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A Pilot Application of the Sliding Window Screening Method on Virginia Roadways

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In this study, the sliding window screening method, executed in Python, was applied to the newly generated homogeneous segments. The evaluation of the performance of this method encompassed multiple aspects, including an assessment of potential for safety improvement (PSI) values, segment rankings, and comparison of results with the current VDOT PSI list. Further, the study investigated the sensitivity of window size selection to the inherent stochastic nature of crash occurrences. Specifically, smaller window sizes were more effective in identifying localized crash "hotspots," and larger window sizes delivered a more general overview of the entire segment. The study also advises against the use of a single year's ranking for determining high-risk PSI segments, owing to this stochastic variation.

The study found that the sliding window screening method does not have inherent bias toward two roadway attributes: segment length and median presence. This finding mitigates the existing segment length variation problem in the current approach. The study concludes that the sliding window screening method holds promise in enhancing current practices employing the simple ranking method.

The study recommends that VDOT consider deploying the new segmentation network and adopting the sliding window screening method for the computation of PSI values on a statewide basis to enhance the effectiveness of network screening processes.

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ABSTRACT

This study evaluated the practicality and efficacy of implementing the sliding window screening method recommended in the *Highway Safety Manual* for systemically identifying high-risk segments in the Virginia roadway network. The current simple ranking method used by the Virginia Department of Transportation (VDOT) to identify high-risk segments has inherent limitations due to the effect of segment length variations, and the sliding window screening method allows segments to be compared on a consistent length basis. The study proposes a homogeneous segmentation network that maintains consistency in segment characteristics based on annual average daily traffic and type of safety performance function.

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INTRODUCTION

Following the introduction of the *Highway Safety Manual* (HSM) (American Society of State Highway and Transportation Officials [AASHTO], 2010), the Virginia Department of Transportation (VDOT) conducted a number of efforts to develop Virginia-specific safety performance functions (VA-SPFs) (Garber and Rivera, 2010; Garber et al., 2010; Kweon and Lim, 2014; Kweon and Lim, 2019). Using those developed VA-SPFs, VDOT has been predicting the number of crashes on segments and determining whether the number of observed crashes on a segment differs substantially from the number of expected crashes.

The HSM introduced three methods for conducting network screening: simple ranking, sliding window, and peak searching. According to the HSM, each method has specific applicability as follows:

- Segments (e.g., roadway segment or ramp) are screened using either the sliding window or peak searching method.
- Nodes (e.g., intersections or ramp terminal intersections) are screened using the simple ranking method.
- Facilities (combination of nodes and segments) are screened using a combination of segment and node screening methods.

The simple ranking method can be used for both nodes and segments. In this approach, the performance measures (such as the potential for safety improvement [PSI] values used in this study) are computed for all the sites under consideration, and the results are arranged in descending order. The strength of this method is its simplicity, as indicated in the HSM. Nonetheless, when applied to segments, the results may not be as reliable as those of other segment screening methods. Specifically, the inclusion of extremely short segments could introduce a high degree of randomness in identifying high-risk sites.

The sliding window screening method conceptually shifts a window of a fixed length along the road segment from start to end, advancing in increments of a specific size. The chosen performance measure for screening the segment is applied to each window position. For all windows relevant to a given segment, the one with the highest potential for crash frequency reduction (i.e., with the highest PSI value) is identified and used to represent the entire segment. After all segments are ranked according to their highest subsegment value, segments with the highest PSI value are subjected to detailed investigation to identify potential countermeasures.

The peak search method subdivides each individual roadway segment into windows of similar length, with potential incremental growth in length until the window length equals that of the entire roadway segment. The selected performance measure is calculated for each window. Based on the statistical precision of the performance measure, the window within a roadway segment with the maximum performance measure value is employed to rank the potential for crash reduction for the entire roadway segment in relation to the other sites under screening. The precision of the performance measure is evaluated by calculating the coefficient of variation (CV) of the performance measure. There is not a specific CV value applicable to all network screening applications. However, by adjusting the CV value, the user can alter the number of sites identified by network screening as candidates for further investigation. In practice, this method is rarely used by state departments of transportation (DOTs) due to its conceptual complexity.

The sliding window screening method may offer a few advantages over other methods:

- *Standardization across varying segment lengths.* The sliding window screening method provides a standardized way to analyze roadway segments of different lengths. By applying a consistent window size across all segments, it allows for more consistent comparisons among segments, regardless of their individual lengths.

- *Flexibility in "hotspot" detection.* This method has the advantage of flexibility when it comes to identifying crash hotspots. Whereas the simple ranking method analyzes a roadway segment as a whole, the sliding window screening method can detect more localized crash hotspots within larger segments.

- *Reduction of randomness*. The sliding window screening method can help reduce the randomness that might occur in analyses when very short segments are included, especially when compared to methods like the simple ranking method.

The HSM also states:

> Sliding window and peak searching methods can be used to identify the location within the segment which is likely to benefit from a countermeasure. The simple ranking method can also be applied to segments, but unlike sliding window and peak searching methods, performance measures are calculated for the entire length (typically 0.1 mile) of the segment.

Although the simple ranking method is easy to implement, the sliding window and peak searching methods offer potentially better screening results at the cost of increased computation efforts.

Since the sliding window screening method was introduced (AASHTO, 2010), Harwood et al. (2010), several state DOTs including those in California (Kwon et al., 2013), Connecticut

(Connecticut Transportation Safety Research Center, 2020), Florida (Matata et al., 2023), and Texas (Tsapakis et al., 2019) have studied or implemented the sliding window method to conduct network screening to identify high crash locations.

VDOT's Traffic Operations Division (TOD) has recognized the problem with variations in segment length and has taken steps to aggregate segments using intuitive methods based on natural roadway breaks to mitigate the issue. Further, the Virginia Transportation Research Council (VTRC) recently completed a technical assistance study for the TOD (unpublished data) on this topic. The study indicated that the use of links clustered by annual average daily traffic (AADT) showed some promising properties in the development of the sliding window screening method for interstate networks. In response, the TOD suggested a pilot study focusing on assessing the application of AADT-clustered segments in conjunction with the sliding window screening method to understand their potential to improve network safety screening analysis.

PURPOSE AND SCOPE

The purpose of this study was (1) to develop a new homogeneous segmentation network using multiple roadway types in the Virginia roadway network; (2) to develop the HSM-recommended sliding window screening method on the new segmentation network; (3) to document the data prerequisites and preprocessing procedures; and (4) to assess the strengths and limitations of the sliding window screening method. It was hoped that the insights drawn from these analyses would help VDOT's TOD gauge the effort necessary to apply HSM-recommended methods on a statewide scale.

Based on discussions with the technical review panel (TRP) for this study, the scope of the study was limited to routes within VDOT's Fredericksburg District. The Fredericksburg District encompasses a range of roadway types (e.g., interstate, primary, and secondary routes) and roadway characteristics (e.g., divided/undivided, urban/rural, and so on) as defined as subtypes in VA-SPFs.

METHODS

Three tasks were performed to achieve the study objectives:

1. data preparation and assessment
2. segmentation with current VA-SPF types
3. screening with the HSM-recommended methods.

Data Preparation and Assessment

In this task, roadway inventory and crash data from VDOT's Roadway Network System (RNS) database, AADT from VDOT's Traffic Management System (TMS) database, and VA-SPFs were compiled. Five years of crash and AADT data (2016-2020) were collected.

Determined in conjunction with the TRP, the spatial range of data was limited to all primary roads and selected secondary roads in the Fredericksburg District area.

Road Inventory Data

VDOT roadway inventory data were collected from VDOT's RNS database. This inventory included information on administrative elements (district, route name or ID, maintenance jurisdiction, ownership, functional class, mile point, etc.); facility characteristics (lane width, pavement surface type, curb type, shoulder width, etc.); and traffic data (TMS link ID, AADT, speed limit) for each segment. The study network used in this study consisted of interstate, primary, and secondary routes. The primary routes encompassed both US routes and state primary routes. Due to practical considerations related to data preparation and determined in conjunction with the TRP, the compilation of secondary routes used in this study was limited to a portion of the secondary route network. This decision was based on the observation that approximately 85% of the links presented in VDOT's top 100 PSI list are primary roads with higher AADT volumes. The selection criterion used for secondary roads was to include the entire route if a segment was identified in VDOT's top 100 PSI list. For example, if segment SC00601 from mile point 8.51 to mile point 9.23 was selected, the entire route of SC00601 within the Fredericksburg District (from mile point 0.00 to mile point 19.61) was included in the study network. It should be noted that there may be potential bias in the selection process. For example, a segment on a non-selected route might have ranked high using a certain method but was not included in VDOT's current top PSI list. However, it was determined in conjunction with the TRP that this potential bias was unlikely to result in significant differences in the study's conclusions.

Crash Data

Crash data contain crash characteristics (collision type, severity, description, etc.), time information, and location information (latitudes and longitudes including RNS mile point and direction). In agreement with the TRP, this study focused solely on segment analysis and thus included only crashes that occurred on segments. Intersection crashes, usually defined as incidents that occur within 250 feet of an intersection, were excluded from the crash dataset. For a fair comparison with VDOT's current PSI list, VDOT's TOD provided a dataset consisting solely of segment crashes. These data, which had undergone rigorous quality assurance measures carried out by the TOD, were used in this study. The crash location's "direction" column captures all four possible directions (EB, WB, NB, SB). However, the roadway inventory dataset may feature the "primary direction" (i.e., EB, NB) for the purpose of calculating route-level AADT. As a consequence, crashes that occurred in non-prime directions were combined to "prime direction" on the same segment. For example, crashes labeled WB and EB were combined onto the same segment. Following this step, crashes were conflated to roadway links using RNS route name and mile point.

AADT Data

AADT data are stored in VDOT's TMS database with a unique link ID. Although the TMS link ID and the RNS roadway network link ID are not the same, RNS roadway inventory data contain a matching TMS link ID column for most segments, allowing those segments in the

RNS roadway inventory data to have AADT data. It was found that approximately 4.6% of primary road segments in the RNS dataset lacked AADT data because of misaligned TMS link IDs. Since AADT data are crucial factors in calculating the PSI index, these missing data needed to be estimated. The research team inserted the missing AADT data by manually verifying segments using the VDOT ArcGIS Traffic Volume ADT map. It should be noted that this inconsistency issue is specific to the use of the current RNS database, which was not designed specifically for safety analysis applications. If a new database were created for safety analysis purposes, the problem might no longer persist.

For interstates, it was found that boundaries of TMS link IDs (and matched AADT) do not precisely align with exact mile markers of locations of on- and off-ramps on the road. Depending on the interchange type and number of on- and off-ramps at an interchange, there could be multiple AADTs. For example, a diamond interchange has only one off-ramp and one on-ramp, leading to three different AADTs (upstream of off-ramp, between off-ramp and on-ramp, downstream of on-ramp). On the other hand, each full cloverleaf interchange has two on- and off-ramps and, therefore, five different AADTs. For the simplicity and ease of calculation, VDOT uses only one link for the interchange area, not specifying on-ramp and off-ramp locations. The SPF denotes this as an "interchange area" with parameters different from the mainline, so it is advisable to specify those areas for the roadway network.

The *Highway Capacity Manual* (HCM) (National Academies of Sciences, Engineering, and Medicine, 2022) defines the merge (downstream of on-ramp) and diverge (upstream of off-ramp) influence areas as 1,500 ft (0.28 miles). For diamond interchanges in the Fredericksburg area, the distance between the off-ramp and on-ramp was found to be approximately 2,500 ft. For the sake of simplicity and conservative calculations, this study set the interchange area as 0.5 miles upstream and downstream of the location of the split in TMS links, dividing one-half mile into two sections and adding the merge and diverge influence area.

Safety Performance Functions

SPFs provide an estimate of average crash frequency for a site based on models that used data from a population of similar sites. VDOT has developed SPFs using the Federal Highway Administration's (FHWA) predefined facility subtypes in AASHTO's SafetyAnalyst software. These types are categorized by four factors: area type (urban/rural), facility (highway/interstate freeway), median division (divided/undivided), and number of lanes. Specific subtypes (with site code) are as follows:

- 101: Rural two-lane highways
- 102: Rural multilane undivided highways
- 103: Rural multilane divided highways
- 104: Rural freeway segments – 4 lanes
- 105: Rural freeway segments – 6 lanes
- 106: Rural freeway segments within an interchange area – 4 lanes
- 107: Rural freeway segments within an interchange area – 6 lanes
- 151: Urban two-lane arterials
- 152: Urban multilane undivided arterial segments

- 153: Urban multilane divided arterial segments
- 155: Urban freeway segments – 4 lanes
- 156: Urban freeway segments – 6 lanes
- 157: Urban freeway segments – 8+ lanes
- 158: Urban freeway segments within an interchange area – 4 lanes
- 159: Urban freeway segments within an interchange area – 6 lanes
- 160: Urban freeway segments within an interchange area – 8+ lanes.

SPFs are mathematical equations that predict the number of crashes for a specific site type from variables of AADT and segment length. The general form of a freeway segment SPF is shown as follows:

$$N = L \times exp^{\alpha} \times AADT^{\beta\mathbf{1}}$$

where

$N =$ predicted number of crashes at a site per year
$L =$ segment length (in miles)
$AADT =$ annual average daily traffic
α and β1 are regression parameters estimated during the modeling process.

Each equation includes an adjustment coefficient to compensate for the overrepresentation of crash frequency on shorter segments. The dispersion functional form is shown in the following equation:

$$Dispersion = \ L^{\beta_3} \times e^{\gamma}$$

Summary statistics for each SPF are provided in Table 1, which were developed by the consulting engineering company VHB. It should be noted that separate alpha values are provided depending on segment length for certain segments. It is also worth mentioning that the columns for beta 3 and gamma provide the coefficients for the dispersion model.

Segmentation With Current VA-SPF Types

Develop New Segmentation Network

A new segmentation method was developed from the data detailed in the previous section. This new method created homogeneous segments in terms of AADT (TMS link) and SPF types, meaning each homogeneous segment shares the same characteristics in terms of AADT (TMS link), urban/rural, functional class, facility type, divided/undivided, access control, and number of lanes.

