting the need for region-specific modeling approaches. Section 1.5 offers a summary of the findings and their implications.

Sections 2.1 to 2.6 focus on the second phase of the project. Section 2.2 reviews existing research on traffic control devices and speed management strategies used in work zones across different states, along with commonly applied evaluation methods. Section 2.3 describes the video data processing techniques developed for this study, which were essential for extracting speed information from drone footage. Section 2.4 presents statistical analyses of the available datasets on a case-by-case basis. Finally, Section 2.5 discusses key limitations encountered during the research and provides specific recommendations for Caltrans, particularly emphasizing the need for systematic data collection and centralized data storage. Implementing these improvements is critical for supporting more comprehensive evaluations of speed management strategies and enhancing work zone safety efforts across California.

# 1.1. INTRODUCTION

Work zones play a significant role in maintaining and upgrading our roads; however, several studies agree that the presence of work zones significantly increases the risk of road crashes (Wang et al., 1996; Pal and Sinha, 1996; Garber and Zhao, 2002; Khattak and Council, 2002; Srinivasan et al., 2011; La Torre et al., 2017).

Based on the NHSTA FARS report, there has been a 10.8 percent rise in work zone fatalities, with the numbers increasing from 863 in 2020 to 956 in 2021. 81 percent of these fatalities involve drivers and passengers, while 18 percent involve bicyclists and workers[1]. On the other hand, work zones are responsible for approximately 10 percent of congestion across the nation, resulting in a cumulative delay of 1.75 billion hours for vehicles and $4.6 billion in user delay costs. This alarming trend highlights the need for increased safety measures in work zones.

Unfortunately, California was included among the top 10 states with the highest occurrence of fatal work zone crashes and fatalities involving commercial motor vehicles between 2012 and 2017. Despite numerous initiatives aimed at enhancing safety for both workers and motorists in work zones, the number of fatal crashes related to these areas has experienced a staggering 61 percent increase, rising from 70 incidents in 2019 to 113 incidents in 2021. Moreover, the fatality rate has doubled during this period[2].

On the other hand, due to the aging U.S. highways, road systems will need to undergo more maintenance and construction activities in the future, and this makes improving work zone safety a top priority across

[1] FHWA's 2023 National Work Zone Awareness Week (NWZAW) Factsheet; https://ops.fhwa.dot.gov/publications/fhwahop23057/fhwahop23057.pdf

[2] Fatality Analysis Reporting System (FARS), National Highway Traffic Safety Administration, U.S. Department of Transportation

all transportation sectors. The Federal Highway Administration (FHWA) has actively supported various initiatives to address this issue. One notable initiative is the development of *the A10.47-2021: Standard on Work zone Safety for Highway Construction by the American National Standard Institute*[3]. Additionally, the Center for Construction Research and Training (CPWR)[4] and the Roadway Work Zone Safety and Health Partners Alliance[5] are actively working towards improving safety in work zones. In line with this, the California Department of Transportation (Caltrans) has prioritized safety as the central objective in its 2020-2024 Strategic Plan. They have implemented various educational programs, such as *the California move-over law, be work zone alert, and slow for the cone zone*, to raise awareness and promote safety in work zones. These collaborative initiatives demonstrate a shared dedication to enhancing work zone safety and emphasize the ongoing importance of such endeavors. Nevertheless, there is still much work to be done in this realm to further improve and address the existing challenges.

# 1.2. LITERATURE REVIEW

First, we will provide a comprehensive overview of work zone terminology, classifications, and key components, including the different types of work zones and their specific characteristics. Additionally, we will discuss various temporary traffic control (TTC) strategies designed to enhance safety and manage traffic flow effectively. Following this foundational overview, we will examine existing literature on the impact of work zones on roadway safety, emphasizing factors contributing to crash risks and driver speed behavior.

## 1.2.1. Work zone Terminology

This section defines terminology related to work zones as outlined by Lewis (1989).

**Work Zone/ Work Area/Work Site**: is an area of a highway where construction, maintenance, or utility work activities are being conducted. It denotes the general location of work activity or the subject of work area traffic control.

**Traffic Control**: Traffic control is the process of regulating, warning, and guiding road users and advising them to traverse a section of highway or street in the proper manner.

**Temporary Traffic Control (TTC) Zone**: A traffic control zone for temporary traffic control at a work zone is the entire section of the roadway over which control related to the work operation is exercised and in which any temporary traffic control devices are placed. The traffic control zone extends from the first advanced warning sign to the last device, typically a sign indicating the end. The traffic control zone includes an advance warning area, a transition area, an activity area, and a termination area.

**Traffic Control Device (TCD)**: Traffic control devices are signs, signals, markings, or other devices placed on or adjacent to a street or highway by an authority or a public body, or official jurisdiction to regulate, warn, or guide road users.

**Traffic Barrier**: For work-zone traffic control, a barrier is a device designed to prevent vehicular penetration into areas behind the barrier.

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[3] American National Standards Institute and American Society of Safety Engineers, Washington, DC.
https://webstore.ansi.org/.
[4] CPWR—The Center for Construction Research and Training.
https://www.cpwr.com/
[5] Roadway Work Zone Safety and Health Partners.
https://www.osha.gov/alliances/roadway/roadway.

## 1.2.2. Work zone classification

Work duration is a crucial factor in classifying work zone types and determining the number and types of devices used in those zones. According to FHWA, there are five categories of work zones based on the work duration and the time spent at a specific location[6]:

**Long-term stationary**: This category refers to work that occupies a location for more than 3 days continuously.

**Intermediate-term stationary**: This category includes work that occupies a location for more than one daylight period, ranging from more than 1 hour up to 3 days, or nighttime work that lasts more than 1 hour.

**Short-term stationary**: This category involves daytime work that occupies a location for more than 1 hour but less than 12 hours.

**Short duration**: This category comprises work that occupies a location for a brief period of time, up to 1 hour.

**Mobile**: This category represents work that moves intermittently or continuously, with no fixed location.

These categorizations help in determining the appropriate measures and devices required for maintaining safety and efficiency within each type of work zone.

## 1.2.3. TTC Work Zone Components

Figure 1 demonstrates a typical TTC work zone layout. As stated before, A TTC work zone comprises several key components, namely the advance warning area, transition area, activity area, and termination area, which can be defined as follows:

**Advance warning area:** This area plays a crucial role in informing drivers about upcoming changes in road conditions. According to the MUTCD, it is recommended to place advance warning signs on freeways and expressways at a distance of at least 1/2 mile or more from the work zone (FHWA 2009).

**Transition area**: It is designed to redirect traffic from its normal path, if necessary, and guide it onto a temporary path around the work area.

**Activity area**: It encompasses two sections: the buffer space and the workspace.

**Buffer space:** A closed portion of the roadway that provides additional safety space for both motorists and workers. It is located between the transition area and the work area.

**Work space**: It is the specific portion of the roadway where work activities are carried out. It must be clearly delineated and protected from traffic intrusion, as it is occupied by workers, materials, and equipment.

**Termination area**: It marks the point where traffic exits the work zone and returns to the normal roadway path. This area is typically short in length, allowing drivers to safely resume their regular routes.

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[6] Manual on Uniform Traffic Control Devices (MUTCD), 2009 Edition

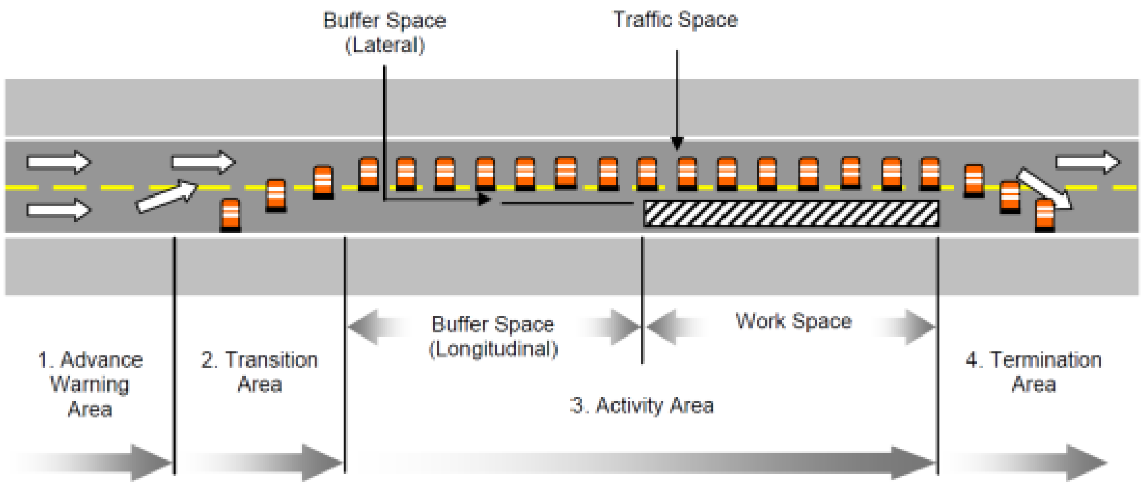


Fig.1. Work zone components

## 1.2.4. Temporary Traffic Control (TTC)

The purpose of implementing temporary traffic control (TTC) is twofold: to ensure the safe passage of road users through work zones and to optimize the movement of vehicles through and around work zones, all while protecting the safety of road users, workers, responders to traffic accidents, and equipment (FHWA, 2009). Part 6 (Temporary Traffic Control) of the Manual on Uniform Traffic Control Devices (MUTCD) and Chapter 9 (Traffic Barriers, Traffic Control Devices, and Other Safety Features for Work Zones) of the American Association of State Highway and Transportation Officials (AASHTO) Roadside Design Guide provide comprehensive guidelines for proper implementation of the traffic control strategies and devices within work zones.

### Traffic control/construction strategies

Control strategies include various traffic control methods implemented to facilitate the movement of travelers within a work zone while ensuring sufficient access to the roadway for construction activities. The extent of the work zone's impact on traffic relies on the specific control strategies employed. The Caltrans Transportation Management Plan guidelines have summarized several of these strategies as follows:

**Lane Requirement Charts**: Charts that determine the number of open lanes during work to minimize traffic delays, with restrictions during peak travel demand.

**Construction Phasing/Staging**: Sequential plan showing the order of construction activities to minimize public impacts.

**Traffic Handling Plans**: Detailed plans guiding traffic through the work zone based on the construction staging plan.

**Full Facility Closures**: Complete closure of roadways or connectors to expedite projects and enhance worker safety. Full closures can vary in duration, including brief (intermittent, off-peak), short-term closures during nights or weekends, or long-term continuous closures throughout the project.

Caltrans has outlined several factors that should be taken into consideration when deciding whether to implement full facility closures.

**Lane Modifications**: Alterations to maintain existing lane numbers, such as lane width reductions or closures. Several factors, such as accommodating extra-high and extra-wide trucks, ensuring the needs of bicycle and pedestrian users are met, and providing emergency parking, need to be taken into consideration.

**One-Way Reversing Operation**: Alternating traffic flow to facilitate work in one lane while stopping traffic in the other.

**Two-Way Traffic on One Side of Divided Facility (contra-flow or crossover)**: Closing one side of a divided highway while accommodating traffic on the opposing side. In such a case, work would proceed without traffic interference.

**Reversible Lanes (Variable lanes)**: Sharing lanes to accommodate peak-period traffic flow where the direction of travel switches by time of day or day of the week.

**Split Lanes**: Dividing lanes to perform work on a specific lane on the same side of the highway.

**Bypass Lanes**: Shifting a lane to the opposite side of the highway while keeping other lanes operational on the same side of highway.

**Ramp Closure/Relocation**: Temporarily closing or relocating ramps to facilitate work access.

**Connector Closure**: Temporary closure of connectors to restrict traffic flow in or near the work zone for specific periods or construction phases.

**Night Work**: Performing work during nighttime hours to minimize impacts on motorists and adjacent businesses.

**Extended Weekend Work**: Allowing work to be conducted during weekend periods from the end of the Friday afternoon peak period to the beginning of the Monday morning peak period.

**Pedestrian/Bicycle Access Improvements**: Providing alternate facilities and accommodations for pedestrians and cyclists affected by the work zone.

**Maintain Business Access**: Ensuring access to businesses affected by the work zone with signage or specific information for direct motorists to the businesses.

**Cost + Time Bidding**: Method of determining the lowest bidder and contract working days by considering both cost and project duration.

**Incentive/Disincentive Clauses**: Using contractual clauses to incentivize timely completion or penalize delays.

**Innovative Construction Techniques**: Employing special materials or techniques to expedite construction and minimize its impact.

**Railroad Crossing Controls**: Enhancements at rail crossings to ensure safety when a rail crossing is located within a work zone or on a detour. Enhancements may include advance warning signs, railroad crossing signs, pavement markings, flashing lights, gate arms, flaggers or law enforcement officers, and possibly closure of railroad crossing to traffic during work periods.

**Coordination with Adjacent Construction Projects**: Coordinating projects in the same corridor to minimize overall impacts.

**Speed Limit Reduction**: Lowering speed limits in work zones for improved safety.

**Traffic or "Gawk" Screens**: Installing barriers to prevent driver distractions by blocking their view of the activities and promoting smooth traffic flow.

**Bus Priority Access**: Implementing measures to ensure buses have minimal delays through the work zone.

### 1.2.5. Impact of work zone characteristics on crashes

As mentioned earlier, work zone activities create unique roadway conditions that significantly increase the risk of crashes. According to the FARS data between 2019 and 2020, work zone fatalities increased by 10.8 percent, while overall roadway fatalities increased by 10.3 percent. In 2021, fatal work zone crashes involving CMVs also increased significantly, rising from 210 fatal crashes in 2020 to 291 fatal crashes in 2021[7]. With a similar trend, fatal work zone crashes in California increased from 91 in 2020 to 113 in 2021, and total fatalities also rose from 100 in 2020 to 120 in 2021.

Work zone safety remains a major concern as the number of fatal incidents in work zones has shown an upward trend in recent years. Consequently, numerous studies have been conducted to investigate the characteristics of work zone crashes and injuries, aiming to identify contributing factors and develop effective strategies to enhance safety and reduce both fatal and nonfatal crashes.

Khattak et al, (2002) investigated crash rates and crash frequencies in the pre-work zone and during-work zone periods integrating crash data (crash frequency and injury severity), road inventory data (average daily traffic (ADT), and urban/rural character), and work zone related data (duration, length, and location) of California freeway work zones. Their results suggested that during the work zone period, the total crash rate, non-injury, and injury crash rates are 21.5,23.8, and 17.3 percent higher compared to the pre-work zone period. Furthermore, crash frequencies were examined using negative binomial models, and the results indicated that frequencies were positively influenced by work zone duration, length, and average daily traffic.

work zone characteristics, such as work zone type, configuration, and location, have a significant impact on crash severity and injury. For example, Salem et al. (2006) identified the spatial distribution and characteristics of fatal and injury crashes at various work zone locations on interstate freeways in Ohio for three years. The findings suggested that the activity area within the work zone is the most hazardous location with a higher proportion of fatal and injury crashes, as well as rear-end crashes. Li and Bai (2008) found that rear-end crashes were the predominant type in highway construction zones. This generally occurs because the presence of a work zone often causes congestion and high variance in speeds. For this reason, in work zone-related crashes, the analysis of the speed variance, in addition to the analysis of the mean speed, can provide more relevant information. Weng et al. (2015) concluded that the risk of rear-end increases with a shorter transition area. They developed a mixed probit model to describe the merging behavior in the work zone merging area.

Another study by Yu et al. (2020) utilized a random parameters logit approach with heterogeneity in means and variances to analyze factors influencing the injury severity of rear-end crashes in work zones using the data collected in North Carolina.

[7] FARS 2021 Annual Report File, NHTSA. FARS data shown here are from the 50 States, the District of Columbia, and Puerto Rico.

Qi et al. (2011) investigated the factors influencing the occurrence of rear-end crashes in work zones, specifically focusing on their frequency and severity. They used truncated count data models, including truncated Poisson and negative binomial models, as well as zero-inflated Poisson (ZIP) and negative binomial (ZINB) models, to also consider the work zones without any crash records. They selected eight variables: (1) work zone type, (2) control device, (3) layout, (4) lane closure, (5) work zone operations, (6) intersection, (7) road classification, and (8) traffic volume to calibrate the above-mentioned models employing NYSDOT work zone crash data

# 1.3. STATISTICAL ANALYSIS

## 1.3.1 Methodology

Fig 2 illustrates the proposed research framework, consisting of four main phases. In the initial phase, data from various sources are acquired, matched, and preprocessed to create a comprehensive database including crash records at California work zones from 2018 to 2021. Subsequently, the Boruta Algorithm (BA) is applied to identify significant features in the dataset associated with the different crash injury severities. Significant features confirmed by BA were then used to develop the multinomial logit model (MNL) for all work zones over CA called the "General Model". Finally, separate models have been developed for the Southern and Northern CA, and a log-likelihood test has been done to test whether the proposed general model is transferable across different regions.

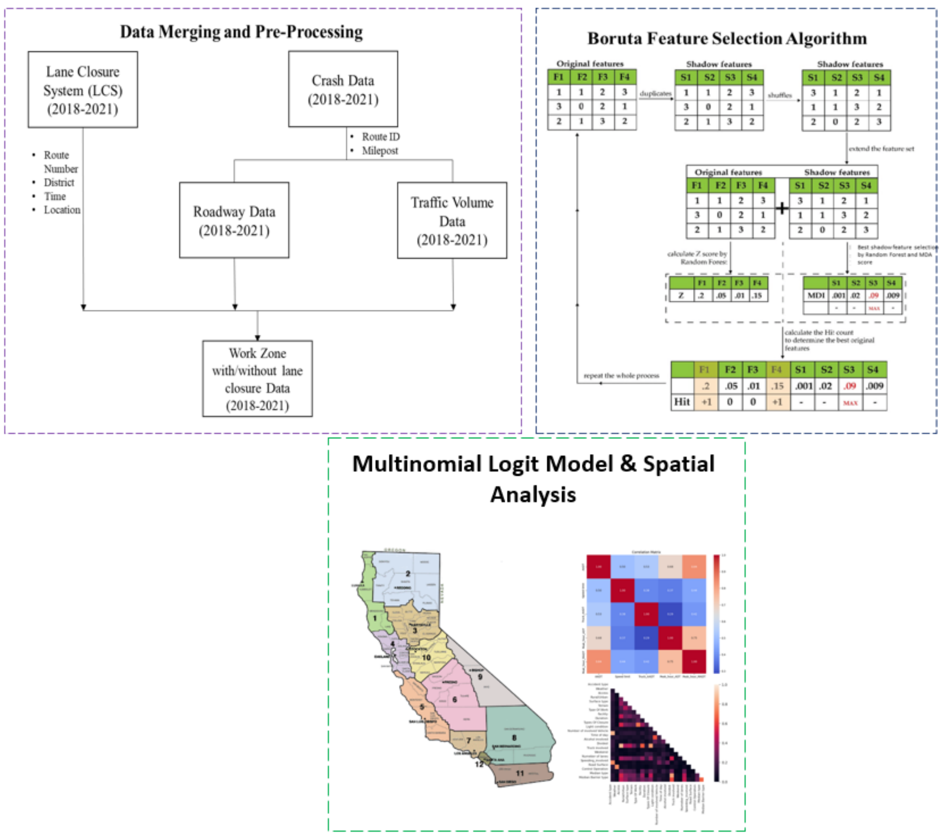


Fig.2. Research Framework

## 1.3.2. Data Preparation

In this section, we will provide a detailed overview of the datasets used in our research. We will elaborate on the matching and cleaning process used to create the final dataset, which includes over 30 features such as environmental, roadway, work zone, and crash characteristics.

### The Highway Safety Information System (HSIS) Dataset

HSIS has provided us with a comprehensive dataset of California state crash records, which are based on police collision reports collected by the California Highway Patrol (CHP). This dataset includes a variety of features, such as crash type, lighting, weather, and surface condition, as well as the location and time of the crashes. We have filtered the data to specifically include crashes that occurred in the Highway's "construction-repair zone" between 2018 and 2021.

In addition to the crash dataset, HSIS has also provided us with a dataset that describes the features of each state route along its length, specified by the beginning and ending post mile. This dataset includes features such as surface type (concrete, gravel, etc.), median type (paved, striped, etc.), median barrier type (metal beam, concrete, etc.), terrain type (flat, rolling, mountainous), access type (freeway, expressway, etc.), and road division type (divided, undivided).

The two datasets, crash and roadway, are matched by “route ID” and “Milepost” so that each record now includes the roadway features along with the crash features.

### Traffic Volumes

Traffic volume datasets are publicly accessible through the California Traffic Census program[8]. This dataset includes Annual Average Daily Traffic (AADT), truck traffic percentage, and peak hour/month volume data for each year, along state routes specified by route number, district, and post mile. The ADT refers to the volume of traffic moving in both directions on a highway for the average traffic day of the year, for 24 hours. However, due to the short duration and seasonal fluctuations, ADTs are often annualized, resulting in AADT, which mainly describes the traffic volume characteristics of a roadway. In this dataset, volumes are measured back and ahead of the counting devices, so an average value would be used for each segment. We combined the datasets by linking the route ID in the crash dataset with that in the traffic volumes file. Then, we matched the traffic volumes based on the milepost of each crash record creating an integrated dataset with roadway, crash, and traffic characteristics.

### Lane Closure System

We acquire the Lane Closure System (LCS) reports from Caltrans, containing records of submitted lane closure requests across the state. Our analysis focuses on features such as work duration (standard, long term, intermittent), closure type (lane, full, moving, one-way), facility (connector, freeway, on/off-ramp, etc.), and work type (maintenance, construction, traffic). Filtering for "Approved" lane closure requests, we align this dataset with the crash file based on the location and timing of approved closures, where the crash milepost and crash time fall within the beginning and end of the work closure.

Before analyzing the combined dataset, we did a preliminary analysis of the safety in CA work zones to investigate the statistical distribution of different crash types, crash severities, and weather and lighting conditions corresponding to crash severities.

## 1.3.3. Preliminary Analysis of Work Zone Safety

As mentioned earlier, the HSIS includes comprehensive crash records reported to the CHP. HSIS data from 2018 to 2021 were collected for all counties in California. The data was filtered to include only construction or repair zones crash records, providing raw information about the crashes, including crash severity, crash type (e.g., hit object, rear-end, etc.), lighting, and weather conditions.

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[8] California Department of Transportation. (2019). Traffic Census Program. [Online] Available at: https://dot.ca.gov/programs/traffic-operations/census

In this section, we conducted a preliminary analysis to summarize the crash data and explore the relationship between crash frequency, crash severity, and various influencing factors.

Figure 3 illustrates the historical trends of the total number of crashes in CA work zones between 2018 and 2021.

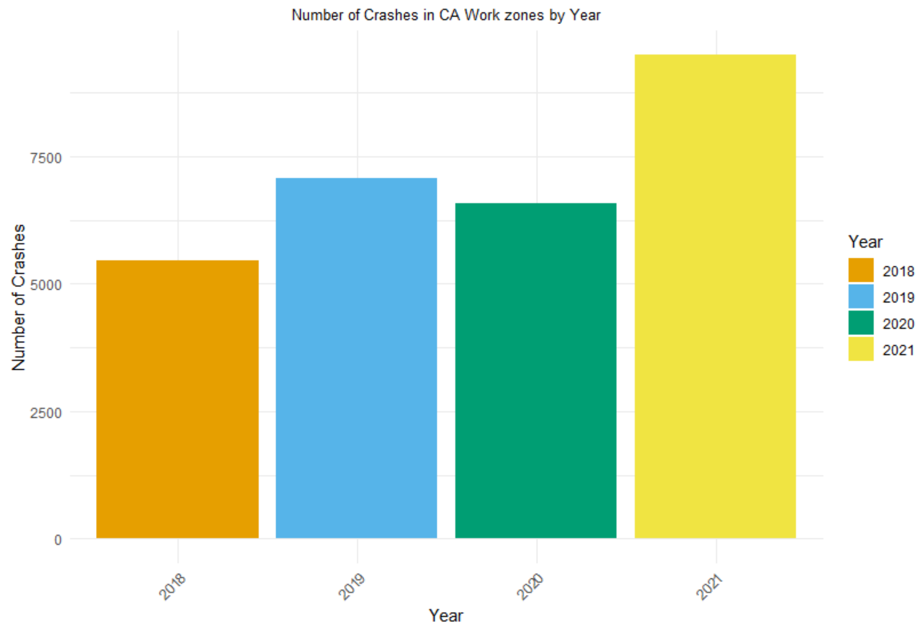



Fig.3. Number of Crashes in California Work zones by year

When analyzing work zone safety, it is crucial to examine the trends in crash severity. Table 2 presents the distribution of crash severity for the years 2018 through 2021. As expected, there is an increasing trend in the number of crashes across all severity types. However, it is important to contextualize these numbers by comparing them with the total work zone crashes during each respective year to gain a better understanding of the trends. In this case, there is no apparent trend in the percentage distribution of different types of crashes over the analyzed period, and the proportions of various crash types appear to remain relatively stable. Crashes with property damage only account for the highest number of crashes, comprising over 65 percent, while crashes with fatalities comprise around 1 percent of the total number of crashes.

