Advancing Multimodal Safety by Reducing Pedestrian Crash Potential

WA-RD 900.1

Linda Ng Boyle
Anne Vernez Moudon
Haena Kim
Mingyu Kang

November 2020

Washington State Department of Transportation

Office of Research & Library Services

WSDOT Research Report

21-09-0211

Research Report
Agreement T1461, Task 56
WSDOT Multimodal
WA-RD 900.1

ADVANCING MULTIMODAL SAFETY BY REDUCING PEDESTRIAN CRASH POTENTIAL

by

Linda Ng Boyle, Professor
Industrial and Systems Engineering
Civil and Environmental Engineering

Anne Vernez Moudon, Professor Emeritus
Urban Design and Planning

Haena Kim, Graduate Research Assistant
Civil and Environmental Engineering

Mingyu Kang, Graduate Research Assistant
Urban Design and Planning

Washington State Transportation Center (TRAC)
University of Washington, Box 359446
University Tower
4333 Brooklyn Ave NE
Seattle, Washington 98195-8690

Washington State Department of Transportation
Technical Monitor
Mike Dornfeld
John Milton
Charlotte Claybrooke
Ida van Schalkwyk

Prepared for

The State of Washington
Department of Transportation
Roger Millar, Secretary

November 2020

TECHNICAL REPORT STANDARD TITLE PAGE

. REPORT NO.	2. GOVERNMENT ACCESSION NO.	3. RECIPIENT'S CATALOG NO.
WA-RD 900.1		

4. TITLE AND SUBTITLE	5. REPORT DATE
ADVANCING MULTIMODAL SAFETY BY REDUCING PEDESTRIAN CRASH POTENTIAL *Original title: "ADVANCING MULTIMODAL SAFETY THROUGH PEDESTRIAN RISK REDUCTION"*	November 2020 6. PERFORMING ORGANIZATION CODE
7. AUTHOR(S) Linda Ng Boyle, Anne Vernez Moudon, Haena Kim, Mingyu Kang	8. PERFORMING ORGANIZATION REPORT NO.
9. PERFORMING ORGANIZATION NAME AND ADDRESS Washington State Transportation Center (TRAC) University of Washington, Box 359446 University Tower; 4333 Brooklyn Ave NE Seattle, Washington 98195-8690	10. WORK UNIT NO. 11. CONTRACT OR GRANT NO. Agreement T1461, Task 56
12. SPONSORING AGENCY NAME AND ADDRESS Research Office Washington State Department of Transportation Transportation Building, MS 47372 Olympia, Washington 98504-7372 Project Manager: Jon Peterson, 360.705.7499	13. TYPE OF REPORT AND PERIOD COVERED Research Report 14. SPONSORING AGENCY CODE

15. SUPPLEMENTARY NOTES

This study was conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.

16. ABSTRACT:

Pedestrian safety is a priority of Washington State Department of Transportation's (WSDOT) Target Zero Plan. This report provides the findings of the data used and the models developed to support our understanding of pedestrian safety. The project used data from WSDOT, the Census, the King County GIS Center, the University of Washington Urban Form Lab, and National Historical Geographic Information. The models created aimed to (1) identify factors and locations in Washington State that are associated with a higher number of pedestrian-vehicle crashes (frequency models) and (2) explore factors that contribute to pedestrian-vehicle crashes that result in serious injuries and fatalities (severity models).

The outcome of interest for the frequency models was the number of pedestrian-vehicle crash(es) per 100-meter Euclidian buffer around intersection and non-intersection locations on state routes in King County, Washington, and in the entire State of Washington. Mixed-effects Poisson regression was used for these frequency models because the mean and variance of the outcome variable were not significantly different. The state route variable was treated as a random intercept to account for pedestrians' characteristics that were specific to each state route. Microenvironmental factors that were positively correlated with the frequency of pedestrian-vehicle crashes included intersection type (intersection or non-intersection), being on a principal arterial road, total width of lanes, presence of a park and ride facility, and commercial area. The findings suggest that locations with these characteristics should be considered during rankings of locations within the pedestrian subcategory of the WSDOT I2 – Safety Program. Macroenvironmental factors (measured in a 400-meter buffer) that were negatively correlated with pedestrian-vehicle crash frequency included area household income and industrial land use. Higher-income households were related to a lower number of pedestrian-vehicle crashes, suggesting that reduction in crash potential should consider including identifying low-income neighborhoods. The Washington State model also accounted for state routes as a random effect. As expected, state routes within King County (SR 99, I-5) showed a higher number of pedestrian-vehicle crashes per 100-meter buffer.

Binary logistic regression models were developed to examine the likelihood of pedestrian-vehicle crashes that result in serious injuries or fatalities. Older pedestrians (age groups: 45–64, 65–74, and 75+) involved in crashes were more likely to suffer serious injuries or to die than pedestrians in the age group 25–44. The likelihood of a pedestrian-vehicle crash resulting in serious injury or fatality increased when pedestrians failed to grant the right of way to vehicles, when drivers were moving straight ahead, and under dark light conditions. Crashes occurring on roads with speed limits higher than 40 mph were more likely to result in severe injury or fatality, while crashes occurring in park and ride lots and in areas of higher population densities were less likely to result in severe injury or fatality. Police crash reports often lacked information on vehicle speed, and pedestrians' and drivers' actions at the time of a crash. Complete and accurate crash reports will provide greater insights to enhance pedestrian safety.

17. KEY WORDS	18. DISTRIBUTION STATEMENT
Pedestrian safety, pedestrian-vehicle crashes, crash frequency, crash severity, regression models, injury prevention, geographic information systems	No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22616

19. SECURITY CLASSIF. (of this report)	20. SECURITY CLASSIF. (of this page)	21. NO. OF PAGES	22. PRICE
None	None	63	

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Washington State Department of Transportation or Federal Highway Administration. This report does not constitute a standard, specification, or regulation.

23 U.S.C. Section 409 Disclaimer – This document and the information contained herein is prepared solely for the purpose of identifying and planning safety improvements on public roads which may be implemented utilizing federal aid highway funds; and is therefor exempt from discovery or admission into evidence pursuant to 23 U.S.C. 409.

Table of Contents

Figures

Tables

1. INTRODUCTION

This research aimed to support the Washington State Department of Transportation's (WSDOT) Target Zero safety priorities with a focus on pedestrians. The purpose of this research was to provide models that can associate roadway characteristics with pedestrian-vehicle crash potential. These models can then be used to identify (i) locations most likely to benefit from investments aimed at zero pedestrian fatalities and zero serious injuries, and (ii) characteristics that contribute to pedestrian-vehicle crashes resulting in severe injuries and fatalities. The project team developed data-driven tools that considered the following:

1. The data needed and available data sources to capture pedestrian-vehicle crashes, crash locations, and pedestrian density.
2. The types of models that can be developed using existing data sources.
3. The feasibility and limitations of the developed models to predict pedestrian-vehicle crashes and severity of injury for various factors.

We expect the outcomes of this project to inform operational programs and help WSDOT prioritize safety-related pedestrian projects.

2. PROBLEM STATEMENT AND BACKGROUND

Road traffic crashes have been associated with over 270,000 pedestrian fatalities annually worldwide (World Health Organization, 2013). In Washington State, pedestrian fatalities have remained relatively steady, even though crash fatalities have decreased for motor vehicles (WSDOT, 2016). Reducing pedestrian crashes is critical, but the data available to accurately capture the factors that contribute to pedestrian fatalities is sparse. The pedestrian-vehicle crashes that are reported typically involve serious injuries or fatalities. The examination of these crashes is crucial, and additional variables are needed to help identify the attributes associated with crashes that involve pedestrians.

3. GOALS AND OBJECTIVES

The objective of this project was to develop pedestrian <u>models that associate roadway characteristics with crash potential in order to identify</u> urban and suburban locations with comparatively high pedestrian crash ratios throughout the WSDOT roadway network. Analytical models were developed to identify those locations and the potential contributing factors associated with pedestrian-vehicle crashes. The technical objectives of the study were therefore to achieve the following:

1. Identify and secure data that can be used to analyze pedestrian-vehicle crash characteristics that are associated with crash potential.
2. Identify factors contributing to pedestrian-vehicle crash frequency and crash injury severity levels.

The outcomes of this study included (1) the identification of areas with a high frequency of pedestrian-vehicle crashes, including the number and injury severity of crashes that occur at specific types of locations, and (2) analytical models that identify the factors that are believed to contribute to pedestrian-vehicle crashes, especially those resulting in serious injuries and fatalities.

4. PEDESTRIAN-VEHICLE CRASH FREQUENCY MODELS

This project assessed the factors that contribute to frequency of pedestrian-vehicle crashes at crash-prone intersection and non-intersection locations. Statistical models were developed on the basis of environmental characteristics for locations identified on state routes in King County and Washington State. A number of microenvironment and macroenvironment factors were considered. Microenvironment factors were defined as roadway characteristics influencing the frequency of pedestrian-vehicle crashes in the immediate vicinity (around 100-meter radius circular buffer) of intersections or non-intersection locations. Accounting for microenvironment factors is important because some microenvironments (e.g. bus stops) can attract pedestrians, increasing crash potentials while others (e.g. sidewalks, the number of lanes, roadway classification) have been shown to decrease or increase the pedestrian-vehicle crash potentials (Quistberg et al., 2015). Macroenvironment factors were defined as built environment and land use characteristics around 400-meter radius circular buffer of intersections or non-intersection. Neighborhood effects from the macroenvironment characteristics (e.g. population or employment density) can be used as proxy measures of pedestrian volumes. When there are a high number of pedestrians walking or present, pedestrian-vehicle crash potentials may increase due to higher chances of pedestrian-vehicle conflicts (Lyon and Persaud, 2002). On the other hand, more safety measures may be in place at locations with high pedestrian volumes, which may then lead to lower pedestrian crash potentials (Leden 2002, Elvik 2009).

4.1 Frequency Model Approach

The modeling approach is summarized as follows:

- **Study areas**: King County, Washington, and Washington State.
- **The unit of analysis**: 100-meter Euclidean buffers around crash-prone locations (i.e., intersection or non-intersection) at or near state routes. The method of identifying these locations is summarized in Appendix A.
- **Regression model**: Mixed-effects Poisson regression. The model was chosen after confirming there was no overdispersion in the data. That is, the mean and variance of the outcome of interest were not significantly different. The State Route variable was treated as a random intercept to account for pedestrians' characteristics that are specific to each State Route.
- **Dependent variable**: Number of pedestrian-vehicle crashes on state routes only per 100-meter Euclidean buffer at each location between 2013 and 2017.
- **Explanatory variables**: The pedestrian-vehicle crash data between 2013 and 2017 were obtained from the WSDOT Transportation Data, GIS and Modeling Office (TDGMO) of the WSDOT. Roadway and environmental data were obtained from WSDOT, the Census, the King County GIS Center, the University of Washington Urban Form Lab, and National Historical Geographic Information.
    - **Micro-environments**: Micro-environmental characteristics were quantified by using 100-m Euclidean buffers around crash-prone locations.
        - Microenvironmental data for length of sidewalks and bus ridership were available only for the King County model.
    - **Macro-environments**: Macro-environmental characteristics were measured by applying 400-m Euclidean buffers around crash-prone locations.
        - Macroenvironmental data for employment density and residential density were available only for the King County model.
        - **Number of pedestrians**. We did not have information on the number of pedestrians at each 400-meter buffer. Hence, we used the total population (census block) as a proxy.
    - **Data imputation**: For the King County Frequency Model, there were some missing observations in the explanatory variables. To impute the missing values in the data

set, a bootstrapping and Expectation-Maximization (EM) algorithm was applied. Multiple imputations were conducted by using James Honaker's software package *Amelia.* For the Washington State Frequency Model, the variables with too many missing data were eliminated for simplicity.

4.1.1 Frequency Model Method

Mixed-effect Poisson regression models were used to examine the frequency of pedestrian-vehicle crashes. A random effect component was included in the regression models to account for the correlation within the same state route and to identify state routes that may need attention. Specifically, random intercept models were applied using equation 1 (Eq 1.). The random intercept recognizes the differences between each state route, which is then considered in the overall model prediction.

$$ln\,(L_{ij}) = \gamma_0 + \sum_{p=1}^{r} \gamma_p x_{pij} + U_j + R_{ij} \qquad \text{(Eq 1.)}$$

In this model, L represents the number of pedestrian-vehicle crashes, i represents a specific location, j indicates a state route, γ_o is the intercept, γ_p is a regression coefficient corresponding to the p^{th} explanatory variable x_{pij}, U_j is a random effect for the j^{th} cluster. γ_o+U_j is the random intercept for the j^{th} cluster. R_{ij} is a random error. This model assumes that the set of U_j, set of R_{ij}, and covariates x_{pij} are mutually independent.

Incidence rate ratios (IRR) were obtained from the coefficient estimates of the model. Because the regression coefficients were interpreted as logs, the exponent was used to obtain the number of crashes per exposure to the crashes (i.e., the areas where the crashes could have happened) (see Eq 2). Therefore, IRR can be described in terms of the "crash frequency" and this term is used throughout this report to indicate crash counts per 100-meter buffer.

$$Incident\ Rate\ Ratio\ (IRR) =\ Crash\ rate = \frac{Number\ of\ crashes}{Exposure\ to\ crashes\ (100\ m\ buffer)} =$$
$$e^{-(\gamma_0+\sum_{p=1}^{r}\gamma_p x_{pi}+U_j+R_i)} \qquad \text{(Eq 2.)}$$

A full model with all variables was first estimated as a reference, and then a refined model was developed on the basis of the results from a stepwise variable selection process. The analysis was done in the statistical software package R. The Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) were used to identify the best-fit model. The final models were selected on the basis of the lowest AIC and BIC values. Lower values indicated a better model fit.

4.2 King County Frequency Model

4.2.1 King County Frequency Model Results

The incidence rate ratios (IRR) for the final King County Frequency Model are shown in Table 1. For instance, an IRR of 1.46 (e.g., presence of a park and ride lot) means that locations with a park and ride lot will have 1.46 times (or 146 percent) the incident events (pedestrian-vehicle crashes) that those without a park and ride lot will have.

Table 1. Final King County frequency model using a mixed effect Poisson regression. Data on state routes only for 2013 to 2017.

Variable	Level	Final Model -IRR (95% CI)
Crash-prone location type		
	Intersection	0.72 (0.64-0.81)
	Non-intersection	*Reference*
Micro-environment characteristics (100-m Euclidean area around crash-prone locations)		
Number of Roadway Lanes for one direction		
	1 lane	*Reference*
	2 lanes	2.21 (1.67-2.94)
	3 lanes	2.40 (1.75-3.31)
	4 lanes and more	2.67 (1.67-4.27)
Roadway functional class		
	Principal arterial	2.49 (2.09-2.98)
	Non-principal arterial	*Reference*
Bus ridership density (1,000 person/km^2)		1.02 (1.01-1.02)
Macro-environment characteristics (400-m Euclidean area around crash-prone locations)		
Residential density (100 units/ km^2)		1.01 (1.00-1.01)
Employment density (1,000 jobs/km^2)		1.02 (1.01-1.02)
Park and ride		
	Presence	1.46 (1.26-1.70)
	Absence	*Reference*
Household income ($1,000 USD)	Census block-group	0.91 (0.87-0.94)
Residential area (%)		1.01 (1.01-1.02)
Industrial area (%)		0.89 (0.85-0.94)
Commercial area (%)		1.03 (1.02-1.03)
Observations		1915
AIC / BIC		4089.5 / 4234.0
logLik (LL)		-2018.7

Note: IRR: incidence rate ratio, LL=log likelihood, AIC=Akaike Information Criterion, BIC= Bayesian Information Criterion, CI=confidence interval

Comparisons between intersection and non-intersection location models were developed to better assess the countermeasures that should be prioritized for each type of crash-prone location. Details of the method and resulting identification of intersections and non-intersections were recorded by Kang et al. (2019). Of interest, the variable, number of lanes was significant in the intersection model but not significant in the non-intersection model (see Figure 1).

