Development of Work Zone Crash Modifications Factors for Iowa

Final Report
May 2026

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Jonathan Wood (orcid.org/0000-0003-0131-6384), Skylar Knickerbocker (orcid.org/0000-0002-0202-5872), Maroa Mumtarin (orcid.org/0000-0002-1802-5148), and Ye Dong (orcid.org/0000-0001-9335-389X)	InTrans Project 23-874

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16. Abstract

Automated queue warning systems are a common safety countermeasure deployed in Iowa work zones. This report documents the development and evaluation of crash modification factors (CMFs) for Iowa work zones with automated queue warning systems. The study utilized crash data from 2016 to 2023, focusing on crashes in smart work zones equipped with queue warning systems.

Data were collected from multiple sources, including the Iowa Traffic Critical Project (TCP) program, law enforcement-reported crash data, and the Iowa Roadway Asset Management System (RAMS). The TCP program provided detailed historical data on work zones during the study period and the various devices deployed as part of smart work zone systems. Crash data included spatial coordinates and dates, which were used to identify work zone-related incidents, while RAMS provided roadway characteristics relevant to CMF development.

Two buffer zones around the work zone's dynamic message sign (for smart work zones) or around the start of the work zone location (for work zones without a queue warning system) were analyzed: a 1 mi upstream and 0.5 mi downstream buffer, and a 0.5 mi upstream and 0.5 mi downstream buffer. The evaluation involved the development of multiple regression models, specifically the negative binomial-P (NB-P) and Sichel models, which are well suited for handling overdispersed count data. These models were selected based on their log-likelihood values and cumulative residual (CURE) plots.

The results indicate that the presence of a queue warning system leads to a slight decrease in total crashes (up to 3.1%) and a significant reduction in fatal, major injury, and minor injury (KAB) crashes (up to 31.9%). The impact is more pronounced for the 1 mi upstream and 0.5 mi downstream buffer, suggesting that the queue warning system influences vehicle speeds around 1 mi upstream of the work zone. The reduction in crash severity is likely due to decreased vehicle speeds in the presence of a queue warning system. This study also explored connected vehicle data to assess speed profiles across four work zones and found consistent patterns of speed reduction in most of these work zones compared to periods without construction.

Despite promising results, the study acknowledges several limitations, including potential discrepancies in work zone location and duration data and the need for more precise data collection. In conclusion, implementing queue warning systems in work zones presents a viable strategy for mitigating work zone crash severity and enhancing road safety.

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DEVELOPMENT OF WORK ZONE CRASH MODIFICATION FACTORS FOR IOWA

Final Report
May 2026

Principal Investigator
Jonathan Wood, Associate Professor
Department of Civil, Construction and Environmental Engineering, Iowa State University

Co-Principal Investigator
Skylar Knickerbocker, Research Engineer
Institute for Transportation, Iowa State University

Authors
Jonathan Wood, Skylar Knickerbocker, Maroa Mumtarin, and Ye Dong

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A report from
Institute for Transportation
Iowa State University
2711 South Loop Drive, Suite 4700
Ames, IA 50010-8664
Phone: 515-294-8103 / Fax: 515-294-0467
https://intrans.iastate.edu

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EXECUTIVE SUMMARY

Automated queue warning systems are a common safety countermeasure deployed in Iowa work zones. This report documents the development and evaluation of crash modification factors (CMFs) for Iowa work zones with automated queue warning systems. The study utilized crash data from 2016 to 2023, focusing on crashes in smart work zones equipped with queue warning systems.

Data were collected from multiple sources, including the Iowa Traffic Critical Project (TCP) program, law enforcement-reported crash data, and the Iowa Roadway Asset Management System (RAMS). The TCP program provided detailed historical data on work zones during the study period and the various devices deployed as part of smart work zone systems. Crash data included spatial coordinates and dates, which were used to identify work zone-related incidents, while RAMS provided roadway characteristics relevant to CMF development.

Two buffer zones around the work zone's dynamic message sign (for smart work zones) or around the start of the work zone location (for work zones without a queue warning system) were analyzed: a 1 mi upstream and 0.5 mi downstream buffer, and a 0.5 mi upstream and 0.5 mi downstream buffer. The evaluation involved the development of multiple regression models, specifically the negative binomial-P (NB-P) and Sichel models, which are well suited for handling overdispersed count data. These models were selected based on their log-likelihood values and cumulative residual (CURE) plots.

The results indicate that the presence of a queue warning system leads to a slight decrease in total crashes (up to 3.1%) and a significant reduction in fatal, major injury, and minor injury (KAB) crashes (up to 31.9%). The impact is more pronounced for the 1 mi upstream and 0.5 mi downstream buffer, suggesting that the queue warning system influences vehicle speeds around 1 mi upstream of the work zone. The reduction in crash severity is likely due to decreased vehicle speeds in the presence of a queue warning system. This study also explored connected vehicle data to assess speed profiles across four work zones and found consistent patterns of speed reduction in most of these work zones compared to periods without construction.

Despite promising results, the study acknowledges several limitations, including potential discrepancies in work zone location and duration data and the need for more precise data collection. In conclusion, implementing queue warning systems in work zones presents a viable strategy for mitigating work zone crash severity and enhancing road safety.

INTRODUCTION

Background and Problem Statement

Work zone safety has been a key area of concern for transportation agencies. A number of studies have been performed to try to understand how the design and operation of work zones affect the frequency and severity of work zone-related crashes.

Crash modification factors and functions (CMFs) are widely used for predicting the safety performance of countermeasures or changes from specified base conditions. The current CMFs related to work zones, available in the *Highway Safety Manual* (HSM) and the CMF Clearinghouse, are based on comparisons to roads without work zones as the base condition. These CMFs do not capture the complexity of differences in work zone operations and countermeasures that may be deployed to improve traffic operations (which could have an impact on safety) or countermeasures that target safety. Another limitation of the existing work zone CMFs is the geographic specificity of these factors: the current work zone CMFs in the HSM were mostly developed based on data from California work zones. This geographical specificity posits an obstacle for their accurate application to other states with unique conditions, particularly Iowa, where existing work zone strategies may not align with those considered in the HSM.

Previous studies have revealed that the frequency of rear-end crashes has a significant relationship with the presence of a work zone (Rouphail et al. 1988, Hall and Lorenz 1989, Venugopal and Tarko 2000, Salem et al. 2006, Akepati and Dissanayake 2011). However, the safety impacts of countermeasures that have the potential to reduce rear-end crashes in work zone areas, like end-of-queue warning systems, have seldom been assessed.

To address this gap, this research aimed to develop Iowa-specific crash modification factors for work zones where automated queue warning systems have been deployed by evaluating work zone-related crashes. This research resulted in high-quality work zone CMFs that will be invaluable not only for intra-state application but also for the broader transportation engineering community through the CMF Clearinghouse.

The subsequent sections of the report are structured as follows:

- The rest of the Introduction chapter documents studies related to work zone safety.
- The Data Description chapter describes the data retrieval process, while the Methodology chapter describes the regression models used in this study.
- The Results and Discussion chapter then summarizes the CMF estimation results.
- In addition to the crash analysis, connected vehicle data were utilized in the Connected Vehicle Data chapter, which shows examples of speed reduction phenomena in work zone areas from connected vehicle data.
- A summary of the findings is then presented in the Conclusions chapter.
- Additional details about the model results are provided in the Appendix.

Existing Literature on Work Zone CMFs

A number of CMFs have been developed specifically for work zone-related areas. Notably, the CMFs from the HSM and CMF Clearinghouse have been cited frequently and have been applied to numerous transportation safety management projects. The CMFs featured in the HSM were derived using an empirical before-and-after method based on data primarily from principal arterial roads and Interstates in California (Bahar 2010). These CMFs can reflect the impact of work zone duration and length on different crash severity types. For a broader scope of work zone operations and countermeasures, the CMF Clearinghouse offers a comprehensive collection of 84 CMFs categorized under various subcategories for different work zone features and countermeasures, including increased work zone duration, modified work zone length, presence of active work with lane closures, increased inside or outside shoulder width, presence of left-hand merge and downstream lane-shifting, and crossover closure for two-way two-lane roadway work zones (Khattak et al. 2002, Ozturk et al. 2014, Tarko et al. 2011, Ullman et al. 2008, Dudek et al. 1986, See 2008). Most of these CMFs were developed through before-and-after analysis (no work zone versus work zone) specifically for principle arterial roadways.

Although these existing CMFs are extensive, challenges arise when applying these CMFs in regions like Iowa. This is primarily due to the fact that the HSM CMFs were derived from California work zone data, potentially limiting their accuracy when applied to Iowa's unique traffic conditions and infrastructure. Moreover, these existing CMFs cannot fully capture the effects of several newer work zone operations and advanced countermeasures such as dynamic message signs and queue warning systems, which have increasingly been deployed for the enhancement of work zone safety.

