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A Safe System Approach to Pedestrian High Injury Network Development in Oakland, California

Author
Chen, Angie

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A Safe System Approach to Pedestrian High Injury Network Development in Oakland, California

Author Angie Chen, University of California, Berkeley

Advisor Daniel A. Rodriguez, University of California, Berkeley

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16. Abstract

As jurisdictions update their High Injury Networks, discrepancies between the initial and updated HINs are to be expected. However, this lack of stability and consistency can negatively impact the prioritization of limited resources. In order to mitigate known issues with crash data underreporting and statistical biases, I examined strategies for utilizing data on underlying roadway characteristics to augment traditional collision analysis.

Using the City of Oakland as a case study city, I assessed the stability of the pedestrian High Injury Network across two consecutive five-year periods (2012-2016 and 2017-2021), created with the same methodology. I found that the two HINs identified similar segments, particularly along arterials, but were less consistent in identifying the segments' start and end points due to variation in crash data. I propose a methodology for finalizing High Injury Network extents based on segment characteristics (number of lanes, posted speed limit, and functional classification), and intersection characteristics (traffic signal presence and estimated pedestrian volumes). Applied to the Oakland case study, this approach results in a High Injury Network that is more stable over time, more focused (fewer street miles), and captures a higher percentage of fatal and severe crashes. This approach has the potential to smooth over inconsistencies in crash reporting, reduce the frequency of network updates needed, and shift High Injury Networks from being reactive to more proactive.

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The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* The program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

US Department of Transportation Disclaimer

Disclosure

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A Safe System Approach to Pedestrian High Injury Network Development in Oakland, California

Angie Chen

University of California, Berkeley

Department of City and Regional Planning

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Abstract

High Injury Networks (HINs) are a relatively new method of analyzing collision data, first used in 2013 and becoming more widespread in the years following. An HIN identifies the corridors in a municipality's street network that have the highest concentration of traffic collisions, particularly those that result in fatal or serious injuries. Many jurisdictions are preparing to update their HINs for the first time since the initial adoption. Since collision data varies from year to year, discrepancies between the initial and updated HINs are to be expected. However, this lack of stability and consistency can negatively impact the prioritization of limited resources. I argue that agencies should not solely rely on collision data, which has known issues with underreporting and statistical biases, to create their HINs. A Safe System Approach is one promising strategy to improve road safety, comprised of five key principles: deaths and serious injuries are unacceptable, humans make mistakes, humans are vulnerable, responsibility is shared, safety is proactive, and redundancy is crucial. However, there is limited research on how the concepts of a Safe System Approach can be applied to the HIN development process.

In this project, I use traditional collision data to identify an HIN and assess the HIN similarity over time. I then examine strategies for utilizing data on underlying roadway characteristics to augment traditional collision analysis and follow a Safe System Approach to HIN development. Specifically, using the City of Oakland as a case study city, I assess the stability of the pedestrian HIN across two consecutive five-year periods (2012-2016 and 2017-2021), created with the same methodology. I find that the two HINs identify similar segments, particularly along arterials, but are less consistent in identifying the segments' start and end points due to variation in crash data. As a result, I propose a methodology for finalizing HIN extents based on segment characteristics (number of lanes, posted speed limit, and functional classification), and intersection characteristics (traffic signal presence and estimated pedestrian volumes). Applied to the Oakland case study, this approach results in an HIN that is more stable over time, more focused (fewer street miles), and captures a higher percentage of fatal and serious injury crashes. This approach has the potential to smooth over inconsistencies in crash reporting, reduce the frequency of network updates needed, and shift HINs from being reactive

to more proactive. In addition to presenting this proposed methodology, I make additional recommendations for agencies updating and utilizing HINs.

Introduction

Current Approach to Road Safety in the United States

Traffic crashes and fatalities in the U.S. have increased over time despite technological improvements in vehicle safety.[i] Approximately 41,000 people in the U.S. died in a motor vehicle collision in 2023. In the last decade, crash fatalities steadily climbed from about 33,000 in 2013 and peaked at over 43,000 deaths in 2021.[ii] This trend disproportionately affects vulnerable road users, with pedestrian deaths increasing faster than all other traffic fatalities. Pedestrian fatalities reached a 41-year high in 2022, increasing by 19 percent in just three years and 77 percent since 2010.[iii] Faced with these challenges, road safety is a more salient issue than ever for the transportation planning field.

The U.S. Department of Transportation Federal Highway Administration endorses a Safe System Approach to address roadway safety. The Safe System Approach includes the following principles: deaths and serious injuries are unacceptable, humans make mistakes, humans are vulnerable, responsibility is shared, safety is proactive, and redundancy is crucial.[iv] Under this framework, transportation infrastructure, safety regulations, and emergency response protocols can work together in a way that prevents crashes from happening in the first place, and when they do, ensures that they do not result in a serious injury or fatality. The fifth principle of the Safe System Approach, "safety is proactive," emphasizes that transportation planning agencies must "identify and address safety issues in the transportation system, rather than waiting for crashes to occur and reacting afterwards."[v]

Along with the Safe System Approach, Vision Zero has been gaining popularity in cities across the world as a strategy to achieve zero traffic fatalities and serious injuries. The Vision Zero Network, a U.S.-based nonprofit focused on advancing Vision Zero in American cities, recommends that "all Vision Zero cities research and adopt a High Injury Network, and focus resources on the corridors identified."[vi] High Injury Networks (HINs) are an increasingly common tool for analyzing collision data on a citywide or larger scale. An HIN identifies the corridors in a municipality's street network that have the highest concentration of traffic collisions, particularly those that result in fatal or serious injuries. To create an HIN, collision data, typically over a timeframe of several years, is mapped onto a street network to identify the segments with the most collisions. There is a wide range of methodologies used to create HINs, which may differ in segment length, normalization methodology, weight assignments for collision severity or disadvantaged populations, mode-specific versus combined HINs, and thresholds for determining whether a segment is included in the HIN. Through developing an HIN, a jurisdiction can confirm the existing conditions and begin to understand how to address corridors where a disproportionate number of collisions occur. The process can also help create consensus among key stakeholders and serve as an avenue for communicating with the public about road safety.

