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16. ABSTRACT

This report evaluates the performance of Continuous Risk Profile (CRP) compared with the Sliding Window Method (SWM) and Peak Searching (PS) methods. These three network screening methods all require the same inputs: traffic collision data and Safety Performance Functions (SPFs), however, depending on how these input parameters are analyzed at the network screening level, the result of the analysis can vary significantly. Findings indicated that the CRP method produced far fewer false positives than SWM and PS. The false negative rates for CRP, SWM and PS were comparable. These findings indicate that by using the CRP method, California Department of Transportation (Caltrans) can significantly reduce the resources spent on investigating falsely identified locations and better utilize the resources in improving high collision concentration locations. It will also help Caltrans in reducing the backlog in Caltrans Table C.

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Experimental Evaluation of the Continuous Risk Profile (CRP) Approach to the Current Caltrans Methodology for High Collision Concentration Location Identification

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Final Report

California Department of Transportation
Division of Research and Innovation

March 31, 2012

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Final Report

UC Berkeley Report Number: UCB-0373

Prepared by the

UC Berkeley Institute of Transportation Studies

for the

California Department of Transportation

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Offer Grembek, PhD
Kwangho Kim, PhD
Oh Hoon Kwon
Jinwoo Lee
Haotian Liu
Min Ju Park
David Ragland, MPH, PhD
Simon Washington, PhD
Samer M. Madanat, PhD

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DISCLAIMER STATEMENT

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EXECUTIVE SUMMARY

An experimental evaluation was conducted to compare how three different network screening methods perform with respect to high collision concentration location identification (i.e., hotspot identification). The study evaluates the performance of the Continuous Risk Profile (CRP) compared to the Sliding Window Method (SWM) and Peak Searching (PS) network screening methods. Three main research efforts were carried out: (i) comparing the performance using empirical data; (ii) comparing the performance using simulated data; (iii) developing a web-based tool for safety engineers.

The three network screening methods require the same inputs: traffic collision data and Safety Performance Functions (SPFs). Extensive empirical data was collected for this purpose, including traffic collision data, traffic volume data, and several other types of data about road characteristics. In addition to the Caltrans SPF, an alternative definition of SPF was used to evaluate the changes in the performance of SWM, PS, and CRP methods with respect to different segment lengths. The main difference between the three methods is the technique used to segment sites. Therefore, after the endpoints are determined in each method, the same guidelines are applied to prioritize detected sites for safety investigation according to their Potential Safety Improvement (PSI). The detected sites for each method are compared with the true hotspot for the study section. The empirical comparisons were conducted for 10 different routes spanning 473 miles across 8 different districts. The simulation analysis was conducted along a representative California route with simulated true hotspots.

In a parallel effort, the California Safety Analyst (CASA) was developed as a web-based tool for safety engineers. CASA can be used to perform network screening using all three methods. At the core of the system is an innovative user interface which allows the user to select the relevant route on a map and perform the analysis to identify hotspots on the whole route or on selected sections of it. CASA includes all the data necessary for safety engineers to manage road safety in their jurisdictions.

A survey of 98 Caltrans professionals who are involved in road safety management in 10 different districts was conducted to obtain practical feedback about the features and usability of the application. An operational application was presented in a webinar to demonstrate how CASA can be used to assist Caltrans's mission to improve the safety of the road system.

The main findings of this evaluation are:

1. Careful examination of the performance of the three methods produced comparable levels of false negatives (i.e., not identifying true high collision concentration locations). However, the CRP method produced far fewer false positives (i.e., identifying a site as a hot-spot when it is not) than SWM and PS.

2. The CRP method is able to accurately track the collision profile of simulated crashes along a representative California highway.

3. The results of the CASA survey revealed that the users agree that using the CASA web-based tool will enhance their productivity in performing their Caltrans duties and agree that implementation of CASA should be a high priority for Caltrans.

These findings indicate that by using the CRP method, Caltrans can significantly reduce the resources spent on investigating falsely identified locations and better utilize the resources in improving true high collision concentration locations. It will also help Caltrans in reducing the backlog in Caltrans Table C.

1 INTRODUCTION

The California Department of Transportation (Caltrans) has been continuously monitoring the traffic collisions on state highways in an effort to identify High collision concentration location (HCCL) that might require further safety improvements. Caltrans' existing HCCL monitoring procedure can be qualitatively explained with the aid of Figure 1. Each of the steps is further explained in detail later in the section.

Numerous sites have been identified and improved using the Sliding Window Method (SWM) approach [1]. However, a recent survey among Caltrans safety investigators revealed that the performance measures used by the SWM produce a high rate of false positive locations (i.e., sites identified for in-depth safety investigation when it is not needed). This unnecessarily increases the total number of sites to be investigated. Moreover, researchers have emphasized the need for more research about screening methods to monitor traffic collisions [18].

Recognizing the need to optimize the allocation of available resources, Caltrans called for an experimental evaluation of the ability of the Continuous Risk Profile (CRP) [2,3] to: (i) identify HCCL consistent with the current standard; and (ii) significantly reduce the number of false positive results produced by the current standard.

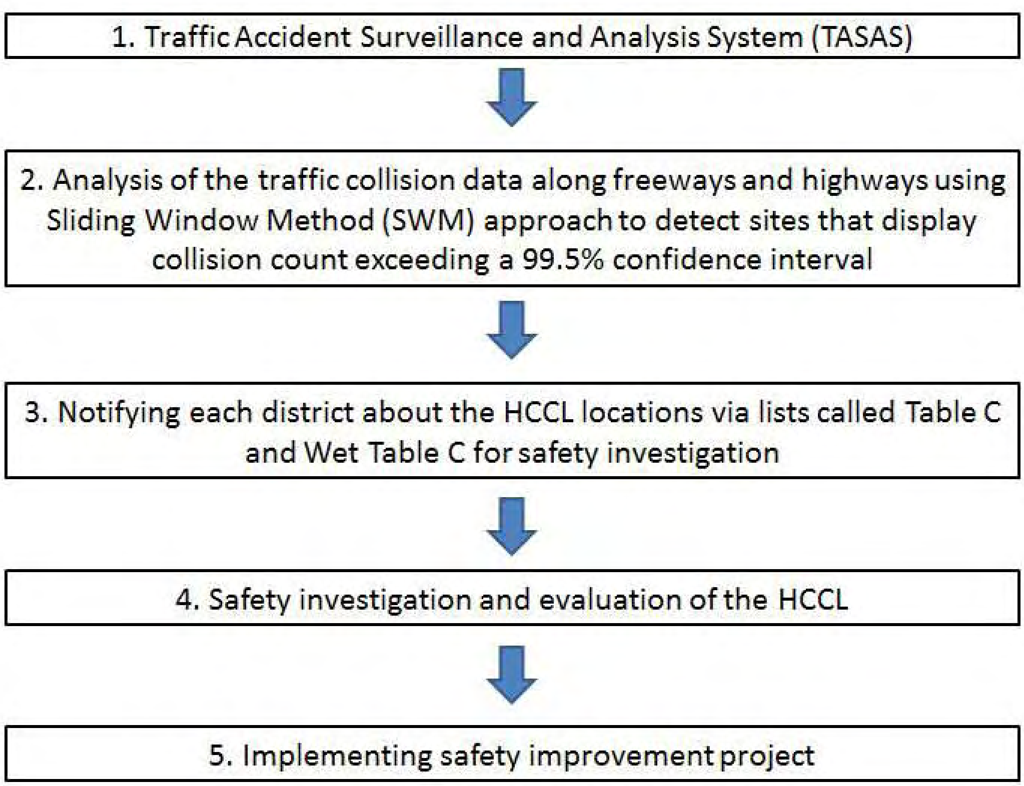


Figure 1: Caltrans' existing hot-spot monitoring procedure

1.1. TRAFFIC ACCIDENT SURVEILLANCE AND ANALYSIS SYSTEM (TASAS)

Figure 2 describes the collision report flow chart. When traffic collisions occur, the information related to the collision is first reported by the California Highway Patrol (CHP) officer in the form of a Traffic Collision Report (TCR). The CHP production controls unit then sends the TCR to the Caltrans Traffic operations coding unit which codes the location of the collision. The TCR is then sent to the CHP coding unit to code all the relevant attributes of the collision, and parties involved into the CHP Statewide Integrated Traffic Records System (SWITRS). The highway collisions from SWITRS are imported into the Caltrans Traffic Accident Surveillance and Analysis System (TASAS), where additional corrections may be applied. The data is then stored by the Caltrans TASAS unit.

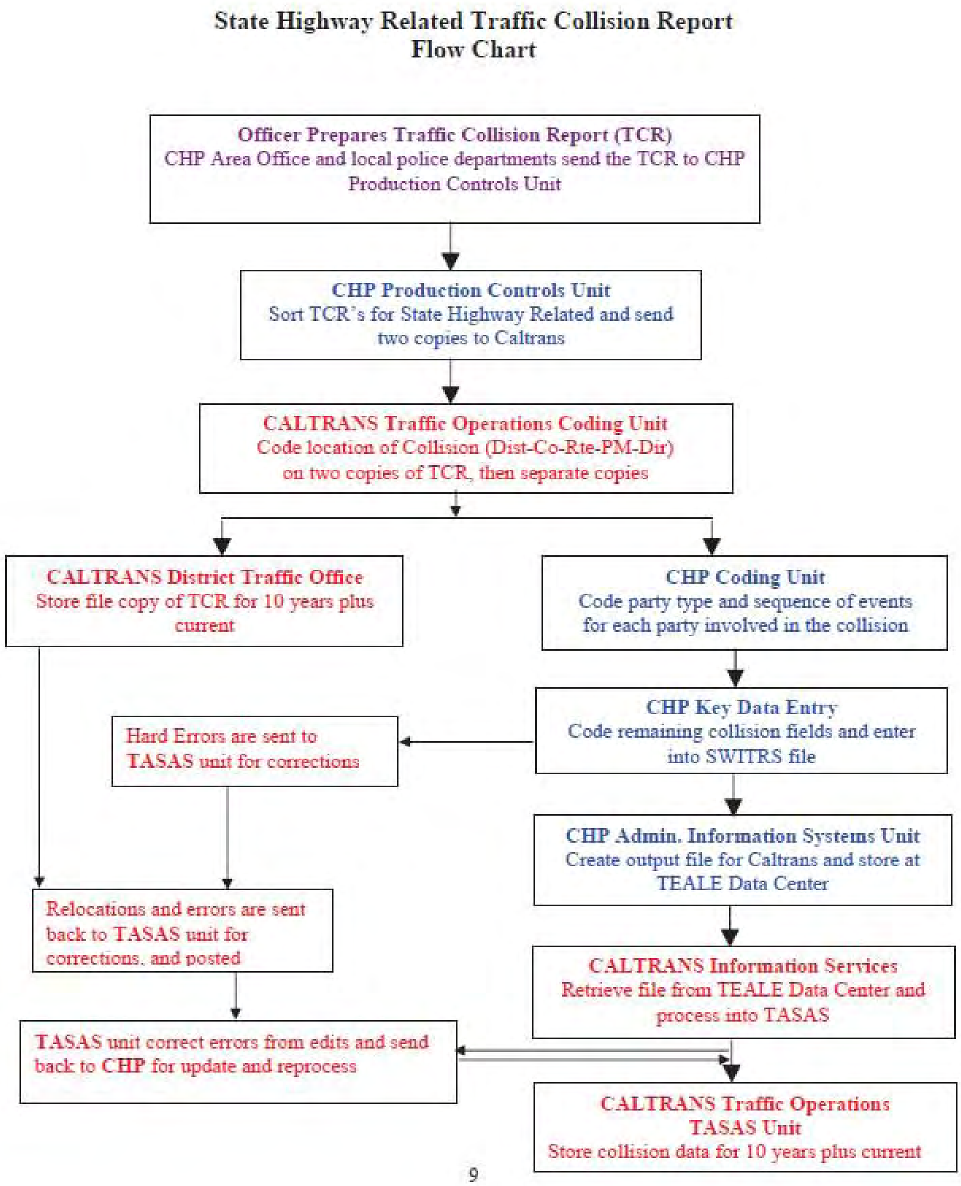


Figure 2: Collision Report Flow Chart (Source: Caltrans TASAS Intranet)

1.2. EXISTING CALTRANS PROCEDURE FOR DETECTING HIGH COLLISION CONCENTRATION LOCATIONS

Caltrans current hot-spot identification procedure can be explained with the aid of Figure 3. The analysis starts by comparing the observed collision rate within a window of 0.2 mile with a predetermined threshold value obtained from a Safety Performance Function (SPF, a mathematical relationship observed between the collision count and explanatory variable). More detailed description of SPF will be provided in section 2.

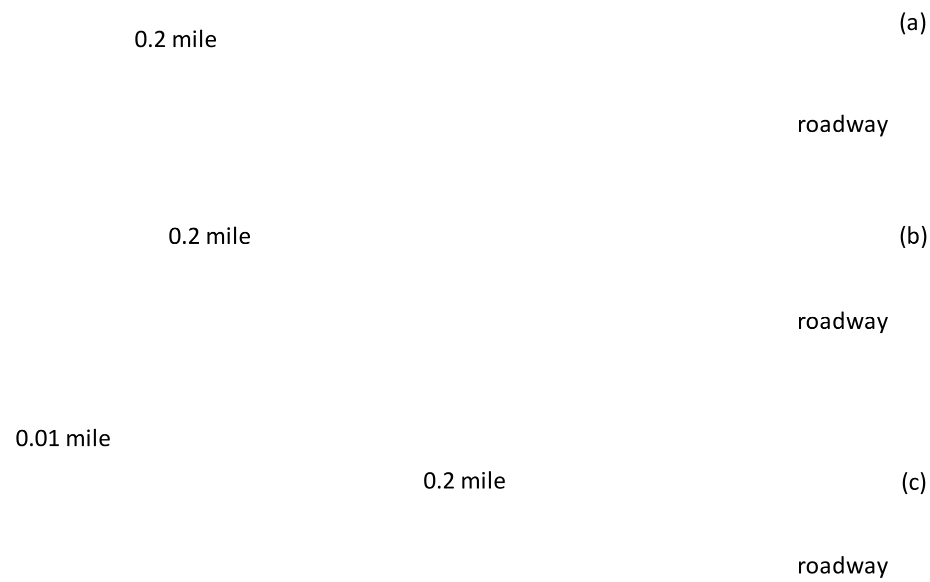


Figure 3: Existing network screening procedure

When the observed collision count exceeds the threshold, the site is flagged for safety investigation. If the observed collision count does not exceed the threshold, the procedure slides the window by an increment of 0.01 miles and repeats the procedure. Sites identified in this manner are then included in a list called Table C (Figure 4) and sent to each of 12 districts on a quarterly basis. Wet Table C, which contains list of HCCL's detected based on wet pavement conditions, are generated once a year.

Additional steps include not reporting repeat locations (i.e., exact sites identified in any of the previous three quarters), and combining sites that are adjacent to each other.

* * * S A M P L E * * *

TASAS TABLE C POTENTIAL INVESTIGATION LOCATIONS .2 MILE AXR254-A 04-08-97
DISTRICT 04 DATA FOR 94-01-01 THRU 96-12-31
ALL ACCIDENTS
CONFIDENCE LEVEL 99.5 PERCENT

LOCATION	DESCRIPTION	SCL RMP LNS	R U S	RATE GRP	TOTAL ACCIDENTS 36MO ACCS	24MO ACCS	12MO ACCS	6MO ACCS	3MO ACCS	AVE ADT 1000 MAIN	VEH X-ST	12 MOS RATE ACTUAL F+I	TOT	ACCS/MV-MVM AVERAGE F+I	TOT	INV REQ
037 SOL	8.445 SACRAMENTO ST	XXX	S	I24	29 Y	19 Y	8 N	4 N	0 N	27.9	4.0	0.00	0.69	0.18	0.39	+
037 SOL	9.287 TO 9.487 EAST	02D	U	H14	17 Y	11 Y	5 N	3 N	1 N	14.6	-	0.94	4.68	0.78	2.00	
037 SOL	9.844 BROADWAY	XXX	U	I14	64 Y	41 Y	22 Y	16 Y	10 Y	45.0	8.9	0.37	1.12	0.20	0.45	+REQ
037 SOL	R 11.147 TO R 11.347 EAST	03D	U	H64	15Y	12 Y	4 N	2 N	1 N	37.0	-	0.00	1.48	0.28	0.81	

Figure 4: Table C sample

HCCL's identified using the procedure explained here result in a high false positive rate (i.e., investigations that result in a recommendation of "No Action"). A Task force was convened by Caltrans to identify steps that need to be taken to improve the detection rate [17]. Table 1 shows the false positive rate reported. Note that in a survey conducted under this task force, more than 50% of Caltrans engineers agreed that they frequently investigate required locations that result in no action due to peak hour congestion related collisions.

Table 1: Table C - Proposed Improvement Locations (1/1/98 – 6/13/01)

	District Table C's				PERCENTAGES OF IMPROVEMENTS	
District	All	All IMPROVEMENT RECOMMENDED	WET	WET IMPROVEMENT RECOMMENDED	ALL - IMPROVEMENTS RECOMMENDED	WET- IMPROVEMENTS RECOMMENDED
1	245	116	43	19	47.35%	44.19%
2	124	44	16	8	35.48%	50.00%
3	411	85	122	48	20.68%	39.34%
4	2783	68	1382	36	2.44%	2.60%
5	456	128	144	42	28.07%	29.17%
6	1368	36	37	0	2.63%	0.00%
7	2690	252	1207	70	9.37%	5.80%
8	1131	74	255	14	6.54%	5.49%
9	23	5	0	0	21.74%	0.00%
10	397	129	40	16	32.49%	40.00%
11	366	123	45	13	33.61%	28.89%
12	1064	198	158	42	18.61%	26.58%
Statewide Totals	**11058**	**1258**	**3449**	**308**	**11.38%**	**8.93%**

2 BACKGROUND OF SAFETY PERFORMANCE FUNCTIONS

This section of the report explains Safety Performance Function (SPF), highway segmentation and different performance measures that can be used in HCCL identification procedure.

2.1. HIGHWAY RATE GROUP, SEGMENT, AND SITES

Caltrans currently classifies its roadway into 67 groups. For each of the classifications, there are corresponding SPFs, however, since the existing SPFs were developed prior to 1973, several roadway groups defined in existing roadway group classifications are in limited existence, as shown in Figure 1. In addition, SPFs for some existing facilities no longer explain the traffic collision data adequately.

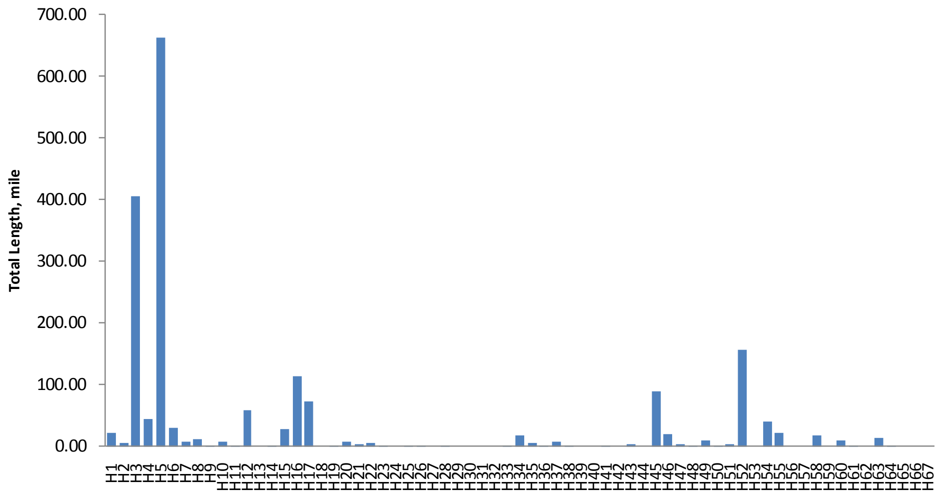


Figure 5: Length of Different Highway Rate Groups in District 1

According to the Highway Safety Manual [1, volume 1, page 4-5], a roadway segment can be defined as a portion of a facility that has a consistent roadway cross-section and is defined by two endpoints. The HSM discusses a number of potential characteristics that can be used to define the endpoints of the segment within a highway rate group. Since utilizing all the potential characteristics to define endpoints of segments will make the analysis unnecessarily complicated, the end points defined by changes in highway rate group and changes in volume were used in this report to define the end points. Appendix A includes lengths of different highway groups across the California districts.

The term "site" will be used to refer to sections of the roadway detected as HCCL's based on the Sliding Window Method (SWM), Peak Searching (PS), and Continuous Risk Profile (CRP) methods. In the case of SWM and PS, the end points of sites are consistent with the end points of segments. In the case of CRP, the end points of sites are independent of the end points of segments. More detailed descriptions of these three methods are explained in section 2.2 followed by section 2.3 which discuses SPFs.

2.2. SAFETY PERFORMANCE FUNCTION (SPF)

Safety Performance Function is an observed mathematical relationship between explanatory variables and the collision frequency among similar roadway groups (i.e., sections of roadway that share similar features) [4, 5]. In order to develop SPF for a roadway group, one needs to have access to: (i) explanatory variables; (ii) endpoint postmiles of different roadway groups; and (iii) traffic collision data. Section 2.3 of this report discusses issues related to these three input data. However, due to the issues in data used in developing SPF, the variance of SPF and the value of SPF itself can be contaminated with bias [2]. Therefore, it is important to evaluate the robustness of HCCL detection procedure with respect to perturbation of SPFs. If the result of HCCL detection procedure that a state uses markedly varies with respect to a small perturbation of SPF, the state may need to allocate additional resources to improve the performance of SPF. Section 2.4 describes how SPFs were developed in this present study and reports on their performance compared with Caltrans' existing SPFs.

