Updates to Risk Factors for SHSP Emphasis Areas

Motorcycle Crashes

PREPARED FOR

Massachusetts Department of Transportation

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 motorcycle crashes using crash data from 2017 through 2021. For this analysis, VHB used the default "Motorcycle" query[1] in the MassDOT IMPACT tool. The definition reads as: any crash in which the person was a rider or passenger on a Vehicle Configuration Code of "Motorcycle".[2]

Note that the purpose of this report is to identify the factors most correlated with the frequency and severity of motorcycle 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) motorcycle crashes. To identify overrepresented crash attributes, VHB compared KA motorcycle 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 motorcycle 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.

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

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.

[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

- 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.

Crash Field	Crash Attribute	Percent of Motorcycle KA Crashes	Percent of All KA Crashes
Access Control	No Access Control	82.78%	79.22%
Age of Driver – Youngest Known	25-34	30.43%	27.33%
County Name	Franklin	2.20%	1.28%
	Hampden	10.49%	8.56%
	Worcester	16.06%	13.61%
Crash Day of Week	Sunday	18.84%	14.51%
	Saturday	22.14%	16.09%
Crash Month	May	13.39%	8.82%
	June	14.55%	9.58%
	July	16.17%	9.63%
	August	15.71%	9.49%
	September	14.26%	9.46%
Curb	Left side only	5.97%	4.00%
	None	44.35%	40.86%
Driver Contributing Circumstances[4]	Exceeded authorized speed limit	6.13%	4.04%
	Failed to yield right of way	10.26%	6.49%
	Over-correcting/over-steering	1.84%	0.99%
Federal Functional Class	Minor Arterial	33.80%	30.21%
First Harmful Event	Collision with animal – deer	0.99%	0.24%
	Collision with curb	5.57%	2.61%
	Collision with motor vehicle in traffic	59.01%	46.32%
	Collision with other	4.52%	1.57%
	Other non-collision	3.48%	0.74%
	Overturn/rollover	5.45%	2.18%
First Harmful Event Location	Roadway	80.81%	73.00%
Left Shoulder Type	No Shoulder	70.32%	64.16%
Light Conditions	Daylight	67.71%	57.75%
	Dusk	5.16%	3.11%
Manner of Collision	Angle	32.00%	22.70%

[4] Vehicle-level data

Crash Field	Crash Attribute	Percent of Motorcycle KA Crashes	Percent of All KA Crashes
Median Type	None	80.75%	75.76%
Road Contributing Circumstances	Rut, holes, bumps	0.81%	0.26%
Road Surface Conditions	Dry	91.54%	79.41%
	Sand, mud, dirt, oil, gravel	1.22%	0.47%
Roadway Junction Type	T-intersection	19.48%	15.66%
	Y-intersection	3.59%	2.18%
Traffic Control Device Type	Stop signs	13.16%	10.42%
Trafficway Description	Two-way, not divided	65.51%	60.16%
Urban Type	Large Urban Cluster	2.61%	1.54%
	Rural	5.28%	3.78%
	Small Urbanized Area	9.10%	7.00%
Weather Conditions	Clear	84.04%	68.20%

The results in Table 1 are strongly influenced by when motorcyclists tend to drive[5], including on weekends (Saturday and Sunday) and, especially in Massachusetts, during warmer weather (May through September). Additionally, more than half of severe motorcycle collisions were a result of a collision with another motor vehicle in traffic, a proportion 13 percent higher than all severe crashes. The overrepresentation in severe crashes with other motor vehicles is likely associated with the vulnerability of motorcyclists compared to those in passenger cars and other motor vehicles. Another noteworthy finding relates to the roadway surface, where ruts, holes, and bumps, as well as sand, mud, dirt, oil, and gravel contributed to an overrepresented portion of severe motorcycle crashes.

MassDOT should consider these findings when identifying potential countermeasures targeting motorcyclists. The National Highway Traffic Safety Administration's (NHTSA) *Countermeasures that Work*[6] includes several examples targeting motorcyclists including universal motorcycle helmet use laws, motorcycle helmet use promotion programs, and alcohol-impaired motorcyclists: detection, enforcement, and sanctions. While all of these are notable results, MassDOT elected to include all motorcycle crashes as the focus crash type for this analysis.