A Safe System Approach in HIN Development

In the context of the Safe System Approach, several potential issues arise with the use of HINs. While HINs are an important tool to help jurisdictions understand the conditions on the street, their reliance on past collision data results in a reactive, not proactive analysis. Despite this, HINs are increasingly being used as a long-term planning tool. For example, the Metropolitan Transportation Commission prioritizes HIN projects for One Bay Area (OBAG) funding, which has impacts on major capital funding allocations.[vii] Although there is a place for reactive transportation planning, such as rapid response protocols and quick-build implementation following a fatal or serious injury collision, long-term planning presents an opportunity to utilize a more comprehensive approach. The Vision Zero Network recommends a combination of proactive, systemic planning to "mitigate potential crashes and crash severity," and responsive, hot spot planning.[viii] Furthermore, the HIN process does not always result in a network of long, connected segments, which would be ideal for capital improvement projects. Depending on the nature of the road network and collision data, a jurisdiction's HIN may look more like a patchwork of disconnected segments.

HINs cannot predict future crashes, so interventions that utilize an HIN analysis may not prevent future crashes. The fact that a collision happened in the past is, alone, not an indicator that a collision may happen again in the future. Some jurisdictions have begun to build predictive collision models, which require more advanced inputs than just collision data, including land use, traffic volumes, and roadway characteristics. Despite the lack of predictive power, HINs are often used as the primary safety analysis tool for prioritizing resources and funding. Moreover, cities are constantly changing, and retrospectively analyzing crash data over the course of the past five years may not account for changes in transportation infrastructure and land use that influence present-day and future collision risk.

The question of how appropriate HINs are as a primary determinant of funding allocation is timely because several jurisdictions in the San Francisco Bay Area are slated to update their HINs over the next few years, including the City of Oakland, the City of Berkeley, the City and County of San Francisco, and Alameda County. There is also an effort underway to establish statewide guidance for HINs, which could standardize methodology across California jurisdictions.[ix]

Background

Biases in Collision Data

Crash data is incomplete, with approximately 30 percent of all crashes and 10 percent of injury crashes going unreported.[x] Bicyclist-involved collisions are the most likely to go unreported of all modes.[xi] The City and County of San Francisco's work linking hospital and police traffic injury and fatality records found that over 5,800 crashes, or about a third of total crashes, were absent from the police data. The linkage revealed that injuries of bicyclists, Black and Hispanic patients, and male patients were under-reported in police data compared to hospital data.[xii] Furthermore, collision data commonly suffers from statistical issues such as over-dispersion, under-dispersion, small sample size, time interval variations, temporal and spatial autocorrelations, omitted variables bias, and non-linear relationships bias.[xiii] Small sample sizes may be a particular concern in smaller cities or when developing mode-specific HINs for bicycle and pedestrian collisions, which make up a small percentage of total mode share and collisions. However, including more years of collision data to mitigate small sample sizes can also pose issues, as older data may not accurately represent current travel patterns or safety conditions. Crash factor data on behaviors that are difficult to observe and factors involving emerging technologies are also under-reported, making it difficult to understand critical crash factors such as distracted or fatigued driving, drug and alcohol influence, and driver speed.[xiv]

HINs are not representative of risk or exposure because they represent crash frequencies, rather than adjusting for traffic volumes to represent crash risk rates. This leads to an intrinsic bias towards streets with higher traffic volumes across modes.[xv] As a result, they do not necessarily reveal how dangerous the roadway conditions are, particularly for vulnerable road users. Since safety infrastructure such as bike lanes and wider sidewalks are associated with higher active transportation mode shares,[xvi] locations that have an extremely high crash risk may not be reflected in crash data if few people are walking or biking there. When exposure rates are accounted for by adjusting for miles traveled, Black and Hispanic road users experience more traffic fatalities per mile traveled than Whites, and this disparity worsens for Black and Hispanic bicyclists and pedestrians.[xvii]

Relationship between the Built Environment and Pedestrian Collisions

Roadway characteristics such as traffic signals, marked crosswalks, intersection density, and wider right-of-way are associated with increased pedestrian collision rates at intersections and midblock locations, whereas one-way streets are associated with lower collision rates.[xviii] Urban arterials,[xix] principal and minor arterials,[xx] wide right shoulders,[xxi] number of turn lanes,[xxii] driveways,[xxiii] and undivided roads[xxiv] are associated with increased collision severity. Traffic volumes and pedestrian crossing volumes are correlated with decreased pedestrian safety.[xxv] In turn, pedestrian volumes are positively correlated with the posted speed limit, number of bus stops, sidewalk width, and land use.[xxvi] Higher speeds are associated with higher collision rates due to reduced reaction and braking times, as well as more serious collisions due to the transfer of more kinetic energy.[xxvii] Speed also greatly influences pedestrian fatality rates — pedestrians struck by a driver driving at 24.1 miles per hour have a 90 percent chance of survival, but that likelihood decreases to 50 percent at 40.6 miles per hour and 25 percent at 48 miles per hour.[xxviii]

Land use also impacts collision rates and risk. Commercial areas are associated with higher pedestrian crash risk,[xxix] and a higher land use mix increases collision rates due to increased pedestrian volumes[xxx] but reduces collision severity[xxxi] due to reduced speeds.[xxxii] Intersections with higher bus ridership and employment, residential, and population densities have increased collision rates due to increased pedestrian activity, whereas intersections with higher surrounding residential property values have lower collision rates.[xxxiii]

Most of the literature associating built environment characteristics with collision rates utilizes data at the intersection level. However, traffic safety projects in transportation planning are typically delivered on a corridor level, with the exception of some quick-build programs. This creates a potential gap between literature and practice, where corridor-level analyses like HINs do not incorporate existing literature about the impact of the built environment. There is little research that incorporates HINs, perhaps because HINs are a relatively new method of analysis. The only paper that does so to my knowledge compares a nationwide tract-level analysis of pedestrian fatality risk based on traffic volumes, land use, intersection density, road classification, employment density, and other factors to the City of Los Angeles' HIN. It finds that 43% of pedestrian fatalities are identified by both models, 19% are identified by the tract model but not the HIN, 23% are identified by the HIN but not the tract model, and 15% are not identified by either method.[xxxiv] This result shows potential for built environment data to augment a traditional HIN approach for a more comprehensive analysis of pedestrian risk.