2.3. DISCUSSION OF DATA FOR DEVELOPING SPF

2.3.1 TRAFFIC VOLUME

SPFs used by Caltrans [9] and included in the Highway Safety Manual [1] only use traffic volume as an explanatory variable. These SPFs implicitly assume that the traffic volume within a segment is constant (i.e., section of freeway within a same roadway group further segmented based on the changes in the value of the common feature compared to adjacent segments). however the traffic volume within the same type of roadway segment can be non-uniform [6] since they are measured at sporadic locations along the freeway. It is also important to note that depending on the type of detectors used, there can be more than a 30% difference in daily traffic volume even if the data are collected at the same location. At locations where conventional loop detectors are not installed, traffic volumes are typically collected once every three years, with only a few weeks per year being used to estimate annual average daily traffic (AADT). Therefore, AADT used in SPFs can be often plagued by large variances due to the small number of samples and measurement error due to detector bias [7].

2.3.2 MISSING TRAFFIC COLLISION DATA

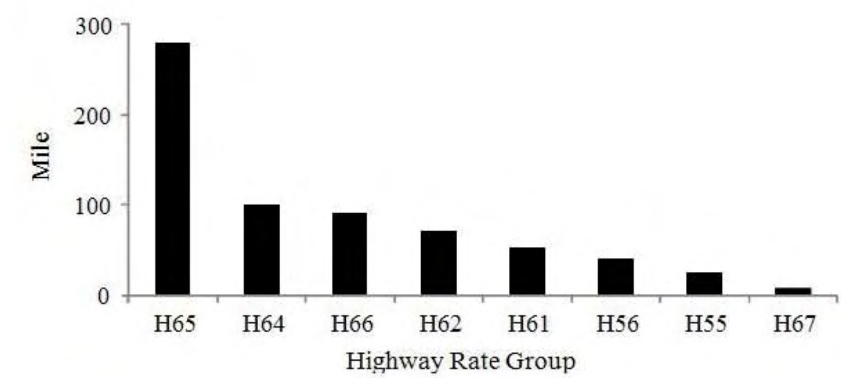
In California, all vehicle collisions that occur on a public roadway are reported into the Statewide Integrated Traffic Records System (SWITRS), which is owned and maintained by the California Highway Patrol (CHP). The information about the collisions is then sent to the Traffic Accident Surveillance and Analysis System (TASAS), which is the source of collision data for this study.

Theoretically, TASAS should be a subset of SWITRS. However, inconsistencies between TASAS and SWITRS are often reported due to the fact that only Collisions identified as having taken place on a state facility are transferred from SWITRS to TASAS, and since postmile information is entered manually after the fact by someone not present at the collision site at time of the event. In addition, about 21% of injury collisions and about 43% of all collisions are not reported to the collision database due to concerns about insurance, legal repercussions or other procedural errors [8]. The amount of missing traffic collision data has not been quantified. However, it is important to evaluate the impact of any efforts to mitigate these issues on any network screening methods.

2.3.3 ROADWAY GROUP

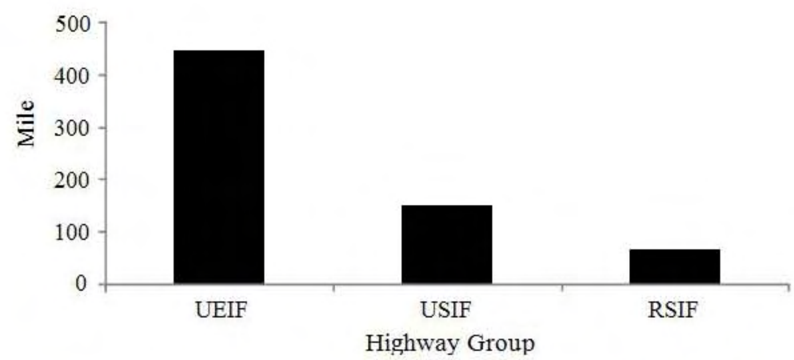
Caltrans currently classifies each state-owned freeway and highway to one of 67 groups based on facility features (e.g., speed limit, number of lanes), and has established SPFs for each group [9]. The origin of Caltrans roadway classification predates 1973; thus, several roadway groups defined in existing roadway group classification can rarely even be found. In addition, some of the existing SPFs for existing facilities no longer explain the traffic collision data adequately: empirical evidence that supports this statement will be presented momentarily.

In this study, information from 663 miles of freeway was used to develop SPFs, and the number of miles belonging to different roadway groups is shown in Figure 6. Notice how the distribution of miles across the various Caltrans existing roadway groups is disproportionate. If one were to construct a figure similar to Figure 6 using data from the entire state, the magnitude of the disproportionate distribution would increase even more sharply due to the number of miles that are not included in the Caltrans existing roadway groups shown in Figure 6.



Caltrans Roadway Classification	Description	Relationship to New Roadway Classification
H55	Rural Freeway 5-6 lanes	RSIF
H56	Rural Freeway 7 lanes or more	RSIF
H61	Suburban Freeway 5-6 lanes	USIF
H62	Suburban Freeway 7 lanes or more	UEIF
H64	Urban Freeway 5-6 lanes	USIF
H65	Urban Freeway 7-8 lanes	UEIF
H66	Urban Freeway 9-10 lanes	UEIF
H67	Urban Freeway 11 lanes or more	UEIF

Figure 6: Distribution of Caltrans Roadway Groups Used for the Study



New Roadway Classification	Description	Relationship to Caltrans Roadway Classification
RSIF	Rural Freeway 5 lanes or more	H55,H56
USIF	Urban or Suburban Freeway 5-6 lanes	H61,H64
UEIF	Urban or Suburban Freeway 7 lanes or more	H62,H65,H66,H67

Figure 7: Distribution of the Figure 2 Roadway Groups After Reclassification

The roadway groups shown in Figure 6 were reclassified into three groups sample sites for each roadway group for developing SPFs. This was done based on roadway descriptions provided in [5] to have enough sample sites for each roadway group in developing SPFs. This reclassification resulted in combining two or more of the groups shown in Figure 6 into single groups. The relationship between Caltrans roadway groups and the new roadway group is shown in Figure 7.

Based on the description in Figure 7, the endpoints of the roadway groups were obtained from the Caltrans highway database. The roadways were then further divided into segments. According to the Highway Safety Manual (HSM) [1], a roadway segment can be defined as a portion of a facility that has a consistent roadway cross-section, and its endpoints can be designated by changes in traffic volume, median type, and other roadway features. For the present study, the endpoints of segments were defined in two different ways (see Figure 8). It is important to note that the length of segments is always less than or equal to the length of a roadway group.

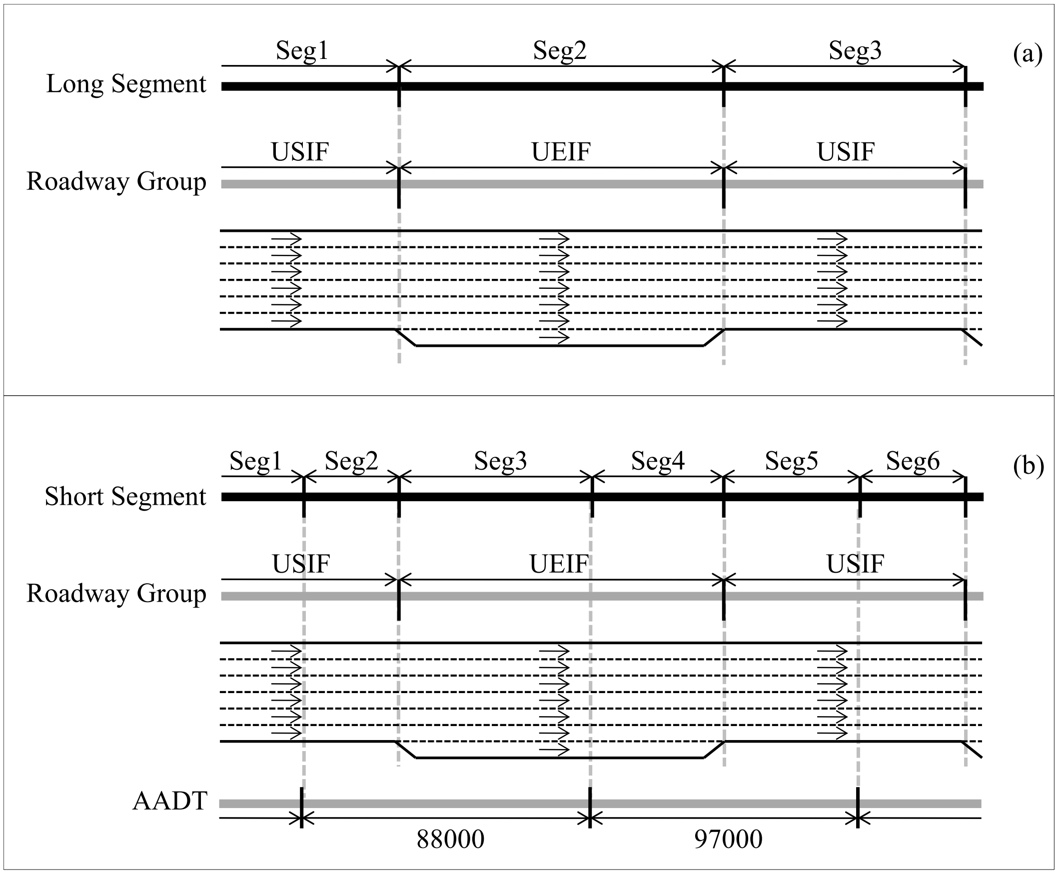


Figure 8: Two Ways to Define Segments: (a) Long Segment, (b) Short Segment

Figure 8(a) shows segments whose endpoints coincide with the endpoints of roadway groups. In this case, the length of the segment is the same as the length of roadway group, which for the present study varied from 0.05 to 11.38 miles. Traffic volume measurement locations were also used to further subdivide segments as shown in Figure 8(b). The length of segments defined as illustrated in Figure 8(b) varied from 0.04 to 3.64 miles for the present study. From this point forward, this report will refer to segments similar in length to those of the roadway rate group as Long Segments (LS), while the segments with endpoints defined by the system illustrated in Figure 8(b) will be referred to as Short Segments (SS). The traffic collision data from the short segments were used to develop SPFs in the present study.

The purpose of using two different segment definitions is to evaluate the changes in the performance of SWM, PS and CRP methods with respect to different segment lengths. Evaluating the effect of changing segment length is important since there are various guidelines for defining the segment endpoints. In addition, the endpoints of existing segments can also change over the years due to changes in traffic volume and geometric configuration.

2.4 DEVELOPING SPF

Traffic collision data along 663 miles of freeways collected between 2004 and 2008 were used to develop SPFs for the highway group shown in Figure 7. All SPFs were assumed to have the same functional form [1, 4, 5] (see Equation 1) and the parameters were estimated for each of the roadway groups using a negative binomial regression model. The values of the estimated parameters are shown in Table 2 including the overdispersion factor, k.

(1)

Where, α and β are regression parameters and SL is segment length, $SPF_{O,\ RSIF}$ is SPF for roadway group RSIF and subscript "$_O$" has been used to differentiate between the existing Caltrans SPF and the SPFs developed in the present study. In referring to Caltrans existing SPFs, subscript "$_C$" will be used and its roadway group information will be subscripted in similar manner. For example, $SPF_{C,H66}$ will be used to refer Caltrans existing SPF for highway group 66. The regression parameters were estimated by the statistics program package R.

Table 2: Estimated Regression Parameters of SPF_O

Highway Group	Using Fatality and Injury data						Total					
	α		β		1/k		α		β		1/k	
	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err
RSIF	-6.49	2.06	0.85	0.19	7.79	2.72	-8.58	1.74	1.14	0.16	7.57	2.23
USIF	-3.29	1.45	0.61	0.13	2.28	0.27	-4.21	1.41	0.81	0.13	1.97	0.19
UEIF	-11.25	1.18	1.32	0.10	3.69	0.28	-6.42	1.35	1.01	0.12	2.31	0.15

It is important to note that SPF_C for urban divided freeways and highways are developed for each direction, and Caltrans specifies the location of HCCL's for each direction. Therefore, the HCCL list generated using SPFs developed utilizing the traffic collision and volume data from both directions will not be compared with Caltrans HCCL list known as Table C. Comparing these two lists would results in misleading and erroneous conclusions. [19].

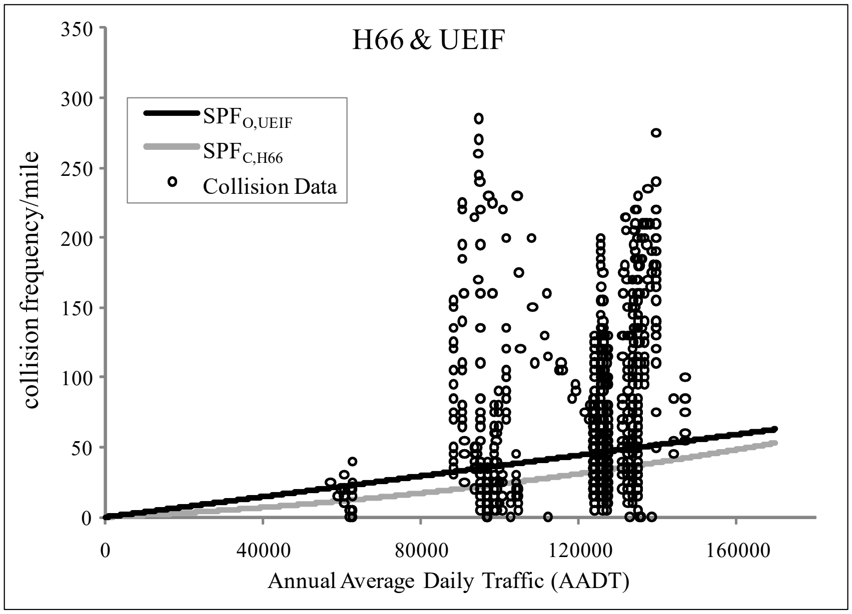


Figure 9: $SPF_{O,UEIF}$ and $SPF_{C,H66}$ for the Corresponding Collision Data

Traffic collision and AADT data that meet both the description of H66 and UEIF were used to plot the circles shown in Figure 9: in developing $SPF_{O,UEIF}$, the information from segments that meets UEIF description has been used. The solid black line represents $SPF_{O,UEIF}$ and the solid grey solid line represents $SPF_{C,H66}$. The performance of two different sets of SPFs has been evaluated using Log-likelihood ratio test as shown in Equation 2. LL in Equation 2 denotes the Log-likelihood function. The difference of Log-likelihood for two models, D, approximately follows chi-square distribution with the degree of freedom determined by the difference of degree of freedoms between SPF_C and SPF_O. SPF_C is used as a null model and SPF_O as alternative model. The results of the test summarized in Table 2 and they indicate that SPF_O explains the variance in the data more appropriate than SPF_C in all the highway groups examined in the present study.

(2)

Table 3: Difference of Log-Likelihood of SPFs

	$LL(SPF_C)$	$LL(SPF_O)$	D	P-value
$SPF_{C,H55}$ & $SPF_{O,RSIF}$	-684.28	-681.63	5.30	0.0213
$SPF_{C,H56}$ & $SPF_{O,RSIF}$	-1761.47	-1663.60	195.73	0.0000
$SPF_{C,H61}$ & $SPF_{O,USIF}$	-2648.28	-2598.62	99.32	0.0000
$SPF_{C,H62}$ & $SPF_{O,UEIF}$	-2232.49	-2087.79	289.40	0.0000
$SPF_{C,H64}$ & $SPF_{O,USIF}$	-2988.69	-2572.61	832.15	0.0000
$SPF_{C,H65}$ & $SPF_{O,UEIF}$	-9294.89	-7153.34	4283.11	0.0000
$SPF_{C,H66}$ & $SPF_{O,UEIF}$	-10534.45	-5050.47	10967.97	0.0000
$SPF_{C,H67}$ & $SPF_{O,UEIF}$	-9080.48	-1091.56	15977.84	0.0000

Table 4: Lengths for Developing New SPF's

RSIF	63.3
UEIF	448.5
USIF	151.4

2.5. PERFORMANCE MEASURE

Crash frequencies naturally fluctuate up and down over time at any given site. When a period with a comparatively high crash frequency is observed, it is statistically probable that a lower crash frequency will be observed in the following period. This tendency is known as regression-to-the-mean (RTM). Failure to account for the effects of RTM introduces the potential for “RTM bias,” also known as “selection bias.”

A performance threshold value provides a reference point for comparison of performance measure scores within a reference population. The method for determining a threshold performance value is dependent on the performance measure selected. Tables B-1 and B-2 in Appendix B summarize whether or not each of the performance measures accounts for regression-to-the-mean bias and/or estimates a performance threshold.

The Average Crash Frequency performance measure gives the highest rank to the site with the greatest total number of crashes or the most crashes of a particular crash severity or type, in a given time period. While this measure is simple, it does not account for RTM bias and traffic volume, does not estimate a threshold to indicate sites experiencing more crashes than predicted for sites with similar characteristics, and does not identify low volume collision sites where simple cost-effective mitigating countermeasures could be easily implemented.

The crash rate performance measure normalizes the frequency of crashes with the exposure, measured by traffic volume. It is straightforward and could be modified to account for severity if an Equivalent Property Damage Only (EPDO) or Relative Severity Index (RSI)-based crash count is used. However, it does not account for RTM bias and does not designate a threshold to identify sites experiencing more crashes than predicted for sites with similar characteristics. Also, comparisons cannot be made across sites with significantly different traffic volumes. The crash rate performance measure mistakenly prioritizes low-volume, low-collision sites.

The EPDO Average Crash Frequency performance measure assigns weighting factors to crashes by severity (fatal, injury, property damage only) to develop a combined frequency and severity score for each site. The EPDO Average Crash Frequency Performance measure is simple and considers crash severity, but it does not account for RTM bias and traffic volume. Furthermore, it does not designate a threshold to identify sites experiencing more crashes than predicted for sites with similar characteristics and may overemphasize locations with a low frequency of severe crashes depending on weighting factors used.

The resulting RSI performance measure determines whether a site is experiencing higher crash costs than the average for other sites with similar characteristics. Monetary crash costs are assigned to each crash type and the total cost of all crashes is calculated for each site. The RSI performance measure is straightforward and considers collision type and crash severity. However, it does not account for RTM bias and traffic volume. Furthermore, it may overemphasize locations with a small number of severe crashes depending on weighting factors used, and will mistakenly prioritize low-volume low-collision sites.

The critical crash rate is a threshold value that allows for a relative comparison among sites with similar characteristics. The critical rate performance measure reduces exaggerated effects of sites with low volumes, considers variance in crash data and establishes a threshold for comparison. However, it does not account for RTM bias.

As mentioned earlier, Caltrans currently uses SWM method and critical rate as the measure to detect HCCL's [1]. The detected spots are not ranked. The critical count being used by Caltrans is based on a 99.5% confidence interval and the sites where collision rate exceeds the threshold are flagged as potential safety investigation locations [17]. Both critical rate and Potential for Safety Improvement (PSI) are one of the several potential measures that can be used as a guideline for determining sites for safety investigation [1].

All the sites that are flagged using SWM do not necessarily end up being reported to Caltrans quarterly HCCL list known as Table C. For the purpose of illustration, these initial sets of sites that are detected based on critical rate will be referred as generic Table C list from hereon. This list is superset of final Table C and includes many sites that had been reported in the previous three quarters of Table C,: when the collision patterns are reproducible, the sites detected in previous quarters are often detected again in the following quarter. Caltrans currently applies additional procedure to generic Table C list to eliminate those repeat locations prior to finalizing Table C. The locations detected in previous three quarters are excluded and some of the adjacent sites are combined as one site during the additional procedure.

Generic Table C list, for an example, reported 46 sites based on 12 months collision data in 4th quarter of 2008, whereas final Table C for the same period reported only 4 sites. Such significant differences in the number of sites between generic Table C list and final Table C are observed in each quarter. Since the list of HCCL's in final Table C reflects the additional change described in the previous paragraph, simply comparing the list of sites detected in three methods with Table C list without applying the same additional procedure would make SWM, PS and CRP methods appear to have higher false positive rate than existing Table C procedure.

The final Table C from each quarter from 1st quarter of 2007 to 4th quarter of 2008 are used to evaluate the performance of three different methods and these lists are collectively referred as Confirmed Hot Spots (CHS) in the proceeding sections: CHS can be considered a subset of True Hot Spots (THS) which cannot be obtained in an empirical study. The sum of all the site lengths in CHS used in this study was 6.5 miles. The findings from comparing the performances of these methods are discussed in the next section.

3 EMPIRICAL ANALYSIS

3.1. CRP, SWM AND PS DESCRIPTIONS

Sliding Window Method (SWM), Peak Searching (PS) and Continuous Risk Profile (CRP) are different methods for determining the endpoints of a *site*. The data requirements for each method are the same and differ only in the way they segment sites. After the endpoints are determined, the same set of guidelines can be applied to prioritize detected sites for safety investigation.

In the present study, the data with the segments identified in each of these methods are used to estimate excess expected average crash frequency with Empirical Bayes (EB) adjustment [10] which is the difference between the expected average crash frequency with EB adjustment [see black circles labeled E in Figure 10(b), Figure 10(d), and Figure 10(e)] and SPFs. This estimate has been considered as the site's Potential for Safety Improvement (PSI). PSI of each site was computed using both SPF_C and SPF_O, and was used to rank the sites for safety investigation.