An end-of-queue warning system is an emerging traffic enforcement strategy in work zone areas that alerts drivers of slow traffic and mitigates rear-end crashes. The system accomplishes this by providing timely information about queue lengths and expected delays. Given that queue warning system deployments are typically in work zone areas with wider shoulder widths or continuous shoulders (Ullman et al. 2013), few studies have attempted to evaluate their effectiveness.

In 2011, the Texas Department of Transportation (TxDOT) deployed an end-of-queue warning system along I-35, amidst multiple ongoing construction projects (Ullman et al. 2016). The main objective was to examine the system's impact during nighttime lane closures. Data from more than 200 nighttime lane closures with queue warning systems along I-35 were collected. According to the results of an empirical Bayes analysis, the end-of-queue system overall decreased crashes by 44% compared to scenarios without the system and led to fewer severe crashes, likely due to the mitigation of high-speed crashes. Similarly, Illinois implemented queue warning systems on two Interstate construction projects from 2010 to 2011 (Ullman and Schroeder 2014). Preliminary before-and-after analyses suggested a nearly 14% decrease in queue-related crashes and an 11% reduction in injuries associated with these installations. Hourdos et al. (2017) designed a queue waring system based on the detection of crash-prone areas and evaluated its impact by implementing this system on one Interstate without a work

zone (I-94) in Minnesota, where the researchers observed a 22% decrease in crashes and a 54% reduction in near crashes.

While these studies provide compelling evidence of the positive impact of queue warning systems on reducing work zone crashes, their small sample sizes limit their direct application to broader safety projects. This limitation underscores the need for further research and larger-scale evaluation to validate the effectiveness of queue warning systems.

DATA DESCRIPTION

This chapter describes the various data sources and the data processing methods used for this project. This study was carried out using 8 years (2016 to 2023) of work zone-related crash data in Iowa. The Iowa DOT utilized smart work zones on 10 to 20 projects each year during this time period, with most work zones utilizing a queue warning system. The details of each of these work zones were obtained from the Iowa Traffic Critical Project (TCP) program website, which provided detailed historical data about the locations of the work zones along with the various devices deployed as part of the smart work zone and queue warning systems. The data collection process, data processing methods, and limitations of the data are discussed in this chapter.

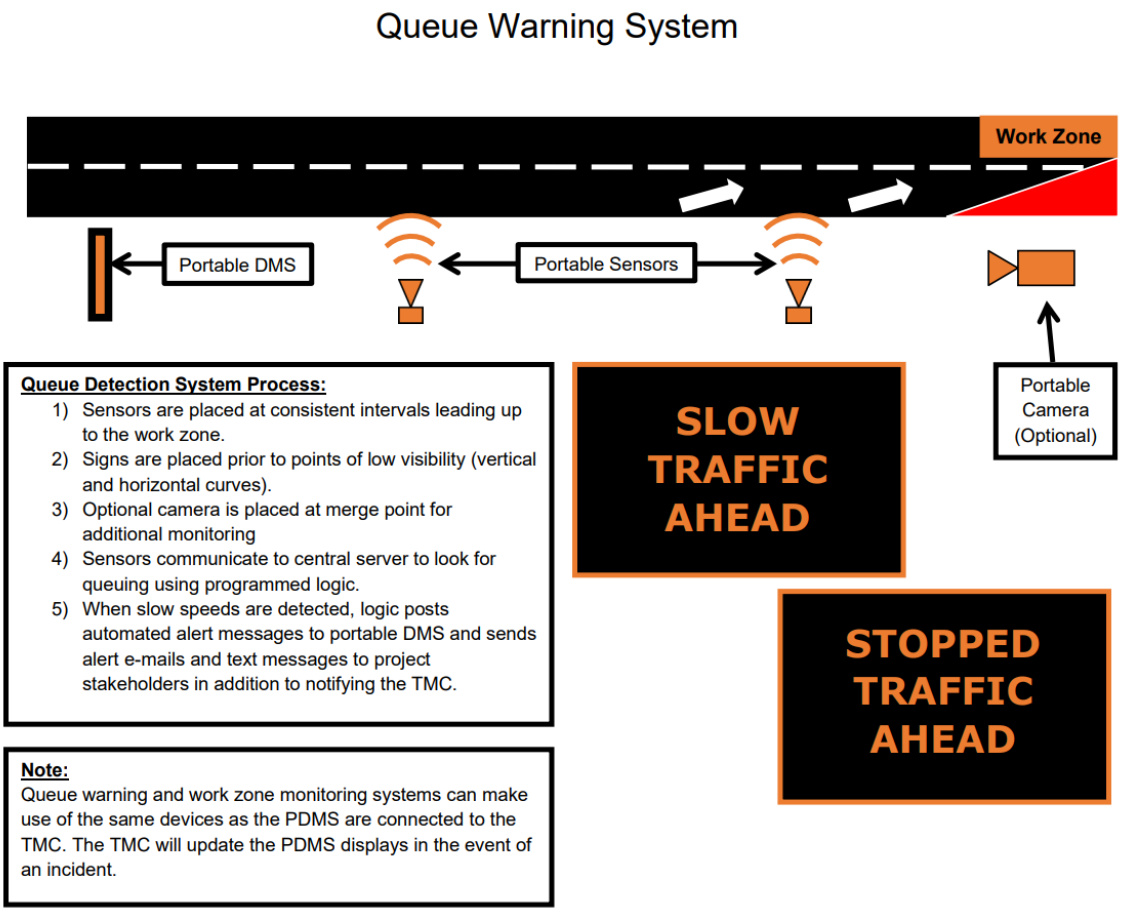
Data Sources

Work Zone Data

Work zone-related information was collected from the archive provided by the Iowa DOT on the TCP program website, available at https://sites.google.com/site/iowatcp/archives. The website has information related to each of the traffic critical work zones deployed each year as well as logs (including location and time data) for the devices deployed as part of the smart work zone systems. The TCP program website provides this information in the form of a map and/or list of the work zones deployed each year and map of the devices (sensors, portable dynamic message sign [PDMS], cameras, etc.) deployed in these work zones.

Because the objective of this study was to develop CMFs for Iowa work zones with an automated queue warning system (relative to work zones with no queue warning system), one critical piece of information was whether the work zones deployed each year included an automated queue warning system. These data were gathered by reviewing the "Mitigation Strategy" variable in the list of TCP program projects for each year.

Figure 1 shows the current process used by the Iowa DOT's automated queue warning system.



Iowa DOT, https://drive.google.com/file/d/1O83Q2bxIkW-CojUQdueDcwPRSbiSlb5q/view

Figure 1. Automated queue warning system used by the Iowa DOT

The work zone data from the TCP program website also includes information related to the construction activities within the work zones and the durations of the work zones. Work zone duration information was compiled from two different sources within the TCP program archive: the device deployment information and the project list. In the project list, several dates were recorded for the different phases of each work zone, including the preconstruction meeting date, earliest traffic impact date, deployment date, and end date. Ideally, the earliest traffic impact date and end date were designated as the starting date and ending date, respectively, for the work zone project. In cases where the earliest traffic impact date was unavailable due to missing values, an alternative logic was applied to select the work zone's starting date. The confirmed starting date was prioritized, followed by consideration of the anticipated and estimated starting dates, based on a comprehensive review of the project records.

In the project database, a significant number of work zones did not have any start or end date. When no dates were available in the maps/lists of TCP program projects, the information from the device maps was used to identify work zone duration. The device maps provide information on the deployed date and harvest date for the devices in each work zone area. The earliest deployed date and the latest harvest date among all devices in a given work zone area were identified as the starting date and ending date for that particular work zone. Upon completing the

collection of dates from both sources, the final work zone duration was determined as the earliest starting date and the latest ending date derived from the two sources of information. Only work zones that had both a starting and ending date were included in the final analysis.

Crash Data

Law enforcement-reported crash data in Iowa from 2016 to 2023 were considered as part of this study. The crash data are provided in a SQL database that includes the spatial coordinates of each crash location as well as route and measure information to associate each crash with Iowa's linear referencing system. The crash data do include an indicator variable showing whether the crash was coded as work zone-related by the officer submitting the report. However, work zone-related crashes are not always documented properly; in some cases, the crash narrative describes a crash within a work zone, but the work zone-related indicator is not selected in the crash database. For this analysis, the work zone location and duration information was used to identify work zone-related crashes due to the higher confidence that the information on the TCP program website could be used to identify whether crash occurred within a work zone.