Crash Tree and Focus Facility Type

After concluding that the motorcycle focus crash type should include all motorcycle crashes, VHB developed a crash tree to identify the roadway conditions under which severe motorcycle crashes tend to occur most often. Figure 3 shows the crash tree. It is evident that severe motorcycle crashes primarily occur in urban areas. There is a relatively even split between motorcycle crashes at junctions and not at junctions. Of those not at junctions, they mostly occur on principal arterial – other and minor arterial roadways. For those that occur at intersections, they are primarily split between three-leg (T- and Y-intersections) and four-leg intersections. At four-leg intersections, the primary traffic control for most

[5] Select Risk Factors Associated with Causes of Motorcycle Crashes. https://www.ntsb.gov/safety/safety-studies/Documents/SR1801.pdf

[6] https://www.nhtsa.gov/book/countermeasures/countermeasures-work/motorcycle-safety

crashes is either a signal or stop-control, while at three-leg intersections most occur when no control is present.

While the analysis above points toward some potential focus for this emphasis area (e.g., urban area, not at a junction), there are few site-level countermeasures which specifically target motorcycles. As such, an appropriate method for addressing motorcycle crashes may be targeting behavior surrounding motorcyclists (e.g., helmet use, conspicuity and protective clothing), encouraging drivers to be aware of motorcyclists on the road, and promoting safe operating behaviors for motorcyclists (e.g., increasing awareness to check side mirrors, and motorcycle rider training). As such, VHB recommends a town-level analysis, identifying the cities and towns predicted to have the highest risk of severe motorcycle crashes so those communities can implement targeted strategies to proactively mitigate those crashes.

