Updates to Risk Factors for SHSP Emphasis Areas

Speeding Crashes

PREPARED FOR

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PREPARED BY

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Purpose & Background

The Massachusetts Department of Transportation (MassDOT) is updating the risk-based network screening maps in the IMPACT tool to incorporate recent crash data and build on lessons learned from previous analyses. This document describes the updated systemic analysis performed by VHB for "speeding" crashes using crash data from 2017 through 2021. For this analysis, VHB used the default "speeding" query[1] in the MassDOT IMPACT tool. The definition reads as: "any crash in which "exceeding the speed limit" is reported in a driver's "Driver Contributing Circumstances" field.[2]

Ideally, a risk-based approach to speeding crashes would consider operational speed data so MassDOT and stakeholders could target facilities where data indicate speeding occurs at an elevated rate. Unfortunately, these data sources are not yet ready for inclusion in such an analysis. As such, MassDOT has prepared this town-level speeding analysis and plans to follow-up with a site-level speeding analysis once reliable site-level speed data are available. Additionally, these risk models will be updated once the data on operating and regulatory speed data are available.

Note that the purpose of this report is to identify the factors most correlated with the frequency and severity of speeding-related crashes; causality was not directly investigated. As such, agencies interested in developing targeted countermeasure programs are encouraged to perform some initial investigation into causality of the target crash in their jurisdiction. This will allow the agency to develop targeted countermeasures.

Data Analysis and Focus Crash Types

To establish context, VHB first used the MassDOT IMPACT "Test of Proportions" tool[3] to summarize fatal injury (K) and suspected serious injury (A) speeding crashes. To identify overrepresented crash attributes, VHB compared KA speeding crashes to all KA crashes in the State. Where the proportion for a given attribute is statistically larger than the proportion for the comparison group, that attribute is flagged as a potential risk factor. Statistical overrepresentation is checked by building 95 percent confidence intervals around the proportion using sampling errors. Figure 1 and Figure 2 show how the lower and upper bounds, respectively, are calculated based on the proportion of crashes (*p*) and the number of crashes in the sample (*N*). If the lower bound of speeding KA crashes is larger than the upper bound of the comparison group, the attribute was considered "overrepresented" for the data.

$$95\%\ Confidence\ Interval, Lower\ Bound\ =\ p - 1.96 * \sqrt{\frac{p(1-p)}{N}}$$

Figure 1. Calculation of the lower bound of the 95 percent confidence interval for the proportion of crashes with an attribute.

[1] https://www.mass.gov/info-details/impact-emphasis-area-definitions

[2] MassDOT. *Impact Emphasis Area Definitions.* Available at: https://www.mass.gov/info-details/impact-emphasis-area-definitions. Accessed March, 2023.

[3] https://apps.impact.dot.state.ma.us/sat/TestofProportions

$$95\%\ Confidence\ Interval, Upper\ Bound\ =\ p + 1.96 * \sqrt{\frac{p(1-p)}{N}}$$

Figure 2. Calculation of the upper bound of the 95 percent confidence interval for the proportion of crashes with an attribute.

Table 1 summarizes notable overrepresentations found in the analysis. VHB included the following data elements in their analysis:

- Access Control.
- Age of Driver – Oldest known.
- Age of Driver – Youngest Known.
- Age of Non-Motorist – Oldest Known.
- Age of Non-Motorist – Youngest Known.
- County Name.
- Crash Day of Week.
- Crash Month.
- Curb.
- Driver Contributing Circumstances.
- Driver Distracted By.
- Facility Type.
- Federal Functional Class.
- First Harmful Event.
- First Harmful Event Location.
- FMCSA Reportable.
- Functional Class.
- Jurisdiction.
- Left Shoulder Type-linked.
- Left Shoulder Width-linked.
- Light Conditions.
- Manner of Collision.
- Max Injury Severity Reported.
- Median Type.
- Operation.

- Opposite Number of Travel Lanes.
- Right Shoulder Type-linked.
- Right Shoulder Width-linked.
- Road Contributing Circumstance.
- Road Surface Condition.
- Roadway Junction Type.
- Speed Limit.
- Terrain Type.
- Total Lanes.
- Traffic Control Device Type.
- Trafficway Description.
- Urban Type.
- Weather Conditions.