The SWM uses the traffic collision data from a fixed window size [see *w* in Figure 10(a)] to screen the network. The observed collision frequency within the window [see the white circle in Figure 10(b)] is readjusted using EB method [see the black circle labeled *E* in Figure 10(b)] to estimate the site's PSI. Then, the window is offset by a small increment [see *l* in Figure 10(a)] to repeat the procedure (see the dotted box). The PSIs from all the windows are then compared and the maximum value is used to represent the potential for collision reduction for the whole segment. The window can span two or more sites when the length of segment is small compared to the window size. The size of the site detected in SWM is equal to segment length.

The Peak Searching (PS) method first subdivides the segment into small windows of similar lengths [see w_1 in Figure 10(c)]. The data that belongs to each of the window is used to estimate the PSI [see Figure 1(d)] in the manner described in preceding paragraphs. Then the estimated PSIs are subjected to precision testing using the coefficient of variation (CV) as described in HSM [1]. A large CV means a low level of precision and a small CV indicates a high level of precision. If CV value of a window is lower than or equal to the CV limiting value, it means that the PSI of the window satisfies the desired precision level. According to HSM (AASHTO, 2010), appropriate CV limiting value is 0.5.

If the PSI for at least one of windows satisfies the desired precision level, the maximum PSI value from all of the windows satisfying the desired precision level is chosen to represent the crash reduction potential for the whole segment. If none of PSIs for the windows meets the desired precision level, the size of window is increased (see w_2 in Figure 10(c)) and then the calculation is repeated to assess the precision of the PSI. This procedure continues until a maximum PSI with the desired precision is found or the size of the window reaches the length of entire segment (see W_N in Figure 10(c)). Similar to SWM, the chosen maximum PSI value represents the potential for collision reduction for the whole segment. The size of detected site in PS method is the same as the segment length.

The CRP method first filters out the random noise in the data using weighted moving average technique and continuously plots the collision risk profile along the freeway [(see the bold line in Figure 10(f)] [2, 3]. Then, the predicted collision frequency based on the AADT for the segment is obtained from corresponding SPFs [see F_1 and F_2 in Figure 10(e)]. The unit of the value obtained from SPF is converted to the unit comparable to CRP to be plotted together as shown in Figure 10(f) (see the dotted line labeled SPF). The location where CRP exceeds the dotted line defines the endpoints of a site (see location labeled s_i and e_i). Thus, the size of the site defined by the CRP is not influenced by endpoints of segments. The area between the horizontal dotted lines (i.e., SPFs) and the CRP denote the excess crash frequency [see the light grey area labeled B in Figure 10(f)]. The area enclosed by s_i, e_i, and the vertical dotted lines [see the dark grey area labeled A in Figure 10(f)] denotes the crash frequency of the SPFs. $A + B$ is the observed collision [see white circle in Figure 10(e)], which is readjusted using the EB method [see the black circle labeled E in Figure 10(e)] to estimate PSI in the same manner to rank sites for safety investigation [see Figure 10(e)].

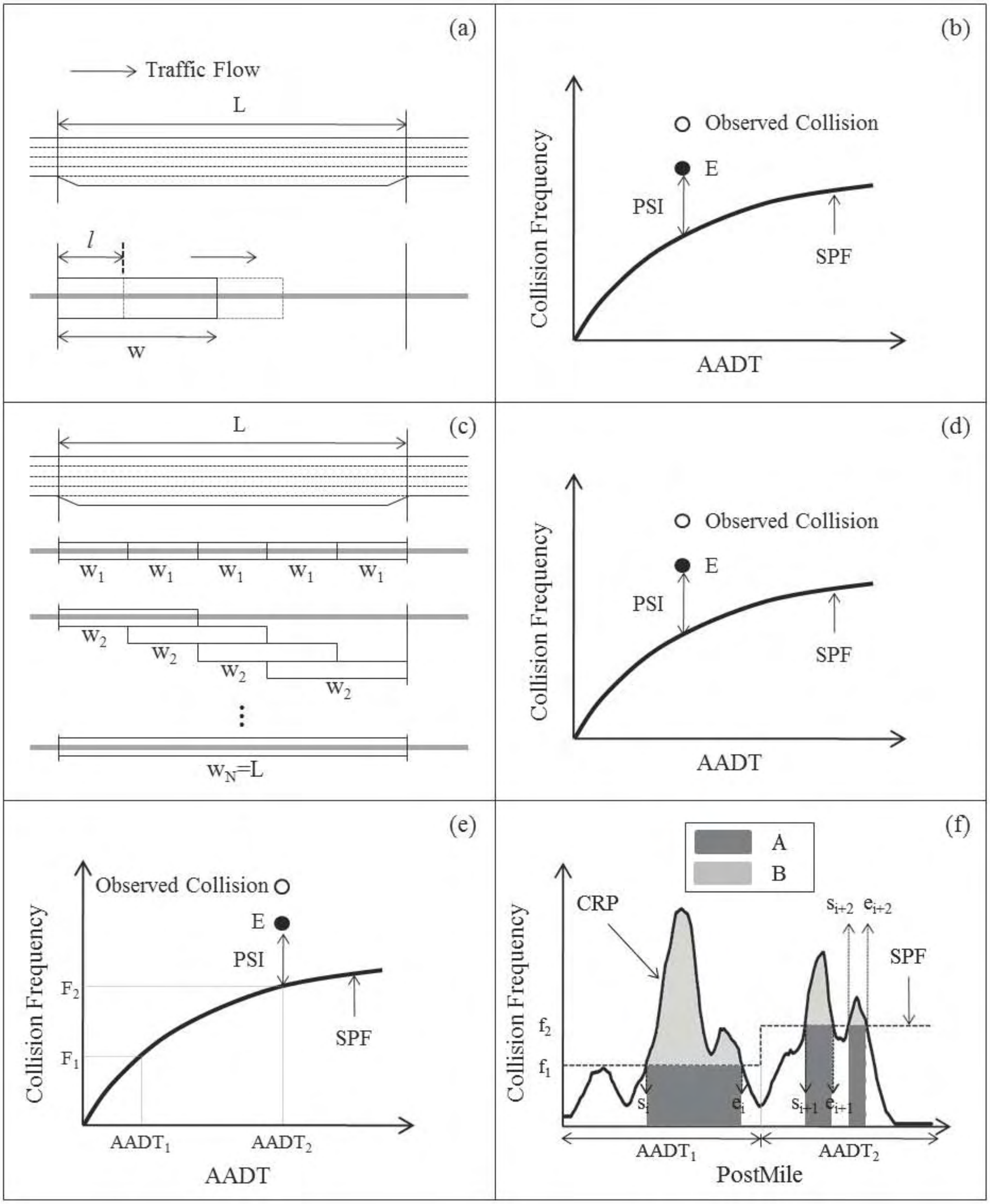


Figure 10: (a) Description of SWM; (b) PSI estimated in SWM; (c) Description of PS; (d) PSI estimated in PS; (e) PSI estimated in CRP; and (f) Description of CRP

3.2. PERFORMANCE OF EACH SEGMENTING METHODS

The performance of the SWM, PS and CRP methods were evaluated using data from Caltrans. Findings indicated that the performance of these three methods varied more markedly under Short Segment segmentation.

3.3. URBAN DISTRICT

Three different performance measures have been developed to evaluate the performance of the SWM, PS and CRP methods. These performance measures compare: (i) number of sites that each method requires to cover the Confirmed Hot Spots (CHS); (ii) the number of miles that safety engineers need to investigate to detect CHS; (iii) the changes in HCCL detection efficiency (HSDEr) (i.e., the ratio between number of miles that belongs to CHS and miles detected in each methods up to r^{th} ranked site of each method with respect to changes in ranks.

The performance of SWM, PS and CRP methods can be explained with the aid of Figure 11 and Figure 12. Figure 11(a)~(c) shows the performance of each method using SPF_C and LS, whereas Figure 14(d)~(f) shows the corresponding results using SPF_C and SS. Then, replacing SPF_C with SFP_O, changes in the performance of each method were evaluated under LS and SS. These findings are summarized in Figure 12. In all figures, the dark dotted line represents the performance of the SWM method. The solid grey and black lines show the performance of PS and CRP methods, respectively.

Figure 11(a) and (d) graphically show the number of sites required to detect all sites listed in CHS using the SWM, PS and CRP methods under two different segment definitions, LS and SS. The sum of all the site lengths in CHS was 6.5 miles. To detect all the sites in CHS, top 72nd, 66th, and 57th sites are required respectively for SWM, PS and CRP methods under LS. These ranks represent the number of sites that each method requires to cover all CHS. Under SS, the number of sites required to cover CHS markedly increased from 72 to 114 for SWM and 66 to 113 for the PS method. However, the number of sites required to cover CHS under LS and SS did not change using the CRP method. This is due to the fact that the length of site changes when segment length changes when using the SWM and PS methods, while the length of the site is independent of segment length using the CRP method.

When SPF_C was replaced with SPF_O, the number of sites required to cover CHS by the SWM and PS methods was notably decreased from 72 to 30 and 66 to 31: representing an approximately 50% reduction. Similarly, the number of sites required by the CRP method was reduced from 57 to 54. Such improvement could contribute to using SPFs that better fit the traffic collision data. Changing the segment definition from LS to SS led to the number of sites required by SWM and PS methods to markedly increase to 76 and 68, respectively, while that of CRP method did not change.

The number of sites required for safety investigation reflects the number of times that safety investigators must visit sites in person. If the cost associated with site investigation is constant regardless of the length of the site, using the SWM method with SPF_O under LS would result in the minimum cost. However, this is not likely to be the case in practice because the longer the site, the more time that the investigator must spend at the site and be exposed to traffic. Therefore, the HCCL detection efficiency (HSDE) must be considered at the same time, and these results are shown in Figure 11(b), Figure 11(e), Figure 11(b), and Figure 11(e).

The slope of the line connecting the origin and the end point of each graph represents the HSDE of each method: the slope is the ratio between the numbers of miles that is in CHS per mile identified by each method. For an example, the CRP method identified 37 miles [see Figure 11(b) and Figure 11(e)] in its 57 sites under LS and SS assumption using SPF_C. CRP's overall HSDE is 17%. The performance of the SWM and PS methods under LS and SS are also shown in the figures.

The HSDE of PS slightly improved when SPF_O were used while that of SWM did not change. However, the HSDE of CRP improved by 6% when SPF_O were used. The length of site using the CRP method is determined by SPF. Using SPF_O resulted in vertically shifting the dotted line upward without surpassing the peaks (without missing HCCLs) in each site shown in Figure 10(f). Thus, the HSDE of CRP method was more significantly affected by SPFs than those of the SWM and PS methods.

The HSDE of CRP outperformed the SWM and PS methods in all four cases. The HSM states that after ranking the site, both the SWM and PS methods can subsequently select segments for further investigation. Such subsequent procedure was not considered in comparing the HSDE of the SWM and PS methods in the present study since that would have required addressing multiple collision concentration locations within each site. Depending on the procedure chosen for the subsequent analysis, it can both increase and decrease the HSDE of the SWM and PS methods [11]. It is also important to note that the magnitude of the HSDE of the SWM, PS, and CRP methods are all underestimated for the reasons explained in section 4.1 of this report.

One of the issues of the SWM and PS methods observed during the analysis is that the PSI of a whole segment is represented by the PSI of the maximum window within the segment [1]. Suppose there are three segments A, B, and C. Segment A has windows that display the 1st and 3rd highest PSI value; segment B has 4th and 5th; and segment C has 2nd and 6th. In this case, segment A will be ranked 1st, C 2nd and B 3rd. Suppose the SWM and PS methods subsequently select a single site (or a limited number of sites) within each segment for the safety investigation. This subsequent procedure will then select sites that display 1st (from segment A), 2nd (from segment C) and 4th (from segment B) PSI rather than selecting sites with top three PSIs. Such issue can be resolved if the PSI of all the sites from different segments are compared rather than only the maximum PSI value from each segment. Notice how then SWM and PS essentially become similar to CRP method as they reduce the size of the segment.

The HSDE of each method with respect to different ranks, $HSDE_r$, is also evaluated and is shown in Figure 11(c), Figure 11(f), Figure 11(c), and Figure 11(f). Except for the case shown in Figure 11(f), the $HSDE_r$ of CRP method remained greater for the other three cases. The $HSDE_r$ of SWM and PS methods peak before they reach 5th and 3rd ranked sites, respectively. The difference between $HSDE_r$ among the three methods diminishes after reaching 21st ranked site.

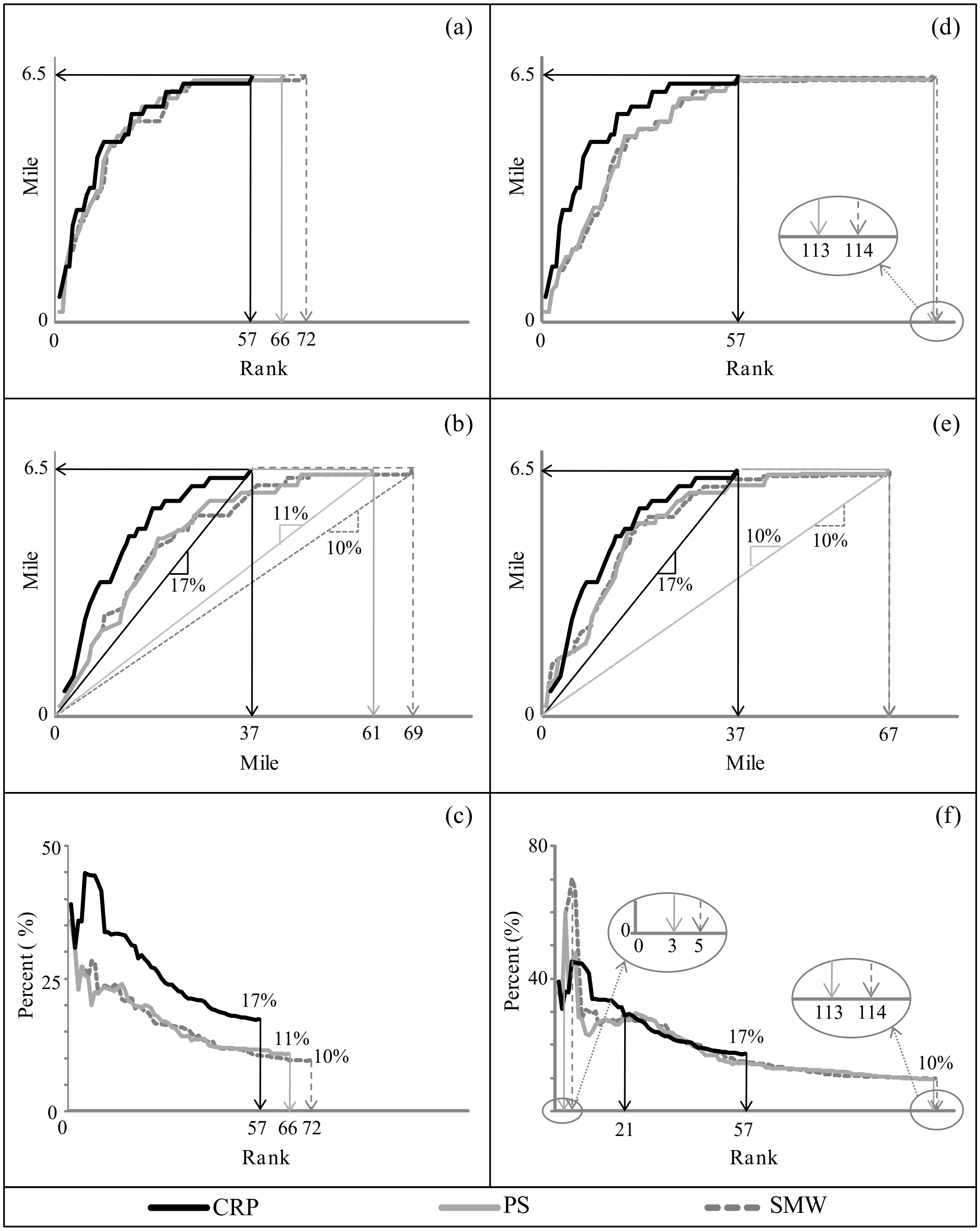


Figure 11: Performance Plots of Three Network Screening Methods Using SPF_C: (a) Number of Sites Required to Detect CHS Using LS, (b) HSDE of Each Method Using LS, (c) Change in $HSDE_r$ with Respect to Change in Rank Using LS, (d) Number of Sites Required to Detect CHS Using SS, (e) HSDE of Each Method Using SS, (f) Change in $HSDE_r$ with Respect to Change in Rank Using SS

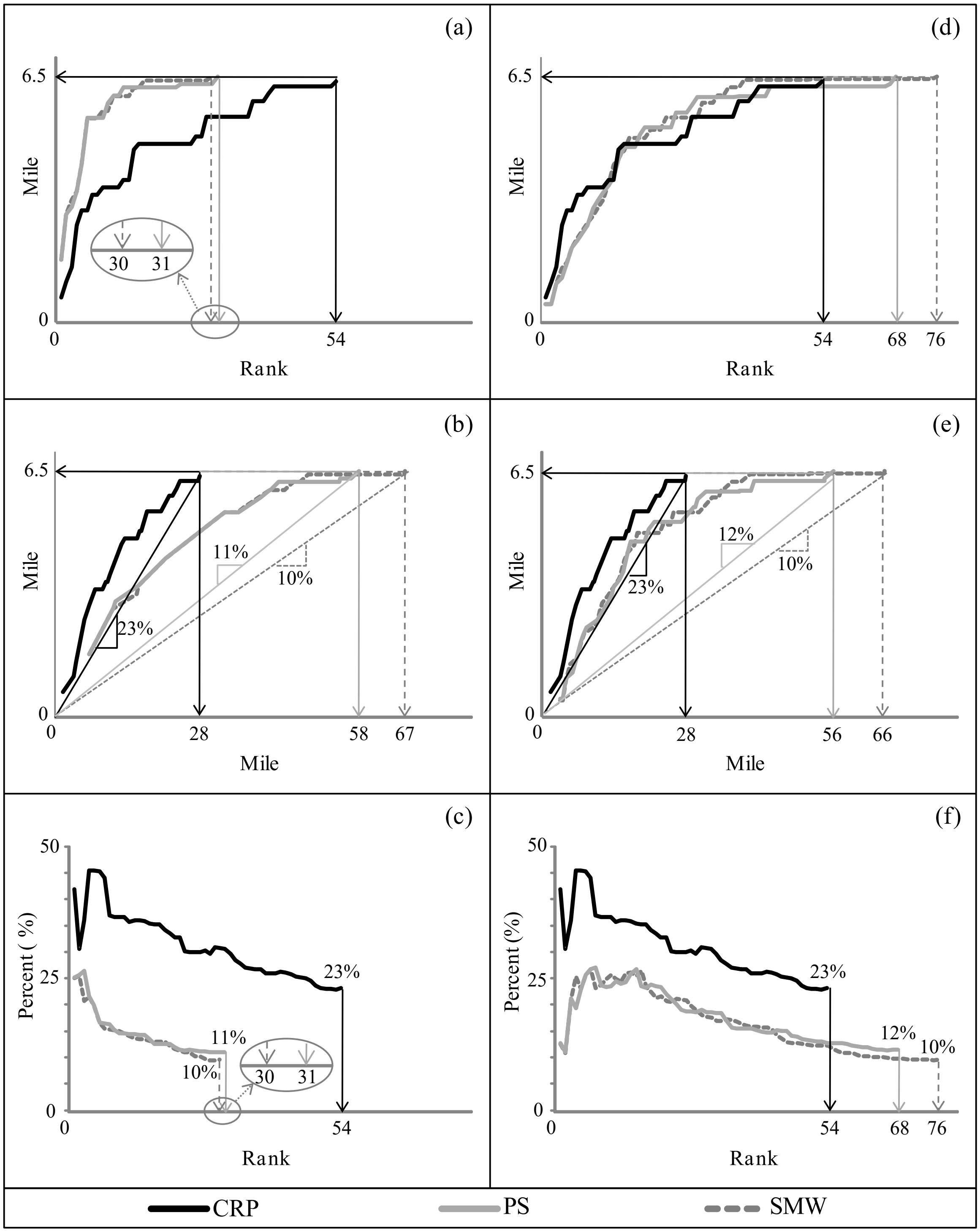


Figure 12: Performance Plots of Three Network Screening Methods Using SPF_O: (a) Number of Sites Required to Detect CHS Using LS, (b) HSDE of Each Method Using LS, (c) Change in $HSDE_r$ with Respect to Change in Rank Using LS, (d) Number of Sites Required to Detect CHS Using SS, (e) HSDE of Each Method Using SS, (f) Change in $HSDE_r$ with Respect to Change in Rank Using SS

3.4 COMPARISON OF CRP, SWM AND PS ACROSS URBAN, SUBURBAN, AND RURAL SITES

Figure 13(a) and (c) graphically show the number of sites required to detect all urban and suburban sites listed in CHS using the SWM, PS and CRP methods under two different SPF definition, SPFc and SPFo, both under SS segment definition. The sum of all the site lengths in CHS in SPFc is 24.73 miles, but the sum of all the site lengths in CHS in SPFo is 24.62 miles. The difference between these two lengths is due to the filtered segments which are classified into urban and suburban, but do not have SPFo, such as UMDA, UTWA and UMUA. Therefore, these highway rate groups are filtered in analysis, and the sites in CHS in the filtered segments are not counted. According to Figure 13(b), the proportion of the filtered sections is relatively small, so it can be assumed that there is not a considerable difference between two methods of analysis. To detect all the sites in CHS, the top 578th, 584th, and 444th sites are required respectively for the SWM, PS and CRP methods using SPFc. Using SPFo, the number of sites required to cover CHS notably decreased from 444 to 407 for SWM, from 584 to 414 for the PS method and from 444 to 390 for the CRP method.