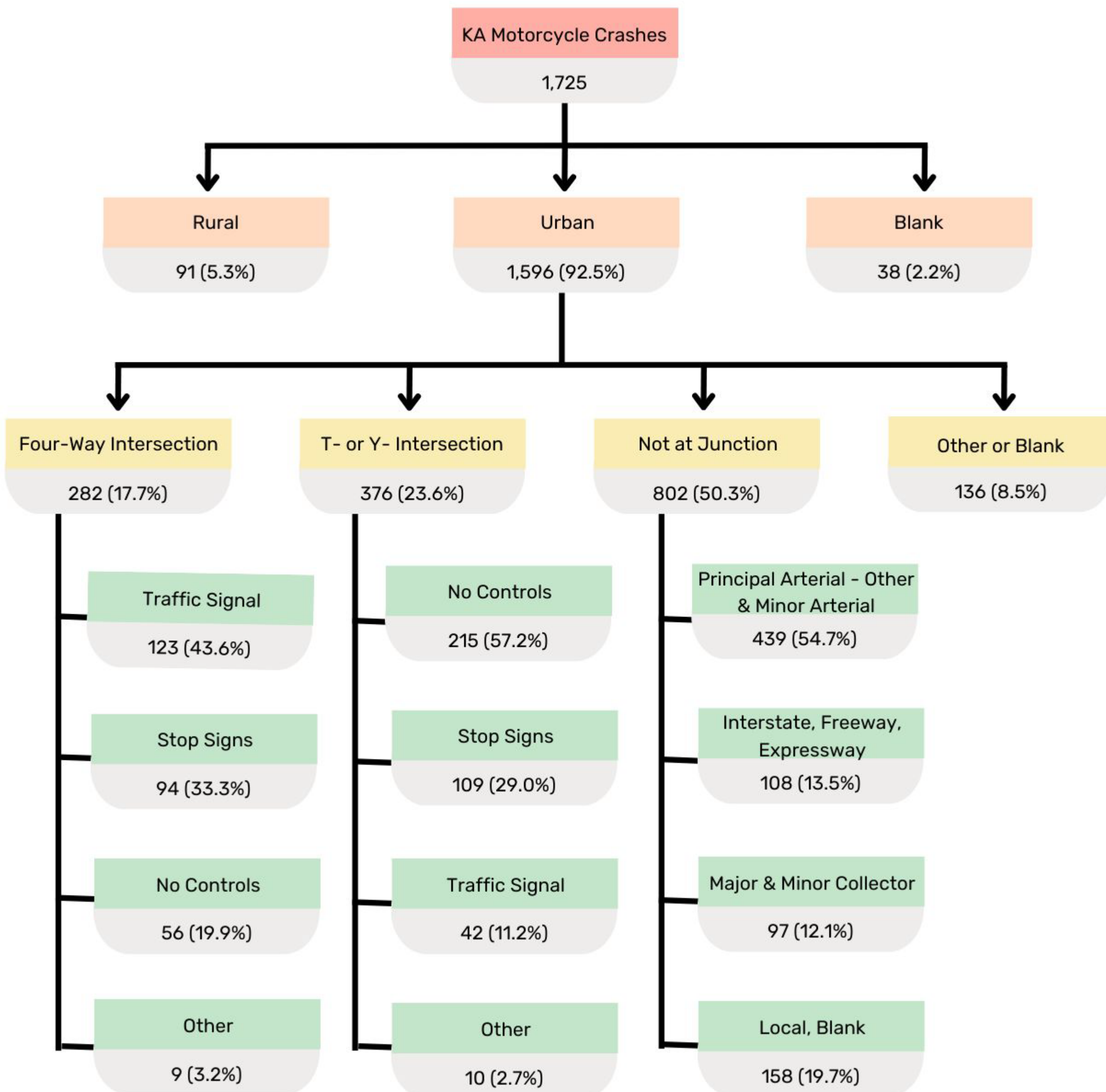

Figure 3. Crash tree summarizing KA motorcycle crashes in Massachusetts.

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 modelling given that crash frequency data are typically over-dispersed count data. As such, VHB used a negative binomial count regression modeling approach to identify community-level characteristics associated with higher frequencies of motorcycle 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 motorcycle-related 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. Negative binomial regression functional form.

Where:

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

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

β = vector of estimated parameters.

X_i = vector of independent variables that characterize location i and influence motorcycle 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]

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 jurisdiction. 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) motorcycle crashes by town using the MassDOT IMPACT Test of Proportions tool. VHB then joined these totals to the town-level data set.

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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.

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. VHB then calculated the average number of licensed drivers by age group for each town and integrated with town-level data. This also included number of motorcycle licenses and registration garaging by town, which was totaled at the town-level as well.

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). VHB then used spatial analysis to determine the total number of schools in each town.

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. VHB then used spatial analysis to determine the total number of colleges and universities in each town.

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. VHB then aggregated these totals annual for each town and normalized against centerline mileage.

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), alcohol shop location data, healthy aging data from DPH, seatbelt use survey data at the county level, and environmental justice (EJ) data provided by Environmental Justice Community Block Group Data Update. Note that, 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. VHB used spatial analysis tools to integrate these data.

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). 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 7 variables (listed here) included in the final motorcycle model. Note the maximum correlation between any two variables is -0.49, below the standard value of 0.7, above which there are concerns of serial correlation.

1. Proportion of centerline mileage that is interstate, freeway, or expressway[9].
2. Natural log of motorcycle garaging in the town.
3. Annual impaired driving citations per centerline mile in the town.
4. The town is not an EJ – Minority community.
5. The town is an EJ – ESL community.
6. Weighted average posted speed limit for known speed limit segments.

[9] Federal functional class 1 or 2.

Table 2. Correlation Matrix of Input Variables.

Variables	1. Interstate, freeway, expressway	2. Motorcycles	3. Impaired driving	4. Not EJ Minority	5. EJ – ESL	6. Speed limit
1. Interstate, freeway, expressway	1.00					
2. Motorcycles	0.07	1.00				
3. Impaired driving	0.15	0.42	1.00			
4. Not EJ Minority	-0.04	-0.49	-0.27	1.00		
5. EJ – ESL	0.02	0.34	0.21	-0.35	1.00	
6. Speed limit	0.30	-0.18	-0.16	0.35	-0.28	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 model predicts the number of KA motorcycle crashes expected in a town. 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 independent variables tested included a mix of population, roadway, citation, and environmental justice variables.