Methodology

I investigate strategies for incorporating built environment characteristics into pedestrian HIN development and implementation using Oakland, California as a case study city. I focus on pedestrian HINs due to the availability of data relating to pedestrian crash factors and volumes. Using an approach based on the City's current HIN methodology, I create initial HINs for two subsequent five-year periods to understand how the HIN changes over time due to crash data variation and other factors. I then integrate information about roadway characteristics and pedestrian volumes into the methodology to test whether a proactive approach yields a more focused, stable HIN than a purely retrospective approach.

Creating the Initial High Injury Networks

I use geocoded pedestrian collision data from UC Berkeley SafeTREC's Transportation Injury Mapping System (TIMS), which pulls records from the California Statewide Integrated Traffic Records System (SWITRS). SWITRS data complies collision reports from local law enforcement agencies submitted to the California Highway Patrol (note that Caltrans publishes independent collision reports for state highways only, which utilize SWITRS in addition to several other data reporting systems). The SWITRS data comprises of pedestrian-involved crashes from two five-year time periods, 2012-2016 and 2017-

2021, excluding property damage only crashes and freeway crashes. In order to recreate the City of Oakland's current pedestrian HIN as closely as possible, I adhere to the City's methodology for crash exclusion, crash weighting, segment length, and HIN coverage (as a percentage of total street miles). I complete the analysis in ArcGIS Pro.

I start with a shapefile of the City of Oakland's street network and use a definition query on the functional classification field to remove freeways from the analysis. I utilize the sliding window methodology recommended by the Federal Highway Administration to smooth out errors in the crash location reporting and geocoding process.[xxxv] Following a workflow published by the Texas A&M Transportation Institute, I create overlapping street segments by generating points along the street network 0.1 miles apart, then assigning each of those points an ID number of 1-5 and creating separate feature classes for each ID group.[xxxvi] I split the street network into segments using each of the five feature classes and merge the results into one dataset, resulting in overlapping street segments approximately 0.5 miles long with offsets of 0.1 miles.

After creating the street segments, I assign pedestrian crashes to the segment layer by creating a buffer of 50 feet around each segment. This allows me to capture crashes that have a latitude and longitude slightly offset from the street network. I segment the crash data by time period (2012-2016 and 2017-2021) and collision severity (Killed/Serious Injury and non-KSI). I then assign a weight of 3x to the KSI collisions and a weight of 1x to the non-KSI collisions, adhering to the City of Oakland methodology, and calculate a weighted collision total for each five-year time period. To decide whether a segment should be included on the HIN, I use a threshold of 10 weighted collisions, which results in a pedestrian HIN of approximately 48 miles or 4% of the City of Oakland's total street miles, consistent with the coverage of the City's adopted 2018 pedestrian HIN. The resulting 2016 (Figure 1) and 2021 (Figure 2) pedestrian HINs are displayed below. I discuss similarities and discrepancies between the two initial HINs in the results section. In the recommendations section, I then test my proposed methodology for incorporating roadway characteristics on the 2021 initial HIN, creating a final proposed 2021 HIN.