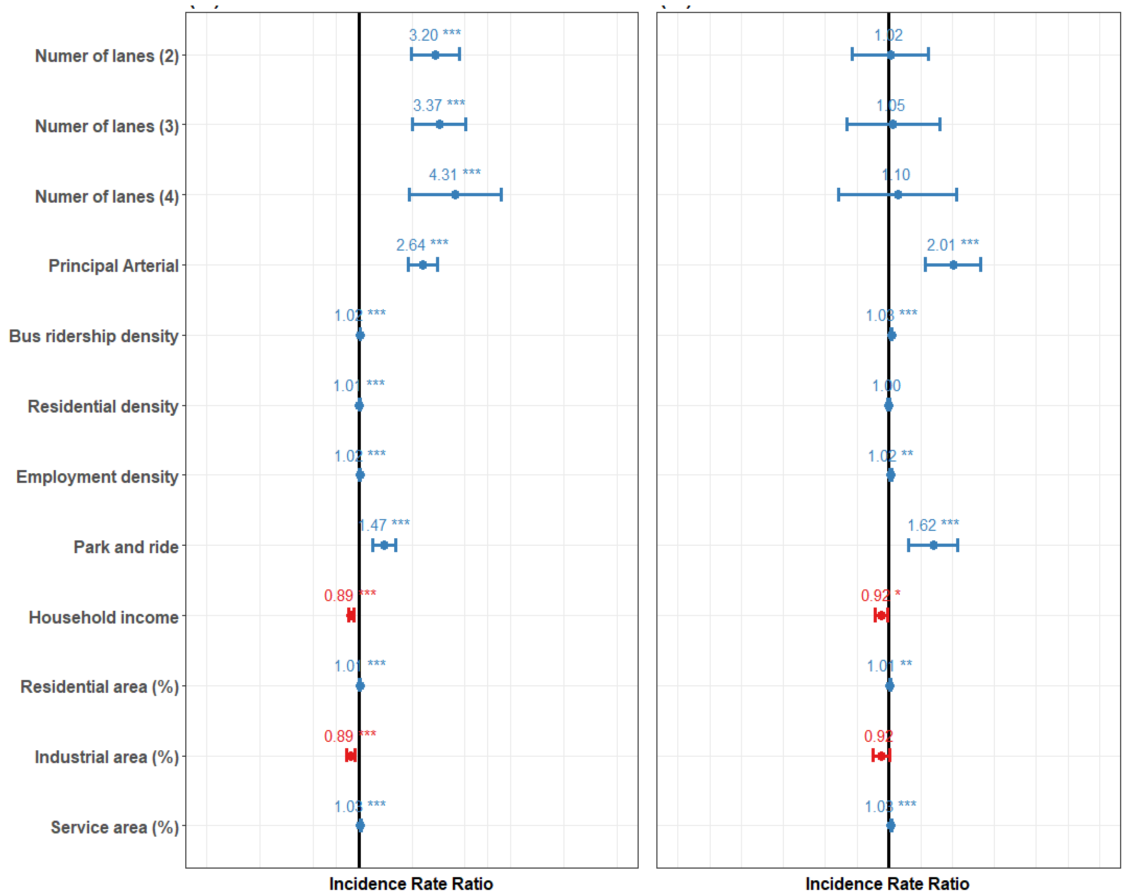


Figure 1 Separate King County frequency models for intersection only (left) and non-intersection only (right)
Note: Factors that cross the vertical black line on each panel do not have a significant impact on the outcome.

The results of the King County frequency model were then exported as CSV format files using a unique identifier for each intersection and non-intersection location. The expected counts of pedestrian crashes were merged with the original intersection and non-intersection location GIS layers in ArcGIS. A planar kernel density estimation (PKDE) map was created to calculate the density of predicted pedestrian crashes in a neighborhood around each crash-prone location. A smooth curved surface was fitted over each crash-prone location as a distance decay function.

Figure 2 shows the PKDE map for the predicted count of pedestrian-vehicle crashes along the state routes. Downtown areas and parts of arterial roadways were identified as locations with high crash frequencies. The PKDE value shows the predicted count of pedestrian-vehicle crashes per square kilometer.

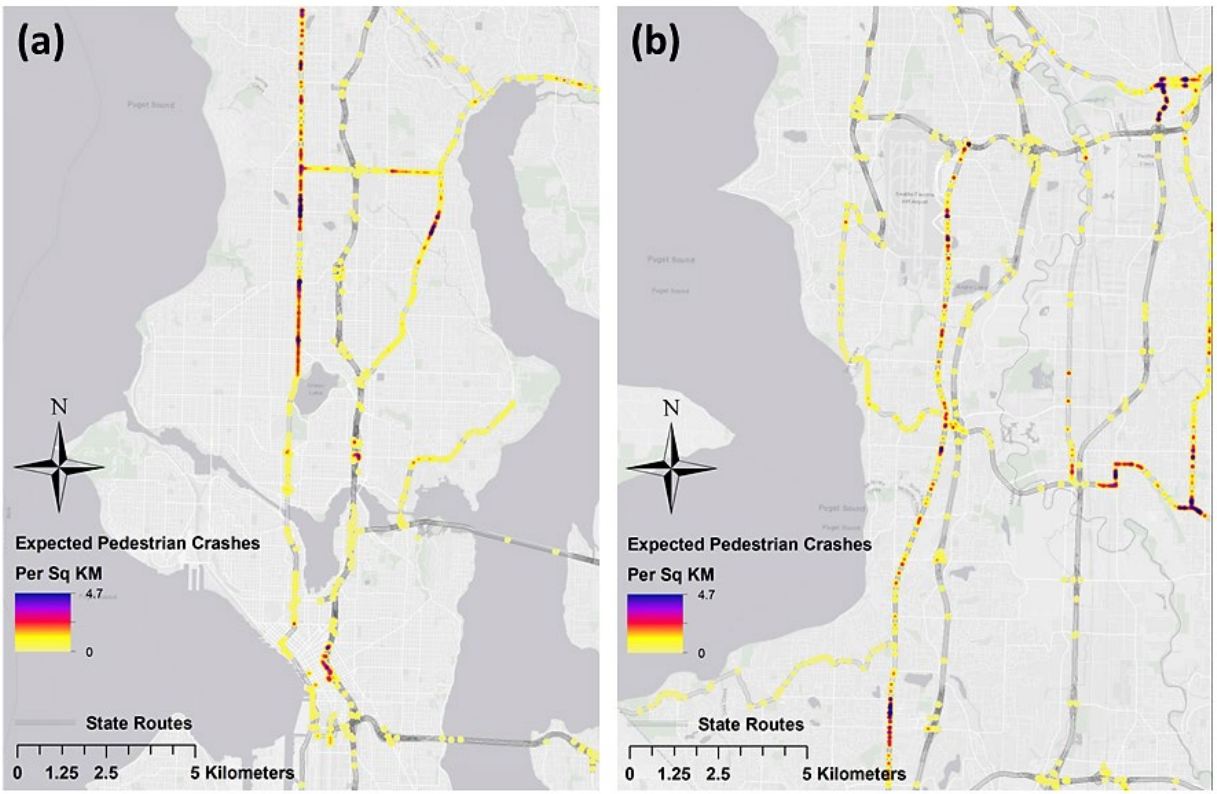


Figure 2. Planar kernel density estimation (PKDE) maps of expected crash frequency of pedestrian-vehicle crashes on state routes only (per 100-meter Euclidean buffer) between 2013 and 2017 at intersection and non-intersection locations along the state routes in the city of Seattle (a), Renton and Kent (b).

4.2.2 Summary of King County Frequency Model

The final King County frequency model shows some crash-prone locations and micro-environment variables were significantly associated with the pedestrian crash frequency per 100-meter Euclidean buffer. The number of roadway lanes (≥2) was associated with a higher crash frequency. Principal arterial roads were associated with a higher crash frequency than non-principal arterial roads. Bus ridership density was also associated with a higher crash frequency. Given that high transit ridership is often associated with high pedestrian activity (Ryan et al., 2009), bus ridership density provides insights on the relationship between pedestrian activity and crash frequency.

Macro-environment characteristics considered in our model included neighborhood and land-use characteristics. Locations with higher numbers of residences and businesses were depicted in our model with residential density, employment density, and proportion of service areas. These factors are likely to capture high levels of pedestrian activity and were found to be associated with a higher frequency of pedestrian-vehicle crashes. This shows that areas with higher development densities, which often have higher pedestrian movements, do not necessarily change the crash likelihood (Aldred et al.,2019, Jacobsen et al., 2015, Moudon et al., 2011, Jacobsen, 2003). The presence of park and ride lots, which likely generate walking trips between individual vehicles and transit stops (Cervero et al., 2001), was associated with higher crash frequencies. A higher proportion of residences near a crash-prone location was also associated with a higher frequency of pedestrian-vehicle crashes. Higher household income and a larger proportion of industrial land uses were associated with a reduced number of pedestrian-vehicle crashes (also known as a protective effect which reduces or eliminates any negative impact on the outcome). Lower income areas were associated with higher crash frequencies, similar to findings in previous studies (Noland et al., 2004, Laflamme et al., 2000, LaScala et al., 2004). Industrial areas are not conducive to walking and often lack pedestrian infrastructure facilities (Koh et al., 2012).

Different factors were found to be associated with the intersection and non-intersection models for pedestrian-vehicle crashes. The number of roadway lanes was statistically significant only in the intersection model. When pedestrians have greater exposure to a roadway (e.g., crossing a four-lane roadway), the likelihood of being involved in a crash is also greater. Residential density and industrial land use were only statistically significant in the intersection model. This suggested that the effects of some macro-environment characteristics differ between the two location types. The results of other micro/macro-environment factors were consistent between the two models.

The models proved to have many benefits. First, spatial autocorrelation was mitigated in the study by using unique crash-prone locations and statistical models that controlled the correlation within the same state routes. Specifically, we used a systematic protocol to create unique crash-prone location data without overlaps (Kang et al., 2019). Furthermore, the spatial autocorrelation within the same state routes with similar environmental attributes was mitigated by using Poisson mixed-effects models. Fixed and random effects accounted for variations within and between state routes. While these approaches required extensive GIS data processing and computational power, they led to enhanced performance of the model.

Second, a comparison between intersection and non-intersection location models provided insight into the kinds of countermeasures that could be prioritized in each type of location. The number of lanes was significant only in the intersection model, indicating that pedestrian safety strategies may need to be tailored differently for intersection vs non-intersection locations. At non-intersection locations where traffic control devices are less likely to be implemented when compared to intersections, countermeasures targeted toward changing driver or pedestrian behavior may be more effective for reducing the frequency of pedestrian crashes (Moudon et al., 2011, Quistberg et al., 2015).

A study limitation was that our data only covered intersection and non-intersection locations along state routes within the boundaries of King County, Washington. Although we collected extensive environmental data sets from various sources, some data were not available to the project team. Previous studies conducted with city-level data included more detailed information on traffic conditions (Ukkusuri et al., 2012, Chen, 2015, Chen et al., 2016). Additional models that include detailed traffic condition variables should be considered even if the models cover smaller areas.

4.3 Washington State Frequency Model

The same modeling tool used for King County was also used for the Washington State frequency model. To account for the characteristics that were shared by the crashes that occurred on the same state routes, different intercepts were allowed in the model as a random effect for each state route. Rather than comparing the intersection and non-intersection models (Figure 2), the Washington State frequency model focused on the expected number of crashes for different state routes. This allowed us to generate a state route ranking in terms of pedestrian-vehicle crash frequencies while also controlling for all explanatory variables.

4.3.1 Washington State Frequency Model Results

The incidence rate ratios (IRR) were calculated for the final Washington State Frequency Model (see Table 2). As an example, an IRR of 1.28 (e.g., presence of a park and ride lot) indicates that locations with a park and ride lot would have 1.28 times (or 128 percent) the incident events (pedestrian-vehicle crashes) that those without a park and ride would have.

Table 2. Final Washington State frequency model using a mixed effect Poisson regression. Data on state routes only for 2013 to 2017.

Variables	**levels**	**Final Model - IRR (95% CI)**
(Intercept)		0.23 (0.20-0.26, p<0.001)
Intersection type	Intersection	*Reference*
	Non-intersection	1.95 (1.80-2.11, p<0.001)
Micro-environment characteristics (100-m Euclidean area around crash-prone locations)		
Functional class	Non-Principal Arterial	*Reference*
	Principal Arterial	2.18 (1.96-2.44, p<0.001)
Total width of lanes (m)		1.17 (1.13-1.21, p<0.001)
Traffic signal presence	N	*Reference*
	Y	1.66 (1.50-1.84, p<0.001)
Macro-environment characteristics (400-m Euclidean area around crash-prone locations)		
Intersection density (count/km^2)		1.26 (1.22-1.30, p<0.001)
Park and Ride	Absence	*Reference*
	Presence	1.28 (1.15-1.43, p<0.001)
Length of Trail (100 m)		0.95 (0.92-0.99, p=0.024)
Total population (1,000 counts)	Census block	1.23 (1.19-1.27, p<0.001)
Percent of Caucasian population (%)		1.06 (1.01-1.11, p=0.023)
Household income (1,000 USD)	Census block-group	0.88 (0.84-0.92, p<0.001)
Industrial area (%)		0.89 (0.84-0.95, p<0.001)
Commercial area (%)		1.20 (1.16-1.24, p<0.001)
Observations		9130
AIC/BIC		7824.14/ 7923.81
Log-Likelihood		-3898.07
Random Effects	σ2	2.07
	τ00	0.2666 Route number
	ICC	0.11
	Random effect group #	184 Route number

Note: IRR: incidence rate ratio, LL=log likelihood, AIC=Akaike Information Criterion, BIC= Bayesian Information Criterion, CI=confidence interval

The final model for Washington State was a mixed effects model that accounted for the random effects of state routes. Figure 3 is a visualization (with the 95 percent confidence interval) of the parameter estimates for the model. Appendix B includes the rankings (in a caterpillar plot) for random (or state route) effects. Appendix C provides detailed maps with estimated crash frequencies per 100-meter Euclidean buffer for different state routes.

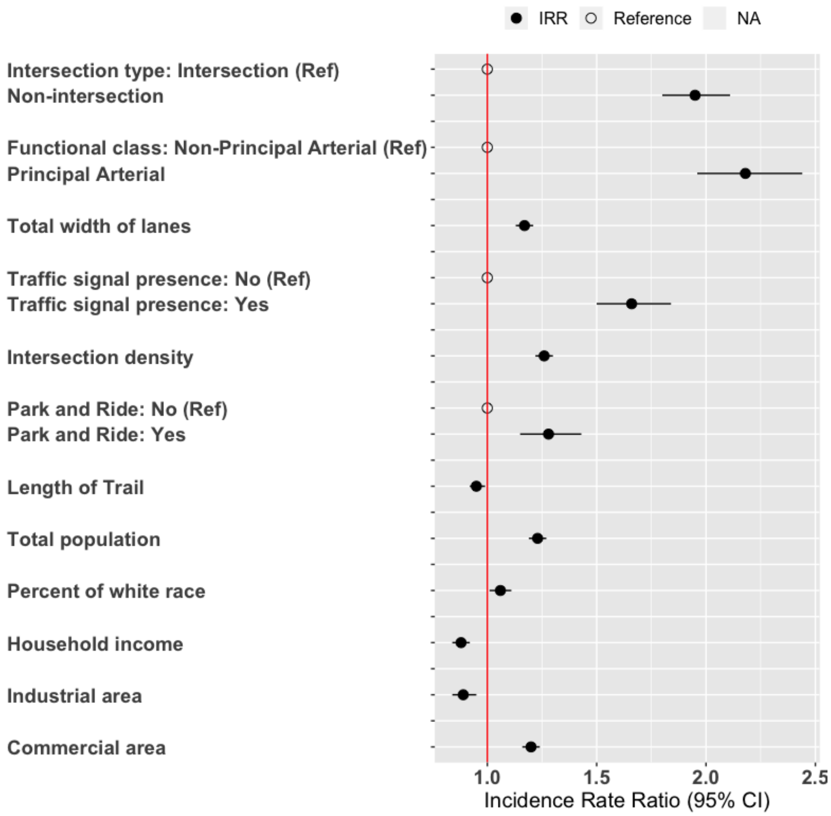


Figure 3. Forest plots for the Washington State Frequency Model.
Note: A vertical red line represents the null hypothesis (IRR=1).

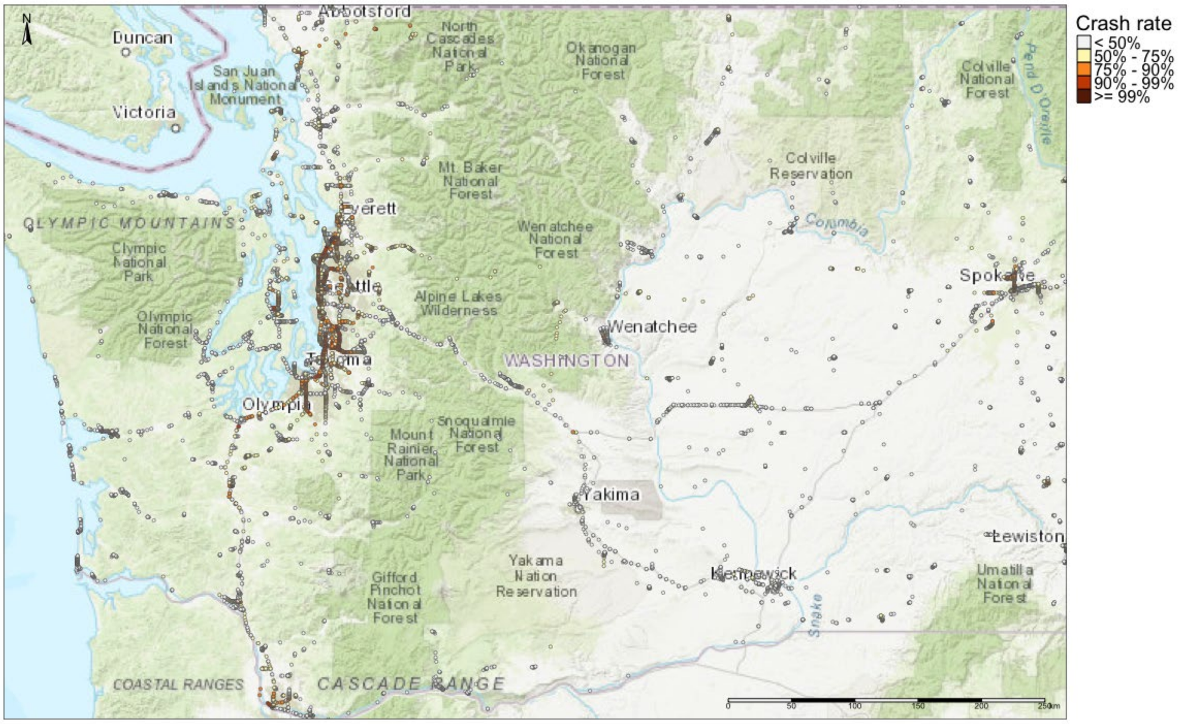


Figure 4. Map of expected crash frequencies (on state routes only) per 100-meter Euclidean buffer of pedestrian-vehicle crashes between 2013 and 2017 at intersection and non-intersection locations along the state routes in Washington State.