Table 2. Number of work zone crashes by injury severity levels

| Year | Total Crashes | Total WZ-related Crashes | Fatal injury | Percentage (%) | Suspected serious Injury | Percentage (%) |
|---|---|---|---|---|---|---|
| 2018 | 192542 | 5453 | 47 | 0.86 | 114 | 2.09 |
| 2019 | 187283 | 7064 | 49 | 0.69 | 156 | 2.21 |
| 2020 | 136126 | 6579 | 56 | 0.85 | 147 | 2.23 |
| 2021 | 161139 | 9487 | 59 | 0.62 | 215 | 2.27 |
| **Year** | **Suspected minor injury** | **Percentage (%)** | **Possible injury** | **Percentage (%)** | **Property damage only** | **Percentage (%)** |
| 2018 | 476 | 8.73 | 1005 | 18.43 | 3811 | 69.89 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2019 | 606 | 8.58 | 1435 | 20.31 | 4818 | 68.20 |
| 2020 | 571 | 8.68 | 1246 | 18.94 | 4559 | 69.30 |
| 2021 | 943 | 9.94 | 1799 | 18.96 | 6471 | 68.21 |

The next section of the report discusses the trends among specific crash attributes, such as crash type, lighting, and weather conditions that could potentially affect work zone safety.

The "Type of crash" attribute indicates the specific type of crash that occurred, such as a head-on or overturn crash. As depicted in Figure 4, "Rear-end" crashes are the most prominent crash type in California work zones, accounting for 52% of all crash types. Following that, "Sideswipe" and "Hit object" have the highest numbers.

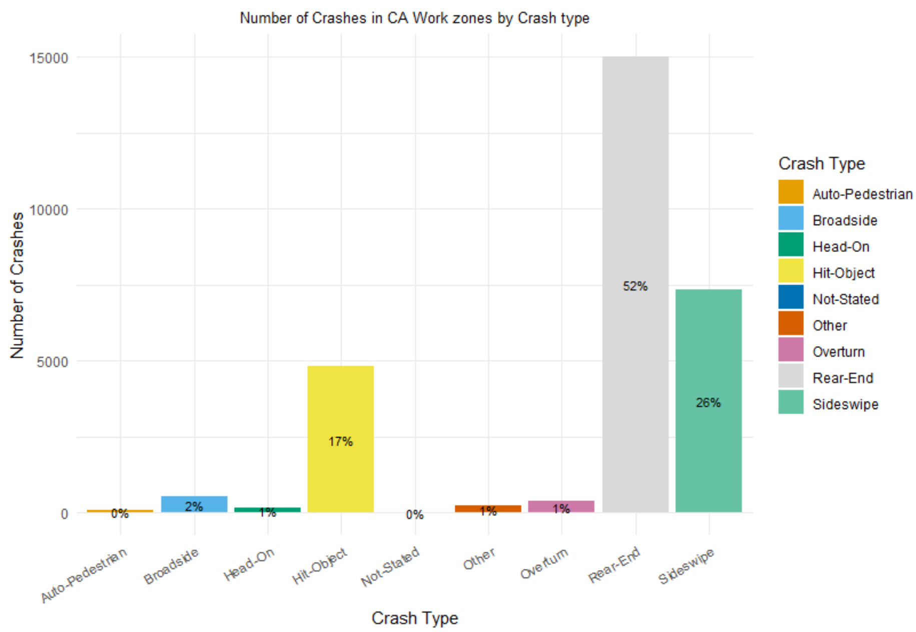



Fig.4. Number of Crashes in California Work Zones by Crash Type

Furthermore, Figure 5 shows the distribution of the number of work zone crashes concerning the crash cause recognized by police in crash scenes. As depicted, “speeding” is the main cause of over 50 percent of work zone crashes while “improper turn” and “Alcohol involvement” are other key causes.

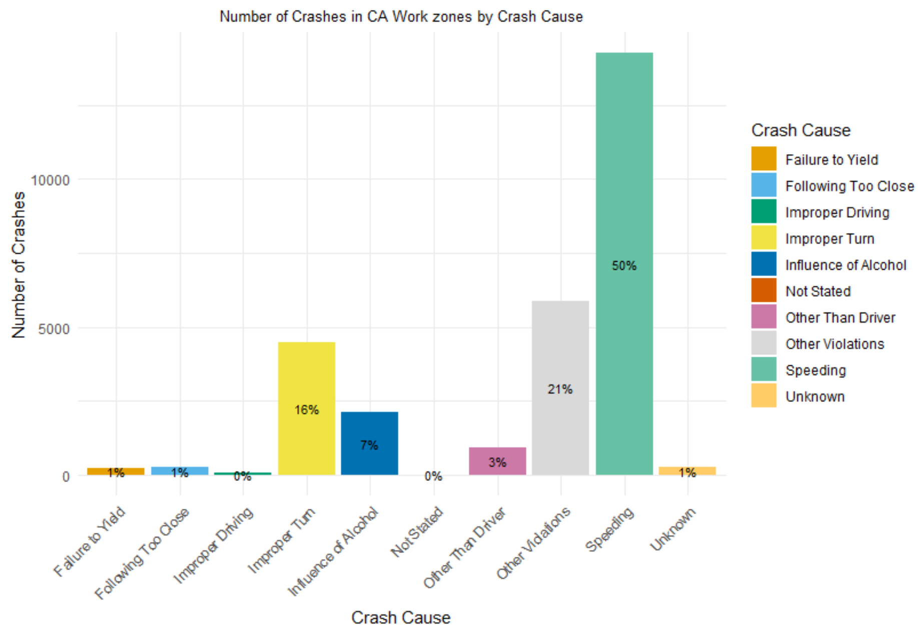
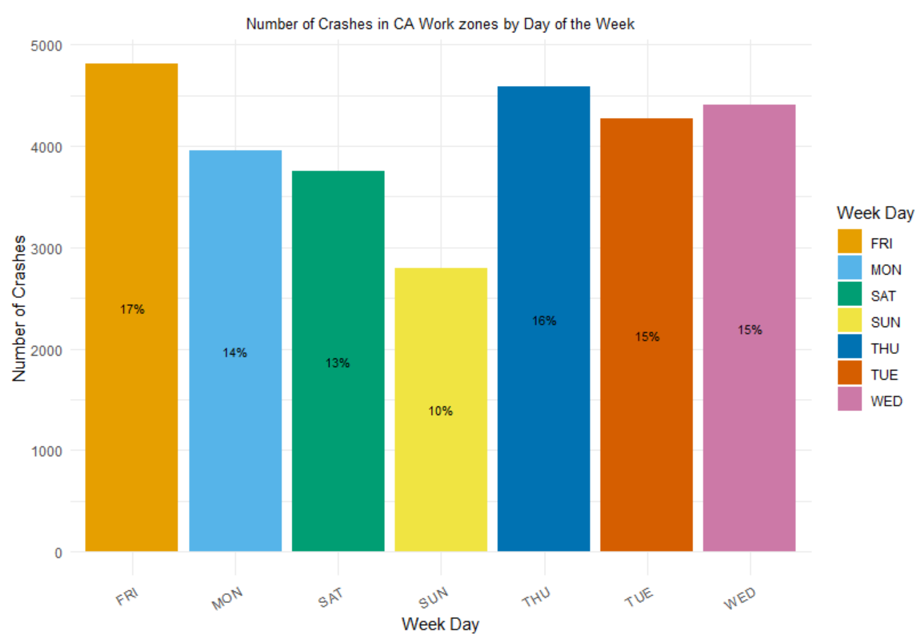
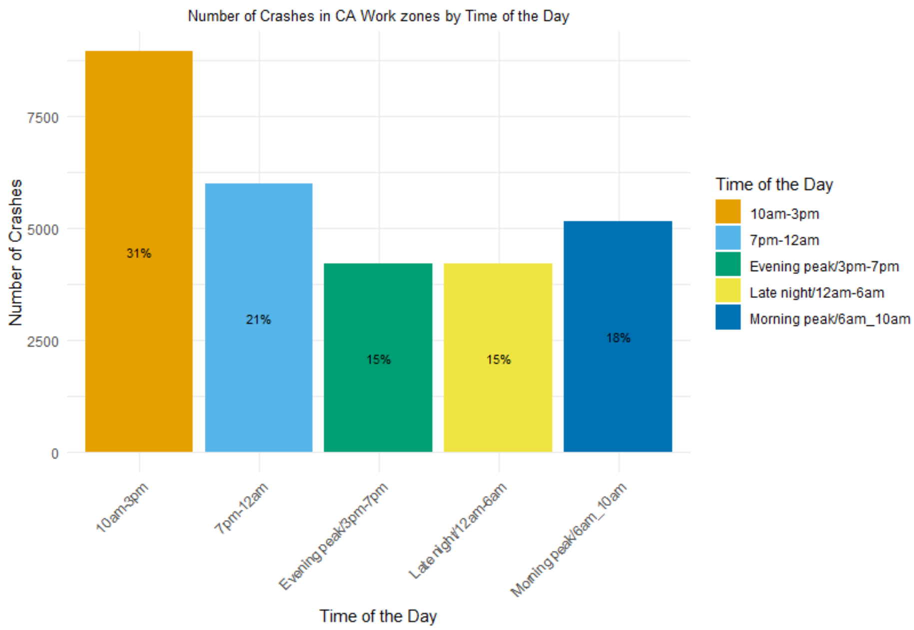



Fig.5. Number of Crashes in California Work Zones by Crash Cause

Figures 6a and 6b illustrate the distribution of total work zone crashes by the day of the week and the time of day. The majority of crashes occur between 6 AM and 6 PM, coinciding with higher traffic flow. Additionally, crashes are evenly distributed across days of week, with the lowest number of crashes occurring on Sundays.




(a)




(b)

Fig.6. Number of Crashes in California Work Zones by (a) Day of the week, (b) Time of the day

Interestingly, a significant number of work zone crashes happen between 7 PM and 6 AM, which could be attributed to lighting conditions during nighttime hours. It's also important to explore the injury severity level of crashes happening on different days of the week and at different times of the day. Table 3 exhibits this detailed information.

Table 3. Number of work zone crashes by injury severity levels, categorized by injury time of day and day of the week.

| Time of the Day | Fatal injury | Suspected serious injury | Suspected minor injury | Possible injury | Property damage only |
|---|---|---|---|---|---|
| 10am-3pm | 27 | 134 | 762 | 1821 | 6205 |
| 7pm-12am | 54 | 162 | 562 | 1116 | 4115 |
| Evening peak/3pm-7pm | 22 | 81 | 349 | 884 | 2871 |
| Late night/12am-6am | 80 | 182 | 515 | 663 | 2784 |
| Morning peak/6am_10am | 24 | 72 | 408 | 999 | 3664 |

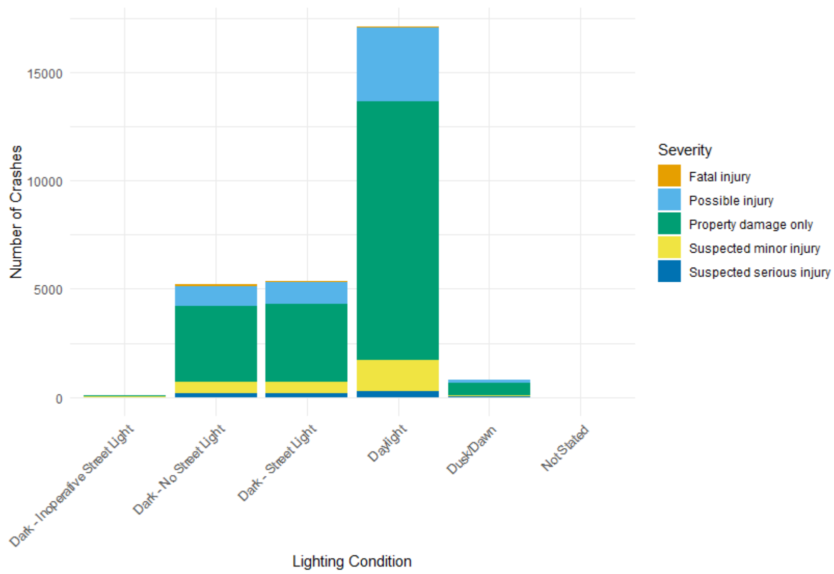
| Day of the Week | Fatal injury | Suspected serious injury | Suspected minor injury | Possible injury | Property damage only |
|---|---|---|---|---|---|
| MON | 27 | 74 | 341 | 740 | 2770 |
| WED | 27 | 77 | 379 | 842 | 3084 |
| FRI | 29 | 107 | 409 | 942 | 3322 |
| SUN | 30 | 99 | 346 | 527 | 1796 |
| SAT | 31 | 105 | 397 | 757 | 2465 |

| | | | | | |
|---|---|---|---|---|---|
| TUE | 33 | 82 | 342 | 785 | 3033 |
| THU | 34 | 88 | 382 | 892 | 3189 |

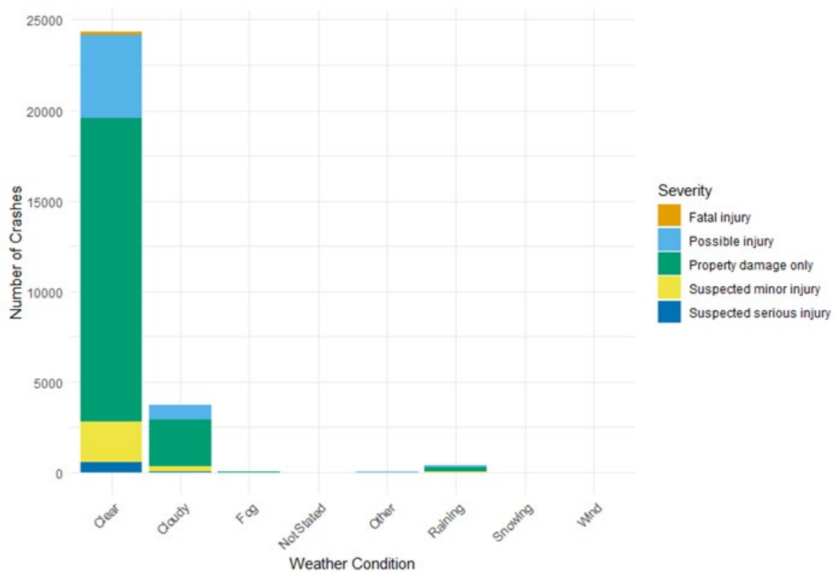
| Time of the Day | Fatal injury | Suspected serious injury | Suspected minor injury | Possible injury | Property damage only |
|---|---|---|---|---|---|
| 10am-3pm | 27 | 134 | 762 | 1821 | 6205 |
| 7pm-12am | 54 | 162 | 562 | 1116 | 4115 |
| Evening peak/3pm-7pm | 22 | 81 | 349 | 884 | 2871 |
| Late night/12am-6am | 80 | 182 | 515 | 663 | 2784 |
| Morning peak/6am_10am | 24 | 72 | 408 | 999 | 3664 |

| Day of the Week | Fatal injury | Suspected serious injury | Suspected minor injury | Possible injury | Property damage only |
|---|---|---|---|---|---|
| MON | 27 | 74 | 341 | 740 | 2770 |
| WED | 27 | 77 | 379 | 842 | 3084 |
| FRI | 29 | 107 | 409 | 942 | 3322 |
| SUN | 30 | 99 | 346 | 527 | 1796 |
| SAT | 31 | 105 | 397 | 757 | 2465 |
| TUE | 33 | 82 | 342 | 785 | 3033 |
| THU | 34 | 88 | 382 | 892 | 3189 |

Two other contributing factors, lighting and weather conditions during the work zone crashes, have been explored in Figures 7a and 7b. Most of the existing crash data belongs to daylight and clear weather conditions. However, an analysis of the crash severity with lighting and weather conditions shows that although most of the crashes happen in daylight, the fatal crashes are evenly distributed between daylight, dark-street light, and dark-no street light conditions.




(a)




(b)

Fig.7. Number of Crashes in California Work Zones by (a) lighting conditions, (b) weather conditions

## 1.3.4. Boruta Method for Feature Selection

Feature selection is a crucial step in identifying the most influential contributors to the prediction of the target variable. In this study, we employ the Boruta Algorithm (BA), a wrapper built around the random forest classification algorithm, to select features that carry meaningful information. This approach aims to mitigate issues such as overfitting, complexity, and multicollinearity, which can arise from an abundance of excessive or irrelevant features. The Boruta Algorithm extends the concept introduced by Stoppiglia et al. (2003), where significant features are determined by comparing the actual features to randomly generated probes known as shadow features. The algorithm breaks down into the following steps:

1. The algorithm generates randomly ordered duplicated variables ($S_i$) for each input variable ($V_i$), referred to as shadow features. This shuffling process eliminates correlations between duplicated variables and the dependent variable.
2. A random forest or another tree-based classifier is trained on the expanded dataset. The Z-score of features is then calculated by dividing the accuracy loss of each feature by its standard deviation, as a measure of the significance of each feature.
3. These values are compared with the maximum Z-score among shadow features (MZSA). Features with Z-scores < MZSA are identified as unimportant and removed, while features with Z-scores > MZSA are deemed important.
4. This iterative process continues until all features are confirmed as significant, tentative, or rejected, or until the iteration threshold is reached.

## 1.3.5. Spatial Stability Analysis

To statistically explore whether the injury severity models for work zone crashes in CA are significantly different over space (e.g., northern and southern California), two groups of spatial stability tests will be conducted.

The first group of likelihood ratio tests was proposed to compare the models for two regions and examine if the parameter estimation remains stable between these regions:

$$\boldsymbol{\chi}_{s_1}^2 = -2[LL(\boldsymbol{\beta}_{y_1y_2}) - LL(\boldsymbol{\beta}_{y_1})]$$

Where $LL(\boldsymbol{\beta}_{y_1y_2})$ denotes the log-likelihood at the convergence of the model containing parameters from $y_2$ while using subgroup $y_1$'s data, and $LL(\boldsymbol{\beta}_{y_1})$ is the log-likelihood at convergence of the model using subgroup $y_1$'s data. The degree of freedom equals the number of estimated parameters in the model $\boldsymbol{\beta}_{y_1y_2}$ and the resulting $\boldsymbol{\chi}^2$ value under the $\boldsymbol{X}^2$ distribution can be used to determine the confidence level at which the null hypothesis that the parameters are stable between two regions can be accepted or rejected.

The second group of likelihood ratio tests is between the joint spatial model and each separate model utilized to test the transferability of estimated crash injury severity models across northern and southern regions as follows:

$$\boldsymbol{\chi}_{s_2}^2 = -2[LL(\boldsymbol{\beta}_{joint}) - LL(\boldsymbol{\beta}_{northern\ CA}) - LL(\boldsymbol{\beta}_{southern\ CA})]$$

Where $LL(\boldsymbol{\beta}_{joint})$ is the log-likelihood at the convergence of the model with all available CA crash data, $LL(\boldsymbol{\beta}_{northern\ CA})$ represents the log-likelihood at the convergence of the northern CA crash severity model, and $LL(\boldsymbol{\beta}_{southern\ CA})$ represents the log-likelihood at the convergence of the southern CA crash severity model. The degrees of freedom equal to the summation of parameters found to be statistically significant in the separate models excluding the number of parameters found statistically significant in the combined model.

## 1.3.6. Analysis of CA work zones with lane closure

As the initial step in our methodological framework, we integrated data from various sources based on spatial and temporal information associated with each record. In particular, we collected four years of work zone crash records in California (2018-2021) and merged them with roadway and traffic volume datasets. The combined dataset provides detailed information about these crashes, including roadway characteristics, traffic features, and lane closure characteristics. Out of the total 667,090 crashes during this period, 26,766 occurred in work zones. After matching lane closures' approved requests and removing missing and incomplete records, only a total of 3,372 crashes that occurred in work zones with lane closures were used for further descriptive analysis and model development.

Overall, among the 3,372 crashes analyzed, 2,281 crashes resulted in property damage only (referred to as "no-injury"), 674 crashes resulted in possible injury, 323 in suspected minor injury, 70 in serious injury, and 24 in fatal crashes. Serious injury and fatal injury crashes were combined into one severity class (denoted as "severe injury") with 94 observations, while possible injury and suspected minor injury crashes were combined into the "minor injury" severity level with a total of 997 observations.

Table 4 presents descriptive statistics for categorical features across all three injury severity levels, including environmental, work zone, roadway, and crash characteristics. The dataset reflects that Northern California has the highest proportion of crashes for all injury levels. Additionally, rear-end crashes dominate as the primary accident type in work zones, resulting in a significant number of fatalities and severe injuries (Federal Highway Administration, 2019; Chen et al., 2015). The mean and standard deviation for continuous attributes such as AADT and speed limit are provided in Table 5.

Table 4. Statistical description of categorical explanatory variables

| **Characteristic** | **Levels** | **Severe Injury** | **Minor Injury** | **No Injury** |
|---|---|---|---|---|
| **Zone** | | | | |
| | Central CA | 8 (8.5%) | 93 (9.4%) | 230 (10%) |
| | Northern CA | 69 (73%) | 650 (65%) | 1,336 (59%) |
| | Southern CA | 17 (18%) | 251 (25%) | 714 (31%) |
| **Crash Type** | | | | |
| | Auto-Pedestrian* | 3 (3.2%) | 1 (0.1%) | 1 (<0.1%) |
| | Broadside | 2 (2.1%) | 11 (1.1%) | 29 (1.3%) |
| | Head-On | 4 (4.3%) | 2 (0.2%) | 6 (0.3%) |
| | Hit-Object | 18 (19%) | 126 (13%) | 348 (15%) |
| | Overturn | 9 (9.6%) | 31 (3.1%) | 10 (0.4%) |
| | Rear-End | 50 (53%) | 680 (68%) | 1,137 (50%) |
| | Sideswipe | 8 (8.5%) | 143 (14%) | 749 (33%) |
| **Weather** | | | | |
| | Clear* | 85 (90%) | 875 (88%) | 1,995 (88%) |
| | Cloudy | 8 (8.5%) | 99 (10.0%) | 243 (11%) |
| | Raining | 1 (1.1%) | 20 (2.0%) | 42 (1.8%) |
| **Access** | | | | |
| | Conventional* | 13 (14%) | 65 (6.5%) | 136 (6.0%) |
| | Expressway | 9 (9.6%) | 38 (3.8%) | 72 (3.2%) |
| | Freeway | 72 (77%) | 891 (90%) | 2,072 (91%) |
| **Population** | | | | |

| | | | |
|---|---|---|---|
| Rural* | 28 (30%) | 228 (23%) | 563 (25%) |
| Urban | 5 (5.3%) | 30 (3.0%) | 43 (1.9%) |
| Urbanized | 61 (65%) | 736 (74%) | 1,674 (73%) |
| **Surface Type** | | | |
| AC - Base & Surface < 7"" Thick* | 2 (2.1%) | 21 (2.1%) | 27 (1.2%) |
| AC - Base & Surface > 7' Thick | 43 (46%) | 296 (30%) | 668 (29%) |
| PCC - Bridge Deck | 1 (1.1%) | 13 (1.3%) | 37 (1.6%) |
| PCC - Concrete | 48 (51%) | 664 (67%) | 1,548 (68%) |
| **Terrain** | | | |
| Flat* | 55 (59%) | 695 (70%) | 1,550 (68%) |
| Mountainous | 18 (19%) | 90 (9.1%) | 232 (10%) |
| Rolling | 21 (22%) | 209 (21%) | 498 (22%) |
| **Type of Work** | | | |
| Construction* | 53 (56%) | 508 (51%) | 1,032 (45%) |
| Maintenance | 41 (44%) | 486 (49%) | 1,248 (55%) |
| **Facility Type** | | | |
| Conventional Hwy* | 27 (29%) | 125 (13%) | 269 (12%) |
| HOV | 1 (1.1%) | 10 (1.0%) | 52 (2.3%) |
| Mainline | 63 (67%) | 839 (84%) | 1,922 (84%) |
| Toll Bridge | 3 (3.2%) | 20 (2.0%) | 37 (1.6%) |
| **Work Duration** | | | |
| Intermittent* | 4 (4.3%) | 34 (3.4%) | 98 (4.3%) |
| Long Term | 5 (5.3%) | 25 (2.5%) | 77 (3.4%) |
| Standard | 85 (90%) | 935 (94%) | 2,105 (92%) |
| **Closure Type** | | | |
| Alternating Lanes* | 23 (24%) | 229 (23%) | 516 (23%) |
| Lane | 31 (33%) | 413 (42%) | 890 (39%) |
| Moving | 27 (29%) | 303 (30%) | 758 (33%) |
| One-Way Traffic | 13 (14%) | 49 (4.9%) | 116 (5.1%) |
| **Light Condition** | | | |
| Dark* | 54 (57%) | 387 (39%) | 957 (42%) |
| Daylight | 40 (43%) | 607 (61%) | 1,323 (58%) |
| **Number of Involved Vehicle** | | | |
| Single | 23 (24%) | 123 (12%) | 308 (14%) |
| Multiple* | 71 (76%) | 871 (88%) | 1,972 (86%) |
| **Time_of_day** | | | |
| 10am-3pm* | 20 (21%) | 290 (29%) | 705 (31%) |
| 7pm-12am | 21 (22%) | 234 (24%) | 564 (25%) |
| Evening peak/3pm-7pm | 11 (12%) | 153 (15%) | 283 (12%) |
| Late night/12am-6am | 30 (32%) | 125 (13%) | 316 (14%) |
| Morning peak/6am_10am | 12 (13%) | 192 (19%) | 412 (18%) |
| **Alcohol_involved** | | | |
| No* | 68 (72%) | 919 (92%) | 2,162 (95%) |

| | | | | |
|---|---|---|---|---|
| | Yes | 26 (28%) | 75 (7.5%) | 118 (5.2%) |
| **Divided** | | | | |
| | No* | 15 (16%) | 67 (6.7%) | 144 (6.3%) |
| | Yes | 79 (84%) | 927 (93%) | 2,136 (94%) |
| **Truck_involved** | | | | |
| | No* | 92 (98%) | 971 (98%) | 2,207 (97%) |
| | Yes | 2 (2.1%) | 23 (2.3%) | 73 (3.2%) |
| **Weekend** | | | | |
| | No* | 78 (83%) | 861 (87%) | 2,036 (89%) |
| | Yes | 16 (17%) | 133 (13%) | 244 (11%) |
| **Number of lanes** | | | | |
| | 5 and less* | 36 (38%) | 212 (21%) | 490 (21%) |
| | 5_8 | 17 (18%) | 250 (25%) | 554 (24%) |
| | 8 and more | 41 (44%) | 532 (54%) | 1,236 (54%) |
| **Speeding_involved** | | | | |
| | No* | 53 (56%) | 352 (35%) | 1,214 (53%) |
| | Yes | 41 (44%) | 642 (65%) | 1,066 (47%) |
| **Road_surface** | | | | |
| | Wet* | 2 (2.1%) | 38 (3.8%) | 70 (3.1%) |
| | Dry | 92 (98%) | 956 (96%) | 2,210 (97%) |
| **Control Operation** | | | | |
| | No* | 64 (68%) | 851 (86%) | 1,888 (83%) |
| | Yes | 30 (32%) | 143 (14%) | 392 (17%) |
| **Median_type** | | | | |
| | Other* | 19 (20%) | 91 (9.2%) | 223 (9.8%) |
| | Paved Median | 46 (49%) | 604 (61%) | 1,371 (60%) |
| | Unpaved Median | 29 (31%) | 299 (30%) | 686 (30%) |
| **Median_Barrier_type** | | | | |
| | Concrete Barrier* | 37 (39%) | 611 (61%) | 1,379 (60%) |
| | Guardrail Barrier | 6 (6.4%) | 55 (5.5%) | 157 (6.9%) |
| | Metal Barrier | 4 (4.3%) | 31 (3.1%) | 110 (4.8%) |
| | No Barrier | 33 (35%) | 154 (15%) | 357 (16%) |
| | Thrie Beam Barrier | 14 (15%) | 143 (14%) | 277 (12%) |

