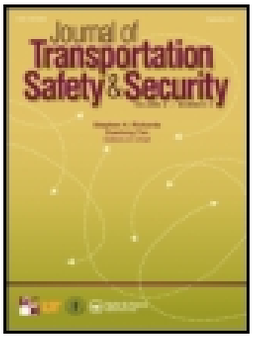

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Evaluation of hot spot identification methods for municipal roads

Kai Wang[a], Shanshan Zhao[a], John N. Ivan[b], Ishraq Ahmed[b], and Eric Jackson[a]

[a]Connecticut Transportation Safety Research Center, Connecticut Transportation Institute, University of Connecticut, Storrs, Connecticut, USA; [b]Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut, USA

ABSTRACT

Estimating crash prediction models and applying the Empirical Bayesian approach in identifying hotspots for roads under municipal jurisdiction is often challenging due to the lack of traffic count data. This study presents five hotspot identification (HSID) methods in which annual average daily traffic (AADT) information is not required (i.e., crash frequency [CF], equivalent property damage only, relative severity index, excess predicted average crash frequency using method of moments [MOM], and cross sectional analysis [CSA]), to identify hotspots for road segments under municipal jurisdiction in Connecticut. The segments were categorized into 11 homogenous groups based on the roadway geometric characteristics. The five HSID methods were applied to all segments in each roadway group separately and across the entire State for a systemic analysis. Four quantitative tests (i.e., site consistency test, method consistency test, total rank difference test, and total score test) were used to compare the performance of the five HSID methods. The results indicate that the MOM outperforms others in identifying hotspots for urban one-way arterials, urban one-way local roads, urban two-lane two-way local roads, urban multilane two-way arterials, and urban multilane two-way collectors; the CF outperforms others for rural arterials and collectors, rural local roads, urban one-way collectors, urban two-lane two-way arterials, urban two-lane two-way collectors and urban multilane two-way local roads, and the CSA performs best in all of the five HSID methods in identifying and ranking the roadway hotspots for all roadway groups together.

KEYWORDS

hotspot identification; hotspot identification comparison; municipal roads; roads without AADT

1. Introduction and motivation

Identifying crash hotspots (also known as sites with promise, hazardous locations, black-spot locations, crash-prone locations, crash concentration locations, and priority investigation locations) is the first step of the highway safety management process. A crash hotspot has been defined as a

CONTACT Kai Wang kai.wang@uconn.edu Connecticut Transportation Safety Research Center, Connecticut Transportation Institute, University of Connecticut, 270 Middle Turnpike, Unit 5202, Storrs, CT 06269-5202, USA.

location that experienced a higher number of crashes than other similar locations during a specific time period due to the presence of local risk factors (Elvik, 2007). The purpose of finding crash hotspots is to identify roadway locations with over-represented crashes or crash potentials and to implement countermeasures to improve highway safety. Therefore, selecting a valid crash hotspot identification (HSID) method plays a dominant role in identifying roadway sites that are prioritized for safety improvement. Using inappropriate methods might result in false negatives (i.e., hazardous locations that are wrongly identified as safe) and false positives (i.e., nonhazardous locations that are wrongly identified as hazardous) (Montella, 2010) and thus result in the inefficient use of safety improvement resources and limit the systematic effectiveness of the safety management process. Having reliable HSID methods is imperative for rigorously identifying hazardous roadway locations and successfully implementing a relevant highway safety improvement plan.

In recent years, a number of HSID methods have been developed by highway agencies to identify and rank hazardous roadway locations; the *Highway Safety Manual* (*HSM*, 2010) provides a comprehensive review of some commonly used approaches. Two of the most commonly applied methods are crash frequency and crash rate (Elvik, 2007; Montella, 2010; Cheng & Washington, 2008; Persaud, 2001; Tarko & Kanodia, 2004; Srinivasan et al., 2016; Gross et al., 2016). Laughland et al. (1975) jointly used the crash frequency and crash rate to locate sites with promise. To take crash costs into account, researchers have used the equivalent property damage only (EPDO) and relative severity index (RSI) methods (PIARC, 2004; TAC, 2004). However, all of the above methods use only simple observed crashes and cannot correct for regression-to-mean bias (RTM) (Hauer, 1980). To address this issue, crash prediction models have been developed and the Empirical Bayes (EB) technique has been increasingly applied in identifying hazardous roadway locations (Elvik, 2007; Montella, 2010; El-Basyouny & Sayed, 2006; Persaud et al., 1999; Wellner & Qin, 2011; Wang et al., 2017; Kwon et al., 2013; Hauer, 1986; Higle & Witkowski, 1988; Miranda-Moreno et al., 2007). The EB approach estimates the expected crashes for a specific site by combining the observed crashes at the site with a crash count predicted based on similar sites. The sites with higher EB estimated crashes are identified as potential locations for safety improvement.