4.3.2 Summary of Washington State Frequency Model

The final model showed that three micro- and five macro-environmental characteristics were positively correlated with pedestrian crash frequencies (on state routes only) per 100-meter Euclidean buffer. Within the same state route, non-intersection locations had a 1.95 times higher crash frequency than intersections, with all other variables held constant. This differed from Schneider (2010), who showed that intersections have a higher crash frequency. The difference may be explained by our focus on crashes that occurred on state routes, which have fewer intersections, fewer pedestrians and fewer pedestrian characteristics (including pedestrian crossing treatments) than other roads or streets. On state routes, pedestrians may find crash potential lower at intersections than non-intersections because intersections at state routes have design and operational characteristics (median, traffic signals) to account for higher traffic volumes, higher traffic speeds, and wider roadways, as well as increased driver awareness of pedestrians at these locations. Some state route pedestrian crossings even have pedestrian crossovers (e.g,, SR 99).

At the micro-level (100-m buffer), pedestrian-vehicle crash frequencies at principal arterial roads were 2.18 times higher than at non-arterial roads, within the same state routes. The greater the total width of lanes, the higher the frequency of pedestrian-vehicle crashes. Given that more lanes are associated with more vehicles (Moudon et al., 2011), it would suggest that pedestrians have more opportunities to be involved in these crashes as crossing distance and crossing times increases, as does more conflict with increased traffic volumes.

Locations with a traffic signal had a 1.66 times higher crash frequency than locations without traffic signals. While these findings were very similar to those from previous models that used City of Seattle pedestrian crash data (Quistberg et al., 2015), they were contrary to the finding that non-intersections have a higher crash frequency because non-intersections are, by definition, less likely to have a traffic signal.

For every unit increase of intersection count per square kilometers, the crash frequency increased 1.26 times. The locations around park and ride facilities showed a higher crash frequency than those with no park and ride facility (1.28 times). The percentage change in the crash frequency was 23 percent for every 1,000-person increase in total population, 6 percent for every 1 percent increase in Caucasian population, and 20 percent for every 1 percent increase in commercial space. For every 100-m increase in the length of the trail, the pedestrian crash frequency decreased by 5 percent. This is likely because there is usually more pedestrian traffic at trails, and motorists may be more aware of pedestrians for that reason. For every increase in household income of $1,000 USD, the state route location had a 12 percent lower pedestrian crash frequency. This seems reasonable, as other studies have shown that lower-income areas are associated with a higher crash frequency (Laflamme and Diderichsen, 2000; LaScala et al., 2004; Noland and Quddus, 2004). For every 1 percent increase in the proportion of industrial land use, there was a decrease in the crash frequency 11 percent. This is likely because industrial areas are typically less attractive places for walkers, and they lack pedestrian infrastructure facilities (Koh and Wong, 2013).

Accounting for State Route Effects

As noted earlier, our models included state routes as a random effect. By accounting for the effects within state routes, we were able to identify locations that might require attention with respect to pedestrian-vehicle crashes such as SR 310 in Bremerton, Kitsap County, and SR 501 in Vancouver, Washington. Without this random effect, the results could have been a biased representation of the real world.

Our multilevel models identified which state route locations were more prone to higher crash frequencies, while also controlling for all the variables included in the model. The rankings of these state routes are represented in caterpillar plots in Appendix B. Expected pedestrian crashes, accounting for the autocorrelation between different state routes, were estimated for the Washington State Frequency Model. As expected, the King County area showed a higher number of pedestrian crashes per 100-meter buffer. The state routes for this area included SR 99 and Interstate 5 in Seattle, Renton, and Kent.

Summary of Frequency Models

The pedestrian-vehicle crash counts at intersection and non-intersection locations were examined using micro- and macro-environment data as the explanatory variables. Roadway characteristics, traffic conditions, neighborhood characteristics, and land use were all associated with higher pedestrian-vehicle crash frequencies. The model results offer insights into the factors that affect pedestrian crash counts within and between state routes, and can be used to prioritize pedestrian safety programs throughout King County and Washington State.

For both the King County and Washington State frequency models, the factors that were positively correlated with a pedestrian crash frequency included intersection type being a non-intersection, principal arterial road, total width of lanes (number of lanes), presence of a park and ride facility, and commercial area. Locations with these characteristics should be prioritized to reduce the number of pedestrian crashes. Factors that were negatively correlated with a pedestrian crash frequency included household income and industrial area. Higher-income households were related to a lower number of pedestrian crashes, suggesting that opportunities to reduce crash potential may exist in low-income neighborhoods. Lastly, future studies are warranted to investigate the effects of more specific traffic conditions and behavioral characteristics of drivers and pedestrians on crashes.

5 PEDESTRIAN-VEHICLE CRASH INJURY SEVERITY MODEL

This chapter describes the models developed to assess pedestrian injury severity at crash locations. Statistical models were developed on the basis of environmental characteristics of crash locations and pedestrian socio-demographic factors identified for state routes in King County and Washington State.

5.1 Severity Model Approach

The summary of modeling approach is as follows:

- **Study area**: King County and Washington State.
- **The unit of analysis**: Crash locations along state routes.
- **Regression model**: Binary logistic regression.
- **Dependent variable:** Pedestrian injury severity from a pedestrian-vehicle crash on state routes only between 2013 and 2017. Police records on pedestrian injury contained seven categories of severity: dead at scene, dead on arrival, died at hospital, disabling injury, non-disabling (evident) injury, possible injury, and no injury or property damage only.
  - Injury severity was first aggregated into the five classes that are defined in the Federal Highway Administration (FHWA)'s KABCO injury recording system. The KABCO method of injury rating was developed by the National Safety Council (NSC) and included in the Manual on Classification of Motor Vehicle Traffic Accidents in 1966. KABCO rates injury severity on a decreasing scale, where "K" is a fatality, "A" is an incapacitating injury, "B" is a non-incapacitating injury, and "C" is a possible injury. Injury severity rated "O" is property damage-only, or in other words, the crash victim did not sustain any injuries in the crash.
  - Our models then aggregated injury severity into two classes, following past pedestrian crash severity research practices (Ballesteros et al., 2004; MacLeod et al. 2012; Moudon et al. 2011; Oh 2005; Plurad et al. 2006; Sarkar et al., 2011):
    - Fatal or serious injury (K and A),
    - Evident injury (B) or possible or no injury (C and O).
- **Explanatory variables:** The crash data were obtained from the Transportation Data, GIS and Modeling Office (TDGMO) of the WSDOT. Individual characteristics such as pedestrians, drivers, and crash conditions were gathered from crash data that were reported by police officers and citizens. Roadway and environmental data were obtained from WSDOT, the Census, the King County GIS Center, the University of Washington

Urban Form Lab, and National Historical Geographic Information. The data processing steps are summarized in Appendix D.

- **Individual characteristics:**
  - Pedestrian sociodemographic characteristics
  - Pedestrian and driver behaviors
  - Crash conditions (temporal and lighting).
- **Micro-environments**: Micro-environmental characteristics were based on 100-m Euclidean buffers around crash locations.
  - Microenvironmental data for length of sidewalks and bus ridership were available only for the King County model.
- **Macro-environments**: Macro-environmental characteristics were based on 400-m Euclidean buffers around crash locations.
- Macroenvironmental data for employment density and residential density were available only for the King County model.
- **Number of pedestrians**. We did not have information on the number of pedestrians at each 400-meter buffer. Hence, we used the total population (census block) as a proxy.
- **Data preparation**: Missing data points regarding pedestrian injury type, gender, lighting conditions (approximately 8- to 9 percent) were excluded.

5.1.1 Severity Model Method

Binary logistic regression models were used to examine factors associated with the severity of pedestrian injuries in pedestrian-vehicle crashes. The models included environmental, traffic, and roadway factors while also accounting for pedestrian and driver characteristics. A binary logistic regression with random state route effects was also considered to account for the correlation within the same state route. However, no statistically significant differences in variances between different state routes existed. Hence, the simpler binary logistic binary regression model was used.

Our model aggregated injury severity to a binary outcome: 1=Fatal or Serious injury (K and A), and 0=Evident injury (B) and Possible or no injury (C and O). The binary logistic model used in this analysis follows:

$$Log\frac{Pr\ (y=1|x)}{Pr\ (y=0|x)} = \gamma_0 + \sum_{p=1}^{r} \gamma_p x_{pi} + R_i \qquad \text{(Eq 3.)}$$

where i represents a crash location, γ_o is the intercept, γ_p is a regression coefficient corresponding to the p^{th} predictor variable x_{pij}. A full model with all variables was first estimated as a reference, and then a refined model was developed on the basis of the results from stepwise variable selection processes in R programming (see Table 2). All variables were examined at a significance level of α=0.05.

$$Odds\ Ratio = \frac{Pr\ (y=1|x)}{Pr\ (y=0|x)} = e^{-(\gamma_0+\sum_{p=1}^{r}\gamma_p x_{pi}+R_i)} \qquad \text{(Eq 4.)}$$

The results were expressed as coefficients in the form of odds ratios, with the associated 95 percent confidence interval (CI). That is, each estimated coefficient was exponentiated as follows.

5.2 King County Severity Model

A model with all of the explanatory variables was first developed as a reference, and then a refined model was created on the basis of the stepwise variable selection processes. The refined model showed a better fit with the lower Akaike Information Criterion (AIC) than the full model.

5.2.1 King County Severity Model Results

The odds ratios (OR) calculated for the final King County Severity Model are shown in Table 3. For instance, pedestrians 65 to 74 years old were found to be 2.54 times more likely to be involved in a fatal or severe injury than pedestrians between 25 and 44.

Table 3. Final King County severity model using binary logistic regression (fatal or serious injuries vs. other types of injuries). State routes only for 2013–2017.

Independent variables	**Measures**	**Dependent variables**		**Final model - OR (95% CI)**
		Other types of injuries (B,C,O)	**Fatalities and serious injuries (K,A)**	
Pedestrian age	Age 25-44	222 (77.9)	63 (22.1)	*Reference*
	Age 0-9	8 (100.0)	0 (0.0)	0.00 (NA, p=0.990)
	Age 10-14	20 (87.0)	3 (13.0)	0.46 (0.10-1.59, p=0.259)
	Age 15-24	164 (80.8)	39 (19.2)	0.66 (0.39-1.12, p=0.130)
	Age 45-64	158 (77.1)	47 (22.9)	1.13 (0.68-1.90, p=0.635)
	Age 65-74	27 (69.2)	12 (30.8)	**2.54 (0.99-6.31, p=0.048)**
	Age over 75	22 (91.7)	2 (8.3)	0.35 (0.05-1.59, p=0.228)
Pedestrian contribution	None/Blank	390 (89.4)	46 (10.6)	*Reference*
	Inattention	39 (79.6)	10 (20.4)	1.16 (0.44-2.84, p=0.758)

Independent variables	Measures	Dependent variables		Final model - OR (95% CI)
		Other types of injuries (B,C,O)	**Fatalities and serious injuries (K,A)**	
	Did Not Grant RW to Vehicle	53 (62.4)	32 (37.6)	**2.68 (1.26-5.74, p=0.011)**
	Under Influence of Alcohol	34 (75.6)	11 (24.4)	0.83 (0.31-2.11, p=0.703)
	Failure to Use Xwalk	18 (58.1)	13 (41.9)	**2.83 (1.04-7.63, p=0.040)**
	Other Unknown	69 (61.1)	44 (38.9)	**3.20 (1.61-6.38, p=0.001)**
	Other Known	18 (64.3)	10 (35.7)	2.48 (0.87-6.84, p=0.082)
Driver contribution	None/Blank	167 (63.3)	97 (36.7)	*Reference*
	Fail to Yield Row to Pedestrian	186 (92.1)	16 (7.9)	0.55 (0.24-1.23, p=0.148)
	Inattention	98 (89.9)	11 (10.1)	0.60 (0.25-1.40, p=0.251)
	Driver Distraction	29 (87.9)	4 (12.1)	0.56 (0.15-1.73, p=0.348)
	Under Influence of Alcohol	5 (38.5)	8 (61.5)	**4.90 (1.19-22.61, p=0.032)**
	Other Unknown	87 (87.9)	12 (12.1)	**0.34 (0.14-0.77, p=0.013)**
	Other Known	49 (73.1)	18 (26.9)	1.08 (0.50-2.27, p=0.844)
Driver action	Other Actions	56 (84.8)	10 (15.2)	*Reference*
	Going Straight Ahead	224 (64.6)	123 (35.4)	2.19 (0.99-5.28, p=0.064)
	Making Left Turn	134 (88.7)	17 (11.3)	0.95 (0.37-2.58, p=0.919)
	Making Right Turn	207 (92.8)	16 (7.2)	0.72 (0.28-1.95, p=0.504)
Vehicle type	Passenger Vehicle	349 (81.5)	79 (18.5)	*Reference*
	Pickup truck/Van	231 (77.8)	66 (22.2)	**1.79 (1.15-2.80, p=0.010)**
	Bus/Heavy-Duty Vehicle	10 (47.6)	11 (52.4)	**6.71 (2.39-19.37, p<0.001)**
	Other/Not Stated	31 (75.6)	10 (24.4)	**3.91 (1.48-9.89, p=0.005)**
Light conditions	Daylight, dawn, dusk	351 (85.6)	59 (14.4)	*Reference*
	Dark, Other	270 (71.6)	107 (28.4)	**1.80 (1.17-2.77, p=0.008)**
Micro-environment characteristics (100-m Euclidean area around crash-prone locations)				
Traffic signal presence	Y	73 (89.0)	9 (11.0)	*Reference*
	N	548 (77.7)	157 (22.3)	2.09 (0.90-5.32, p=0.101)
Max posted speed (MPH)	35 MPH	178 (84.0)	34 (16.0)	*Reference*
	25 MPH	29 (100.0)	0 (0.0)	0.00 (NA, p=0.982)
	30 MPH	54 (78.3)	15 (21.7)	1.85 (0.82-4.07, p=0.130)
	40 MPH	159 (75.7)	51 (24.3)	**1.81 (1.02-3.24, p=0.044)**
	45 MPH	90 (76.3)	28 (23.7)	1.37 (0.71-2.64, p=0.349)
	50 MPH +	111 (74.5)	38 (25.5)	**2.30 (1.18-4.54, p=0.015)**
Bus ridership (1,000 person/km^2)		9.9 (16.4)	10.7 (16.9)	*Reference*
Macro-environment characteristics (400-m Euclidean area around crash-prone locations)				
Employment density (1,000 jobs/km^2)		4.1 (12.7)	1.8 (2.2)	0.93 (0.85-0.99, p=0.106)
Park and Ride	N	481 (77.5)	140 (22.5)	*Reference*
	Y	140 (84.3)	26 (15.7)	0.64 (0.36-1.10, p=0.115)
Industrial area (%)		0.5 (1.3)	0.3 (1.1)	0.85 (0.68-1.02, p=0.104)
Observations				787
Log-likelihood				-304.33
Akaike Inf. Crit (AIC)				678.66
Bayesian Inf. Crit (BIC)				842.05

Note: OR: Odds ratio, LL=log likelihood, AIC=Akaike Information Criterion, BIC= Bayesian Information Criterion, CI=confidence interval

The final King County Severity Model was visualized to help interpret the results. The odds ratios and 95% confidence intervals are shown in Table 3 are visualized in Figure 5. All variables that did not overlap zero were statistically significantly different from the reference group.

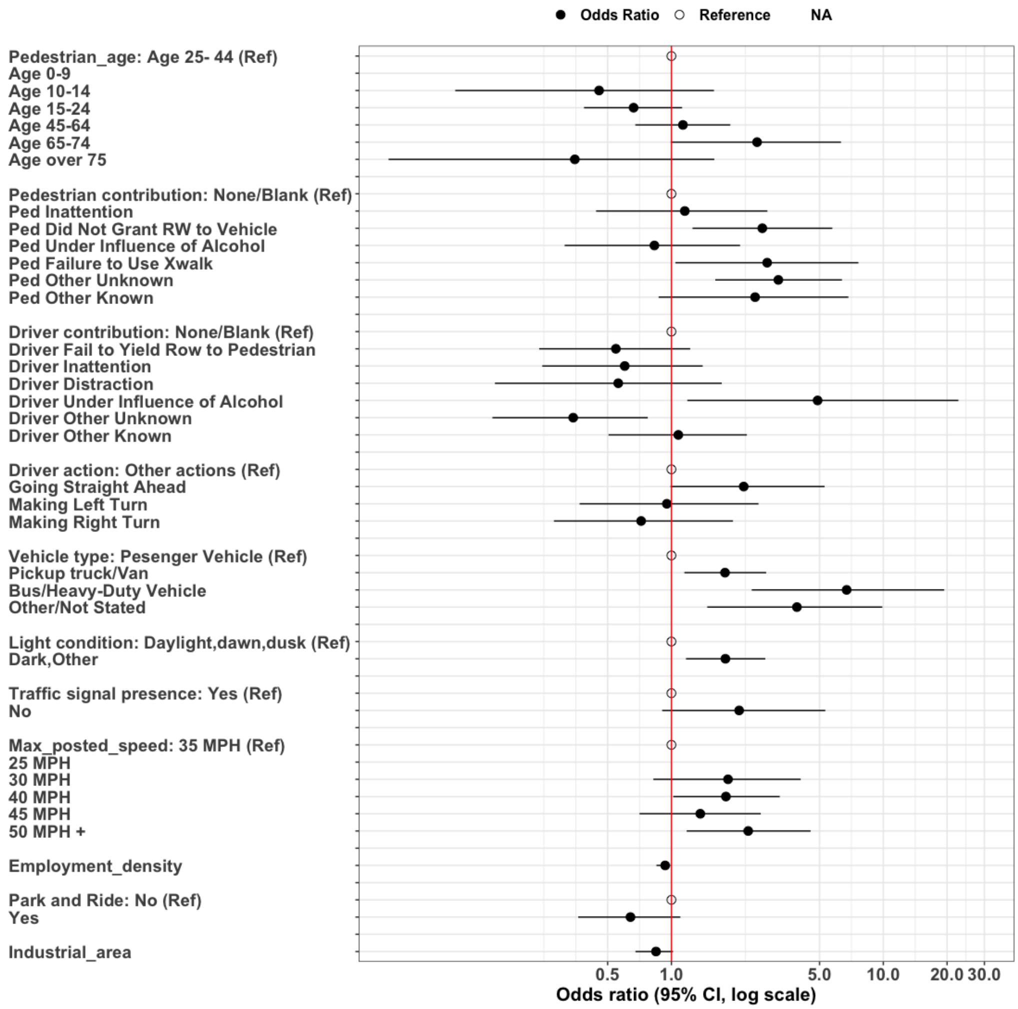


Figure 5. Forest plot for the King County severity model (state routes only).
Note: A vertical red line represents the null-hypothesis (OR=1).