Roadway Asset Management System Data

To enhance CMF estimation, this study also included roadway-related information for each work zone. This roadway information was collected from Iowa's Roadway Asset Management System (RAMS). The following roadway-level attributes from RAMS were used in the CMF development:

- Annual average daily traffic (AADT): https://gis.iowadot.gov/rams/rest/services/lrs/FeatureServer/102
- Federal functional class: https://gis.iowadot.gov/rams/rest/services/lrs/FeatureServer/95
- Median type: https://gis.iowadot.gov/rams/rest/services/lrs/FeatureServer/34
- Number of lanes: https://gis.iowadot.gov/rams/rest/services/lrs/FeatureServer/97
- Speed limit: https://gis.iowadot.gov/rams/rest/services/lrs/FeatureServer/78
- Type of development: https://gis.iowadot.gov/rams/rest/services/lrs/FeatureServer/84

Data Collection and Processing

Multiple steps were undertaken to prepare the data for subsequent analysis, including collecting work zone information, adding roadway characteristic variables, and merging work zone and crash data. Figure 2 provides an overview of the three data sources and the specific elements that were utilized from the data sources in the creation of the dataset used for the model. The details for each of these steps are provided below.

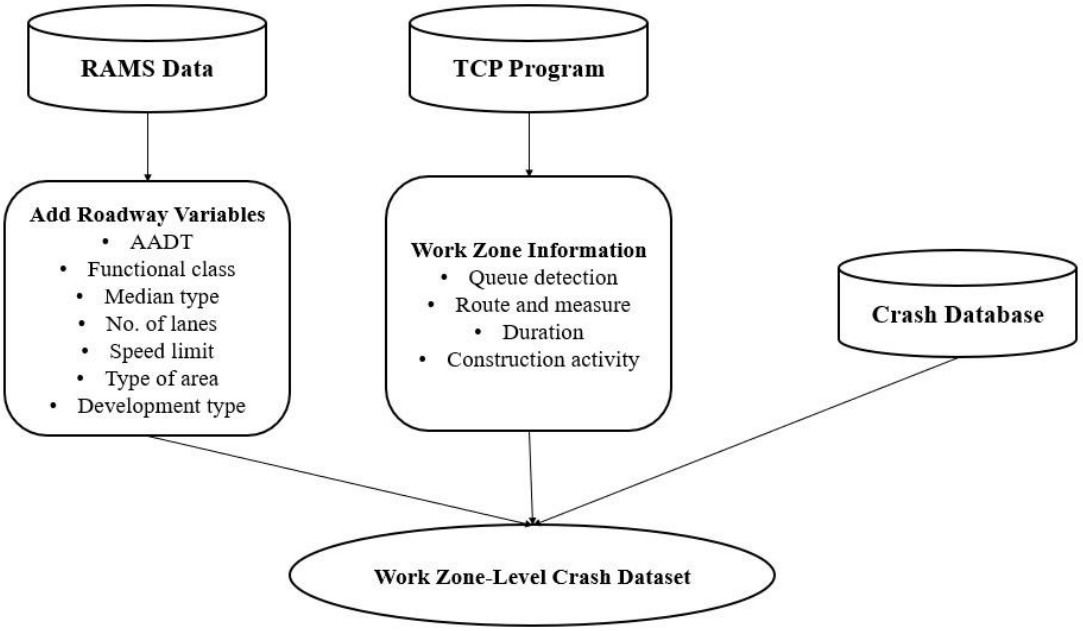


Figure 2. Flowchart of the data accumulation process

Selecting Impact Area

The essential geographic details (e.g., Route ID, Measure) for each work zone were collected by utilizing a combination of the device maps and project lists/maps on the TCP program website. The goal of this effort was to identify the location of each work zone within RAMS, including the Route ID and start/end measures, for easier integration with the other data sources. The work zone data are represented by the line feature class while the device data are provided as point features in the archive maps/lists on the TCP program website. The combination of the two layers was used to identify the start and end location of each work zone, as shown in Figure 3. In the figure, the red line shows the work zone location from the TCP program website, and a layer from RAMS is utilized to identify the Route ID and measure values for the begin and end locations of the work zone. If a work zone was located on a divided roadway, the location information was obtained for both directions of travel (i.e., the starting points circled in yellow in Figure 3).

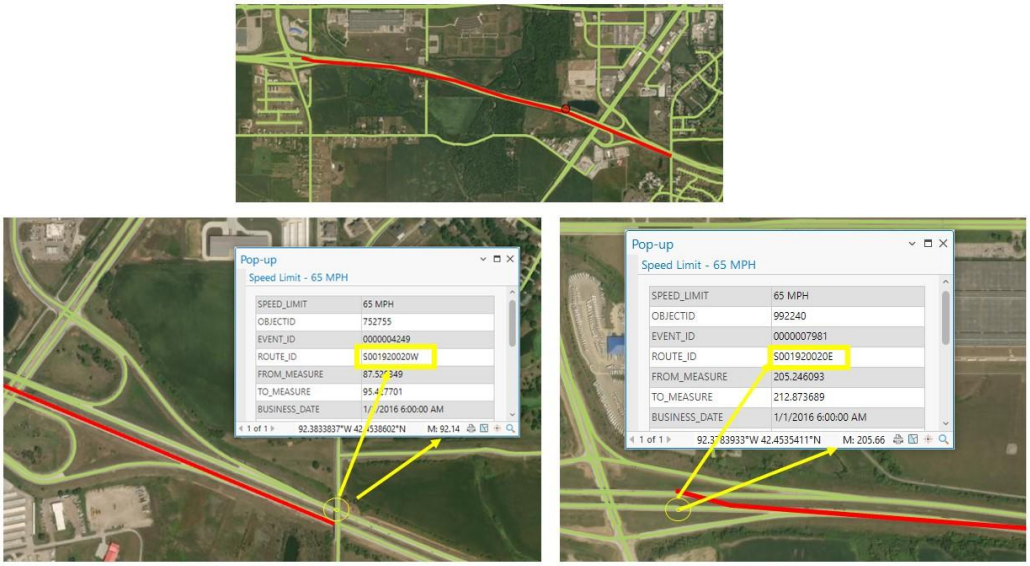


Figure 3. Data collection for work zones without a queue warning system (the red line indicates the work zone area)

Queue warning systems are designed to contribute to work zone safety by helping to prevent rear-end and other types of collisions that may happen when vehicles unexpectedly encounter a queue area or work zone starting area. With this consideration, when identifying the start and end locations of work zones without a queue warning system, the begin and end locations of the work zone layer were used. For work zones with a queue warning system, the data collection differed slightly, in that the start and end locations were recorded based on the locations of the work zones' PDMS in each direction. Figure 4 provides an example where the red line indicates the work zone and the red points indicate the PDMS locations. In the figure, the start of the work zone in the eastbound (EB) direction for the analysis would be located at the PDMS location. This was required because the CMFs were developed in this study based on a comparison of work zones with a queue warning system versus those without a queue warning system.

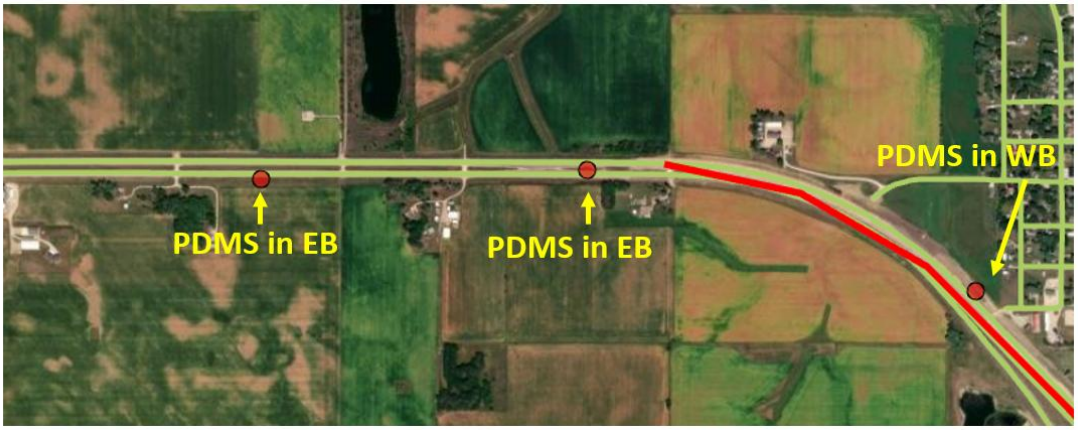


Figure 4. Data collection for work zones with a PDMS showing a queue warning system (the red line indicates the work zone area)

Adding Roadway-Level Attributes

After the Route ID and start/end measures were collected for all work zones, two different pairs of buffer value were used to delineate the work zone impact area (around the starting point/location of the PDMS) for the queue warning system:

- Upstream 1 mi and downstream 0.5 mi
- Upstream 0.5 mi and downstream 0.5 mi

Several work zones had multiple PDMS. For these, multiple segments were selected in a way that the buffer area of one segment did not overlap another segment's buffer area. This was done so that one crash could not be joined with two different segments. To focus the analysis, selected roadway characteristic variables were integrated into the work zone data from RAMS using the geographic information systems (GIS) tool Overlay Route Event. During this process, some work zone impact areas were divided into multiple small roadway segments depending on the segmentation of the RAMS data for each roadway attribute. The weighted average value was then calculated for each variable across these segments, with the rounded average value employed for categorical variables.