Similarly, some researchers have suggested using the level of service of safety (LOSS) method HSID procedure (Kononov & Allery, 2000; Kononov et al., 2015) to address the issue of RTM. This method categorizes the LOSS into four groups based on the degree to which the observed crashes is different from the EB estimated crashes, and sites located in the highest group level are identified as hazardous locations. The study conducted by

Kononov et al. (2015) indicates that the LOSS method can address the skewness issue of crash distribution.

Extended statistical models have been developed and implemented in HSID with a focus on improving crash prediction accuracy. Qin et al. (2010) used a quantile regression model to identify the top 5% hotspots. The study shows that the quantile regression model provides a more refined list of crash-prone locations than the traditional mean-based crash prediction models by accounting for the data heterogeneity. Miaou and Song (2005) used a Bayesian method to rank the sites with promise based on the posterior probability of the site being worse than others. The study also concludes that the spatial correlation has significant affects model goodness of fit and should be considered in HISD. Miranda-Moreno et al. (2009) introduced a Bayesian framework to identify highway–railway risk locations by incorporating the number of occupants involved in a crash and occupant severity levels. The study indicates that considering the occupant injury severities can improve the reliability of identifying highway–railway hazardous locations compared to traditional methods that estimated crash counts in total. Thakali et al. (2015) used two geostatistical-based models, that is, kernel density and kriging methods to identify highway hotspots. The methods can account for the spatial autocorrelation between crashes caused by the unobserved factors, and the study verifies that kriging method outperforms the kernel density approach in terms of hotspot ranking accuracy. Cheng et al. (2018) used the multivariate spatial and temporal models to estimate motorcycle, bicycle, pedestrian, and vehicle crashes simultaneously and conduct HSID. The study illustrated that the method yields more accurate results at HSID by accounting for the temporal and spatial correlations between crashes, which is consistent with the findings of studies conducted by Liu and Sharma (2017, 2018).

To verify the reliability of HSID, researchers have paid increasing attention to comparing the performance of different HSID methods. Higle and Hecht (1989) conducted a simulation experiment to compare the performance of two methods for identifying hotspots using crash rates: classical statistical analysis and a Bayesian method. The study indicates that the Bayesian method improves the HSID accuracy by providing a lower number of false negative and false positive errors. Similarly, Maher and Mountain (1988) used a simulation-based approach to compare the performance between annual crash frequency and model-based predictions in HSID. The study demonstrates that the crash frequency method might perform better than the prediction method due to the possibly inaccurate crash prediction by statistical models. Wu et al. (2014) compared the Sichel model and the negative binomial (NB) model in HSID using a simulation data. The study indicates that the Sichel model provides a better HSID than the NB model. Cheng and Washington (2005) used experimentally

derived simulated data to compare three HSID methods: simple ranking using crash frequency, ranking by confidence interval, and ranking by EB method. Using simulated data, sites with promise are known a priori, and false negatives and false positives can be calculated for method comparison. The study illustrates that the EB approach outperforms the other two methods in HSID accuracy. Cheng et al. (2017) compared the EB approach with traffic volume with the EB approach without traffic volume in HSID. The study verified that the EB approach with traffic volume outperformed the other and concluded that the traffic volume is one of the most critical variables in crash prediction models. Elvik (2008) compared five HSID techniques: crash frequency, crash rate, combination of crash frequency, crash prediction model with EB adjustment, and potential for improvement method. The study confirms the results of Cheng and Washington that the EB approach is better than others in HSID. Srinivasan et al. (2016) conducted a study to describe the data required for performing a reliable HSID. The study compared several methods including crash frequency, crash rate, LOSS, and crash prediction with EB adjustment; discussed the strengths and limitations of each method; and summarized the tools and resources that are currently available to support different HSID methods.