The first correlation in the model is the proportion of centerline mileage that is interstate, freeway, or expressway, indicating that a high proportion of high-speed facilities in the town is correlated with severe motorcycle crash frequency. This is likely due to the connection between speed, the severity of collisions, and the vulnerability of motorcyclists – the weighted average posted speed limit is similarly correlated. The natural log of motorcycles garaged in the town is also positively correlated, suggesting that more motorcycles in the town are likely associated with more motorcycles using the town's roads, thus more likelihood of a severe motorcycle crash in the town. Annual impaired driving citations points toward a correlation between impaired driving in a town and severe motorcycle crashes, likely due to increased risk behaviors. Finally, there are two correlations with EJ indicators: increased severe motorcycle crash frequency in EJ – ESL communities and increased severe motorcycle crash frequency in towns that are not an EJ – Minority community. The ESL finding points toward the need for multilingual campaigns encouraging safe operation of motorcycles as well as additional investment for these historically underserved communities.

Table 3. Negative Binomial Count Regression Model Results.

Variable (Number)	Coefficient	Standard Error	z-value	P>|z|	95% Confidence Interval	
Intercept	-9.10	0.56	-16.36	<0.001	-10.19	-8.01
Proportion of Centerline Mileage that is Interstate, Freeway, Expressway	2.48	1.16	2.13	0.033	0.39	0.60
Natural Log of Motorcycle Garaging in the Town	0.49	0.05	9.01	<0.001	0.39	0.60
Annual Impaired Driving Citations per Mile	0.31	0.06	4.76	<0.001	0.18	0.43
The town is not an EJ – Minority community	0.19	0.09	2.06	0.039	0.01	0.37
The town is an EJ – ESL community	0.49	0.11	4.29	<0.001	0.27	0.72
Weighted Average posted speed in the town	0.02	0.01	1.68	0.093	-0.003	0.044
Natural Log of the product of Centerline Mileage and Years – Offset	1	n/a	n/a	n/a	n/a	n/a
alpha	0.13	0.03	n/a	n/a	0.09	0.21

Note: Number of observations = 350; Log likelihood = -719.228.

Conclusions and Recommendations

The purpose of this analysis is to identify town-level risk factors for fatal and serious injury motorcycle crashes. 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. VHB and MassDOT made this decision to avoid overly weighting any one risk factor, especially considering potential data issues with the risk factor data which may cause biases. Table 4 summarizes the suggested risk scoring schema. Where a binary predictive variable was used, binary risk scores are applied.

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

Risk Factor for Motorcycle KA Crashes	Suggested Scoring
Proportion of Centerline Mileage that is Interstate, Freeway, Expressway	Continuous from 0 to 1 for the range of values.
Natural Log of Motorcycle Garagings in the Town	Continuous from 0 to 1 for the range of values.
Annual Impaired Driving Citations per Mile	Continuous from 0 to 1 for the range of values.
The town is not an EJ – Minority community	1 if true; 0 otherwise.
The town is an EJ – ESL community	1 if true; 0 otherwise.
Weighted Average posted speed in the town	Continuous from 0 to 1 for the range of values.
Maximum Potential Score for a Town:	**6.0**

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 of risk factors 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 58.5 percent (3.51 divided by 6.0).

Table 5. Example Risk Score Calculation for Motorcycle Crashes.

Variable	Town Characteristic	Risk Factor	Risk Score
Proportion of Centerline Mileage that is Interstate, Freeway, Expressway	0.02	Continuous from 0 to 1 for the range of values.	0.31
Natural Log of Motorcycle Garagings in the Town	3.95 (52 motorcycles)	Continuous from 0 to 1 for the range of values.	0.45
Annual Impaired Driving Citations per Mile	0.10	Continuous from 0 to 1 for the range of values.	0.6
The town is not an EJ – Minority community	True	1 if true; 0 otherwise.	1
The town is an EJ – ESL community	True	1 if true; 0 otherwise.	1
Weighted Average posted speed in the town	35.1 MPH	Continuous from 0 to 1 for the range of values.	0.15
Total Risk Score:			**3.51**
Risk Percent Score (Out of 6.0):			**58.5%**