Table 1. Summary of Key Overrepresentation Findings.[4]

Crash Field	Crash Attribute	Percent of Speeding KA Crashes	Percent of All KA Crashes
Access Control	Full Access Control	22.44%	15.03%
Age of Driver – Youngest Known	18-20	13.75%	9.32%
	21-24	20.63%	13.87%
	25-34	35.06%	27.32%
County Name	Hampden	12.40%	8.56%
Crash Day of Week	Sunday	21.42%	14.51%
Crash Month	April	9.92%	7.12%
Curb	None	52.54%	40.86%
Driver Contributing Circumstances[5]	Exceeded authorized speed limit	49.75%	4.04%
	Operating vehicle in erratic, reckless, careless, negligent or aggressive manner	13.57%	8.57%
Federal Functional Class	Interstate	15.67%	9.85%
First Harmful Event	Collision with curb	6.88%	2.61%
	Collision with embankment	2.25%	1.09%
	Collision with guardrail	7.78%	4.03%
	Collision with tree	13.87%	7.43%
	Collision with utility pole	8.34%	5.13%
	Overturn/rollover	3.72%	2.18%

[4] Test of Proportions. https://apps.impact.dot.state.ma.us/sat/TestofProportions Accessed on 07/10/2023
[5] Vehicle-level data

Crash Field	Crash Attribute	Percent of Speeding KA Crashes	Percent of All KA Crashes
First Harmful Event Location	Median	4.51%	2.50%
	Outside Roadway	16.80%	10.08%
	Roadside	15.90%	9.29%
Left Shoulder Type	Hardened bituminous mix or penetration	19.28%	13.43%
Left Shoulder Width	4 feet	12.74%	8.28%
Light Conditions	Dark – lighted roadway	37.32%	26.43%
	Dark – roadway not lighted	17.36%	9.60%
Manner of Collision	Single vehicle crash	57.61%	42.37%
Median Type	Positive barrier – semi-rigid	7.67%	5.27%
	Positive barrier - unspecified	7.78%	5.47%
Opposite Number of Travel Lanes	3	12.29%	7.93%
Right Shoulder Type	Stable – unruttable compacted subgrade	14.43%	10.63%
	Unstable shoulder	8.79%	5.62%
Road Surface Condition	Dry	85.12%	79.41%
Roadway Junction Type	Not at junction	67.87%	59.26%
	Off-ramp	3.61%	1.67%
Speed Limit	65 MPH	11.72%	7.77%
Total Lanes	6	11.72%	7.72%
Traffic Control Device Type	No Controls	80.05%	71.77%
Trafficway Description	Two-way, divided, positive median barrier	21.42%	16.13%
Weather Conditions	Clear	75.45%	68.20%
RPA Abbreviation	NMCOG	7.22%	4.61%
	PVPC	14.77%	10.48%

Reviewing these data, there are consistent results indicating severe speeding crashes are primarily overexposed on high speed, multilane, fully access controlled roadways. This is not surprising, as vehicles are already traveling at high speeds on these facilities, so traveling in excess of the speed limit produces an even larger increase in energy present in a possible collision, contributing to elevated likelihood of a fatality or severe injury. The first harmful event results all point towards correlation between severe speeding crashes and lane departures, whether those departures begin with striking a curb, embankment, guardrail, tree, or utility pole. As such, transportation managers interested in addressing severe speeding crashes should also consider lane departure crashes. Speeding KA crashes were overrepresented during nighttime, likely due to limited sight distance offered by the headlights. Finally, young drivers (i.e., those aged 18-34) are overrepresented for speeding crashes. While these are typically the most resilient drivers, they may engage more in speeding, thus speeding programs should also consider targeting young drivers. MassDOT should consider these findings when identifying potential countermeasures to control speeding. The National Highway Traffic Safety Administration's (NHTSA) *Countermeasures that Work*[6]

[6] https://www.nhtsa.gov/book/countermeasures/countermeasures-work/speeding-and-speed-management

includes several strategies targettting speeding behavior that include setting appropriate speed limits, automated enforcement, high-visibility enforcement, and communications and outreach supporting enforcement.

While the lane departure, nighttime, and young driver correlations are notable, MassDOT still considers all speeding crashes the focus crash type.

Crash Tree and Focus Facility Type

After concluding that the speeding focus crash type should include all speeding crashes, VHB developed a crash tree to identify the roadway conditions under which severe speeding crashes tend to occur most often. Figure 3 shows the crash tree.