5.2.2 Summary of King County Severity Model

We examined factors associated with the severity of pedestrian injuries by using binary logistic models. Our findings showed that the likelihood of a fatal or serious injury for pedestrians is affected by the surrounding environment and the roadway type. The model accounted for pedestrian and driver characteristics (age, gender) and behaviors (actions, contributing circumstances).

The final model showed that pedestrian age (socio-demographic variables) and pedestrian and drivers' contributing circumstances (action variables) are associated with the likelihood of a severe pedestrian injury.

Pedestrian-Related Variables

The pedestrians' age—being in the older age category—increased the association with fatalities or serious injuries in crashes. This result aligned with the findings from multiple studies that have shown that older pedestrians are more vulnerable and prone to incurring fatal or serious injuries (Jang et al. 2013; Kim et al. 2010; Lee and Abdel-Aty 2005; Moudon et al. 2011; Sarkar, Tay, and Hunt 2011; Tarko and Azam 2011). The odds of being in crashes that result in fatalities or serious injuries are 2.54 times higher for the age group between 65 and 74 than for the age group between 25 and 44.

In past studies, pedestrians' behaviors (e.g., crossing the road, walking along the road) were shown to be associated with an increased likelihood of incurring fatal or serious injuries (Al-Shammari et al., 2009; Byington and Schwebel 2013; Haleem et al., 2015; Moudon et al., 2011; Nasar and Troyer 2013; Tarko and Azam, 2011). Our results showed that when pedestrians did not grant right of way (RW) to a vehicle (OR=2.68), failed to use a cross walk (OR=2.83), and exhibited "other unknown" behaviors (OR=3.20), the odds of incurring a higher severity of pedestrian injury increased significantly. Our analysis showed that unknown "other" pedestrian behaviors were significantly correlated with the likelihood of fatal or serious injuries. The police reports that were available included a limited number of categories of pedestrian behaviors that contribute to pedestrian crashes. This shows potential room for improvement in documentation that could help researchers find more detailed and specific factors associated with fatal or serious injuries.

Driver-Related Variables

Driving under the influence of alcohol was associated with fatal or severe pedestrian injuries (OR=4.90). This finding is supported by previous research (Jang et al., 2013; Zajac and Ivan, 2003). The category "other unknown" did not include detailed documentation of driver behaviors but was included in the model. This category was negatively correlated with fatal or serious injuries.

Vehicles traveling straight ahead were positively associated with severe injuries and fatalities, whereas vehicles making a right or left turn were negatively associated (but not significantly). These findings were consistent with other studies (Roudsari et al., 2005). Pickups/vans (OR: 1.79), buses/heavy-duty vehicles (OR: 6.71), and other types of vehicles/not stated (OR: 3.91) were more likely to result in fatal or serious injuries than passenger vehicles. Heavy vehicles have been found to be associated with a higher likelihood of severe injury in other studies (Lefler et al., 2004, Paulozzi. 2005, Charters et al., 2018).

Lighting Conditions

Lighting conditions labeled as "dark" were found to increase the likelihood of a severe injury or fatality in comparison to daylight (OR=1.80). This is consistent with other studies that have shown that darkness (late in the day or at night) is associated with serious and fatal pedestrian crashes (Kim et al., 2010; Lee and Abdel-Aty, 2005; Mohamed et al., 2013)

Micro-Environment Variables

Maximum posted speed was associated with fatal or severe injury crashes. Speed has been previously associated with the severity of pedestrian injuries in pedestrian-vehicle crashes (Davis, 2001). However, in other studies the posted speed limits have been reported to not significantly affect injury severity (Zahabi et al., 2011). Although the posted speed limit is not the same speed that all drivers of motor vehicles follow, posted speeds of 40 MPH and 50 MPH+ showed greater positive correlations with fatal or serious injuries than a posted speed of 35 MPH in our analysis.

Macro-Environment Variables

Employment density, the presence of park and ride facilities, and industrial areas showed weak associations ($p<0.1$) with fatalities or serious injuries. Areas with park and ride facilities showed a lower likelihood of fatalities or serious injuries than areas without such facilities. This could be because more traffic calming signs or lower speeds are often imposed around these facilities. Lastly, areas with higher percentages of industrial facilities were associated with a lower likelihood of fatalities or serious injuries.

5.3 Washington State Severity Model

A model with all of the explanatory variables was first developed as a reference, and then a refined model was created on the basis of the stepwise variable selection processes. The refined model showed a better fit with the lower Akaike Information Criterion (AIC) than the full model.

5.3.1 Washington State Severity Model Results

The odds ratios (OR) calculated for the final King County Severity Model are shown in Table 4. For instance, pedestrians over 65 to 74 years old were found to be 3.30 times more likely to be involved in a fatal or severe injury than pedestrians between 25 and 44.

Table 4. Final Washington State severity model using binary logistic regression (fatal or serious injuries vs. other types of injuries). State routes only for 2013–2017.

Independent Variables	**Levels**	**Dependent variables**		**OR (multivariable reduced)**
		Other types of injuries Count (%) or Mean (SD)	**Fatalities and serious injuries Count (%) or Mean (SD)**	
Pedestrian age	Age 25-44	539 (74.7)	183 (25.3)	*Reference*
	Age 0-9	28 (87.5)	4 (12.5)	0.50 (0.13-1.52, p=0.260)
	Age 10-14	60 (85.7)	10 (14.3)	0.53 (0.24-1.10, p=0.105)
	Age 15-24	381 (79.0)	101 (21.0)	0.83 (0.60-1.14, p=0.248)
	Age 45-64	404 (71.6)	160 (28.4)	**1.35 (1.01-1.80, p=0.043)**
	Age 65-74	68 (64.2)	38 (35.8)	**3.30 (1.94-5.58, p<0.001)**
	Age over 75	46 (63.0)	27 (37.0)	**3.46 (1.88-6.29, p<0.001)**
Gender	Female	635 (80.4)	155 (19.6)	*Reference*
	Male	891 (70.8)	368 (29.2)	1.24 (0.97-1.59, p=0.086)
Pedestrian action	All Other Actions	369 (72.1)	143 (27.9)	*Reference*
	Walking in roadway	49 (50.5)	48 (49.5)	1.05 (0.63-1.75, p=0.861)
	XingNon Int	146 (52.3)	133 (47.7)	**1.72 (1.18-2.53, p=0.005)**
	At Int. No Xwalk	84 (65.6)	44 (34.4)	1.40 (0.84-2.30, p=0.195)
	At Int. W Signal	583 (90.8)	59 (9.2)	0.73 (0.46-1.16, p=0.181)
	At Int. No Signal	163 (77.6)	47 (22.4)	1.36 (0.85-2.16, p=0.195)
	At Int. Against	132 (72.9)	49 (27.1)	1.04 (0.65-1.66, p=0.858)
Pedestrian contribution	None/Blank	930 (86.1)	150 (13.9)	*Reference*
	Inattention	139 (72.8)	52 (27.2)	1.29 (0.81-2.02, p=0.273)
	Did Not Grant RW to Vehicle	108 (58.4)	77 (41.6)	**1.89 (1.19-3.00, p=0.007)**
	Under Influence of Alcohol	84 (59.6)	57 (40.4)	1.42 (0.87-2.29, p=0.154)
	Failure to Use Xwalk	45 (65.2)	24 (34.8)	1.64 (0.85-3.11, p=0.136)
	Other Unknown	162 (54.7)	134 (45.3)	**2.49 (1.71-3.63, p<0.001)**
	Other Known	58 (66.7)	29 (33.3)	1.67 (0.93-2.93, p=0.079)
Driver contribution	None/Blank	394 (60.2)	260 (39.8)	*Reference*
	Fail to Yield Row to Ped.	474 (87.0)	71 (13.0)	1.23 (0.77-1.95, p=0.387)
	Inattention	233 (86.6)	36 (13.4)	0.81 (0.49-1.31, p=0.394)
	Driver Distraction	68 (73.1)	25 (26.9)	1.18 (0.65-2.09, p=0.583)

Independent Variables	Levels	Dependent variables		OR (multivariable reduced)
		Other types of injuries Count (%) or Mean (SD)	Fatalities and serious injuries Count (%) or Mean (SD)	
	Under Influence of Alcohol	12 (37.5)	20 (62.5)	**4.06 (1.78-9.63, p=0.001)**
	Other Unknown	210 (79.5)	54 (20.5)	0.78 (0.50-1.20, p=0.255)
	Other Known	135 (70.3)	57 (29.7)	1.09 (0.71-1.66, p=0.701)
Driver action	Other Actions	127 (78.4)	35 (21.6)	*Reference*
	Going Straight Ahead	595 (59.7)	401 (40.3)	**2.10 (1.37-3.29, p=0.001)**
	Making Left Turn	358 (86.7)	55 (13.3)	0.89 (0.52-1.53, p=0.663)
	Making Right Turn	446 (93.3)	32 (6.7)	**0.45 (0.25-0.81, p=0.007)**
Vehicle type	Passenger Vehicle	752 (76.4)	232 (23.6)	*Reference*
	Pickup truck/Van	647 (73.8)	230 (26.2)	**1.28 (1.00-1.63, p=0.048)**
	Bus/Heavy-Duty Vehicle	25 (42.4)	34 (57.6)	**4.47 (2.37-8.60, p<0.001)**
	Other/Not Stated	102 (79.1)	27 (20.9)	1.07 (0.62-1.82, p=0.804)
Light condition	Daylight,dawn,dusk	871 (82.5)	185 (17.5)	*Reference*
	Dark,Other	655 (66.0)	338 (34.0)	**1.84 (1.44-2.36, p<0.001)**
Intersection presence	Y	1265 (79.5)	326 (20.5)	*Reference*
	N	261 (57.0)	197 (43.0)	1.30 (0.92-1.83, p=0.140)
Max posted speed (mph)	35 MPH	460 (81.1)	107 (18.9)	*Reference*
	25 MPH	163 (83.6)	32 (16.4)	0.88 (0.53-1.43, p=0.599)
	30 MPH	197 (79.1)	52 (20.9)	1.08 (0.71-1.65, p=0.708)
	40 MPH	226 (73.6)	81 (26.4)	**1.74 (1.18-2.55, p=0.005)**
	45 MPH	182 (74.3)	63 (25.7)	**1.53 (1.01-2.30, p=0.043)**
	50 MPH +	298 (61.3)	188 (38.7)	**1.66 (1.13-2.44, p=0.009)**
Length of Trail (100 m)		1.2 (3.3)	0.8 (2.5)	**0.96 (0.92-1.00, p=0.046)**
Total population		1.8 (1.2)	1.6 (1.2)	**0.89 (0.81-0.99, p=0.031)**
Observations		1526	523	2049
Log-likelihood				-916.92
Akaike Inf. Crit (AIC)				1915.83
Bayesian Inf. Crit (BIC)				2146.46

Note: OR: Odds ratio, LL=log likelihood, AIC=Akaike Information Criterion, BIC= Bayesian Information Criterion, CI=confidence interval

The final Washington State Severity Model was visualized to help interpret the results. The odds ratios (and 95 percent confidence interval) are shown in Table 4 and Figure 6. All variables that did not overlap zero were statistically significantly different from the reference group.

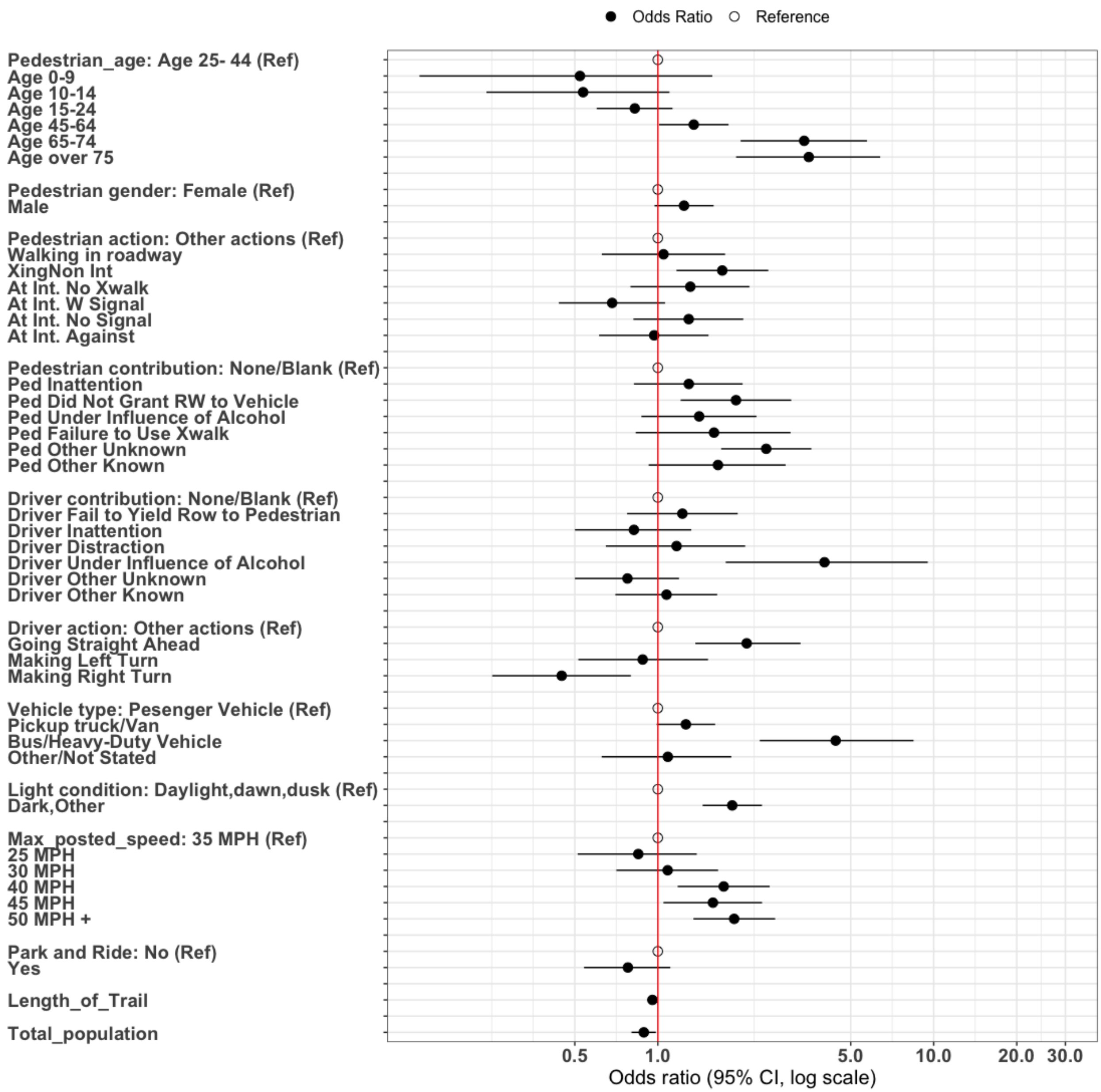


Figure 6. Forest plot for the Washington State Severity Model.
Note: A vertical red line represents the null-hypothesis (OR=1).

5.3.2 Summary of Washington State Severity Model

We examined factors associated with the severity of pedestrian injuries by using binary logistic regression models. The final model showed that pedestrian age (socio-demographic variables) and pedestrian and drivers' contributing circumstances (action variables) were associated with the likelihood of a severe pedestrian injury.

Pedestrian-Related Variables

Pedestrians in the "45 to 64" and "over 75" age groups were more likely to have a fatality or serious injury in a pedestrian-vehicle crash when compared to pedestrians in the "25 to 44" age group. Our model also showed that male pedestrians were more likely to be involved in crashes resulting in fatal or serious injuries ($p<0.1$). This is consistent with Henary et al (2006) and Raharjo (2016).

For pedestrians on state routes in Washington State, actions associated with the highest likelihood of fatalities and serious injuries were crossing at non-intersections (OR=1.72), whereas the least likelihood of fatalities or serious injuries was associated with crossing at an intersection with a signal. This finding emphasizes that the current design of intersections with a signal supports the safety of pedestrians at intersections.

Driver-Related Variables

Motorist' maneuvers have been shown to be a significant factor in the severity of pedestrian injuries. Our model showed that vehicles traveling straight ahead was positively (OR=2.10) associated with severe injuries and fatalities, whereas vehicles making a right turn (OR = 0.45) or a left turn were negatively associated. Similar findings were also observed by Roudsari et al. (2005).