Figure 1: 2012-2016 Initial Pedestrian High Injury Network

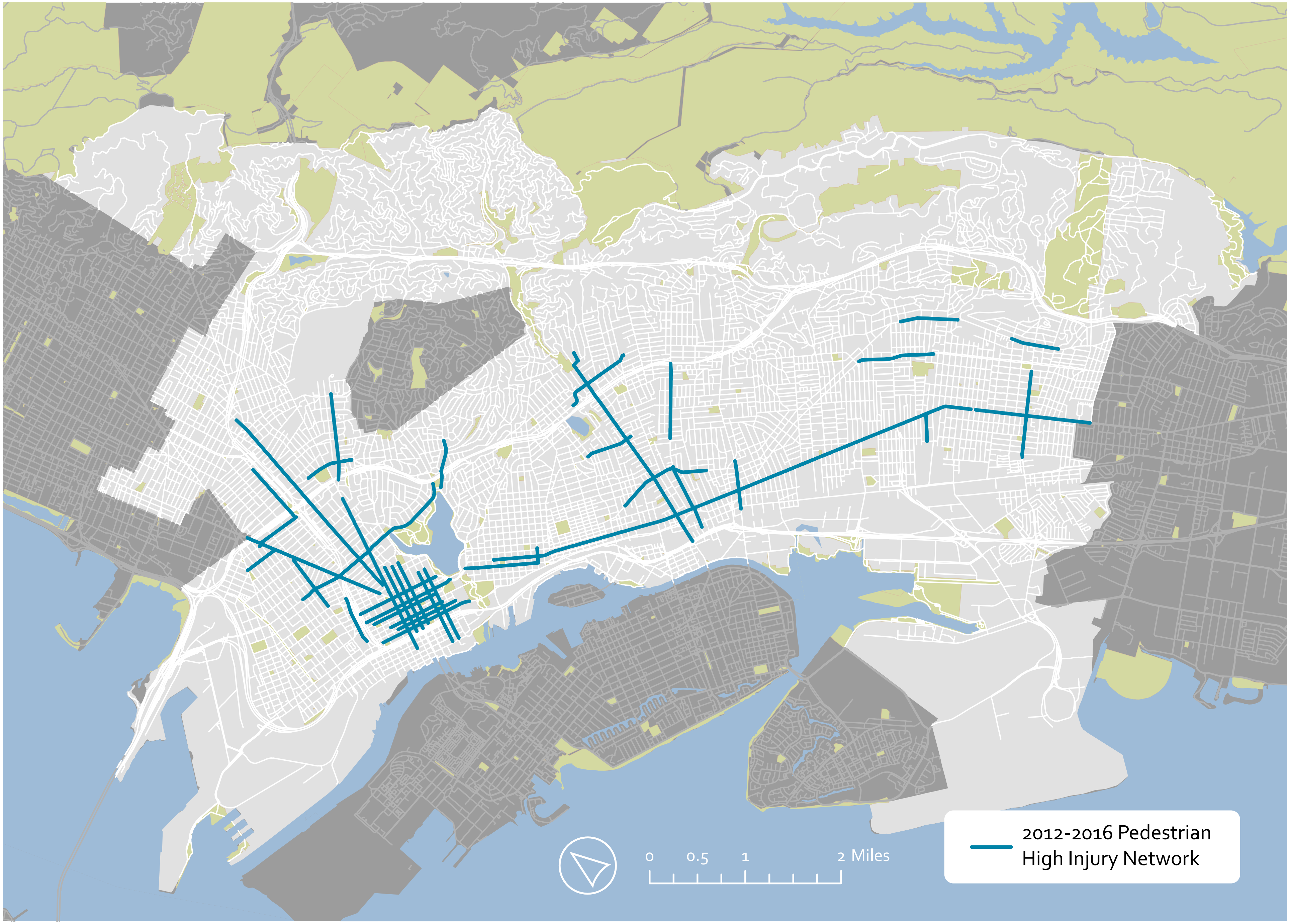
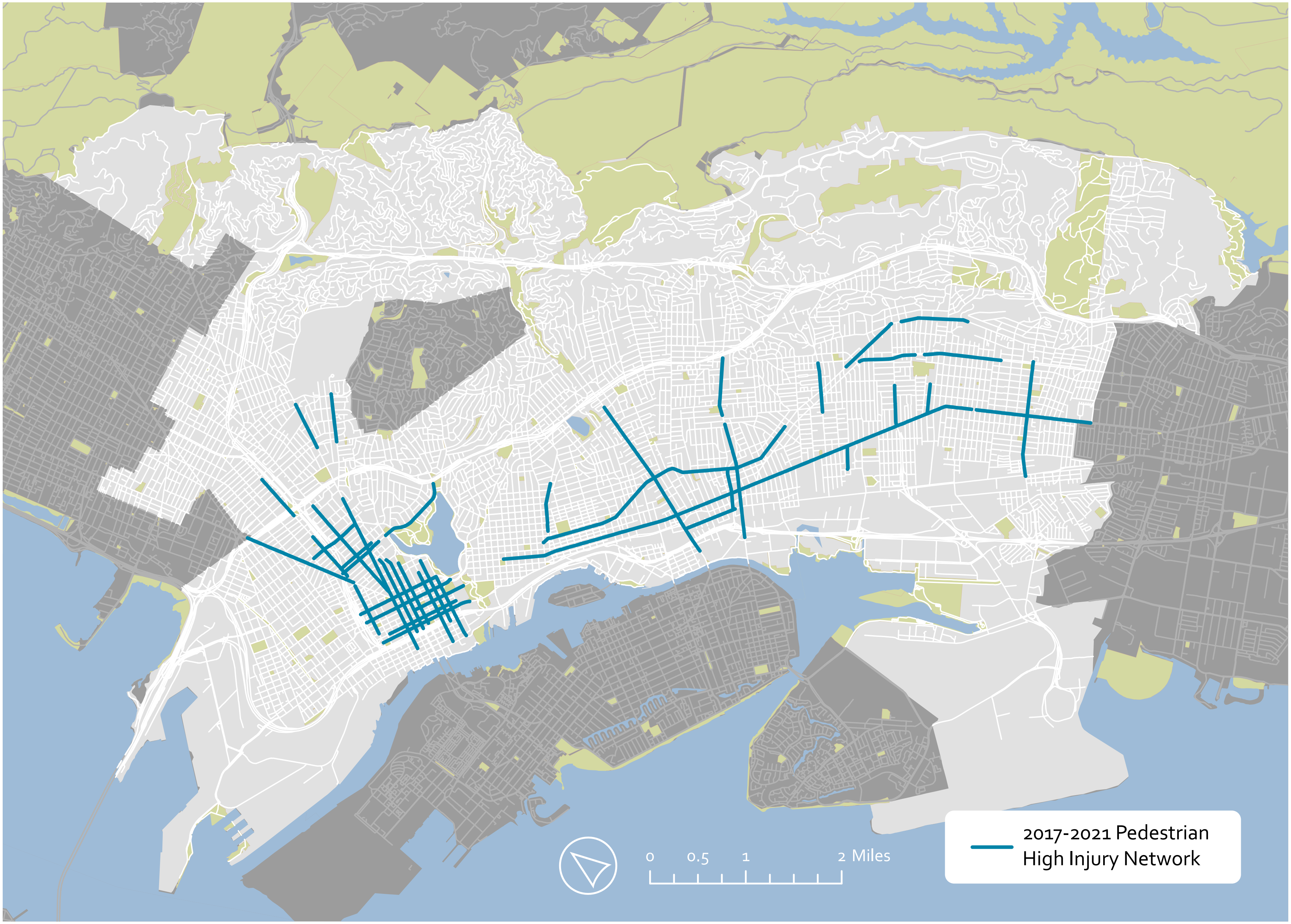


Figure 2: 2017-2021 Initial Pedestrian High Injury Network



Gathering Data on Built Environment Characteristics and Pedestrian Volumes

I employ the following built environment data based on the literature and available data: posted speed limit, functional classification, number of lanes, and number of traffic signals. The first four characteristics are included in the City of Oakland's street network layer, whereas the traffic signal data is a separate point feature layer. I spatially join all five datasets to the sliding window segment layer created previously. I then dissolve the street network layer by street name, posted speed limit, functional classification, and total number of lanes. This merges segments into longer corridors with the same characteristics, allowing for a comparison between the HIN extents and the roadway characteristics that have previously-studied effects on collision risk.

Existing literature shows that pedestrian volumes and proxies for pedestrian volumes are strongly correlated with increased collision frequency. Identifying the corridors where pedestrian activity is high, and overlaying this information with roadway characteristics, can augment historical collision data with a systemic analysis. In order to estimate pedestrian volumes, I employ a model created by Schneider et. al, which was based on a sample of 50 intersections in Alameda County.[xxxvii] The model uses the inputs detailed in Table 1 to estimate intersection-level weekly pedestrian crossings. For my analysis, I use up-to-date versions of the same data sources as the original model and use the coefficients estimated by the model to predict expected pedestrian crossing volumes at each intersection.