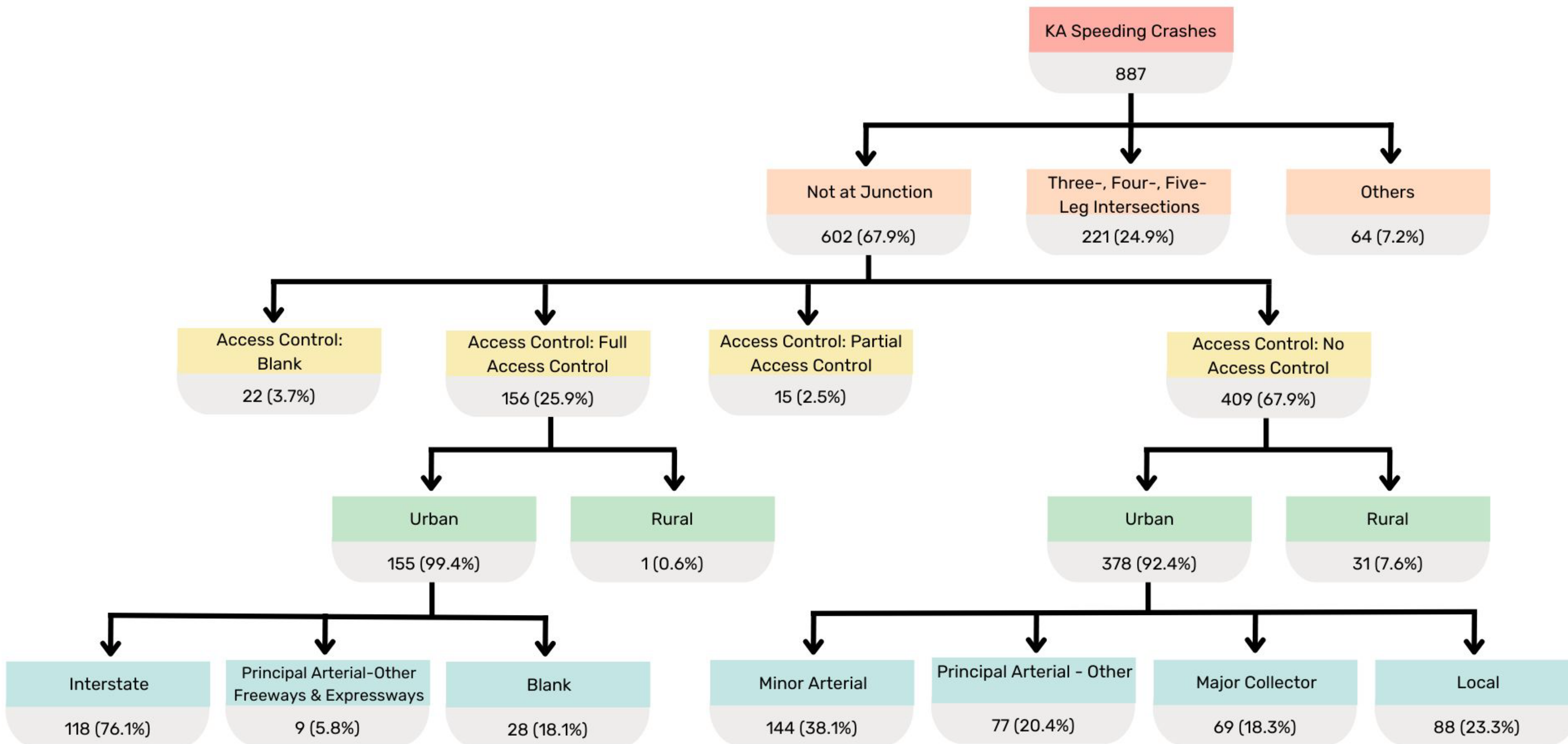

Figure 3. Crash tree summarizing KA speeding crashes in Massachusetts.

It is evident that the majority of speeding-related KA crashes occur outside junction areas. Of these crashes outside junction areas, a larger portion were on urban roadways with no access control, followed by roadways with full access control. While the analysis above points towards some potential focus for this emphasis area (e.g., urban interstates, urban minor arterials), the lack of site-level speeding data has encouraged MassDOT to, for the time being, perform a town-level analysis of speeding crashes.

Risk Factor Analysis

After identifying focus crash types and trends, VHB proceeded with the risk factor analysis. The following sections describe the methodology, data, and results of this analysis.

Methodology

Negative binomial regression is a standard approach to crash frequency modeling given that crash frequency data are typically overdispersed count data. VHB used a negative binomial count regression modeling approach to identify community-level characteristics associated with higher frequencies of speeding KA crashes. Negative binomial regression is commonly used in transportation safety as it applies to over-dispersed count data (i.e., the variance exceeds the mean of the observed data). The dependent variable in the model is the number of speeding KA crashes, making a count model appropriate for the data. The functional form of the negative binomial regression model is shown in Figure 4.[7]

$$\lambda_i = e^{\beta X_i + \varepsilon_i}$$

Figure 4. Equation. Negative binomial regression functional form.

Where:

$e^{\varepsilon i}$ = gammadistributed error term with a mean equal to one and variance equal to α.

λ_i = expected number of speeding KA crashes at location i.

β = vector of estimated parameters.

X_i = vector of independent variables that characterize location i and influence speeding KA crash frequency.

When modeling, VHB began with road exposure variables and added additional variables one at a time, monitoring the coefficients to ensure the inclusion of a variable did not result in large changes in magnitude. Additionally, VHB included variables with p-values upwards of 0.25 assuming the magnitude of the results made sense. VHB did not select a strict level of significance, as Hauer notes this could lead to misunderstanding or outright disregard for potentially noteworthy results.[8]

VHB included data from the sources listed in the next section to test whether correlations were present between those features and speeding crash frequency. If a statistical correlation was identified and reliable, VHB reviewed the relationship to determine if the correlation makes sense – does the coefficient indicate a reasonable relationship between the dependent variable and the risk of a severe crash. If so, VHB included the feature as a risk factor.