Generally, the model and risk factors produce results that were expected by the VHB and MassDOT team. The number of motorcycles garaged in the town suggests increased exposure for motorcycle usage leading to increased severe motorcycle crash frequency. The functional class finding and speed limit finding are likely due to increased speeds in motorcycle collisions, which elevate the likelihood of a severe outcome for vulnerable motorcyclists. The impaired driving citations finding points toward a correlation between observed impaired driving and severe motorcycle crashes in the town. Finally, the EJ ESL result points toward the need for targeted motorcycle safety outreach in languages other than English. Findings from the study align with prior research evaluating actors associated with motorcycle crash severities.[10,11,12]

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 motorcycle crashes, normalized risk scores range from 0.19 to 0.75. The maximum value (0.75) received a percentile rank of 100 and other values received a percentile rank accordingly. For example, a town with a normalized risk score of 0.60, the calculated state percentile rank was 89.45, and fell in the secondary risk town 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 motorcycle crashes. Note that it may be more appropriate to utilize statewide ranking for towns, particularly for the ones that are in the MPOs/RPAs with few towns, as the results for these towns may be skewed. There is a total of 18 towns in the primary risk category (top 5 percent), that captured 10.67 percent of the severe motorcycle crashes. Similarly, there are 35 towns in the secondary risk category (next top 10 percent), which captured an additional 15.54 percent of the severe motorcycle crashes. The towns that are in the primary risk category for severe motorcycle crashes are Revere, West Bridgewater, New Bedford, Raynham, Swansea, Uxbridge, Littleton, Sutton, Sturbridge, Charlton, Middleborough, Erving, Mansfield, Deerfield, Northborough, Millbury, Auburn, 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 motorcycle crashes were also under these two MPOs.

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[10] A comparative study of factors associated with motorcycle crash severities under different causal scenarios. https://www.tandfonline.com/doi/abs/10.1080/19439962.2022.2063464?journalCode=utss20

[11] Assessment of Motorcycle Safety in Wyoming: Fatal and Severe Crashes, Contributing Factors and Potential Countermeasures. https://rosap.ntl.bts.gov/view/dot/65699

[12] Motorcycle Safety Assessment in Wyoming and Utah: Crash Characteristics and Contributing Factors. https://www.ugpti.org/resources/reports/details.php?id=1090

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	64.77%	75.36%	18	5.13%	10.67%
	Secondary Risk Site	57.98%	64.67%	35	9.97%	15.54%

Table 7. Distribution of Risk Towns my 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	57.50%	60.02%	2	6.25%	7.27%
	Secondary	53.80%	56.36%	3	9.38%	5.45%
Boston Region MPO	Primary	62.77%	67.19%	5	5.15%	7.71%
	Secondary	56.93%	62.49%	10	10.31%	15.42%
Cape Cod Commission	Primary	64.43%	64.43%	1	6.67%	1.43%
	Secondary	58.83%	59.64%	2	13.33%	28.57%
Central Massachusetts Regional Planning Commission	Primary	74.79%	75.07%	2	5.00%	5.91%
	Secondary	66.81%	68.66%	4	10.00%	17.20%
Franklin Regional Council of Governments	Primary	65.29%	66.52%	2	7.69%	21.05%
	Secondary	56.17%	56.60%	2	7.69%	26.32%
Martha's Vineyard Commission	Primary	53.85%	53.85%	1	14.29%	20.00%
	Secondary	45.11%	45.11%	1	14.29%	20.00%
Merrimack Valley Planning Commission	Primary	64.67%	64.67%	1	6.67%	5.43%
	Secondary	59.16%	62.87%	2	13.33%	19.57%
Montachusett Regional Planning Commission	Primary	56.36%	61.49%	2	9.09%	12.09%
	Secondary	56.27%	56.32%	2	9.09%	27.47%
Nantucket Planning and Economic Development Commission	Primary	34.66%	34.66%	1	100.00%	100.00 %
	Secondary	0	0	0	0	0
Northern Middlesex Council of Governments	Primary	53.51%	53.51%	1	11.11%	8.45%
	Secondary	53.32%	53.32%	1	11.11%	38.03%
Pioneer Valley Planning Commission	Primary	53.99%	58.74%	3	6.98%	14.35%
	Secondary	52.90%	53.89%	4	9.30%	34.08%
Old Colony Planning Council	Primary	64.77%	64.77%	1	5.88%	7.05%
	Secondary	58.17%	60.16%	2	11.76%	4.49%
Southeastern Regional Planning and Economic Development District	Primary	75.17%	75.36%	2	7.41%	13.67%
	Secondary	65.53%	67.62%	3	11.11%	6.25%