Cheng and Washington (2008) proposed five quantitative evaluation tests that can be used to compare and evaluate the performance of different HSID approaches. The five tests evaluate a variety of aspects of the performance of each HSID method, including (1) site consistency test (SCT), (2) method consistency test (MCT), (3) total rank difference test (TRDT), (4) false identification test (FIT), and (5) Poisson mean difference test (PMDT). The SCT evaluates the ability of a HSID method to consistently identify a site as high risk over different observation periods. The MCT evaluates the performance of a HSID by measuring the number of same hotspots identified over subsequent observation periods, given that no significant changes have been made to the site and given the assumption that the site is actually high risk. The TRDT evaluates the ability that a HSID method can consistently rank the identified hotspots during different observation periods. The FIT and PMDT measure each method's performance in terms of to what extent the false negative and false positive locations were identified by each method. The study clarifies that the EB method is significantly better than other HSID methods including crash frequency, crash rate, and potential for improvement in terms of the overall HSID performance. However, the last two tests require that the truly hazardous locations be known a priori, which is only the case when using simulated data. Instead, Montella (2010) proposed an additional test—total score test (TST)—to be used together to evaluate the performance of HSID methods which only requires the observed crashes. The total score test combines the

SCT, MCT, and TRDT and provides a synthetic index to evaluate the effectiveness of each HSID method. The results verify the finding in the study conducted by Cheng and Washington that the EB method is the most reliable method in identifying roadway hazardous locations.

To date, most studies focus mainly on identifying hotspots for roads under state jurisdiction. The EB prediction method has been verified as the most reliable approach and has been widely used by highway agencies to identify state roadway hotspots. Traffic volume (e.g., annual average daily traffic [AADT], vehicle miles travelled [VMT]) is the most critical variable used as exposure in the crash prediction models needed for this approach (Kwon et al., 2013). This presents a problem for roads under municipal or county jurisdiction where traffic counts are generally not available because it is economically impractical to implement traffic-counting programs for so many facilities on which the traffic volume is typically below 400 per day (Souleyrette et al., 2010). Although a variety of studies have been conducted to predict crashes on roads under municipal jurisdiction or crashes lacking exposure measurements using the demographic data as a surrogate for traffic data (Kwon et al., 2013; Souleyrette et al., 2010; Pulugurtha et al., 2004; Ladron de Guevara et al., 2004; Lovegrove & Sayed, 2006; Naderan & Shahi, 2010; Lee et al., 2015; Abdel-Aty, Lee, Siddiqui, & Choi, 2013; Cai et al., 2017), all of these studies estimated crashes at a zonal level (e.g., Traffic Analysis Zone (TAZ) level, county level, municipal level and block group level). There are also research that combines macrolevel and microlevel safety analysis to compensate for the deficiencies of each (Cai et al., 2018a; Cai et al., 2018b). When identifying hotspots for roadway sites (e.g., roadway segments or intersections) that miss exposure measures, zonal level crash prediction models are not suitable. It is thus desirable to investigate HSID methods that do not require traffic counts and identify the most reliable HSID method for identifying hazardous roadway locations on roads under municipal jurisdiction (i.e., without traffic counts).

The objective of this study is to use five HSID methods in which traffic counts are not required, that is, (1) crash frequency (CF), (2) equivalent property damage only (EPDO), (3) relative severity index (RSI), (4) Excess predicted average crash frequency using method of moments (MOM), and (5) cross sectional analysis (CSA) to identify hotspots for roadway segments under municipal jurisdiction. Four quantitative assessment tests proposed by Montella (2010), that is (1) SCT, (2) MCT, (3) TRDT, and (4) TST are used to evaluate and compare the performance of the five HSID methods. The roadway segment data and crash data for roads under municipal jurisdiction were collected from State of Connecticut sources. To account for crash data and roadway class heterogeneity, roadway segments under municipal jurisdiction were classified into 11 categories based on roadway

functional class, area type (rural/urban), number of through lanes, and travel direction (one-way or two-way). The five HSID methods and four tests were applied for each roadway category and for all categories together, respectively. Note that the term *local* is used in this study as one of the roadway functional classes (arterial, collector and local). To avoid confusion, we define *municipal roads* to represent roadways under municipal jurisdiction. Note also that there are no roads in the State of Connecticut under county jurisdiction.

The rest of the article is organized as follows. The next section presents the five HSID methodologies and four quantitative assessment tests. The third section describes the process of data preparation. The fourth section discusses the HSID results and comparison, and the conclusions and recommendations are drawn in the final section.

2. Methodologies

2.1. HSID methodologies

This section defines five HSID methods in which the traffic counts are not required and were used to identify roadway hotspots in this study.

2.1.1. Crash frequency

CF is the simplest HSID method. The site with the highest number of total crashes during a specific time period is ranked first. The site with the second highest number of total crashes is ranked second, and so on (*HSM*, 2010). To account for differences in segment length, the crash frequency in this study is calculated as total crashes divided by the segment length and time period and defined as crashes per mile per year (Montella, 2010).