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[7] Lord, D., Mannering, F., 2010. The Statistical Analysis of Crash-Frequency Data: A Review and Assessment of Methodological Alternatives. Transp. Res. Part A Policy Pract. 44 5 , 291–305. doi:10.1016/j.tra.2010.02.001
[8] Hauer, E. (2004). The harm done by tests of significance. *Accident Analysis & Prevention*, *36*(3), 495-500.

Data

VHB used ArcGIS to manage and integrate data for this analysis. VHB aggregated data at the city and town level. In Massachusetts, all roads and geographic areas are covered by town jurisdictions. Due to limitations with crash data acquisition, VHB excluded the City of Boston from the analysis. MassDOT provided VHB with various sources of data, as described in the following sections.

Crash Data

VHB obtained severe (KA) speeding crashes by town using the MassDOT IMPACT Test of Proportions tool. VHB then joined these totals to the town-level data set.

Roadway Data

VHB downloaded the Massachusetts statewide Road Inventory 2021 file, available at https://geo-massdot.opendata.arcgis.com/datasets/342e8400ba3340c1bf5bf2b429ad8294/about. Based on discussions with MassDOT, VHB filtered the roadway data in ArcGIS using mileage counted (equal to 1), jurisdiction (not equal to null), and facility type (less than 7) to identify unique segments that were counted for the Highway Performance Monitoring System (HPMS). Filtering the roadway inventory in this way prevented potential double-counting of mileage and VMT for divided roads and roads with overlapping route numbers. VHB aggregated the roadway data at the town-level, including summing total centerline miles and centerline miles for each Federal Functional Class.

Driver License Data

MassDOT provided driver license data by age, town, and zip code for 2021. VHB used spatial analysis to assign driver license zip codes to the relevant town, joining the driver license totals by age. Additionally, VHB calculated the proportion of drivers that fell within the Young Driver query definition for each town.

School Location Data

VHB obtained primary and secondary school location data from the Massachusetts Bureau of Geographic Information (MassGIS) open data portal (https://www.mass.gov/info-details/massgis-data-massachusetts-schools-pre-k-through-high-school).

College and University Data

VHB accessed college and university location data from the MassGIS open data portal (https://www.mass.gov/info-details/massgis-data-colleges-and-universities). Although these data contain several categories of trade schools and other atypical technical training institutions, VHB only included "Colleges, universities, and professional schools," "Fine arts schools," "Junior colleges," and "Other technical and trade schools" for the purposes of this analysis.

Citation Data

VHB obtained traffic citation count data by town for a five-year period between 2015 and 2019. These data included total citations, as well as subsets of counts for speeding-, seat belt-, impaired driving-, and distraction-related traffic citations.

Speed Data

MassDOT is in the process of acquiring, processing, and calibrating probe-level speed data which reveal operating speeds for vehicles across the Massachusetts roadway network. Unfortunately, as of this project, these data were not yet reliably available. As such, MassDOT plans to use these data in future, more refined iterations of this analysis.

Additional Data

VHB obtained several additional data sources for integration into the data set, including census and American Community Survey (ACS) data, public health data from the Massachusetts Department of Public Health (DPH), seatbelt use survey data at the town level, and environmental justice (EJ) data provided by Environmental Justice Community Block Group Data Update. Note that, county-level seat belt data were utilized for towns with missing seat belt use rate information. Additionally, regarding EJ data, the reports may change if the final layers were used but they were not available at the time the analyses were performed. The version of Massachusetts 2020 Environmental Justice Block Group data available at the time of the analysis was a preliminary version that was later updated with a final.

Results

The following sections describe the results of the negative binomial regression modeling effort.

Variables of Interest

To account for unobserved influences due to road facilities and traffic exposure, VHB established a base model that included the natural log of the mile years (i.e., the product of five years of data and total centerline mileage in the town) – this accounts for exposure. Before including additional variables in the negative binomial, VHB developed a correlation matrix of input variables. Highly correlated variables are indicators of potential complications in the model development process. Although VHB considered all potential variables in this matrix, Table 2 shows the correlation matrix for the following 5 variables included in the final speeding model. Note the maximum correlation between any two variables is 0.58 (unbelted citations per centerline mile and ABCC license density).

1. Natural log of active drivers licenses in the town.
2. Annual speeding citations per centerline mile in the town.
3. Annual unbelted citations per centerline mile in the town.
4. Percent of drivers observed using a seat belt in the town (or town’s county for towns without seatbelt inoformation) is fewer than 80 percent.
5. ABCC licenses per square mile in the town.
6. Natural log of total centerline mile-years.