Table 1: Inputs for Pedestrian Crossing Volume Model

Data	Source	Level of Aggregation
Total population within 0.5-miles of the intersection	U.S. Census 2022 5-Year ACS estimates	Census tract
Total employment within 0.25-miles of the intersection	Metropolitan Transportation Commission employment projections, 2025	Census tract
Number of commercial retail properties within 0.25-miles of the intersection	Alameda County Assessor's Office parcel data	Parcel
Number of regional rail transit stations within 0.10-miles of the intersection	Metropolitan Transportation Commission regional rail station layer	Point

The regression equation from the Schneider et. al (adjusted R2 = .897) is:

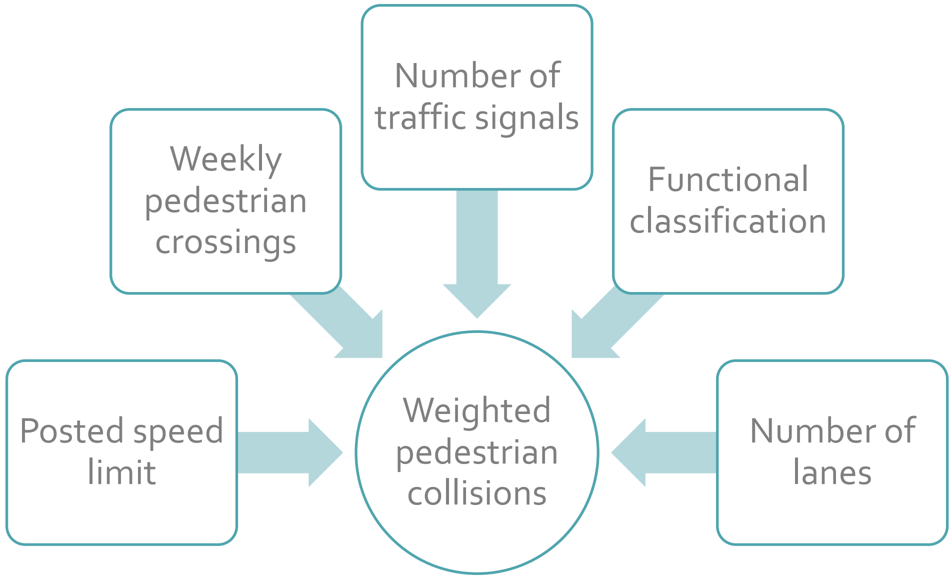
Total pedestrian intersection crossings per week =
*0.928 * Total population within 0.5-miles of the intersection*
*+ 2.19 * Total employment within 0.25-miles of the intersection*
*+ 98.4 * Number of commercial retail properties within 0.25-miles of the intersection*
*+ 54,600 * Number of regional transit stations within 0.1-miles of the intersection*
- 4910

I use a point feature layer of City of Oakland intersections and create 0.1, 0.25, and 0.5 mile buffers around each intersection to summarize the population, employment, retail, and transit data within the respective buffers. After joining each buffer layer back to the original point feature layer, I calculate the estimated weekly pedestrian crossings for each intersection. I then join the intersection-level data to the sliding window segment layer, resulting in estimated pedestrian crossings for each segment.

Next, I run an Ordinary Least Squares regression with the variables detailed in Figure 3. I create two dummy variables for arterials and collectors to test the influence of functional classification. I also create a dummy variable for streets with 3 to 6 travel lanes. This threshold is hypothesized to be associated with a higher rate of pedestrian crashes, and the upper threshold of 6 lanes is used to exclude limited access roads that typically see minimal pedestrian volumes. I do not test factors influencing pedestrian activity levels, such as proximity to bus stops or land use characteristics, that were tested for statistical significance and excluded from the Schneider pedestrian volume model.

I use the regression in two ways: to confirm assumptions derived from existing literature about the impacts of roadway characteristics and pedestrian volumes on collision rates in an Oakland-specific context, and to generate an HIN based on point-based predicted crashes.

Figure 3: Hypothesized Explanatory Variables Associated with Pedestrian Collisions



Results

Comparing the 2016 and 2021 Initial High Injury Networks

The 2016 and 2021 initial HINs are both approximately 48 miles long, covering 4% of Oakland's street network. The two HINs have some overlap and some significant differences (Figure 4). 74% of the 2016 HIN is included in the 2021 HIN, and 74% of the 2021 HIN is included in the 2016 HIN.

The 2016 HIN captures 58% of fatal and serious injury crashes from 2012-2016 and the 2021 HIN captures 57% of fatal and serious injury crashes from 2017-2021 (Table 2). However, the 2016 HIN does not perform as well in predicting crashes that happened in the subsequent five years, capturing 48% of fatal and serious injury crashes from 2017-2021.

The differences between the HINs can be grouped into the following categories:

1. **Extension or subtraction** on the edges of a segment included in the comparison HIN
2. **Addition of a noncontiguous segment** that is on the same corridor as a segment included in the comparison HIN
3. **Addition of a new corridor** that is entirely excluded from the comparison HIN

Table 2: Descriptive Statistics for 2016 and 2021 Initial High Injury Networks

	2016 HIN	2021 HIN	2016 and 2021 HINs Combined	Segments in Both 2016 and 2021 HINs
Length (Miles)	48.2	48.1	63.6	42.3
% of Oakland Street Network	4%	4%	5%	4%
% of 2012-2016 Crashes Captured	58%	46%	58%	40%
% of 2017-2021 Crashes Captured	48%	57%	59%	40%
% of 2012-2016 KSI Crashes Captured	58%	50%	63%	45%
% of 2017-2021 KSI Crashes Captured	48%	57%	61%	43%
% Arterial Streets	75%	77%	79%	79%

I find that even when both HINs identify a segment for inclusion, 76% or 19 of the 25 segments have discrepancies in start and end points (Table 3). In several cases, segments that only appear on one HIN have noncontiguous counterparts that appear on the other HIN. These results show that HINs across different time periods are relatively consistent in identifying corridors, particularly on arterials, but produce less replicable results when determining where an HIN segment should start and end. This is likely due to variations in the exact locations of crashes along a high-risk corridor from year to year. This finding is consistent with the City of Los Angeles' recent experience with updating their HIN. They saw that a "high number of bicycle and pedestrian collisions occurred at the edges of the existing HIN," and made the decision to extend 13 of the original HIN corridors to capture these new hotspots of collision activity.[xxxviii] Additional data, such as information about pedestrian volumes and roadway characteristics, may be a helpful augmentation of existing HIN methodology to improve accuracy of segment extents. If the extents of an HIN do not align with the safety conditions along the corridor, implementing interventions may result in unintended downstream effects, simply pushing collisions to another portion of the corridor.