Micro-Environment Variables

With more observations in Washington State, the maximum posted speed of 45 MPH was significant in the Washington State model and was positively associated with fatal or severe injury crashes (OR=1.53).

Macro-Environment Variables

The length of trails and the total population became significant in the Washington State model. These variables were negatively associated with the likelihood of fatalities or serious injuries. This suggests that living in a denser area and with higher exposure to trails in Washington State reduced the likelihood of fatalities, given the higher concentration of pedestrians.

5.4 Comparison between King County Refined Model and Washington State Model

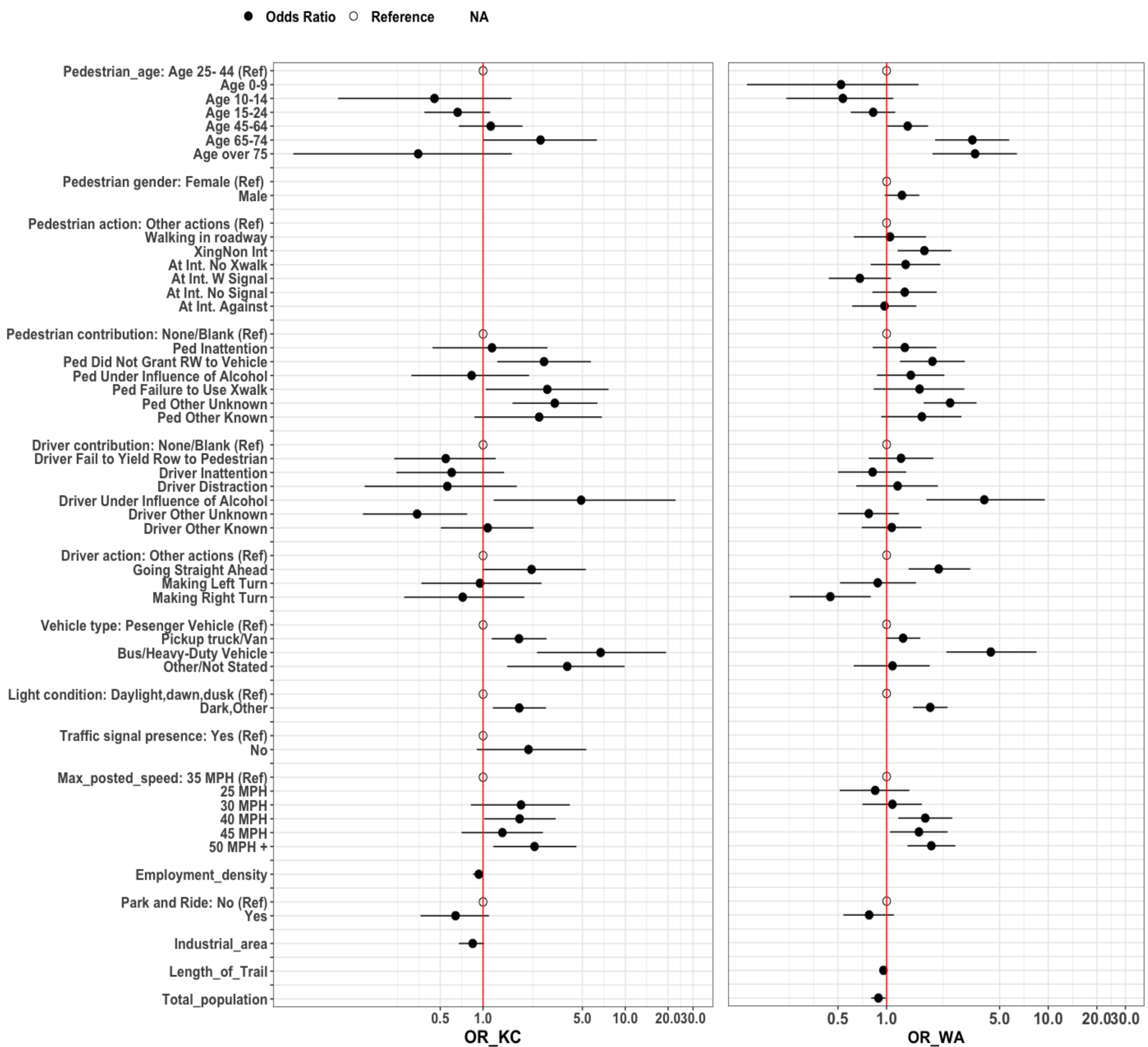


Figure 7 Forest plots comparison between the Washington State and King County severity models.
Note: A vertical red line represents the null-hypothesis (OR=1)

We examined factors associated with the severity of pedestrian injuries (caused by crashes between pedestrians and motor vehicles) by using logistic binary regression models. Our findings showed that the likelihood of a fatal or serious injury for pedestrians is affected by the surrounding environment and the roadway type. The model accounted for pedestrian and driver characteristics (age, gender) and behaviors (actions, contributing circumstances).

Both the full and refined models showed that pedestrian age (socio-demographic variables) and pedestrian and driver contributing behaviors are correlated with the likelihood of a severe pedestrian injury or death. The Washington State severity model did not account for variables such as length of sidewalks, bus ridership, and employment density, as these variables were only available for King County severity model.

We then compared the odds ratios for final versions of the Washington State and King County severity models. Variables that significantly impacted the likelihood of a fatal or serious injury in a pedestrian-vehicle crash in Washington State but not in King County include:

- Pedestrian age 45 – 64 (+)
- Pedestrian age over 75 (+)
- Pedestrian action: Crossing at a non-intersection (+)
- Driver action: Making a right turn (–)
- Max posted speed: 45 MPH (+)
- Length of trails (–)
- Total population (–).

Variables that did not show any significant impact in the Washington State model but were significant in the King County model include:

- Pedestrian contribution: Failure to use crosswalk
- Driver contribution: Other unknown
- Vehicle type: Other/not stated.

5.5 Findings of the Severity Models

Most of the explanatory variables in the Washington State and King County severity models had similar coefficients. Older pedestrian age groups (ages 45 to 64, 65 to 74, and over 75) showed a larger increase in the likelihood of fatal or serious pedestrian injuries in the Washington State model than in the King County model.

As expected, pedestrians' and drivers' characteristics presented strong associations with pedestrian injury severity. By taking into account micro- and macro-environment variables around crash locations, our model aimed to identify environmental factors associated with the severity of pedestrian injuries. While individual-level variables were controlled for, several environmental factors that captured posted traffic speed and nearby land uses were associated with a higher likelihood of crashes ending in severe injuries or fatalities. A better understanding of the environmental factors associated with pedestrians' involvement in severe injury or fatal crashes could provide insights into safety strategies to reduce pedestrian-vehicle crashes in the future.

It is important to note that great portions of data were missing from crash reports, including several factors that were found to be significantly correlated with fatal or serious injuries. For example, although we found that "unknown" pedestrian and driver actions were significantly correlated with fatal or serious injuries, we could not identify the specific actions because they were listed as "unknown" in the crash reports. Because car speeds at the time of a crash were also not known, we used the posted speed limit as a proxy for motor-vehicles' speeds. This was a limitation, as speed was found to be significantly correlated with pedestrian injury severity. This underscores the importance of gathering accurate information at the time of a crash. As the quality of crash reports improves, the increased information will offer greater potential for improvements in crash safety analysis.

6 REFERENCES

Aldred R, Goel R, Woodcock J, et alContextualising Safety in Numbers: a longitudinal investigation into change in cycling safety in Britain, 1991–2001 and 2001–2011Injury Prevention 2019;25:236-241

Al-Shammari, Naif, Salaheddine Bendak, and Saad Al-Gadhi. 2009. "In-Depth Analysis of Pedestrian Crashes in Riyadh." Traffic Injury Prevention 10(6): 552–59.

Ballesteros, Michael F, Patricia C Dischinger, and Patricia Langenberg. 2004. "Pedestrian Injuries and Vehicle Type in Maryland, 1995–1999." Accident Analysis & Prevention 36(1): 73–81.

Byington, Katherine W., and David C. Schwebel. 2013. "Effects of Mobile Internet Use on College Student Pedestrian Injury Risk." Accident Analysis & Prevention 51: 78–83.

Cervero R. Walk-and-Ride: Factors Influencing Pedestrian Access to Transit. Journal of Public Transportation 2001;3. doi:https://doi.org/10.5038/2375-0901.3.4.1.

Charters, Kate E., Belinda J. Gabbe, Biswadev Mitra 2018. "Pedestrian traffic injury in Victoria, Australia" International Journal of the Care of the injured.

Chen P, Zhou J. Effects of the built environment on automobile-involved pedestrian crash frequency and risk. Journal of Transport & Health 2016;3:448–56. doi:10.1016/j.jth.2016.06.008.

Chen P. Built environment factors in explaining the automobile-involved bicycle crash frequencies: A spatial statistic approach. Safety Science 2015;79:336–43. doi:10.1016/j.ssci.2015.06.016.

Davis, G. A. (2001). Relating severity of pedestrian injury to impact speed in vehicle-pedestrian crashes: Simple threshold model. Transportation research record, 1773(1), 108-113.

Elvik R. The non-linearity of risk and the promotion of environmentally sustainable transport. Accid Anal Prev. 2009;41(4):849-855. doi:10.1016/j.aap.2009.04.009

Haleem, Kirolos, Priyanka Alluri, and Albert Gan. 2015. "Analyzing Pedestrian Crash Injury Severity at Signalized and Non-Signalized Locations." Accident Analysis & Prevention 81: 14–23.

Henary, BasemY., Johan Ivarsson, and JeffR. Crandall. 2006. The Influence of Age on the Morbidity and Mortality of Pedestrian Victims. Traffic Injury Prevention 7(2): 182–90.

Holland, Carol, and Roslyn Hill. 2007. The Effect of Age, Gender and Driver Status on Pedestrians' Intentions to Cross the Road in Risky Situations. Accident; Analysis and Prevention 39(2): 224–37.

Jacobsen PL. Safety in numbers: more walkers and bicyclists, safer walking and bicyclingInjury Prevention 2003;9:205-209

Jang, Kitae et al. 2013. "Evaluation of Pedestrian Safety: Geographical Identification of Pedestrian Crash Hotspots and Evaluating Risk Factors for Injury Severity." Transportation Research Board 92nd Annual Meeting. http://koasas.kaist.ac.kr/handle/10203/259126 (October 14, 2019).

Kang, M.; Moudon, A.V.; Kim, H.; Boyle, L.N. Intersections and Non-Intersections: A Protocol for Identifying Pedestrian Crash Risk Locations in GIS. Int. J. Environ. Res. Public Health 2019, 16, 3565.

Kim, Joon-Ki, Gudmundur F. Ulfarsson, Venkataraman N. Shankar, and Fred L. Mannering. 2010. "A Note on Modeling Pedestrian-Injury Severity in Motor-Vehicle Crashes with the Mixed Logit Model." Accident Analysis & Prevention 42(6): 1751–58.

Kim, Joon-Ki, Gudmundur F. Ulfarsson, Venkataraman N. Shankar, and Sungyop Kim. 2008. "Age and Pedestrian Injury Severity in Motor-Vehicle Crashes: A Heteroskedastic Logit Analysis." Accident; Analysis and Prevention 40(5): 1695–1702.

Kim, J. K., Ulfarsson, G. F., Shankar, V. N., & Mannering, F. L. (2010). A note on modeling pedestrian-injury severity in motor-vehicle crashes with the mixed logit model. Accident Analysis & Prevention, 42(6), 1751-1758.

Koh PP, Wong YD. Comparing pedestrians' needs and behaviours in different land use environments. Journal of Transport Geography 2013;26:43–50. doi:10.1016/j.jtrangeo.2012.08.012.

Laflamme L, Diderichsen F. Social differences in traffic injury risks in childhood and youth—a literature review and a research agenda. Injury Prevention 2000;6:293–8. doi:10.1136/ip.6.4.293. https://doi.org/10.1136/ip.6.4.293

LaScala, E. A., Gruenewald, P. J., & Johnson, F. W. (2004). An ecological study of the locations of schools and child pedestrian injury collisions. Accident Analysis & Prevention, 36(4), 569–576. https://doi.org/10.1016/S0001-4575(03)00063-0

Leden L. Pedestrian risk decrease with pedestrian flow. A case study based on data from signalized intersections in Hamilton, Ontario. Accid Anal Prev. 2002;34(4):457-464. doi:10.1016/s0001-4575(01)00043-4

Lee, Chris, and Mohamed Abdel-Aty. 2005. “Comprehensive Analysis of Vehicle–Pedestrian Crashes at Intersections in Florida.” Accident Analysis & Prevention 37(4): 775–86.

Lefler, Devon E., Hampton C. Gabler, 2004. "The fatality and injury risk of light truck impacts with pedestrians in the United States" Accident Analysis & Prevention

Lyon C, Persaud B. Pedestrian Collision Prediction Models for Urban Intersections. Transportation Research Record. 2002;1818(1):102-107. doi:10.3141/1818-16

MacLeod, Kara E., Julia B. Griswold, Lindsay S. Arnold, and David R. Ragland. 2012. “Factors Associated with Hit-and-Run Pedestrian Fatalities and Driver Identification.” Accident Analysis & Prevention 45: 366–72.

Mohamed, M.G., Saunier, N., Miranda-Moreno, L.F., Ukkusuri, S.V., 2013. A clustering regression approach: a comprehensive injury severity analysis of pedestrian-vehicle crashes in New York, US and Montreal, Canada. Safety Science 54, 27–37.

Moudon, A. V., Lin, L., Jiao, J., Hurvitz, P. M., Reeves, P. (2011). The Risk of Pedestrian Injury and Fatality in Crashes with Motor Vehicles, A Social Ecological Study of State Routes and City Streets in King County, Washington. Accident Analysis and Prevention, 43:11-24

Nasar, Jack L., and Derek Troyer. 2013. “Pedestrian Injuries Due to Mobile Phone Use in Public Places.” Accident Analysis & Prevention 57: 91–95.

Noland, R. B., & Quddus, M. A. (2004). Analysis of Pedestrian and Bicycle Casualties with Regional Panel Data. Transportation Research Record: Journal of the Transportation Research Board, 1897(1), 28–33. https://doi.org/10.3141/1897-04

Oh, Cheol. 2005. “Analysis of Pedestrian-Vehicle Crashes in Korea.” : 9.

Quistberg DA, Howard EJ, Ebel BE, Moudon AV, Saelens BE, Hurvitz PM, Curtin JE, Rivara FP. (2015) Multilevel models for evaluating the risk of pedestrian-motor vehicle crashes at intersections and mid-blocks. *Accident Analysis and Prevention*, 5, 84:99-111. PMID: 26339944.

Paulozzi L J., 2005, "United States pedestrian fatality rates by vehicle type", Injury Prevention

Plurad, David et al. 2006. “Pedestrian Injuries: The Association of Alcohol Consumption with the Type and Severity of Injuries and Outcomes.” Journal of the American College of Surgeons 202(6): 919–27.

Raharjo, Tatok Raharjo, The Effects of Age and Gender on Pedestrian Traffic Injuries: A Random Parameters and Latent Class Analysis (2016). Graduate Theses and Dissertations. https://scholarcommons.usf.edu/etd/6360

Roudsari, Bahman S., Charles N. Mock, and Robert Kaufman. 2005. “An Evaluation of the Association Between Vehicle Type and the Source and Severity of Pedestrian Injuries.” Traffic Injury Prevention 6(2): 185–92.

Ryan S, Frank L. Pedestrian Environments and Transit Ridership. Journal of Public Transportation 2009;12:39–57. doi:10.5038/2375-0901.12.1.3.

Sarkar, Sudipta, Richard Tay, and John Douglas Hunt. 2011. “Logistic Regression Model of Risk of Fatality in Vehicle–Pedestrian Crashes on National Highways in Bangladesh.” Transportation Research Record: Journal of the Transportation Research Board 2264(1): 128–37.

Schneider, R. J., M. C. Diogenes, L. S. Arnold, V. Attaset, J. Griswold, and D. R. Ragland. Association Between Roadway Intersection Characteristics and Pedestrian Crash Risk in Alameda County, California. In Transportation Research Record: Journal of the Transportation Research Board, No. 2198, Transportation Research Board of the National Academies, Washington, D.C., 2010, pp. 41–51.

Tarko, Andrew, and Md. Shafiul Azam. 2011. “Pedestrian Injury Analysis with Consideration of the Selectivity Bias in Linked Police-Hospital Data.” Accident Analysis & Prevention 43(5): 1689–95.

Tay, Richard, Jaisung Choi, Lina Kattan, and Amjad Khan. 2011. “A Multinomial Logit Model of Pedestrian-Vehicle Crash Severity.” International Journal of Sustainable Transportation 5(4): 233–49.

Ukkusuri S, Miranda-Moreno LF, Ramadurai G, Isa-Tavarez J. The role of built environment on pedestrian crash frequency. Safety Science 2012;50:1141–51. doi:10.1016/j.ssci.2011.09.012.

World Health Organization (2013), Pedestrian safety: A road safety manual for decision- makers and practitioners

WSDOT, (2016) Washington State Strategic Highway Safety Plan 2016. [Online]. Available: http://www.targetzero.com/PDF2/targetzero.pdf. [Accessed Jun 1 2017].

Zahabi, S. A. H., Strauss, J., Manaugh, K., & Miranda-Moreno, L. F. (2011). Estimating potential effect of speed limits, built environment, and other factors on severity of pedestrian and cyclist injuries in crashes. Transportation research record, 2247(1), 81-90.