Table 2. Correlation Matrix of Input Variables.

Variables	1. Drivers licenses.	2. Speeding citations.	3. Unbelted citations.	4. Belted drivers.	5. ABCC licenses.
1. Drivers licenses.	1.00				
2. Speeding citations.	0.26	1.00			
3. Unbelted citations.	0.47	0.45	1.00		
4. Belted drivers.	0.005	-0.08	-0.03	1.00	
5. ABCC licenses.	0.44	0.13	0.58	-0.08	1.00

Model Results

Table 3 documents the negative binomial regression results and presents coefficients, standard error, z-value, p-value, and 95 percent confidence intervals for each variable included in the final model. The natural log of the product of centerline mileage and 5 years of crash data were included in the model to offset exposure for each town. The number of active driver licenses in the town is also a measure of exposure, indicating that if a town has more active licenses, there is likely more driving in the town, and thus more likelihood for a severe speeding crash. The correlation with speeding citations is obvious – if police are observing and citing speeding behavior at a high level, there is a higher likelihood of speeding crashes in the town. The unbelted citations and percent of drivers unbelted have two correlations with speeding – one being an indicator of increased risk taking behavior by drivers in the town, and the other being increased vulnerability for vehicle occupants in a town when they enter a speeding crash due to their lack of use of a seat belt. Finally, the inverse relationship between ABCC license density and severe speeding crash frequency suggests that there is a correlation with severe speeding crashes in towns with low ABCC license density. This is likely an indicator for towns with lower population density, higher speed roads, and where persons need to drive longer distances to access these establishments.

Table 3. Negative Binomial Count Regression Model Results.

Variable (Number)	Coefficient	Standard Error	z-value	P>|z|	95% Confidence Interval	
Natural log of active drivers licenses in the town	0.395	0.056	7.01	<0.001	0.285	0.505
Annual speeding citations per centerline mile in the town.	0.030	0.011	2.74	0.006	0.009	0.052
Annual unbelted citations per centerline mile in the town.	0.095	0.032	2.98	0.003	0.032	0.157
Indicator that fewer than 80 percent of drivers were observed using their seatbelt in the town's county.	0.257	0.101	2.54	0.011	0.059	0.455
ABCC licenses per square mile in the town.	-0.018	0.012	-1.53	0.127	-0.041	0.005
Constant	-9.581	0.527	-18.19	<0.001	-10.614	-8.548
Natural log of the product of centerline mile length and 5 years of crash data in the town. (Offset)	1 (offset)	n/a	n/a	n/a	n/a	n/a
alpha	0.183	0.049	n/a	n/a	0.107	0.310

Note: Number of observations = 350; Log likelihood = -556.80364; Pseudo R2 = 0.1015; LR chi2(5) = 125.75; Prob > chi2 < 0.0001.

Conclusions and Recommendations

The purpose of this analysis is to identify town-level risk factors for fatal and serious injury speeding crashes. VHB recommends MassDOT adopt the features identified in the negative binomial regression model as risk factors. Further, instead of using the coefficients in the negative binomial regressions results from Table 3, VHB recommends that MassDOT assign risk scores between 0 and 1 based on the character of the risk factor. Table 4 summarizes the suggested risk scoring schema. Where the statistical significance of the variable was not strong (i.e., p-value < 0.05), VHB suggests a maximum risk score of 0.5 instead of 1 for the risk factor. For continuous variables, VHB recommends a continuous risk score ranging from 0 to 1 associated with the individual values of the continuous variables.

Table 4. Town-level risk factors for Speeding KA Crashes.

Risk Factor for Speeding-related KA Crashes	Suggested Scoring
Natural log of active drivers licenses in the town.	Continuous from 0 to 1.
Annual speeding citations per centerline mile in the town.	Continuous from 0 to 1.
Annual unbelted citations per centerline mile in the town.	Continuous from 0 to 1.
Indicator that fewer than 80 percent of drivers were observed using their seatbelt in the town's county.	1 if true; 0 otherwise.
ABCC licenses per square mile in the town.	Inverted continuous from 0 to 0.5 (0 for high density, 0.5 for low density).
Maximum potential score for a town:	**4.5**

Table 5 provides an example application of the risk factors of a hypothetical town. To provide context for these risk factor scores in relation to other emphasis areas, MassDOT can normalize the cumulative score by dividing by the total potential score for a town. This would generate a risk score out of 100 percent for each town. Under this approach, the normalized risk score for the example town is 43 percent (1.93 divided by 4.5).

Table 5. Example Risk Score Calculation for Speeding Crashes.