Table 5. Statistical descriptive of Continuous explanatory variables

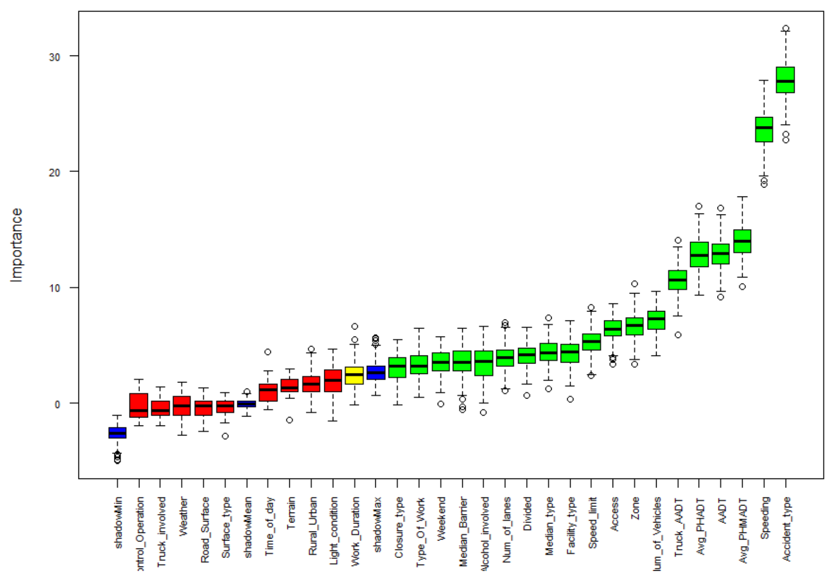
| **Characteristic** | **Severe Injury** | **Minor Injury** | **No Injury** |
|---|---|---|---|
| **AADT** | 120,213 (86,273) | 152,316 (75,456) | 151,160 (75,985) |
| **Design Speed** | 67.2 (5.5) | 68.2 (5.3) | 68.6 (4.6) |
| **Truck AADT percentage** | 9.6 (5.9) | 8.9 (5.7) | 9.4 (5.7) |
| **Average Peak Hour ADT** | 9,681 (10,793) | 10,445 (5,291) | 10,571 (6,728) |
| **Average Peak Hour Monthly ADT** | 117,391 (82,063) | 140,505 (75,759) | 143,320 (76,552) |

# 1.4. RESULTS AND DISCUSSION

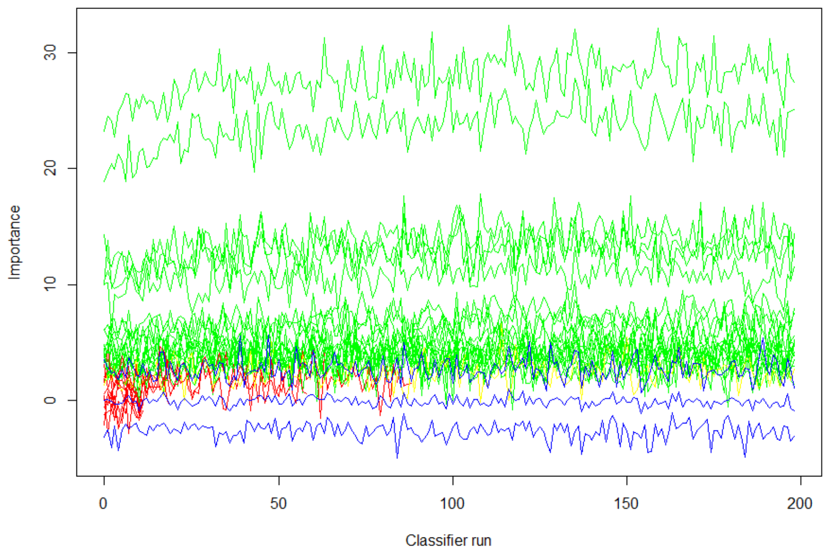
## 1.4.1. Feature Selection

We aim to develop a multinomial logit model to predict the injury severity of work zone crashes based on the attributes outlined in Table 4 and Table 5. To do so, the categorical features in Table 1 are converted into dummy variables, generating k-1 binary covariates for a feature with k categories, which increases the number of features to 60 features. Therefore, the Boruta feature selection method is applied to identify major factors contributing to the probability of injury severity of work zone crashes. The resulting features are then utilized to build the MNL model.

Figure 8a illustrates box plots for all attributes, indicating their associated significance values. The blue boxplots represent the lowest, average, and highest Z-scores for each shadow feature, while the red, yellow, and green boxplots correspond to the Z-scores for rejected, tentative, and confirmed attributes, respectively. Features with higher importance scores than the random shadow variables are intuitively identified as confirmed. Figure 8b depicts the Z-score evolution during Boruta runs, with green lines indicating confirmed features and blue lines representing the minimal, average, and maximal shadow attribute importance.



(a)




(b)

Fig.8. Boruta Algorithm outputs (a) Box plots of features based on importance values, (b) the Importance value of features in each classifier run.

The analysis determined that out of 29 features, 19 were confirmed as important, one was tentative, and nine were deemed unimportant. Notably, the "accident type" emerged as the most significant factor contributing to work zone crashes in California, with a mean importance value of 27.8, as per the Mean Decrease in Impurity (MDI) according to the Boruta algorithm. This was followed by the "Speeding_involved" feature with a mean importance value of 23.9, "average peak hour monthly ADT" with a mean importance value of 14.1, and the "Zone" feature with a mean importance value of 6.6.

Table 6 provides a detailed overview of specific aspects derived from the Boruta outputs. The normHits measure indicates the number of hits normalized to the total number of runs. For instance, if the feature "Alcohol_involved" has a normHits value of 0.69, it signifies that this feature was deemed more important than the shadow feature in 69 percent of the runs, confirming its significance. Conversely, if the feature "Terrain" has a normHits value of 0.015, it indicates that this feature is considered unimportant in nearly 99 percent of the runs, warranting its exclusion from further analysis.

Table 6. Boruta output

| **Characteristics** | **Mean-Imp** | **Median-Imp** | **Min-Imp** | **Max-Imp** | **normHits** | **Decision** |
|---|---|---|---|---|---|---|
| Median_Barrier | 3.577 | 3.564 | -0.533 | 6.435 | 0.709 | Confirmed |
| Median_type | 4.357 | 4.363 | 1.219 | 7.381 | 0.884 | Confirmed |
| Control_Operation | -0.268 | -0.658 | -1.929 | 2.095 | 0.000 | Rejected |
| Road_Surface | -0.413 | -0.209 | -2.441 | 1.308 | 0.000 | Rejected |
| Speeding | 23.586 | 23.769 | 18.867 | 27.919 | 1.000 | Confirmed |
| Num_of_lanes | 3.928 | 3.899 | 1.079 | 6.953 | 0.814 | Confirmed |
| Weekend | 3.537 | 3.512 | -0.085 | 5.758 | 0.739 | Confirmed |
| Truck_involved | -0.475 | -0.601 | -1.950 | 1.380 | 0.000 | Rejected |

| | | | | | | |
|---|---|---|---|---|---|---|
| Divided | 4.129 | 4.205 | 0.648 | 6.516 | 0.854 | Confirmed |
| Alcohol_involved | 3.484 | 3.586 | -0.825 | 6.661 | 0.693 | Confirmed |
| Time_of_day | 1.109 | 1.146 | -0.561 | 4.389 | 0.010 | Rejected |
| Num_of_Vehicles | 7.211 | 7.294 | 4.083 | 9.646 | 0.995 | Confirmed |
| Light_condition | 1.891 | 1.971 | -1.544 | 4.704 | 0.141 | Rejected |
| Zone | 6.622 | 6.679 | 3.348 | 10.272 | 0.990 | Confirmed |
| Avg_PHMADT | 14.054 | 14.025 | 10.053 | 17.804 | 1.000 | Confirmed |
| Avg_PHADT | 12.758 | 12.792 | 9.315 | 17.047 | 1.000 | Confirmed |
| Truck_AADT | 10.584 | 10.668 | 5.928 | 14.054 | 1.000 | Confirmed |
| Closure_type | 3.096 | 3.170 | -0.110 | 5.519 | 0.648 | Confirmed |
| Work_Duration | 2.422 | 2.464 | -0.127 | 6.598 | 0.452 | Tentative |
| Facility_type | 4.246 | 4.392 | 0.343 | 7.100 | 0.864 | Confirmed |
| Type_Of_Work | 3.271 | 3.198 | 0.544 | 6.450 | 0.658 | Confirmed |
| Terrain | 1.436 | 1.287 | -1.451 | 2.950 | 0.015 | Rejected |
| Surface_type | -0.423 | -0.196 | -2.812 | 0.926 | 0.000 | Rejected |
| Rural_Urban | 1.684 | 1.685 | -0.769 | 4.674 | 0.080 | Rejected |
| Speed_limit | 5.308 | 5.293 | 2.366 | 8.230 | 0.975 | Confirmed |
| Access | 6.410 | 6.424 | 3.360 | 8.624 | 0.990 | Confirmed |
| AADT | 12.913 | 12.899 | 9.190 | 16.830 | 1.000 | Confirmed |
| Weather | -0.220 | -0.256 | -2.771 | 1.813 | 0.000 | Rejected |
| Accident_type | 27.887 | 27.770 | 22.758 | 32.335 | 1.000 | Confirmed |

## 1.4.2. Developing MNL Model

Next, the optimal subset of attributes selected by the BA was fed into an MNL model. This step aimed to yield an interpretable and informative model, providing policymakers and decision-makers insights into how various factors influence different crash injury severity levels in CA work zones with lane closures. Table 7 presents the modeling results utilizing the MNL approach serves as the base model for developing the random parameter logit model with heterogeneity in means and variances.

It should be noted that the no-injury severity level is the baseline in our model, and its severity function is set to zero without loss of generality. The final model has been developed using the Forward stepwise method, and only statistically significant features with p-values less than 0.05 are presented in Table 7. Since the model coefficients are not directly interpretable, and to accurately indicate the influence of individual features on the probabilities of injury severity outcomes, we compute the marginal effect. The resulting marginal effects of the model's features are outlined in Table 8 for further discussion.

Table 7. Multinomial logit model for crash severity in CA work zones

| Variables | Minor Injury | | Severe Injury | |
|---|---|---|---|---|
| | Parameter Estimate | Wald-test | Parameter Estimate | Wald - test |
| Constant | -1.34 | 14.3 | -1.96 | 12.9 |

| | | | | |
|---|---|---|---|---|
| Accident_type_Hit_Object (1 if the type of collision is hit object; 0 otherwise) | _ | _ | -1.46 | 6.6 |
| Accident_type_Overturn (1 if the type of collision is overturn; 0 otherwise) | 2.24 | 19.1 | 1.74 | 6.2 |
| Accident_type_Rear_End (1 if the type of collision is rear-ended; 0 otherwise) | _ | _ | -1.78 | 14.5 |
| Accident_type_Sideswipe (1 if the type of collision is sideswipe; 0 otherwise) | -0.68 | 4.1 | -2.79 | 26.7 |
| Alcohol_involved_1 (1 if alcohol is involved; 0 otherwise) | 0.71 | 15.7 | 1.94 | 31.3 |
| Speeding_involved_1 (1 if speeding is involved; 0 otherwise) | 0.45 | 12.4 | _ | _ |
| Weekend_1 (1 if the crash occurs on the weekend; 0 otherwise) | 0.23 | 3.8 | _ | _ |
| Type_Of_Work_Maintenance (1 if the type of work zone is maintenance; 0 otherwise) | -0.23 | 8.64 | _ | _ |
| Number_of_involved_Vehicle_Single (1 if the number of involved vehicles in the crash is 1; 0 otherwise) | -0.37 | 2.6 | _ | _ |
| Duration_Standard (1 if the duration of the work zone is standard; 0 otherwise) | 0.31 | 3.8 | _ | _ |
| Light_condition_Daylight (1 if the light condition is day; 0 otherwise) | 0.17 | 4.3 | _ | _ |
| Barrier_type_No_Barrier (1 if No barrier:0 otherwise) | _ | _ | 0.96 | 13.7 |
| Barrier_type_Thrie_Beam_Barrier (1 if Thrie beam barrier type:0 otherwise) | _ | _ | 0.69 | 4.6 |
| **Model Statistics** | | | | |
| Number of Observation | 3372 | | | |
| Log-likelihood at zero | -2188 | | | |
| Log-likelihood at convergence | -2023 | | | |
| McFaddenR2 | 0.076 | | | |
| Akaike information criterion (AIC) | 4102 | | | |
| Bayesian information criterion (BIC) | 4381 | | | |

Table 8. Average marginal effects for crash severity in CA work zones

| **Variables** | **Marginal effects** | | |
|---|---|---|---|
| | **No Injury** | **Minor Injury** | **Severe Injury** |
| Accident_type_Hit_Object (1 if the type of collision is hit object; 0 otherwise) | -0.0004 | 0.0387 | -0.0383 |
| Accident_type_Overturn (1 if the type of collision is overturn; 0 otherwise) | -0.4464 | 0.4235 | 0.0229 |
| Accident_type_Rear_End (1 if the type of collision is rear-ended; 0 otherwise) | 0.0136 | 0.0323 | -0.0459 |
| Accident_type_Sideswipe (1 if the type of collision is sideswipe; 0 otherwise) | 0.1716 | -0.1073 | -0.0644 |
| Alcohol_involved_1 (1 if alcohol is involved; 0 otherwise) | -0.1630 | 0.1205 | 0.0426 |
| Speeding_involved_1 (1 if speeding is involved; 0 otherwise) | -0.0899 | 0.0855 | 0.0043 |
| Weekend_1 (1 if the crash occurs on the weekend; 0 otherwise) | -0.0455 | 0.0430 | 0.0025 |
| Type_Of_Work_Maintenance (1 if the type of work zone is maintenance; 0 otherwise) | 0.0467 | -0.0437 | -0.0030 |

| | | | |
|---|---|---|---|
| Number_of_involved_Vehicle_Single (1 if the number of involved vehicles in the crash is 1; 0 otherwise) | 0.0752 | -0.0676 | -0.0076 |
| Duration_Standard (1 if the duration of the work zone is standard; 0 otherwise) | -0.0599 | 0.0604 | -0.0005 |
| Light_condition_Daylight (1 if the light condition is day; 0 otherwise) | -0.0265 | 0.0378 | -0.0113 |
| Barrier_type_No_Barrier (1 if No barrier:0 otherwise) | -0.0126 | -0.0118 | 0.0244 |
| Barrier_type_Thrie_Beam_Barrier (1 if Thrie beam barrier type:0 otherwise) | -0.0433 | 0.0275 | 0.0158 |

Akaike's information criterion (AIC) and Bayesian information criterion (BIC) are usually used to evaluate the quality of statistical models, which are estimated by considering the goodness of fit and complexity of the model simultaneously. Smaller AIC and BIC values indicate a better-fitting model. So, after all relevant features entered the model based on the likelihood ratio test, the AIC and BIC of different models were used to obtain the best MNL model shown in Table 7.

Alcohol and speeding have been identified as two major contributors to injury severity in work zone crashes in CA. The positive values of the marginal effects of minor and severe injury levels and negative values of no injury in Table 5  indicate that the involvement of alcohol/drugs and speeding resulted in more severe injuries. Such findings have been verified in previous research efforts.

As shown in Tables 7 and 8, among environmental characteristics, daylight proves to be a statistically significant indicator for minor injury level. Positive marginal effects for a minor injury and negative marginal effects of no injury and severe injury indicate that daylight results in an increased possibility of a minor injury while dark light condition increases the likelihood of severe and no injury levels. This aligns with the findings of Yu et al. (2020). Moreover, work zone crashes occurring during weekends result in crashes with more injuries as the positive marginal effect of minor and severe injury and negative value for no injury suggests. The number of vehicles involved in a crash turned out to be a significant factor in the work zone crash severity model, which results in a lower likelihood of severe injury and minor injury outcomes (positive marginal effects for no injury and negative marginal effects for minor and severe injury levels) compared to crashes involving multiple vehicles. Intuitively, crashes involving more than one vehicle would result in more severe crashes and a higher likelihood of both minor and severe injuries.

Within work zone-related features, both the duration and type of work zone are found to be statistically significant in our model. The marginal effect in Table 8 indicates that maintenance activities decrease the probability of minor and severe injuries by 0.0437 and 0.0030, respectively, and increase the probability of no injury or property damage only by 0.0467 when compared to construction activities. This could be because construction work zones tend to have more workers and equipment, which can distract drivers and increase the likelihood of injuries. Additionally, work zones with standard durations significantly increase the likelihood of minor injuries, while resulting in a lower likelihood of severe injury and no injury outcomes (positive marginal effects for minor injury and negative marginal effects for severe injury and no injury levels) compared to intermittent work zones.

Among roadway-related characteristics, barrier type was found to be statistically significant in the injury severity of CA work zone crashes. The marginal effects of no barrier and Thrie beam barrier show that they result in a higher likelihood of severe injury and a lower likelihood of property damage only crashes compared to concrete barriers.

Finally, as specified by BA, types of crashes were found to be a significant factor in the developed crash severity model. As indicated in Table 5, the marginal effect of drivers involved in rear-end, hit-object, and sideswipe crashes shows a lower likelihood of severe injuries compared to those involved in auto-pedestrian or vehicle-worker crashes. Conversely, drivers involved in overturned crashes were found to have a higher likelihood of severe injuries. The results also showed that the likelihood of getting minor injuries for drivers involved in rear-end, hit-object, and mainly overturn was higher. Although the sideswipe crash type is associated with a lower probability of minor and severe injuries, it greatly increases the probability of no-injury crashes. It should be noted that these values are relative to the auto-pedestrian crash type as the reference category.

## 1.4.3. Northern and Southern California work zones

In this section, we categorized crash records into those occurring in Northern California (NorCal) and those in Southern California (SoCal) work zones, based on the districts where the crashes occurred. This division allows us to develop separate MNL models for SoCal and NorCal, regarding the potential differences that may exist in driving habits, vehicle composition, traffic management policies, and safety measures between these regions.

Given the limited crash records for central California districts, we have combined the records of central and southern California for modeling purposes. Figure 9 illustrates Caltrans districts, with districts 1, 2, 3, and 4 designated as NorCal, while the remainder are considered SoCal for further analysis. Table 9 also summarizes the crash records in these two regions regarding their injury severity levels.


Fig.9. Caltrans Districts

Table 9. Number of crashes in NorCal and SoCal

| Injury Severity Levels | NorCal | | SoCal | |
|---|---|---|---|---|
| | Number of crashes | Percentage (%) | Number of crashes | Percentage (%) |
| No Injury | 1336 | 65 | 945 | 71.8 |
| Minor Injury | 651 | 31.7 | 346 | 26.3 |
| Severe Injury | 69 | 3.4 | 25 | 1.8 |

Then, we developed the models and the marginal effect of the attributes using the above-mentioned data. Tables 10 and 11 present the MNL models developed separately for NorCal and SoCal respectively. Subsequently, the average marginal effect for the models' features in Tables 12 and 13.

Table 10. Multinomial logit model for crash severity in NorCal work zones

| **Variables** | **Minor Injury** | | **Severe Injury** | |
|---|---|---|---|---|
| | **Parameter Estimate** | **Wald-test** | **Parameter Estimate** | **Wald -test** |
| Constant | -0.72 | 13.5 | -3.09 | 46.6 |
| Accident_type_Head_on (1 if the type of collision is head on; 0 otherwise) | _ | _ | 2.99 | 14.4 |
| Accident_type_Overturn (1 if the type of collision is overturn; 0 otherwise) | 1.66 | 14.1 | 3.5 | 34.2 |
| Accident_type_Sideswipe (1 if the type of collision is sideswipe; 0 otherwise) | -0.76 | 22 | -1.28 | 6.1 |
| Alcohol_involved_1 (1 if alcohol is involved; 0 otherwise) | 0.52 | 6.6 | 1.76 | 19.3 |
| Speeding_involved_1 (1 if speeding is involved; 0 otherwise) | 0.4 | 8.4 | _ | _ |
| Facility_Mainline (1 if the facility type of collision is mainline; 0 otherwise) | _ | _ | -0.87 | 6.4 |
| Control Operation_1 (1 if control is operationg; 0 otherwise) | _ | _ | 0.57 | 3.6 |
| Type_Of_Closure_One way Traffic (1 if the type of closure type is one way traffic; 0 otherwise) | -0.23 | 8.6 | _ | _ |
| Time_of_day_Late night_12am-6am (1 if the collision time is 12 am to 6 am; 0 otherwise) | _ | _ | 1.09 | 14 |
| Speed Limit | -0.12 | 4.6 | 0.26 | 2.4 |
| **Model Statistics** | | | | |
| Number of Observation | 2056 | | | |
| Log-likelihood at zero | -1470 | | | |
| Log-likelihood at convergence | -1366 | | | |
| McFaddenR2 | 0.067 | | | |
| Akaike information criterion (AIC) | 2780 | | | |
| Bayesian information criterion (BIC) | 2915 | | | |

Table 11. Multinomial logit model for crash severity in SoCal work zones

| **Variables** | **Minor Injury** | | **Severe Injury** | |
|---|---|---|---|---|
| | **Parameter Estimate** | **Wald-test** | **Parameter Estimate** | **Wald -test** |
| Constant | -1.2 | 24.7 | -4.1 | 29.9 |
| Accident_type_Overturn (1 if the type of collision is overturn; 0 otherwise) | 3.4 | 18.2 | 2.9 | 4.8 |
| Accident_type_Sideswipe (1 if the type of collision is sideswipe; 0 otherwise) | -0.7 | 8.3 | -1.3 | 3.1 |
| Alcohol_involved_1 (1 if alcohol is involved; 0 otherwise) | 0.9 | 7.7 | 2.3 | 13.6 |
| Speeding_involved_1 (1 if speeding is involved; 0 otherwise) | 0.6 | 7.9 | _ | _ |

| | | | | |
|---|---|---|---|---|
| Weather_Cloudy (1 if the weather is cloudy; 0 otherwise) | -0.46 | 3.8 | _ | _ |
| Control Operation_1 (1 if control is operationg; 0 otherwise) | -0.57 | 7.5 | _ | _ |
| Type_Of_Closure_Moving (1 if the type of closure type is moving; 0 otherwise) | _ | _ | 1.31 | 5.8 |
| Light_condition_Dusk & Dawn (1 if the light condition is dusk & dawn; 0 otherwise) | _ | _ | 2.1 | 9.3 |
| Number_of_involved_Vehicle_Single (1 if the number of involved vehicles in the crash is 1; 0 otherwise) | -0.44 | 2.67 | _ | _ |
| Weekend_1 (1 if the crash occurs on the weekend; 0 otherwise) | 0.57 | 6.8 | _ | _ |
| **Model Statistics** | | | | |
| Number of Observation | | 1316 | | |
| Log-likelihood at zero | | -854 | | |
| Log-likelihood at convergence | | -773 | | |
| McFaddenR2 | | 0.092 | | |
| Akaike information criterion (AIC) | | 1595 | | |
| Bayesian information criterion (BIC) | | 1719 | | |

Table 12. Average marginal effects for crash severity in NorCal work zones

| **Variables** | **Marginal effects** | | |
|---|---|---|---|
| | **No Injury** | **Minor Injury** | **Severe Injury** |
| Accident_type_Head_on (1 if the type of collision is head on; 0 otherwise) | -0.0091 | -0.0843 | 0.0934 |
| Accident_type_Overturn (1 if the type of collision is overturn; 0 otherwise) | -0.3586 | 0.2808 | 0.0779 |
| Accident_type_Sideswipe (1 if the type of collision is sideswipe; 0 otherwise) | 0.1502 | -0.1250 | -0.0252 |
| Alcohol_involved_1 (1 if alcohol is involved; 0 otherwise) | -0.1375 | 0.0914 | 0.0461 |
| Speeding_involved_1 (1 if speeding is involved; 0 otherwise) | -0.1068 | 0.0983 | 0.0085 |
| Facility_Mainline (1 if the facility type of collision is mainline; 0 otherwise) | 0.0212 | 0.0036 | -0.0248 |
| Control Operation_1 (1 if control is operationg; 0 otherwise) | 0.0212 | -0.0394 | 0.0182 |
| Type_Of_Closure_One way Traffic (1 if the type of closure type is one way traffic; 0 otherwise) | 0.0908 | -0.1070 | 0.0161 |
| Time_of_day_Late night_12am-6am (1 if the collision time is 12 am to 6 am; 0 otherwise) | -0.018 | -0.0129 | 0.0309 |
| Speed Limit | 0.0211 | -0.0301 | 0.0090 |

Table 13. Average marginal effects for crash severity in SoCal work zones

| **Variables** | **Marginal effects** | | |
|---|---|---|---|
| | **No Injury** | **Minor Injury** | **Severe Injury** |
| Accident_type_Overturn (1 if the type of collision is overturn; 0 otherwise) | -0.6097 | 0.5873 | 0.0311 |

| | | | |
|---|---|---|---|
| Accident_type_Sideswipe (1 if the type of collision is sideswipe; 0 otherwise) | 0.1367 | -0.1161 | -0.0191 |
| Alcohol_involved_1 (1 if alcohol is involved; 0 otherwise) | -0.2026 | 0.1529 | 0.0358 |
| Speeding_involved_1 (1 if speeding is involved; 0 otherwise) | -0.1045 | 0.1100 | -0.0072 |
| Weather_Cloudy (1 if the weather is cloudy; 0 otherwise) | 0.0923 | -0.0746 | -0.0186 |
| Control Operation_1 (1 if control is operationg; 0 otherwise) | 0.1027 | -0.1030 | 0.0069 |
| Type_Of_Closure_Moving (1 if the type of closure type is moving; 0 otherwise) | -0.0151 | 0.0161 | 0.0219 |
| Light_condition_Dusk & Dawn (1 if the light condition is dusk & dawn; 0 otherwise) | -0.0603 | 0.0244 | 0.0359 |
| Number_of_involved_Vehicle_Single (1 if the number of involved vehicles in the crash is 1; 0 otherwise) | 0.07143 | -0.0803 | 0.00803 |
| Weekend_1 (1 if the crash occurs on the weekend; 0 otherwise) | -0.10568 | 0.09652 | 0.00915 |

The models reveal that the "head-on" crash type holds statistical significance in the crash severity model developed for NorCal but not for SoCal. Conversely, both "Overturn" and "sideswipe" crash types are significant factors in both regions, with similar effects observed in the "general model".