Table 1. Power Function SPF Parameters for Segment Total Crashes

Site Code	Descriptor	α	β1	β3	γ	Sites	Length	Max. AADT
101	0 mile < Segment Length ≤ 0.30 mile	-6.448	0.834	-0.172	-0.981	84,840	43,437.27	25,510
	0.30 mile < Segment Length ≤ 0.60 mile	-6.402						
	Segment Length > 0.6 mile	-6.376						
102	0 mile < Segment Length ≤ 0.50 mile	-4.883	0.637	-0.443	-1.403	674	239.17	22,844
	Segment Length > 0.5 mile	-5.000						
103	0 mile < Segment Length ≤ 0.25 mile	-5.956	0.756	-0.502	-1.736	3,698	1483.39	54,230
	0.25 mile < Segment Length ≤ 0.50 mile	-6.038						
	Segment Length > 0.5 mile	-6.144						
104	0 mile < Segment Length ≤ 0.25 mile	-6.647	0.821	-0.401	-1.707	1,257	1,171.97	36,500
	0.25 mile < Segment Length ≤ 0.50 mile	-6.826						
	Segment Length > 0.5 mile	-6.961						
105	0 mile < Segment Length ≤ 0.50 mile	-18.744	1.936	-0.376	-1.184	101	83.95	68,500
	Segment Length > 0.5 mile	-18.976						
106	All Segments	-6.038	0.771	-0.721	-2.147	319	90.84	36,150
107	All Segments	-19.472	2.047	-1.765	-3.466	22	7.53	69,400
151	0 mile < Segment Length ≤ 0.25 mile	-6.983	0.929	-0.446	-0.778	54,622	11796.01	69,964
	0.25 mile < Segment Length ≤ 0.50 mile	-7.099						
	Segment Length > 0.5 mile	-6.924						
152	0 mile < Segment Length ≤ 0.50 mile	-6.477	0.902	-0.450	-0.946	4,333	842.32	57,856
	Segment Length > 0.5 mile	-7.194						
153	0 mile < Segment Length ≤ 0.25 mile	-5.714	0.807	-0.442	-0.803	9,236	2019.39	103,441
	0.25 mile < Segment Length ≤ 0.50 mile	-6.003						
	Segment Length > 0.5 mile	-6.377						
155	0 mile < Segment Length ≤ 0.25 mile	-9.144	1.122	-0.544	-0.910	1,520	850.71	68,000
	0.25 mile < Segment Length ≤ 0.50 mile	-9.609						
	Segment Length > 0.5 mile	-9.876						
156	0 mile < Segment Length ≤ 0.25 mile	-11.809	1.372	-0.483	-1.140	707	344.62	132,750
	0.25 mile < Segment Length ≤ 0.50 mile	-12.005						
	Segment Length > 0.5 mile	-12.401						
157	0 mile < Segment Length ≤ 0.25 mile	-14.336	1.570	-0.142	-1.153	432	210.01	132,750
	0.25 mile < Segment Length ≤ 0.50 mile	-14.393						
	Segment Length > 0.5 mile	-14.536						
158	All Segments	-6.631	0.862	-0.246	-1.094	686	160.53	96,500
159	All Segments	-12.640	1.452	0.391		390	390	99.26
160	All Segments	-10.946	1.300	-0.324	-1.115	258	58.37	132,750

SPF = safety performance function; AADT = annual average daily traffic.

The detailed algorithms are as follows:

1. Prepare the road inventory data that were processed in the previous section.

2. Select the relevant columns from approximately 120 columns of roadway inventory data features and disregard the remaining. The selected 14 columns include route name, route prefix, route number, route suffix, length, route mile point, urban/rural designation, functional system, functional class, divided, facility type, access control, TMS link ID, and lane count.

3. Organize the data by route name, route number, and route mile point in ascending order.

4. Begin from the first row and identify all subsequent rows that have matching values in every column with the exception of the length and route mile point columns. These identified rows are grouped together and assigned a new segment ID. This process is looped until the end of the data is reached.

5. Aggregate rows by the new segment ID. For the route mile point, the first (smallest) record will be selected.

6. For interstates, separate the interchange area upstream and downstream of the TMS link ID boundary using the designated length (0.5 miles each).

7. Divide the new segment network by the designated size (0.1 miles, 0.2 miles, etc.) of subsegment. The size of the subsegment will be the incremental size of steps in the sliding window screening method.

8. Add new starting and ending mile points with the size of the subsegment data.

9. Add columns for AADT (matched by TMS link ID), crash (matched by route name and mile point) for each year, and SPF type and parameters to the subsegment data.

Table 2 presents the outcome of the aforementioned algorithm, illustrating the correspondence between the new segmentation and the existing RNS segmentation. It should be noted that the data columns from RNS in Table 2 represent only a subset of all the available columns.

Table 2. Correspondence Between the New Segmentation and the Existing RNS Segmentation

New Segmentation	Data Columns From RNS							
	Route Number	**Length**	**Route Mile Point**	**Urban/ Rural**	**……**	**Divided/ Undivided**	**TMS Link ID**	**AADT**
Segment 1	88 SC 601	0.25	0	Rural	……	Undivided	302263	1012
	88 SC 601	0.56	0.25	R	……	U	302263	1012
	88 SC 601	0.2	0.81	R	……	U	302263	1012
	88 SC 601	0.14	1.01	R	……	U	302263	1012
	88 SC 601	0.3	1.15	R	……	U	302263	1012
	88 SC 601	0.26	1.45	R	……	U	302263	1012
	88 SC 601	0.02	1.71	R	……	U	302263	1012
	88 SC 601	0.11	1.73	R	……	U	302263	1012
Segment 2	88 SC 601	0.019	1.84	R	……	U	302264	1518
	88 SC 601	0.009	1.859	R	……	U	302264	1518
	88 SC 601	0.872	1.868	R	……	U	302264	1518
	88 SC 601	0.25	2.74	R	……	U	302264	1518
	88 SC 601	0.17	2.99	R	……	U	302264	1518
	88 SC 601	0.12	3.16	R	……	U	302264	1518
	88 SC 601	0.01	3.28	R	……	U	302264	1518
	88 SC 601	0.24	3.29	R	……	U	302264	1518
	88 SC 601	0.37	3.53	R	……	U	302264	1518
	88 SC 601	0.24	3.9	R	……	U	302264	1518
	88 SC 601	0.23	4.14	R	……	U	302264	1518
	88 SC 601	0.02	4.37	R	……	U	302264	1518
	88 SC 601	0.54	4.39	R	……	U	302264	1518
	88 SC 601	0.12	4.93	R	……	U	302264	1518
Segment 3	88 SC 601	0.26	5.05	R	……	U	302265	2231
	88 SC 601	0.07	5.31	R	……	U	302265	2231
	88 SC 601	0.07	5.38	R	……	U	302265	2231
	88 SC 601	0.07	5.45	R	……	U	302265	2231
	88 SC 601	0.29	5.52	R	……	U	302265	2231
	88 SC 601	0.88	5.81	R	……	U	302265	2231
	88 SC 601	0.27	6.69	R	……	U	302265	2231
	88 SC 601	0.63	6.96	R	……	U	302265	2231
	88 SC 601	0.39	7.59	R	……	U	302265	2231
	88 SC 601	0.28	7.98	R	……	U	302265	2231
	88 SC 601	0.52	8.26	R	……	U	302265	2231

RNS = Roadway Network System; TMS = traffic management system.

Screening With the HSM-Recommended Methods

Implementation of Sliding Window Screening Method

The application of the HSM-recommended sliding window screening method was carried out on the homogeneous segments that were generated in the previous section. With the use of Python for computational purposes, the HSM-suggested parameters—0.3 miles for window length (W) and a moving increment of 0.1 miles—were incorporated into each segment to compute the expected crash frequency for each window (see Figure 1).

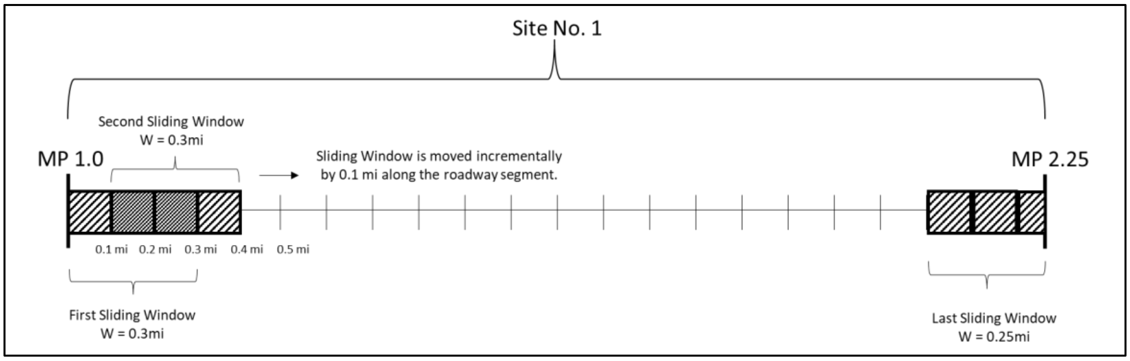


Figure 1. Example Showing the Application of the Sliding Window Screening Method at a Site. Adapted from Harwood et al. (2010).

The calculation of excess predicted average crash frequency was performed as follows:

Step 1. Determine the size of the subsegment network and the length of the sliding window (W). The length of the sliding window (W) is equivalent to the length of the segment (L) for subsequent calculations if it is less than or equal to the overall link length.

Step 2. Calculate the predicted number of crashes by applying appropriate SPFs to each segment.

$$n_{pred.} = L \times exp^{\alpha} \times AADT^{\beta}$$

where

$L =$ segment length (in miles)
$AADT =$ annual average daily traffic
α and β are regression parameters estimated during the modeling process.

where

$n_{pred.}$ = annual number of all crashes for a segment
AADT = annual average daily traffic (number of vehicles per day)
L = segment length (mile), which is equivalent to window size (L = W).

Step 3. Using the model predictions computed in Step 1, compute the calibration factor C_i:

$$C_i = \frac{\sum n_{Obs.\_Allsites}}{\sum n_{Pred.\_\ Allsites}}$$

C_i is calculated by dividing the total number of observed crashes by the total number of predicted crashes, for each year, within the study area.

Step 4. Compute the weights (w). Weight (w) is calculated using dispersion parameter k and the sum of predicted crashes $n_{pred.}$ at the segment.

$$w = \frac{1}{1+(k \times \sum n_{Pred.})}$$

$$k = L^{\beta_3} \times e^{\gamma}$$

where

L = segment length (in miles)
β_3 and γ are model parameters for dispersion.

Step 5. Calculate the empirical Bayes (EB)–adjusted expected number of crashes for each segment. The expected (EB-adjusted) number of crashes ($n_{Exp.}$) is determined using the predicted number of crashes ($n_{Pred.}$) from step 1 and the observed number of crashes ($n_{Obs.}$), multiplied by the EB weight (w) that is calculated using the sum of predicted crashes at the segment in the previous step:

$$n_{Exp.} = \text{w} \times (n_{Pred.}) \times C_i + (1 - \text{w}) \times n_{Obs.}$$

Step 6. Calculate the PSI for each segment each year. PSI is an important criterion that measures excess crash frequency, the difference between the expected (EB-adjusted) number of crashes ($n_{Exp.}$) and the predicted number of crashes ($n_{Pred.}$).

$$\text{PSI} = n_{Exp.} - n_{Pred.}$$

The key variables, specific to each window, obtained through this calculation were stored in a separate file for further examination and analysis.

Assessment of Sliding Window Screening Method

The assessment of the sliding window screening method encompassed several dimensions, as follows:

1. *PSI values.* The computed PSI values served as a benchmark for identifying high-risk segments that might necessitate safety enhancements (positive PSI values indicate excess crash frequencies). The distribution of PSI values across all network segments provided a holistic image of the reliability of the computed values as well as SPFs. A positive PSI value denotes an excess crash frequency.

2. *Spatial and temporal ranking of segments.* Roadway segments were ranked in both an all-encompassing manner and as categorized by specific roadway types (i.e., interstates, US routes, state routes, and secondary routes). The objective was not only to pinpoint the most hazardous segments universally but also to examine the influence of roadway types on segment rankings. An effort was also made to observe the temporal shifts in the risk associated with each roadway segment.

3. *Derived measures from ranks.* The model was used to examine the stability of the risk index associated with each segment. As an example, the analysis measured the frequency of a particular segment's appearance in the top 5 or top 10 most risky segments from 2016 to 2020.

4. *Segment ranks with other attributes.* The ranks of segments were analyzed in conjunction with attributes such as the AADT value associated with each segment. This allowed a deeper exploration of the relationship between these ranks and specific roadway attributes.

5. *Comparison with current VDOT PSI list.* The outcomes derived from the model were juxtaposed with the current VDOT PSI list, allowing a comparison of the HSM-recommended method with the current practice.

6. *Evaluation against simple ranking methods.* Last, a comparative assessment was conducted between the results determined from the HSM-recommended sliding window screening method and those derived from the conventionally used simple ranking method. The simple ranking methods are applied to two distinct segment sets, each resulting from different network segmentation techniques: (1) the segments, recommended by the HSM, with a length of 0.1 mile, and (2) the approach of treating the entire homogeneous segment within the network as a singular unit.

Sensitivity Analysis of Model Parameters

Window size selection plays a pivotal role in data analysis. The adoption of a smaller window size may prove to be suitable for the identification of localized crash hotspots, and a larger window size can yield a smoothed interpretation of the data. The selection of window size is a crucial consideration as it should be aligned with the spatial scale at which one seeks to analyze and interpret the data. As a consequence, the necessity for conducting experiments with various window sizes and assessing their impacts on the final analytical results become apparent.

In response, an evaluation of the model parameters was conducted via sensitivity analysis focused on window sizes. The assessment incorporated a range of window sizes, spanning from the HSM-recommended 0.3 miles up to 0.7 miles, increasing in 0.1-mile increments, for the comparison of computed PSI values and segment ranks across these varying window sizes. The determination of a suitable window size was based on the following three considerations:

1. *Robustness across scales.* Suitable window sizes should yield segment ranks that remain relatively unchanged across a range of segment lengths. To be more specific, the highest PSI segments identified should be robust and not overly sensitive to changes in window sizes.

2. *Compatibility with the crash data.* By analyzing the influence of crash distribution on segment rank alterations, an informed decision can be made regarding the selection of appropriate window sizes.

3. *Alignment with safety improvement measures.* Most potential safety improvement measures do not function as "spot" treatments, e.g., adding chevron signs or a short

guardrail. Given improvement treatments over longer roadway segments may be more cost-efficient, the selection of window sizes must take into account the balance between identifying localized crash hotspots and providing an overview of an entire segment.