Variable	Town Characteristic	Risk Factor	Risk Score
Natural log of active drivers licenses in the town.	6.11 (450 licenses)	Continuous from 0 to 1.	0.14
Annual speeding citations per centerline mile in the town.	0.25	Continuous from 0 to 1.	0.45
Annual unbelted citations per centerline mile in the town.	0.37	Continuous from 0 to 1.	0.24
Indicator that fewer than 80 percent of drivers were observed using their seatbelt in the town's county.	76 percent of drivers	1 if true; 0 otherwise.	1
ABCC licenses per square mile in the town.	3.24	Inverted continuous from 0 to 0.5 (0 for high density, 0.5 for low density).	0.1
		Total Risk Score:	1.93
		Risk Percent Score (Out of 4.5):	43

Generally, the model and risk factors produce results that were expected by the VHB and MassDOT team. Most factors points towards correlation between speeding and other risk taking behavior (e.g., not using a seat belt) in a town and severe speeding crash frequency in a town. Additionally, the number of active licenses suggests the more drivers in a town, the more crashes expected. Similarly, the lack of ABCC license density suggests lower density and perhaps higher speeds and more driving occur in the town.

MassDOT ranked the towns at both the statewide and MPO levels using the normalized risk score and the percentile score of ranking (rank kind equal to weak) function in ArcGIS. For each normalized risk score, a percentile rank for the given score was computed relative to all the normalized risk scores. If there are repeated occurrences of the same normalized risk score, then the percentile rank corresponds to values that are less than or equal to the given score. The advantage of the weak ranking approach is that it guarantees that the highest normalized score will receive a percentile rank of 100 percent. For speeding-related crashes, normalized risk scores range from 0.11 to 0.86. The maximum value (0.86) received a percentile rank of 100 and other values received a percentile rank accordingly. For example, a town with a normalized risk score of 0.70, the calculated state percentile rank was 90.60, and fell in the secondary risk category. MassDOT then assigned risk categories using the computed ranks. For example, towns ranked in the top 5 percentile (95 through 100) were categorized as "Primary Risk Town" and towns ranked in the next 10 percentile (85 through 95) were categorized as "Secondary Risk Town"; the remaining towns were not categorized. In instances where there are large, repeated occurrences of the same normalized risk score, the percentage of segments computed for top 5 percent or next 10 percent may not be equal to 5 or 10 percent. This is a byproduct of the weak ranking approach.

Table 6 and Table 7 show the distribution of towns and crashes with the normalized risk score (presented as percentages) across these categories for statewide and MPO rankings, respectively. Note the goal was to see a higher proportion of target crashes for primary and secondary risk sites than proportion of towns. Similarly, Figure 5 is a map of the risk towns ranked statewide, while Figure 6 is a map of the risk towns ranked by MPO. These figures indicate the towns in the State that may deserve a higher-level of attention to reduce statewide speeding-related crashes. For smaller MPOs, such as the Nantucket Planning and Economic Development Commission (NPEDC), MPO rankings are not valuable, because there are few, and in the case of the NPEDC, only one, town to be ranked and sorted. As such, those interested in the relative risk of towns in smaller MPOs may consider the Statewide risk ranking rather than the MPO risk ranking. There is a total of 18 towns in the primary risk category (top 5 percent), that captured 18.69 percent of the severe speeding-related crashes. Similarly, there are 35 towns in the secondary risk category (next top 10 percent), which captured additional 21.17 percent of the severe speeding-related crashes. The towns that are in the primary risk category for severe speeding-related crashes are Holyoke, Fall River, Westminster, Woburn, Leominster, Southbridge, Methuen, West Bridgewater, Brockton, Taunton, Raynham, Quincy, Haverhill, Worcester, Randolph, Salem, Charlton, and Lakeville. Five of these towns were under Boston Region MPO, and three of these were under Pioneer Valley Planning Commission. A higher number of secondary risk category towns for speeding-related crashes were also under these two MPOs.

Table 6. Statewide Risk Categories.

State	Risk Category	Minimum Normalized Risk Score Percentage	Maximum Normalized Risk Score Percentage	Number of Towns	Percent of Scored State Towns	Percent of Target Crashes
MA	Primary Risk Site	76.57%	85.47%	18	5.13%	18.69%
	Secondary Risk Site	62.58%	76.42%	35	9.97%	21.17%

Table 7. Distribution of Risk Towns when ranked by MPO.