Alcohol and speeding involvement continue to emerge as significant factors contributing to increased injury severity levels in both NorCal and SoCal. Additionally, cloudy weather appears to correlate with a decreased likelihood of minor and severe injuries in SoCal, although the underlying reason for this trend is not readily apparent, aside from the possibility that drivers exercise greater caution under such conditions.

Regarding work zone-related features, "Type of Closure_Moving" increases the likelihood of minor and severe injuries in SoCal, while "Type of Closure_One way traffic" is associated with an increased likelihood of severe and no injury crashes in NorCal. Furthermore, control operation in both regions tends to elevate the likelihood of severe injuries while reducing the likelihood of minor injuries.

### 1.4.4. Spatial Stability Test Results

Finally, to examine the spatial stability of the influence that contributing factors have on crash injury severity, two groups of spatial stability tests were conducted. Table 14 summarizes the results of the test. Using the converged parameters of the NorCal model, the starting values, and applying them to the SoCal data gave $\boldsymbol{\chi^2 = 35.41}$ with 24 degrees of freedom, illustrating that the null hypothesis that the two regions are the same can't be rejected. Likewise, using the converged parameters of the SoCal model as the starting values and applying them to the NorCal model gave $\boldsymbol{\chi^2 = 27.31}$ with 22 degrees of freedom, this also indicates that the null hypothesis can't be rejected. This shows that there was no potential spatial instability in the Northern and Southern CA regions.

On the other hand, the second group of likelihood ratio tests between the "general model", "NorCal", and "SoCal" with $\boldsymbol{\chi^2 = 55.38}$ with 28 degrees of freedom indicates that the null hypothesis that SoCal and NorCal are the same can be rejected with >99.99% confidence.

In summary, the results from both tests suggest that developing separate models could be a valuable approach to understanding the contributing factors to crash severity injury in Northern and Southern California work zones.

Table 14. Likelihood ratio test results between NorCal and SoCal

| y1 | y2 | |
|---|---|---|
| | NorCal | SoCal |
| NorCal | - | 35.41 (df=24) p_value=0.0625 |
| SoCal | 27.31 (df=22) p_value=0.1997 | - |

# 1.5. CONCLUSIONS

In this research, we investigated the factors that contribute to injury severity levels of work zone crashes as a representative of work zone safety. We integrated data from various sources based on spatial and temporal information associated with each record. In particular, we collected four years of work zone crash records in California (2018-2021) and merged them with roadway and traffic volume datasets. The combined dataset provides detailed information about these crashes, including roadway characteristics, environmental characteristics, traffic features, and work zones' lane closure characteristics. Out of the total 667,090 crash records during this period, 26,766 crashes occurred in work zones. After matching lane closure approved requests and removing missing and incomplete records, 3,372 crash records of those that occurred in work zones with lane closures were used for further descriptive analysis and model development. Afterward, the Boruta feature selection method was applied to identify major factors contributing to the probability of injury severity of these work zone crashes. This analysis determined that out of 29 features, 19 were confirmed as important, one was tentative, and nine were deemed unimportant. So, the optimal subset of attributes selected by the BA was fed into an MNL model. This step aimed to yield an interpretable and informative model, providing policymakers and decision-makers insights into how various factors influence different crash injury severity levels in CA work zones with lane closures.

The model highlighted the importance of alcohol and speeding as two major contributors to injury severity in work zone crashes in CA. Moreover, among environmental characteristics, daylight is a statistically significant indicator for minor injury levels, while work zone crashes occurring during weekends result in more severe injuries. The model also identified the number of vehicles involved in a crash as a significant factor that results in a lower likelihood of severe injury and minor injury outcomes. Within work zone-related features, both the duration and type of work zone are found to be statistically significant in our model. The marginal effect indicates that maintenance activities decrease the probability of minor and severe injuries compared to construction activities. Additionally, work zones with standard durations significantly increase the likelihood of minor injuries, while resulting in a lower likelihood of severe injury and no injury outcomes compared to intermittent work zones.

We then categorized crash records into those occurring in Northern California (NorCal) and those in Southern California (SoCal) work zones and we developed separate MNL models for SoCal and NorCal, regarding the potential differences that may exist in driving habits, vehicle composition, traffic management policies, and safety measures between these regions. These models illustrate how different factors may have different effects on the injury severity of crashes in Northern and Southern CA work zones.

Finally, we conducted a statistical test to determine whether separate models for Northern California and Southern California are required or if one general model would be sufficient. The test indicated that developing separate models is necessary, as the impact of the influencing factors is not consistent across these regions.

# 2.1. INTRODUCTION

Work zones present a significant safety challenge on roadways, as they change normal traffic patterns and introduce temporary hazards that can lead to increased crash risks. Speeding has been consistently recognized as a major contributing factor to work zone crashes, directly impacting both the likelihood and severity of crashes. Higher speeds not only increase the stopping distance required to avoid hazards but also reduce driver reaction time and amplify crash impact forces, making accidents more severe. Additionally, speed variability—differences in speed between vehicles—can lead to sudden braking, erratic lane changes, and an increased risk of rear-end crashes, which are among the most common crash types in work zones.

To mitigate these risks, various speed management strategies have been implemented in work zones, including DSFS, police enforcement, changeable message signs, portable rumble strips, and drone radar. Among these, DSFS has gained attention as a non-intrusive and cost-effective measure that provides real-time speed feedback to drivers, encouraging voluntary compliance with posted speed limits. While DSFS has been widely used in various roadway settings, its effectiveness in work zones requires further evaluation, particularly regarding its influence on different vehicle types and speed variability.

This research focuses on evaluating the impact of DSFS on speed reduction in work zones by analyzing speed data collected from several work zones in California. The study examines speed distribution patterns, mean speeds, speed variance, and the proportion of high-speed vehicles to assess the effectiveness of DSFS in different settings. While an ideal study design would involve a before-and-after comparison, such data were unavailable for most sites. However, for one specific work zone, speed data were collected both upstream (before encountering the DSFS) and adjacent to the DSFS, providing a more direct assessment of DSFS effectiveness. To obtain detailed traffic behavior insights, Unmanned Aerial Vehicles (UAVs) were deployed at selected work zones. UAVs provided high-resolution video footage, which was then processed to extract vehicle speeds and classify vehicles into cars and heavy vehicles. This UAV-based data allowed for a more comprehensive and accurate assessment of speed behavior in work zones.

Through this analysis, the study aims to determine whether DSFS effectively reduces speeds in work zones, identify its impact on different vehicle types (cars vs. heavy vehicles), and assess its limitations. The findings will contribute to a better understanding of DSFS as a speed control measure and provide insights for future improvements in work zone speed management strategies and overall safety.

# 2.2. LITERATURE REVIEW

Research has consistently identified high speeds and speed variability as major contributors to injuries and fatalities in work zones (Daniel et al., 2000). Excessive speed is strongly linked to increased crash severity and overall crash risk, while high-speed variance is associated with a greater likelihood of collisions (Quddus, 2013; Ravani and Wand, 2018). To address these concerns, several studies have focused on establishing appropriate work zone speed limits to mitigate accident risks and minimize speed fluctuations.

Migletz et al. (1999) developed a procedure to determine optimal work zone speed limits, demonstrating that reducing the speed limit by 10 mph effectively decreased accident rates. Similarly, Hou et al. (2013) conducted a field study in three short-term work zones on Interstate 70 in Missouri, evaluating the effectiveness of three different speed limit reduction scenarios: no reduction, a 10 mph reduction, and a 20 mph reduction. Their findings revealed that as the speed limit reduction increased from 0 to 10 mph, the percentage of speeding drivers nearly halved. Further reducing the speed limit by an additional 10 mph lowered the percentage of speeding vehicles to just one-fifth of that observed in work zones without speed reductions. Their study, conducted in short-term maintenance work zones along a rural interstate with a 70 mph baseline speed limit, concluded that a 20 mph speed limit reduction was the most effective in reducing both prevailing speeds and speed variance.

Another study conducted in Texas examined motorists' compliance with work zone speed limits, highlighting the discrepancy between posted regulatory speed limits and drivers' actual speed choices. The field studies revealed that motorists adjusted their speeds in work zones primarily based on their perception of roadway conditions rather than strictly adhering to the posted speed limit. The extent of speed reduction depended on factors such as the normal operating speed of the roadway, the severity of work zone conditions, and the presence of enforcement activities. High levels of non-compliance were observed when reduced speed limits were enforced despite minimal visible work zone hazards, underscoring the importance of aligning speed reduction strategies with actual roadway conditions.

To improve speed compliance and enhance safety in work zones, various speed management technologies and enforcement strategies have been developed and tested by state Departments of Transportation (DOTs). This section explores commonly used traffic control devices and speed management strategies aimed at reducing vehicle speeds in advanced warning zones, transition areas, buffer zones, and active work areas to enhance safety for both motorists and workers.

### Portable Changeable Message Signs (PCMS)

PCMSs, commonly used in all states, have proven to be highly effective in guiding drivers, reducing travel speeds, and lowering the percentage of speeding traffic. These devices are equipped with lighting and programming functions that enable the display of dynamic messages to road users, providing real-time information about upcoming work zone conditions. PCMSs can be conveniently mounted on either a trailer or a work vehicle. Notably, their effectiveness in reducing speed is further enhanced when integrated with radar drones. Caltrans has provided comprehensive guidelines and recommendations regarding their installation and usage. These guidelines aim to optimize the conditions under which PCMS are deployed, ensuring their maximum impact in work zones[9].

A study conducted by the Texas Transportation Institute focused on the effectiveness of PCMS when used sequentially. The study found that it is crucial to limit the messages to a maximum of four units, as exceeding this length resulted in low comprehension rates. However, when the message length was kept to four units, the sequential use of PCMS yielded comparable comprehension rates to those achieved by presenting the same information on a single large dynamic message sign. Additionally, repeating one line of the message on both PCMS in a sequence can enhance comprehension (Ullman et al., 2007).

Bham and Leu (2018) examined the impact of different messages displayed on PCMS in a work zone's advance-warning area. Using a driving simulator, the study evaluated the combined effects of four sequentially placed PCMS on drivers' mean speeds. The message "Prepare to Stop/Stopped Traffic Ahead" had the most significant reduction in speed compared to the other messages, particularly just upstream of the lane closure. It showed the largest overall reduction in mean speed (30.3 mph, 44.1%) compared to a control scenario. They concluded that the most significant impact on drivers' speeds was observed when a strong and clearly worded message was displayed.

A research project conducted by Brewer et al. (2006) aimed to identify effective measures to encourage drivers to adhere to posted speed limits in work zones. Three devices were tested: a speed display trailer, a

[9] Changeable Message Sign (CMS) Guideline, the Division of Traffic Operations, Caltrans, 2021

changeable message sign with radar, and an orange border speed limit sign. Field testing results showed that devices displaying drivers' speeds had the potential to reduce speeds and improve compliance.

Huang and Bai (2018) presented the findings of a two-phase research project focused on exploring driver responses to graphic-aided PCMSs. In this project, various text and graphic-aided PCMSs representing roadwork and flagger scenarios were set up upstream of highway work zones, and speed data from over 2,700 vehicles were collected using five speed sensors to analyze vehicle speed reduction. The results showed that graphic-aided PCMSs led to a reduction in mean vehicle speed ranging from 13% to 17%. Furthermore, the study found that the impact on speed differed significantly for passenger cars and trucks depending on their locations within the work zone. Additionally, between 52% and 71% of drivers expressed a preference for PCMS messages that included graphics. Overall, this research project demonstrated the positive effects of incorporating graphics into PCMS messages, resulting in reduced vehicle speeds and increased driver preference.

## Dynamic Speed Feedback Sign (DSFS)

Dynamic Speed Feedback Sign (DSFS) systems are traffic control devices that use radar or LiDAR technology to detect the speed of approaching vehicles and display their real-time speed on a digital screen. These systems serve as a visual deterrent, encouraging drivers to reduce their speed by providing immediate feedback on their compliance with posted limits.

Pesti and McCoy (2002) evaluated the long-term effectiveness of DSFS in work zones located along rural interstate highways in Nebraska. Their study found that DSFS led to a reduction in mean speeds by 3 to 4 mph, a decrease in 85th percentile speeds ranging from 2 to 7 mph, and a notable increase in speed limit compliance by 20% to 40%. These effects remained consistent over a five-week observation period, demonstrating the sustained impact of DSFS on driver behavior. Additionally, the study found that speed reductions were more pronounced for passenger vehicles compared to heavy vehicles, suggesting that different vehicle types respond differently to DSFS interventions.

Similarly, Fontaine and Carlson (2001) examined the effectiveness of DSFS in four rural two-lane maintenance work zones. Their study compared three scenarios: (1) no work zone traffic control, (2) standard work zone traffic control, and (3) DSFS installation. The results indicated that DSFS was generally more effective than rumble strips in reducing speeds within advance warning areas. Speed reductions of up to 10 mph were observed as vehicles approached the work zone, and the proportion of vehicles exceeding the speed limit also decreased significantly in the advance warning area.

A broader meta-analysis of 43 studies conducted by Flynn et al. (2020) reinforced these findings, demonstrating that DSFS is effective across multiple environments, including school zones and work zones, and for various vehicle types, including passenger cars and heavy-duty vehicles. The analysis found that DSFS installations resulted in statistically significant speed reductions, with passenger cars experiencing an average decrease of 4 mph, while reductions of 2 to 4 mph were observed across all vehicle types in different settings.

More recently, Mahmud et al. (2024) conducted a comprehensive review of DSFS effectiveness across different locations, including work zones. Their study aimed to evaluate the benefits of DSFS implementation, identify optimal placement and messaging strategies, assess public perception, and examine the temporal effectiveness of DSFS over time. Additionally, the study explored potential locations where DSFS could be deployed to further enhance speed management and traffic safety.

## Arrow Panels

Arrow panels are traffic control devices that provide advance warning in situations where a lane is closed, and traffic needs to merge with vehicles in an adjacent lane. They are typically used for lane closures and slow-moving maintenance activities. It is recommended to use flashing arrow panels for all lane closures on highways with a posted speed limit of 45 mph or higher. In areas with limited visibility, the arrow panel vehicle may need to lag behind or stop to maintain optimal visibility for approaching traffic. As sight distance improves, the arrow panel vehicle should close the gap. However, the distance between the arrow panel vehicle and the work activity should be kept short to discourage drivers from re-entering the closed lane[10].

Utah and Oregon were pioneers in implementing the "dancing diamonds" pattern as part of their traffic control devices. The Utah Department of Transportation has been utilizing the “dancing diamonds” display since June 1972. To assess its effectiveness, a field experiment compared the “dancing diamonds” with the "flashing box" display. The results indicated that the dancing diamond display led to a statistically significant reduction of 3 km/h (2 mph) in mean speeds, while the flashing box display did not show a significant reduction. These findings suggest that the dancing diamonds are more effective in controlling speed near highway work zones compared to the flashing box (Turley et al., 2003).

Nevertheless, the field tests conducted by the Oregon Department of Transportation (ODOT) in 2001 provided evidence that the effectiveness of the "dancing diamonds" display was on par with, if not superior to, other caution displays.

## Portable Temporary Signal (PTS)

A Portable Traffic Signal (PTS) is a self-contained, illuminated signal used to regulate traffic flow specifically at temporary work zones where the adjacent travel lane is closed. Traditionally, flaggers were responsible for managing vehicle queues at each end of such work zones by manually stopping and releasing traffic. However, due to escalating costs and concerns about flagger safety, PTS systems have gained popularity.

Normally, the PTS system comprises two portable trailers equipped with signals mounted on a pole and a mast arm. These systems operate on solar power and can function as actuated traffic signal controllers, allowing for prioritized travel time through the work zone for higher directional flows.

A research project supported by the Kansas Department of Transportation (KDOT) was conducted to investigate the efficacy of PTS systems in monitoring one-lane, two-way traffic at long work zones, considering factors like pilot car operations and the presence of a flagger. The evaluation of average vehicle wait times, queue lengths, and signal timing operations revealed that the "flagger only" condition had the longest average wait time, while the "PTS without a flagger" condition had the shortest average wait time throughout the data collection period. Furthermore, the "PTS without a flagger" condition also had the longest average queue length, while the "flagger only" condition had the shortest average queue length. Finally, they developed a volume model to identify volume thresholds that indicate when the PTS systems would become less effective.

Furthermore, Jeon and Benekohal (2023) conducted a study where they introduced a novel signal timing approach known as WorkZoneQ-Pro (WZQ-Pro). This method takes into account various factors such as the work zone speed limit, work intensity, speed control techniques, and work zone length to determine the average operating speed of the work zone. The researchers utilized data from three distinct work zones located in California, New York, and Idaho to calculate signal timing parameters, queue lengths,

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[10] NY DOT, https://www.dot.ny.gov/divisions

and delays. The analytical and simulation outcomes were subsequently compared to validate the effectiveness of the newly proposed method.

## Portable Rumble Strip (PRS)

Temporary rumble strips provide a significant benefit by effectively alerting drivers to various traffic control devices and upcoming conditions in work zones (Morgan, 2003). These strips generate audible and vibratory stimuli, enhancing driver awareness, especially for inattentive or fatigued drivers. Assessing the effectiveness of temporary rumble strips in alerting motorists often involves comparing the sound levels they produce with those generated by permanent rumble strips.

Elghamrawy et al. (2013) focused on evaluating the effectiveness of temporary rumble strips and the sound levels they generated, considering five key parameters: rumble strip type, number of strips per set, strip spacing, vehicle type, and vehicle speed. Their results indicate that the temporary rumble strips positioned at the edge of work zones produce sufficient sound levels to alert inattentive drivers. Furthermore, the experiments revealed that the effectiveness of temporary rumble strips can be enhanced by increasing the number of strips per set and utilizing wider temporary rumble strips.

Numerous research studies have investigated the use of temporary rumble strips in work zones, consistently demonstrating their effectiveness in reducing vehicle speeds. For example, Fontaine and Carlson (2001) evaluated the effectiveness of speed displays and portable rumble strips at reducing speeds in rural maintenance work zones. Their findings show that the effectiveness of portable rumble strips varied depending on the type of vehicle. Passenger cars showed a modest reduction in mean speed approaching the temporary traffic-control zone, with less than a 3.2 km/h (2 mph) decrease. However, trucks experienced a more significant impact, with mean speed reductions approaching the temporary traffic-control zone of up to 11.6 km/h (7.2 mph) lower than the normal traffic control conditions.

Moreover, in a study conducted by Caltrans in 2012, rumble strips implemented in the vicinity of work zones were tested, and results revealed that 46 percent of traffic exhibited a reduction in speed by an average of 8 mph.

A recent study in Texas, U.S., aimed to investigate the occurrence of distracted driving on roadways as drivers approach a work zone, as well as to examine the potential influence of PRS on those rates. The data collected through observation downstream of the PRS indicated a decreasing rate of distracted driving at locations closer to the work zones within the 1500 ft downstream of the device itself (Ullman, 2023).

Another study conducted by MoDOT aimed to assess the effectiveness of temporary rumble strips used by MoDOT and other state DOTs. The study involved field observations of driver behavior, installation and removal considerations of TRPs, collection and analysis of speed data, and economic analysis. The implementation of short-term rumble strips resulted in a 21.2% decrease in speed violations, while long-term rumble strips showed an 18.2% decrease. Moreover, 52.4% of drivers applied brakes for short-term temporary rumble strips in a nighttime flagger situation, while the range was 0.7% to 6.7% for long-term temporary rumble strips on a divided highway during the daytime. Overall, the study concluded that TRPs are an effective tool in reducing vehicle speeds and decreasing crashes, offering high benefit-cost ratios (Brown et al., 2022).

California, Texas, and Washington have specific guidelines for installing and implementing rumbling on state highways[11,12,13].

### Channelizing device

Channelizing devices serve the purpose of warning and alerting drivers about potential hazards in work zones, ensuring the safety of workers, and providing clear guidance to drivers as they navigate through these hazards. These devices include a range of tools such as cones, tubular markers, drums, vertical panels, temporary raised islands, directional indicators, and longitudinal channelizing devices. Among these, traffic cones are the most commonly used channelizing device in short-term work sites[14].

Domenichini et al (2017) assessed drivers' behavior in a virtual environment when confronted with various configurations of a motorway crossover work zone. The impact of variable message signs, channelizing devices, and perceptual treatments based on Human Factor principles was also examined. Their results indicated that among the analyzed perceptual treatments, the implementation of a visual pattern on the median barrier, coupled with taller and denser vertical delineators along the advance warning and transition areas, resulted in significant reductions in speed and improved uniformity of speeds among drivers.

Furthermore, Greenwood et al (2016) performed two consecutive experiments to examine the impact of the design and layout of different channelizing devices on a driver's ability to accurately comprehend a roadway diverge within a work zone scenario. The results indicated that portable concrete barriers and a linear channelizing device exhibit higher rates of correct interpretation compared to channelized drums. In addition, their study highlights that even minor deviations in the spacing of individual drums can significantly diminish a participant's ability to correctly interpret the work zone.

### Mobile Barrier

The Mobile Barrier is a mobile temporary barrier designed to ensure the safety of workers and vehicles in short-term work zones where there is a significant risk of workers being struck by vehicles that intrude into the designated work areas. While devices like truck-mounted attenuators (TMAs), traffic cones, and barrels are commonly used to separate workers from the traveling public during construction and maintenance, they do not provide sufficient lateral protection for workers in case of an errant vehicle intrusion. Although concrete barriers and similar structures are being used to separate the work area from live traffic in long-term work zones, such devices are impractical for short-duration and maintenance-type work zones due to the time-consuming and challenging process involved in their deployment. So, easy mobility, both during transportation to the work site and while operating within the site for any road construction project, makes them a great option for controlling traffic[15].

Banerjee et al., (2018) investigated the impact of barriers (cone pylons, concrete jersey barriers, and metal barriers) on driver behavior; speeding, and lateral movement, using a high-fidelity driving simulator. The findings indicated that drivers exhibited a tendency to approach the cone pylons, implying that they perceived them as less obstructive compared to the concrete jersey barriers.