The CRP method identified 114 miles [see Figure 13(b)] in its 444 sites using SPFc under SS assumption. The overall HSDE of CRP in urban and suburban sites is 21.61%. The SWM and PS methods identified 313 miles [see Figure 13(b)] using SPFc under SS assumption, and the overall HSDE in urban and suburban sites is 7.9%.

The HSDE of PS and SWM are almost constant when SPFo were used while that of CRP showed improvement and increased by 4%. Recall that the HSDE of the CRP method is more significantly affected by SPFs than that of the SWM and PS methods.

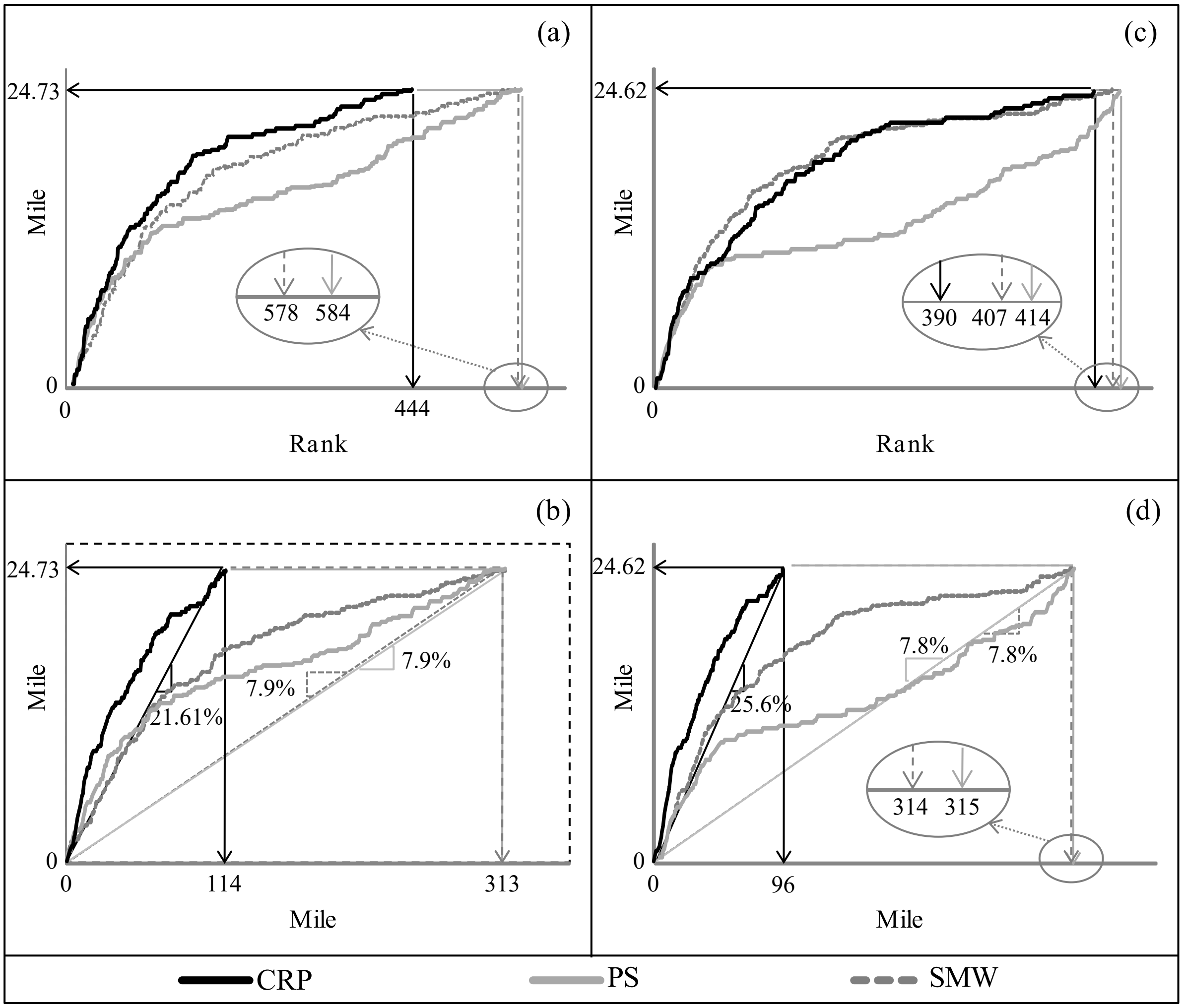


Figure 13: (a) Number of sites required to cover CHS on urban and suburban area using SS and SPFc; (b) HSDE of each method on urban and suburban area using SS and SPFc; (c) Number of sites required to cover CHS on urban and suburban area using SS and SPFo; (d) HSDE of each method on urban and suburban area using SS and SPFo;

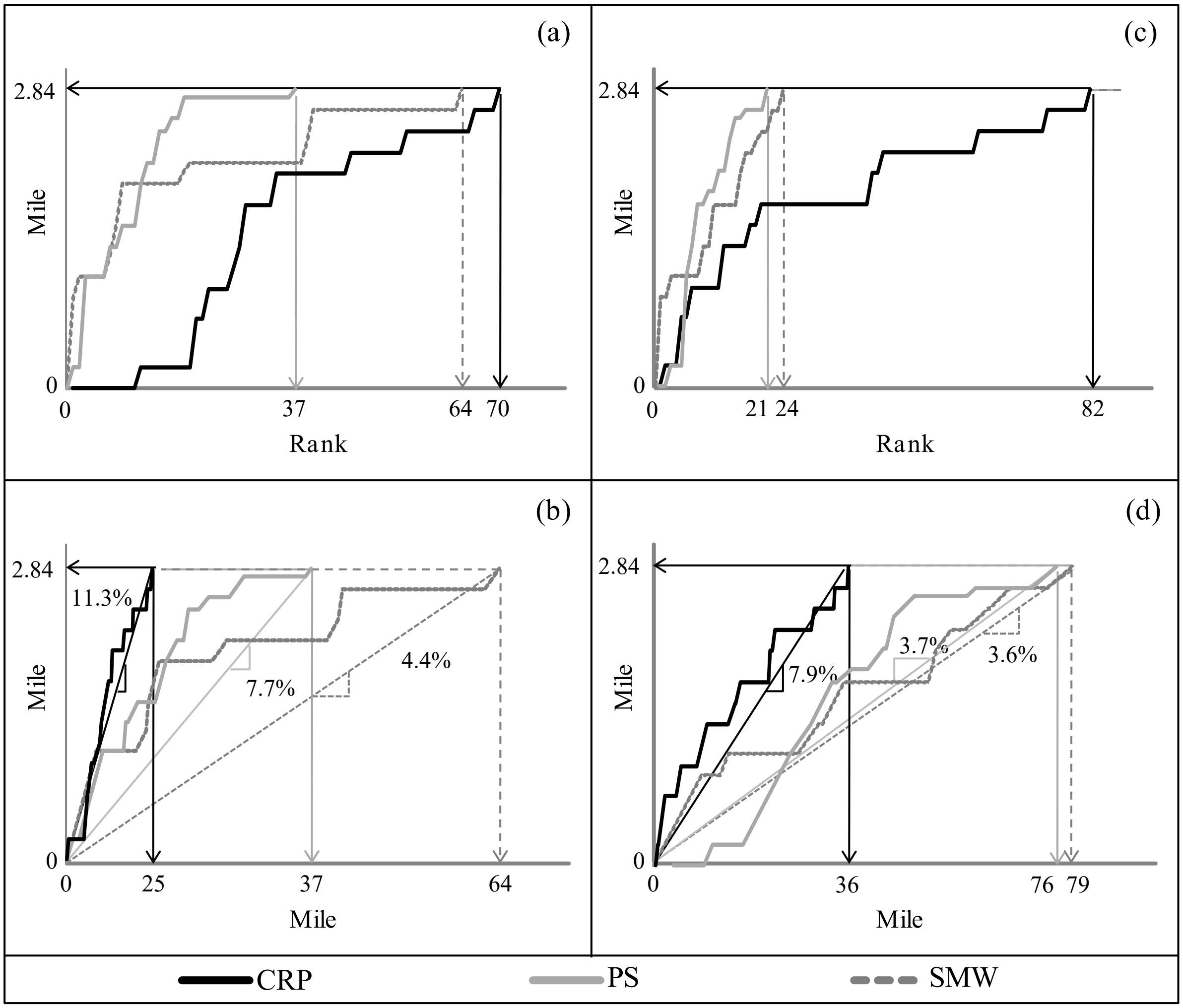


Figure 14: (a) Number of sites required to cover CHS on rural area using SS and SPFc; (b) HSDE of each method on rural area using SS and SPFc; (c) Number of sites required to cover CHS on rural area using SS and SPFo; (d) HSDE of each method on rural area using SS and SPFo;

Figure 14(a) and Figure 14(c) graphically show the number of sites required to detect all rural sites listed in CHS using the SWM, PS and CRP methods under two different SPF definition, SPFc and SPFo, both under SS segment definition. The sum of all the site lengths in CHS is 2.84 miles in both cases using SPFc and SPFo. The reason for the lack of difference between these two lengths is that filtered segments which are rural but do not have SPFo such as RTWH and RMUH do not include the site in CHS. To detect all the sites in CHS, the top 64th, 37th, and 70th sites are required respectively for the SWM, PS and CRP methods using SPFc. Using SPFo, the number of sites required to cover CHS decreased from 64 to 24 for SWM, from 37 to 21 for the PS method, but it increased from 70 to 82 for the CRP method.

As shown in Figure 14(b) and Figure 14(d), the tendencies of performance change in SWM, PS and CRP method differ between SPFc and SPFo. Overall HSDE of CRP in urban and suburban sites is 11.3%. The HSDE of CRP was reduced by 3.5% when SPFo were used, while that of SWM improved by 1.4%. In ordinary cases, AADT in rural groups is relatively smaller than in urban and suburban areas, so the expected number of crashes (50% and 99.5% threshold) is smaller when determined as a function of AADT. The total length of the study site in rural groups is half that of urban and suburban groups, but the sum of all the site lengths in CHS in rural groups is 11% that of urban and suburban groups. Such a small sample size could have a negative or a positive effect on the results of performance in rural groups.

4 SIMULATION

This chapter presents the design and results of a simulation study used to evaluate the performance of the Continuous Risk Profile network screening method.

4.1. INTRODUCTION

The strength of the empirical evaluation presented in Chapter 3 lies in using real empirical crash data, including the location and frequency of crashes within the study area. However, based on the empirical data, we cannot know which sites are truly hazardous, but only which sites have been recommended for safety improvements. The strength of the simulation study lies in the ability to define the "ground truth" by assigning higher underlying risk to certain locations (i.e., HCCL). This makes it possible to compare the fit between the "ground truth" and CRP. The objective of the simulation presented here is to serve as an additional level of testing of the performance of CRP.

To accomplish this, numerous simulation runs were conducted with varying values of parameters associated with either the generation of simulation database or with network screening conditions.

The site used for the simulation is a 32-mile stretch on the northbound direction of Interstate 880 between Dixon-Landing Road in Milpitas, CA and 7th Street in Oakland, CA, as shown in Figure 15.

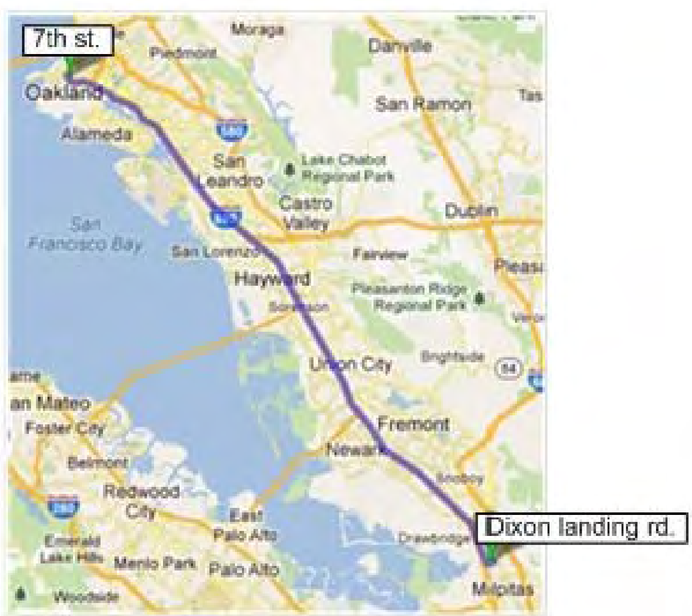


Figure 15: Simulation Site (Postmile 0~33.9, I-880, CA)

The locations of each traffic collision that occurred along the site between 2006 and 2008 were used as some of the key inputs to generate the simulated crash dataset. In addition, detailed data on the variation in geometry and AADT along the site were used as inputs to divide the study site into a number of segments used for the network screening in the simulation. All those empirical data were extracted from TASAS.

4.2. LITERATURE REVIEW

There have been some simulation studies conducted to investigate the performance of hotspot identification methods. The procedures used in these studies can be grouped largely into three parts: i) generation of crash dataset; ii) identification of hotspot locations by different methods; and iii) comparison of the hotspot identification methods using certain performance measures. This review focuses on the first part: generation of crash dataset.

4.2.1 GENERATION OF "TRUE MEANS" ON THE CRASH FREQUENCY OR RATE

Mather and Mountain (1988) generated "true means" of crash frequency for a hypothetical site from a Gamma distribution, whose parameters (i.e., mean and variance) were arbitrarily specified. To add reality to the simulation, Higle and Hecht (1989) used the annual average in crash rates that were empirically measured at each highway intersection as its "true mean" of the crash rate (i.e., crash frequency per annual traffic volume). In line with this, Cheng and Washington (2005) estimated the parameters of Gamma distribution using mean crash frequencies that were empirically measured at many intersections. Furthermore, Leung and Washington (2010) calibrated a negative binomial regression model to predict the "true mean" of crash frequency at each simulation unit (spans of 0.02 mile) on a generic freeway. This crash prediction model was intended to capture the influence that either geometric or traffic attributes has on the "true mean" of the crash frequency corresponding to each simulation unit.

4.2.2 GENERATION OF "REALIZED" CRASH FREQUENCY

Mather and Mountain (1988) created "realized" crash frequencies via Poisson distributions with parameters (i.e., means of crash frequency) generated from a Gamma distribution. The "realized" crash frequency was intended to replicate the random fluctuations of annual crash frequency. Higle and Hecht (1989) also used the Poisson distribution to generate "realized" crash frequency at each intersection. In this study, a parameter of the Poisson distribution was obtained by multiplying a true mean of annual crash rate by its corresponding annual traffic volume. Furthermore, other researchers (e.g., Cheng and Washington, 2005; Leung and Washington, 2010) generated "realized" crash frequencies on numerous simulation units (constituting a freeway corridor) from the Poisson distribution with "true means" empirically estimated.

4.3. FRAMEWORK OF THE SIMULATION STUDY

Figure 16 presents the framework under which the present simulation study was conducted. The procedures enclosed by the box of dotted lines show how crash datasets were generated for our simulation purposes. The procedure starts with uniformly dividing the study site into numerous simulation units by a predefined unit length (0.05 mile). Then, a "true mean" of annual crash frequency is derived by combining the information of "empirical observed" crash frequency with mean frequency "predicted" by the negative binomial model calibrated in Arthur and Washington (2010). The "true mean" of annual crash frequency for each simulation unit is used to generate its annual "realized" crash frequencies to replicate the random fluctuation of crash frequency across years.

The simulation study is distinguished from the empirical analysis in the following two aspects: i) the simulation study deploys artificially generated "realized" crash data, which should be realistic to some extent, ii) in the simulation study, the true mean crash frequency is perfectly known.

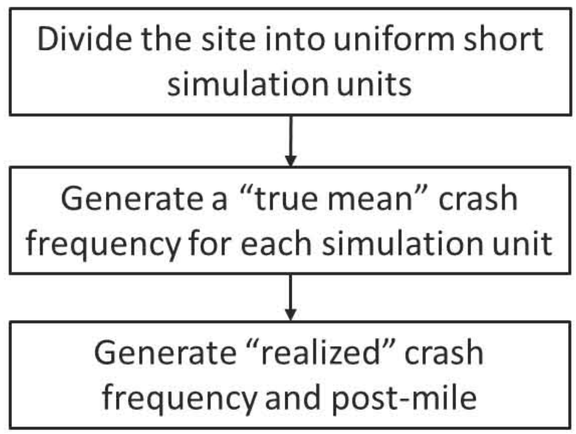


Figure 16: Framework of the simulation study

The present study improves the reality of simulation by considering both traffic and geometric attributes in predicting the "true mean" of crash frequency on each simulation unit. This "true mean" value is used as the parameter for the Poisson distribution to randomly generate multiple values of "realized" crash frequency, which replicates the random fluctuation of annual crash frequency on each simulation unit. Furthermore, given the values of "realized crash frequency," the uniform distribution is used to generate the postmiles corresponding to the locations of all the collisions that occur within each simulation unit. Apart from the postmiles of crash occurrence, locations of hotspots are determined based on the "true mean" of crash frequency on each simulation unit.

4.3.1 DIVISION OF THE STUDY SITE INTO SIMULATION UNITS

The study site is uniformly divided into numerous simulation units by a predefined unit length. The unit length should be chosen considering the following trade-off between long and short lengths. If each simulation unit is too long, the variation in traffic or geometry along the corridor would become obscured. On the other hand, using too short simulation units would result in random fluctuation and as a result, the underlying crash frequency profile along the corridor would not be pronounced. In light of this, trial-and-error experiments were conducted to find out the appropriate range of the simulation unit length.

4.3.2 GENERATION OF THE "TRUE MEANS" ON CRASH FREQUENCY

As an initial step, a negative binomial model was used to predict mean crash frequency for each simulation unit. The negative binomial model is denoted by in Equation (3) by:

$f(\hat{\beta}, X_n)$.

$$Y_n = \hat{Y}_n + \varepsilon_n \text{ (n=1,2,}\cdots\text{, N)} \quad (3)$$

$$\hat{Y}_n = f(\hat{\beta}, X_n)$$

Where,

n: index for each simulation unit

Y_n: observed empirical crash frequency (number of crashes per simulation unit)

$\hat{Y}_n$: predicted mean crash frequency (number of crashes per simulation unit)

$\hat{\beta}$: estimated coefficients

X_n: explanatory variables

ε_n: residuals

Explanatory variables and their corresponding coefficients of the negative binomial model are listed in Table 5. The coefficients were obtained by conducting a meta-analysis that consisted of a rigorous synthesis of the US literature on safety performance functions (SPFs) of freeways. Negative binomial model coefficients were reviewed, as well as identification of the list of statistically significant predictor variables found in SPFs nationwide. These statistically significant coefficients were then summarized and incorporated into a meta-analytic safety performance model that reflects 'average' safety performance of freeway segments in the US. The resulting model is then calibrated to match perfectly the average conditions in the study section, using the calibration procedure outlined in the Highway Safety Manual. This calibration results in a set of SPFs that predict crashes in the study segments and capture the variability in crashes from section to section which are known to exist and have been verified by peer-reviewed, credible studies throughout the United States. As a final step, the observed correlation in crashes from site to site observed in the study corridor is added to the SPFs, in order to produce as realistic a set of observations as possible. The resulting set of SPFs is used to represent true crashes in the corridor and to conduct the simulation experiments. This approach has been used in prior studies and has been vetted by the peer review process. This method of producing “true” crashes is the only viable way of identifying “true” crashes so that false positives and false negatives can accurately be identified across different hot-spot identification methods. Values corresponding to most of the explanatory variables could be obtained from TASAS (currently, values for horizontal and vertical curves are not available).

Table 5: Explanatory Variables (X_n) and Their Coefficients ($\hat{\beta}$)

Explanatory variables	Coefficients	Availability of TASAS data regarding explanatory variables
AADT/lane	0.0000767	Available
horizontal curve radius (m)	-0.00041	Not Available
vertical curve grade (%)	0.162	Not Available
urban/rural indicator	0.302	Available
# of lanes	0.196	Available
Segment length	2.09	Available
speed limit (km/hr)	-0.01043	Available

The difference between the predicted crash frequency and its corresponding observed empirical crash frequency is calculated for each simulation unit, and then the spatial correlation of crash occurrence between three neighboring simulation units are modeled using equations (4):

$$\begin{aligned}\varepsilon_n &= \hat{\varepsilon}_n + \xi_n \qquad (4)\\ \hat{\varepsilon}_n &= \hat{\rho}_1 \varepsilon_{n-1} + \hat{\rho}_2 \varepsilon_{n+1}\end{aligned}$$

Where,

$\varepsilon_n = Y_n - \hat{Y}_n$ (n=2, ,· ··, N-1)

$\hat{\varepsilon}_n$: predicted residual

$\hat{\rho}_1, \hat{\rho}_2$: estimated coefficients

ξ_n : error

Finally, the "true mean" of crash frequency for each simulation unit was generated by adding the "residual" to the "predicted" mean crash frequency, as shown in equation (5).

$$Y_n^* = \hat{Y}_n + \hat{\varepsilon}_n \qquad (5)$$

Where,
Y_n^* : "true mean" of crash frequency (annual crash occurrence per simulation unit)

4.3.3 GENERATION OF "REALIZED" CRASH DATASET

The "true mean" of crash frequency on each simulation unit was used as the parameter for the Poisson distribution, which was in turn used as the probability density function for the so-called Inverse Transform Method (ITM) to randomly generate "realized" crash frequency. The ITM was conducted three times to produce three-year dataset of "realized" crash frequency on each simulation unit.
Given a "realized" crash frequency on each simulation unit, locations of crash occurrence were determined by assuming that the crash occurrence within each simulation unit follows the uniform distribution with the probability density of 1/(simulation unit length).