MPO	Risk Category	Minimum Normalized Risk Score Percentage	Maximum Normalized Risk Score Percentage	Number of Towns	Percent of Scored MPO Towns	Percent of Target Crashes in MPO
Berkshire Regional Planning Commission	Primary	69.67%	73.66%	2	6.25%	38.89%
	Secondary	59.23%	62.87%	3	9.38%	11.11%
Boston Region MPO	Primary	76.42%	80.50%	5	5.15%	14.40%
	Secondary	61.95%	68.72%	10	10.31%	11.93%
Cape Cod Commission	Primary	70.47%	70.47%	1	6.67%	25.00%
	Secondary	50.97%	64.42%	2	13.33%	12.50%
Central Massachusetts Regional Planning Commission	Primary	83.54%	84.30%	2	5.00%	36.17%
	Secondary	60.15%	78.19%	4	10.00%	15.96%
Franklin Regional Council of Governments	Primary	49.29%	50.93%	2	7.69%	35.71%
	Secondary	44.60%	45.65%	2	7.69%	35.71%
Martha's Vineyard Commission	Primary	34.35%	34.35%	1	14.29%	20.00%
	Secondary	27.16%	27.16%	1	14.29%	0.00%
Merrimack Valley Planning Commission	Primary	82.72%	82.72%	1	6.67%	16.07%
	Secondary	69.01%	78.66%	2	13.33%	23.21%
Montachusett Regional Planning Commission	Primary	77.81%	78.92%	2	9.09%	41.46%
	Secondary	57.83%	61.51%	2	9.09%	12.20%
Nantucket Planning and Economic Development Commission	Primary	40.99%	40.99%	1	100.00%	
	Secondary	n/a	n/a	n/a	n/a	n/a
Northern Middlesex Council of Governments	Primary	70.62%	70.62%	1	11.11%	12.50%
	Secondary	66.64%	66.64%	1	11.11%	34.38%
Pioneer Valley Planning Commission	Primary	57.83%	80.66%	3	6.98%	54.96%
	Secondary	51.73%	57.71%	4	9.30%	12.21%
Old Colony Planning Council	Primary	83.51%	83.51%	1	5.88%	27.12%
	Secondary	75.75%	76.57%	2	11.76%	16.95%
Southeastern Regional Planning and Economic Development District	Primary	77.71%	85.47%	2	7.41%	15.27%
	Secondary	76.32%	76.89%	3	11.11%	17.56%