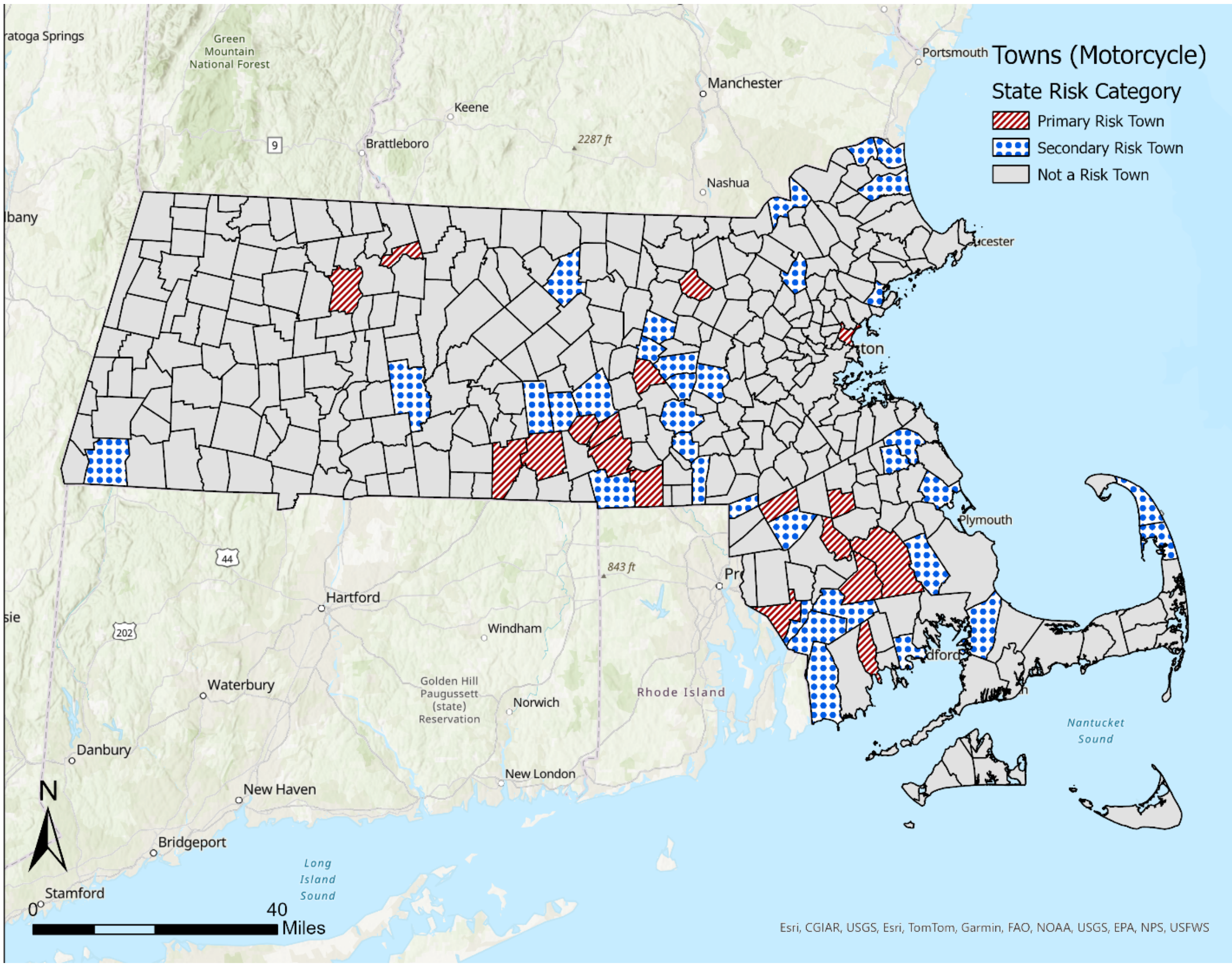

Figure 5. Map depicting the primary and secondary risk towns for severe motorcycle crashes, ranked statewide.