Comparison of Results With Results From the Simple Ranking Method

The simple ranking method, frequently used by traffic safety professionals to screen for segments with high PSI values, is popular due to its straightforward implementation and the convenience of using existing operations database segmentations. To evaluate the relative effectiveness of the HSM-recommended sliding window screening method in comparison to the widely used simple ranking method, a comparative study of the rankings derived from both methods was conducted.

There are two commonly used segmentation approaches for implementing the simple ranking method. The first approach involves segmenting the road into 0.1-mile units and considering each of these units as an individual entity in line with the HSM (AASHTO, 2010). The second approach aligns with the current VDOT practice where the simple ranking method is applied to each homogeneous segment (RNS segments in the case of VDOT), treating each as a single unit.

It is worth noting that although the sliding window screening method offers a standardized way of evaluating segments of different lengths, applying the simple ranking method to each 0.1-mile portion of the road provides the opportunity to identify multiple crash hotspots within a homogeneous segment.

The advantages and disadvantages of each method can be assessed based on the following four considerations:

1. *Ease of implementation.* The ease of data preparation, implementation, and interpretation can be considered. The simple ranking method might be easier to implement and understand, which could be beneficial in certain situations.

2. *Alignment with safety improvements*. It is essential to take into account which method better aligns with the type of safety improvements that are planned.

3. *Robustness and consistency.* This involves checking if the identified top PSI segments remain the same or similar across various parameter settings, segmentation approaches, and the stochastic nature of crash data.

4. *Capability to identify multiple hotspots.* Per the request of the project champion, the method’s ability to identify multiple crash hotspots within a segment should be considered.

RESULTS AND DISCUSSION

Data

RNS Network and New Segmentation Network

This section summarizes and compares the RNS road network and the new segmentation network in terms of the characteristics of segment length and matched crashes. Table 3 shows the detailed characteristics of the RNS road network and crash data for the Fredericksburg District. The table includes the total number of segments, total and average length of segments, minimum and maximum length of segments, and total crashes by route type. It should be noted that for the limited access freeways, only the mainlines are included; ramps are excluded. The Fredericksburg District has only one corridor (I-95) of interstate highway. For secondary roads, as previously stated, only routes from VDOT's PSI list were selected. It was found that the minimum length of segments on the RNS road network was about 0.001 miles and the maximum length of segments was 3.36 miles. The average length of segments was about 0.2 miles.

Table 4 shows characteristics of the new segmentation network of the Fredericksburg District. For comparison to the RNS data, the table also includes the total number of segments, total and average length of segments, and minimum and maximum length of segments by route type. It was found that the minimum length of the new segmentation network was about 0.01 miles, which was due to the split by urban/rural designation. For interstate highways, the minimum length was 0.5 miles, which is the length of a weaving section. The maximum length of segments varied from 6.02 to 9.84 miles by type, and the average length of segments was about 1.5 miles. One may note that discrepancies exist in the total segment length between Tables 3 and 4 due to the removal of certain data entries from the RNS database. These discrepancies are attributable to the existence of segments with non-primary directions (applicable to both state routes and secondary roads) in the original RNS data, which have been excluded in the new segmentation.

Table 3. Summary of the Fredericksburg District RNS Road Inventory

Roadway Type	Total Number of Segments	Total Length (Miles)	Average Length of Segments (Miles)	Minimum Length of Segments (Miles)	Maximum Length of Segments (Miles)	Total Crashes (2016-2020)
Interstates	300	93.7	0.31	0.001	3.36	7,161
US Routes	1,457	272.8	0.19	0.001	2.40	3,489
State Primary Routes	2,297	478.5	0.21	0.001	2.59	3,723
Secondary Roads	985	190.9	0.19	0.001	2.12	1,620
Total	5,039	1035.9	0.21	0.001	3.36	15,993

RNS = Roadway Network System.

Table 4. Summary of the New Segment Network of the Fredericksburg District

Roadway Type	Total Number of Segments	Total Length (Miles)	Average Length of Segments (Miles)	Minimum Length of Segments (Miles)	Maximum Length of Segments (Miles)
Interstates	71	93.7	1.32	0.5	7.10
US Routes	169	272.8	1.61	0.01	9.84
State Primary Routes	250	476.6	1.91	0.01	9.74
Secondary Roads	184	191.1	1.04	0.01	6.02
Total	674	1034.2	1.53	0.01	9.84

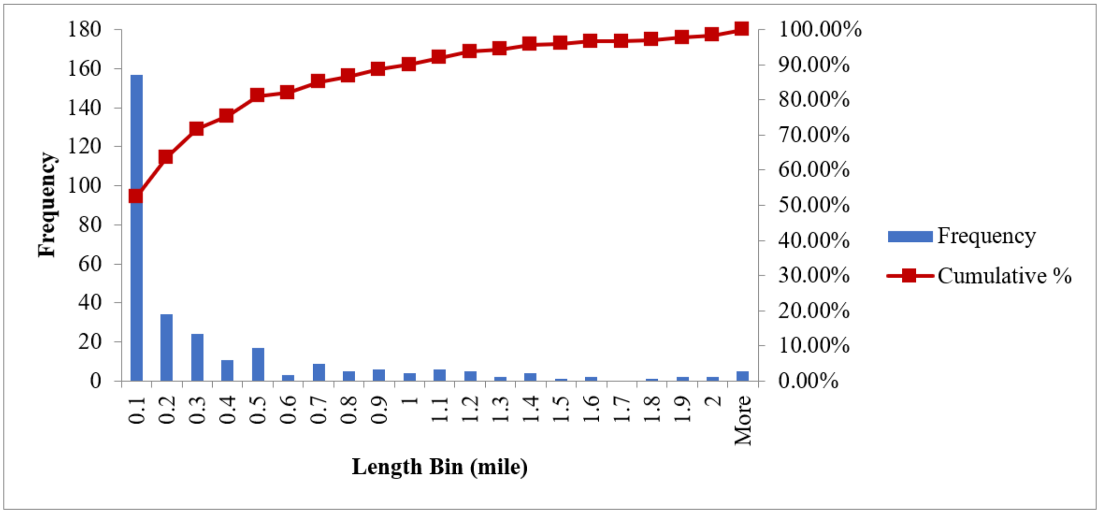
A histogram and cumulative percentage of the RNS segment lengths on interstate highways and non-interstate highways are shown in Figure 2. About 52% of segments were less than 0.1 miles in length for interstate highways. Particularly, 27% (81 of 300) segments of interstate highways were 0.001 miles in length. About 49% of segments of non-interstate highways were less than 0.1 miles in length, and frequencies logarithmically decreased for each 0.1-mile increasing length bin.

Figure 3 shows the histogram and cumulative percentage of the new segmentation network's segment length of interstate highways and non-interstate highways, respectively. In Figure 3(a) (interstate highways), about 66% of segments are less than 0.6 miles in length, which includes weaving areas. The rest of the sections are widely distributed from 1 mile to 7 miles. In Figure 3(b) (non-interstate highways), it is shown that about 10.6% of segments are still less than 0.1 miles in length. This is due to fluctuations in AADTs, urban/rural designation, or functional class difference on secondary roads interrupting longer homogeneous segments.

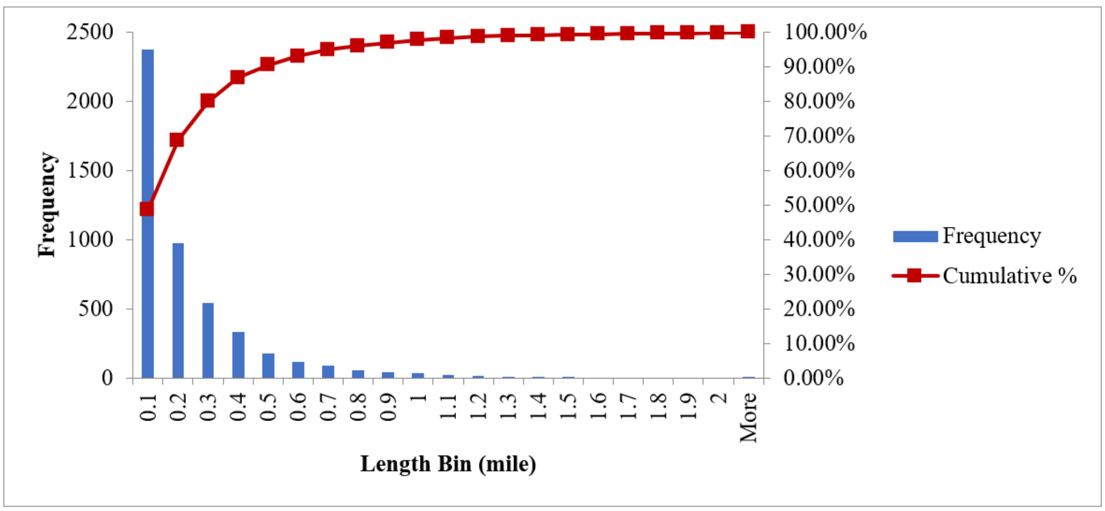
The histograms and cumulative percentage of the annual number of crashes per mile, using both the RNS segmentation and the new segmentation developed in this study, are shown in Figure 4(a) and 4(b), respectively. The crash data from 2016 to 2020 were matched to the segments for both segment types. The annual number of crashes per mile was determined by dividing the total number of crashes matched to a segment by its segment length, and then by 5, which is the total number of years.

It was found that approximately 65% of RNS segments (3,359 of 5,039) had less than one crash per mile per year. Further, of these segments, around 86% (2,900 of 3,359) had 0 crashes. Comparatively, in the segments developed for this study, approximately 41% (279 of 674) had less than one crash per mile per year, with about 43% (121 of 279) of these segments having 0 crashes.

Figure 5 shows scatterplots of the annual number of crashes per mile and average AADT, which is traditionally used for the representation of an SPF. It should be noted that for visual clarity the figure does not show all data points; points with an AADT between 30,000 and 85,000 and more than 25 crashes per mile per year are hidden. In Figure 5(a), the RNS network plot shows vertical lines since the average AADT could be the same on different segments in a corridor. The new segmentation network, shown in Figure 5(b), eliminates those.



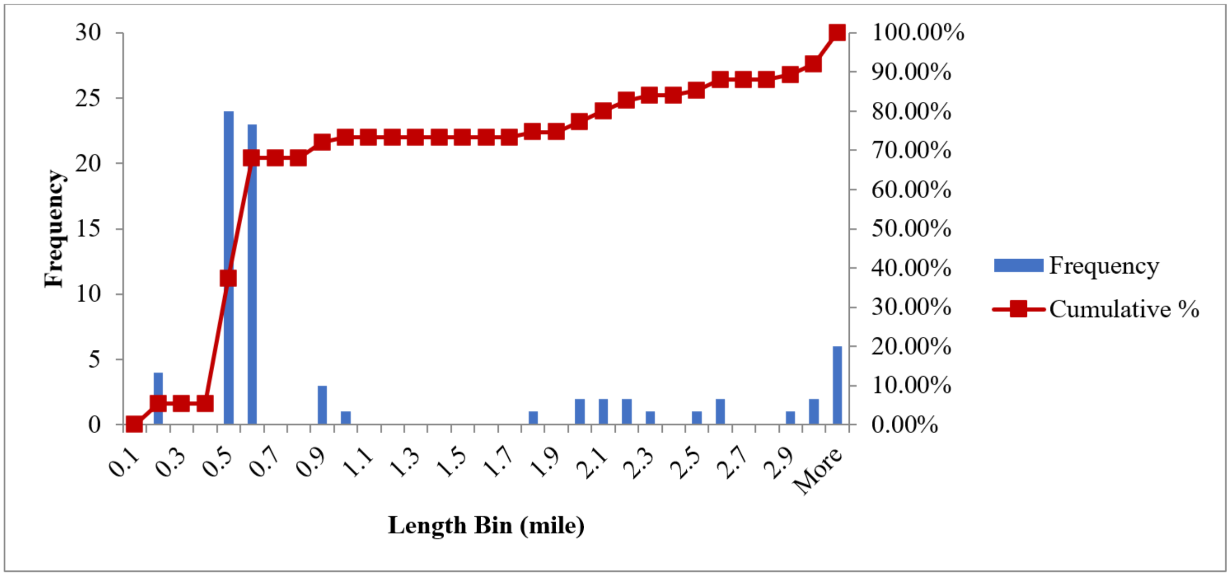
(a) Interstate Highways



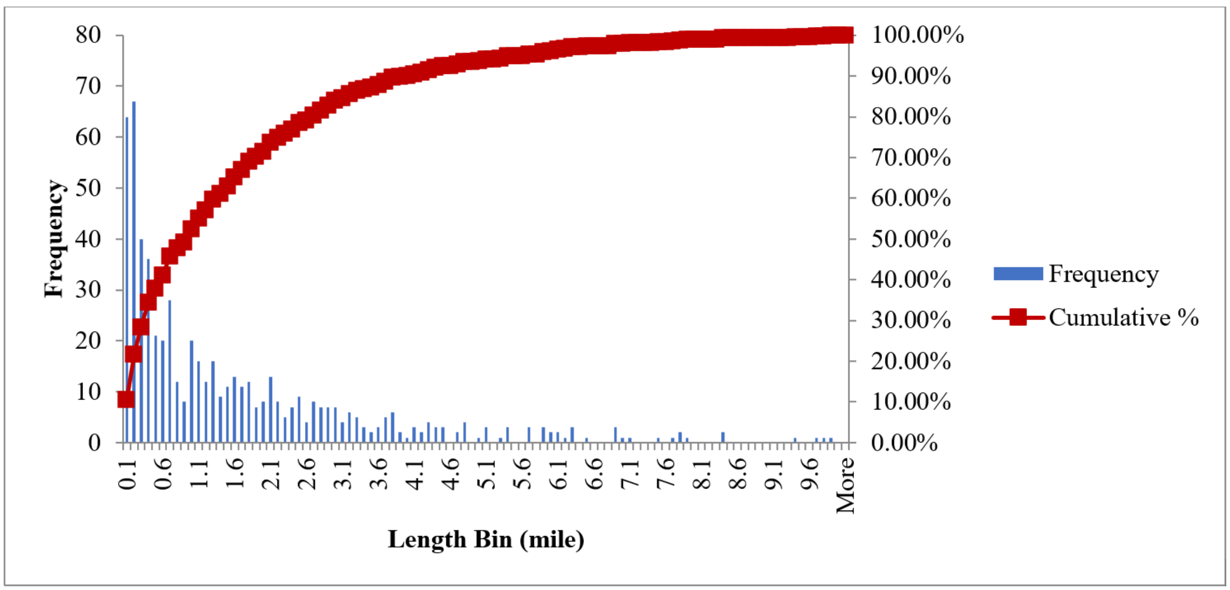
(b) Non-Interstate Highways

Figure 2. Histogram and Cumulative Percentage of RNS Segment Length: (a) interstate highways; (b) non-interstate highways. RNS = Roadway Network System.