Zajac, Sylvia S, and John N Ivan. 2003. "Factors Influencing Injury Severity of Motor Vehicle–Crossing Pedestrian Crashes in Rural Connecticut." Accident Analysis & Prevention 35(3): 369–79.

APPENDIX A – UNIT OF ANALYSIS FOR FREQUENCY MODELS

The ***unit of analysis for the frequency models was a*** 100-meter buffer around crash-prone locations (either intersection or non-intersection) at or near state routes. This appendix describes the process for identifying these locations.

- **Intersection:** According to the American Association of State Highway and Transportation Officials' (AASHTO), *A Policy on Geometric Design of Highways and Streets*, an intersection is defined as the general area where two or more highways join or cross, including the roadways and roadside facilities.
  - **Intersection point**: WSDOT intersection point data were obtained and used as a baseline data set for further analysis.
  - **Intersection location**: Unique intersection locations were identified by excluding overlapping intersection points.
- **Non-intersection:** A non-intersection is defined as a location where two or fewer segments join where pedestrians may cross a facility legally (traffic sign, signal, marked crosswalk, etc.) or illegally (no traffic sign).
  - **Non-intersection point**: Non-intersection points were detected by segmenting the state route roadway network.
  - **Non-intersection location**: Unique non-intersection locations were identified by excluding redundant non-intersection points.

Intersection and non-intersection locations may or may not have had a crash during the study period (2013-2017), but they were all locations where a crash between a motor-vehicle and a pedestrian could occur (locations with crash risk) and hence had to be identified for modeling purposes. The study team thoroughly investigated WSDOT intersection and roadway network data and clarified possible issues and problems. In addition we suggested detailed approaches to identify crash-prone locations.

The study team used WSDOT intersection point data as a baseline data set to identify pedestrian crash-prone locations. The flowchart shows the decisions made for cleaning the data and identifying unique crash-prone locations at intersections and non-intersections. Details of the method and resulting identification of intersections and non-intersections were recorded by Kang et al. (2019).

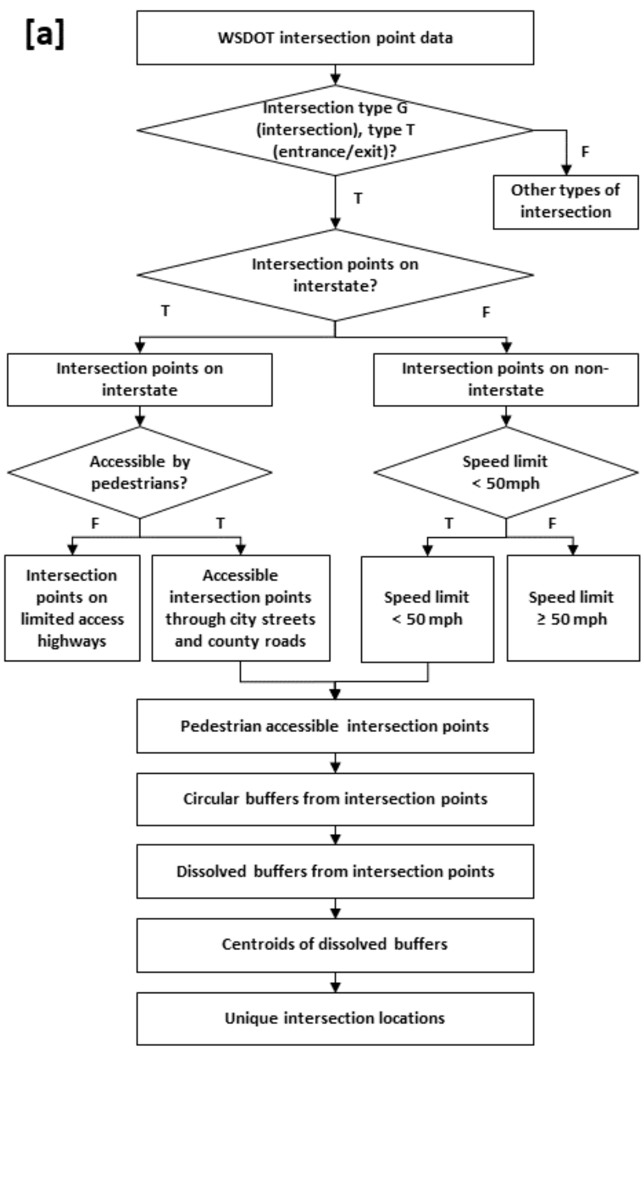
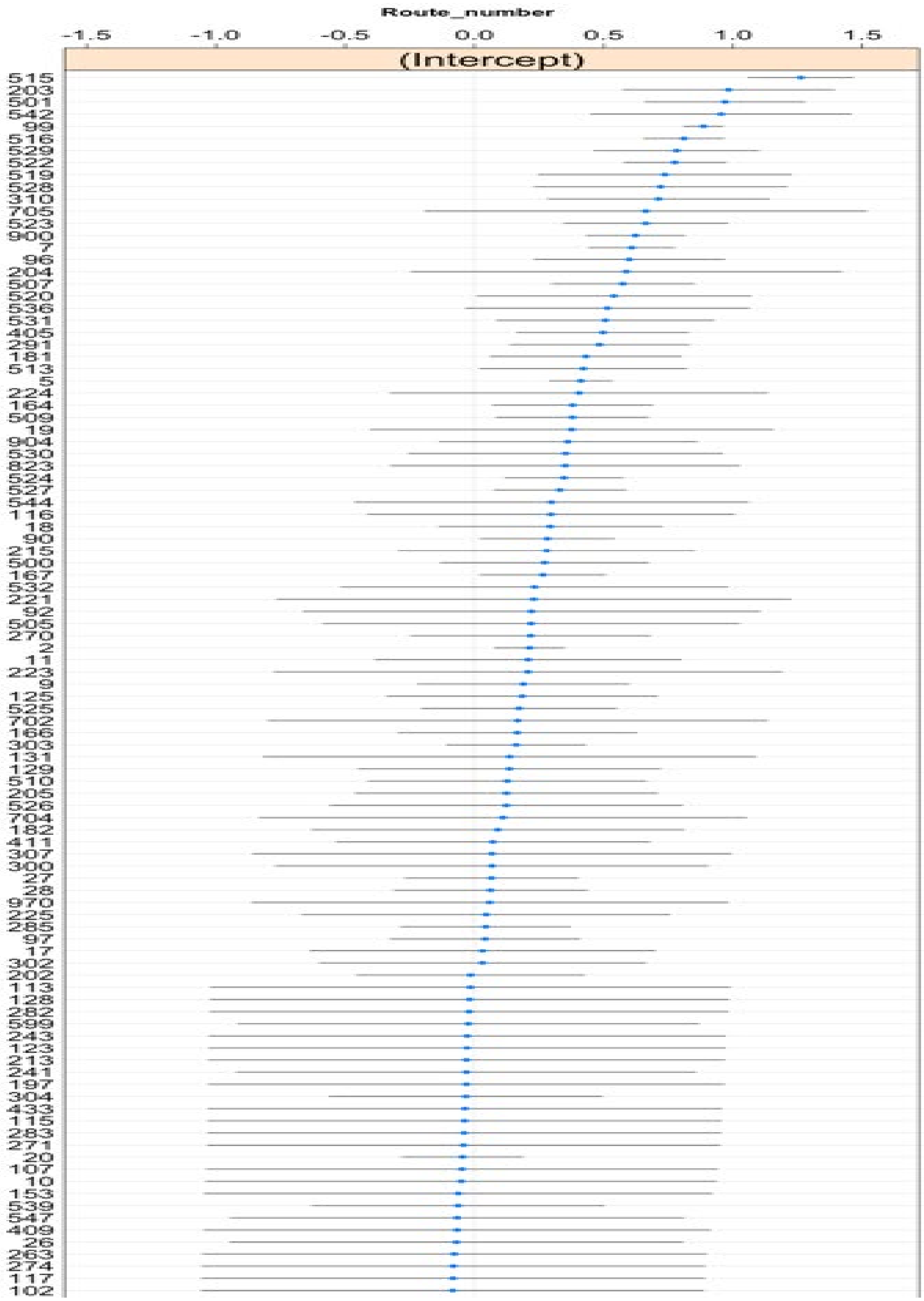


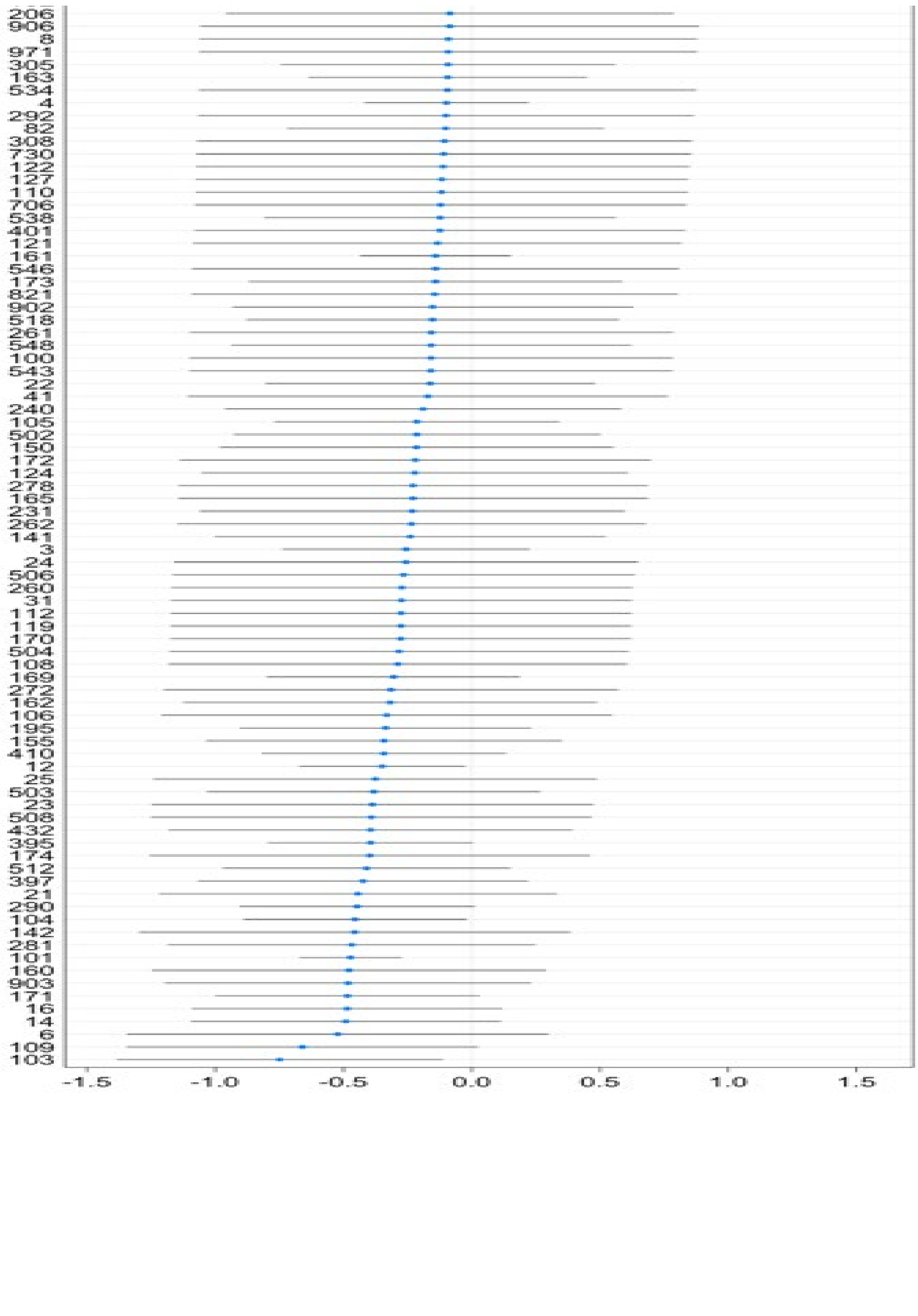
Figure A-1. Decision trees for identifying unique intersection locations [a] and non-intersection locations [b] (Kang et al., 2019)

Once the intersection and non-intersection locations had been identified, we developed separate models for King County and Washington State. Our focus was on pedestrian-vehicle crashes that occurred on state routes.

Reference: Kang, M.; Moudon, A.V.; Kim, H.; Boyle, L.N. Intersections and Non-Intersections: A Protocol for Identifying Pedestrian Crash Risk Locations in GIS. Int. J. Environ. Res. Public Health 2019, 16, 3565.

APPENDIX B – CATERPILLAR PLOT



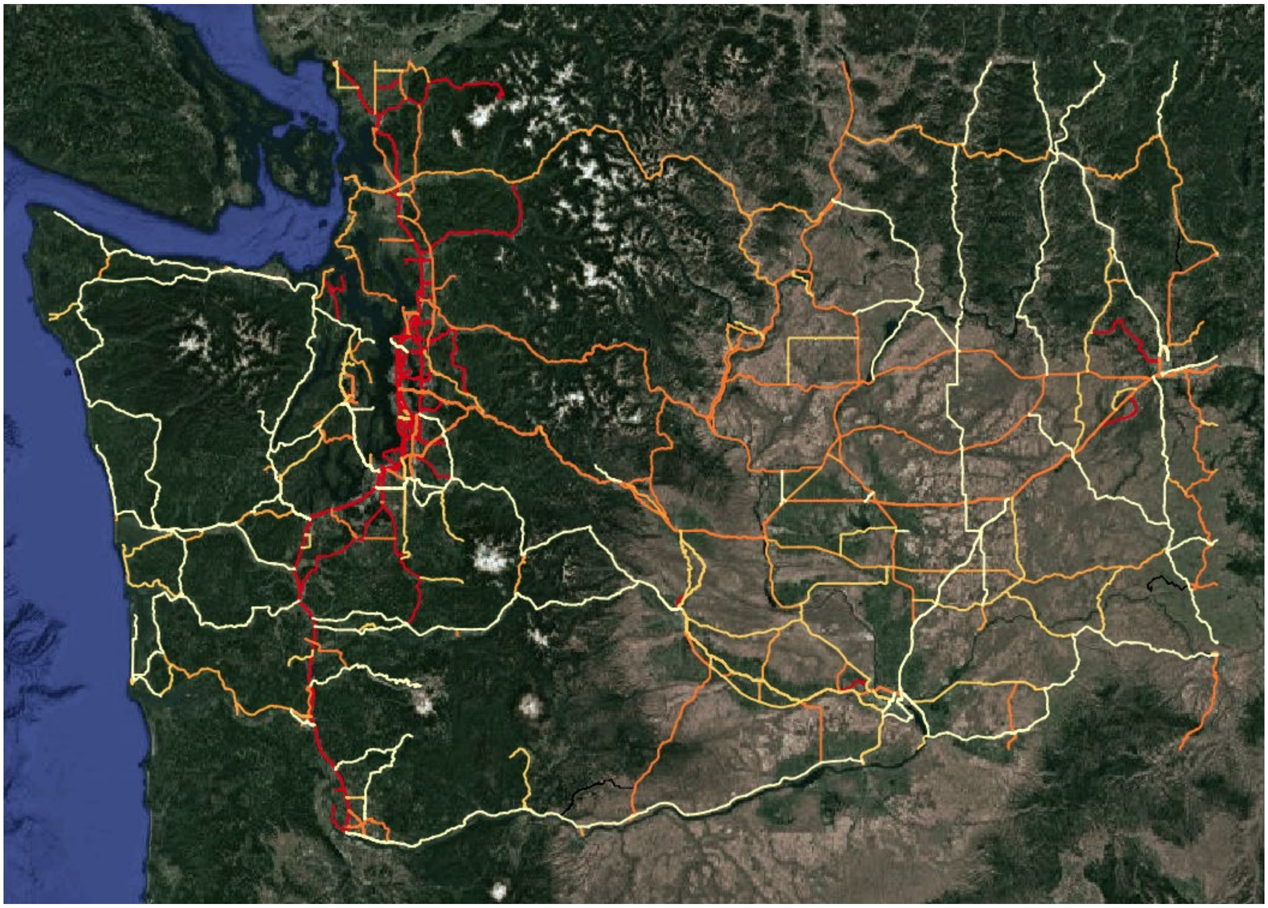

206
906
8
971
305
163
534
4
292
82
308
730
122
127
110
706
538
401
121
161
546
173
821
902
518
261
548
100
543
22
41
240
105
502
150
172
124
278
165
231
262
141
3
24
506
260
31
112
119
170
504
108
169
272
162
106
195
155
410
12
25
503
23
508
432
395
174
512
397
21
290
104
142
281
101
160
903
171
16
14
6
109
103
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5

The state route numbers that fell within these percentiles are shown in the table below.

Table B-1. State routes by percentiles of random effects

Random Effects Percentiles	**State Route numbers (In the order random effects decreases)**
>80%	515, 203, 501, 542, 99, 516, 529, 522, 519, 528, 310, 705, 523, 900, 7, 96, 204, 507, 520, 536, 531, 405, 291, 181, 513, 5, 224, 164, 509, 19, 904, 530, 823, 524, 527, 544, 116
60–80%	18, 90, 215, 500, 167, 532, 221, 92, 505, 270, 2, 11, 223, 9, 125, 525, 702, 166, 303, 131, 129, 510, 205, 526, 704, 182, 411, 307, 300, 27, 28, 970, 225, 285, 97, 17, 302
40–60%	202, 113, 128, 282, 599, 243, 123, 213, 241, 197, 304, 433, 115, 283, 271, 20, 107, 10, 153, 539, 547, 409, 26, 263, 274, 117, 102, 206, 906, 8, 971, 305, 163, 534, 4, 292
20–40%	82, 308, 730, 122, 127, 110, 706, 538, 401, 121, 161, 546, 173, 821, 902, 518, 261, 548, 100, 543, 22, , 41, 240, 105, 502, 150, 172, 124, 278, 165, 231, 262, 141, 3, 24, , 506, 260
<=20%	31, 112, 119, 170, 504, 108, 169, 272, 162, 106, 195, 155, 410, 12, 25, 503, 23, 508, 432, 395, 174, 512, 397, 21, 290, 104, 142, 281, 101, 160, 903, 171, 16, 14, 6, 109, 103

State routes that were within the 80th percentile of random effects are marked in cyan in Figure B-1. They were spread out among many cities, including Seattle, Renton/Kent, Bellingham, Yakima, and Bremerton, Washington. State routes by percentiles are shown in the Figure B-1.