Joining with Crash Data

Iowa crash data from 2016 to 2023 were merged with the work zone data by using the Route ID, measures, and crash dates. Any crashes that were located within the work zone extents and that occurred during the work zone's active period were associated with the work zone and retained for analysis in a work zone-level crash dataset. In the dataset, crash frequencies for each work zone are reported for crashes of all severity levels; fatal, major injury, and minor injury (KAB) crashes; and minor injury and property damage-only (CO) crashes. In the final dataset, there were 650 work zone segments.

Table 1 shows the counts of KAB, CO, and total crashes from 2016 through 2023 within a 1 mi upstream and 0.5 mi downstream buffer area. The data for the earlier years (2016 through 2019) are less reliable in terms of the work zone location as well as the less frequent use of queue warning systems. Hence, the joined crash counts are lower for the earlier years

Table 1. Crash counts by year (1 mi upstream and 0.5 mi downstream)

Year	KAB Crash Count	CO Crash Count	Total Crash Count
2016	19	140	159
2017	30	216	246
2018	29	209	238
2019	11	102	113
2020	25	236	261
2021	31	305	336
2022	41	309	350
2023	35	368	403
Total	221	1885	2106

Table 2 shows the crash counts for work zones with and without automated queue warning systems. This table also shows the average durations of work zones with and without queue warning systems.

Table 2. Crash counts for work zones with and without queue warning systems

Has Queue Detection	Count of Work Zones	Sum of KAB Crashes	Sum of CO Crashes	Sum of Total Crashes	Average Time per Work Zone (Days)
No	298	113	841	954	209.43
Yes	352	108	1044	1152	237.46
Total	650	221	1885	2106	224.61

Variables for Modeling

For analysis, several variables were recategorized. The crash counts for different variables are presented in Table 3. In addition to these variables, AADT, work zone segment length, and work zone duration were used in the models as categorical variables.

Table 3. Categorical variable counts

Variable	Count of Segments
Segment with Queue Warning System	352
Segment with No Queue Warning System	298
Number of Lanes -1	5
Number of Lanes - 2	462
Number of Lanes - 3	129
Number of Lanes - 4	28
Number of Lanes -5	4
Number of Lanes - Unknown	22
Speed Limit - Less than or Equal to 45 mph	48
Speed Limit - 65 mph	218
Speed Limit - 70 mph	192
Speed Limit - 50 to 60 mph	170
Speed Limit - Unknown	22
Federal Functional Class - LOCAL	4
Federal Functional Class - MAJOR COLLECTOR	17
Federal Functional Class - MINOR ARTERIAL	32
Federal Functional Class - PRINCIPAL ARTERIAL OTHER	235
Federal Functional Class - INTERSTATE	340
Federal Functional Class - UNKNOWN	22
Median with Barrier	205
Median without Barrier	347
Median Unknown	98
Type of Development - RURAL	312
Type of Development - DENSE	10
Type of Development - Unknown	328
Construction Activity - Bridge Replacement	192
Construction Activity - HMA Related	40
Construction Activity - ITS Equipment	8
Construction Activity - PCC Pavement Related	105
Construction Activity - Barrier Related	4
Construction Activity - Bridge Deck Overlay	47
Construction Activity - Bridge Rehabilitation	14
Construction Activity - Bridge Repair	41
Construction Activity - New Interchange	37
Construction Activity - Other	39
Construction Activity - Other Bridge Work	28
Construction Activity - Other Pavement Work	24
Construction Activity - Pavement Grading	58
Construction Activity - Unknown	13

Limitations of the Data

The preparation of this dataset involved the manual collection of location data related to the work zone areas. There may be discrepancies between the actual field locations of the work zone

impact areas and their mapped representations. This dataset has several limitations in this regard that should be considered when interpreting the results of the analysis:

- Although the work zone location data were collected using a combination of both the work zone lists/maps and the device maps on the TCP program website, the actual start points and PDMS locations in the field could be different. There is typically higher confidence in the locations of the PDMS because that information is collected using a mobile application, whereas the work zone extents are often estimated based on the project plans.
- Some of the work zone areas were long (around 50 to 70 mi). These long work zones were not included in the final analysis. This issue is present mostly in the data from earlier years (2016 through 2019). For long work zones, it is possible that construction occurred at different times on different segments. However, that information was not available, and the selection of work zone crashes by duration and location can be impacted by this.
- For work zones that included an interchange area, connecting ramps were not included in the study unless the map directly specified that the work zone area was on an onramp.
- In the maps/lists of TCP program projects, the values of some of the date variables were written as text (like "ongoing," "early May," "early spring"). In these cases, assumptions were made when the start and end dates were input in the dataset. For work zones with a date value of "ongoing" or with a start date earlier than the project year, the first date (January 1) of the project year was used for the start date and the last date (December 31) was used for the end date. Since some work zone duration information was gathered from the deployed date and harvest date values in the device lists, this could increase the uncertainty of the data.
- Different approaches were used to select the buffer area in work zones with and without queue warning systems. For work zones with a queue warning system, the buffer area was measured upstream and downstream of the PDMS milepost to evaluate the impact of the PDMS. For work zones without a queue warning system, the buffer area was measured around the milepost of the work zone start location. So, if there were multiple PDMS in one work zone, multiple segments were considered for that work zone.

METHODOLOGY

This chapter describes the negative binomial-P (NB-P) and Sichel models, which were considered as the final models for CMF estimation in this study.

NB-P Model

In this analysis, two different models were developed: one accounting for total crashes (KABCO) and the other focusing on fatal, major injury, and minor injury crashes (KAB). The dependent variable in these models is crash count, necessitating the exploration of various count models to best fit the data, as guided by prior literature in safety research. A Poisson distribution is widely used to model count data. However, the assumption of a Poisson distribution, where mean is equal to variance, often cannot be met for crash data due to overdispersion phenomena. For this overdispersion issue, negative binomial models are used in crash prediction models. Negative binomial (NB) distributions such as NB-1 and NB-2, which consider a linear and quadratic relationship, respectively, between mean and variance, are widely used in safety research. Greene (2008) introduced the NB-P model, which does not constrain the mean-variance relationship and thus can handle data with heterogeneity. The probability distribution function (PDF), mean, and variance of NB-P are as follows:

$$f_{NBP}(y|\mu,\alpha,P) = \frac{\Gamma\left(y+\frac{\mu^{2-P}}{\alpha}\right)}{\Gamma\left(\frac{\mu^{2-P}}{\alpha}\right)\Gamma(y+1)}\left(\frac{\mu}{\mu+\frac{\mu^{2-P}}{\alpha}}\right)^{y}\left(\frac{\frac{\mu^{2-P}}{\alpha}}{\frac{\mu^{2-P}}{\alpha}+\mu}\right)^{\frac{\mu^{2-P}}{\alpha}}$$

$$\mu_{NBP} = exp(X \cdot \beta)$$

$$\mathrm{Var}_{NBP}(\mu_{NBP}) = \mu_{NBP} + \alpha\frac{\mu_{NBP}^{2}}{\mu_{NBP}^{2-P}} = = \mu_{NBP} + \alpha \cdot \mu_{NBP}^{P}$$

where μ is the predicted value for the outcome (or mean value), α is the overdispersion parameter, and P is an additional shape parameter. The details of the NB-P models are provided in Greene (2008).

Several studies have used NB-P distribution for developing crash prediction models. A study in Minnesota used NB-1, NB-2, and NB-P models to develop safety performance functions (SPFs) for rural two-lane intersections (Wang et al. 2019), where the NB-P model outperformed the other two NB models in terms of goodness of fit and capturing overdispersion (Wang et al. 2020). In a similar study that developed SPFs for urban intersections, an NB-P model outperformed NB-1 and NB-2 models for signalized intersections, and a generalized Poisson (GP) model outperformed the other NB models for unsignalized intersections (Khattak et al. 2021). In a different study, different functional forms of NB models (NB-1, NB-2, NB-P) and negative binomial Lindley (NBL) models were compared to develop a crash prediction function

for non-federal aid system roads. In this study, the data consisted mostly of low-volume roads with very few crashes, and the NBL models outperformed the NB models (Khodadadi et al. 2021). Another study developed SPFs using different forms of NB models for rural Interstate roads in Wyoming for crashes involving trucks carrying hazardous materials HAZMAT (hazardous materials). The NB-P models outperformed the NB-1 model in terms of a likelihood ratio test and prediction accuracy (Gaweesh et al. 2022).