Figure 6 shows the annual number of crashes by mile point on I-95 NB for the RNS network and the new segmentation network. For the 48.9-mile corridor, there are 181 segments for the RNS network, whereas there are only 35 segments for the new segmentation network. It should be noted that columns are mapped by start mile point of segment, and segments with zero crashes are not shown in the plot. On the RNS network, 55 of 181 segments have no crashes; on the new segmentation network, no segments have zero crashes.

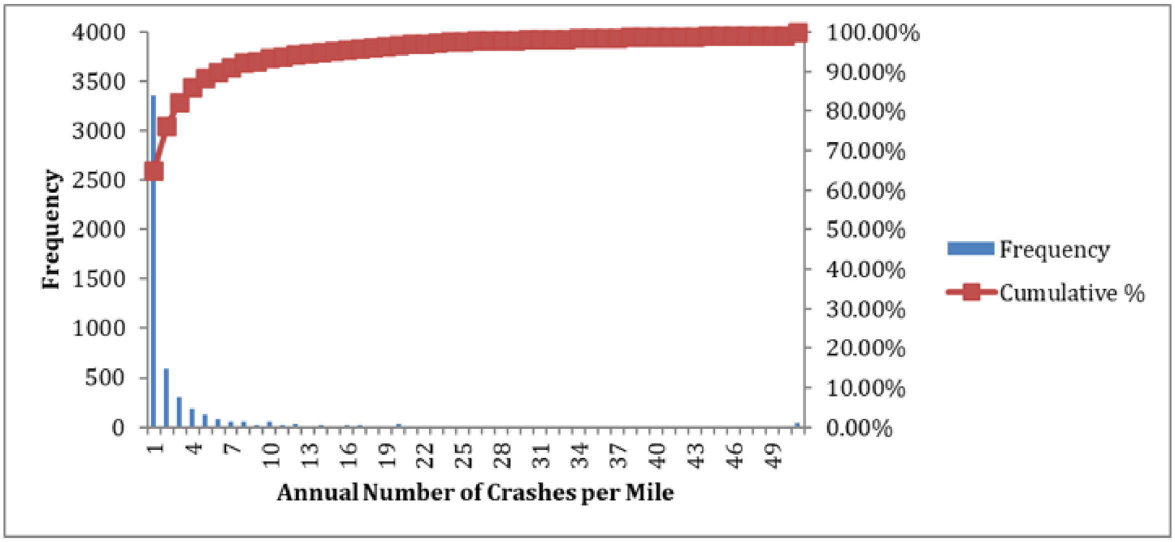


(a) Interstate Highways

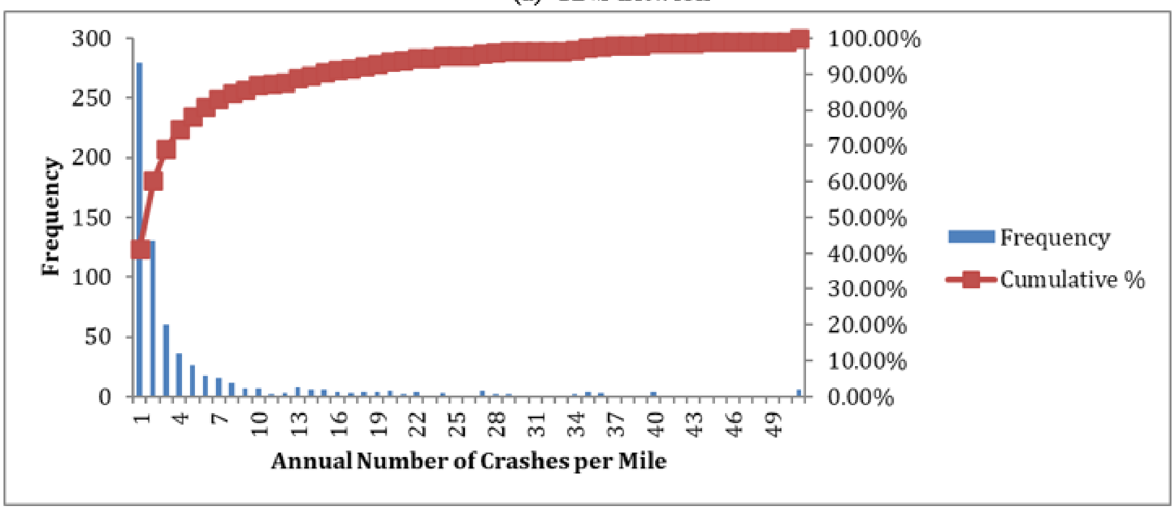


(b) Non-Interstate Highways

Figure 3. Histogram and Cumulative Percentage of Segment Length on New Segmentation Network: (a) interstate highways; (b) non-interstate highways.

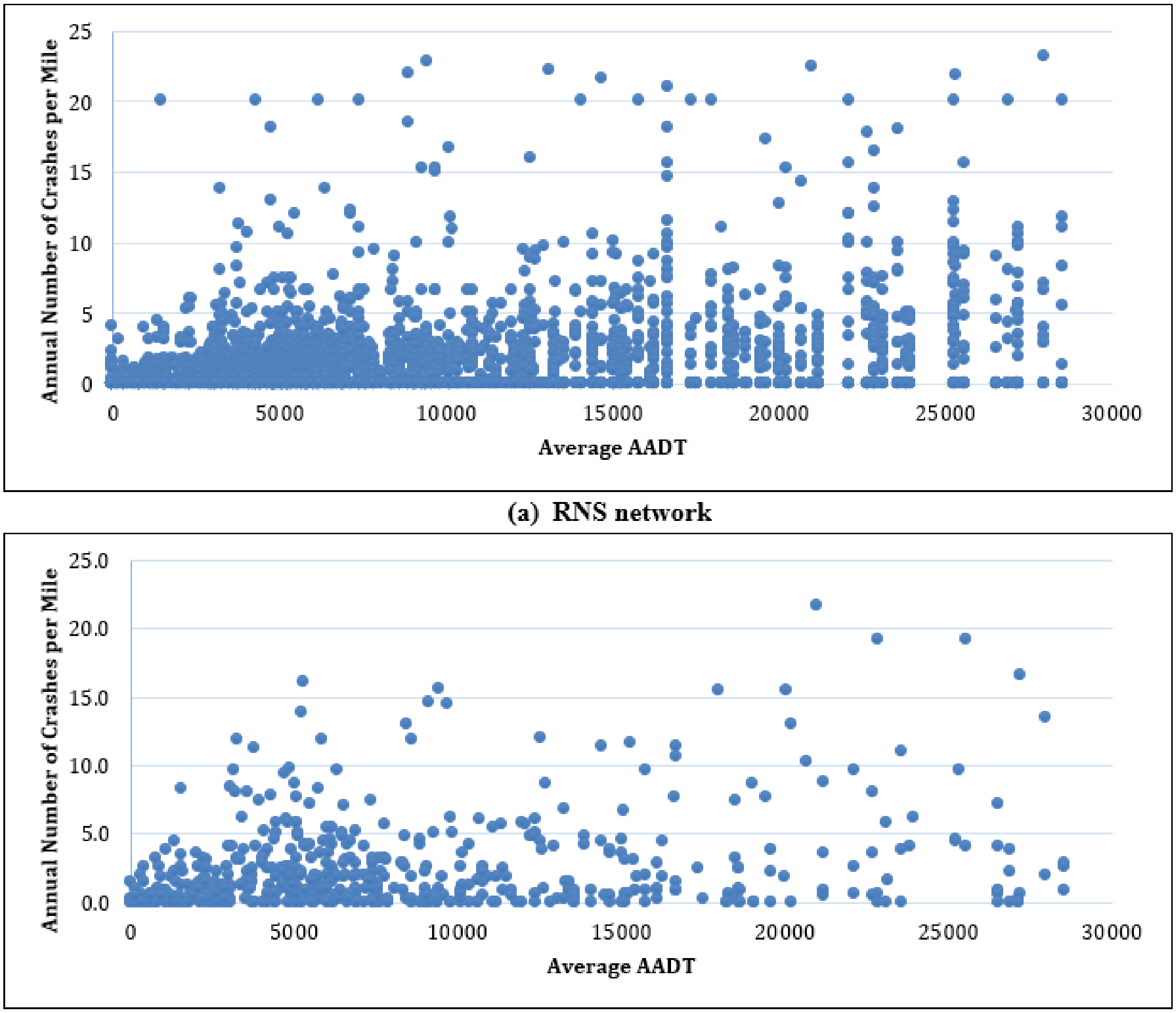


(a) RNS network



(b) New Segmentation Network

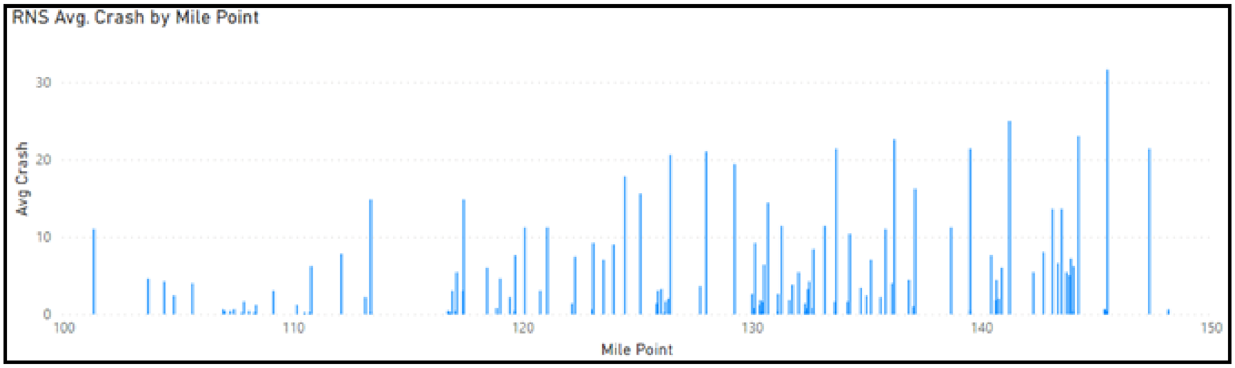
Figure 4. Histogram and Cumulative Percentage of Annual Number of Crashes per Mile: (a) RNS network; (b) new segmentation network. RNS = Roadway Network System.



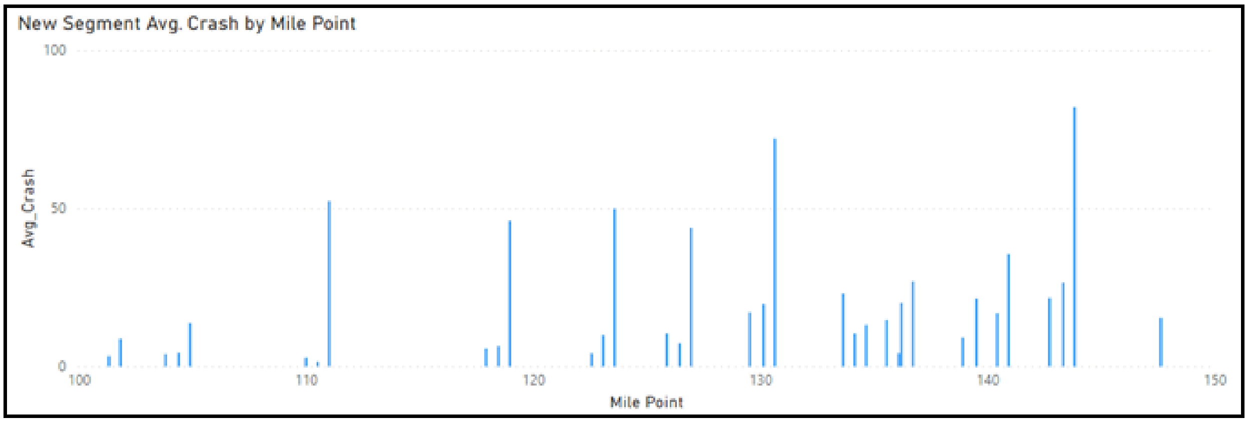
(a) RNS network

(b) New Segmentation Network

Figure 5. Scatterplot of Annual Number of Crashes per Mile and Average AADT: (a) RNS network; (b) new segmentation network. AADT = annual average daily traffic; RNS = Roadway Network System.



(a) RNS Network



(b) New Segmentation Network

Figure 6. Distribution of Annual Number of Crashes by Mile Point for I-95 NB: (a) RNS network; (b) new segmentation network. RNS = Roadway Network System.

The new segmentation network, which combines the densely fragmented RNS network segments that have the same roadway and traffic characteristics, overcomes certain drawbacks of the RNS network such as the presence of very short (0.001 miles) segments, large number of segments with no crashes, and biased relationships between crashes per mile and AADT. However, as Table 3 and Figure 6(b) show, the new segmentation network may have very long segment lengths, so it may be difficult to detect precise crash and PSI hotspot locations. Creating subsegments of the new segmentation network using a designated size such as 0.1 miles solves that problem. Figure 7 shows the annual number of crashes distributed by mile point in the same corridor using 0.1-mile subsegments of the new segmentation network.