In that manner, we could generate the three-year dataset of postmiles that fall within all the simulation units that constitute the entire study site.

Figure 17 is presented to show the characteristic of crash frequency dataset (i.e., “true mean” and “realized” crash frequency) generated by the above procedure. For comparisons, both “empirically observed” crash frequencies were also shown in the same figure. As expected, a discrepancy exists between the “true mean” and “empirically observed” crash frequencies; note the displacement that exists between the thick and thin solid lines shown in Figure 17. Recall that this discrepancy was intentionally introduced via the “predicted” crash frequency obtained from the negative binomial model (see the section 5.4.2). The profile of the “realized” crash frequency (randomly generated from the “true mean” crash frequency) shows realistic spatial variations similar to the “empirically observed” crash frequency; compare the dotted line with the thin solid line shown in Figure 17.

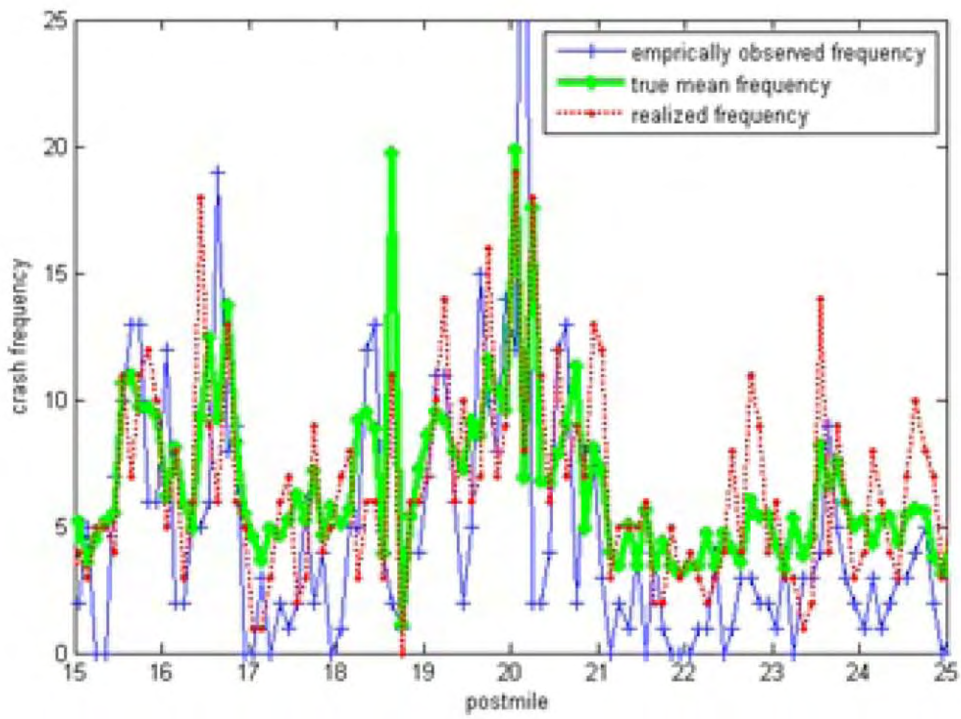
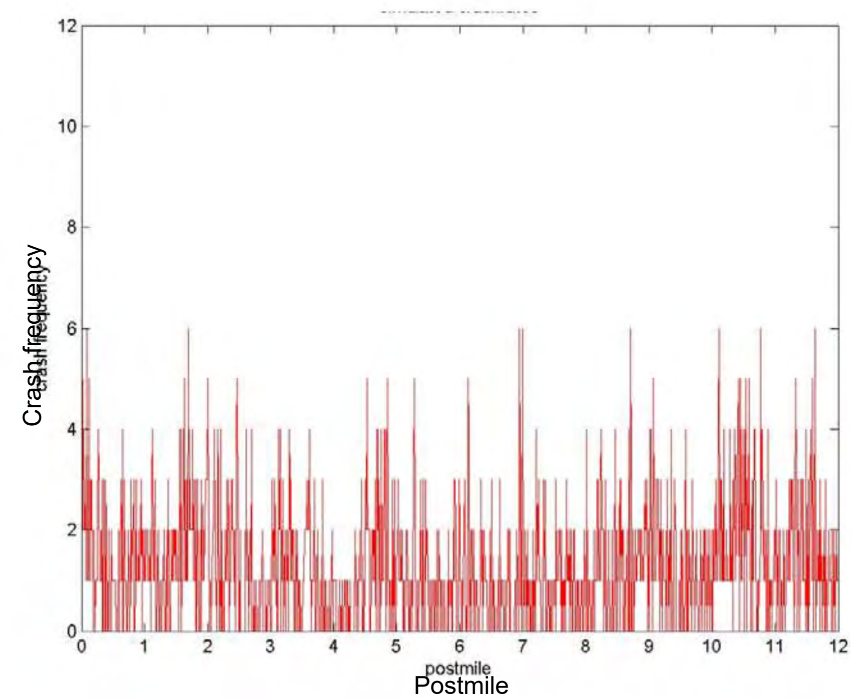


Figure 17: Empirically Observed, True, and Realized Crash Frequency (simulation unit size: 0.05 mile)

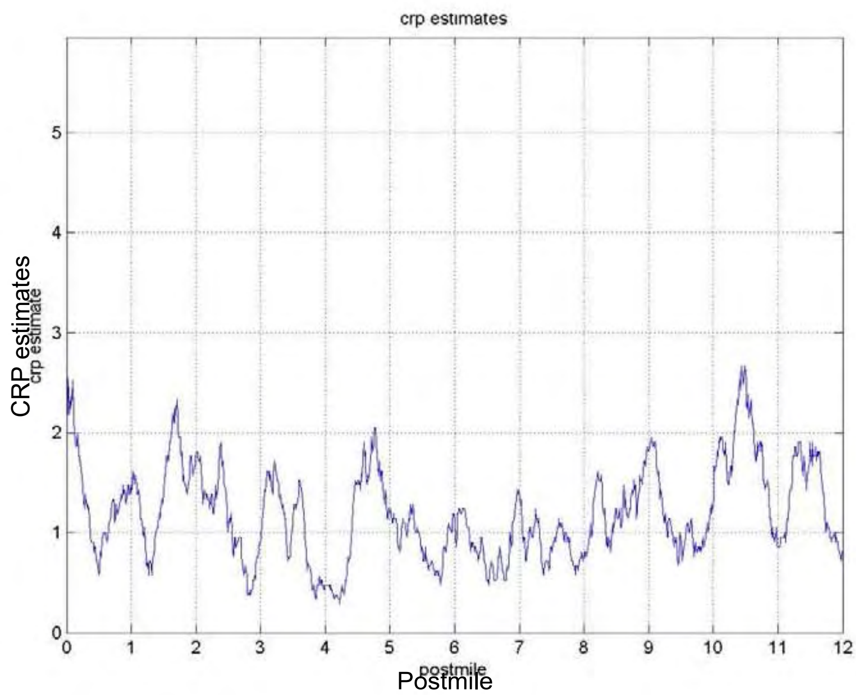
4.4. PERFORMANCE OF THE CRP SCREENING METHOD

The present simulation study is intended to further test the results of empirical analysis. To this end, the former follows most of the basic setting of the latter, particularly regarding network screening. Parameters used for this involve both the generation of a simulation database, which affects the profile of crash occurrence along the corridor, and the CRP network screening conditions. The parameter “crp_smoothing” has an influence on the shape of the CRP curve (i.e., the function of crp estimates against their corresponding postmiles). The higher the value of the "crp_smoothing," the more smoothed (and thus more flattened) the CRP curve.

Figure 18 through Figure 20 show how CRP was able to track the simulated crashes. Each of these figures represents a different section of the selected study site. Figure 18 represents PM 0 to PM 12 and shows that the moderate fluctuations of the simulated crashes in Figure 18(a) are captured well by the CRP in Figure 18(b). Figure 19 represents PM 12 to PM 24 and shows that the high crash frequency around PM 20 in Figure 19(a) is well represented in the CRP shown in Figure 19(b). The last section is shown in Figure 20 and represents PM 24 to PM 34. This again shows that the moderate fluctuations of the simulated crashes in Figure 20(a) are captured well by the CRP in Figure 20(b). Also, CRP captures the overall decline in crash frequency after PM 31.

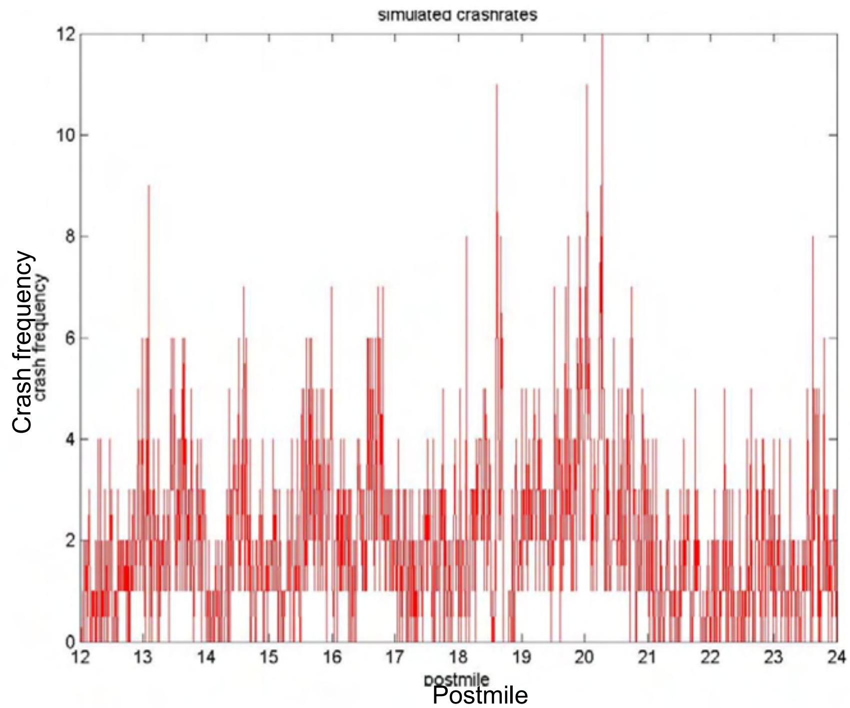


(a) Simulated Crash Frequency

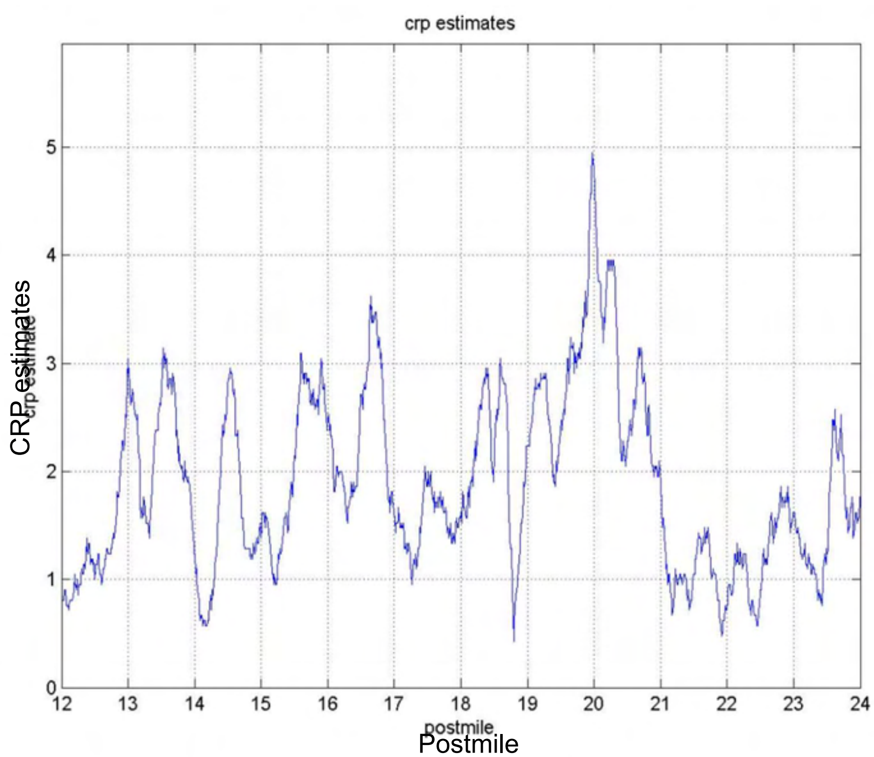


(b) CRP Estimates

Figure 18: Comparison of Simulated Crash Profile and CRP (PM 0-12)

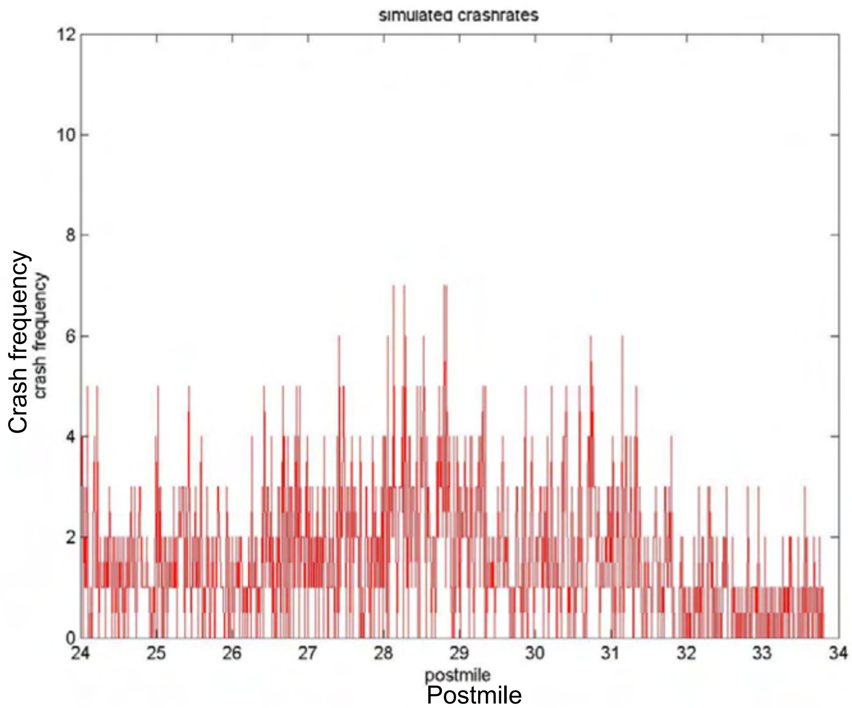


(a) Simulated Crash Frequency

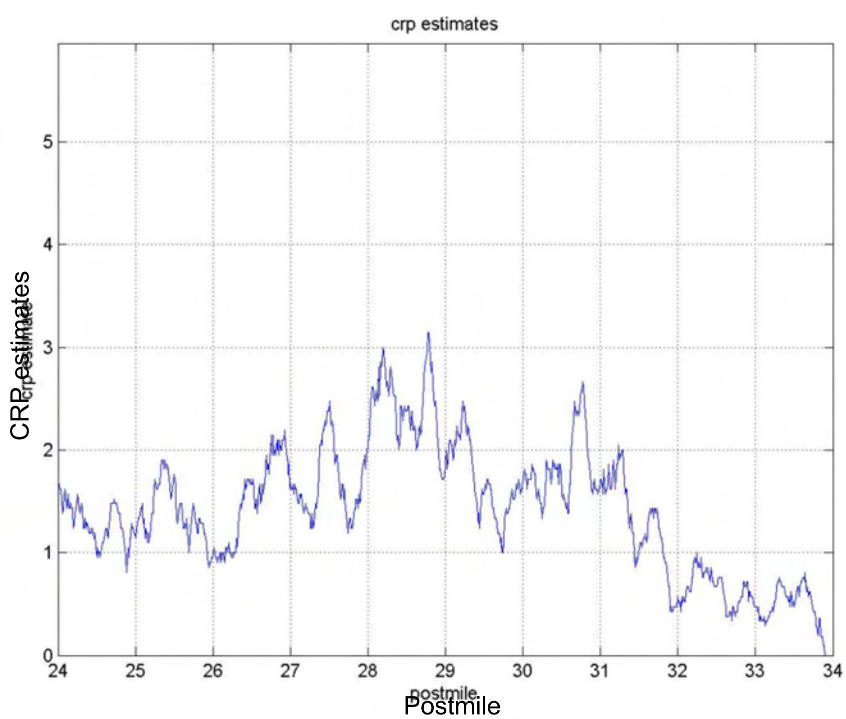


(b) CRP Estimates

Figure 19: Comparison of Simulated Crash Profile and CRP (PM 12-24)



(a) Simulated Crash Frequency



(b) CRP estimates

Figure 20: Comparison of Simulated Crash Profile and CRP (PM 24-34)

5 CASA

5.1. DESCRIPTION OF THE SYSTEM

The California Safety Analyst (CASA) (formerly known Roadway Safety Analyst (ROSA) is a web-based tool for safety engineers. It can be used as an asset management system by addressing safety as an asset. CASA can perform network screening using Sliding Window Method (SWM), Peak Searching (PS), and Continuous Risk Profile (CRP). At the core of the system is an innovative user interface which allows the users to select the relevant route on a map and perform the analysis to identify hotspots on the whole route or on selected sections of it. CASA includes all the data necessary for safety engineers to manage road safety in their jurisdictions.

Described below are the key features of CASA:

- Selection of the analysis section from a map interface
- Ability to use three different network-screening techniques
- Ability to select sub-sections of a route and filter analysis by crash characteristics
- Access to previous STIP and SHOPP information for the section of interest
- Capability to include photo and as-built plans for specific locations
- Restrict access to data according to different users
- Authorization process can be done within the system

Section 5.3 describes the process to Appendix D includes a tutorial for CASA and explains more about the features included in the system.

5.2. FEEDBACK FROM CALTRANS DISTRICTS

A total of 98 respondents from 10 different districts participated in the survey. The participants are primarily professionals who are involved in road safety management in their jurisdiction, and represent the local stakeholders. Figure 21 summarizes the average responses to the 5 survey questions, followed by detailed results of the survey for the individual districts. The results for each district include the average response, representative comments, and a photo of the survey participants.

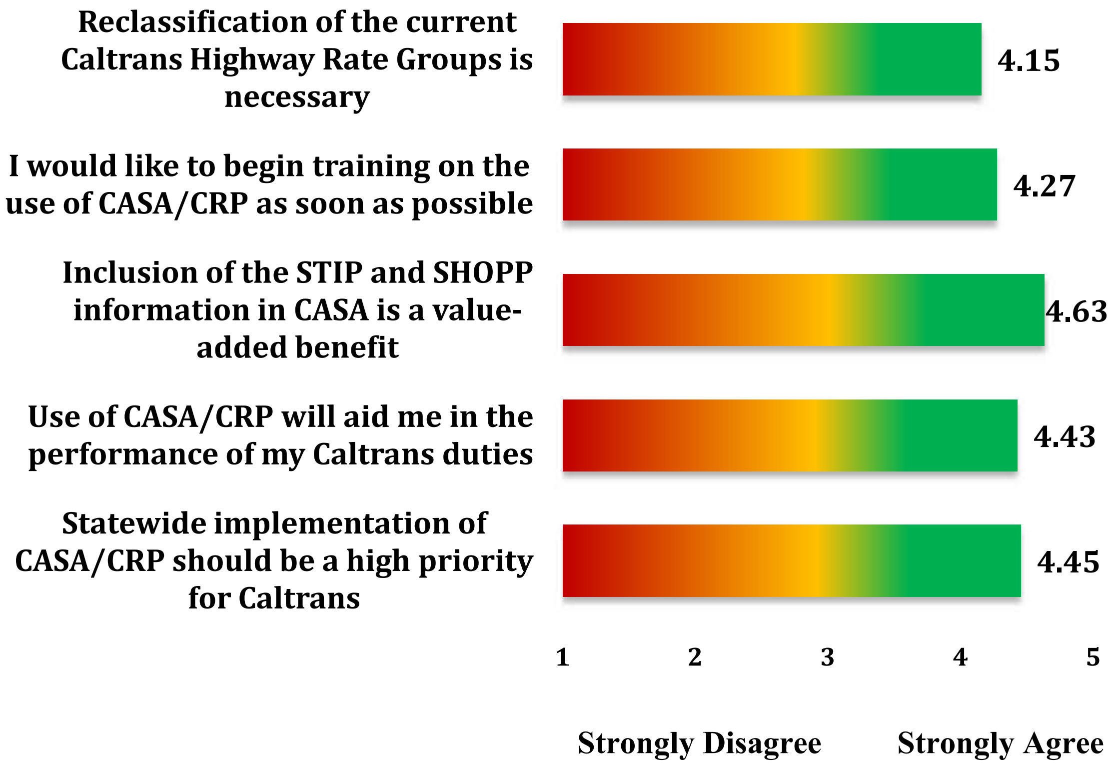


Figure 21: CASA Survey Response Across the Different Districts (n=98)

5.3. CASA DEMONSTRATION WEBINAR

A demonstration of the CASA system was presented in webinar on 3/6/2012 followed by a Q&A session. Figure 22 summarizes the main features presented in the webinar and described below:

(a) A password is necessary to log on to the system. There are three account access levels and only the necessary information is presented to each user.