Sichel Model

The Sichel model is another type of distribution that can handle highly dispersed count datasets. Sichel distribution is a compound Poisson distribution with three parameters (Stein et al. 1987). This distribution is a mixture of Poisson parameters with a generalized inverse gaussian distribution. The PDF of Sichel model is as follows:

$$f(y|\mu,\sigma,\gamma) = \frac{\left(\frac{\mu}{c}\right)^{y} K_{y+\gamma}(\alpha)}{K_{\gamma}(1/\sigma)y!\,(\alpha\sigma)^{y+\gamma}}$$

where σ and γ are distribution parameters with $-\infty < \gamma < \infty$ and $\sigma > 0$.

$c = \frac{K_{\gamma+1}(1/\sigma)}{K_{\gamma}(1/\sigma)}$, $\alpha^2 = \sigma^{-2} + 2\mu(c\sigma)^{-1}$ is a mean value of μ, γ is a non-negative integer, and $K_j(x)$ is a modified Bessel function of the third kind with order *j* and argument *x*.

The variance of the distribution is as follows:

$$V[y] = \mu + \left(\frac{2\sigma(\gamma+1)}{c} + \frac{1}{c^2} - 1\right)\mu^2$$

The details of the Sichel distribution can be found in Stein et al. (1987) and Rigby et al. (2008). The Sichel model is not widely used for crash predictions, but several studies have used Sichel models in safety research. In one study, a negative binomial and a Sichel model were compared for empirical Bayes-based hotspot identification by using simulated crash count data. The study suggested that a Sichel model-based empirical Bayes method provided a more consistent result than NB-based empirical Bayes methods (Wu et al. 2014). In a similar study, a Sichel model was used along with NB models to calculate empirical Bayes estimates. In that study, the NB model and the Sichel model identified different sets of crash hotspots (Zou et al. 2013). In a different study predicting intersection crashes in Texas, Sichel models performed better than NB models (Zou et al. 2004).

Model Selection Criteria

To select the models developed in this study, log-likelihood values and cumulative residual (CURE) plots were used. The log-likelihood function is used to measure the goodness of fit of a statistical model fitted to sample data. It is the natural logarithm of the likelihood function, which represents the probability of the observed data given the model parameters. A higher log-likelihood value indicates a better fit of the model to the sample data. Cumulative residual plots are graphical tools used to assess the goodness of fit of count models and are widely used for comparison of SPFs. These plots display the cumulative sum of residuals, which are the differences between the observed and predicted values, against a set of predictors. In general, a CURE plot is considered to show good fit if the residuals oscillate around 0 randomly. If some parts of the CURE plot are outside of the 95% confidence interval, those parts should be counted as outliers (Hauer 2004).

RESULTS AND DISCUSSION

To develop CMFs for work zones with a queue warning system, several count regression models were built, and the final models were selected based on the variables' statistical significance, CURE plots, and the values of log-likelihood, R^2, Akaike information criterion (AIC), and Bayesian information criterion (BIC). These final models integrate a range of predictor variables—encompassing work zone characteristics—while balancing the inclusion of independent variables that were not statistically significant (to reduce omitted variable bias) with model parsimony. Most variables included in the final models demonstrated statistical significance. Tables A1 and A2 in the appendix summarize the model outcomes for each buffer dataset, highlighting the statistical significance of each coefficient. In each buffer dataset, one model is implemented for total crashes (KABCO), while the other one is implemented for crashes with fatalities, major injuries, and minor injuries (KAB).

Variables such as roadway class, number of lanes, median type, speed limit, and construction activity showed strong correlations with the frequency of work zone-related crashes. This suggests their potential significance in influencing crash occurrence in work zone areas. The positive or negative correlations indicated by these variables' coefficients emphasize their importance in the models, helping to reduce biases associated with variable omission and endogeneity.

The final model estimations were utilized to compute the CMFs for work zones with a queue warning system, as presented in Table 4.

Table 4. Summary of estimated coefficients and CMFs with 95% confidence interval for work zones with a queue warning system

Dataset	Total Crashes		KAB Crashes	
	Est. Coefficient	**CMF**	**Est. Coefficient**	**CMF**
Upstream 1 mi and downstream 0.5 mi	-0.032 [-0.13, 0.066]	0.969 [0.878, 1.068]	-0.384 [-0.611, -0.157]	0.681 [0.543, 0.855]
Upstream 0.5 mi and downstream 0.5 mi	-0.021 [-0.118, 0.097]	0.979 [0.889, 1.101]	-0.266 [-0.111, -0.421]	0.766 [0.656, 0.895]

The developed CMFs indicate that the presence of a queue warning system leads to a slight decrease in overall crashes while significantly reducing the incidence of work zone-related KAB crashes. Additionally, the estimated impact of a queue warning system varies across the two different buffers and the two different crash categories. For a work zone impact area extending 1 mi upstream and 0.5 mi downstream, a queue warning system reduces total crashes by 3.1% and KAB crashes by 31.9%. Narrowing the work zone impact area to 0.5 mi upstream and 0.5 mi downstream results in a 2.1% decrease in total crashes and a 23.4% reduction in KAB crashes. A queue warning system demonstrates a higher effectiveness in preventing KAB crashes compared to all crashes for both of the buffer areas. This crash reduction is higher with a 1 mi upstream and 0.5 mi downstream buffer area, indicating that the queue warning system has an impact on vehicles up to 1 mi upstream of the work zone start location. It is also noteworthy that for total

crashes, the estimated coefficient of a queue warning system is not statistically significant for either buffer area, while for KAB crashes the estimated coefficient is statistically significant for both buffer areas. This difference may be attributed to the reduction in vehicle speed resulting from the queue warning system, which could directly impact crash severity.

The CURE plots show that the cumulative residuals are randomly dispersed within the boundary area, which verifies the effectiveness of the models for each buffer area. The CURE plots are included in the appendix along with model results.

CONNECTED VEHICLE DATA

To explore the real-world scenario of vehicle speeds in work zones, connected vehicle data from Wejo were utilized. Wejo provides real-time vehicle movement data with a 3-second resolution. To explore the Wejo data, four work zone segments with PDMS (labeled 1CR, 4CH, 5AN, 6AB) were selected from the TCP program data. For each work zone, several filters were applied before plotting the speed profile:

- In the Wejo data, each journey is identified by a Journey ID. Journey IDs having four or fewer data points were filtered out.
- Journeys that occurred between 6 a.m. and 7 p.m. were considered in the study.
- The Wejo data provide the direction of vehicular movement in a "heading" value. For example, eastbound roads have a heading of around 90, and westbound roads have a heading of around 270. Heading values that did not align with the Route ID direction were filtered out.
- Journey IDs having excessively long travel times were filtered out.
- Data points having speeds below 25 mph and above 120 mph were filtered out.

These filters were applied by following a prior study where the impact of automated work zone speed enforcement was explored using connected vehicle data (Mathew et al. 2022). For all of the work zones in this exploration, a 2 to 4 mi buffer was taken upstream and downstream from the PDMS to capture the speed differences efficiently.

Speed Profiles

After the connected vehicle data were filtered, the 85th percentile speed and mean speed were plotted along each of the work zone routes. Additionally, the speeds for the same routes during periods when the work zones were not in effect were plotted.

1CR Work Zone

The speed profiles for the 1CR work zone are illustrated in Figure 5. The data collected from May 2 to May 5, 2022, represent the period before the work zone, while the data from September 19 to September 23, 2022, correspond to the work zone period. The speed profiles indicate that vehicle speeds during these two periods do not differ significantly. Comparing the specific points of speed reduction in the profiles with the features of the route in the TCP program map, the first notable decrease occurs near an interchange area, and the second is potentially associated with bridge construction. Despite observing reduced speeds in the work zone, the overall speed profile slightly resembles that of the period before the work zone, possibly due to inaccuracies in the reported duration of the work zone or due to a certain type of construction activity.

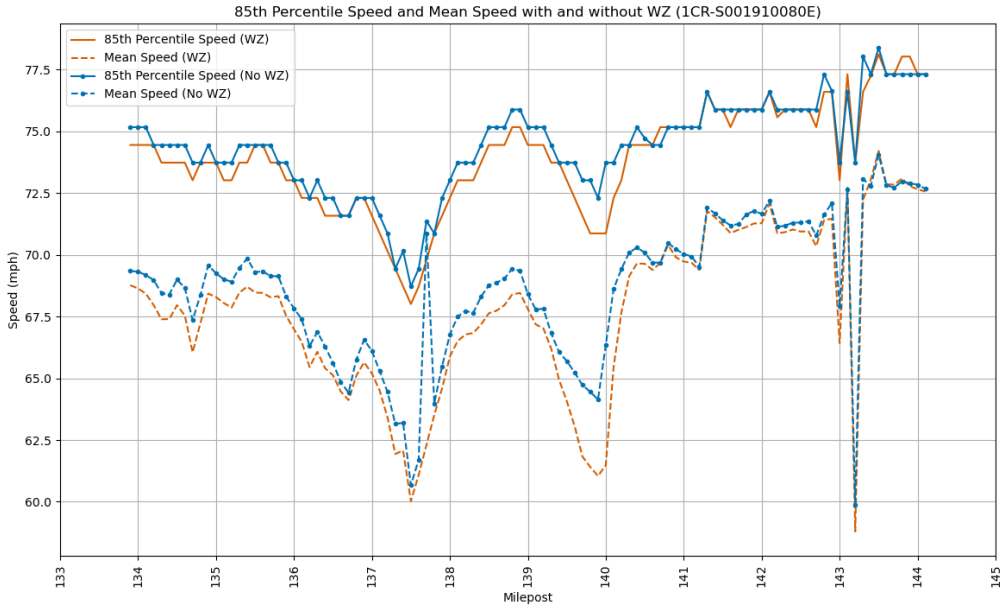


Figure 5. Speed profiles for 1CR work zone

4CH Work Zone

For the 4CH work zone, the data collected from April 4 to April 8, 2022, represent the period before the work zone, whereas the data from April 25 to April 29, 2022, correspond to the work zone period. Figures 6 and 7 depict speed profiles that indicate an obvious speed reduction (approximately 20 mph in both directions) due to ongoing bridge construction work.