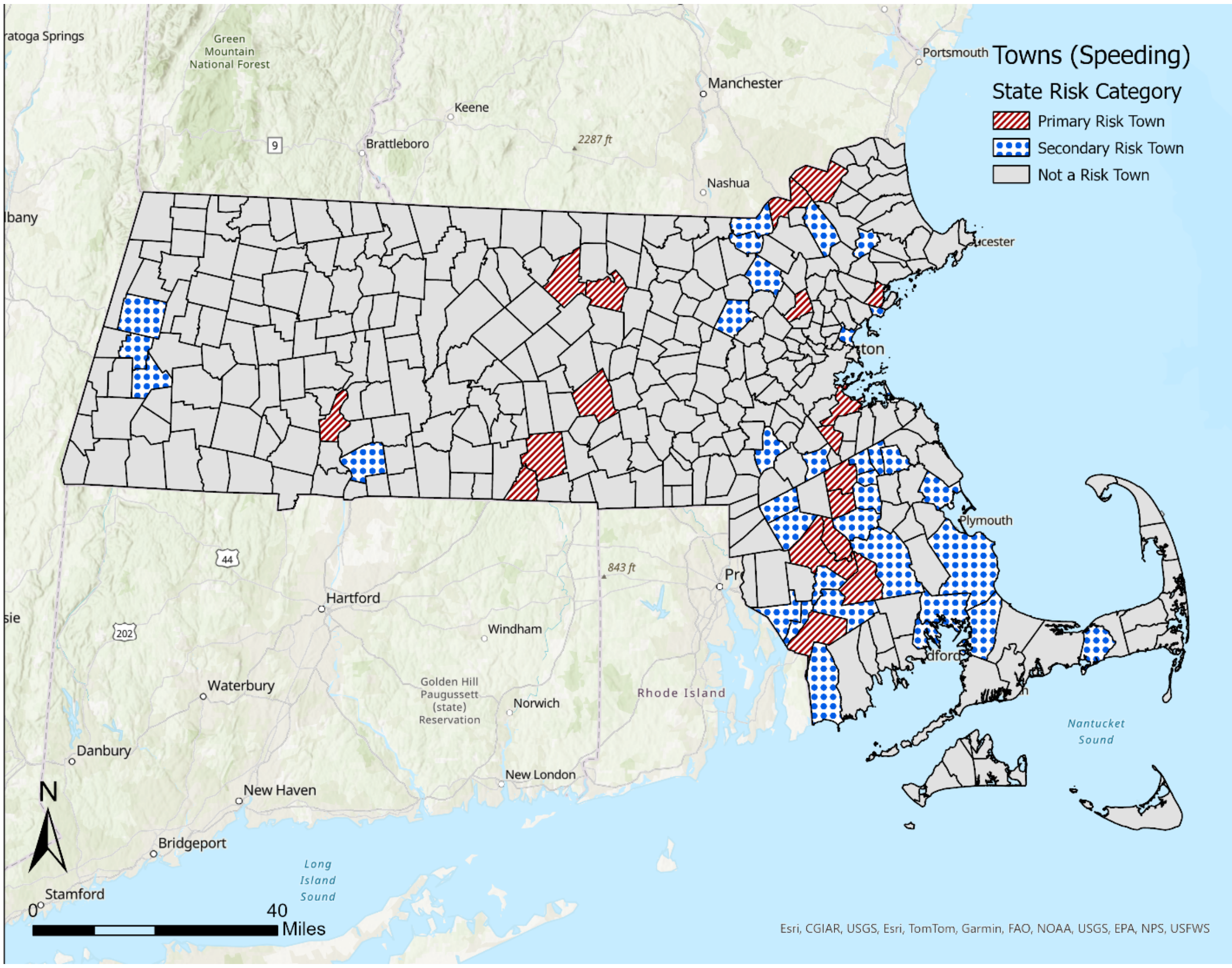

Figure 5. Map depicting the primary and secondary risk towns for severe speeding crashes, ranked statewide.

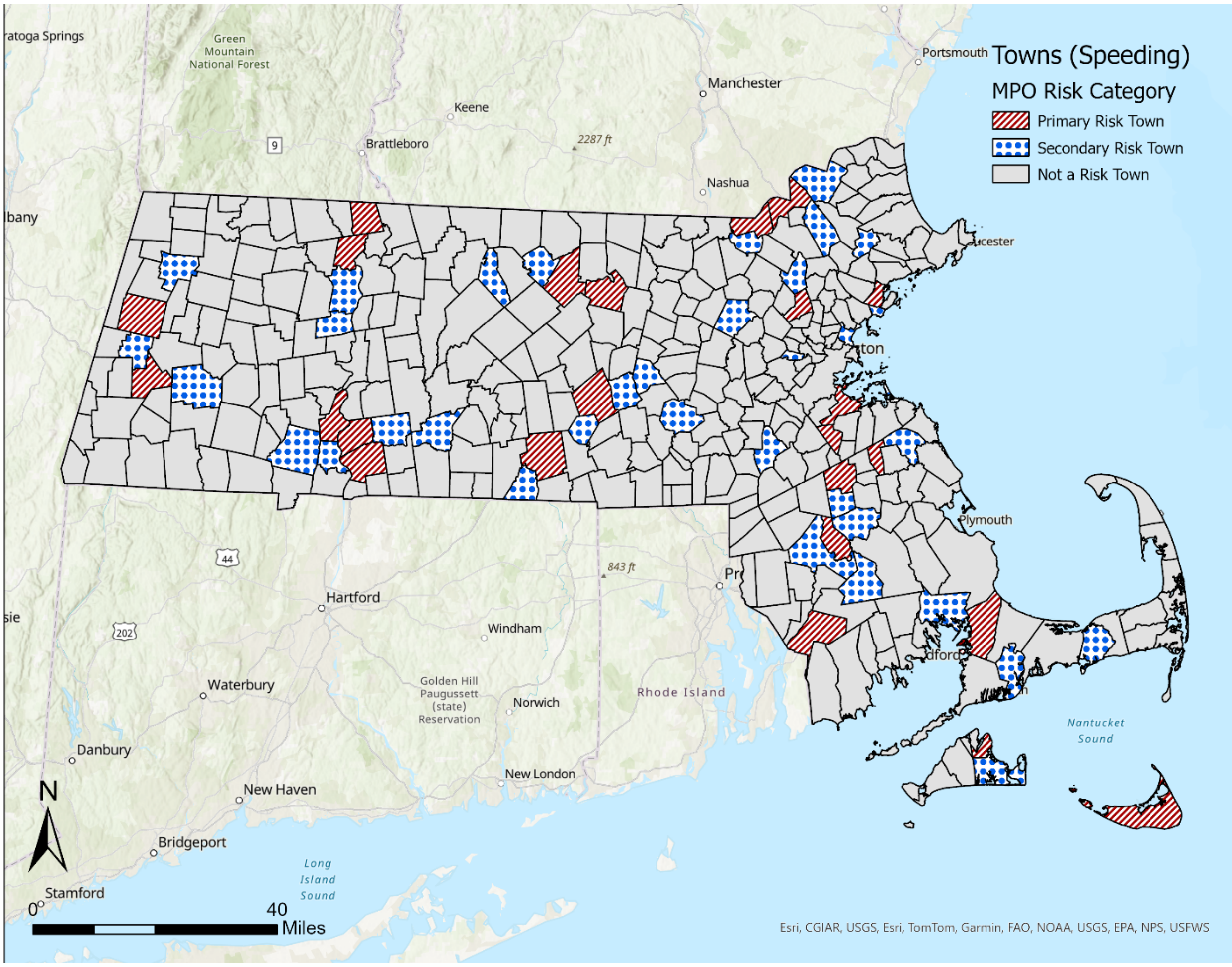

Figure 6. Map depicting the primary and secondary risk towns for severe speeding crashes, ranked by MPO.