(b) Users can click on the map to select the study section of interest using an intuitive tool. Once selected the postmile information is automatically entered in the appropriate fields. If necessary users can manually change the postmile information.

(c) Users select the time period of their study from the drop-boxes at the bottom of the screen. It is possible to check the "display options" to see if there have been any STIP or SHOPP information available in the selected spatiotemporal period.

(d) Relevant previous studies are displayed and detailed information is available by clicking on one of the dots.

(e) The CRP can be generated by clicking at the bottom of the page (other screening methods, such as SWM and PS can be selected this way too).

(f) The CRP is calculated and displayed. A detailed analysis of the crashes is accessible from this screen too.

Figure 22: Screen shots of CASA

6 SUMMARY AND CONCLUSIONS

An experimental evaluation was conducted to compare how three different network screening methods perform with respect to high collision concentration location identification (i.e., hotspot identification). The study evaluates the performance of the Continuous Risk Profile (CRP) compared to the Sliding Window Method (SWM) and Peak Searching (PS) network screening methods. Three main research efforts were carried out: (i) comparing the performance using empirical data; (ii) comparing the performance using simulated data; (iii) developing a web-based tool for safety engineers. The main findings of this evaluation are summarized below:

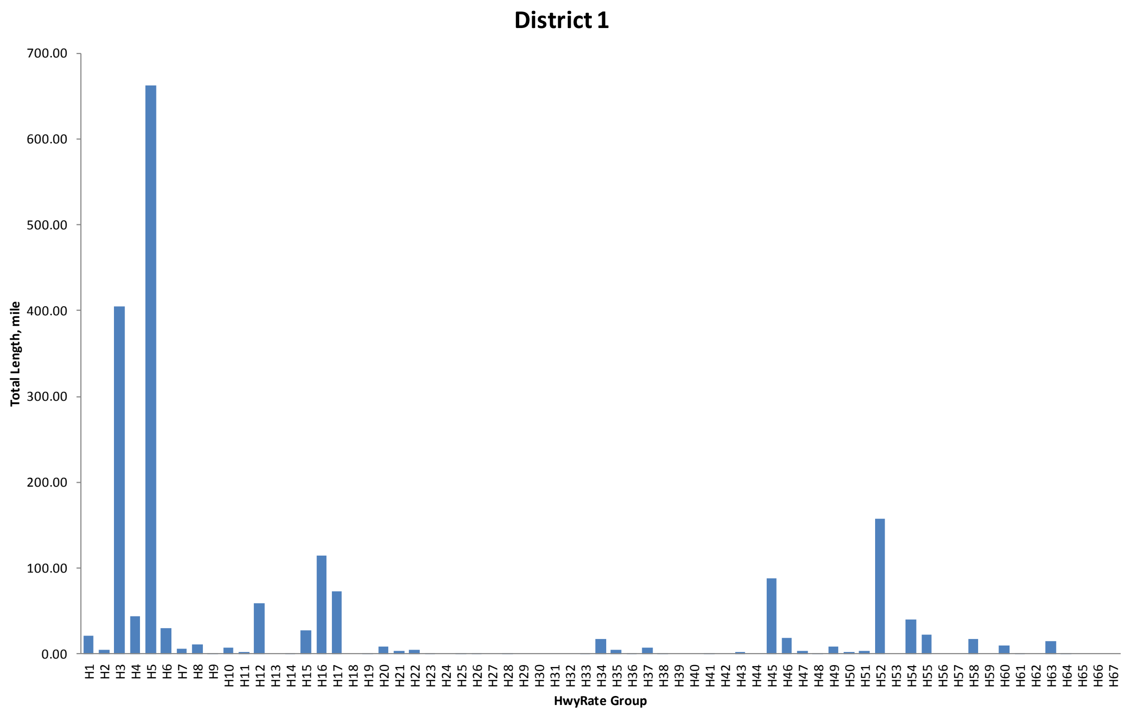
1. Careful examination of the performance of the three methods produced comparable levels of false negatives (i.e., not identifying true HCCL's). However, the CRP method produced far fewer false positives (i.e., identifying a site as a hot-spot when it is not) than SWM and PS.

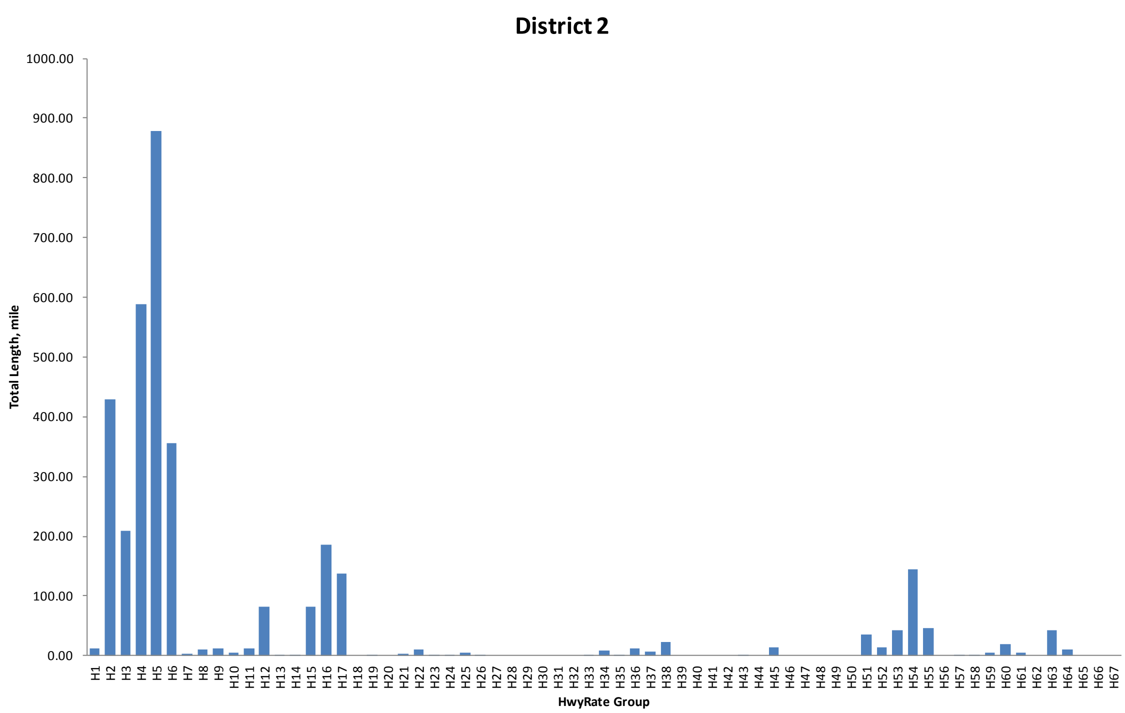
2. The CRP method is able to accurately track the collision profile of simulated crashes along a representative California highway.

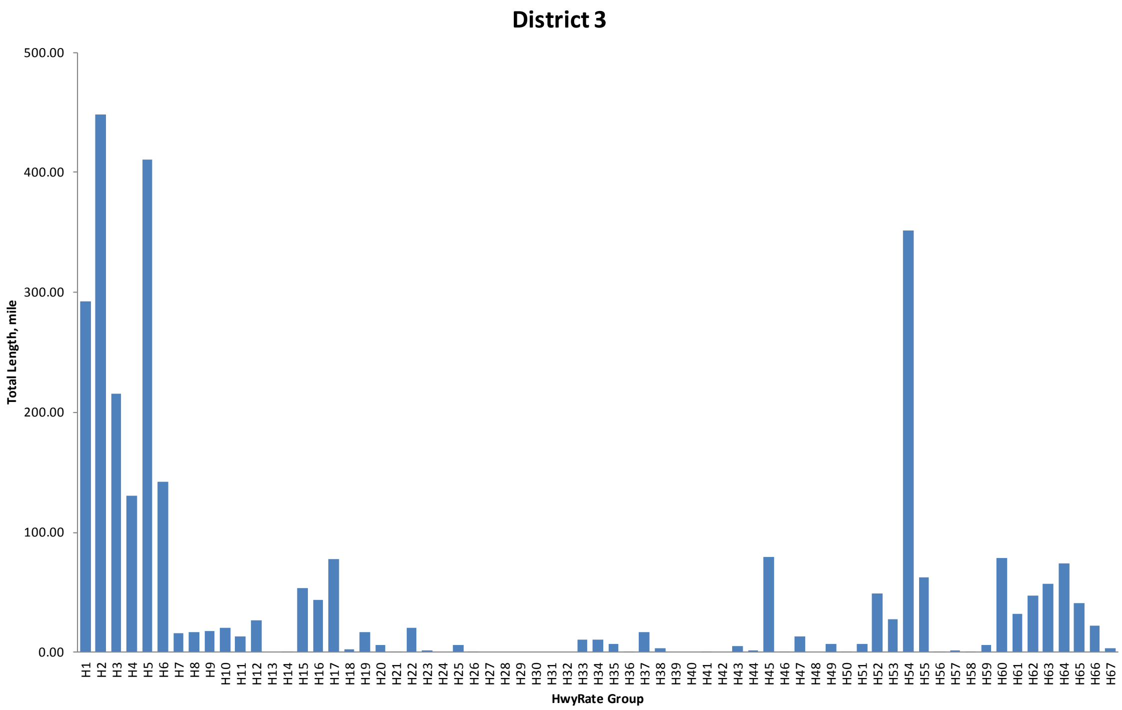
3. The results of the CASA survey revealed that the users agree that using the CASA web-based tool will enhance their productivity in performing their Caltrans duties and agree that implementation of CASA should be a high priority for Caltrans.

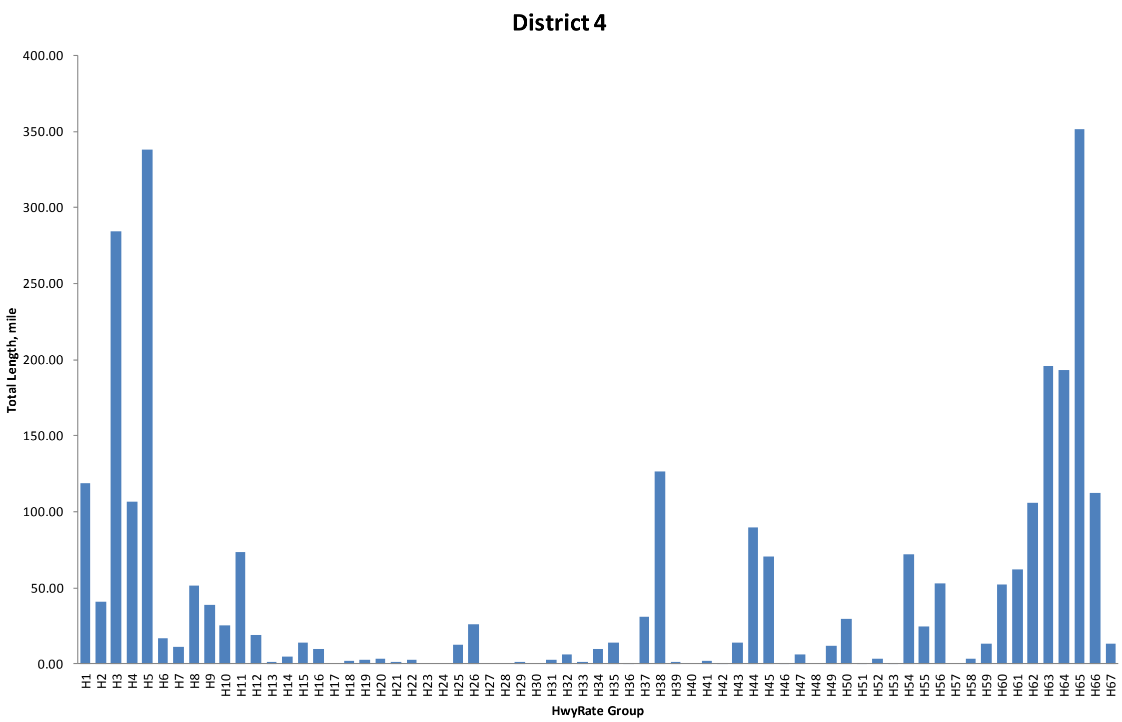
These findings indicate that by using the CRP method, Caltrans can significantly reduce the resources spent on investigating falsely identified locations and better utilize the resources in improving true HCCL's. Based on the findings from current study, implementing the CRP method has the potential to reduce the backlog in Caltrans Table C. The findings from the survey among the safety engineers also revealed that implementing CASA can significantly improve the efficiency in undertaking their daily tasks. Moreover, CASA has the potential to be a useful tool and can be tailored to any network screening method adopted by Caltrans.