: >80%, : 60%, : 40%, : 20%,

: <=20%

Figure B-1. State routes in the greater than 80, 60, 40, 20, less than 20 percentiles of random state route effects

APPENDIX C – ESTIMATED PEDESTRIAN-VEHICLE CRASH FREQUENCY WITH STATE ROUTE EFFECTS

King County

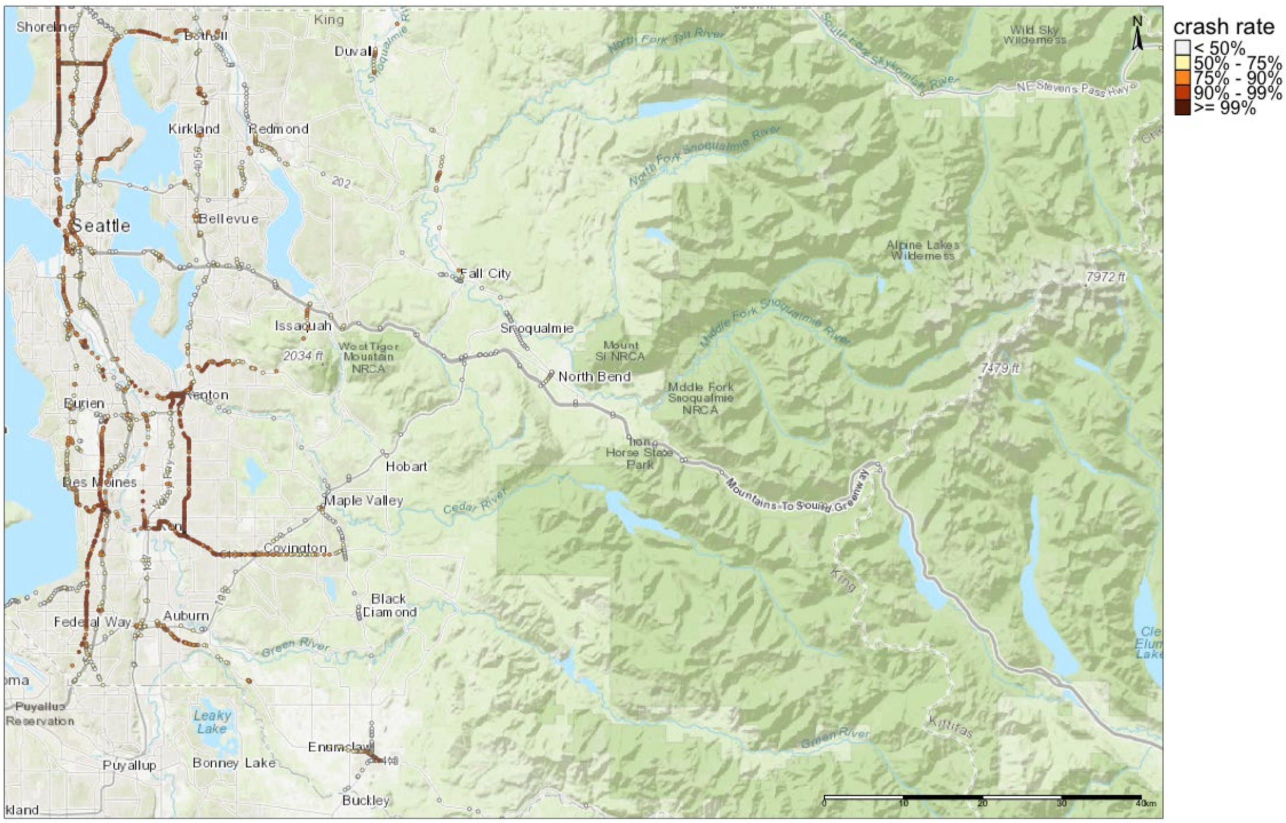


Figure C-1. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state routes in King County

Seattle

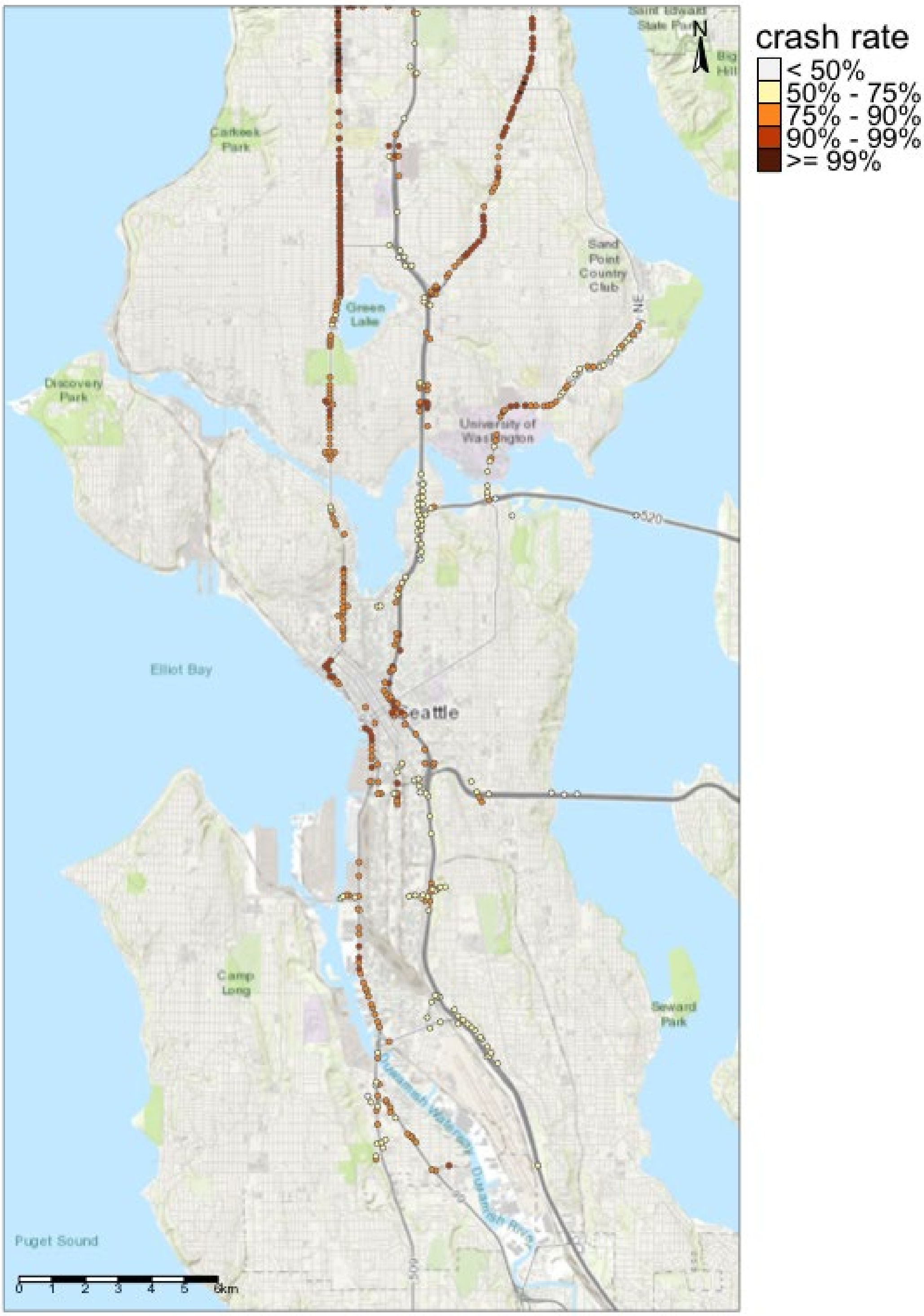


Figure C-2. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state routes in Seattle

Renton/ Kent

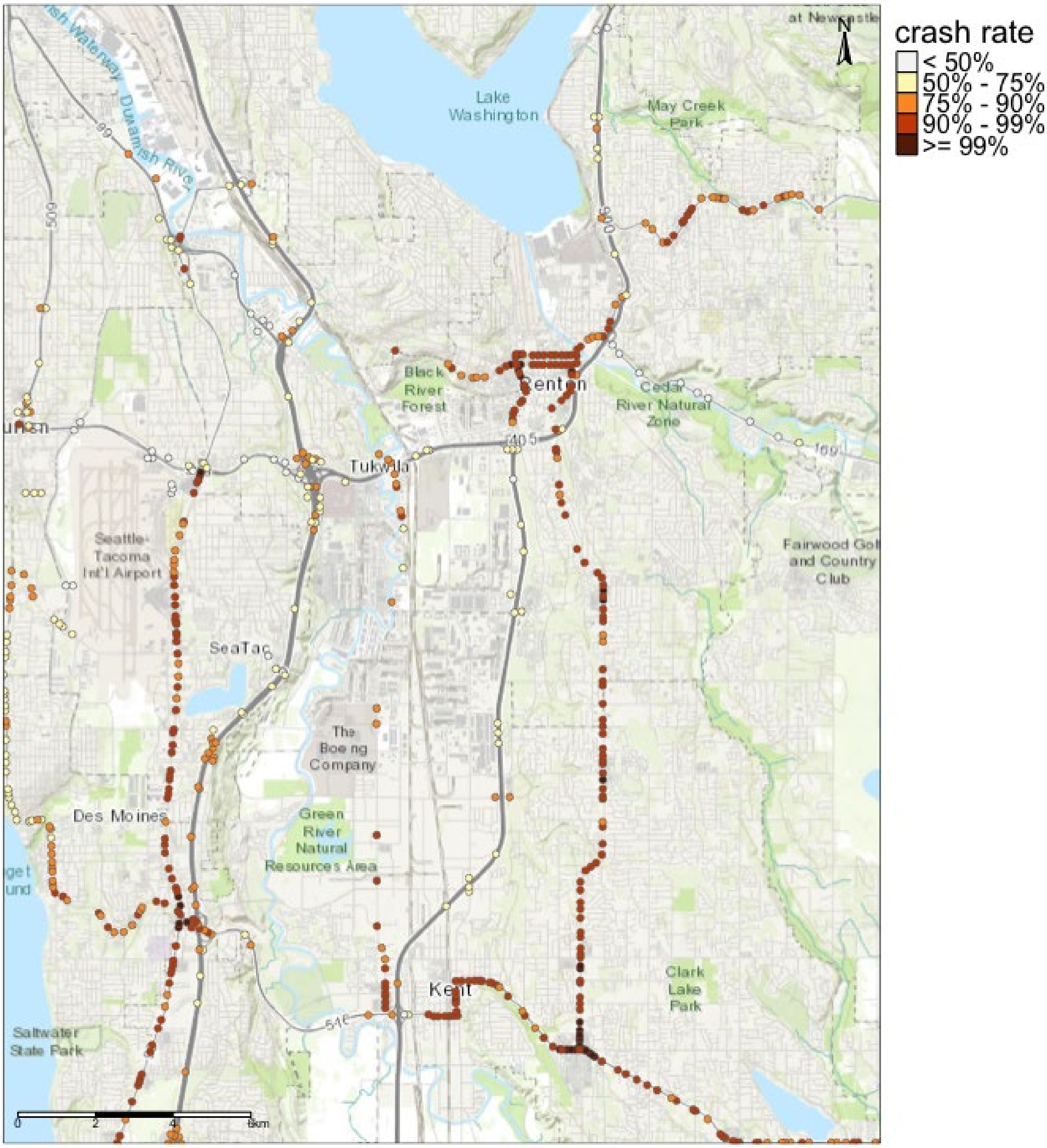


Figure C-3. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state routes in Renton and Kent

Everett

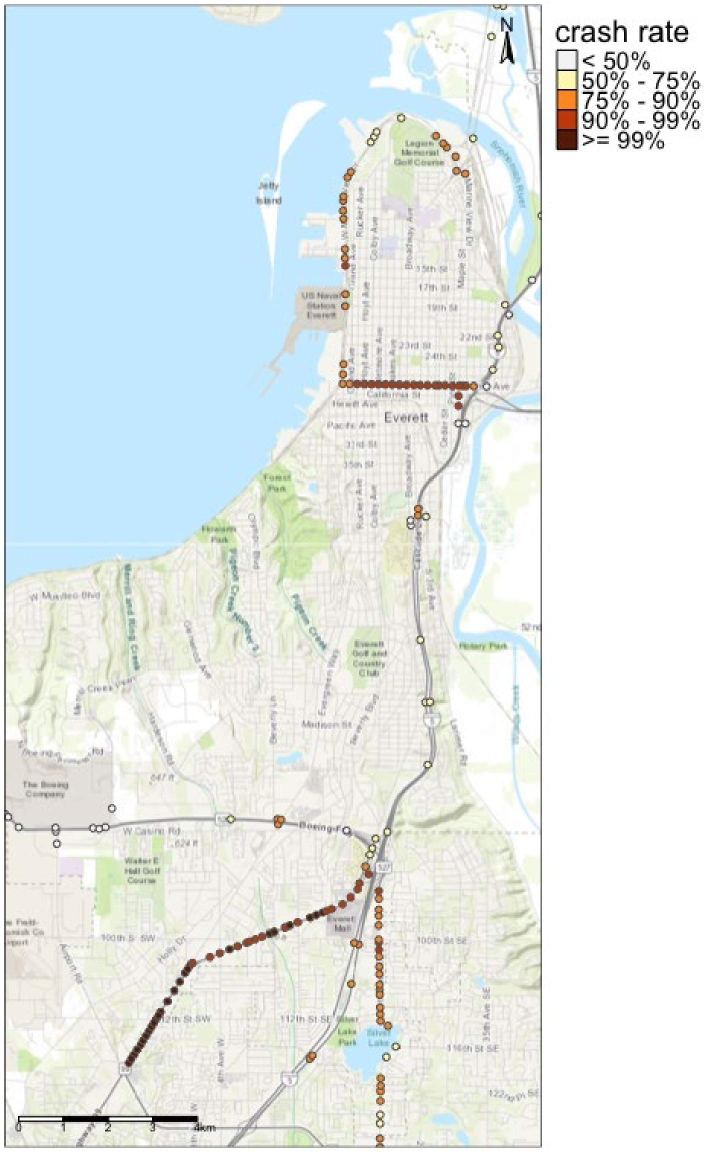


Figure C-4. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state route in Everett

Bellingham

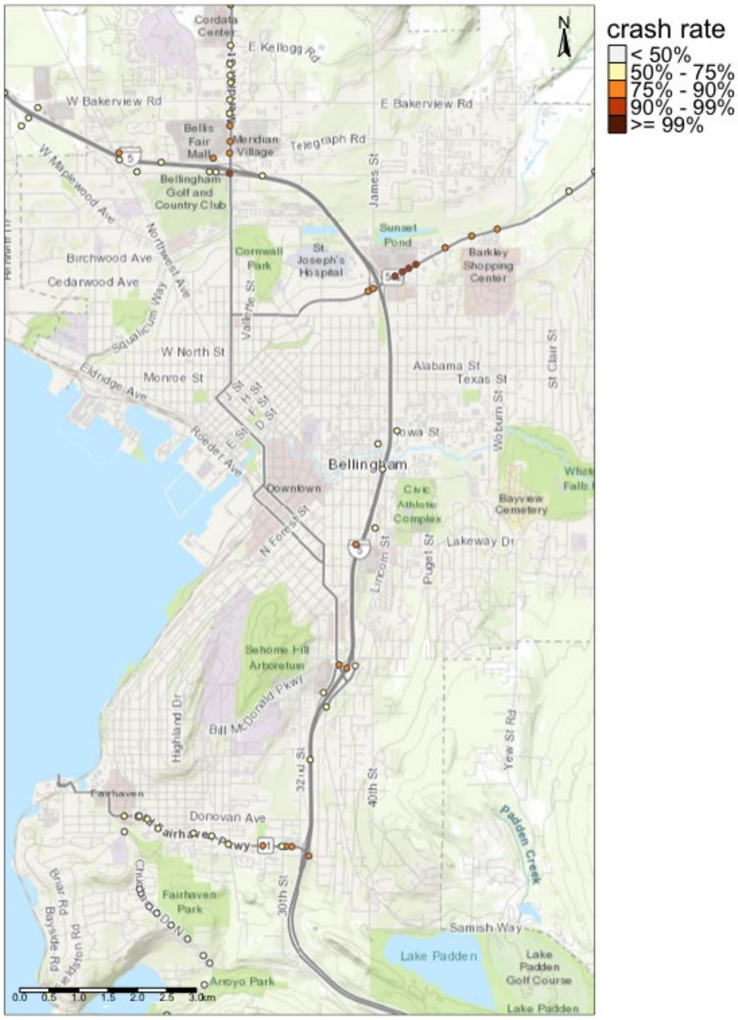


Figure C-5. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state route in Bellingham