2.1.2. Equivalent property damage only

The EPDO method calculates a combined frequency and severity score for each site by assigning weighting factors to crashes by crash severity and monetary consequences (Montella, 2010). The weighting factors are based on property damage only crash costs, and the calculated score accounts for the severity of crashes and the expected crash costs for each site. The weighting factors used in this study are estimated by the Federal Highway Administration (FHWA) based on accepted expected monetary costs for each severity level (Council et al., 2005). Fatal crashes ($4,008,900) thus have a weight factor equal to 542, injury crashes ($82,600) have a weight factor equal to 11, and PDO crashes ($7,400) have a weight factor equal to 1. EPDO calculation method details can be found in the *HSM* (*HSM*, 2010).

2.1.3. Relative severity index

The RSI method assigns a monetary crash cost to each type of crash, and the total costs of crashes are calculated for each site. An average crash cost per site is then calculated divided by the total crash counts and compared to an overall average crash cost for the site's reference population. The site's reference population contains all sites with similar characteristics; details of how we allocated sites to reference groups are described in the next section. Similar with the EPDO method, crash type costs are also estimated by FHWA (Council et al., 2005). RSI calculation details can be found in the *HSM* (*HSM*, 2010).

2.1.4. Excess predicted average crash frequency using Method of Moments

In the MOM, a site's observed crash frequency is transformed based on the Mean and variance of crash frequency for the site's reference population to partially account for the regression-to-mean issue. The transformed crash frequency for each site is then compared to the average crash frequency for the reference population. The sites with larger adjusted crash frequency than the average crash frequency are identified as hotspots and are ranked based on the magnitude of difference between the adjusted crash frequency and the average crash frequency. The MOM method is applied using the following steps (*HSM*, 2010).

1. Divide all roadway segments into similar roadway groups based on roadway characteristics such as functional class, number of lanes and speed limit.
2. Calculate the average crash frequency for each roadway group as:

$$N_{group} = \frac{\sum_{i=1}^{n} N_{observed,i}}{n_{group}} \tag{1}$$

Where, N_{group} is the average crash frequency for each roadway group, $N_{observed,i}$ is the observed crash frequency for segment i in the same group, and n_{group} is the total segment number in the group.

3. Calculate the variance (Var_{group}) for each group as:

$$Var_{group} = \frac{\sum_{i=1}^{n} (N_{observed,i} - N_{group})^2}{n_{group} - 1} \tag{2}$$

4. Calculate the adjusted observed crash frequency per site ($N_{observed,i,adj}$) as:

$$N_{observed,i,adj} = N_{observed,i} + \frac{N_{group}}{Var_{group}} \times (N_{group} - N_{observed,i}) \tag{3}$$

5. Calculate the potential for improvement per site (PI_i) as:

$$PI_i = N_{observed,i,adj} - N_{group} \tag{4}$$

6. Rank sites according to the PIs.

2.1.5. Cross sectional analysis

The CSA method was developed by the State of New Jersey to identify roadway segment hotspots when AADT data is not available (FHWA, 2010). The CSA method is applied using the following steps:

1. Divide all roadway segments into similar "cross-sections" (called roadway groups in this study) following Step 1 in 2.1.4.
2. Calculate the "crash rate" for each segment as:

$$CR_{segment} = \frac{5(F) + 4(A) + 3(B) + 2(C) + PDO}{L} \tag{5}$$

   where $CR_{segment}$ is the crash rate calculated for each segment, F is the number of fatal crashes, A is the number of incapacitating injury crashes, B is the number of non-incapacitating injury crashes, C is the number of possible injury crashes, PDO is the number of PDO crashes, and L is the segment length in miles.
3. Calculate the average crash rate for each cross-section or roadway group as:

$$CR_{group} = \frac{CR_1 + CR_2 + CR_3 + \ldots CR_N}{N} \tag{6}$$

   Where, CR_{group} is the group crash rate, CR_1 through CR_N are the crash rates for all segments in the same group, and N is the total segment number in the group.
4. Compare individual segment rates with the group rate, and segments are identified as hotspots if $CR_{segment} > CR_{group}$.

2.2. HSID evaluation methodologies

The five aforementioned HSID methods were applied to Connecticut data and compared to one another based on four quantitative evaluation tests

proposed by Cheng and Washington (2008) and Montella (2010), that is, SCT, MCT) TRDT, and TST. These are defined in this section.