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[11] Guidelines for Installing Rumble Strips on California State Highways, https://dot.ca.gov/20-07-rumble-strips-guidelines-and-memo

[12] Performance Analysis of Centerline and Shoulder Rumble Strips Installed in Combination in Washington State, https://www.wsdot.wa.gov/research/reports/fullreports/799.1.pdf

[13] Texas Department of Transportation. 2012. Work Zone Temporary Rumble Strip Standard Sheet, Memorandum. ftp://ftp.dot.state.tx.us/pub/txdotinfo/cmd/cserve/standard/traffic/memo11-12-12.pdf

[14] Guidelines for Temporary Traffic Control, VDOT, https://vdot.virginia.gov/

[15] Evaluation of a mobile work zone barrier system, ODOT, https://www.oregon.gov/ODOT

## Drone Radar

Drone radar is a small, lightweight, and weatherproof electronic device that emits radio signals capable of triggering radar detectors commonly used by the general public. It is widely recognized that the presence of police radar or police vehicles influences the speed of drivers. So, when vehicles equipped with radar detectors receive the radar signals transmitted by the drone, they interpret them as an indication of police enforcement in the vicinity and reduce their speed. Drone radar has demonstrated remarkable effectiveness in decreasing the number of vehicles exceeding the speed limit by a significant margin (i.e., 10 mph or more), which leads to a reduction of 6 to 33 percent in the proportion of vehicles classified as excessive speeders. Additionally, drone radar has been observed to lower the average traffic speed by 0 to 4 mph. This speed reduction countermeasure is not only cost-effective but also simple to implement. Furthermore, it has a more pronounced impact on the mean speed of large trucks. However, drone radar only targets motorists with radar detectors and not all drivers. For example, Texas reported that vehicle conflicts, such as severe braking and last minute lane changing were increased when the radar signal was transmitted[16].

Drone Radar has been widely used in several states, and numerous studies have revealed the great impact of radars on decreasing speed in work zones. Wisconsin, Texas, and South Carolina have utilized drone radar in rural work zones, including stationary construction zones, maintenance zones, and mobile operations[17].

Eckenrode et al (2007) assessed the impact of drone radar as a speed reduction measure in work zones on interstates and secondary highways, considering both day and evening conditions for passenger cars and tractor-trailers. Their findings revealed that, on average, the presence of drone radar resulted in a 2 mph reduction in mean speeds across the entire traffic flow. Notably, individual vehicles equipped with radar detectors exhibited even greater speed reductions, ranging from 5 to 8 mph. Furthermore, the implementation of drone radar led to a decrease in the 85th percentile speeds by 1 to 5 mph, while vehicles exceeding the speed limit experienced a substantial 20% reduction in speed.

## Truck Mounted Attenuators (TMA)

A Truck-Mounted Attenuator (TMA) is a crash cushion installed on the rear of a truck, designed to absorb and dissipate the energy of a rear-end collision. Its primary function is to divert traffic to an open lane ahead of a road work site, ensuring a safe working environment for the workers. Additionally, TMAs are built to withstand rear-end collisions themselves.

Mosunmola Aroke et al (2022) conducted a study to explore strategies for enhancing the visibility of Truck-Mounted Attenuators (TMAs), optimizing work zone configurations, and ensuring the safety of workers. The research findings revealed that utilizing a 6-to-8-inch wide yellow and black inverted 'V' pattern of retroreflective chevron markings, sloped at a 45-degree angle downward in both directions from the upper center of a rear panel, effectively alerts drivers to the presence of work zones and improves TMA recognition. Additionally, the study proposes that the use of intelligent transport systems can enhance TMA visibility and reduce work zone fatalities.

Ullman and Iragavarapu (2014) analyzed potential rear-end crashes of motorists with work vehicles in mobile and short-duration operations, and they found that TMAs were highly effective in reducing the

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[16] Use of Drone Radar in work zones, Maryland State Highway Administration, Office of Traffic and Safety, https://www.roads.maryland.gov/OOTS/06DroneRadarW-Summary.pdf

[17] Use of drone radar and automated flaggers in work zones, https://workzonesafety.org/use-of-drone-radar-and-automated-flaggers-in-work-zones/

severity of rear-end crashes and the costs of crashes. In fact, the presence of a TMA in each crash resulted in a cost savings of $196,855 compared to the expenses that would have been incurred in the absence of a TMA.

### Automated flagger assistance device (AFAD)

Automated Flagger Assistance Devices (AFADs) are temporary traffic control devices that operate similarly to traditional flagging methods but with mechanical assistance. They enhance safety by reducing direct exposure of flaggers to traffic, allowing them to control the device from a safer location behind a guardrail, for example. There are two types of AFADs recognized by MUTCD. The first type consists of a remotely controlled Stop/Slow sign mounted on a trailer or movable cart. The second type features a remotely controlled red and yellow lens and a mechanically gated arm. The red/yellow lens device requires a mechanically gated arm, and the Stop/Slow device can have one added for improved visibility and driver compliance[18].

In a recent project conducted by the Texas Department of Transportation, researchers from the Texas A&M Transportation Institute conducted surveys to evaluate motorists' comprehension of two types of Automated Flagger Assistance Devices (AFADs). The objective was to assess the effectiveness of different signage and features in facilitating motorists' understanding of AFAD operations. For the stop-slow AFAD, participants showed the highest level of understanding when a newly designed "Wait on Stop-Go on Slow" symbol sign was used. However, a portion of the participants still indicated a tendency to stop briefly and then proceed instead of waiting for the AFAD's slow sign. To address this issue, the researchers recommend the mandatory use of a gate arm with stop-slow AFADs, as it provides clearer guidance and reduces potential confusion. Regarding the red-yellow lens AFAD, participants demonstrated a good understanding of the stop phase. However, there was evidence of confusion regarding the transition phase. Notably, the inclusion of a gate arm appeared to enhance motorists' understanding of when to proceed and when to stop, serving as a valuable visual indicator (Trout et al., 2013).

In another study, Qing et al (2019) investigated the efficiency of the new AFAD developed by the Missouri Department of Transportation (MoDOT) through field and driving simulator studies. They collected driver behavior measures to compare the effectiveness of the MoDOT AFAD, along with its alternative designs and human flaggers. Results from the field study indicated that the MoDOT AFAD successfully reduced vehicle approach speeds and achieved greater stopping distances compared to flaggers. Similarly, in the driving simulator study, both the MoDOT AFAD and its alternative designs showed significant reductions in average approach speeds and increased distances between completely stopped vehicles and the AFAD/flagger.

### Police Enforcement

Benekohal et al. (1992) were among the first studies to evaluate the effects of police presence on vehicle speeds in work zones and assess the "halo" effect—the lingering impact of police presence on driver behavior after law enforcement has left. The study found that police patrolling the work zone led to reductions in average speeds of 4.3–4.4 mph for cars and 4.3–5.0 mph for trucks compared to the no-police condition. Additionally, the percentage of fast-moving cars and trucks before the work area decreased by 14% and 32%, respectively, indicating that police presence was effective in reducing vehicle speeds and improving speed compliance in work zones.

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[18] Guidance on the use of automated flagger assistance devices, ATSSA, https://workzonesafety

Similarly, Zech et al. (2005) conducted a field study on highway work zones in Western New York State (NYS) and found that a stationary police vehicle positioned near the end of the taper effectively reduced speeds by 4.0–6.0 mph. More importantly, this enforcement method reduced speed variance by about 25%, a crucial factor in mitigating rear-end collisions, which are common in work zones due to sudden braking and speed differentials.

Beyond speed control, police presence has been linked to substantial reductions in work zone crashes. Chen and Tarko (2012), in a study funded by Indiana DOT, found that accident rates decreased by 41.5% in work zones with police presence, regardless of whether citations were issued. This suggests that simply having law enforcement visibly present can improve driver behavior and enhance work zone safety.

Finally, Ravani and Wang (2018) evaluated the impact of four levels of police presence in six work zone locations across Northern and Southern California to determine their effectiveness in reducing vehicle speeds. Their study assessed four key Measures of Effectiveness (MOEs): average speed reduction, speed variance, 85th percentile speed, and the proportion of high-speed vehicles. The findings indicated that radar speed displays combined with police presence and passive police enforcement in rural areas were highly effective in reducing speeds, while active police enforcement in urban areas showed some benefits but lacked consistent statistical significance.

Table 1 provides a summary of the reviewed literature on traffic control devices and their evaluations across various states.

Table.1. summary of the reviewed literature on traffic control devices and their evaluations across various states

| Traffic Control Device | Reference | Evaluation Methodology | Results | State |
|---|---|---|---|---|
| Portable Changeable Message Signs (PCMS) | Huang and Bai, 2019 | Field test, Survey | Speed reduction by 13%-17% | Kansas |
| | Bham and Leu, 2018 | Driving Simulator, Survey | Speed reduction by 44.1% | Missouri |
| Arrow Panels | Griffith and Lynde, 2001 | Field test, Survey | Perception of motorists of various display modes | Oregon |
| | Turley et al., 2003 | Field test, Survey | Speed reduction of "dancing diamonds", 2 mph | Oregon |
| Portable Temporary Signal (PTS) | Schrock et al., 2016 | Field test | Compare the operational efficiency of different conditions of PTS systems in conjunction with pilot car operations | Kansas |
| Portable Rumble Strip (PRS) | Elghamrawy et al., 2013 | Field test | Compare the performance of various PRS layouts | Illinois |
| | Fntaine and Calson, 2001 | Field test | Speed reduction by 2 mph in passenger cars and 7.2 mph in trucks | Texas |
| | Caltrans, 2012 | NA | Speed reduction- 8 mph by 46% of vehicles | California |
| | Zech et al., 2005 | Field test | Speed reduction by 1.4-2.4 mph with RS and speed reduction by 3-6 mph with RS combined with police presence | New York |
| | Brown et al., 2022 | Field test, Survey | Speed violation decreased by 21.2-18.2% for short- and long-term RS, Benefit-cost ratio analysis | Missouri |
| Channelizing device | Domenichini et al., 2017 | Driving Simulator | Speed reduction by 3-4.3 mph by implementing visual patterns on the median barrier | NA |

| | | | | |
|---|---|---|---|---|
| | Greenwood et al, 2016 | Field test | Investigate the design and layout of different types of a channelizing device on the driver's interpretation rate | NA |
| Mobile Barrier | Banerjee et al., 2018 | Driving Simulator | Impact of barriers on driver behavior; speeding and lateral movement | NA |
| Drone Radar | Eckenrode et al, 2007 | Field test | Speed reduction by 5-8 mph in vehicles equipped with radar detectors | NA |
| Truck Mounted Attenuators (TMA) | Mosunmola Aroke et al, 2022 | NA | strategies for enhancing the visibility of TMAs | Lesson from all states |
| | Ullman and Iragavarapu, 2014 | Field test | Rear-end crashes and cost analysis of TMAs | New York |
| Automated Flagger Assistance Device (AFAD) | Qing et al, 2019 | Field test, Driving simulator | significant reductions in average approach speeds and increased distances between completely stopped vehicles and the AFAD/flagger | Missouri |

# 2.3. VIDEO DATA COLLECTION AND DATA PROCESSING

We initially expected to obtain most travel speed data from Caltrans. Unfortunately, we only received a limited amount of data from two Caltrans districts, which is far from adequate for the study. We proceeded to use drones to collect travel speeds in two work zones to supplement the data provided by Caltrans. In this section, we discuss how we detect vehicles and estimate their speeds through image processing.

## 2.3.1. Methodology

We developed a methodology for vehicle speed detection using drone videos, leveraging the YOLOv11 object detection framework. The approach consists of several key steps, including data preparation, model fine-tuning, real-time object detection, speed calculation, and lane-based traffic analysis.

## 2.3.2. Data Preparation

The YOLOv11 model was fine-tuned using a custom dataset comprising 784 augmented images generated from 297 original bird's-eye view images. These images were sourced from publicly available datasets and drone footage captured in Northern California. The dataset was augmented through cropping (0% to 45%), zooming, rotation (-15° to +15°), and exposure adjustments (-28% to +28%).

Each image was manually annotated into two categories: cars and heavy vehicles. The dataset was split into 90% for training, 7% for validation, and 3% for testing, ensuring a robust training process for the model.

## 2.3.3. Model Fine-Tuning

The pretrained YOLOv11 Nano and X-Large models struggled to accurately detect vehicles from a bird's-eye view, frequently misclassifying vehicles as unrelated objects such as suitcases, cell phones, or benches. To address these limitations, the model was fine-tuned to improve recognition accuracy.

The updated model effectively distinguished heavy trucks and buses from lighter trucks and SUVs, leading to improved clustering based on vehicle size and weight. After fine-tuning, the model achieved an 88% accuracy rate, reliably classifying vehicles into the two predefined categories.

## 2.3.4. Object Detection and Speed Calculation

To detect objects, a region of interest (ROI) was established and transformed into a rectangular frame using a perspective transformation matrix, reducing contrast and perspective distortions. Vehicles were detected frame by frame, with their positions tracked across multiple frames.

Speed was calculated using the formula:

$$Speed = \frac{Distance}{Time} \times Conversion\, Factor$$

where:

- Distance is the displacement of the vehicle within the ROI,
- Time is the time interval between the first detection (initial frame) and the current frame,
- Conversion Factor converts pixel movement into real-world speed.

To reduce inaccuracies due to intermittent detections, speed measurements were averaged over multiple frames, leading to more realistic and reliable estimations.

## 2.3.5. Lane Detection and Traffic Analysis

Lane detection was performed by defining polygonal regions corresponding to individual traffic lanes. Vehicles were assigned to specific lanes upon entering these zones, enabling detailed lane-based traffic analysis (as shown in Figure 2). This facilitated the identification of traffic patterns, lane utilization, and congestion points.

## 2.3.6. Validation

The accuracy of the proposed speed detection algorithm was evaluated using two validation methods:

1. Floating Car Method: A vehicle equipped with a calibrated speedometer was recorded by a drone along freeways on Interstate 80 (I-80) between Davis and Sacramento. The recorded speedometer data provided ground truth values for comparison with the system's detected speeds. (Figure 1)

2. Radar Speed Detector Method: A radar-based speed detector was deployed on a single-lane road in Winters, California, a location selected for its low traffic density and reduced external interference. This ensured precise speed measurements with minimal obstructions.

The detected speeds were compared with the ground truth data, revealing an error margin of less than 8%, demonstrating the model's high accuracy. It was also observed that vehicle speedometers tend to overestimate speeds slightly, a well-known safety feature in vehicle design. These findings further reinforced the reliability of the proposed speed detection approach.

## Results

To assess the performance of the vehicle detection and speed estimation system, a series of experiments were conducted at varying drone heights. The region of interest (ROI) was set at 21.94 meters, and the evaluation focused on speed detection accuracy and vehicle classification performance.

### Speed Detection Accuracy

The system's speed estimation accuracy was measured using Mean Squared Error (MSE), Mean Absolute Error (MAE), and percentage error across different speed ranges. The results at different drone heights are summarized as follows:

- 20 meters: Average error of 8.28%, with the highest error (12.33%) in the 15-25 mph range. The lowest error (5.36%) was in the 25-35 mph range.
- 30 meters: Accuracy improved, reducing the average error to 5.90%. The lowest error (2.69%) occurred in the 45-55 mph range.
- 40 meters: Average error remained low at 6.12%, with the best accuracy in the 45-55 mph range (2.69%) and a slightly higher error (9.61%) in the 35-45 mph range.

These findings suggest that increasing the drone height improves accuracy, especially for higher-speed vehicles, while moderate-speed vehicles (25-45 mph) exhibit slightly higher errors due to motion blur and perspective distortions.

### Vehicle Type Classification Accuracy

The fine-tuned YOLOv11 model's classification accuracy was evaluated using the F1 score, which balances precision and recall. The results across different drone heights were:

- 20 meters: F1 score of 0.97 for cars and 0.89 for heavy vehicles.
- 30 meters and 40 meters: F1 score of 1.0 for both cars and heavy vehicles, indicating perfect classification.

The improved accuracy at higher drone altitudes suggests that less perspective distortion and a wider field of view enhance classification reliability.

### Overall Performance Evaluation

The results demonstrate that the proposed method provides highly accurate speed estimation and vehicle classification. The key findings include:

- Speed estimation error remained below 10% across all scenarios, with lower errors for high-speed vehicles.

- Vehicle classification accuracy improved at higher drone heights, achieving perfect detection at 30 meters and above.
- The optimal drone height for balancing accuracy and computational efficiency is 30 meters, as it ensures both precise speed detection and accurate classification.

The system's ability to perform real-time traffic monitoring, vehicle speed estimation, and classification makes it a robust and scalable solution for transportation analysis.


Fig.1. A floating car in the second lane with the speed of 64 mph is tracked along with its speed, lane, and classification as a passenger vehicle.

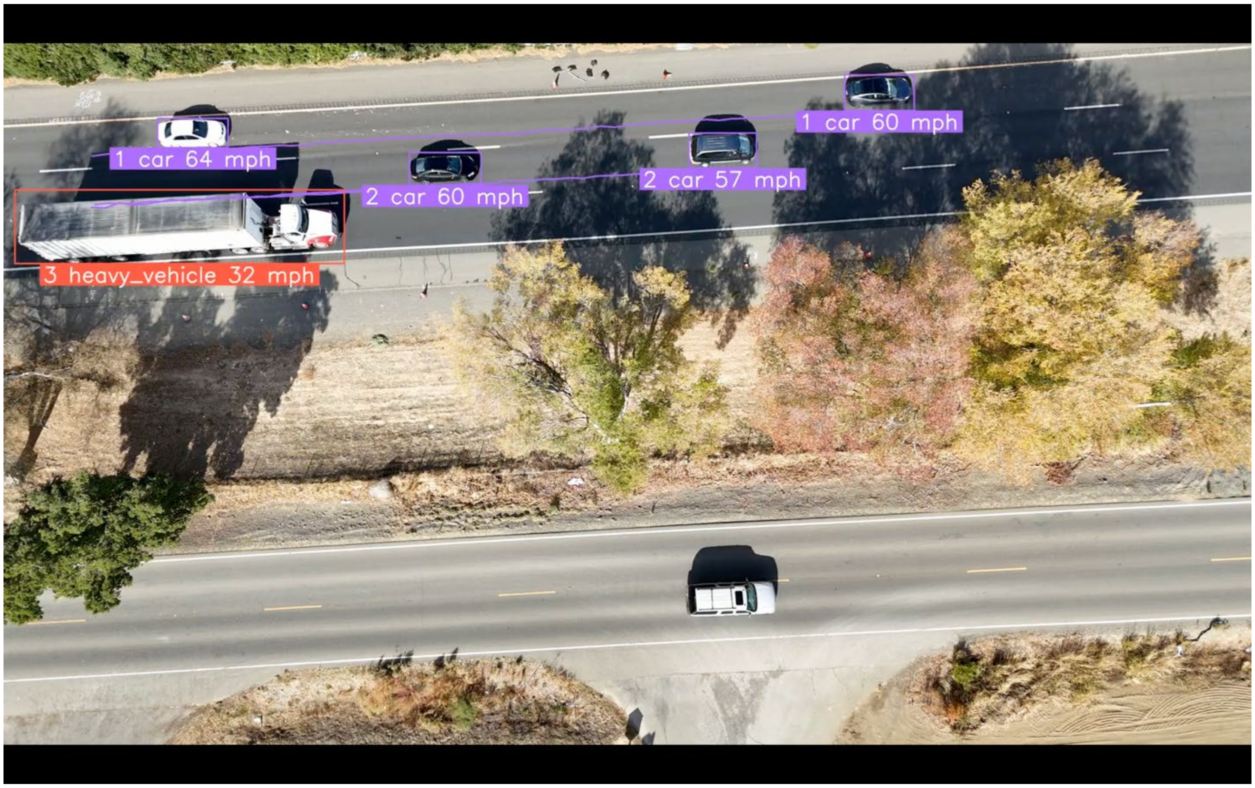



Fig.2. A heavy vehicle in the third lane was detected along with its speed and category as a heavy vehicle.

## 2.3.7. Limitations and Challenges

Collecting and processing drone footage for vehicle detection and speed estimation presented several real-world challenges that influenced both the quality and reliability of our dataset. One of the most prominent issues was the presence of tree shadows on the roadway. In many segments of the footage, overhanging trees cast dense, irregular shadows across the lanes. These shadows often obscured vehicles or fragmented their silhouettes, making consistent detection more difficult, especially for smaller or partially occluded cars.

In addition to shadow artifacts, road surface color played a key role in detection performance. Sections of the road paved with light-colored asphalt created low-contrast conditions when vehicles, particularly white sedans and light-colored trucks, were present. The reduced contrast between the vehicle body and the road surface sometimes resulted in false negatives or poorly bounded detections, as the model struggled to distinguish vehicle edges from the background. These conditions highlight the importance of including diverse lighting and contrast scenarios in the training dataset to improve model robustness.

Drone height was another critical factor. Flying too low improved visual detail but increased perspective distortion, while higher altitudes offered a cleaner, top-down view at the cost of spatial resolution. Finding the optimal altitude was essential to balance detection clarity with wide-area coverage, especially for speed estimation, which depends on accurate tracking across multiple frames.

The video data used for training and evaluation included recordings in two key traffic scenarios. The first consisted of 40.5 minutes of continuous upstream traffic video, in which vehicles moved away from the drone's view. The second involved 16.5 minutes of footage captured near Dynamic Speed Feedback Signs

(DSFS), with vehicles moving toward or laterally across the field of view. Together, these videos provided a balanced dataset that captured vehicles in a variety of orientations, lighting conditions, and lane configurations.

Despite these environmental and technical challenges, the detection system performed robustly. With the YOLOv11 model fine-tuned on custom, augmented data, we achieved high detection rates, including F1 scores up to 99% for both car and heavy vehicle categories under optimal conditions. These results demonstrate the feasibility of drone-based vehicle detection and tracking, even in visually complex real-world environments.

## 2.4. CASE BY CASE STATISTICAL ANALYSIS

Due to the limited number of work zone sites that have detailed speed and work zone data, it is not possible to do a systematic safety analysis that takes into account dynamic speed feedback, reduced speed limits, work zone layout, and other driver/vehicle/environmental factors. We resort to carrying out case-by-case statistical analysis of each collected dataset. It should be noted that high-speed violations are defined as traveling 11 mph or more over the posted speed limit at the given location.

### 2.4.1. Dataset 1

Dataset 1 consists of radar data from District 3, provided by Caltrans. However, detailed information regarding the specific location of the work zone where this speed data was collected is unavailable. Figure 3 presents the speed distribution of vehicles at this location, showing that 94.5% of vehicles exceeded **the reduced speed limit of 55 mph**, while 69.3% traveled at least 11 mph over the reduced speed limit.

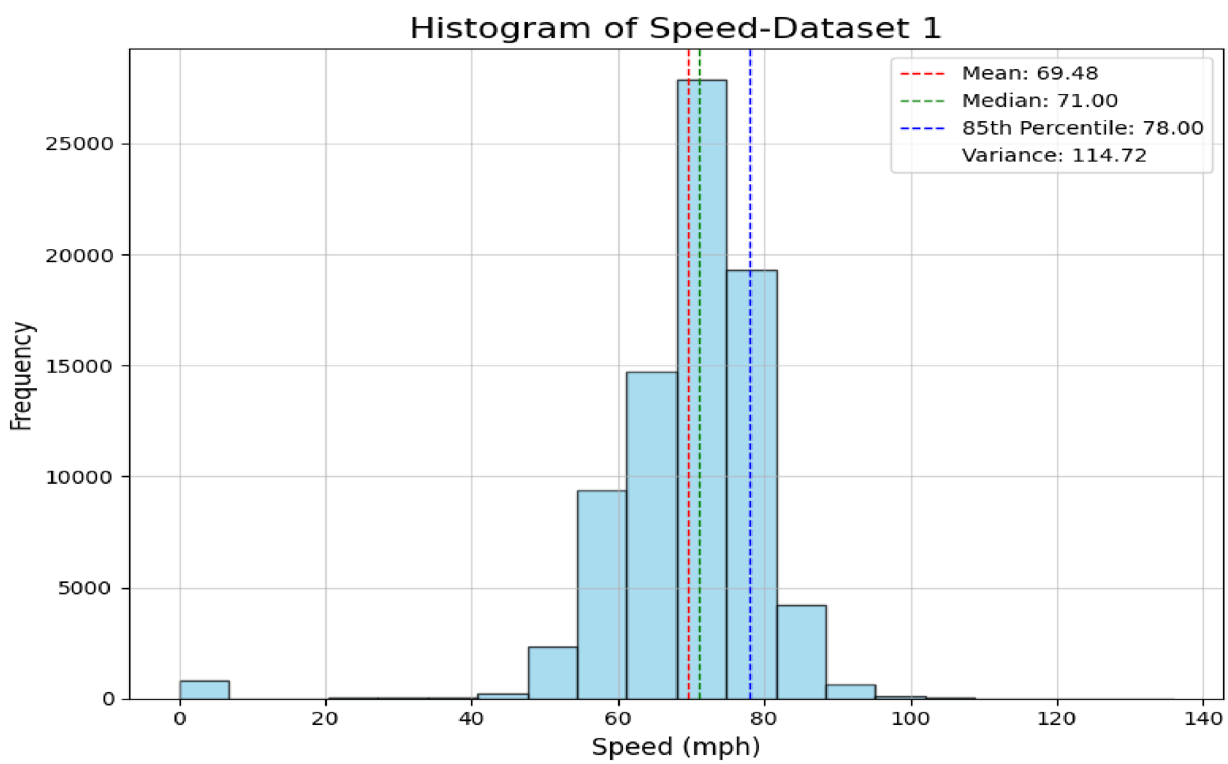



Fig.3. Histogram of speed for Dataset 1

## 2.4.2. Dataset 2

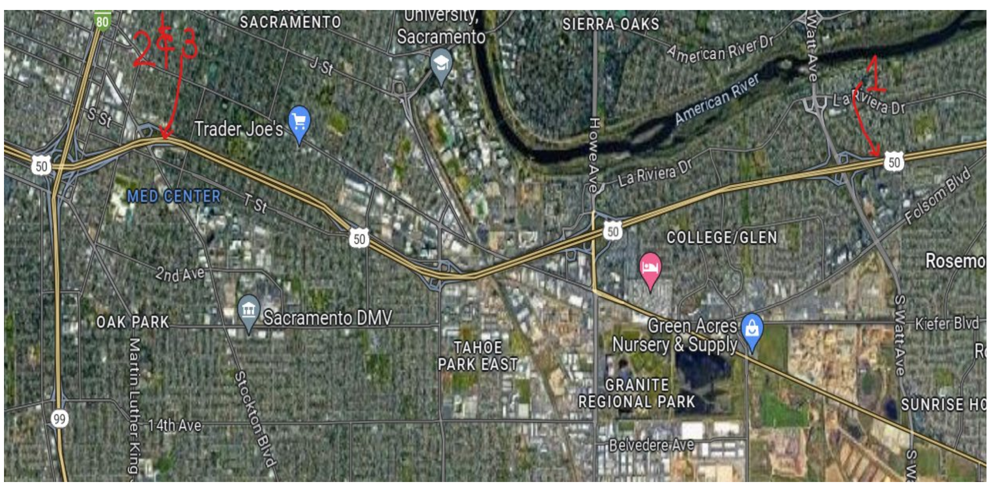
Dataset 2 has also been provided by Caltrans. Figure 4a illustrates the locations where speed data were collected along US-50 at Unit 1 (ingress to the work zone) and Unit 2 (egress from the work zone).