Clark County

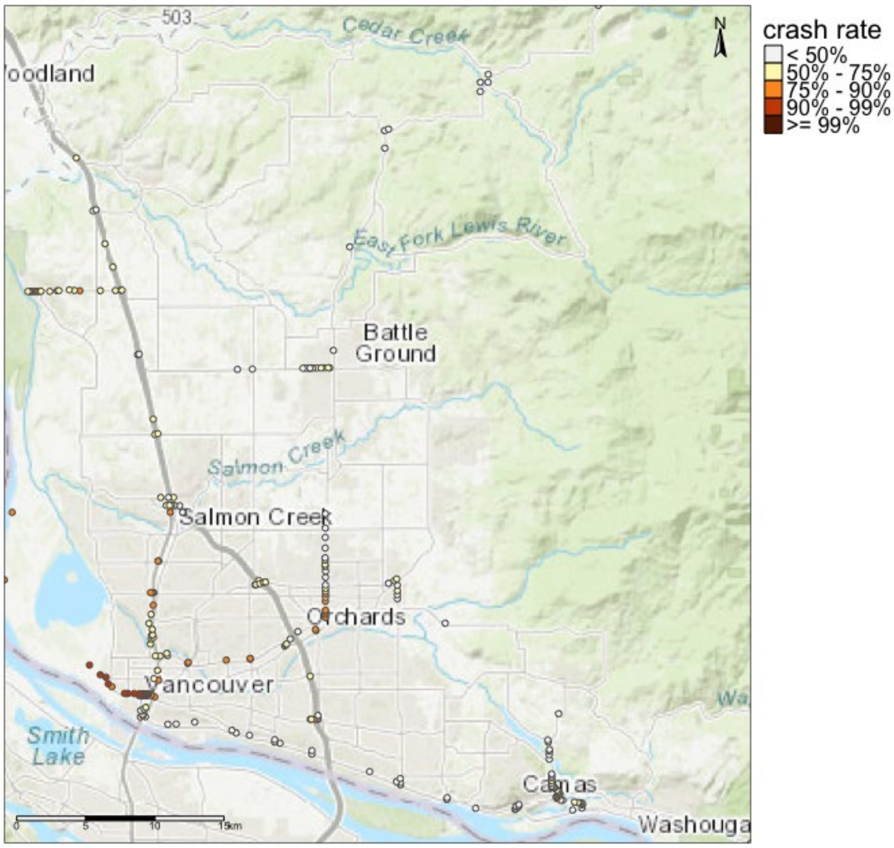


Figure C-6. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state route in Clark County

Spokane County

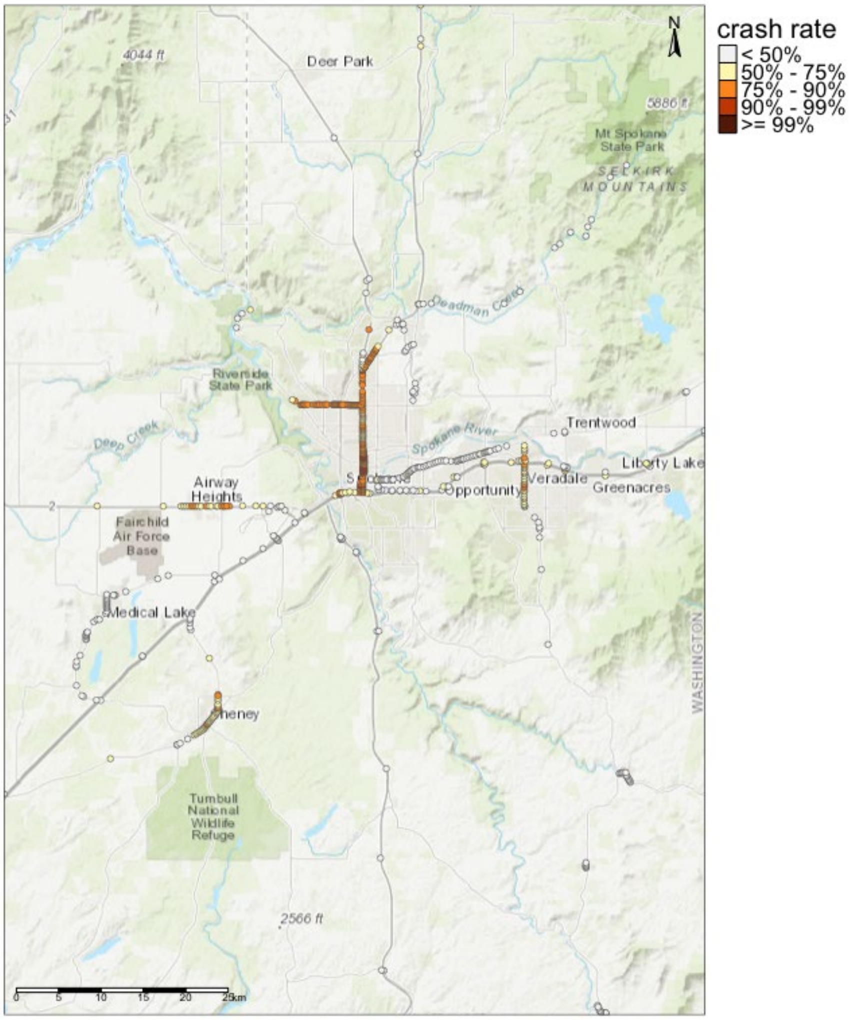


Figure C-7. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state route in Spokane County

Kitsap County

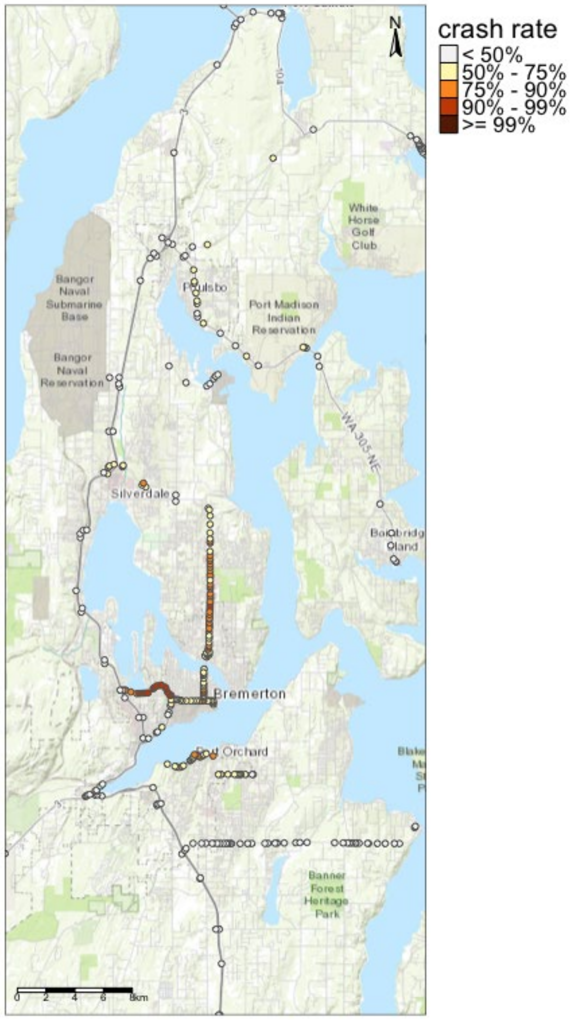


Figure C-8. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state route in Kitsap County

Yakima and Kittitas County

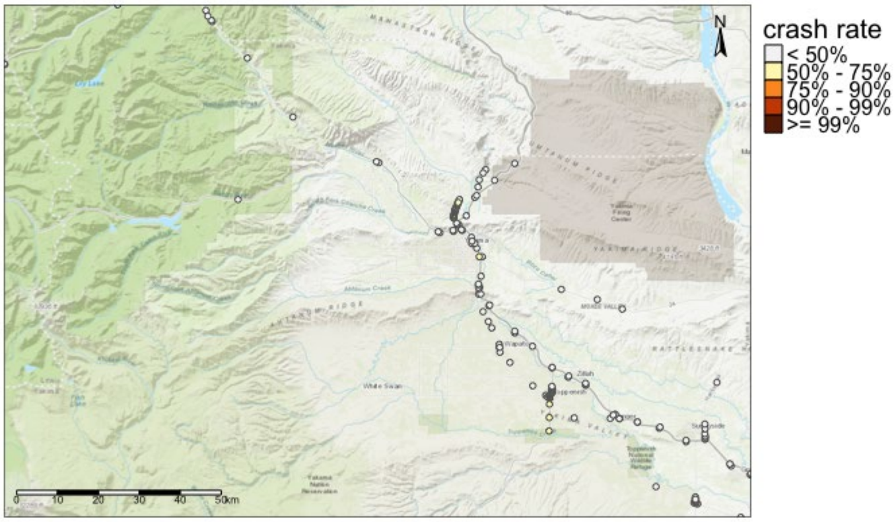


Figure C-9. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state route in Yakima

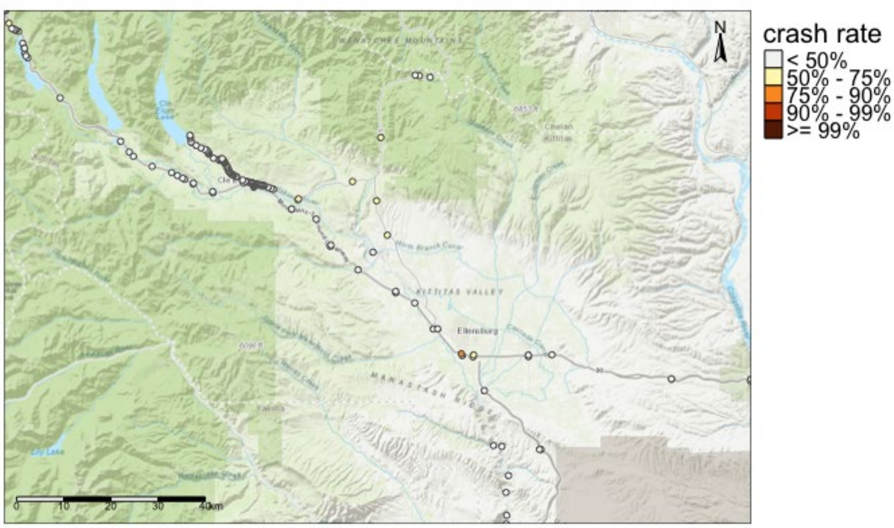


Figure C-10. Map of expected crash frequencies per 100-meter Euclidean buffer of pedestrian-vehicle crashes at intersection and non-intersection locations along the state route in Kittitas County

APPENDIX D – DATA PROCESSING STEPS FOR THE SEVERITY MODELS

<PEDESTRIAN ACTIONS>

Pedestrian actions were categorized into seven groups, including All Other Actions, Walking in Roadway (with Traffic or Opposite Traffic), Xing - Non Intersection - No X Walk, Xing at Intersection with Signal, Xing at Intersection - No Signal, At Intersection Not Using Crosswalk, and Xing at Intersection Against Signal or Diagonally. More detailed categories are shown below.

Detailed pedestrian actions	**Recategorized group**
Xing at Intersection with Signal	Xing at Intersection with Signal
Xing - Non Intersection - No X Walk	Xing - Non Intersection - No X Walk
All Other Actions	All Other Actions
Xing at Intersection - No Signal	Xing at Intersection - No Signal
Xing at Intersection Against Signal	Xing at Intersection Against Signal or Diagonally
At Intersection Not Using Crosswalk	At Intersection Not Using Crosswalk
Not in Roadway	All Other Actions
Walking in Roadway with Traffic	Walking in Roadway
Standing or Working in Roadway	All Other Actions
Walking on Roadway Shoulder with Traffic	All Other Actions
Walking in Roadway Opposite Traffic	Walking in Roadway
Xing - Non Intersection - In X Walk	Xing - Non Intersection - In X Walk
Walking on Roadway Shoulder Opposite Traffic	All Other Actions
Pushing or Working on Vehicle	All Other Actions
Fell or Pushed Into Path of Vehicle	All Other Actions
From Behind Parked Vehicle	All Other Actions
Xing at Intersection - Diagonally	Xing at Intersection Against Signal or Diagonally
Lying in Roadway	All Other Actions
Playing in Roadway	All Other Actions

<PEDESTRIAN CONTRIBUTING CIRCUMSTANCE>

Pedestrian contributing circumstances were categorized into seven groups, including None/Blank, Inattention, Did Not Grant RW to Vehicle, Under Influence of Alcohol, Failure to Use Xwalk, Other Unknown, and Other Known. More detailed categories are shown below.

- If the driver contributing circumstance was shown to be a pedestrian contributing circumstance in the data, then the None/Blank category was assigned because the pedestrian contributing circumstance was not known.
- If the data showed Other, then the Other Unknown category was assigned because the pedestrian contributing circumstance was an unknown category.
- If the data were aggregated although the circumstance was known, then the Other Known category was assigned to distinguish the category from Other Unknown.

Detailed pedestrian contributing circumstance	**Recategorized group**
None	None/Blank
Other	Other Unknown
Did Not Grant RW to Vehicle	Did Not Grant RW to Vehicle
Inattention	Inattention
Under Influence of Alcohol	Under Influence of Alcohol
Failure to Use Xwalk	Failure to Use Xwalk
Blank	None/Blank
Disregard Stop and Go Light	Other Known
Driver Not Distracted	None/Blank
Unknown Driver Distraction	None/Blank
Fail to Yield Row to Pedestrian	None/Blank
Improper Turn	Other Known
Disregard Stop Sign - Flashing Red	Other Known
Disregard Yield Sign - Flashing Yellow	Other Known
Driver Distractions Outside Vehicle	None/Blank

Driver Operating Other Electronic Device	None/Blank
On Wrong Side Of Road	Other Known
Operating Defective Equipment	Other Known
Under Influence of Drugs	Other Known

<DRIVER'S ACTION>

Driver's action: Pedestrian actions were categorized into four groups, including All Other Actions, Going Straight Ahead, Making Right Turn, and Making Left Turn. More detailed categories are shown below.

Detailed driver actions	**Recategorized group**
Going Straight Ahead	Going Straight Ahead
Making Right Turn	Making Right Turn
Making Left Turn	Making Left Turn
Starting in Traffic Lane	All Other Actions
Other*	All Other Actions
Merging (Entering Traffic)	All Other Actions
Changing Lanes	All Other Actions
Slowing	All Other Actions
Backing	All Other Actions
Starting From Parked Position	All Other Actions
Stopped for Traffic	All Other Actions
Stopped in Roadway	All Other Actions
Illegally Parked, Unoccupied	All Other Actions
Overtaking and Passing	All Other Actions

<DRIVER CONTRIBUTING CIRCUMSTANCE >

Driver contributing circumstances were categorized into eight groups, including None/Blank, Fail to Yield Row to Pedestrian, Inattention, Driver Distraction, Under Influence of Alcohol, Exceeding Reas. Safe Speed, Other Unknown, and Other Known. More detailed categories are shown below.

- If the data showed Other, then the Other Unknown category was assigned because the pedestrian contributing circumstance was an unknown category.

- If the data were aggregated although the circumstance was known, then the Other Known category was assigned to distinguish the category from Other Unknown.

Detailed driver contributing circumstance	**Recategorized group**
None	None/Blank
Fail to Yield Row to Pedestrian	Fail to Yield Row to Pedestrian
Inattention	Inattention
Other	Other Unknown
Unknown Driver Distraction	Driver Distraction
Driver Not Distracted	Other Known
Under Influence of Alcohol	Under Influence of Alcohol
Did Not Grant RW to Vehicle	Other Known
Blank	None/Blank
Disregard Stop and Go Light	Other Known
Exceeding Reas. Safe Speed	Exceeding Reas. Safe Speed
Improper Turn	Other Known
Driver Distractions Outside Vehicle	Driver Distraction
Apparently Asleep	Other Known
Disreguard Flagger - Officer	Other Known
Improper Backing	Other Known
Operating Defective Equipment	Other Known
Apparently Fatigued	Other Known
Disregard Stop Sign - Flashing Red	Other Known
Disregard Yield Sign - Flashing Yellow	Other Known
Driver Interacting with Passengers, Anim	Other Known

Follow Too Closely	Other Known
Improper Parking Location	Other Known
Improper Passing	Other Known
Under Influence of Drugs	Other Known

<CONTINUOUS VARIABLES>

- Total width of lanes: The total widths of all lanes were obtained from WSDOT's GIS data on roadway lanes. The width in each increasing and decreasing direction was summed up as the total width of lanes. For example, if there was a 12-ft-wide lane road in the northbound (increasing milepost numbers) and southbound (decreasing milepost numbers) directions, the total width of lanes was 24 ft.
- The maximum posted speeds for both increasing and decreasing directions were compared to get the maximum posted speed in either direction.
- Bus ridership density: This represented the number of daily average boardings and alightings per square km calculated from SmartMaps that were generated by the University of Washington Urban Form Lab (Hurvitz and Moudon, 2012).
- Employment densities: Similar to bus ridership density, these densities were obtained from SmartMaps and represented jobs per square km.
- Total population and racial population (Caucasian) were obtained by using census block information, and the household income was retrieved from census block-group information.
- Residential, industrial, commercial and park areas represented the percentage of a total subject area within the circular area with a 400-m radius. For example, a total of 40,212 m^2 residential areas present in circular area with a 400m radius (502,655 m^2) would give a value of 8 percent.
- Lengths of sidewalks and trails were calculated by adding the lengths within the buffer area.

Reference: Hurvitz, Philip M., and Anne Vernez Moudon. 2012. "Home Versus Nonhome Neighborhood." American Journal of Preventive Medicine 42(4): 411–17.