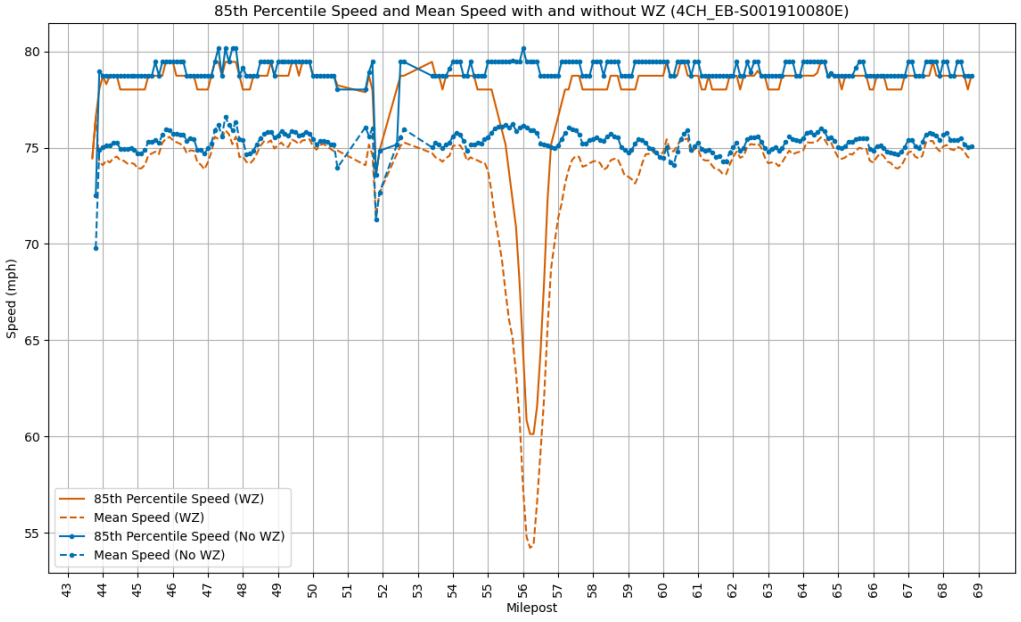


Figure 6. Speed profiles for 4CH eastbound work zone

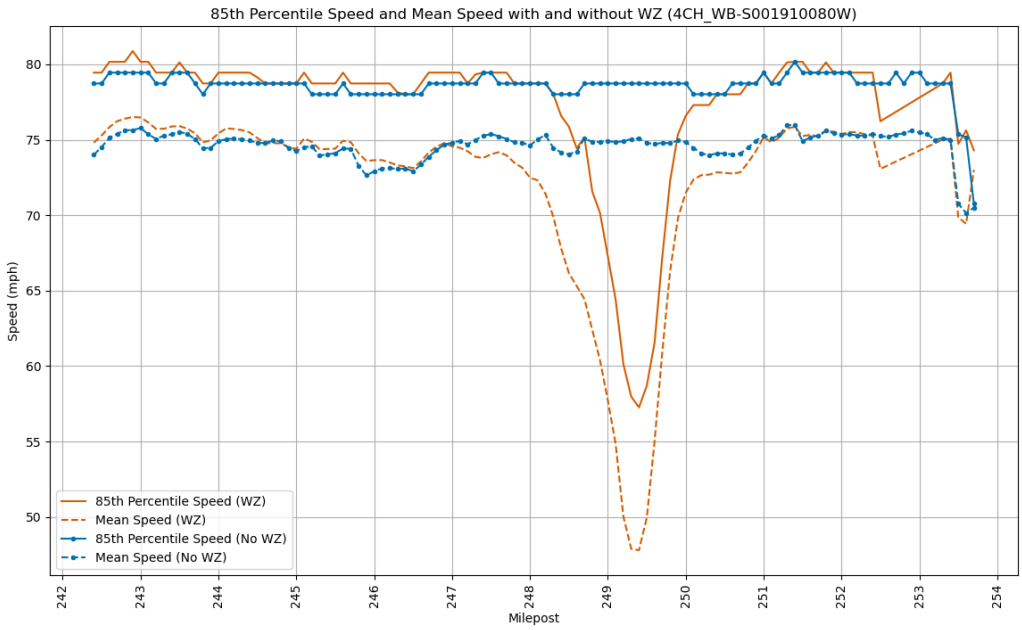


Figure 7. Speed profiles for 4CH westbound work zone

5AN Work Zone

For the 5AN work zone, data collected from April 1 to April 5, 2022, represent the period before the work zone, whereas data from April 25 to April 29, 2022, correspond to the work zone period. According to the speed profiles shown in Figure 8, there is a noticeable speed reduction (approximately 5 to 10 mph) as vehicles enter the work zone area. The first significant decrease in speed in the profiles is attributed to the connecting roadway, which is located some distance from the actual work zone.

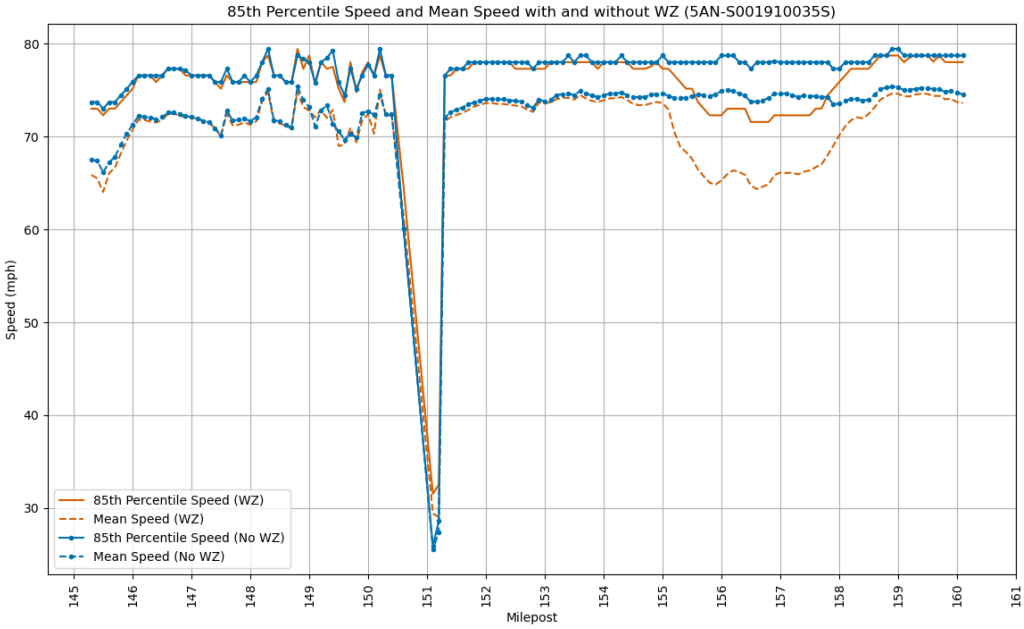


Figure 8. Speed profiles for 5AN work zone

6AB Work Zone

The speed profiles for the 6AB work zone are shown in Figure 9. The data from March 7 to March 11, 2022, represent the period before the work zone, and the data from March 21 to March 25, 2022, represent the work zone period. The profiles indicate a vehicle speed decrease (about 20 mph) within the work zone area.