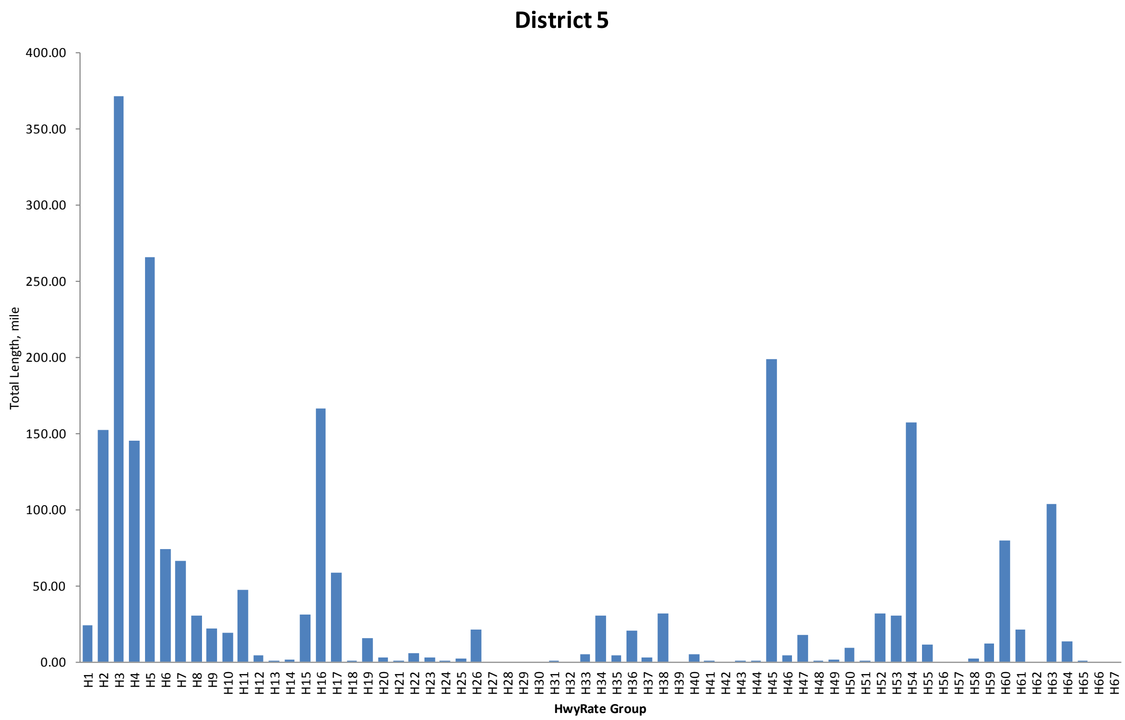
APPENDIX A – LENGTH OF DIFFERENT HIGHWAY GROUPS ACROSS CALTRANS DISTRICTS

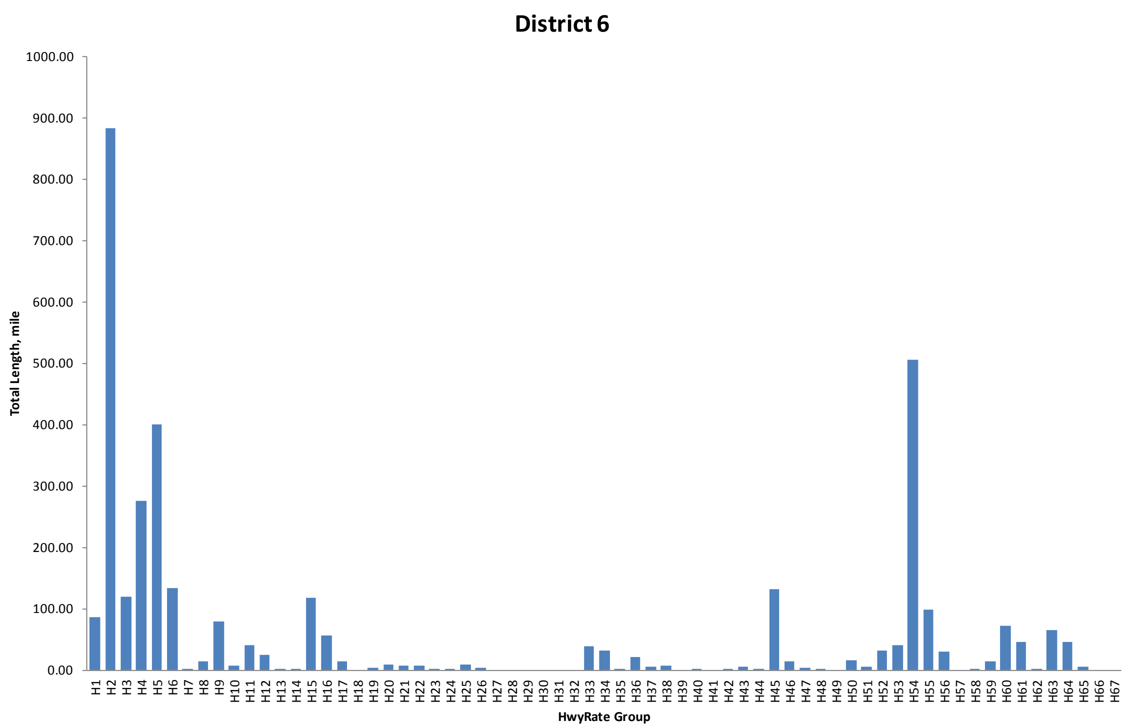


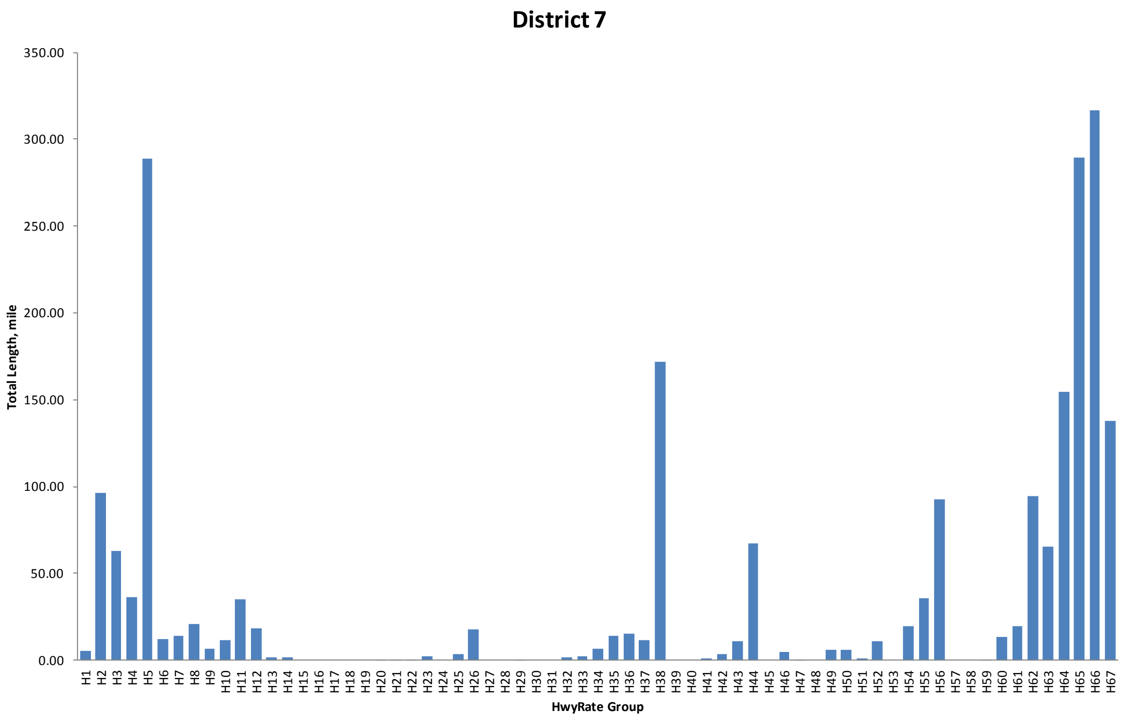


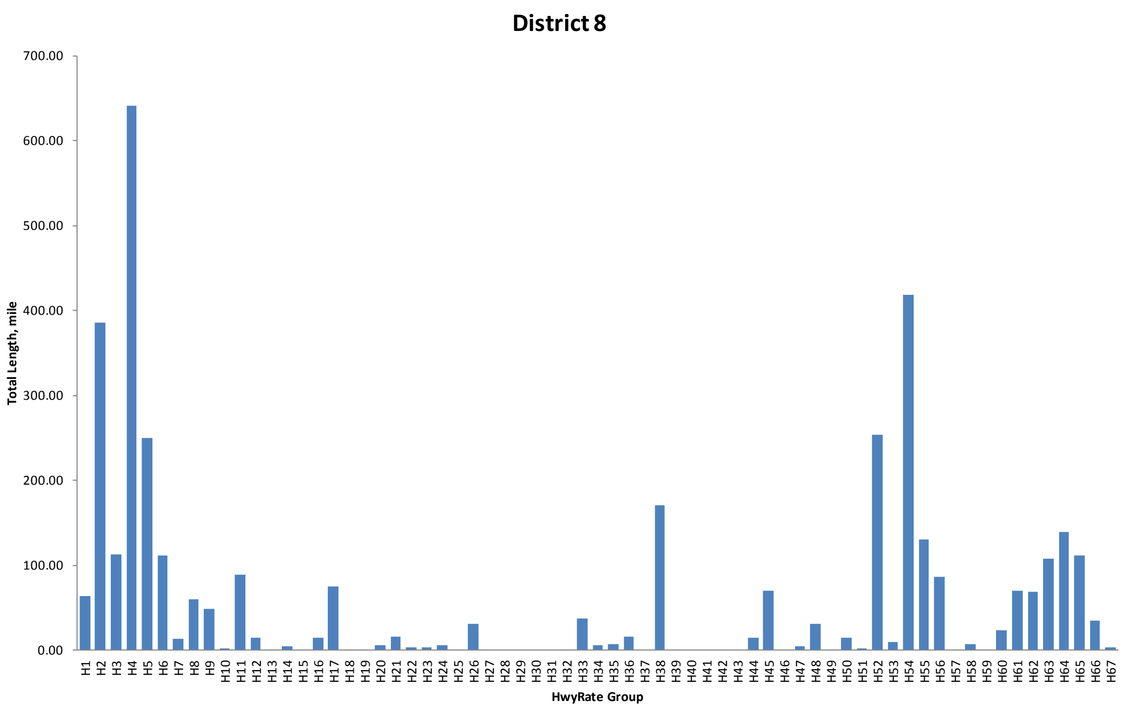

District 3
Total Length, mile
HwyRate Group

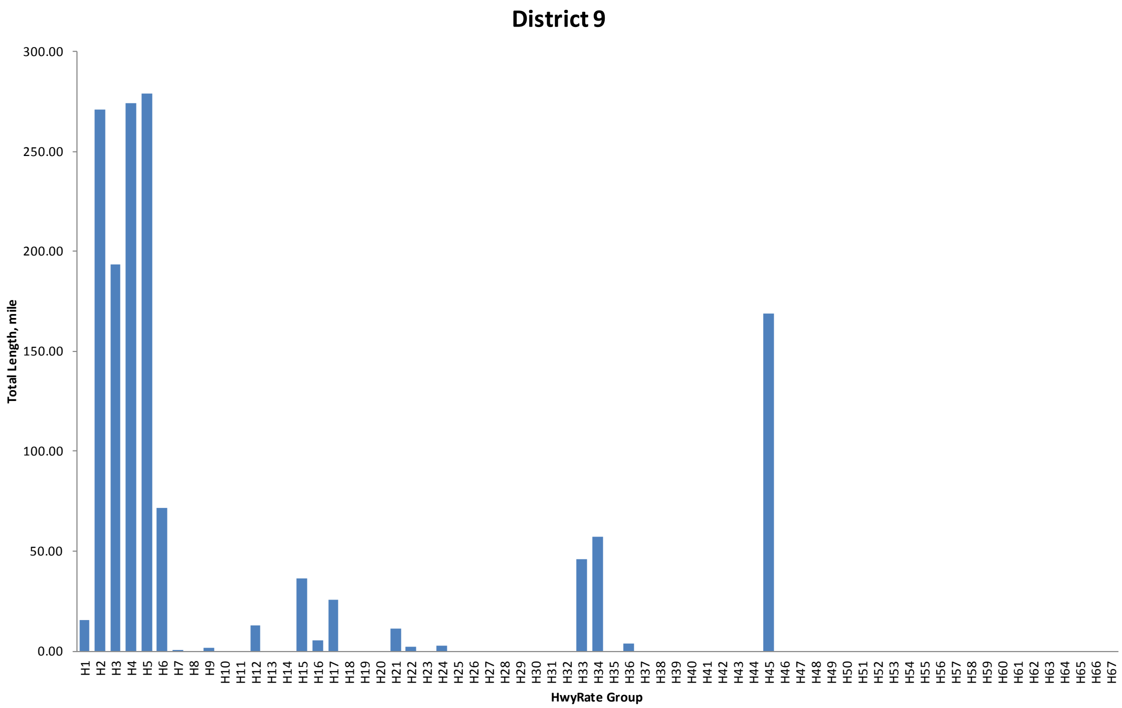

District 4
Total Length, mile
HwyRate Group

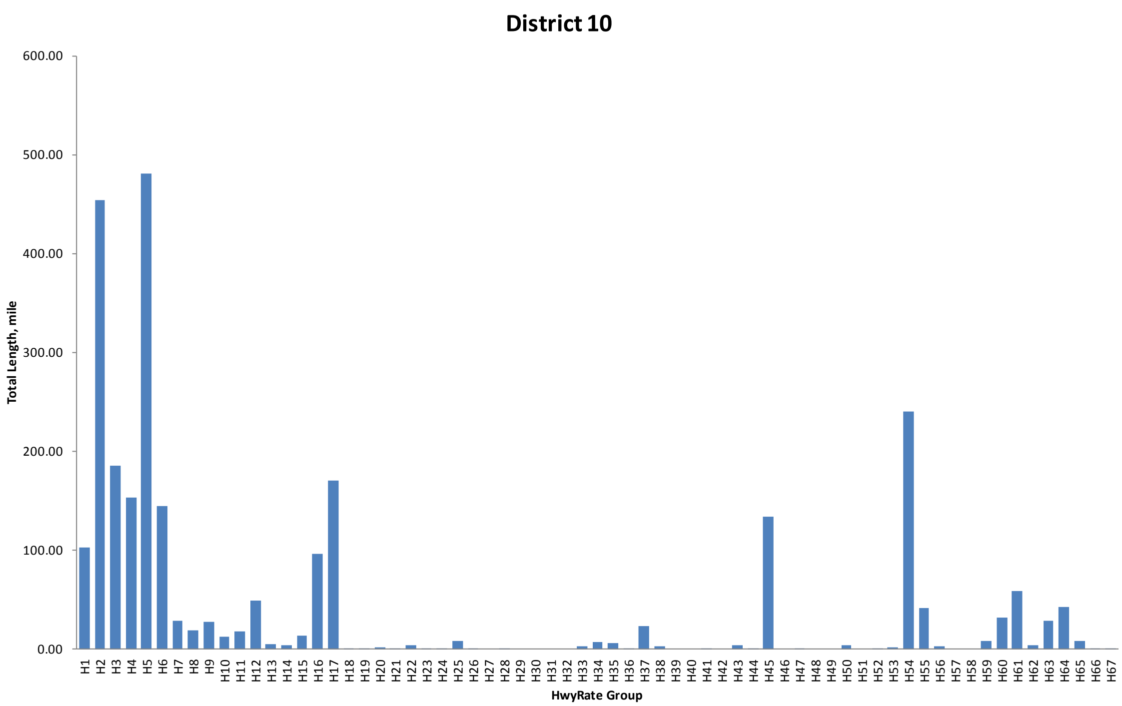

District 5
Total Length, mile
400.00
350.00
300.00
250.00
200.00
150.00
100.00
50.00
0.00
HwyRate Group

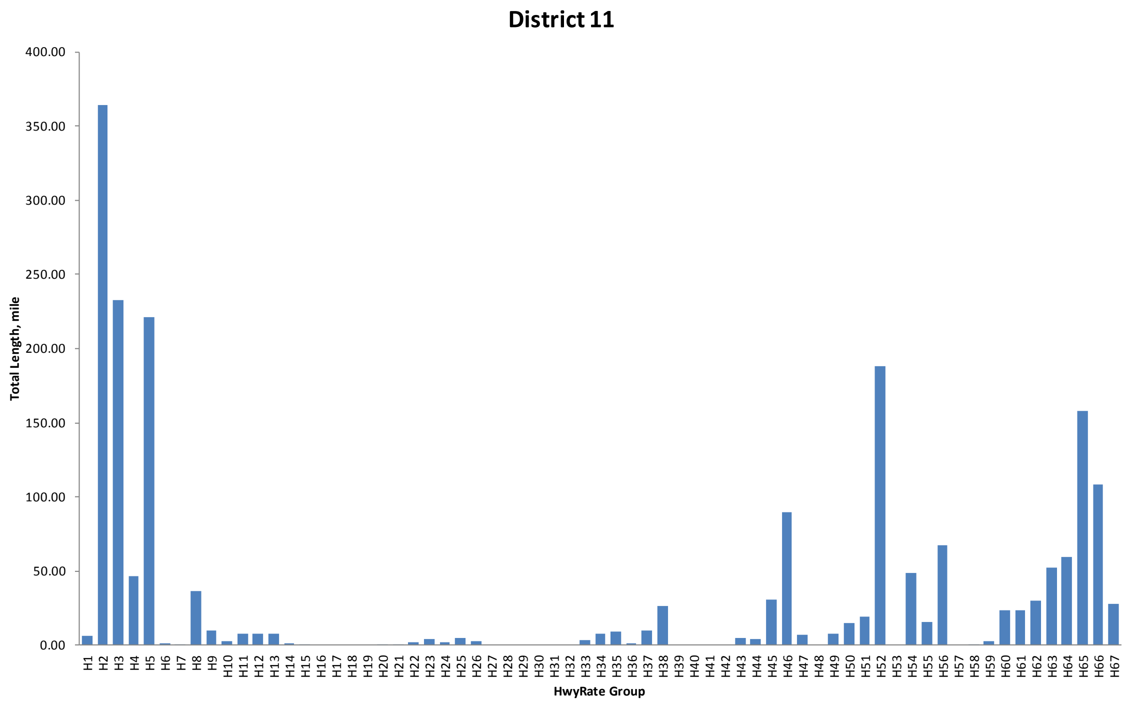

District 6
Total Length, mile
1000.00
900.00
800.00
700.00
600.00
500.00
400.00
300.00
200.00
100.00
0.00
HwyRate Group

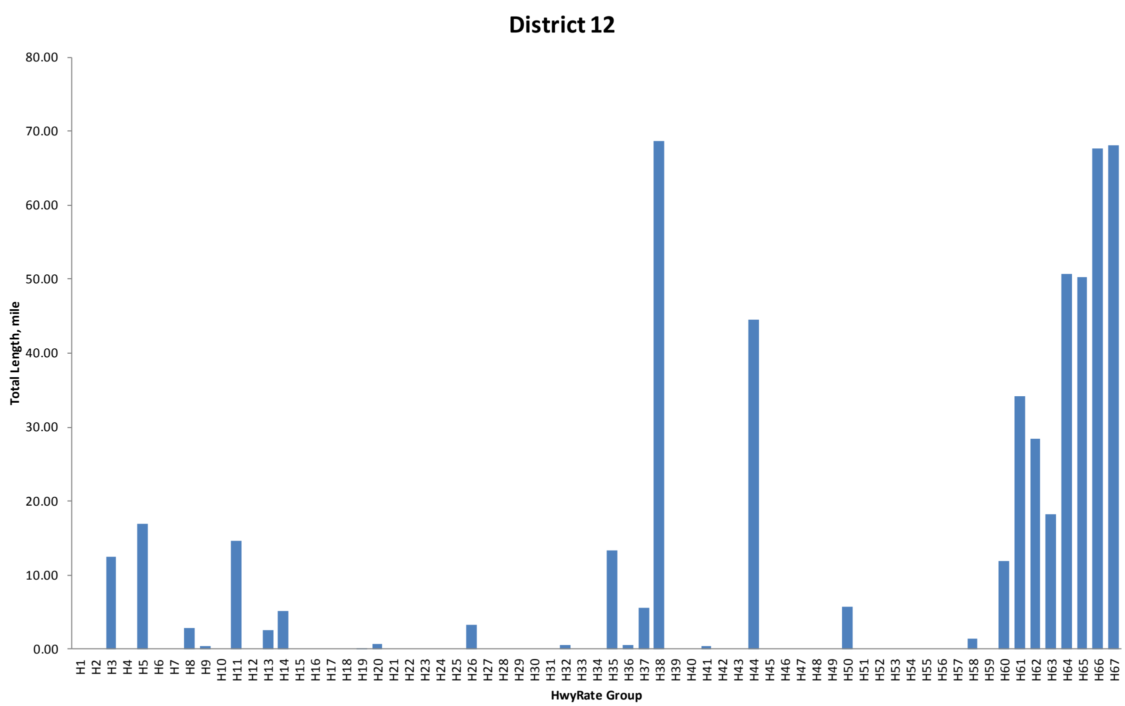

District 7
Total Length, mile
HwyRate Group


District 8
Total Length, mile
HwyRate Group


District 9
Total Length, mile
HwyRate Group


District 10
Total Length, mile
HwyRate Group


District 11
Total Length, mile
HwyRate Group


District 12
Total Length, mile
HwyRate Group

APPENDIX B – CASA SURVEY RESULTS

Performance Measure	Data and Inputs				
	Crash Data	Roadway Information for Categorization	Traffic Volume	Calibrated Safety Performance Function and Overdispersion Parameter	Other
Average Crash Frequency	X	X			
Crash Rate	X	X	X		
Equivalent Property Damage Only (EPDO) Average Crash Frequency	X	X			EPDO Weighting Factors
Relative Severity Index	X	X			Relative Severity Indices
Critical Rate	X	X	X		
Excess Predicted Average Crash Frequency Using Method of Moments2	X	X	X		
Level of Service of Safety	X	X	X	X	
Excess Predicted Average Crash Frequency using Safety Performance Functions (SPFs)	X	X	X	X	
Probability of Specific Crash Types Exceeding Threshold Proportion	X	X			
Excess Proportion of Specific Crash Types	X	X			
Expected Average Crash Frequency with EB Adjustment	X	X	X	X	
Equivalent Property Damage Only (EPDO) Average Crash Frequency with EB Adjustment	X	X	X	X	EPDO Weighting Factors
Excess Expected Average Crash Frequency with EB Adjustment	X	X	X	X	

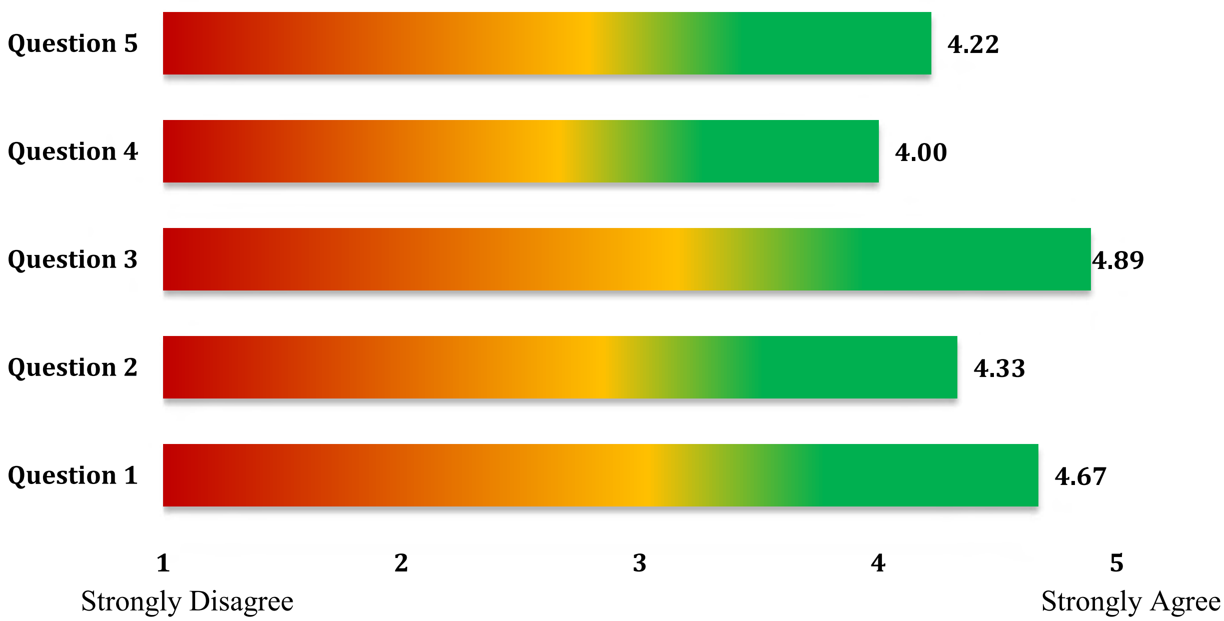
Table B-1: Data and inputs of different performance measures

Performance Measure	Accounts for RTM Bias	Method Estimates a Performance Threshold
Average Crash Frequency	No	No
Crash Rate	No	No
Equivalent Property Damage Only (EPDO) Average Crash Frequency	No	No
Relative Severity Index	No	Yes
Critical Rate	Considers data variance but does not account for RTM bias	Yes
Excess Predicted Average Crash Frequency Using Method of Moments	Considers data variance but does not account for RTM bias	Yes
Level of Service of Safety	Considers data variance but does not account for RTM bias	Expected average crash frequency plus/minus 1.5 standard deviations
Excess Expected Average Crash Frequency Using SPFs	No	Predicted average crash frequency at the site
Probability of Specific Crash Types Exceeding Threshold Proportion	Considers data variance; not effected by RTM Bias	Yes
Excess Proportions of Specific Crash Types	Considers data variance; not effected by RTM Bias	Yes
Expected Average Crash Frequency with EB Adjustments	Yes	Expected average crash frequency at the site
Equivalent Property Damage Only (EPDO) Average Crash Frequency with EB Adjustment	Yes	Expected average crash frequency at the site
Excess Expected Average Crash Frequency with EB Adjustments	Yes	Expected average crash frequency per year at the site

Table B-2: what performance measures accounts for regression-to-the-mean bias and/or estimates a performance threshold

APPENDIX C – CASA SURVEY RESULTS

C.1. DISTRICT 1



CASA survey responses - District 1 (n=9)

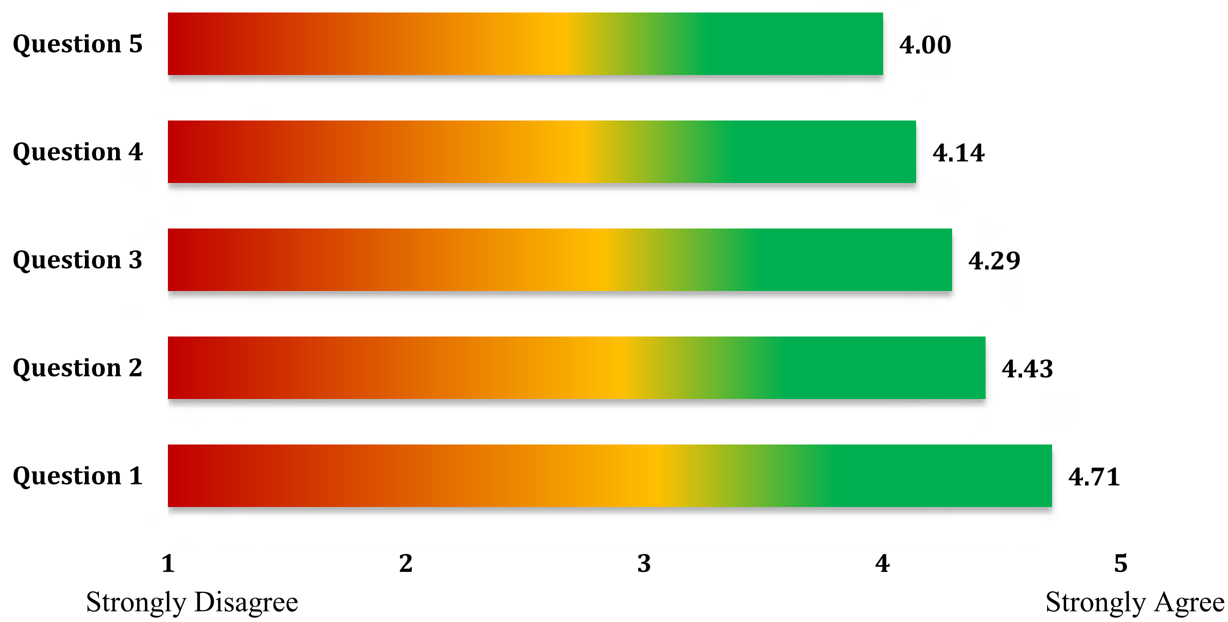
The results indicate that from district 1 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 1

Comment 1	I like the ability to locate specific projects within a given segment of roadway. Also very valuable to be able to pinpoint collision locations
Comment 2	The ability to quickly determine area of collision concentrations

CASA survey participates - District 1

C.2. DISTRICT 2



CASA survey responses - District 2 (n=6)