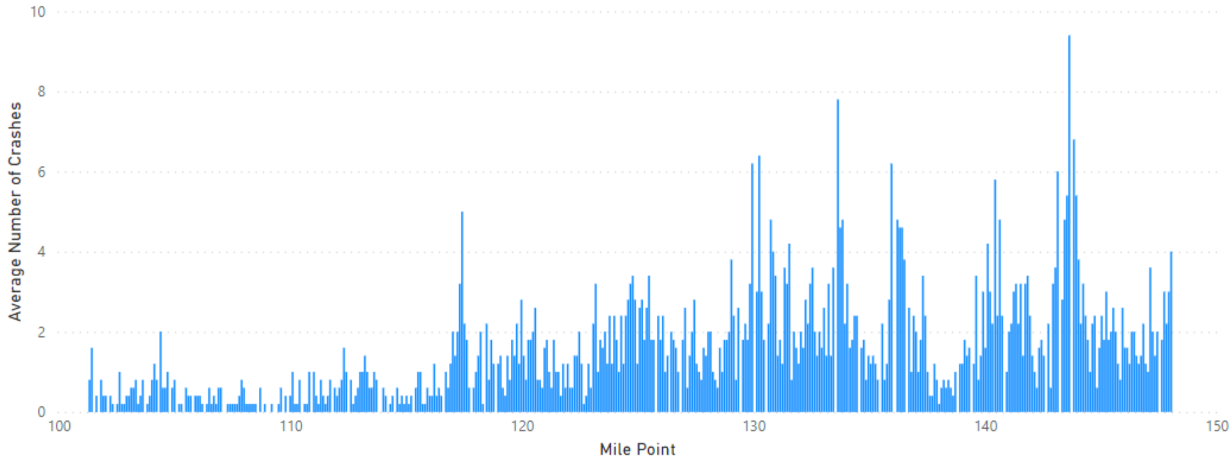


Figure 7. Distribution of Annual Number of Crashes by Mile Point for I-95 NB Using 0.1-Mile Subsegments of the New Segmentation Network.

Implementation and Assessment of Sliding Window Screening Method

Implementation of Sliding Window Screening Method Using Python

To enable the calculation, a dedicated Python script was developed encompassing several essential components, including the following:

- *Setting global parameters.* This step involves defining program folders, sliding window sizes, and the date/time when the analysis was conducted. These parameters are essential for the overall execution of the script.

- *Loading input files.* The script loads the input file that contains the newly generated segments for the study, as well as the corresponding SPFs associated with each segment.

- *Creating sliding windows.* Sliding windows are created for each segment in the network using specified parameters, such as the window size. This allows for the segmentation analysis to be performed on each window.

- *Calculating the expected number of crashes for each segment.* For each segment, the script calculates the expected number of crashes by using the corresponding SPFs and AADT values.

- *Implementing the empirical Bayes method.* The script applies the EB method by considering the observed number of crashes and the previously calculated expected number of crashes for each segment. This allows for the computation of the EB-adjusted expected number of crashes for each segment.

- *Calculating PSI values for each segment.* The script calculates the PSI values for each segment. This is achieved by finding the difference between the EB-adjusted number of crashes and the expected number of crashes. The PSI values serve as an indicator of the relative risk associated with each segment.

- *Ranking the segments based on PSI values.* The script facilitates the ranking of segments based on their PSI values. The segments can be ranked in various ways, such as by each year or by derived measures that consider the frequency with which a segment has been identified as one of the top riskiest segments in previous years.

Notably, the execution of the Python script for the sliding window calculation was efficient, requiring less than 10 seconds on an Intel i7 processor to analyze the 674 segments of the study network. Further, memory consumption (less than 10 Mb) was negligible on modern computing systems. The developed code has been shared with the project champion for further use and examination.

PSI Values Derived From the Sliding Window Screening Method

PSI values, as derived from the sliding window screening method, serve as the most critical safety performance measurement; notably, a positive PSI value implies an excess crash frequency. Figure 8 illustrates the distribution of both the EB-adjusted crash frequency (blue columns) and the predicted crash frequency (red columns) for the I-95 NB corridor subdivided into 0.1-mile subsegments for the year 2018. Within each homogeneous segment, the predicted number of crashes remained consistent, correlating with its constant AADT values. The differences in the predicted number of crashes and the EB-adjusted number of crashes (denoted as the disparity in height between the blue and red columns) constitute the PSI value at that particular point.

Table 5 provides a breakdown of the number of segments with positive PSI values, categorized by roadway type (both in total and in each specific type) and by year. The results presented in Table 5 were generated using a window size of 0.3 miles.

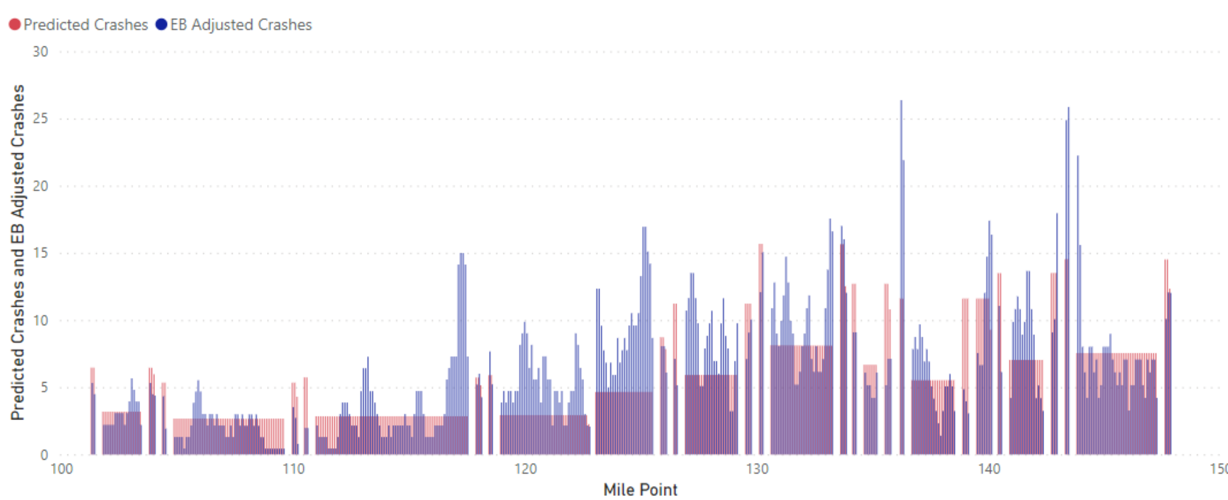


Figure 8. Distribution of Year 2018 EB-Adjusted and Predicted Number of Crashes by Mile Point for I-95 NB of 0.1-Mile–Subsegment Network (Window Size = 0.3). EB = empirical Bayes.

Table 5. Yearly Breakdown of Segments With Positive PSI Values by Roadway Type (Window Size = 0.3 Miles)

Roadway Type	Total Segments	2016	2017	2018	2019	2020
Interstates	71	43 (60.6%)	43 (60.6%)	44 (62.0%)	46 (64.8%)	40 (56.3%)
US Routes	169	97 (57.4%)	103 (60.9%)	91 (53.8%)	93 (55%)	87 (51.5%)
State Routes	250	137 (54.8%)	144 (57.6%)	154 (61.6%)	146 (58.4%)	137 (54.8%)
Secondary Routes	184	87 (47.3%)	81 (44.0%)	89 (48.4%)	73 (39.7%)	86 (46.7%)
Total	674	364 (54.0%)	371 (55.0%)	378 (56.1%)	358 (53.1%)	350 (51.9%)

PSI = potential for safety improvement.

According to the data, 54% of all segments had positive PSI values. Further examination of the data by roadway type revealed stability over the years. However, interstates had a higher proportion of segments with positive PSI values, and secondary routes had a lower proportion.

The HSM method uses the highest PSI value from all windows within a segment to represent the PSI of that segment. As a result, it is plausible to suggest that more than 50% of segments having a positive PSI value could be due to the non-uniform distribution of crashes on a segment, leading to certain windows having higher PSI values than others and, as a consequence, a higher segment PSI value.

Consideration should also be given to the fact that different SPFs correspond to different roadway types. Thus, the occurrence of lower PSI values could potentially be attributed to certain roadway types being underrepresented in the creation of SPFs.

Table 6 displays the maximum and minimum PSI values by roadway type (in total and individually) on a yearly basis. The PSI values ranged from -9.17 to 27.96 (both in year 2018). A segment with a negative PSI value signifies that all of its underlying windows are negative, meaning that every spot within the segment has crash numbers less than the expected number derived from the SPF. It can also be noticed that higher functional class roadway types (i.e., interstates and US routes) are responsible for both maximum and minimum PSI values across all roadway types. Further, given that these types of roads are likely to have the highest AADTs, the aforementioned observation aligns logically with the anticipated patterns.

Figure 9 shows the distribution of PSI values, assessed by segment count, combining all roadway types and years. The distribution reaffirms that approximately 54% of segments had positive PSI values, with only about 7.2% of segments (of a total of 674 segments) having a PSI value exceeding 2. It is essential to note that this distribution is evaluated on a segment-specific basis; hence, numerous shorter segments with a specific PSI value would have greater cumulative representation than a single longer segment.

Table 6. Yearly Breakdown of Maximum and Minimum PSI Values by Roadway Type

Roadway Type	PSI Value	2016	2017	2018	2019	2020
Interstates	Max.	13.55	18.16	27.96	20.09	22.75
	Min.	-8.16	-7.59	-9.17	-8.47	-5.45
US Routes	Max.	21.92	22.13	19.24	17.06	11.10
	Min.	-4.51	-4.91	-5.06	-5.96	-4.08
State Routes	Max.	13.34	15.86	22.78	9.49	8.28
	Min.	-2.85	-3.00	-2.93	-2.23	-2.28
Secondary Routes	Max.	9.77	8.27	7.34	10.05	5.30
	Min.	-2.29	-5.35	-2.46	-5.77	-2.44
Total	Max.	21.92	22.13	27.96	20.09	22.75
	Min.	-8.16	-7.59	-9.17	-8.47	-5.45

PSI = potential for safety improvement.

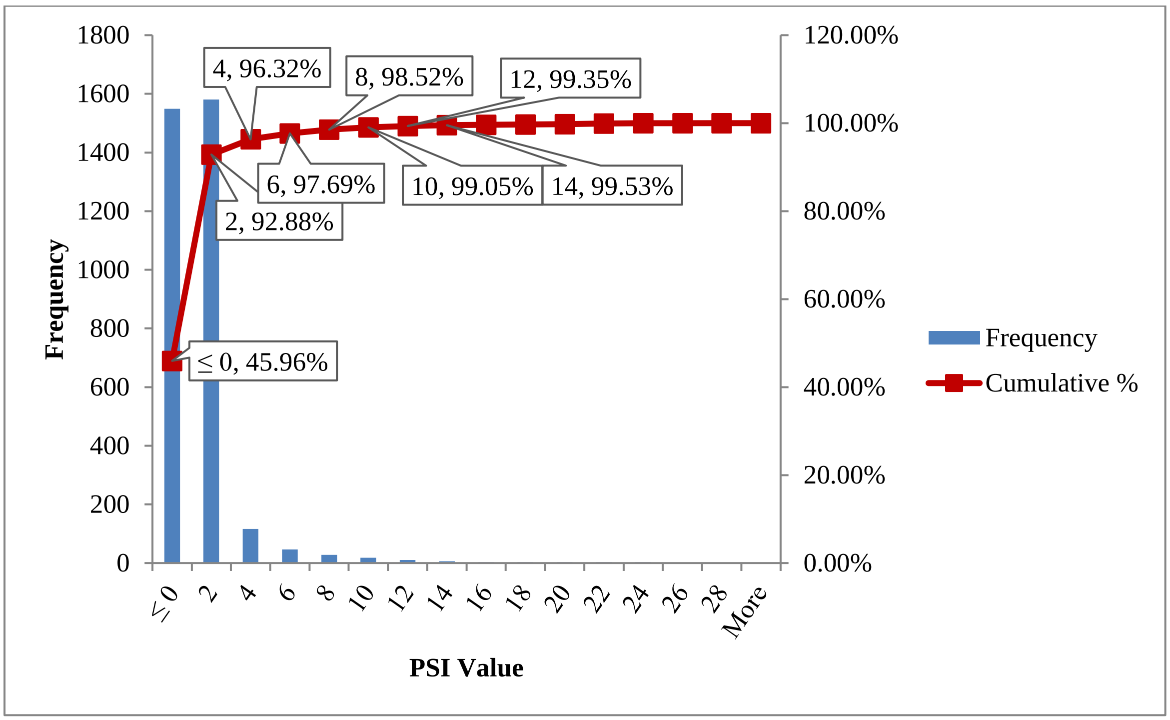


Figure 9. Distribution of PSI Values by Segment Count. PSI = potential for safety improvement.

Figure 10 illustrates the distribution of PSI values, calculated on a per vehicle mile traveled (VMT) basis, combining all roadway types and years. This figure reveals that approximately 82% of the VMT yields positive PSI values, a markedly higher percentage compared to the 54% when assessed in terms of segment counts. This observation, in conjunction with the findings shown in Figure 9, suggests that segments with higher PSI values might be correlated with higher AADT or with longer segment length. The relationship between PSI and three roadway characteristics—length, median presence, and AADT —is explored in the following sections.

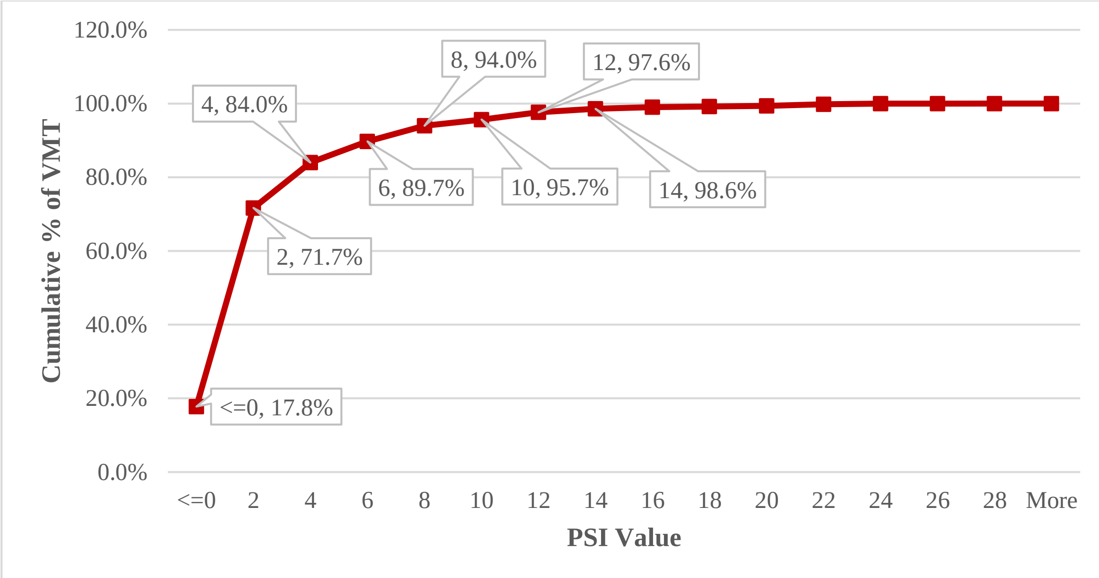


Figure 10. Distribution of PSI Values Based on Vehicle Miles Traveled (VMT). PSI = potential for safety improvement

Ranking of Segments

This section describes a comparison of segment ranks obtained using the HSM-recommended sliding window screening method across various years, in conjunction with some derived measures. These measures were based on the frequency of a segment's appearance in the top riskiest segments. Table 7 shows the top 20 segments based on the frequency of a segment's appearance in the top 10 riskiest segments.