2.2.1. Site Consistency Test

The SCT evaluates the ability of a HSID method to consistently identify a site as high risk over subsequent observation periods. The test relies on the premise that a site identified as a hotspot during time period i should also reveal inferior safety performance in a subsequent time period $i+1$, given that no significant changes have been made to the site and given the assumption that the site is actually high risk. The HSID method with the highest SCT value is the most consistent method that can identify sites with the highest crash frequency in a future period. The test statistic is calculated as:

$$SCT_j = \frac{\sum_{k=1}^{n\alpha} C_{(k,i),j,i+1}}{\sum_{k=1}^{n\alpha} L_{(k,i),j,i+1} \times y_{i+1}} \tag{7}$$

Where, j is the HSID method being compared, n is the total number of sites, α is the percentage of sites to be identified (e.g., $\alpha = 1\%$ represents the top 1% of n sites identified as hotspots), $c_{(k,i),j,i+1}$ is the crash counts for site during the time period $i+1$, which is ranked as k during the time period i, $L_{(k,i),j,i+1}$ is the length of the segment in miles, and y_{i+1} is the length of the time period $i+1$ in years.

2.2.2. Method Consistency Test

The MCT evaluates the consistency of a method to identify the number of same hotspots between two time periods. The test assumes that roadway segments have no significant changes so that the expected safety performance remains the same over the two time periods. A greater MCT value represents a better performance of the HISD method. The MCT statistic is written as:

$$MCT_j = COUNT\left\{ [k_1, k_2, \ldots, \ k_{n\alpha}]_{j,i} \cap \ [k_1, k_2, \ldots, \ k_{n\alpha}]_{j,i+1} \right. \tag{8}$$

Where, $[k_1, k_2, \ldots, \ k_{n\alpha}]_{j,i}$ represents all sites that are ranked through 1 to $n\alpha$ in period i by method j, and $[k_1, k_2, \ldots, \ k_{n\alpha}]_{j,i+1}$ represents all sites that are ranked through 1 to $n\alpha$ in period $i+1$ by method j.

2.2.3. Total Rank Difference Test

The TRDT evaluates the performance of a HSID method by considering the equality of rankings of hotspots identified between the two time periods. A smaller TRDT value represents a better performance of the HSID method. The TRDT statistic is described as:

$$TRDT_j = \sum_{k=1}^{n\alpha} R_{i+1}(k_j) - R_i(k_j) \tag{9}$$

Where, $R_{i+1}(k_j)$ is the total rank value of identified segments ranked through 1 to $n\alpha$ in period $i+1$ for method j, and $R_i(k_j)$ is the total rank value of identified segments in period i. Note that the difference in ranks is calculated based on the segments identified as hotspots in one specific period (Cheng & Washington, 2008; Montella, 2010). To be consistent with the SCT, the rankings of segments identified in period i are used to compare the rankings of these sites in period $i+1$ here. A smaller TRDT value represents a better performance of the HISD method.

2.2.4. Total Score Test

The TST was proposed by Montella (2010) and combines the SCT, MCT, and TRDT. The test statistic is written as:

$$TST_j = \frac{100}{3} \times \left[\left(\frac{SCT_j}{SCT_{max}} \right) + \left(\frac{MCT_j}{MCT_{max}} \right) + \left(1 - \frac{TRDT_j - TRDT_{min}}{TRDT_{max}} \right) \right] \tag{10}$$

The test assumes that the SCT, MCT, and TRDT have the same weight. A greater TRDT value represents a better performance of the HISD method.

3. Data preparation

Roadway geometric data and crash data for municipal road segments only were collected from the Connecticut Department of Transportation (CTDOT) and the Connecticut Crash Data Repository (CTCDR) (2018). CTDOT updates the roadway geometric information for municipal roads every 3 years. The 2015 roadway geometric information was used because it is the most recent data available at the time of this analysis. Functional class (arterial, collector, and local), area type (rural/urban), number of through lanes and travel direction (one-way or two-way) were used to divide municipal roads into homogenous segments and to categorize these segments into reference groups with similar characteristics. To obtain sufficient observations for both segments and crashes in each reference group, some original groups were further aggregated; 11 reference groups were ultimately defined: (1) rural arterials and collectors, (2) rural local roads, (3) urban one-way arterials, (4) urban one-way collectors, (5) urban one-way local roads, (6) urban two-lane two-way arterials, (7) urban two-lane two-way collectors, (8) urban two-lane two-way local roads, (9) urban

Table 1. Descriptive characteristics of roadway group and crash data.