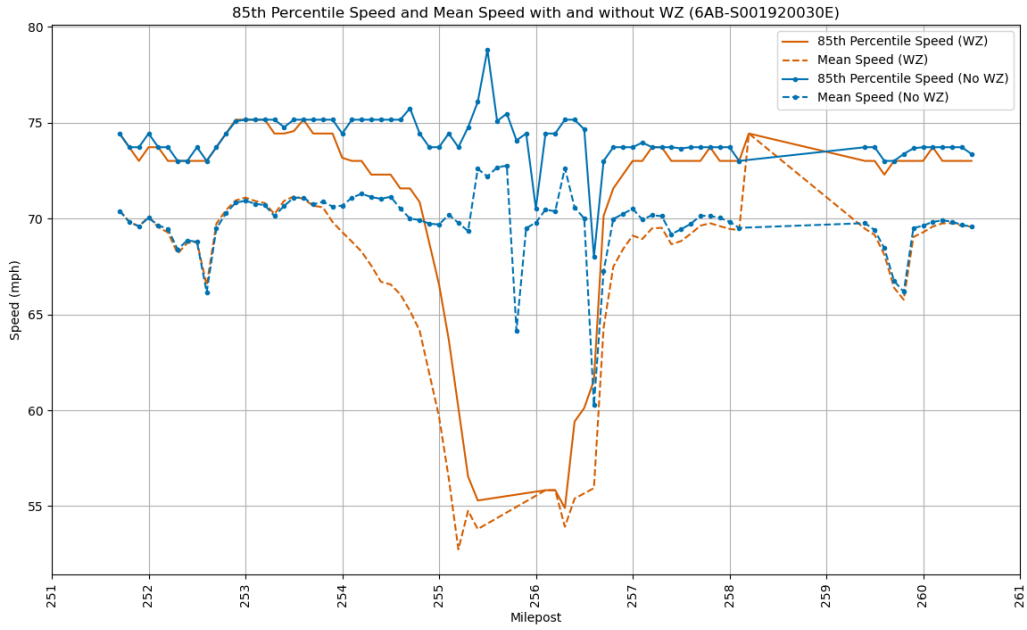


Figure 9. Speed profiles for 6AB work zone

Summary

Analysis of the connected vehicle speed profiles across these four work zones revealed consistent patterns of speed reduction during most work zone periods compared to the periods before the work zones. Instances where the speed profiles fail to capture significant speed decreases within a work zone area could be due to inaccuracies in the reported work zone duration or due to a certain type of construction activity. These findings emphasize the critical need for precise data collection and interpretation to effectively manage traffic and enhance road safety in work zones.

CONCLUSION

The objective of this study was to develop CMFs for Iowa work zones with automated queue warning systems. Work zones with and without automated queue warning systems were considered to estimate the CMFs. The analysis incorporated two distinct buffer areas around the PDMS milepost or work zone start milepost: a 1 mi upstream and 0.5 mi downstream buffer, and a 0.5 mi upstream and 0.5 mi downstream buffer. The NB-P and Sichel models used in this study were carefully selected based on their ability to handle overdispersed count data and were validated through their log-likelihood values and CURE plots.

The results indicate that an automated queue warning system does not impact total crashes significantly, with CMF values for total crashes around 0.96 to 0.97 for both buffer distances. An automated queue warning system was observed to be significantly effective for KAB crashes, with CMF values of 0.681 and 0.766 for the 1 mi to 0.5 mi and 0.5 mi to 0.5 mi buffer areas, respectively. Notably, the impact is more pronounced within the 1 mi upstream and 0.5 mi downstream buffer, suggesting that the queue warning system has a substantial influence up to 1 mi upstream of the work zone. The difference in CMF values for total and KAB crashes could be due to the presence of the queue warning system, which decreased vehicle speeds and thus minimized the severity of crashes.

Despite the promising results, the study acknowledges several limitations, including potential discrepancies in the work zone location and duration data. Future research should aim to address these limitations by incorporating more precise data into the TCP program.

In conclusion, the implementation of queue warning systems in work zones presents a viable strategy for mitigating crashes and enhancing road safety. The CMFs developed in this study provide robust estimates of the safety benefits of queue warning systems, showing a reduction in total crashes by up to 3.1% and KAB crashes by up to 31.9%.

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APPENDIX. MODEL RESULTS

1 mi Upstream and 0.5 mi Downstream Area

Table A1. Model estimation for 1 mi upstream and 0.5 mi downstream

Variables	Categories	Total Crash Model Estimates	KAB Crash Model Estimates
Intercept		-8.61*	-7.127*
log(AADT)		0.86 *	0.487*
log(work zone length)		1.324 *	0.915*
Work Zone Duration (days)		0.005*	0.005*
With Queue Detection		-0.032	-0.384 *
Number of Lanes	1	1.196*	1.453
	3	0.477*	0.541*
	4	0.565*	0.398
	5	1.312*	1.254*
Speed Limit	70 mph	-0.885*	-0.558*
	65 mph	-1.165*	-0.551*
	50~60 mph	-0.725*	-0.474*
Functional Class	Local	0.606	---
	Major Collector	1.44*	0.378
	Minor Arterial	0.654*	0.462
	Principal Arterial	0.383*	---
Median Type	With Barrier	-0.079	0.107
Development Type	Rural	-0.14*	---
Construction Activity	HMA Related	0.141	---
	PCC Pavement Related	-0.17	-0.469
	Barrier Related	-0.983*	-1.146
	Bridge Rehabilitation	0.619*	-0.602
	Bridge Repair	-0.173	0.217
	New Interchange	-0.2	0.456
	Other	-0.3	-1.117
	Other Bridge Work	-0.527*	0.34
	Pavement Grading	---	0.314
Ln(alpha)		-0.036	---
P		1.608*	---
Ln(sigma)		---	0
Gamma		---	1
Num. of Obs.		615	615
Log-Likelihood		-1191.02	-399.848
AIC		2438.039	849.696
BIC		2561.845	960.236
Pseudo R^2		0.456	0.177

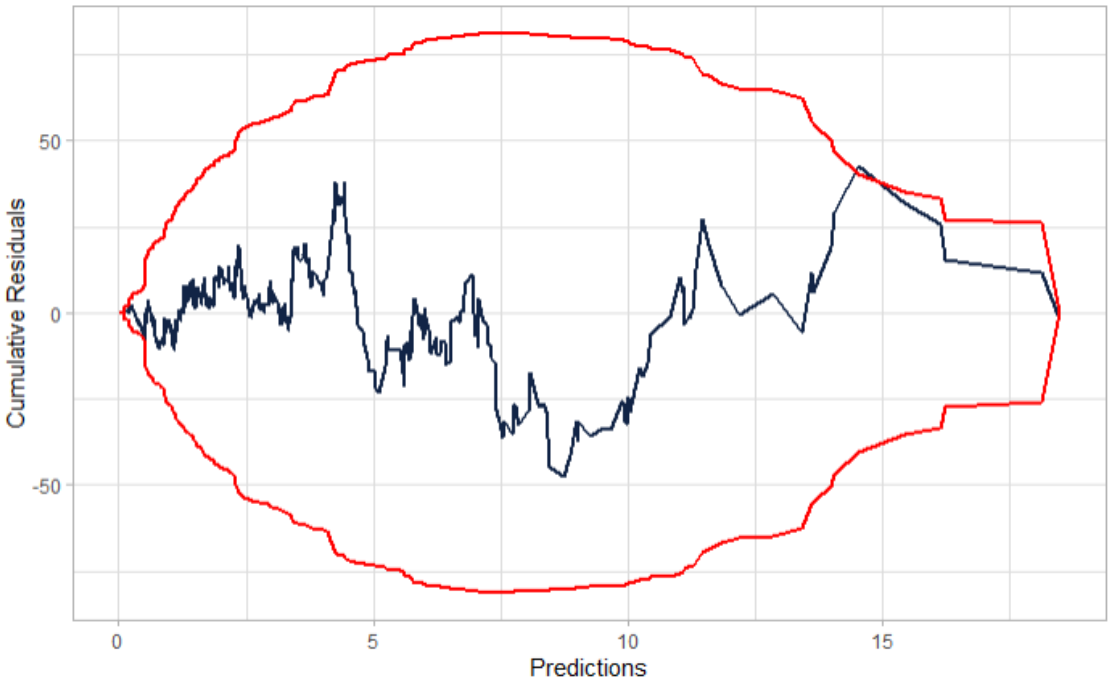

Figure A1. CURE plot total crash (1 mi–0.5 mi)