Each row in Table 7 corresponds to a segment (Link ID) identified by a route name and its start and end mile points (Start MP and End MP). Along with ranks for each year (columns labeled PSI 2016 Rank through PSI 2020 Rank), the table presents three additional derived measures: the number of times a segment is in the top 5 riskiest segments, the number of times a segment is in the top 10 riskiest segments, and the sum of the ranks for the segment from 2016 to 2020. Notably, the top 5 and top 10 segments account for the top 0.7% and top 1.5%, respectively, of the riskiest segments among all roadways in the study area (totaling 674 segments).

Table 7 reveals certain segments consistently ranking at the top, such as US_15, whereas others, such as IS_32, showcase a considerable variation in ranking from year to year. Some segments, such as IS_21, exhibit a clear trend over time, rising from rank 661 in 2016 to the top position in 2020.

Table 7. Yearly Breakdown of Ranking for Top 20 PSI Segments and Associated Derived Measures

Link ID	Route Name	Start MP	End MP	PSI 2016 Rank	PSI 2017 Rank	PSI 2018 Rank	PSI 2019 Rank	PSI 2020 Rank	Count of Year in Top 5	Count of Year in Top 10	Sum of Rank
US_15	US 1	142.29	143	1	1	5	2	2	4	5	11
IS_71	IS 95 NB	141.13	143.63	8	6	3	5	4	2	5	26
IS_74	IS 95 SB	144.66	147.66	5	8	6	6	25	0	4	50
IS_33	IS 95 NB	143.34	143.84	2	5	9	105	35	1	3	156
IS_59	IS 95 SB	133.2	134.1	20	43	7	1	5	1	3	76
IS_72	IS 95 SB	143.63	144.16	204	10	1	3	3	3	3	221
SR_11	SR 3	30.48	31.57	4	4	14	17	6	2	3	45
SR_12	SR 3	31.57	31.91	3	7	2	24	12	2	3	48
IS_34	IS 95 NB	143.84	147.64	15	21	8	4	18	1	2	66
IS_75	IS 95 SB	147.66	148.22	17	2	4	18	654	2	2	695
US_21	US 1	143.96	144.93	7	9	45	51	33	0	2	145
IS_14	IS 95 NB	123.09	125.89	9	15	13	15	24	0	1	76
IS_20	IS 95 NB	130.65	133.65	29	30	12	9	10	0	1	90
IS_21	IS 95 NB	133.65	134.166	661	665	30	16	1	1	1	1373
IS_32	IS 95 NB	142.74	143.34	14	3	23	116	658	1	1	814
IS_60	IS 95 SB	134.1	134.66	21	625	179	244	7	0	1	1076
IS_8	IS 95 NB	111.02	117.92	28	49	18	40	8	0	1	143
SC_104	88 SC 711	0	1.14	18	17	15	7	16	0	1	73
SC_131	89 SC 610	9.4	10.49	6	11	24	10	11	0	1	62
SC_133	89 SC 610	10.63	10.84	80	18	21	8	26	0	1	153

MP = mile post; PSI = potential for safety improvement.

The data suggest significant yearly variation in segment ranking. Hence, relying solely on a single year's rank to identify the top PSI segments is not advisable. Further, a segment that has a year with minimal crashes and thus a lower rank (i.e., a large rank number) could result in the segment having a large sum of rank over the years, leading to its potential exclusion (for example, segment IS_21 has a sum of rank of 1373 whereas it topped the list in 2020). In contrast, screening segments based on the frequency of a segment's appearance in the top 5 or top 10 riskiest segments appears to be a more viable approach. Any link that appears in the top 5 or top 10 warrants further investigation. The number of segments ever ranked in the top 5 and top 10 are 11 and 21, respectively, which is a manageable size for closer scrutiny.

Table 8 presents VDOT's current top PSI segment list (as of the year 2022), along with the corresponding segments from the study's network. A comparative review of Tables 7 and 8 reveals that numerous segments on the current VDOT PSI list also appear in the list generated using the HSM-recommended sliding window screening method, with segment frequency in the top 10 serving as a ranking criterion. As expected, the rankings of segments can differ between the current VDOT PSI list and the one presented in Table 7. It is important to note that in the generation of the VDOT top PSI segment list, the simple ranking method was based on a network segmentation by applying intuitive methods to aggregate short RNS segments for network screening purposes.

Table 8. Current VDOT Top PSI Segments (2016-2020) Matched With the New Segmentation for the Fredericksburg District

VDOT PSI Rank	RNS RTE Name	RNS Start MP	RNS End MP	Matched With New Segmentation	New Segment Start MP	New Segment End MP
1	US 1	142.29	142.67	US_15	142.29	143.00
2	IS 95 SB	144.76	146.214	IS_74	144.66	147.66
3	SR 3	32.36	32.52	SR_13	31.91	32.44
4	SC 711	0	0.96	SC_104	0	1.14
5	SR 3	31.26	31.44	SR_11	30.48	31.57
6	SR 3	32.52	32.78	SR_15	32.52	32.71
7	SR 3	31.64	31.77	SR_12	31.57	31.91
8	IS 95 SB	137.37	139.52	IS_67	137.02	139.22
9	IS 95 SB	143.61	143.84	IS_71	141.13	143.63
10	SR 3	32.23	32.36	SR_13	31.91	32.44
11	IS 95 SB	147.34	148.18	IS_74	144.66	147.66
12	SR 3	30.75	31.06	SR_11	30.48	31.57
13	IS 95 SB	143.34	143.61	IS_71	141.13	143.63
14	US 1	159.97	160.19	US_52	159.81	161.27
15	IS 95 SB	146.214	147.34	IS_74	144.66	147.66
16	IS 95 SB	142.912	143.34	IS_71	141.13	143.63
17	SR 3	33.15	33.39	SR_19	33.15	33.24
18	US 1	148.23	148.41	US_30	148.23	148.27
19	SR 3	34.12	34.33	SR_22	33.92	34.33

PSI = potential for safety improvement; RNS = Roadway Network System; MP = mile point.

It can be observed from Table 8 that the total length of roadways, as derived from VDOT's current PSI list, measures approximately 9.86 miles. In contrast, the total length of roadways configured through the new segmentation is roughly 13.7 miles, representing a length increase of roughly 39%. It should be acknowledged that the study segments have a longer average length than the RNS segments and, unlike RNS segments, their endpoints do not match up with roadway intersections. Therefore, it is expected that there would be a difference observed between the lengths calculated by the study versus the RNS.

However, it is important to recognize that not every segment on the current VDOT PSI list is among the top 20 using the proposed method, and hence, they would not be included in Table 7. These segments may attain a top 20 ranking under different screening criteria, such as rankings based on a single year. Another point of consideration is the discrepancy in the segmentation between the current VDOT PSI list and the proposed network. Segments may have varying start and end points and, as a consequence, different lengths. For instance, the current VDOT segmentation includes segments IS 95 SB, MP 144.76 to MP 146.214; IS 95 SB, MP 146.214 to MP 147.34; and IS 95 SB, MP 147.34 to MP 148.18— all of which are, in fact, consecutive segments. All of these segments align with IS_74 in the proposed new segmentation, as seen in Table 8. Therefore, it may not be practical to establish a direct one-to-one mapping between the two lists. This comparison is primarily intended to cross-verify the similarity of segments identified by both the HSM-recommended method and the current VDOT list.

Roadway Attributes and Segment Ranks

This section provides an analysis of the interrelation between segment rankings and particular roadway attributes including AADT, segment length, roadway divisions (divided/undivided), and urban/rural designation.

A certain relationship between segment rank and AADT was identified. Figure 11 shows the yearly breakdown of the top 5 and top 10 PSI segments along with their corresponding AADT ranks on US routes and state routes from 2016 to 2020.

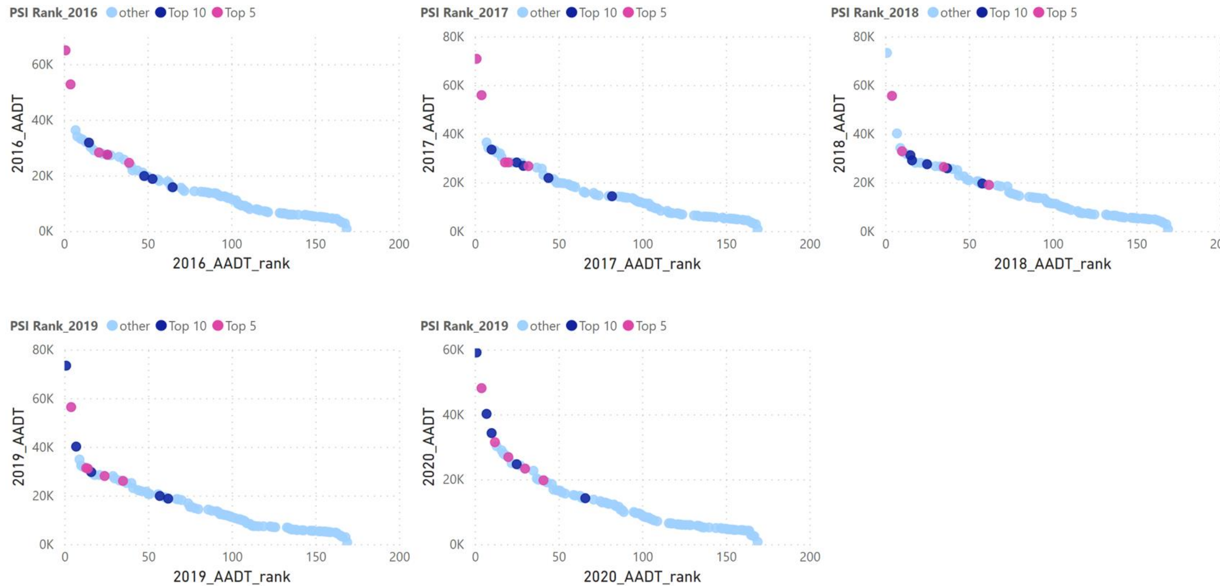
An examination of Figure 11 revealed a consistent trend across both US routes and state routes, where higher-ranking segments were generally associated with higher AADT values. When the scope of analysis was extended to include all roadway types, the correlation coefficients between segment ranks and AADT values ranged from -0.06 to -0.13 over the years 2016 to 2020, indicating a weak to mild correlation.

However, when the correlation analysis was focused on the top 100 PSI segments, a significantly stronger correlation was observed. Specifically, the correlation coefficients between segment ranks and AADT values within this subset ranged from -0.50 to -0.66, thereby suggesting a robust inverse relationship. This correlation evaluation reaffirmed that higher-ranking segments tend to be associated with higher AADT values. There is a potential explanation for this observation. Higher AADT values are often linked with major arterials, which may have more access points or other influencing factors not directly captured by SPFs; the SPFs for these roadway types may not be well-calibrated and might require either re-calibration or the establishment of new SPF types.

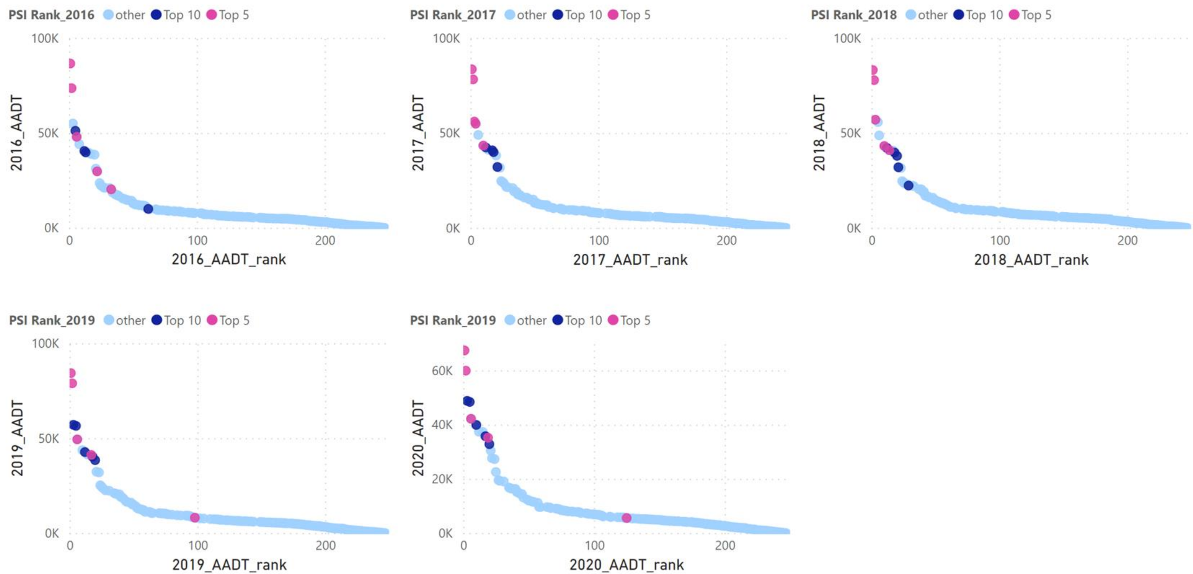
Figure 12 juxtaposes the ranking of the top 100 PSI segments (shown on the x-axis) with the segment length (shown on the y-axis) and urban/rural classification (with light blue representing rural areas and dark blue representing urban areas). It is observable that there is no strong correlation between a segment's rank and its corresponding length. The correlations between the segment rank and its length ranged from 0.01 to 0.21 across the years 2016 to 2020, further confirming the lack of a significant relationship.