- Unit 1 – Ingress: Westbound (WB) traffic entering the work zone, located at the Watt Ave off-ramp (collecting WB traffic).
- Unit 2 – Egress: Westbound (WB) traffic exiting the work zone, located at Stockton Blvd (collecting data from four lanes of WB traffic).

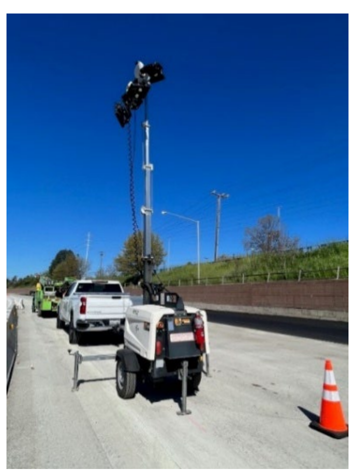
Data was collected within the work zone using a light tower, as shown in Figure 4b, and was recorded at 60-minute intervals in a 5-mph speed bin starting at 55 mph. The collection periods for each unit are as follows:

- Unit 1: October 30 – November 6, November 10 – November 17, November 19 – November 26, and December 1 – December 8.
- Unit 2: October 30 – November 5, November 10 – November 17, and December 1 – December 8.

Additionally, speed data at Unit 1 was collected from six lanes, whereas at Unit 2, data was recorded from only two out of four west bound lanes.




(a)



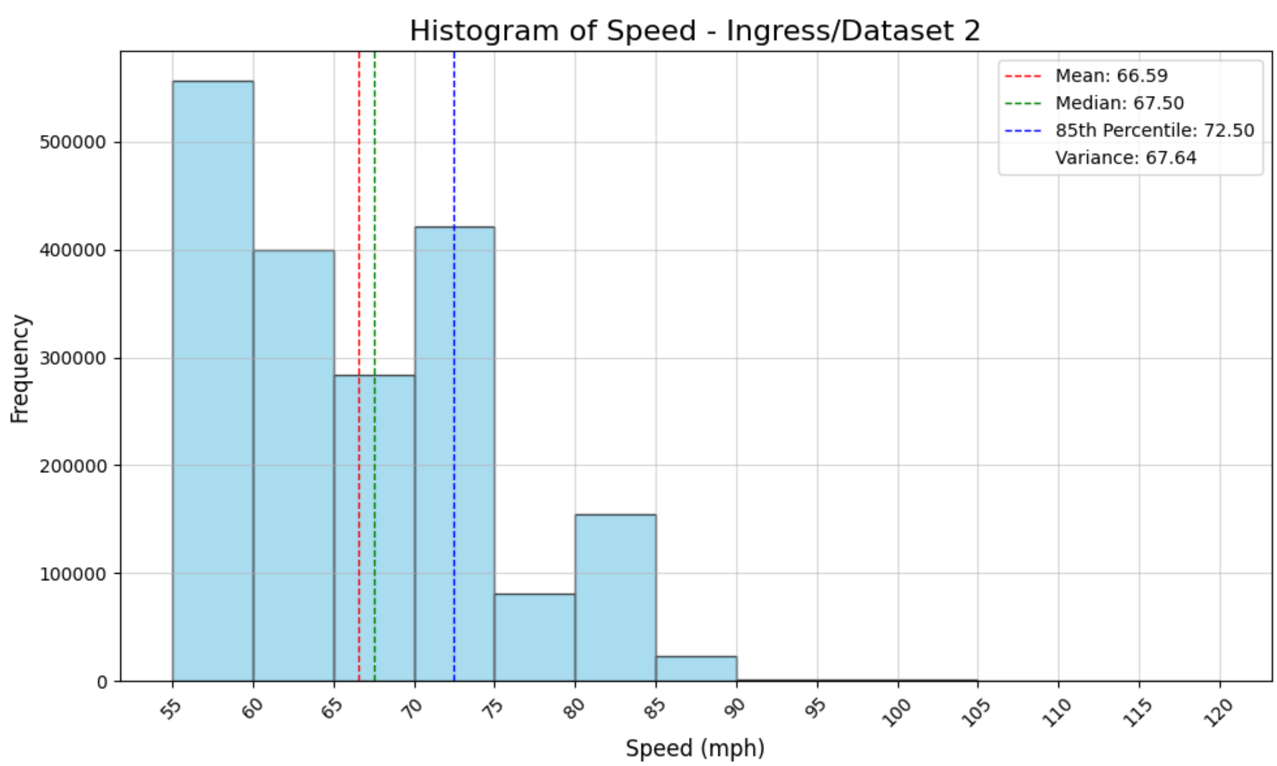
(b)

Fig.4. (a) Data collection locations for Dataset 2, (b) light tower

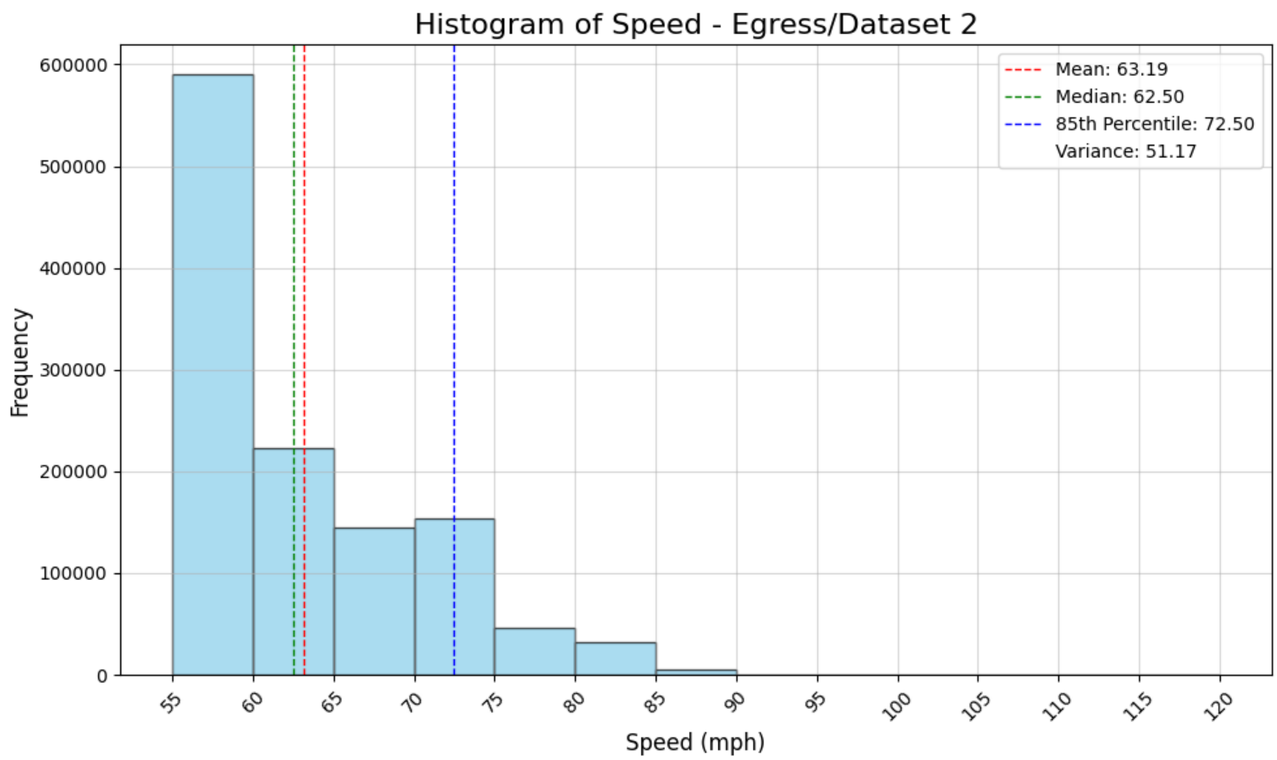
Figures 5a and 5b present the speed distribution at the ingress and egress of the work zone, showing a reduction in mean speed from 66.59 mph at ingress to 63.19 mph at egress. Interestingly, the 85th percentile speed remains constant at both locations, indicating that while the average speed decreases, the speeds of the fastest drivers are not significantly affected.

Additionally, the variance in speed at the ingress is 67.64, whereas at the egress, it is 51.17. This suggests that drivers exhibit erratic deceleration and braking behavior upon entering the work zone, likely due to encountering speed reduction measures and the need to adjust to new traffic conditions. In contrast, by the time vehicles reach the egress, speeds appear to stabilize, as drivers have already adjusted to the reduced speed environment.

Another key observation from the data is that 50.3% of vehicles exceed 66 mph at ingress, whereas at egress, only 32.1% surpass this threshold (11 mph over the reduced speed limit). These numbers indicate that as drivers progress through the work zone, they are gradually reducing their speeds. This reduction can be attributed to speed enforcement measures, work zone signage, lane narrowing, and increased driver awareness of the work zone conditions. Additionally, traffic flow within the work zone may contribute to the reduction, as vehicles naturally slow down due to congestion, lane shifts, or the presence of construction activity. Although 66 mph is still 11 mph over the posted reduced speed limit, the decreasing percentage of speeding vehicles suggests that work zone speed management measures are partially effective in influencing driver behavior. However, further interventions, such as enhanced enforcement, may be needed to improve compliance further.




(a)

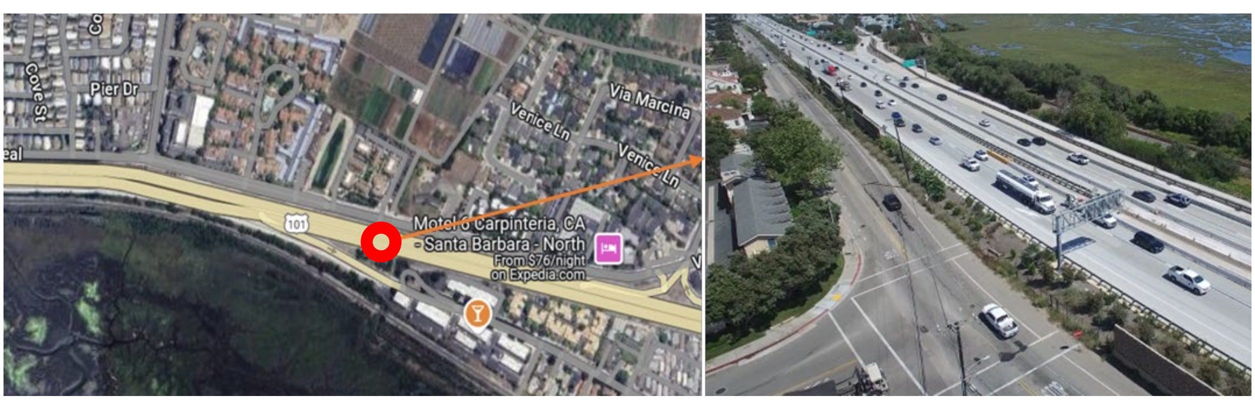



(b)

Fig.5. (a) Histogram of speed at Ingress, (b) Histogram of speed at Egress

### 2.4.3. Dataset 3

A data collection trip was conducted in Southern California, specifically in Santa Barbara, from July 25th to 27th, 2024. During this trip, 45 minutes of drone video data were collected at a work zone along the eastbound of US-101, where a lane closure was in effect. To capture detailed traffic behavior, drone video footage was recorded adjacent to a Dynamic Speed Feedback Sign (DSFS), where the speed limit had been reduced from 65 mph to 55 mph. Figures 6a and 6b illustrate the location of the data collection site and the reduced speed limit sign positioned above the DSFS, respectively.




(a)


(b)

Fig.6. (a) Data collection location for Dataset 3, (b) DSFS and reduced speed limit sign

After applying the developed algorithm mentioned earlier, the detected objects were categorized into cars and heavy vehicles, resulting in 1873 cars and 250 heavy vehicles, as shown in Figure 7. Given the significant differences in characteristics between these two groups, such as vehicle weight, maneuverability within the work zone, braking behavior, and acceleration patterns, they will be analyzed separately to better understand their distinct interactions with the work zone environment. This distinction is crucial, as heavy vehicles often require longer stopping distances and may respond differently to speed reduction measures compared to smaller, more agile cars.

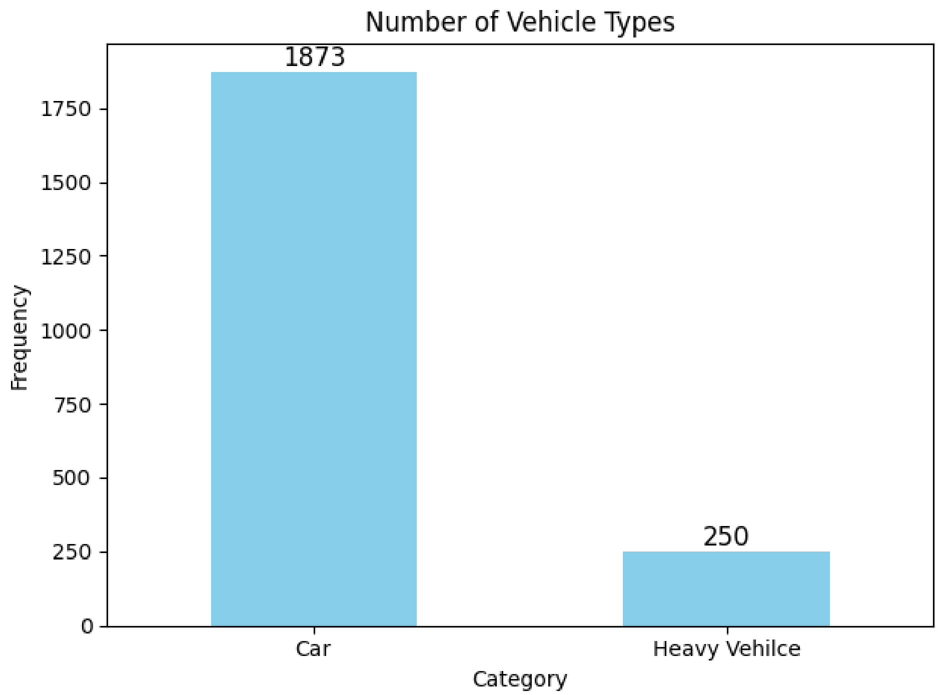
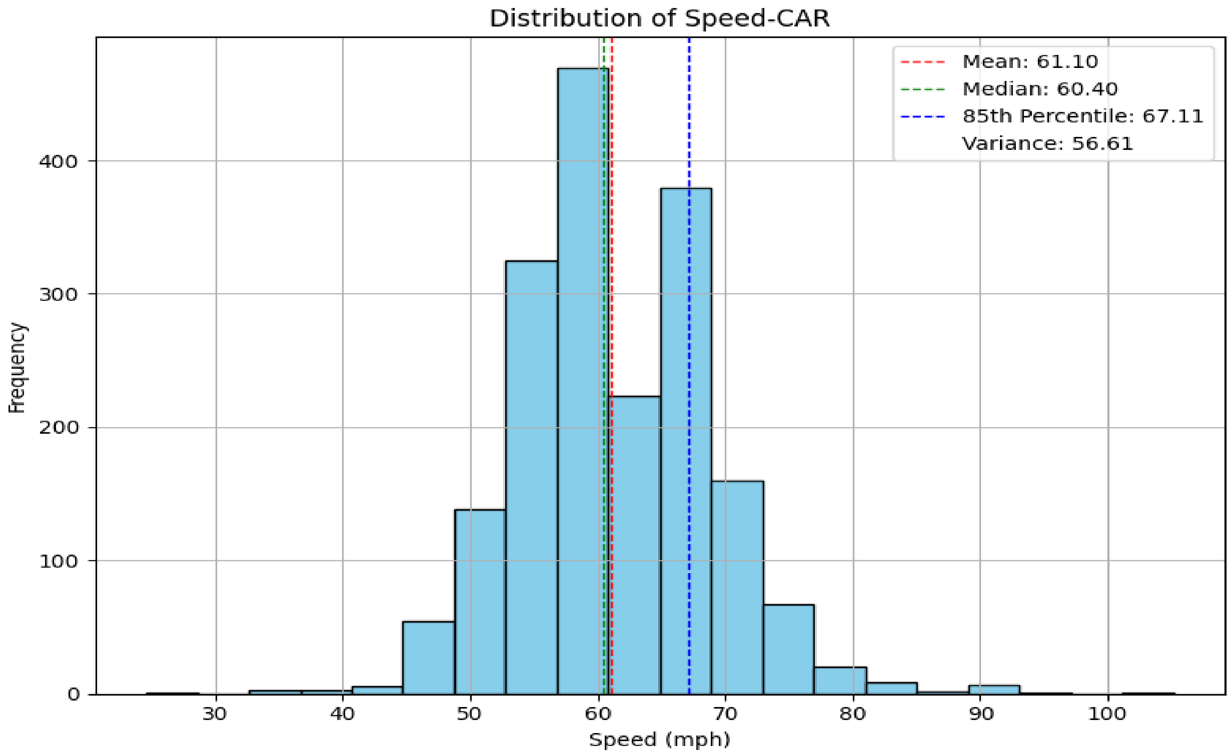



Fig.7. Traffic composition in Dataset 3

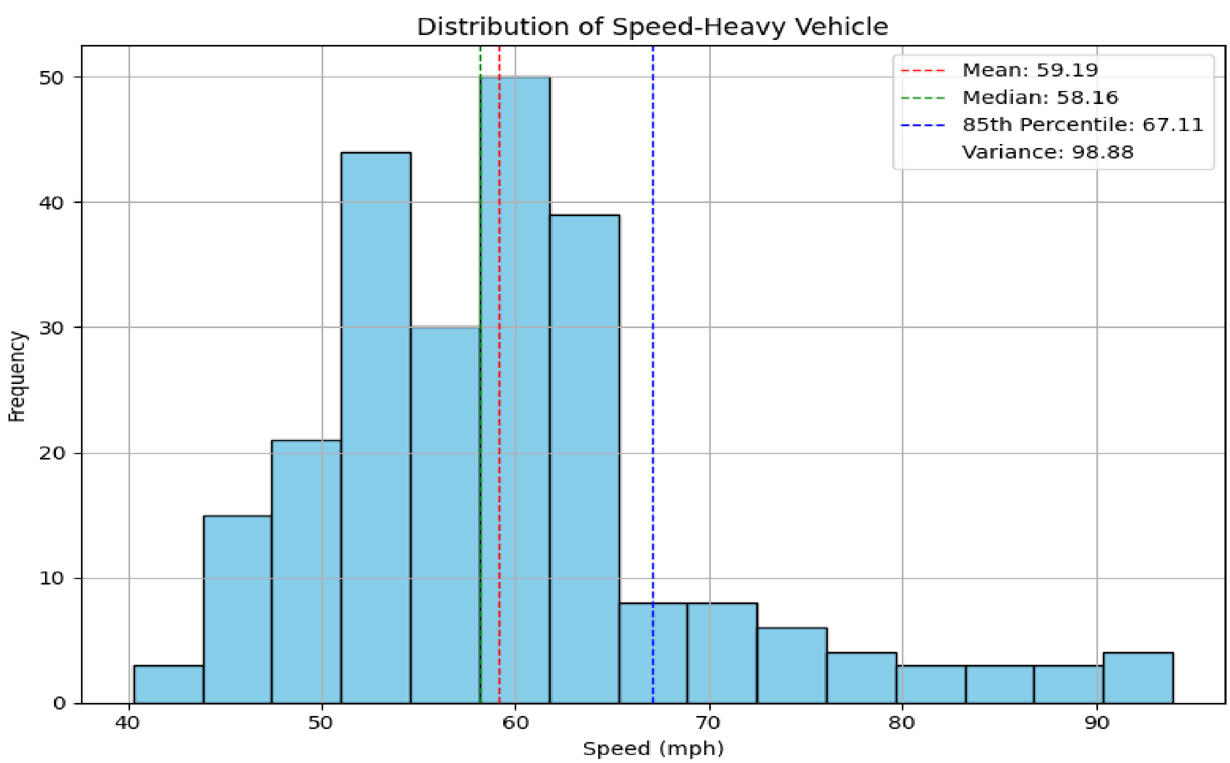
The speed distribution of cars and heavy vehicles is illustrated in Figure 8. As expected, cars exhibit a higher mean speed than heavy vehicles. However, the variance in speed differs significantly between the two groups, with cars showing a variance of 56.61, while heavy vehicles have a variance of 98.88. One possible explanation for the higher speed variance in heavy vehicles could be the geometry of the work zone, where a lane merging was occurring on the right side of the road at the location of the Dynamic Speed Feedback Sign (DSFS), while the lane closure for the work zone was on the left side. Since heavy vehicles require more time and space to merge, their speeds fluctuate more than cars, which can merge more smoothly. Additionally, traffic congestion, inconsistent driver reactions, and varying deceleration patterns contribute to this increased variability. The merging process may also force some heavy vehicles to brake suddenly or accelerate unpredictably, further widening the range of speed values observed. In contrast, cars are more agile and can adjust their speeds more consistently, resulting in lower variance.

A closer examination of the speed distribution reveals that 81.75% of vehicles exceed 55 mph, the reduced speed limit, while 23.70% surpass 66 mph. This trend is even less pronounced for heavy vehicles, where 65.6% exceed 55 mph, and only 16.2% travel over 66 mph.

One notable limitation of this dataset is the lack of control data—we did not have the opportunity to collect speed data in the absence of a speed reduction device or at the upstream segment of the work zone. This makes it difficult to conduct a direct comparison before and after the dynamic speed feedback sign was in place and fully assess the effectiveness of the speed management measures.




(a)




(b)

Fig.8. (a) Histogram of car speeds in Dataset 3, (b) Histogram of heavy vehicle speeds in Dataset 3

## 2.4.4. Dataset 4

During another data collection trip, one hour of video data was recorded using two drones at two different locations along an active work zone on I-80 with a lane closure on November 14, 2024.

- The first location was upstream of the work zone, where drivers had not yet encountered any signs indicating the upcoming work zone.
- The second location was adjacent to the Dynamic Speed Feedback Sign (DSFS).

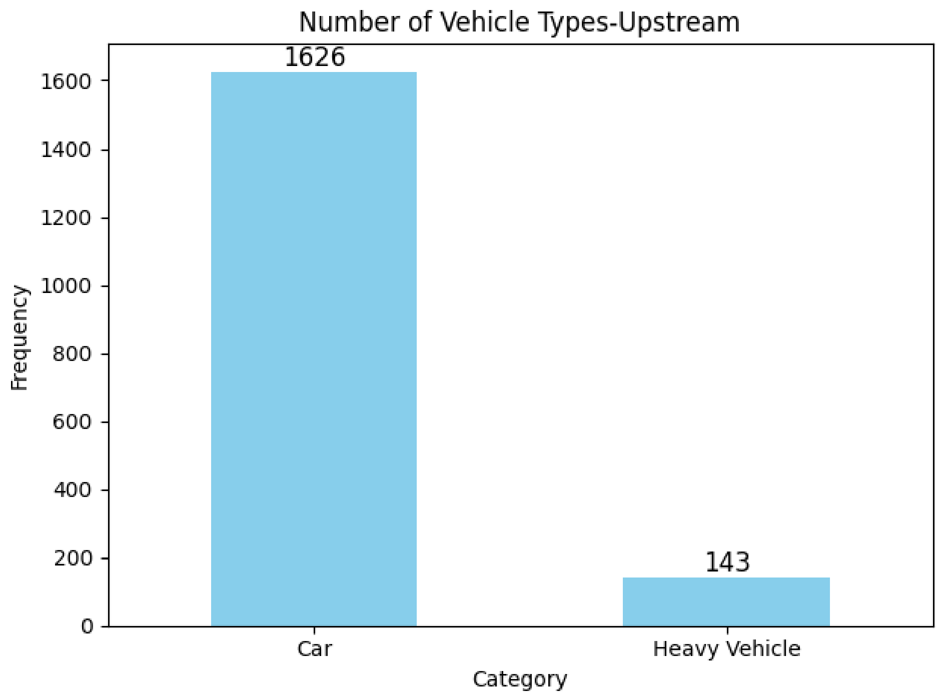
Both drones were flown simultaneously, capturing data during non-peak hours within the same time window between 11:00 AM and 1:00 PM.