While HINs should not be subject to the whims of crash randomness; they should evolve to some degree over time to reflect real changes in travel patterns and collision risk. Aside from crash data variation, there are several possible reasons for the discrepancies between the 2016 and 2021 initial HINs. Travel behavior changed dramatically in the 2017-2021 time period due to the COVID-19 pandemic, reducing commutes to downtowns and total vehicle miles traveled.[xxxix] However, San Francisco saw the same type of segment start and end discrepancies between their 2015 and 2017 HINs, which were not impacted by the pandemic.[xl] Variations could also be a result of infrastructure investments on HIN segments that improved safety outcomes, therefore justifying the removal of a segment from the HIN.

Table 3: Segments on Both 2016 and 2021 Initial High Injury Networks

Street	Start	End
12th Street	Castro Street	Lake Merritt Boulevard
14th Street	Lakeside Drive	I-980
7th Street	Martin Luther King Jr. Way	Fallon Street
8th Street*	Washington Street	Fallon Street
98th Avenue*	E Street	Sunnyside Street
Bancroft Avenue*	Havenscourt Boulevard	78th Avenue
Bancroft Avenue*	79th Avenue	80th Avenue
Broadway	Hawthorne Avenue	3rd Street
Foothill Boulevard*	25th Avenue	40th Avenue
Franklin Street*	6th Street	20th Street
Fruitvale Avenue*	Cordova Street	I-880
Harrison Street	6th Street	19th Street
High Street*	San Leandro Street	Ygnacio Avenue
International Boulevard*	88th Avenue	Durant Avenue
International Boulevard*	7th Avenue	87th Avenue
Jackson Street	Embarcadero West	15th Street
MacArthur Boulevard*	75th Avenue	84th Avenue
Madison Street*	5th Street	15th Street
Martin Luther King Jr. Way*	42nd Street	34th Street
Piedmont Avenue*	Monte Vista Avenue	Pleasant Valley Avenue
San Pablo Avenue*	20th Street	33rd Street
Telegraph Avenue*	34th Street	17th Street
W Grand Avenue*	I-980	Valdez Street
W Grand/Grand Avenue*	Harrison Street	I-580
Webster Street*	6th Street	19th Street

**=Discrepancy in the segment's start and/or end points between 2016 and 2021*

Table 4: Segments on Only the 2016 Initial High Injury Network

Street	Start	End
11th Street	Martin Luther King Jr. Way	Madison Street
12th Avenue	E 12th Street	E 15th Street
32nd Street	Peralta Street	San Pablo Avenue
34th Street	San Pablo Avenue	Martin Luther King Jr. Way
35th Avenue	San Leandro Street	Foothill Blvd
35th Avenue	Paxton Avenue	I-580
9th Street	Clay Street	Madison Street
Brush Street	9th Street	18th Street
E 12th Street	1st Avenue	12th Avenue
E 27th Street	22nd Avenue	Sunset Avenue
Fruitvale Avenue*	Cordova Street	Whittle Avenue
International Boulevard*	5th Avenue	7th Avenue
Lakeshore Avenue	El Embarcadero	Prince Street
MacArthur Boulevard*	Sheffield Avenue	Maple Avenue
Madison Street*	5th Street	Embarcadero West
Market Street	San Pablo Avenue	18th Street
Martin Luther King Jr. Way*	44th Street	41st Street
Piedmont Avenue*	Croxton Avenue	Monte Vista Avenue
San Pablo Avenue*	16th Street	20th Street
Telegraph Avenue*	34th Street	55th Street
W Grand Avenue*	Linden Street	I-980
W Grand Avenue*	Harrison Street	Valdez Street
W MacArthur Boulevard	Ruby Street	Fairmount Avenue

**=Another portion of the corridor is identified in the 2021 HIN*

Table 5: Segments on Only the 2021 Initial High Injury Network

Street	Start	End
10th Street	Webster Street	2nd Avenue
14th Avenue	E 18th Street	E 25th Street
23rd Street	Webster Street	Martin Luther King Jr. Way
27th Street	West Street	Broadway
42nd Avenue	Foothill Boulevard	San Leandro Street
64th Avenue	Fenham Street	International Boulevard
73rd Avenue	International Boulevard	Lockwood Street
80th Avenue	International Boulevard	Plymouth Street
8th Street*	Jefferson Street	Washington Street
98th Avenue	Bancroft Avenue	Sunnyside Street
98th Avenue	San Leandro Street	E Street
Bancroft Avenue*	80th Avenue	92nd Avenue
Broadway*	40th Street	51st Street

Foothill Boulevard*	13th Avenue	25th Avenue
Foothill Boulevard*	40th Avenue	Belvedere Street
Foothill Boulevard*	64th Avenue	73rd Avenue
Franklin Street*	19th Street	20th Street
Fruitvale Avenue*	Chapman Street	I-880
High Street*	San Leandro Street	Jensen Street
High Street*	Lyon Avenue	I-580
High Street*	Congress Avenue	Ygnacio Avenue
MacArthur Boulevard*	84th Avenue	Alley (see map)
Madison Street*	15th Street	19th Street
Martin Luther King Jr. Way*	9th Street	20th Street
Martin Luther King Jr. Way*	22nd Street	30th Street
Oak Street	14th Street	Embarcadero West
San Leandro Street	Fruitvale Avenue	42nd Avenue
Seminary Avenue	Brann Street	Seminary Court
Telegraph Avenue*	15th Street	17th Street
Webster Street*	19th Street	20th Street

**=Another portion of the corridor is identified in the 2016 HIN*

Figure 4: Comparison between 2016 and 2021 Initial Pedestrian High Injury Networks