A mild correlation was observed between the segment rank and its corresponding rural-urban designation. The correlation values ranged from 0.21 to 0.37 during the years 2016 to 2020. This finding aligns with the observation that higher AADT values are often associated with urban areas, hence contributing to the observed correlations between segment rank and urban/rural designation. In addition, no significant correlations were observed between roadway divisions and segment ranks, as indicated by correlation values from -0.08 to -0.03 throughout the years 2016 to 2020.

Upon analysis, it was determined that no specific correlations existed between segment ranks and variables such as segment length and roadway division. This observation is positive, as it implies that the HSM-recommended sliding window screening method is not inherently biased toward these variables. For example, the method does not show any bias toward shorter segments, which is often a concern in existing real-world practices.



(a)



(b)

Figure 11. Top 5 and Top 10 PSI Segments With Their Corresponding AADT Ranks for 2016 to 2020: (a) US routes; (b) state routes. The segments with the top 5 PSI values are magenta, those within ranks 6 to 10 are dark blue, and those rank higher than 10 are light blue.

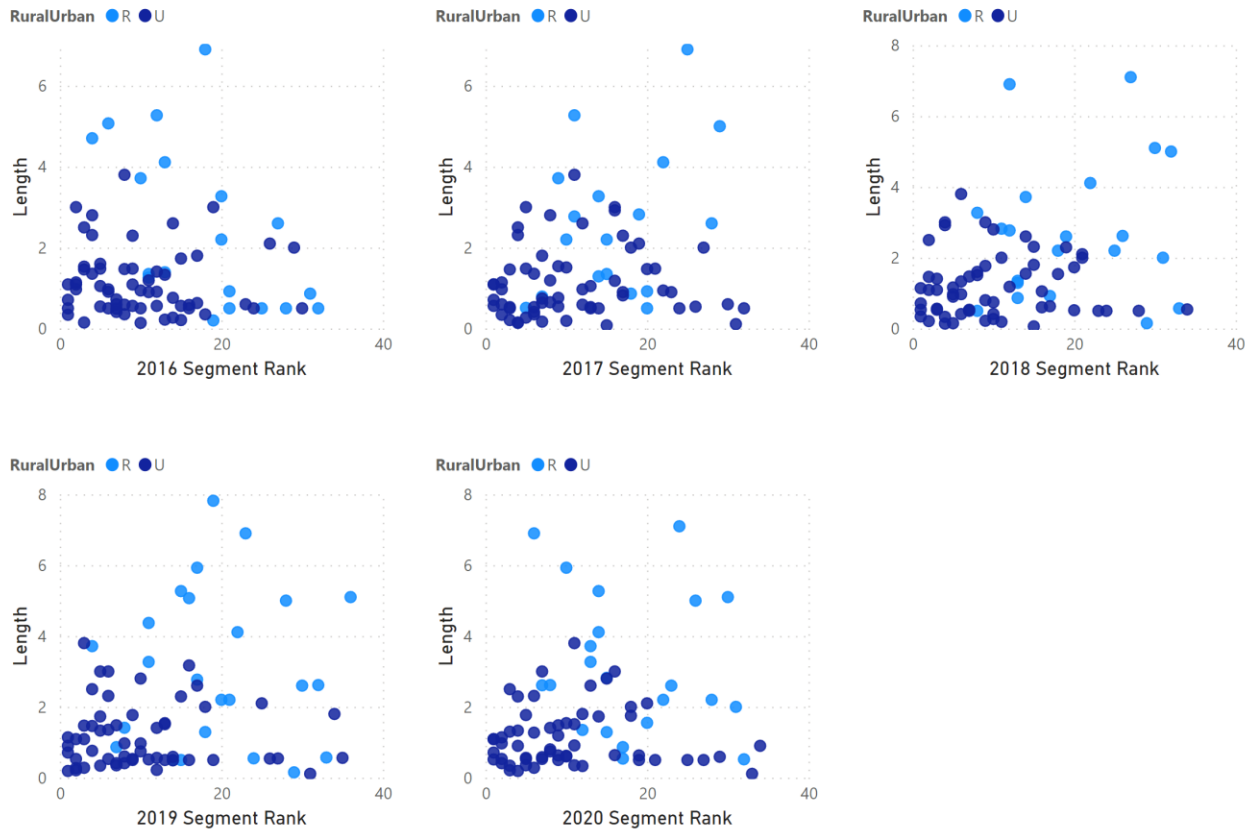


Figure 12. Comparison of Top 100 PSI Segment Ranks With Segment Length and Urban/Rural Designation Over the Year 2016 – 2020. The urban segments are colored in dark blue, and the rural segments are colored in light blue. PSI = potential for safety improvement.

Sensitivity Analysis of Window Sizes

This section discusses a sensitivity analysis that encompassed a variety of window sizes, ranging from 0.3 to 0.7 miles with 0.1-mile increments. The intent was to assess how PSI values and segment ranks changed across these different window sizes.

Table 9 shows a comparison of segments from all roadway types, ranking highest in the year 2016 across various window sizes. Each row represents a segment (Link ID), identified by a route name and the start and end mile points (Start MP and End MP), along with its 2016 rank for different window sizes, ranging from 0.3 to 0.7 miles (columns W=3 through W=7). It is worth noting that in cases where the length of a segment falls short of the predetermined window size set for the sliding window screening method, the window size for that particular segment is set to match its length. In other words, the entire segment is treated as a single window for analysis purposes.

By comparing Tables 7 and 9, it becomes evident that the variation in segment ranks among different window sizes is smaller than that across different years. Most of the top segments maintained a relatively stable rank regardless of window size within a specific year. A deeper analysis was performed by examining a specific roadway type; for instance, Table 10 presents the top 20 PSI interstate segments.

Table 9. Top 20 PSI Segments Ranking Across Various Window Sizes

Link ID	Route Name	Start MP	End MP	PSI 2016 Rank W=3	PSI 2016 Rank W=4	PSI 2016 Rank W=5	PSI 2016 Rank W=6	PSI 2016 Rank W=7
US_15	US 1	142.29	143	1	1	1	1	1
IS_33	IS 95 NB	143.34	143.84	2	4	6	6	6
SR_12	SR 3	31.57	31.91	3	3	4	4	4
SR_11	SR 3	30.48	31.57	4	2	2	2	2
IS_74	IS 95 SB	144.66	147.66	5	5	3	3	3
SC_131	89 SC 610	9.4	10.49	6	7	9	8	9
US_21	US 1	143.96	144.93	7	6	5	5	5
IS_71	IS 95 SB	141.13	143.63	8	9	12	11	7
IS_14	IS 95 NB	123.09	125.89	9	12	7	7	8
US_52	US 1	159.81	161.27	10	11	10	10	10
IS_24	IS 95 NB	135.566	136.11	11	18	22	36	37
US_99	US 17	182.35	184.66	12	10	8	9	11
IS_73	IS 95 SB	144.16	144.66	13	20	35	32	34
IS_32	IS 95 NB	142.74	143.34	14	13	21	60	62
IS_34	IS 95 NB	143.84	147.64	15	14	11	13	17
US_97	US 17	171.61	172.66	16	17	20	18	19
IS_75	IS 95 SB	147.66	148.22	17	8	13	24	25
SC_104	88 SC 711	0	1.14	18	15	14	15	15
IS_70	IS 95 SB	140.63	141.13	19	31	73	71	73
IS_59	IS 95 SB	133.2	134.1	20	23	34	20	20

PSI = potential for safety improvement; MP = mile post.

Table 10. Top 20 PSI Interstate Segments Ranking Across Various Window Sizes

Link ID	Route Name	Start MP	End MP	PSI 2016 Rank W=3	PSI 2016 Rank W=4	PSI 2016 Rank W=5	PSI 2016 Rank W=6	PSI 2016 Rank W=7
IS_33	IS 95 NB	143.34	143.84	1	1	2	2	2
IS_74	IS 95 SB	144.66	147.66	2	2	1	1	1
IS_71	IS 95 SB	141.13	143.63	3	4	5	4	3
IS_14	IS 95 NB	123.09	125.89	4	5	3	3	4
IS_24	IS 95 NB	135.566	136.11	5	9	12	17	17
IS_73	IS 95 SB	144.16	144.66	6	11	17	15	16
IS_32	IS 95 NB	142.74	143.34	7	6	11	22	23
IS_34	IS 95 NB	143.84	147.64	8	7	4	6	8
IS_75	IS 95 SB	147.66	148.22	9	3	6	12	12
IS_70	IS 95 SB	140.63	141.13	10	20	27	26	26
IS_59	IS 95 SB	133.2	134.1	11	14	16	10	10
IS_60	IS 95 SB	134.1	134.66	12	8	13	18	18
IS_11	IS 95 NB	118.98	123.09	13	10	9	9	7
IS_17	IS 95 NB	126.95	129.55	14	13	10	8	11
IS_15	IS 95 NB	125.89	126.45	15	17	18	19	20
IS_62	IS 95 SB	134.77	135.27	16	22	24	23	24
IS_31	IS 95 NB	140.94	142.74	17	12	8	7	6
IS_8	IS 95 NB	111.02	117.92	18	15	7	5	5
IS_20	IS 95 NB	130.65	133.65	19	25	19	16	15
IS_67	IS 95 SB	137.02	139.22	20	19	14	11	9

PSI = potential for safety improvement; MP = mile post.

Table 10 demonstrates that certain segments such as IS_33 maintained high ranks consistently across all window sizes. However, some segments such as IS_24 revealed a clear downward trend with increasing window size, dropping from rank 5 to rank 17 as the window size expanded from 0.3 to 0.7 miles. Inversely, segments such as IS_31 showed an upward trend, rising from rank 17 with a window size of 0.3 miles to rank 6 with a window size of 0.7 miles.

This discrepancy can be traced back to the spatial distribution of crashes on a segment. Table 11 outlines the number of crashes assigned to a specific 0.1-mile section of a roadway, along with the corresponding PSI values for 0.3-mile, 0.5-mile, and 0.7-mile window sizes. As observed in Table 11, IS_24 had the highest crash count of 10 on the fourth 0.1-mile section whereas IS_31 peaked at 5 on the eighth 0.1-mile section. Crashes on IS_24 were relatively concentrated at one hotspot, unlike IS_31, where they are distributed evenly across the entire segment.

One may note that for segment IS_24, with a length of 0.54 miles, setting the window size to either 0.6- or 0.7-miles resulted in the entire segment being treated as a single window. As a consequence, the corresponding PSI value remained the same (i.e., 2.54) for both window sizes. It is worth noting that segments with lengths longer than the window size also exhibited this behavior under different spatial crash distributions. For instance, from Table 11(c), segment SR_10 spanned 1.48 miles and displayed a relatively even distribution of crashes across the entire segment. As the window size varied from 0.3 miles to 0.7 miles, the rank of segment SR_10 declined from 9 to 39.

Table 11(a) shows that with a window size of 0.3 miles, the PSI value peaked at 6.26 on the third window for IS_24. However, when the window size increased to 0.5 miles, the peak PSI value dropped to 4.57 on the second window; moreover, when a window size of 0.7 miles was applied, the entire segment, which was 0.54 miles in length, was considered as a single window with a PSI value of 2.54. Conversely, on IS_31, as observed in Table 11(b), with a window size of 0.3 miles, the highest PSI value was on the sixth window. When the window size was expanded to 0.7 miles, the highest PSI value also increased to 5.76 at the third window. These observations confirm that, in general, a smaller window size may be more effective in identifying localized crash hotspots and a larger window size can provide a smoother and more general overview of the segment. However, bias can emerge when the window size exceeds the segment length.

Consider a scenario involving two segments: Segment A, measuring 0.5 miles in length, and Segment B, measuring 0.8 miles in length. Both segments exhibit the same overall crash density, with five crashes occurring on Segment A and eight crashes on Segment B. However, the spatial distribution of crashes is not identical across the two segments. On Segment A, all five crashes are confined to a single increment, whereas on Segment B, the eight crashes are evenly dispersed across all increments, translating to a rate of one crash per increment. Provided that the window size is less than the segment length, the segment with a concentrated crash distribution (Segment A) will show a higher PSI value. This condition holds until the window size equates to the length of Segment A (i.e., 0.5 miles), at which point the PSI values for both segments level out. Thereafter, the PSI value will remain constant irrespective of any subsequent increase in window size.

In contrast, if the segment with an evenly distributed crash density is shorter (Segment B), the PSI value for that segment will hold steady as the window size expands to match its length. Yet, the PSI value for the lengthier segment (the one with concentrated crashes, Segment A) will progressively decrease with an increasing window size.

Table 11. Crash Distribution on Segments IS_24, IS_31, and SR_10 in 2016

Link ID	Increment	2016 Crash	PSI 2016 (W=3)	PSI 2016 (W=5)	PSI 2016 (W=7)
IS_24 (Length: 0.54 miles)	0	1	-4.23	2.79	2.54
	1	2	-1.53	4.57	N/A
	2	2	5.66	N/A	N/A
	3	4	6.26	N/A	N/A
	4	10	N/A	N/A	N/A
	5	1	N/A	N/A	N/A
IS_31 (Length: 1.8 miles)	0	1	-0.31	0.96	3.87
	1	2	1.20	2.56	3.87
	2	2	1.20	4.16	6.35
	3	3	1.95	3.36	7.17
	4	2	2.70	4.96	5.52
	5	3	1.95	5.76	5.52
	6	4	3.46	4.6	4.70
	7	1	2.70	2.56	2.22
	8	5	2.71	3.36	2.22
	9	3	0.44	0.17	-0.25
	10	1	-0.31	-1.43	-1.08
	11	2	-0.31	-0.63	-1.90
	12	2	-1.06	-0.63	N/A
	13	1	-1.06	-2.23	N/A
	14	1	-0.31	N/A	N/A
	15	2	-1.06	N/A	N/A
	16	2	N/A	N/A	N/A
	17	0	N/A	N/A	N/A
SR_10 (length: 1.48 miles)	0	0	-1.62	-1.00	-1.14
	1	0	-0.91	-0.23	-1.14
	2	1	0.51	0.53	-0.34
	3	1	0.51	-0.23	-1.14
	4	2	0.51	-0.23	-1.14
	5	1	-0.91	-1.77	-2.73
	6	1	-0.91	-1.77	-2.73
	7	0	-1.62	-2.53	-1.94
	8	1	-0.91	-1.77	0.62
	9	0	-1.62	-1.00	N/A
	10	1	-0.91	0.45	N/A
	11	0	-0.20	N/A	N/A
	12	1	2.06	N/A	N/A
	13	2	N/A	N/A	N/A
	14	3	N/A	N/A	N/A

PSI = potential for safety improvement; N/A = not applicable.