Roadway Group	Number of Segments	Total Segment Length (Mile)	Average Segment Length (Mile)	Crashes (2012–2014)	Crashes (2015–2016)
Rural arterials and collectors	1,271	539.0	0.4	1,154	767
Rural local roads	10,581	3,691.2	0.3	2,881	1,886
Urban one-way arterials	383	27.3	0.1	1,253	1,354
Urban one-way collectors	314	21.8	0.1	422	383
Urban one-way local roads	2,209	195.9	0.1	2,107	1,948
Urban two-lane two-way arterials	5,693	624.2	0.1	11,186	9,364
Urban two-lane two-way collectors	11,234	1,644.5	0.1	10,974	8,664
Urban two-lane two-way local roads	78,993	10,366.2	0.1	24,654	19,125
Urban multilane two-way arterials	1,628	123.9	0.1	6,218	5,401
Urban multilane two-way collectors	676	66.6	0.1	1,689	1,231
Urban multilane two-way local roads	931	79.6	0.1	1,195	1,019

multilane two-way arterials, (10) urban multilane two-way collectors, and (11) urban multilane two-way local roads.

Note that the evaluation tests assume the roadway segments have no significant changes across two study periods. To accommodate this assumption with the available geometric data, crashes from 2012 to 2016 were collected and assigned to each segment. To compare the HSID methods, the 5-year crash data were separated into two time periods, that is, period 1 (2012–2014) and period 2 (2015–2016). Table 1 shows the descriptive characteristics for crash data and segment reference groups used for HSID.

4. HSID method test results and discussion

The five HSID methods were applied to each of the 11 roadway groups individually and in aggregate and the four quantitative tests were used to compare the performance of these HSID methods. To evaluate the consistency of the HSID methods with regard to the threshold of hotspots to be identified, the top 10% of segments were selected for testing the sensitivity of HSID methods to number of hotspots identified; the results of the four tests are shown in Table 2 through Table 5 for the top 10% percent of sites, respectively. In each table, the first row for each roadway group shows each of the four testing values of the five HSID methods and the second row shows the ranking of the five HSID methods with regard to each test, with the underlined bold value representing the best for each roadway group.

4.1. SCT results

Table 2 shows the results of the SCT. The CF method performs better than the others for most of the roadway groups, which indicates that the

Table 2. SCT values for the top 10% hot spots.

Roadway Group	CF	EPDO	RSI	CSA	MOM
Rural arterials and collectors	2.2[a]	1.2	0.7	2.0	1.4
	1[a]	4	5	2	3
Rural local roads	0.6[a]	0.4	0.3	0.6[a]	0.4
	1[a]	3	5	1[a]	3
Urban one-way arterials	78.8[a]	54.9	11.2	76.6	63.0
	1[a]	4	5	2	3
Urban one-way collectors	37.1	18.1	5.2	37.2[a]	24.4
	2	4	5	1[a]	3
Urban one-way local roads	17.1[a]	11.5	5.0	15.7	12.5
	1[a]	4	5	2	3
Urban two-lane two-way arterials	34.8[a]	14.7	3.7	34.8[a]	15.4
	1[a]	4	5	1[a]	3
Urban two-lane two-way collectors	12.2[a]	4.6	1.6	11.7	5.2
	1[a]	4	5	2	3
Urban two-lane two-way local roads	4.5[a]	2.0	1.5	4.2	4.3
	1[a]	4	5	3	2
Urban multilane two-way arterials	63.8[a]	34.5	13.8	60.7	37.7
	1[a]	4	5	2	3
Urban multilane two-way collectors	30.0[a]	16.2	5.5	29.6	17.8
	1[a]	4	5	2	3
Urban multilane two-way local roads	28.4[a]	16.8	3.1	24.8	15.7
	1[a]	3	5	2	4
All segments	10.2[a]	4.6	2.7	9.3	2.9
	1[a]	3	5	2	4

Note. CF = crash frequency; EPDO = equivalent property damage only; RSI = relative severity index; CSA = cross sectional analysis; MOM = method of moments.
[a] These values represent the best HSID method for each roadway group.

hazardous segments identified by the CF method in period 1 produce the highest number of crashes in period 2. This is consistent with the finding in the study conducted by Cheng and Washington (2008) that the CF method outperforms others in the SCT. The CSA method performs best of the five HSID methods for rural local roads, urban one-way collectors and urban two-lane two-way arterials, which respectively identifies 0.6, 37.2, 34.8 crashes per mile per year for these roadway groups. The CF and CSA are followed by the MOM and EPDO methods, and the RSI method consistently performed worst for all roadway groups. With regard to all roadway groups together, CF outperforms the other methods, followed by the CSA, EPDO, MOM, and RSI.

4.2. MCT results

The MCT results are presented in Table 3. The MOM is superior in this test for all roadway groups, except for the rural arterials and collectors, in which the RSI methods performs better than the others. The performances of CF, EPDO, and CSA vary by roadway group. Similar to the SCT, the RSI still performs worst for all roadway groups, except for the rural arterials and collectors and rural local roads. When considering all roadway groups together, MOM performs best and is followed by the CSA and

Table 3. MCT values for the top 10% hot spots.