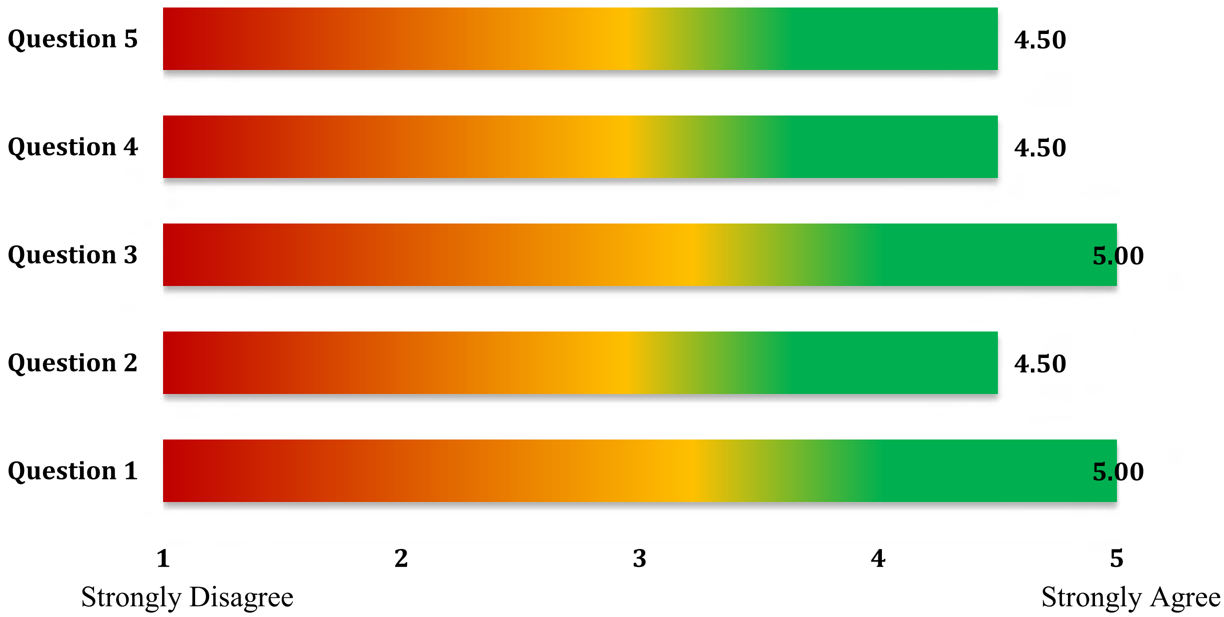
The results indicate that from district 2 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 2

Comment 1 A look at reducing false positives
Comment 2 Excellent! Great quick flexibility to specific request

Figure 3: CASA survey participates - District 2

C.3. DISTRICT 3



CASA survey responses - District 3 (n=2)

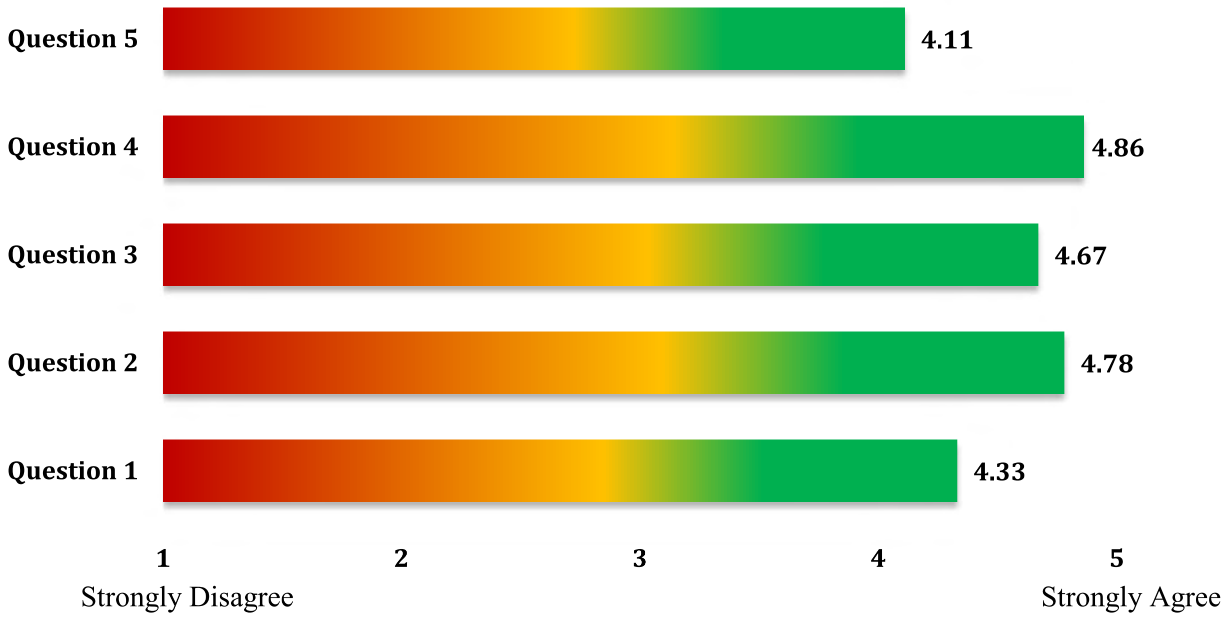
The results indicate that from district 3 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 3

Comment 1 N/A
Comment 2 N/A

CASA survey participates - District 3

C.4. DISTRICT 5



CASA survey responses - District 5 (n=9)

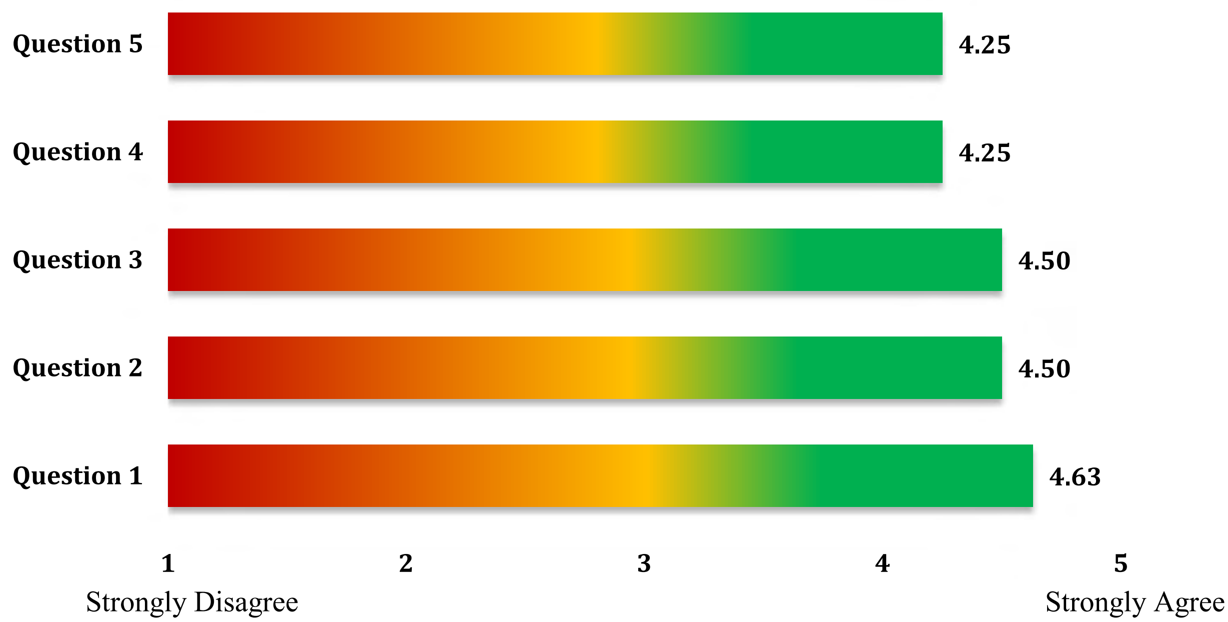
The results indicate that from district 5 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 5

Comment 1	Reduction/elimination of false spot locations
Comment 2	Everything!!! I was not sure what I was going to see but this would be extremely beneficial in my day to day job.

CASA survey participates - District 5

C.5. DISTRICT 6



CASA survey responses - District 6 (n=8)

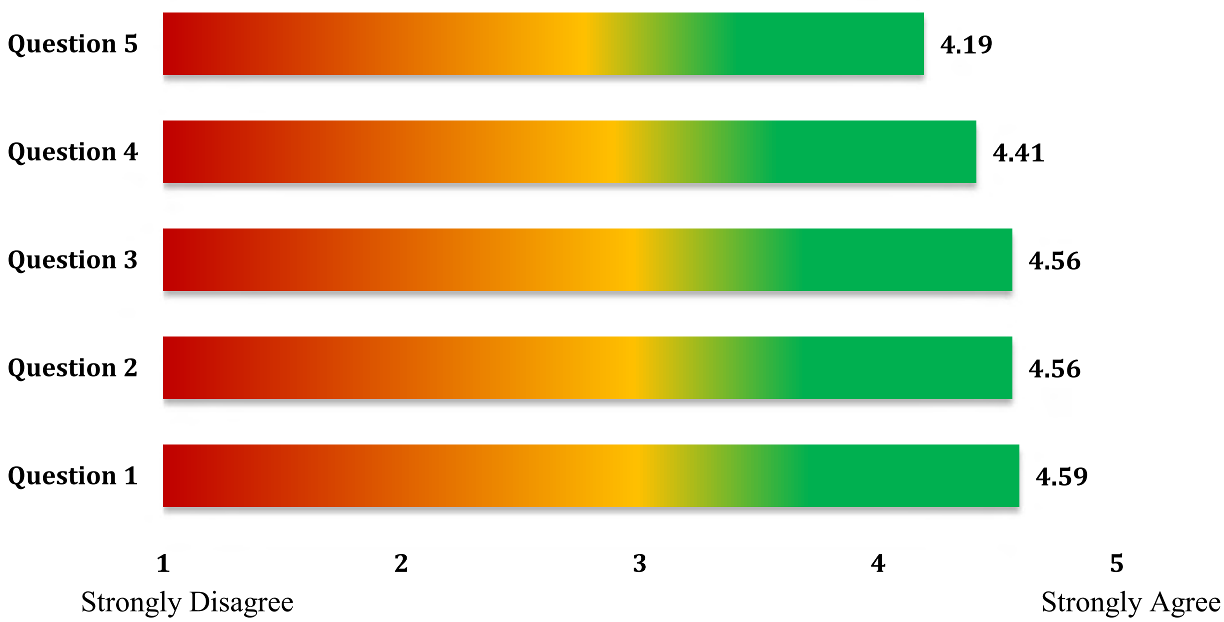
The results indicate that from district 6 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 6

Comment 1	Analysis comes fast and easy!
Comment 2	Once engineer becomes used to this program he/she can accomplish more in less time. Work efficiency will improve. Engineer will have more information to make decisions.

CASA survey participants - District 6

C.6. DISTRICT 7



CASA survey responses - District 7 (n=27)

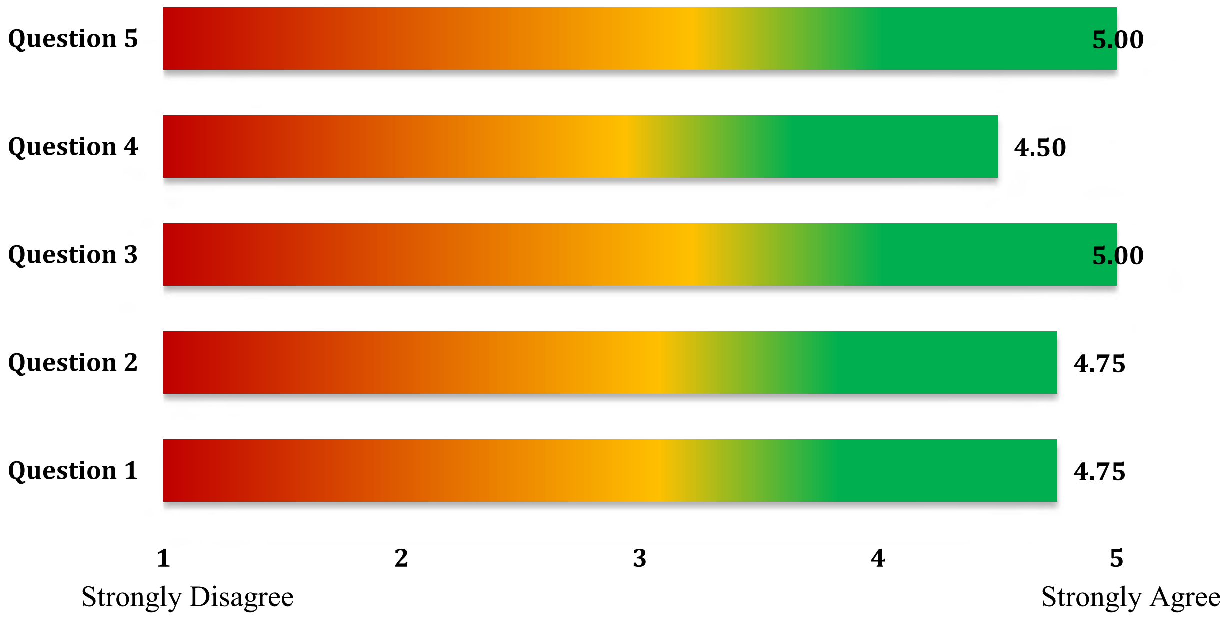
The results indicate that from district 7 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 7

Comment 1 Nice new tool. It's about time to drop that Oracle based system
Comment 2 "Almost" instantaneous identification of hotspots -- long time saver

CASA survey participates - District 7

C.7. DISTRICT 9



CASA survey responses - District 9 (n=4)

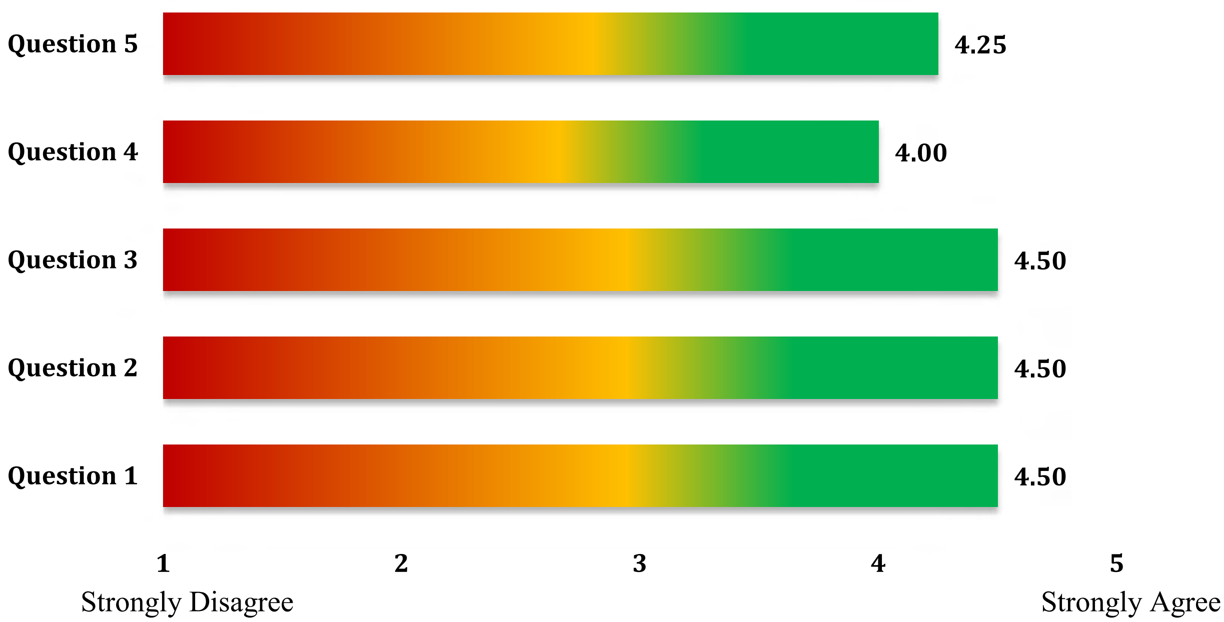
The results indicate that from district 9 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 9

Comment 1	Reducing number of false positives will allow engineers to concentrate on real "hot spots"
Comment 2	The time savings and the reduction of false positives

CASA survey participates - District 9

C.8. DISTRICT 10



CASA survey responses - District 10 (n=4)

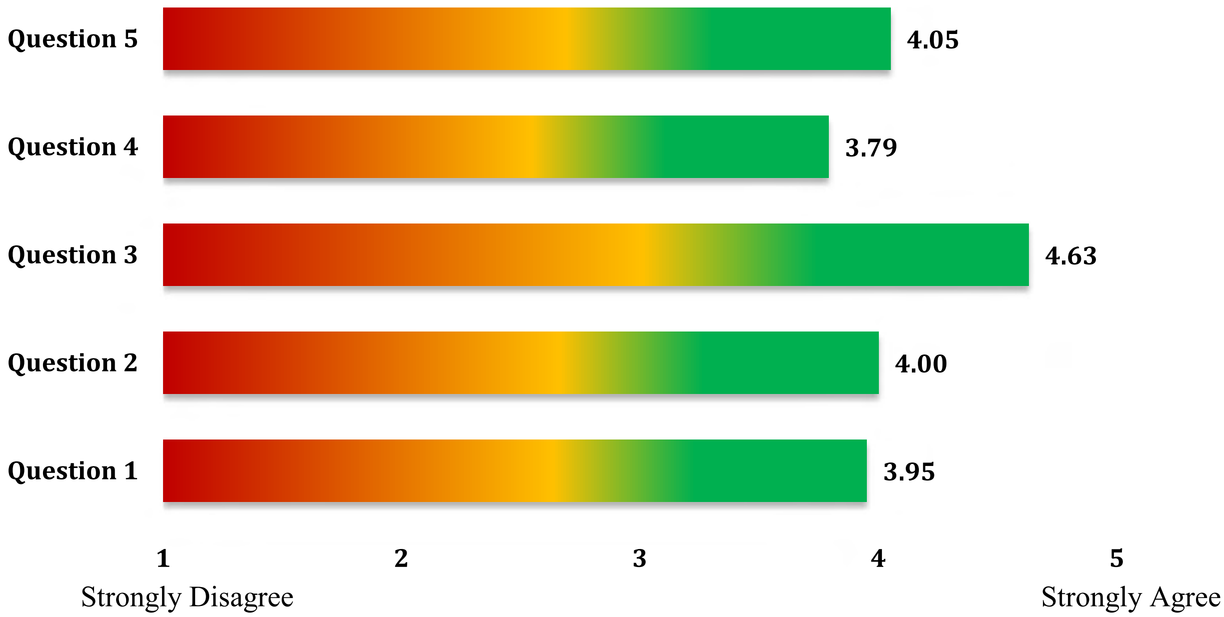
The results indicate that from district 10 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 10

Comment 1	CRP method seems to have a lot of potential
Comment 2	The concept of combining previous, ongoing, and planned projects while identifying Caltrans hotspots

CASA survey participates - District 10

C.9. DISTRICT 11



CASA survey responses - District 11 (n=19)

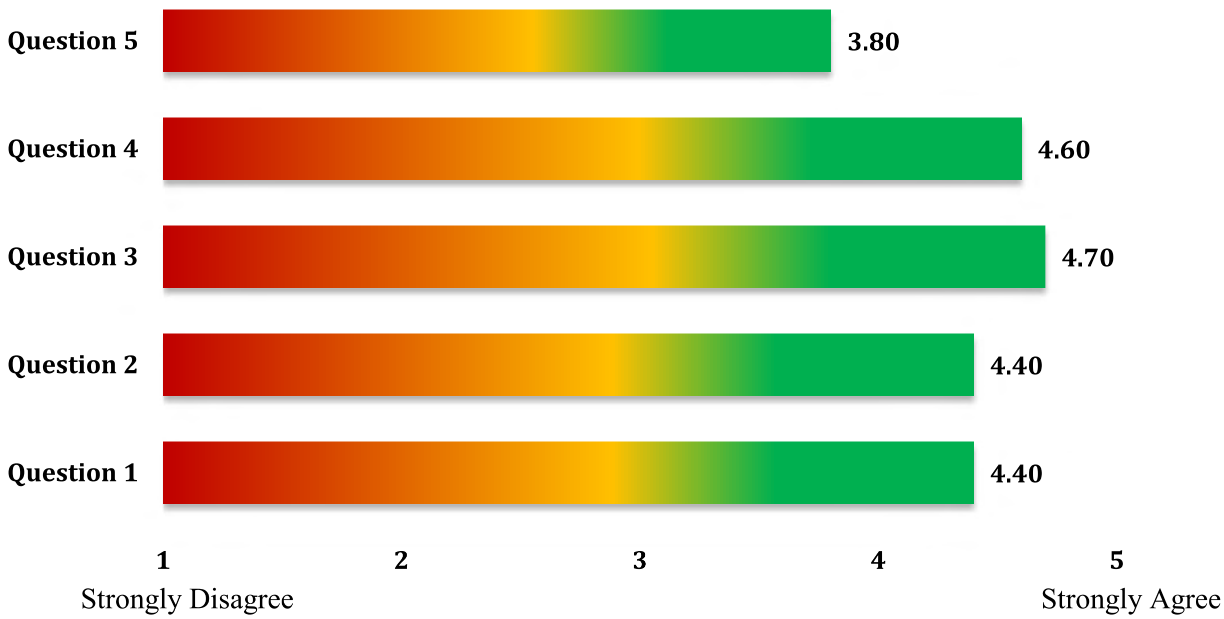
The results indicate that from district 11 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 11

Comment 1	Very user friendly and it's a "one stop ship" for traffic ops investigation
Comment 2	Inclusion of the STIP and SHOPP information in ROSA is very useful

CASA survey participates - District 11

C.10. DISTRICT 12



CASA survey responses - District 12 (n=10)

The results indicate that from district 12 survey respondents believe that CASA is a useful tool.

CASA survey comments - District 12

Comment 1	Faster and easier access to data
Comment 2	Makes finding specific details about types of accidents more efficient

CASA survey participates - District 12

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