Comparative Analysis With Simple Ranking Method

In this section, the results derived from simple ranking methods applied to two segmentation approaches, namely, the 0.1-mile units and the new homogeneous segments, are investigated. The network consists of 10,655 0.1-mile units for the first approach, whereas the second approach incorporates 674 segments.

Simple Ranking Method Analysis on 0.1-Mile Units. Each entry in Table 12 denotes a 0.1-mile unit distinguished by a route name, its start and end mile points, and corresponding yearly rankings from 2016 to 2020.

Table 12. Yearly Breakdown of Rankings for Top 20 PSI Locations by 0.1-Mile Segmentations

Link ID	Route Name	Start MP	End MP	PSI 2016 Rank	PSI 2017 Rank	PSI 2018 Rank	PSI 2019 Rank	PSI 2020 Rank
SR_12	SR 3	31.67	31.77	1	1	1	21	5
US_15	US 1	142.29	142.39	2	6	15	162	8633
US_15	US 1	142.49	142.59	3	22	7	4	4
IS_33	IS 95 NB	143.54	143.64	4	230	211	10583	10029
SR_11	SR 3	30.78	30.88	5	15	32	93	2
SC_131	89 SC 610	10.2	10.3	6	102	70	15	97
IS_74	IS 95 SB	145.46	145.56	7	36	38	10364	461
US_15	US 1	142.39	142.49	8	3	11	12	10
IS_24	IS 95 NB	135.966	136.066	9	18	9745	142	378
SR_20	SR 3	33.24	33.34	10	7	31	212	114
IS_33	IS 95 NB	143.64	143.74	11	2	30	112	10029
SR_11	SR 3	30.58	30.68	12	9	71	61	307
SR_11	SR 3	30.88	30.98	12	4	49	42	98
SR_11	SR 3	31.08	31.18	12	104	108	93	98
SC_131	89 SC 610	10.4	10.49	15	10	48	29	9
IS_59	IS 95 SB	134	134.1	16	73	1589	233	34
IS_70	IS 95 SB	140.83	140.93	17	437	10098	19	8103
US_97	US 17	172.01	172.11	18	9761	9778	9761	10333
US_21	US 1	144.26	144.36	19	41	111	254	59
IS_74	IS 95 SB	145.16	145.26	20	47	58	1564	128

PSI = potential for safety improvement; MP = mile post.

Upon examination of Table 12, it is observed that some units, such as SR_12 from MP 31.67 to MP 31.77, consistently rank high across the years whereas others exhibit notable yearly rank fluctuations. A further investigation into SR_12 (as illustrated in Table 13) revealed that only the 0.1-mile unit from MP 31.67 to MP 31.77 held a high rank whereas adjacent 0.1-mile units ranked significantly lower. Given its high ranking in 3 of 5 years, the 0.1-mile unit could potentially be identified as a crash hotspot. As indicated in Table 14, Segment SC_131 contains multiple hotspots; the first is located from MP 9.9 to MP 10, and the second extends from MP 10.2 to MP 10.3. In contrast, some other units (e.g., IS_64 from MP 136.17 to MP 136.27, as depicted in Table 15) may rank high in specific years due to the stochastic nature of crash occurrences.

It can be concluded that the application of the simple ranking method to 0.1-mile segments can reveal hotspots within the new homogeneous segment. However, the effectiveness of this approach is contingent on the randomness inherent in crash occurrences. In addition, it should be noted that the majority of possible treatments do not function as "spot" treatments. Thus, implementing safety improvement measures over longer roadway segments may prove more cost-efficient.

Table 13. Yearly Breakdown of Rankings for Segment SR_12 With Simple Ranking Methods by 0.1-Mile Segmentations

Link ID	Route Name	Start MP	End MP	PSI 2016 Rank	PSI 2017 Rank	PSI 2018 Rank	PSI 2019 Rank	PSI 2020 Rank
SR_12	SR 3	31.57	31.67	314	9853	92	140	10606
	SR 3	31.67	31.77	1	1	1	21	5
	SR 3	31.77	31.87	10531	9853	10518	10521	10404
	SR 3	31.87	31.91	3625	10378	260	10370	518

MP = mile post; PSI = potential for safety improvement.

Table 14. Yearly Breakdown of Rankings for Segment SC_131 With Simple Ranking Methods by 0.1-Mile Segmentations

Link ID	Route Name	Start MP	End MP	PSI 2016 Rank	PSI 2017 Rank	PSI 2018 Rank	PSI 2019 Rank	PSI 2020 Rank
SC_131	SC 610	9.4	9.5	1944	30	1966	15	1996
	SC 610	9.5	9.6	1944	1996	1966	1997	1996
	SC 610	9.6	9.7	1944	30	1998	1997	1996
	SC 610	9.7	9.8	1944	1996	1966	1997	1911
	SC 610	9.8	9.9	1997	1996	1998	1997	1996
	SC 610	9.9	10	12	3	1998	15	29
	SC 610	10	10.1	1997	1996	1998	1997	1996
	SC 610	10.1	10.2	1997	1996	1998	1997	1996
	SC 610	10.2	10.3	1	8	5	3	7
	SC 610	10.3	10.4	1997	1944	1998	1969	1996

MP = mile post; PSI = potential for safety improvement.

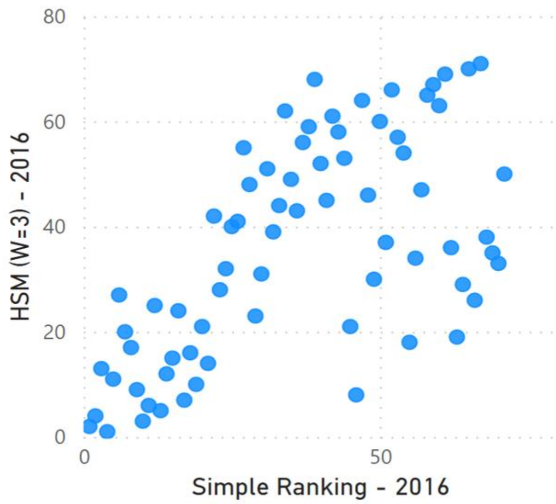
Table 15. Yearly Breakdown of Rankings for Segment IS_64 With Simple Ranking Methods by 0.1-Mile Segmentations

Link ID	Route Name	Start MP	End MP	PSI 2016 Rank	PSI 2017 Rank	PSI 2018 Rank	PSI 2019 Rank	PSI 2020 Rank
IS_64	IS 95 SB	135.87	135.97	10070	10522	10498	10514	10602
	IS 95 SB	135.97	136.07	10643	10615	10618	10514	7788
	IS 95 SB	136.07	136.17	10643	10652	10498	10620	10643
	IS 95 SB	136.17	136.27	132	10652	10498	10514	10602
	IS 95 SB	136.27	136.37	10505	436	10498	10514	10643

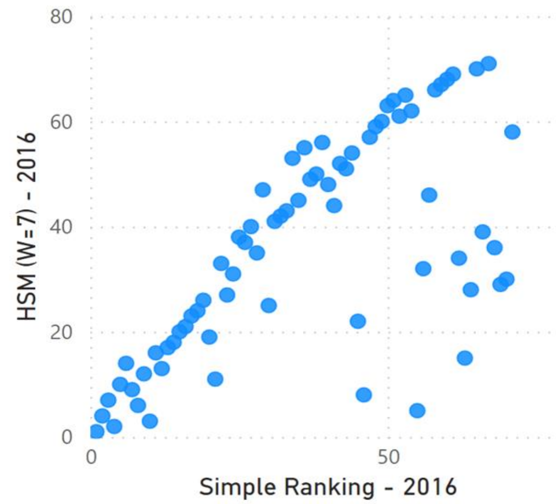
MP = mile post; PSI = potential for safety improvement.

Simple Ranking Method Analysis for the New Homogeneous Segments. The simple ranking method was employed on the newly developed homogeneous segments, treating each of the 674 segments as a discrete unit. Theoretically, the simple ranking method applied to the new homogeneous segments is equivalent to the HSM-recommended sliding window screening method with an infinitely large window size. The broad window size facilitates an overview of the entire segment, as opposed to concentrating on individual locations within a segment.

Figure 13 illustrates a comparison of ranks derived from the simple ranking method with the new segmentation and the HSM-recommended sliding window screening method, with window sizes of 0.3 miles, 0.7 miles, 1 mile, and 2 miles, for interstate segments. The correlations between the ranks produced by the simple ranking method and the sliding window screening method, using window sizes of 0.3 miles, 0.7 miles, 1 mile, and 2 miles, are, respectively, 0.62, 0.67, 0.74, and 0.84. A high correlation between the ranks derived from these methods is evident; this trend is consistent across all road types.



(a) 0.3 miles



(b) 0.7 miles

(c) 1 mile

(d) 2 miles

Figure 13. Comparison Between Ranks Derived From the Simple Ranking Method and the HSM-Recommended Sliding Window Screening Method With Different Window Sizes: (a) 0.3 miles; (b) 0.7 miles; (c) 1 mile; (d) 2 miles. HSM = *Highway Safety Manual.*

Moreover, the correlation between the ranks generated by the simple ranking method and the HSM-recommended sliding window screening method is higher with a window size of 2 miles, as opposed to 0.3 miles. This outcome is consistent with the theoretical equivalence between the two methods. It is important to note that the quantity of segments where the window size exceeds the segment length with window sizes of 0.3 miles, 0.7 miles, 1 mile, and 2 miles is 4, 47, 51, and 52 of 71, respectively.

Discussion

The sliding window screening method presents several key advantages over the simple ranking method, as follows:

- *Standardization across variable segment lengths.* The sliding window screening method provides a standardized way to analyze roadway segments of different lengths. This standardization mitigates inherent bias based on segment length.

- *Adaptability to crash distributions.* One of the strengths of the sliding window screening method is its ability to account for diverse spatial crash distributions. By adjusting the window sizes, traffic engineers can refine their focus to identify either localized hotspots or broader trends across an entire segment. In contrast, the simple ranking method is limited to analyzing the entire segment as a whole.

- *Mitigation of randomness.* The sliding window screening method can smooth out the randomness inherent in crash occurrences, making it a more reliable tool for safety analysis. For example, a specific 0.1-mile unit may rank high in some years due to the stochastic nature of crashes, making the effectiveness of the simple ranking method contingent on this randomness. By reducing the impact of such random fluctuations, the sliding window screening method delivers a more consistent and reliable analysis.

- *Flexibility for various safety measures.* The sliding window screening method can align with different safety improvement measures. Some measures are designed to improve safety across a longer segment, whereas others are intended as spot treatments for specific locations. Traffic engineers can adjust the window size to help identify the most appropriate segments for different types of improvement measures.

Overall, these strengths highlight the capacity of the sliding window screening method to provide a more flexible and reliable analysis of roadway safety than the simple ranking method.

Limitations of the sliding window screening method over the simple ranking method include the following:

- *Increased complexity.* The sliding window screening method involves more complex computations and more data preparation compared to the simple ranking method. It may require more time and resources, especially when applied to large networks.

- *Requirement for greater expert judgment.* As the sliding window screening method involves the selection of the appropriate window size and an understanding of its implication, the method might require a greater level of expert judgment, thus increasing the reliance on the expertise and experience of the personnel involved.

- *Potential for misinterpretation.* Given the complexity of the method and the influence of window size selection, there is the potential for misinterpretation of results, especially if they are not adequately understood or communicated to decision-makers and stakeholders.

CONCLUSIONS

- *The new segmentation network developed in this study overcame several limitations of the current RNS network, such as biased representation of crash rate per mile due to the presence of very short segments (<0.01 mile). However, more effort was required to create the new segmentation network.*

- *When the HSM-recommended sliding window screening method is employed, a smaller window size can be more effective in detecting localized crash hotspots. Conversely, a larger window size facilitates a smoother and more comprehensive overview of the segment.*

- *The HSM-recommended sliding window screening method did not demonstrate inherent bias with regard to roadway attributes including segment length or median presence. However, segments with higher rankings (PSI values) were generally found to be associated with higher AADT values.*

- *The stochastic nature of crash occurrences can cause considerable fluctuations in segment rankings over different years. As a consequence, the use of a single year's ranking to identify the top PSI segments is not recommended due to this inherent variability.*

- *The segments identified on the current VDOT PSI list showed significant overlap with those generated using the HSM-recommended sliding window screening method. Despite potential differences in segment rankings between the VDOT PSI list and the HSM-recommended method, there is a general similarity in the list of segments generated by both approaches.*

- *The simple ranking method, as proposed by the HSM, applied to 0.1-mile segments can potentially identify hotspots within a segment. Conversely, when this method is applied to homogeneous AADT segments, it mirrors the sliding window screening method with an infinite large window size. Nevertheless, it is worth noting that the effectiveness of these approaches, particularly when applied to 0.1-mile segments, is significantly influenced by the inherent randomness of crash occurrences.*

RECOMMENDATION

1. *VDOT's Traffic Operations Division should consider deploying the new segmentation network and adopting the sliding window screening method for the computation of PSI values on a statewide basis to enhance the effectiveness of network screening processes.*

IMPLEMENTATION AND BENEFITS

The researchers and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and to determine the benefits of doing so. This is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

With regard to the recommendation, within 12 months of the publication of this report, VDOT's TOD will initiate a feasibility study to evaluate the resources required, both financially and in terms of necessary expertise, for implementing the suggested methodology on a statewide level. The study should include the evaluation of applying the sliding window approach to fatal and injury PSI analysis. VTRC will provide TOD with the necessary support, including input files, a Python script, Power BI visualization files, and consultation with regard to implementing and evaluating fatal and injury PSIs using the sliding window screening method. If the proposed methodology is implemented, the resulting selected projects should be tracked and compared with projects selected prior to implementation of the proposed methodology.

Benefits

The benefit of implementing this recommendation will be the enhancement of VDOT's TOD safety ranking by allowing for a fairer comparison of segments of varying lengths and tailored selection of segments for specific safety measures. The proposed methodology not only focuses on spot improvements but also adopts a holistic view of the segment. This ultimately leads to better safety project identification and selection, which will produce crash reductions and more efficient resource allocation.

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