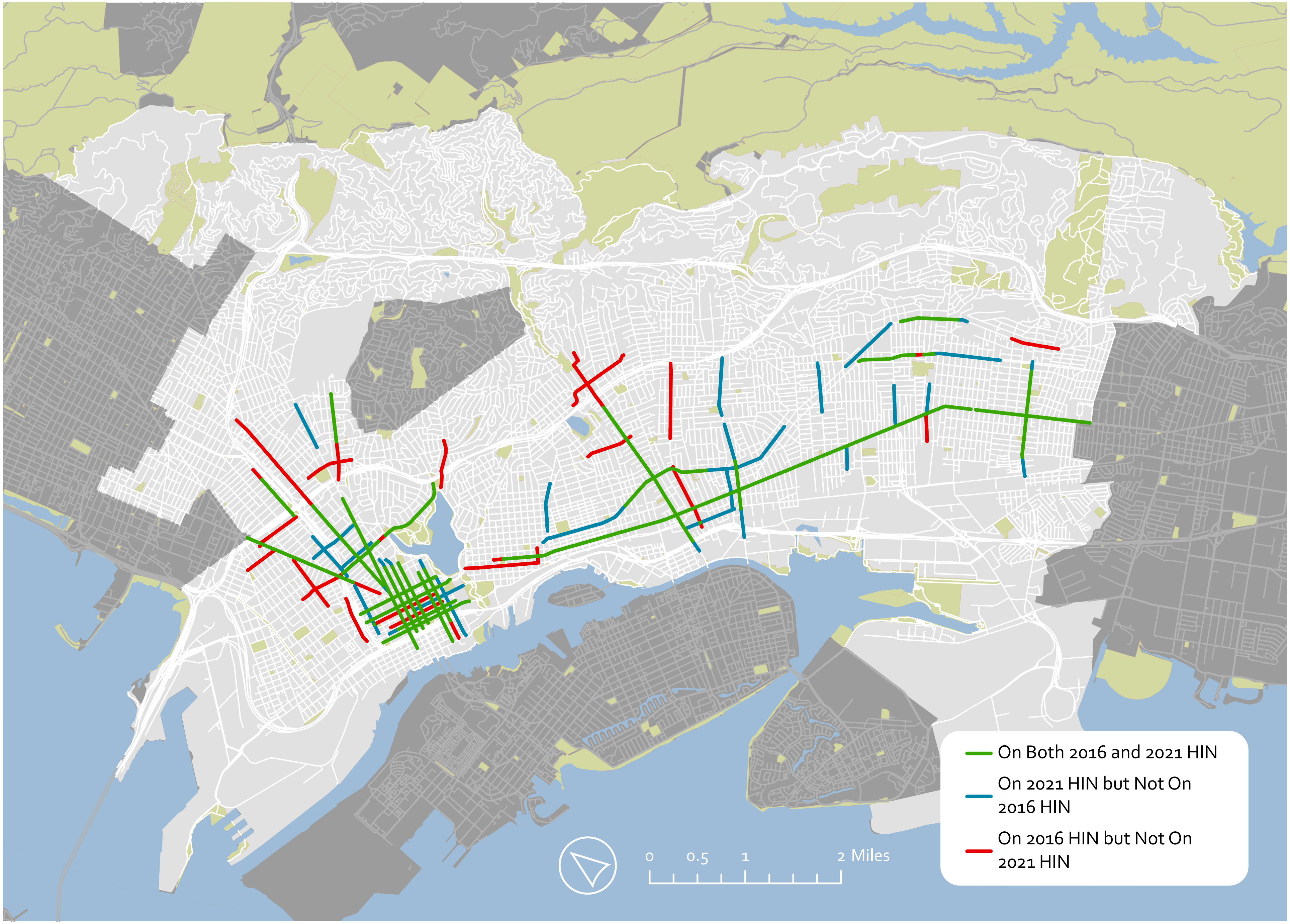
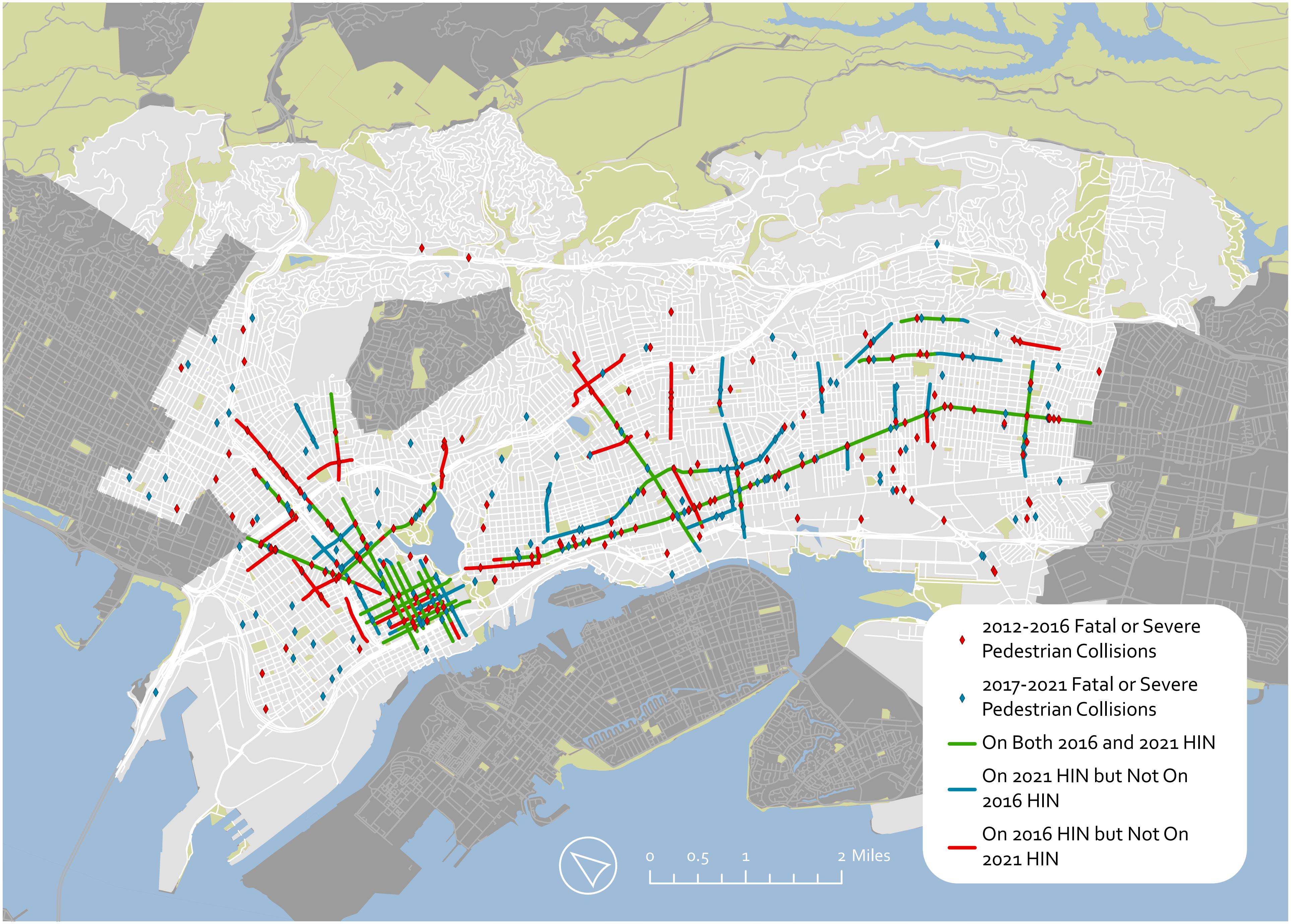