Collecting data at these two locations allows us to assess the impact of the DSFS on vehicle speed reduction and evaluate its overall effectiveness. Ideally, the most precise approach would involve measuring the speed of individual vehicles at the upstream location and then tracking the same vehicles at the downstream location to determine the exact speed difference. However, this method requires continuous vehicle tracking over a distance, which in turn requires flying multiple drones at the same time. Furthermore, it is also time-consuming and challenging to operate multiple drones in an often spatially constrained work zone environment.

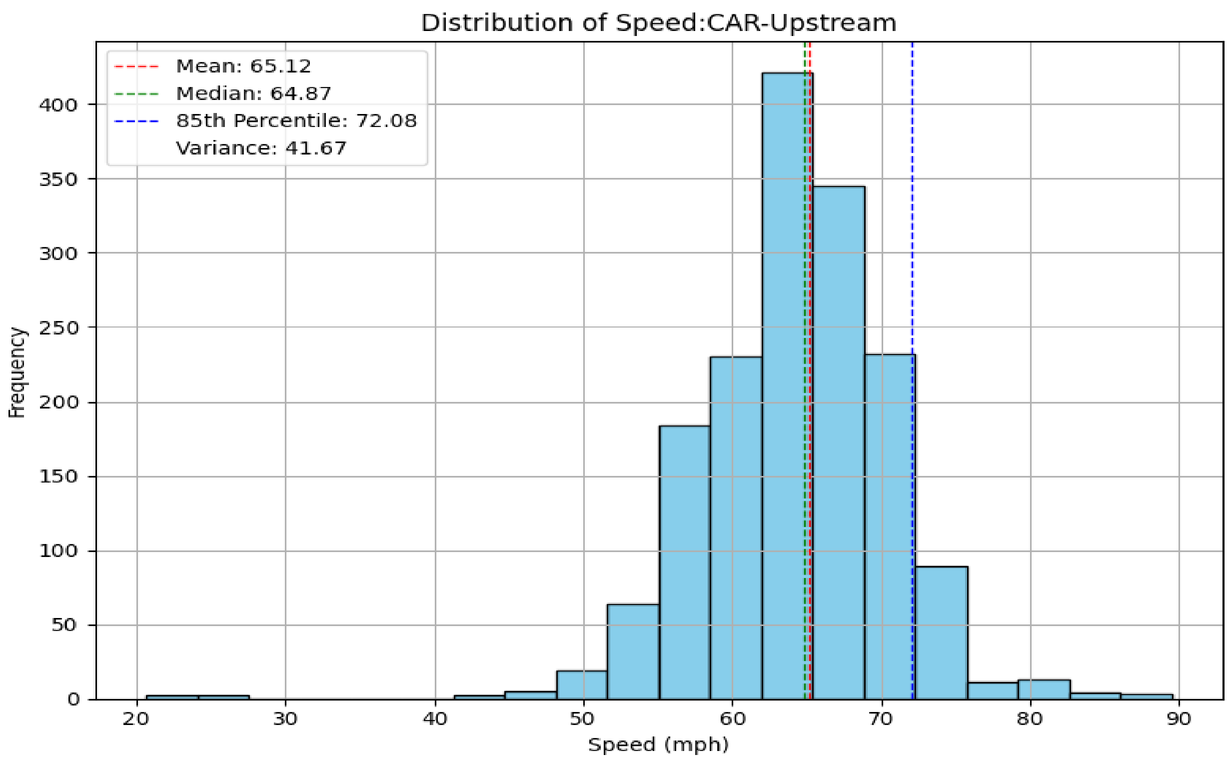
As a more practical alternative, we can compare the average speeds recorded separately at the upstream and downstream locations. This method eliminates the need for vehicle tracking and allows for efficient data collection using drones, making it a feasible and effective approach for evaluating the DSFS's influence on speed behavior. Figure 9 illustrates the data collection location.


Fig.9. Data collection location for Dataset 4

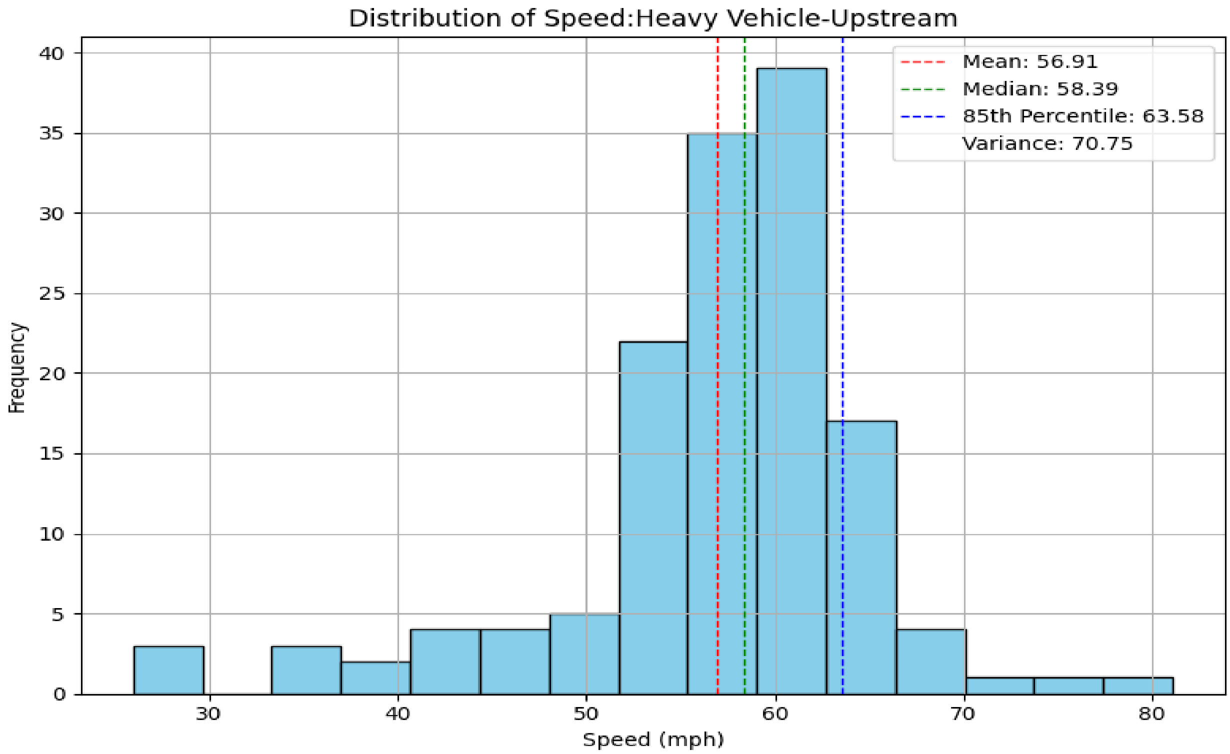
Videos from the upstream location have been processed and analyzed, with the results shown in Figure 10. Similarly, video data from the location adjacent to the DSFS have been analyzed, and the results are presented in Figure 11.


Number of Vehicle Types-Upstream
1626
143
Frequency
0
200
400
600
800
1000
1200
1400
1600
Car
Heavy Vehicle
Category

(a)


Distribution of Speed:CAR-Upstream
Mean: 65.12
Median: 64.87
85th Percentile: 72.08
Variance: 41.67
Frequency
0
50
100
150
200
250
300
350
400
20
30
40
50
60
70
80
90
Speed (mph)

(b)



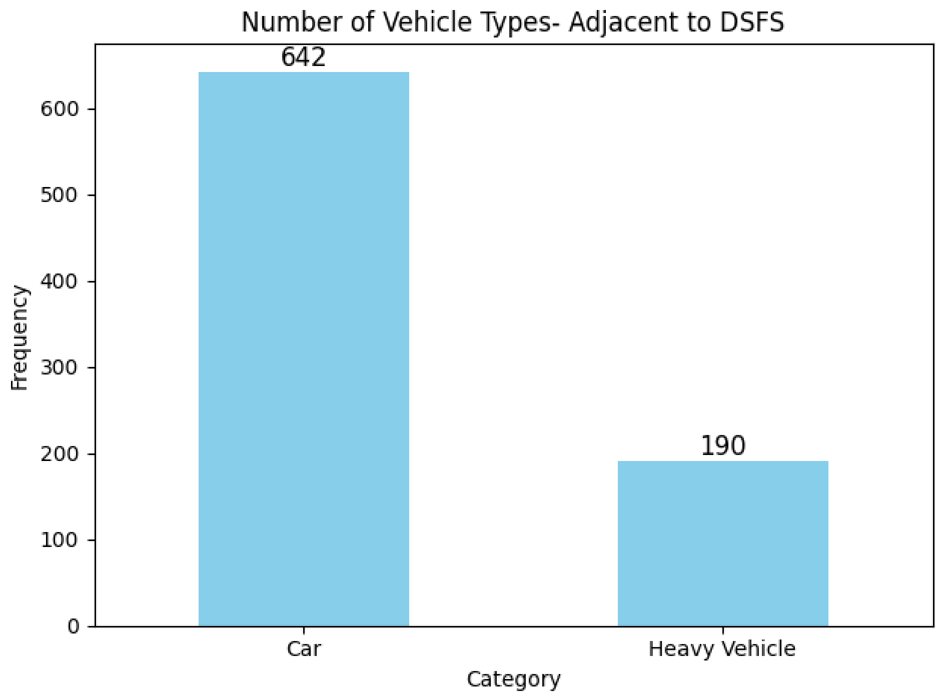

(c)

Fig.10. (a) Traffic composition in Dataset 4 upstream of DSFS, (b) Histogram of car speeds in Dataset 4, (c) Histogram of heavy vehicle speeds in Dataset 4

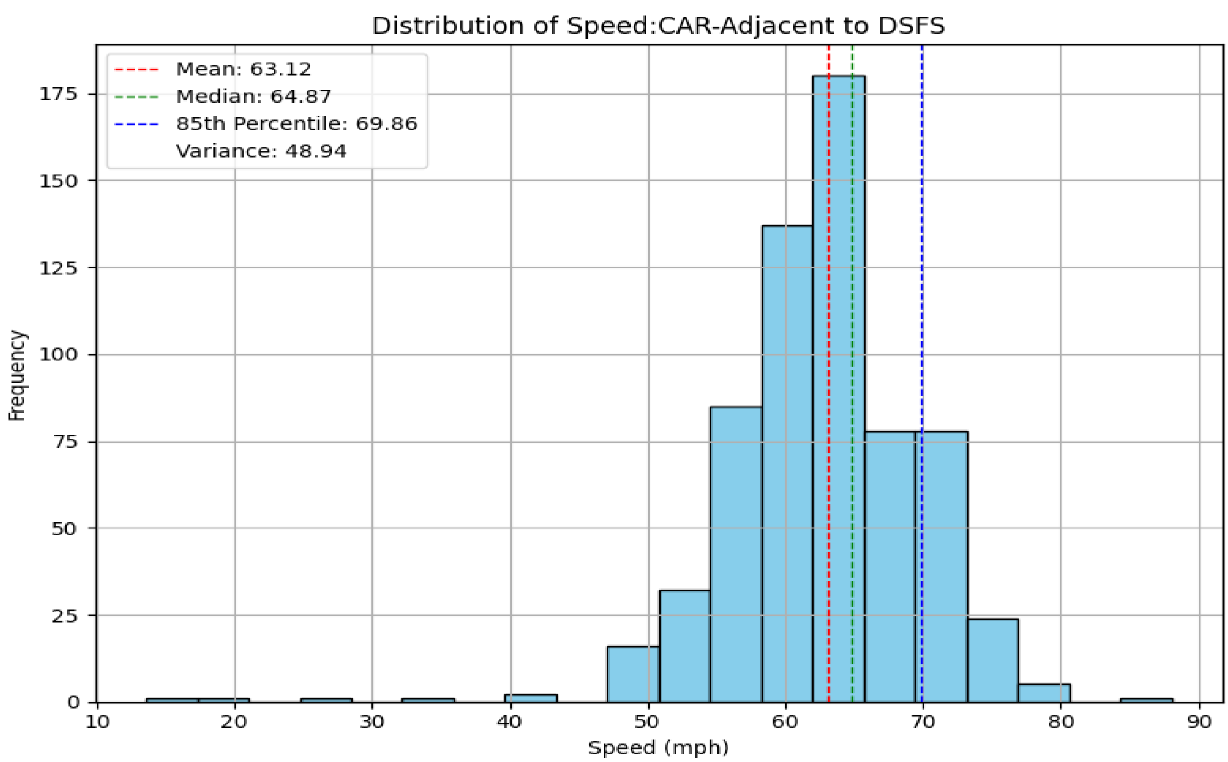
Approximately 1,700 vehicles were recorded at the upstream location of the work zone, where 92% were cars and 8% were heavy vehicles. The mean speed for cars was 65.12 mph, while for heavy vehicles, it was 56.91 mph. These speeds reflect natural driving behavior before drivers encounter any reduced speed limit signs or work zone warnings, providing a baseline for evaluating the effectiveness of speed control measures further downstream.

The 85th percentile speed was 72.08 mph for cars and 63.6 mph for heavy vehicles, suggesting that a substantial portion of traffic was already traveling at higher speeds before encountering the work zone. This aligns with previous studies indicating that drivers often maintain their usual highway speeds until they perceive a clear reason to slow down, such as signage, lane closures, or enforcement presence (Ravani & Wang, 2018).

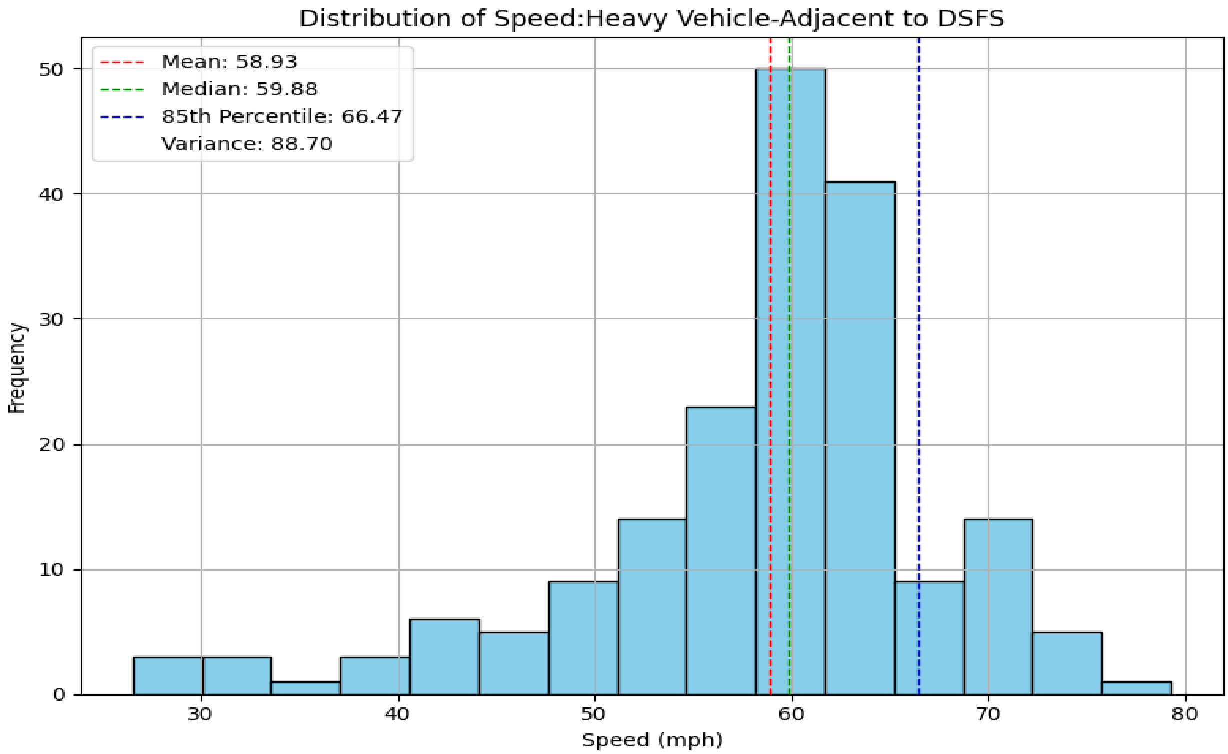
In terms of speeding, 42.9% of cars and 5.8% of trucks were recorded traveling over the posted speed limit of 65 mph, while 2% of cars and 0.7% of heavy vehicles were traveling 11 mph or more above the limit. Another notable observation is the higher speed variance among heavy vehicles compared to cars, which is consistent with the finding from the Santa Barbara work zone (Dataset 3). This is a specifically important consideration as higher speed variance contributes to increased accident risk in work zones (Quddus, 2013).


Number of Vehicle Types- Adjacent to DSFS
642
190
Frequency
0
100
200
300
400
500
600
Car
Heavy Vehicle
Category

(a)


Distribution of Speed:CAR-Adjacent to DSFS
Mean: 63.12
Median: 64.87
85th Percentile: 69.86
Variance: 48.94
Frequency
0
25
50
75
100
125
150
175
10
20
30
40
50
60
70
80
90
Speed (mph)

(b)




(c)

Fig.11. (a) Traffic composition in Dataset 4 adjacent to DSFS, (b) Histogram of car speeds in Dataset 4, (c) Histogram of heavy vehicle speeds in Dataset 4

As previously mentioned, the next data collection location was adjacent to the Dynamic Speed Feedback Sign (DSFS), where over 77% of traveling vehicles were categorized as cars, with a mean speed of 63.12 mph. The remaining 23% were heavy vehicles, which had a mean speed of 58.93 mph.

Interestingly, the results indicate that the mean speed of cars decreased by 2 mph compared to the upstream location, while for heavy vehicles, the mean speed increased by 2 mph. This suggests that the DSFS may have influenced car drivers to slow down, but heavy vehicle drivers either did not respond to the speed reduction message as effectively or possibly compensated for previous speed variations by increasing their speed near this location.

Another notable finding is that speed variance for both cars and heavy vehicles was slightly higher adjacent to the DSFS than at the upstream location. This can likely be attributed to braking behaviors as drivers reacted to the presence of the DSFS, the reduced speed limit, and the upcoming work zone. Some drivers may have responded immediately by slowing down abruptly, while others maintained their speed before making last-minute adjustments, leading to greater variability in speed patterns.

Regarding speed limit violations, the data shows that around 87% of cars exceeded the 55 mph work zone speed limit, yet only 29% of them were recorded traveling over 66 mph. This marks a significant reduction in high-speed violations compared to the upstream location, suggesting that the DSFS may have had a moderating effect on excessive speeding among cars.

However, the speed distribution of heavy vehicles presents a more concerning trend. 74% of heavy vehicles were recorded traveling above 55 mph, and 15.5% exceeded 66 mph (11 mph over the reduced speed limit). Given the larger mass and longer braking distances of heavy vehicles, these high-speed violations could pose significant safety risks in the work zone. The presence of high-speed heavy vehicles may increase the likelihood of rear-end collisions, difficulty in merging, and hazardous interactions with slower-moving traffic and construction workers.

### 2.4.4.1. Comparative Statistical Analysis

While the observed reductions in vehicle speeds and high-speed violations indicate that the DSFS may have influenced driver behavior, a comparative statistical analysis is essential to determine whether these changes are statistically significant. Such an analysis is crucial for a comprehensive assessment of the DSFS's effectiveness as a speed control measure in the work zone.

Ideally, a study design would account for extrinsic influences both spatially (comparing speeds upstream and adjacent to the DSFS) and temporally (before and during DSFS activation). This would allow for a direct evaluation of the hypothesis:

- Compare the difference in vehicle speeds between upstream and adjacent locations before activation with
- The difference in vehicle speeds between upstream and adjacent locations during activation of the DSFS.

However, due to data limitations, this study focuses solely on spatial speed differences, comparing vehicle speeds upstream of the DSFS with those adjacent to it. To evaluate this, we employ statistical tests that specifically assess whether the observed speed variations between these two locations are statistically significant.

Before conducting statistical tests, it is essential to determine whether the speed distributions follow a normal distribution. Since our sample size is less than 5000 observations, we use the Shapiro-Wilk test, which is well-suited for small to medium datasets. The test is performed separately for four groups: cars at the upstream location, cars at the DSFS location, heavy vehicles at the upstream location, and heavy vehicles at the DSFS location.

The p-values from all four tests reject the normality hypothesis, indicating that none of the speed distributions are normally distributed. This deviation from normality could stem from various factors. One major reason is the work zone environment, which disrupts typical speed patterns due to lane closures, merging zones, and varying driver responses to signage and enforcement measures. Additionally, the presence of a reduced speed limit often leads to speed clustering, where some drivers adhere to the lower limit while others continue traveling at higher speeds, creating a skewed or bimodal distribution. Differences in vehicle types also contribute, as heavy vehicles have distinct acceleration and braking patterns compared to cars, resulting in higher speed variability.

Since none of the speed distributions follow a normal distribution, we employ non-parametric statistical tests to evaluate the impact of the DSFS on speed control effectiveness. The analysis is structured around three key aspects: mean speeds, speed variability, and the proportion of high-speed vehicles. Each aspect is tested separately for cars and heavy vehicles, comparing their behavior at the upstream location (before the DSFS) and adjacent to the DSFS.

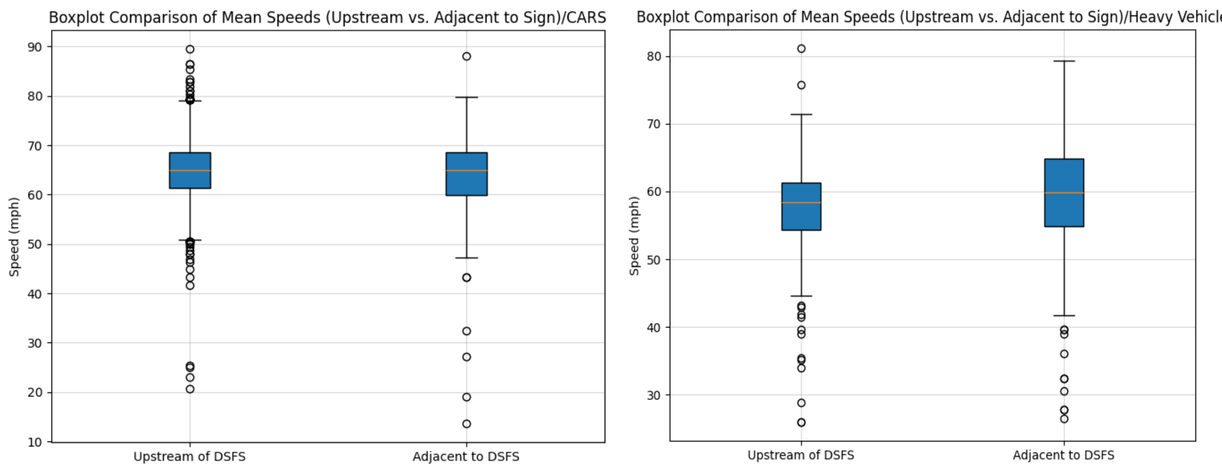
**Comparison of Mean Speeds**

To assess whether the DSFS significantly reduces vehicle speeds, we compare the mean speeds between the upstream ($X_{\text{upstream}}$) and DSFS location ($X_{\text{DSFS}}$) using the Mann-Whitney U test, a rank-based test that evaluates whether one group tends to have higher values than the other. The null hypothesis ($H_0$) states that the distribution of speeds is the same at both locations, meaning there is no significant difference in vehicle speeds. Conversely, the alternative hypothesis ($H_A$ ) suggests that vehicle speeds upstream are significantly higher than those adjacent to the DSFS, indicating the DSFS's effect on speed reduction:

$$\boldsymbol{H_0}\text{: } P(X_{\text{upstream}} > X_{\text{DSFS}}) = P(X_{\text{DSFS}} > X_{\text{upstream}})$$

$$\boldsymbol{H_A}\text{: } P(X_{\text{upstream}} > X_{\text{DSFS}}) > P(X_{\text{DSFS}} > X_{\text{upstream}})$$

If the p-value from the Mann-Whitney U test is less than the significance level (α=0.05), we reject $\boldsymbol{H_0}$ and conclude that the DSFS significantly reduces vehicle speeds. Figures 12a and 12b present the test results for cars and heavy vehicles respectively.




(a) (b)

Fig.12. (a) Boxplot of mean speeds for cars, (b) Boxplot of mean speeds for heavy vehicles

The results of the Mann-Whitney U test on cars indicate a statistically significant reduction in their speeds near the DSFS. Since the p-value (0.000) is well below the 0.05 significance level, we reject the null hypothesis and conclude that the DSFS effectively influences car speed reduction. Furthermore, the effect size, measured by Cliff's Delta (193.39), is exceptionally large, signifying a strong practical impact of the DSFS on controlling vehicle speeds. This suggests that the reduction in speeds is not only statistically meaningful but also substantial in magnitude. Overall, these findings support the effectiveness of the DSFS in reducing car speeds, which is a critical factor in enhancing safety in work zones.