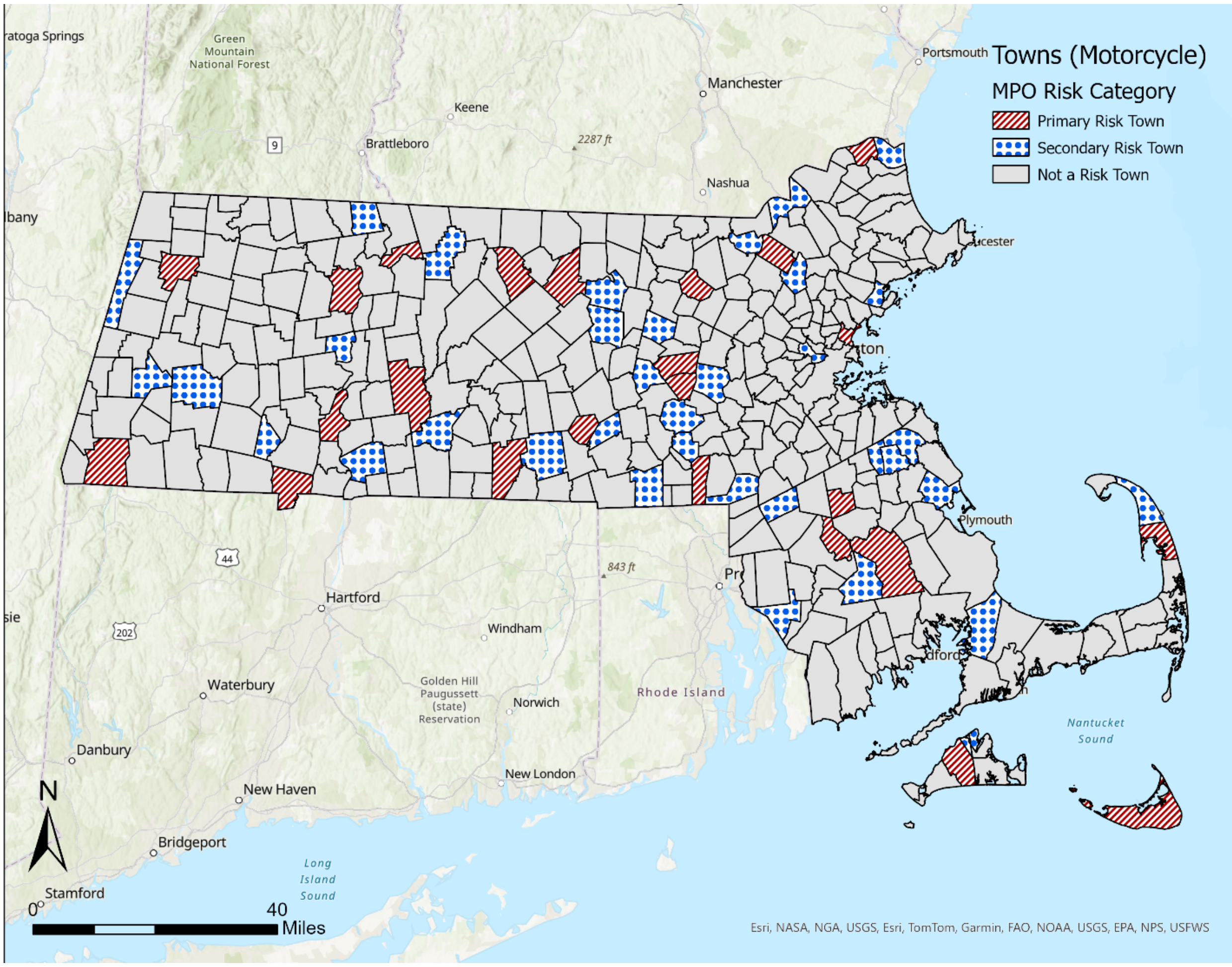

Figure 6. Map depicting the primary and secondary risk towns for severe motorcycle crashes, ranked by MPO.