Roadway Group	CF	EPDO	RSI	CSA	MOM
Rural arterials and collectors	42	46	93[a]	36	64
	3	4	1[a]	5	2
Rural local roads	307	648[a]	316	306	648[a]
	4	1[a]	3	5	1[a]
Urban one-way arterials	20	21	7	18	27[a]
	3	2	5	4	1[a]
Urban one-way collectors	22	13	8	18	29[a]
	2	4	5	3	1[a]
Urban one-way local roads	91	93	74	95	116[a]
	4	3	5	2	1[a]
Urban two-lane two-way arterials	279	273	125	278	383[a]
	2	4	5	3	1[a]
Urban two-lane two-way collectors	512	646	231	447	797[a]
	3	2	5	4	1[a]
Urban two-lane two-way local roads	2,876	5,726	93	2,820	5,727[a]
	3	2	5	4	1[a]
Urban multilane two-way arterials	74	83	30	67	116[a]
	3	2	5	4	1[a]
Urban multilane two-way collectors	31	35	10	28	42[a]
	3	2	5	4	1[a]
Urban multilane two-way local roads	46	40	19	37	73
	2	3	5	4	1[a]
All segments	4,832	6,846	3,211	7,555	8,792[a]
	4	3	5	2	1[a]

Note. CF = crash frequency; EPDO = equivalent property damage only; RSI = relative severity index; CSA = cross sectional analysis; MOM = method of moments.
[a] These values represent the best HSID method for each roadway group.

EPDO methods. The CF and RSI perform significantly worse than the other three methods.

4.3. TRDT results

Table 4 shows the results for the TRDT. The TRDT values vary dramatically among the five HSID methods. Similar to the previous MCT results, MOM consistently outperforms the other five methods for all roadway groups, except for the rural local roads and urban multilane two-way local roads, in which the CF method performs better than the others. The CSA and EPDO methods perform closely for each roadway group, and the RSI method performs worst in all the five methods again. In terms of all roadway groups together, CSA has a significantly lower TRDT value than the others, and is followed by RSI, EPDO, CF, and MOM.

4.4. TST results

As is noted above, the performances of the five HSID method vary among the first three tests, which results in difficulties in selecting the best method for individual roadway group and all roadway segments together. The TST is then calculated by combining the SCT, MCT, and TRDT, and the results are shown in Table 5. A greater TST value represents a better performance of the HSID method. MOM is the best method for urban one-way arterials,

Table 4. TRDT values for the top 10% hot spots.

Roadway Group	CF	EPDO	RSI	CSA	MOM
Rural arterials and collectors	26,753	28,263	85,374	29,930	17,124[a]
	2	3	5	4	1[a]
Rural local roads	699,040[a]	1,021,234	1,169,342	704,349	1,125,259
	1	3	5	2	4
Urban one-way arterials	1,607	2,262	5,671	1,701	731[a]
	2	4	5	3	1[a]
Urban one-way collectors	997	1,608	2,483	1,217	774[a]
	2	3	5	4	1[a]
Urban one-way local roads	74,892	73,312	213,783	87,356	46,687[a]
	3	2	5	4	1[a]
Urban two-lane two-way arterials	421,160	465,072	1,104,829	490,113	340,948[a]
	2	3	5	4	1[a]
Urban two-lane two-way collectors	2,063,522	1,856,030	3,420,200	2,073,667	1,428,894[a]
	3	2	5	4	1[a]
Urban two-lane two-way local roads	45,617,434	75,933,179	67,180,763	46,014,050	30,996,130[a]
	2	5	4	3	1[a]
Urban multilane two-way arterials	40,285	29,974	104,515	48,245	19,060[a]
	3	2	5	4	1[a]
Urban multilane two-way collectors	7,499	6,426	20,692	7,589	3,278[a]
	3	2	5	4	1[a]
Urban multilane two-way local roads	11,237[a]	13,056	22,737	15,246	11,449
	1[a]	3	5	4	2
All segments	279,026,649	172,459,211	157,335,515	110,389,921[a]	381,462,410
	4	3	2	1	5

Note. CF = crash frequency; EPDO = equivalent property damage only; RSI = relative severity index; CSA = cross sectional analysis; MOM = method of moments.
[a] These values represent the best HSID method for each roadway group.

Table 5. TST values for the top 10% hot spots.