However, the results for heavy vehicles tell a different story. The Mann-Whitney U test on heavy vehicles shows no statistically significant difference in mean speeds between the upstream and adjacent locations, as indicated by the p-value (0.9988), which is far above 0.05. This suggests that the DSFS does not significantly influence heavy vehicle speeds. Additionally, the negative effect size (Cliff's Delta = -32.02) indicates a very small practical effect, reinforcing that the DSFS has minimal impact on the speed behavior of heavy vehicles.

## Comparison of Speed Variability (Variance)

As stated earlier, it is crucial to examine whether the DSFS influences speed variability, as a reduction in variance would indicate more consistent speeds near the DSFS. To test for differences in variance, we apply Levene's test, a robust method for comparing the equality of variances between two groups. The null hypothesis ($H_0$) states that the speed variance is the same at both locations, while the alternative hypothesis ($H_A$) posits that the speed variance differs, meaning that the DSFS may either increase or decrease speed consistency:

$$\boldsymbol{H_0}: \sigma^2_{\text{upstream}} = \sigma^2_{\text{DSFS}}$$

$$\boldsymbol{H_A}: \sigma^2_{\text{upstream}} \neq \sigma^2_{\text{DSFS}}$$

The results of Levene's test on cars indicate that there is no significant difference in speed variability between the upstream and adjacent locations of the DSFS. The test statistic (1.3040) and p-value (0.2536) suggest that we cannot reject the null hypothesis, meaning the variances of the two distributions are statistically similar. This implies that while the DSFS significantly reduces car speeds, it does not substantially impact speed consistency—drivers near the DSFS exhibit a similar range of speed variation as those upstream. This finding suggests that while the DSFS is effective in lowering mean speeds, it does not necessarily lead to more uniform driving speeds in the work zone.

Similarly, Levene's test results for heavy vehicles reveal that their speed variability does not differ significantly between the upstream and DSFS locations. The test statistic (2.3637) and p-value (0.1252) indicate that the variance in heavy vehicle speeds remains unchanged, meaning that the DSFS does not contribute to greater speed uniformity for these vehicles. This aligns with the earlier finding that the DSFS has no significant effect on heavy vehicle mean speeds, further suggesting that truck drivers maintain relatively consistent driving behavior regardless of the DSFS's presence.

## Comparison of the Proportion of High-Speed Vehicles

A key measure of DSFS effectiveness is its ability to reduce the proportion of high-speed vehicles, those exceeding a critical speed threshold (e.g., 66 mph). To determine whether the fraction of high-speed vehicles is significantly different between the upstream and DSFS location, we employ the two-proportion Z-test, which compares two population proportions. The null hypothesis ($H_0$) states that the proportion of high-speed vehicles is the same at both locations, while the alternative hypothesis ($H_A$) suggests that the proportion of high-speed vehicles is higher upstream than adjacent to the DSFS:

$$\boldsymbol{H_0}: \boldsymbol{\Theta}_{\text{upstream}} = \boldsymbol{\Theta}_{\text{DSFS}}$$

$$\boldsymbol{H_A}: \boldsymbol{\Theta}_{\text{upstream}} > \boldsymbol{\Theta}_{\text{DSFS}}$$

The results of the two-proportion Z-test indicate a statistically significant reduction in the proportion of high-speed vehicles near the DSFS. Upstream of the DSFS, 42.9% of vehicles exceeded 66 mph, whereas this proportion dropped to 29% adjacent to the DSFS (Figure 13a). The Z-statistic (6.1132) and p-value (0.0000) provide strong evidence to reject the null hypothesis, confirming that the proportion of high-speed vehicles is significantly higher upstream than near the DSFS. This suggests that the DSFS effectively discourages excessive speeding, reinforcing its role as an important speed control measure in the work zone. However, the results for heavy vehicles present a contrasting outcome. The proportion of high-speed heavy vehicles was 5.8% upstream and 15.5% adjacent to the DSFS (Figure 13b), indicating an increase rather than a decrease. The increase in the proportion of high-speed heavy vehicles adjacent to the DSFS can be attributed to a combination of braking limitations, acceleration behavior, and enforcement perception. Unlike cars, heavy vehicles take longer to decelerate and may experience a speed recovery effect, where drivers slow down slightly upstream in anticipation of the DSFS but then accelerate once they pass it. Additionally, some truck drivers may not perceive DSFS as a strong deterrent, leading them to maintain or even increase speed.

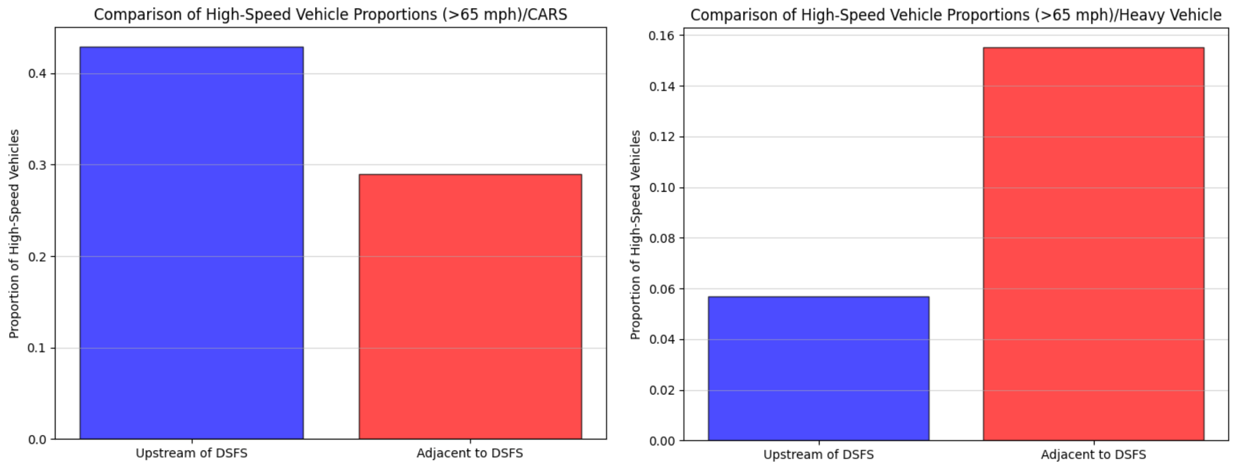
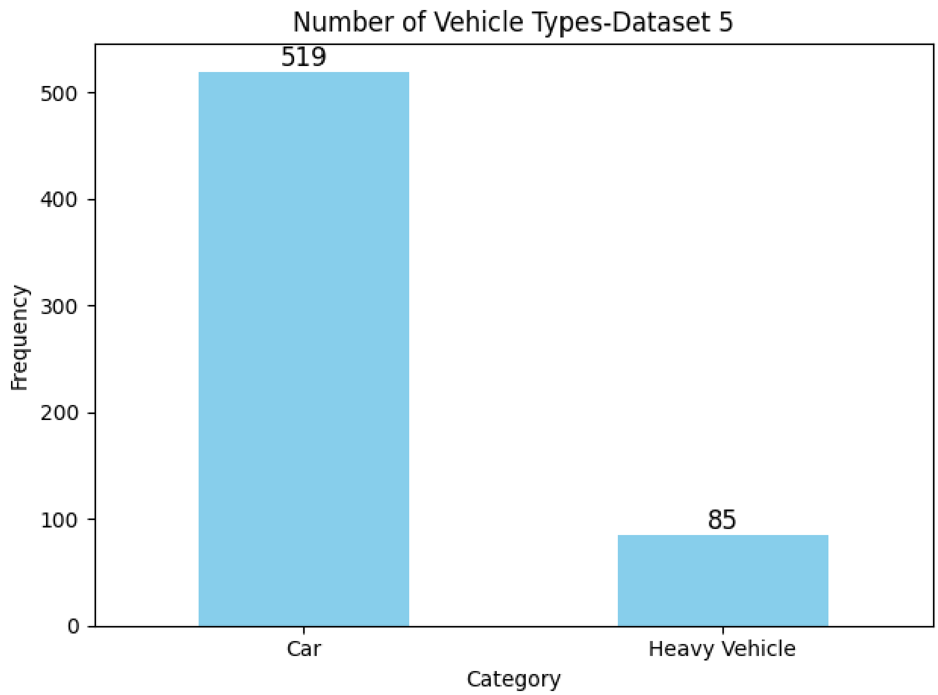


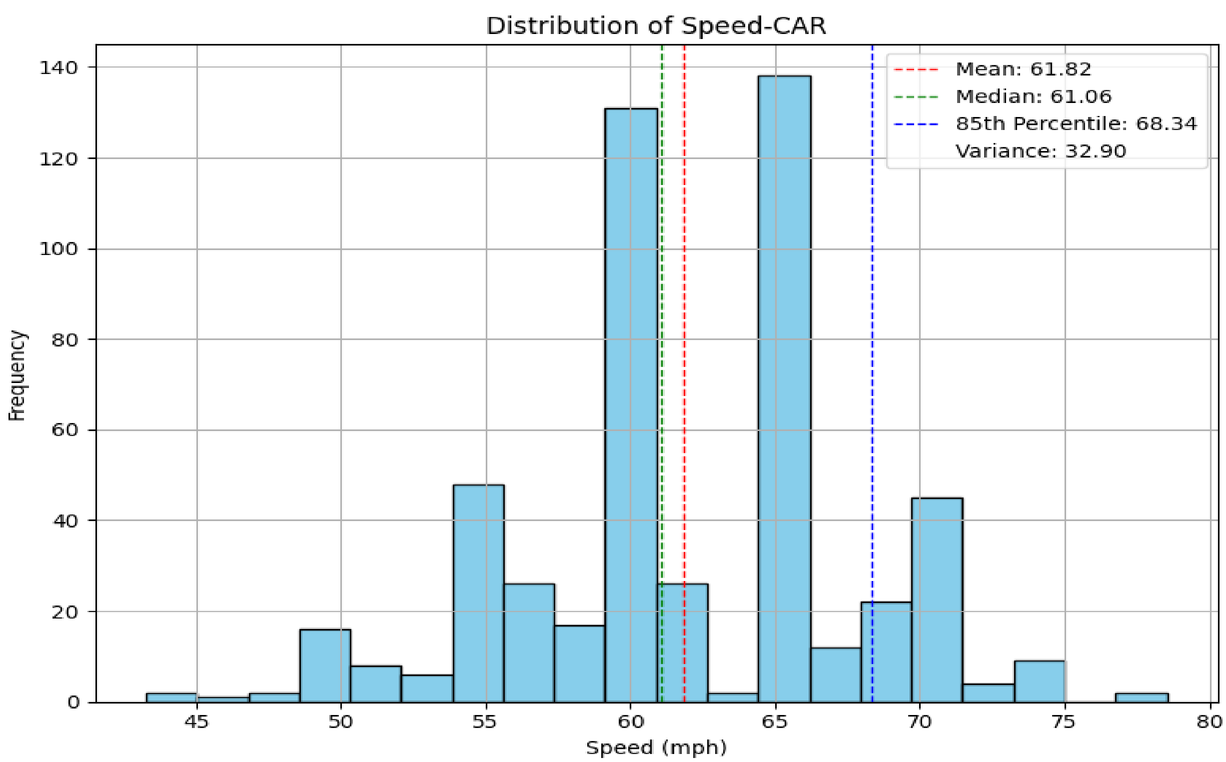

Fig.13. (a) the proportion of high-speed cars upstream and adjacent to DSFS, (b) the proportion of high-speed heavy vehicles upstream and adjacent to DSFS

## 2.4.5. Dataset 5

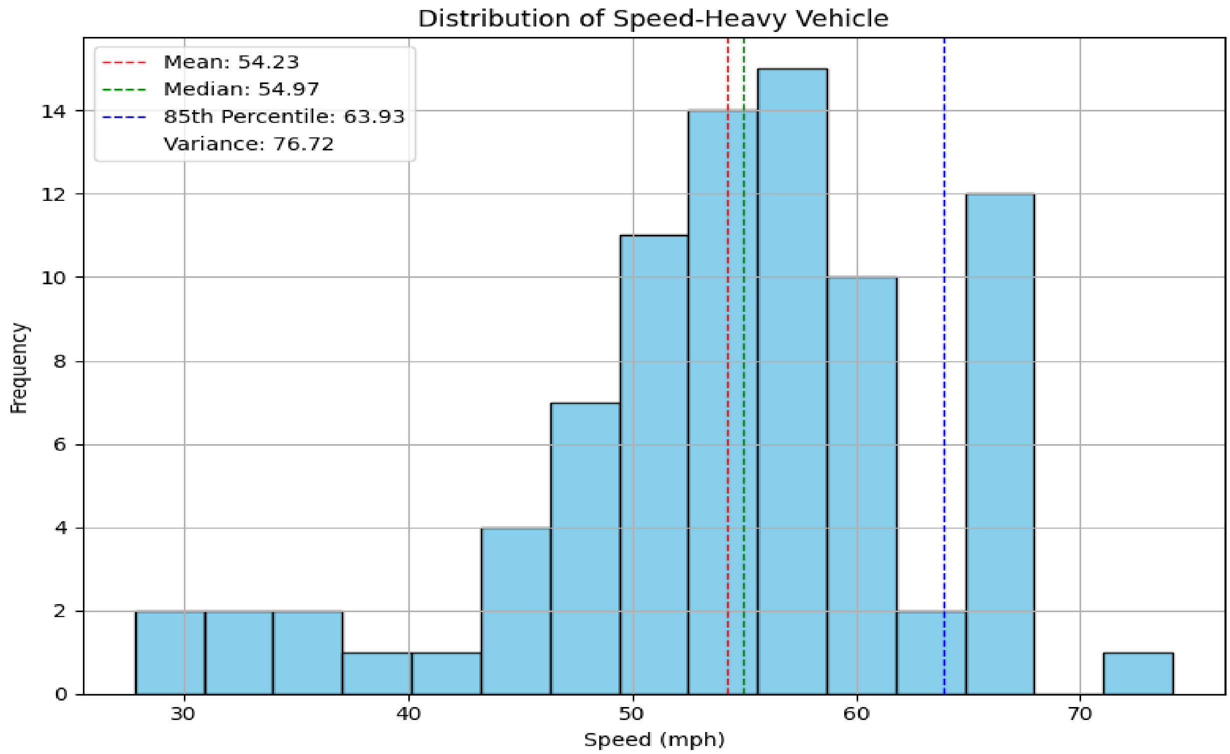
Dataset 5 was collected on November 12th,2024 at the same location as Dataset 4, with two key differences. First, data was recorded only at the location adjacent to the DSFS, rather than at multiple points. Second, the DSFS was turned off, meaning that only the static reduced speed limit sign was present, without any dynamic speed feedback. Figure 14 illustrates the traffic composition at this location in the work zone area along with the speed distribution of each category. The speed distribution of both cars and heavy vehicles reveals important trends in driver behavior in the work zone. The mean speed for cars is 61.82 mph, while for heavy vehicles, it is 58.93 mph. The median speed for cars is slightly lower at 61.06 mph, indicating a slight right-skew in the distribution, while the 85th percentile speed for cars is 68.34 mph, meaning that 15% of cars exceed this threshold. Regarding compliance with the 55 mph work zone speed limit, 84.14% of cars exceed 55 mph, compared to 50.00% of heavy vehicles. However, when looking at high speeding violations, only 18.1% of cars travel over 66 mph, while 1.19% of heavy vehicles exceed this speed. This indicates that while heavy vehicles tend to exceed the 55 mph limit, very few travel at excessive speeds. The speed variance follows a similar trend as observed previously, indicating a moderate level of speed variability for cars. In contrast, heavy vehicles exhibit a much higher variance of 76.72, suggesting a greater variability in speed values.


Number of Vehicle Types-Dataset 5
519
85
Frequency
0
100
200
300
400
500
Car
Heavy Vehicle
Category

(a)


Distribution of Speed-CAR
Mean: 61.82
Median: 61.06
85th Percentile: 68.34
Variance: 32.90
Frequency
0
20
40
60
80
100
120
140
45
50
55
60
65
70
75
80
Speed (mph)

(b)




(c)

Fig.14. (a) Traffic composition in Dataset 5, (b) Histogram of car speeds in Dataset 5, (c) Histogram of heavy vehicle speeds in Dataset 5

Overall analysis of the five datasets indicates that while both cars and heavy vehicles frequently exceed the 55-mph speed limit in work zones, high-speed violations over 66 mph are significantly more common among cars. This suggests that while heavy vehicles tend to stay within a lower speed range, cars contribute more to excessive speeding.

Additionally, the increased variance in heavy vehicle speeds presents potential safety concerns, as greater fluctuations in speed can lead to traffic flow disruptions, sudden braking, and a higher risk of rear-end collisions. The DSFS appears to have a modest effect on reducing mean speed and the proportion of high-speed vehicles, but the impact is not substantial enough to ensure full compliance with the reduced speed limit. The mean speed still remains above the posted limit, and high variance persists, which can increase both the frequency and severity of crashes in the work zone.

These findings emphasize the need for enhanced speed control measures to improve speed consistency and compliance within the work zone. Potential solutions may include increased enforcement, additional signage, or more effective speed reduction strategies, particularly for managing excessive speeds among cars and reducing variability in heavy vehicle speeds to enhance overall safety.

# 2.5. LIMITATIONS AND RECOMMENDATIONS

The foremost challenge in this work was obtaining reliable and comprehensive data from work zones through Caltrans. Ideally, the study would have included multiple work zones across rural and urban areas in Southern and Northern California, with a well-controlled experimental design. The optimal approach would have been to collect speed data at multiple locations within each work zone (upstream, adjacent to the sign, and downstream) both with and without the DSFS, to establish a robust control-treatment comparison. However, due to significant data collection challenges, this ideal study design was not fully realized.

A major issue was that the DSFS units used by contractors store speed data, but contractors are not required to save or report this data to Caltrans. We initially anticipated gaining access to historical DSFS speed records, which would have greatly enhanced our analysis. However, since contractors are not obligated to retain or share this data, it was unavailable for this study. We strongly recommend that Caltrans establish a mandate requiring contractors to store and provide DSFS data for research and evaluation purposes. This data could serve as a valuable resource for assessing speed control measures in work zones and guiding future policy improvements.

Furthermore, Caltrans reached out to multiple districts to obtain work zone data, but only a few districts responded, and the datasets provided (Datasets 1 and 2) lacked essential details such as temporary traffic control, work zone layouts, and speed reduction measures. These missing details significantly limited our ability to contextualize the data and conduct a comprehensive analysis. Without these specifics, drawing definitive conclusions about speed reduction strategies was challenging.

Due to these limitations, we had to conduct independent data collection using drones to obtain detailed speed information. However, selecting appropriate locations for drone flights was another challenge, as we needed to obtain FAA and university approvals to operate near urban areas and airports. This constraint limited us to only two work zones, reducing the generalizability of our findings. Additionally, despite requesting work zone schedules and site access from Caltrans, obtaining timely information and coordination with the responsible personnel was difficult. As a result, we had to manually visit multiple work zones to identify viable locations, which further constrained the study.

Another significant challenge was video data processing and speed estimation accuracy. Since we did not have access to ground-truth speed data for validation, assessing the accuracy of the developed object detection and speed estimation algorithm was complex. The research team had to implement additional verification techniques, which were time-consuming and labor-intensive. Despite our best efforts, the algorithm did not achieve 100% accuracy in object detection, classification, and speed calculation. This introduces a margin of error in the final results, which, combined with the limited number of recorded videos and work zones, may contribute to potential biases or erroneous conclusions.

Given the significant data challenges encountered in this study, several key recommendations are proposed to improve future research, policy development, and safety interventions in work zones across California. First and foremost, Caltrans should establish a clear mandate requiring all contractors to systematically store and share speed data collected at work zones. This requirement should be integrated into contractor agreements and project specifications, with standardized protocols for data formatting, reporting frequency, and secure transfer. The stored data should include time-stamped vehicle speeds, location coordinates, and metadata on SLR operation (e.g., sign activation times and speed thresholds), allowing for accurate post-analysis of speed control effectiveness. Compliance with this mandate should be subject to periodic audits or tied to project performance reviews to ensure data integrity and consistency.

In addition to mandating data sharing for contractors, Caltrans should develop a centralized, statewide digital platform to document and manage comprehensive work zone information. This system should include detailed records for each active work zone, such as:

- Work zone plans and layout schematics (e.g., lane closures, tapers, signage placement)

- Configuration details (e.g., number of lanes open, presence of barriers)
- Start and end dates for each work zone phase or location
- Posted and reduced speed limits
- Speed reduction strategies in use (e.g., DSFS, speed trailers, law enforcement presence)
- Any changes in work zone setup or speed control measures over time

This centralized repository should be accessible to approved researchers and Caltrans personnel, enabling timely and comprehensive evaluations of safety interventions and speed management practices. Furthermore, ensuring that each district adheres to the same data standards and documentation protocols will allow for consistent, statewide analysis and cross-regional comparisons.

By implementing these recommendations, Caltrans can significantly enhance the quality and availability of work zone data, allowing for more rigorous evaluations of speed reduction strategies and their impact on traffic safety. Ultimately, these improvements will support data-driven decision-making, facilitate innovative research, and lead to safer and more efficient work zone operations throughout California.

## 2.6. CONCLUSION AND FUTURE RESEARCH

This study evaluated the impact of Dynamic Speed Feedback Signs (DSFS) on vehicle speed behavior in work zones using multiple datasets collected from different locations in California. In Phase 1 of this research, speed was identified as a major contributing factor to injury severity in work zone crashes. While it is difficult to establish quantitative safety measures, certain traffic attributes—such as mean speed, speed variance, and high-speed vehicle violations—are commonly used to assess the effectiveness of speed control methods. Speed and speed variance are both considered critical causal factors for work zone crashes (Daniel et al., 2000). Excessive speed is strongly linked to increased crash severity, whereas high-speed variance is associated with higher accident rates (Quddus, 2013). Additionally, higher speeds result in longer braking distances and reduced reaction times to hazards, which elevates risks for both drivers and road work crews (Elvik et al., 2004). Given these concerns, the analysis in this study focused on three key aspects: mean speed reduction, speed variability, and high-speed vehicle violations, with separate evaluations for cars and heavy vehicles.

The results from one specific location, where both upstream and adjacent DSFS speed data were available, indicate that DSFS effectively reduces mean speeds and high-speed violations for cars. The Mann-Whitney U test confirmed a statistically significant reduction in mean speed, and the effect size suggests a strong practical impact on car speed control. Additionally, the proportion of high-speed cars exceeding 65 mph decreased significantly, reinforcing the role of DSFS in mitigating excessive speeding in work zones. However, for heavy vehicles, DSFS had minimal influence on speed reduction, with no statistically significant decrease in mean speed, and in some cases, the proportion of high-speed heavy vehicles even increased adjacent to the DSFS. This may be due to factors such as speed recovery effects, braking limitations, or operational constraints of heavy vehicles. Regarding speed variability, Levene's test results showed that DSFS does not significantly affect speed variance for either cars or heavy vehicles. High-speed variability, particularly among heavy vehicles, remains a concern, as it may contribute to traffic flow disruptions, rear-end collisions, and erratic braking behavior.

For the other datasets, only mean speed, speed variance, and the proportion of high-speed vehicles were provided due to data limitations. These datasets revealed a concerning trend—a significant proportion of vehicles exceeded the reduced speed limit, with many traveling 10 mph or more over the posted limit, indicating that speeding remains a prevalent issue in work zones despite existing speed management measures. While DSFS has proven effective in reducing car speeds and excessive speeding violations, its limited impact on heavy vehicles and the persistently high proportion of speeding vehicles suggest that further improvements are needed. Enhancing enforcement, incorporating work zone features that physically slow vehicles down (such as narrower lanes), incorporating additional signage, implementing truck-specific messaging, and strengthening speed monitoring could help achieve better compliance with reduced speed limits.

Future research should focus on expanding data availability and exploring additional speed reduction strategies to develop a more comprehensive understanding of safety in work zones. Gaining access to more extensive and detailed datasets—including continuous DSFS speed records, enforcement data, and vehicle trajectory information—would allow for a more robust evaluation of speed control measures across various work zone configurations and traffic conditions. Additionally, future studies should investigate the effectiveness of alternative speed reduction strategies, such as enforcement-based measures, variable speed limits, speed cameras, and intelligent transportation systems (ITS), to determine the most effective approaches for different work zone scenarios. Beyond speed analysis, conflict-based safety assessment methods should be explored as an alternative or complementary approach to evaluating work zone safety. Metrics such as time-to-collision (TTC), post-encroachment time (PET), and braking reaction times can provide a more dynamic and proactive understanding of crash risk by identifying near-miss events and driver behavior patterns before actual crashes occur. Integrating these advanced safety assessment techniques with trajectory-based data and real-time monitoring systems would enable a more holistic evaluation of work zone risks and guide the development of more effective safety interventions.

As Caltrans begins implementing its new Generative AI (GenAI) initiatives aimed at improving traffic safety and congestion, consistent and high-quality data collection becomes even more critical. GenAI tools rely heavily on large, structured datasets to identify patterns, detect near misses, and support predictive analytics for traffic management. Collecting, storing, and sharing detailed speed and work zone data will not only strengthen traditional safety evaluations but also empower the AI technologies Caltrans is piloting to deliver meaningful insights and targeted interventions.

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