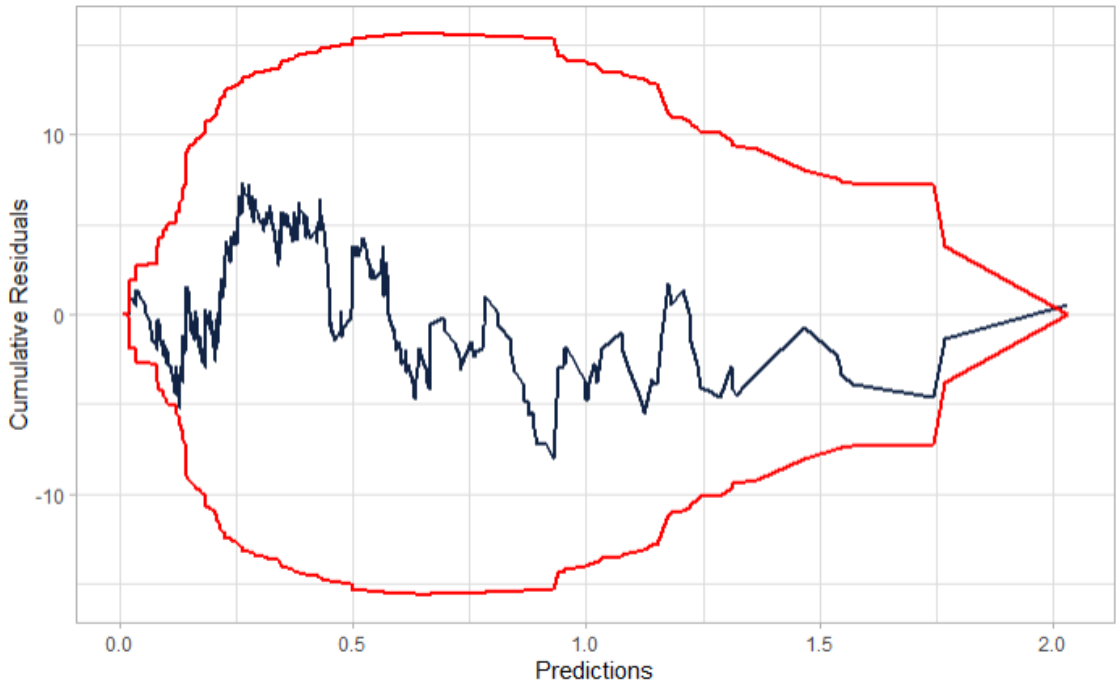

Figure A2. CURE plot KAB crash (1 mi–0.5 mi)

0.5 mi Upstream and 0.5 mi Downstream Area

Table A2. Model estimation for 0.5 mi upstream and 0.5 mi downstream

Variables	Categories	Total Crash Model Estimates	KAB Crash Model Estimates
Intercept		-7.559*	-5.684*
log(AADT)		0.79 *	0.362*
log(work zone length)		1.419*	0.843*
Work Zone Duration (days)		0.005*	0.005*
With Queue Detection		-0.021	-0.266*
Number of Lanes	1	0.994	1.215*
	3	0.36*	0.093*
	4	---	0.128
	5	0.858*	0.733
Speed Limit	70 mph	-1.088*	-0.853*
	65 mph	-1.146*	-0.568*
	50~60 mph	-0.782*	-0.584*
Functional Class	Local	1.31*	-0.252
	Major Collector	1.201*	0.255
	Minor Arterial	0.138	-0.154
	Principal Arterial	0.208*	-0.292*
Median Type	With Barrier	0.023	0.422*
Development Type	Rural	-0.189*	0.08*
Construction Activity	HMA Related	0.182	-0.21
	PCC Pavement Related	-0.08 (0.123)	-0.374*
	Barrier Related	-0.848	-31.478*
	Bridge Deck Overlay	---	-0.211
	Bridge Rehabilitation	0.38	-0.413
	Bridge Repair		0.426
	New Interchange	-0.286	0.344
	Other	-0.452	-1.569*
	Other Bridge Work	-0.423	0.304
	Other Pavement Work	---	0.184
	Pavement Grading	-0.17	0.235
Ln(alpha)		-0.036	-0.601
P		1.608*	2.287*
Ln(sigma)		0	---
Gamma		1*	---
Num. of Obs.		635	635
Log-Likelihood		-1105.681	-352.65
AIC		2265.362	767.299
BIC		2385.61	905.361
Pseudo R^2		0.41	0.158

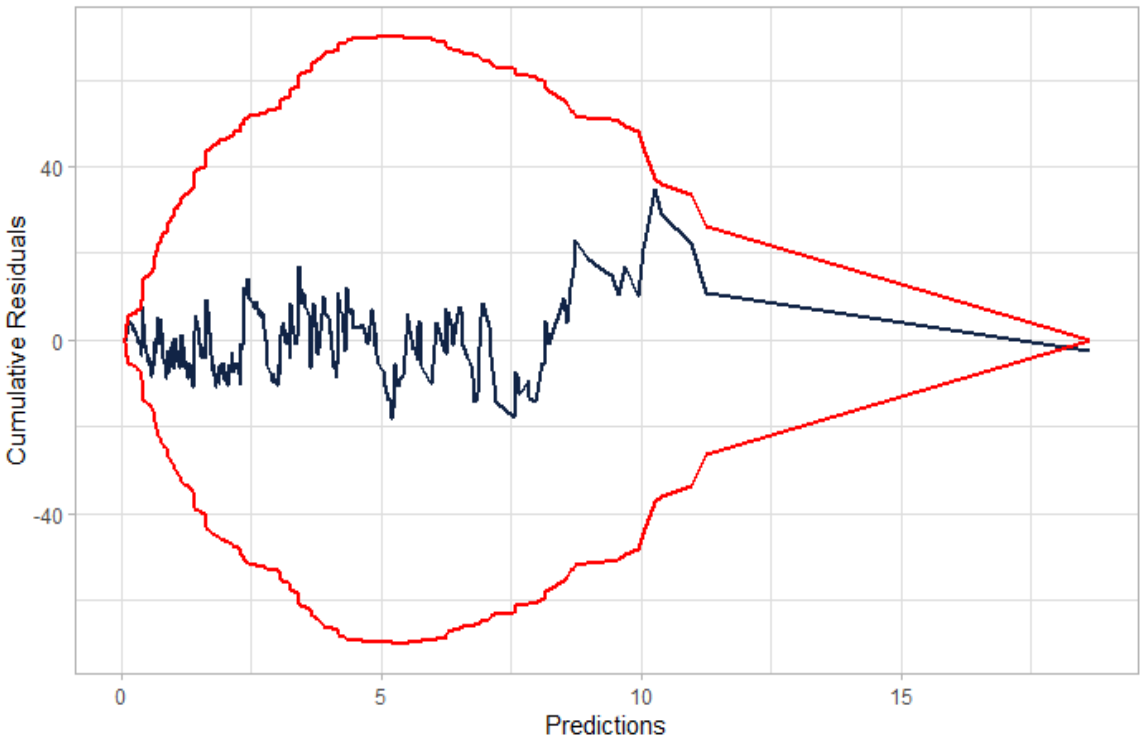

Figure A3. CURE plot total crash (0.5 mi–0.5 mi)

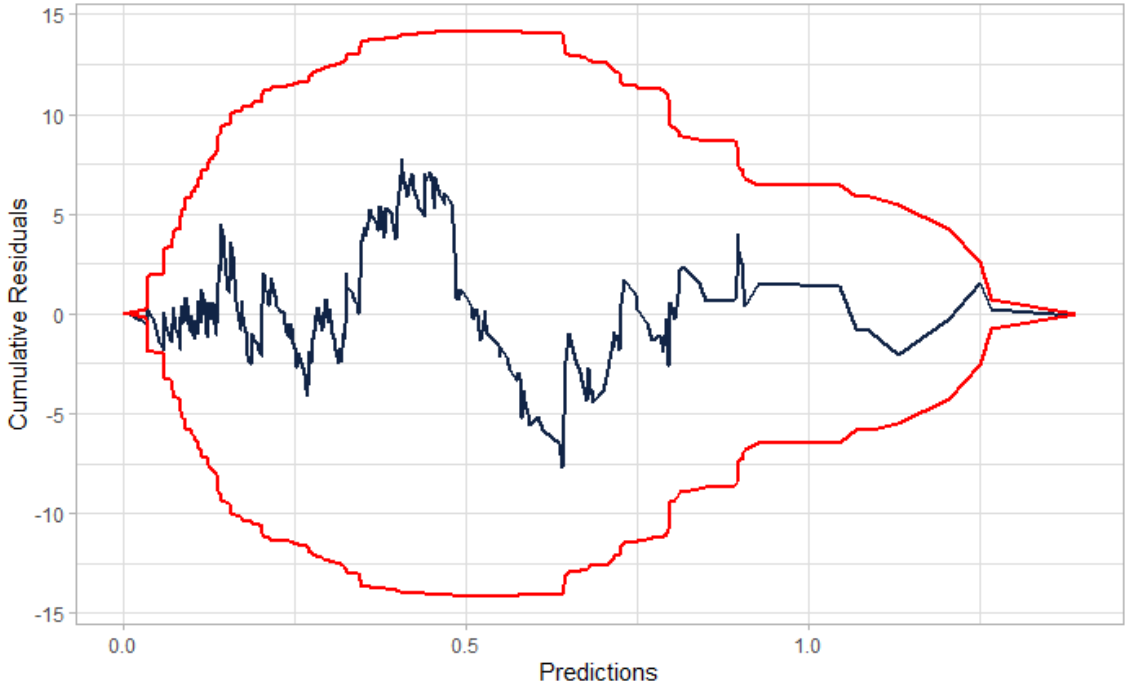

Figure A4. CURE plot KAB crash (0.5 mi–0.5 mi)

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