Roadway Group	CF	EPDO	RSI	CSA	MOM
Rural arterials and collectors	78.0[a]	63.7	50.6	71.5	76.7
	1[a]	4	5	3	2
Rural local roads	82.5[a]	79.7	52.8	82.3	77.9
	1[a]	3	5	2	4
Urban one-way arterials	86.2	73.5	17.7	82.3	93.3[a]
	2	3	4	3	1[a]
Urban one-way collectors	88.9[a]	53.3	24.2	81.4	88.5
	1[a]	4	5	3	2
Urban one-way local roads	88.4	78.3	38.3	84.9	91.0[a]
	2	4	5	3	1[a]
Urban two-lane two-way arterials	88.5[a]	67.4	24.7	86.4	81.4
	1[a]	4	5	2	3
Urban two-lane two-way collectors	81.9[a]	68.8	28.0	77.7	80.9
	1[a]	4	5	3	2
Urban two-lane two-way local roads	77.0	61.7	29.1	74.3	98.5[a]
	2	4	5	3	1[a]
Urban multilane two-way arterials	81.2	71.7	21.9	75.0	86.4[a]
	2	4	5	3	1[a]
Urban multilane two-way collectors	84.5	74.0	19.3	81.5	86.4[a]
	2	4	5	3	1[a]
Urban multilane two-way local roads	87.7[a]	68.6	28.8	73.5	84.8
	1[a]	4	5	3	2
All segments	70.3	68.9	50.2	92.4[a]	52.5
	2	3	5	1[a]	4

Note. CF = crash frequency; EPDO = equivalent property damage only; RSI = relative severity index; CSA = cross sectional analysis; MOM = method of moments.
[a] These values represent the best HSID method for each roadway group.

urban one-way local roads, urban two-lane two-way local roads, urban multilane two-way arterials, and urban multilane two-way collectors. CF performs best for rural arterials and collectors, rural local roads, urban one-way collectors, urban two-lane two-way arterials, urban two-lane two-way collectors, and urban multilane two-way local roads. CSA performs fairly close to the CF method for all roadway groups. In contrast, the EPDO and RSI perform worst among all five methods, consistent with HSM direction that EPDO and RSI heavily depend on the weighting factors used, and overemphasize locations with particular crash types and severities. For all roadway groups together, CSA outperforms the other methods, followed by the CF, EPDO, MOM and RSI. This verifies the notion (FHWA, 2010) that CSA can ameliorate the lack of AADT and be an effective alternative in identifying hotspots where the AADT is usually unavailable.

5. Conclusions and recommendations

This study investigates methodologies for identifying hotspots on roads under municipal jurisdiction where the AADT is not available. Roadway segments and 5-year crashes were collected from Connecticut state data sources. Roadway segments were categorized into 11 groups with similar road characteristics. Five HSID methods were used to identify hotspots for each segment group respectively, as well as for all segments over the entire State. Four quantitative tests were used to compare the performance of the five HISD methods.

Overall, MOM and CF outperform other methods for identifying hotspots by individual roadway group. In particular, MOM performs best among all methods for urban one-way arterials, urban one-way local roads, urban two-lane two-way local roads, urban multilane two-way arterials, and urban multilane two-way collectors. CF performs best for rural arterials and collectors, rural local roads, urban one-way collectors, urban two-lane two-way arterials, urban two-lane two-way collectors, and urban multilane two-way local roads. The performance of CSA is close to that of CF for identifying hotspots by roadway group. EPDO and RSI are the least reliable with the lowest TST values. When identifying and ranking the roadway hotspots for all roadway groups together, CSA outperforms the others, followed by CF, EPDO, MOM, and RSI. In conclusion, for identifying hotspots for roads under municipal jurisdiction when the AADT information is not available, it is recommended to consider MOM for homogenous roadway groups including urban one-way arterials, urban one-way local roads, urban two-lane two-way local roads, urban multilane two-way arterials, and urban multilane two-way collectors; consider CF for rural arterials

and collectors, rural local roads, urban one-way collectors, urban two-lane two-way arterials, urban two-lane two-way collectors and urban multilane two-way local roads; and to consider CSA for all groups together.

It is expected that this study can offer insight about selecting rigorous HSID methods to identify hazardous roadway sections for safety improvement, especially when the traffic counts are not available. However, it might be difficult to directly transfer the selected method to other States, as the roadway facilities may vary among different States. We recommend users to collect their own data, perform the tests and identify the most reliable HSID method for the individual situation. It is also recommended to collect the AADT information for roadway segments, apply the commonly used EB method to identify roadway hotspots and compare the performance of EB method with the five methods used in this study. Future research is also recommended to explore the spatial and temporal correlations among crash counts in the HSID, and investigate HSID methods for roadway intersections.

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