Figure 5: 2016 and 2021 Initial Pedestrian High Injury Networks Overlaid with Fatal or Serious Injury Pedestrian Collisions



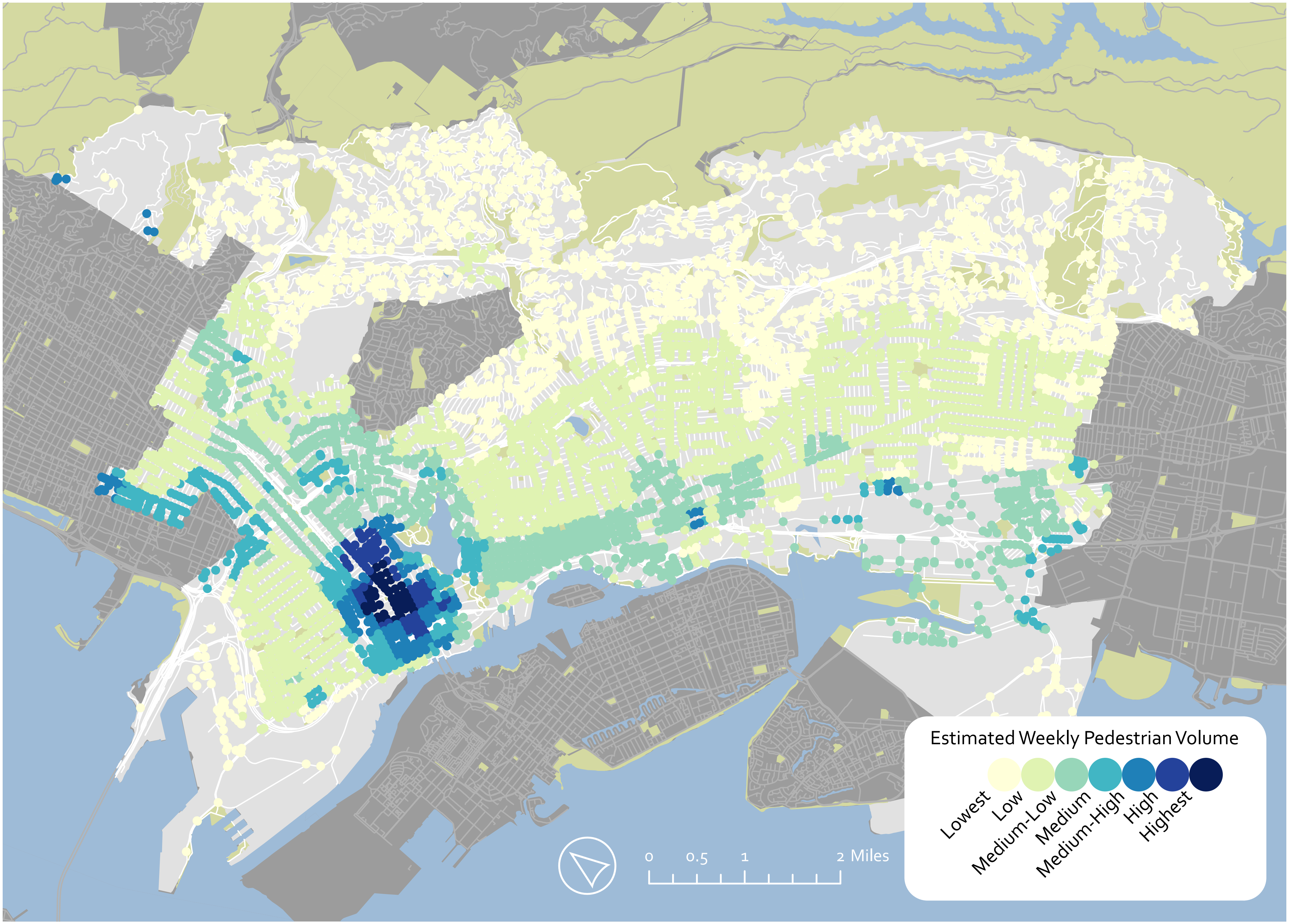
Examining the Impact of Built Environment Characteristics and Pedestrian Volumes on Collisions

Applying the Schneider et. al model results in an estimate of weekly pedestrian volumes for every intersection on the Oakland street network. The highest volumes are observed in downtown Oakland, with the top 15 intersections all located in the downtown core (Table 6). Higher pedestrian volumes are also present around BART stations, in North Oakland, and in the East Oakland flats near International Boulevard. The lowest volumes are observed in the Oakland hills, which are primarily residential. The model seems to overestimate pedestrian volumes next to the University of California, Berkeley campus and near Oakland International Airport. This is likely because these large employment centers do not have strong effects on pedestrian activity within the hypothesized distance, due to geographic barriers such as freeways and hills. Furthermore, some intersections in the Oakland hills are estimated to have a negative pedestrian volume as a result of the regression's negative intercept. Estimated pedestrian volumes are symbolized based on a Jenks classification scheme with seven classes in Figure 6.

Table 6: Top 15 Intersections for Estimated Weekly Pedestrian Volume

Intersection	Estimated Weekly Pedestrian Volume
Franklin St & 12th St	286,640
Franklin St & 13th St	283,453
Franklin St & 14th St	280,061
Broadway & 14th St	260,442
Broadway & 12th St	256,603
Broadway & 13th St	253,127
Telegraph Ave & 18th St	249,360
Franklin St & 11th St	234,475
Webster St & 12th St	231,917
Webster St & 13th St	228,041
Telegraph Ave & 19th St	227,437
Webster St & 14th St	223,567
Broadway & 10th St	213,959
Washington St & 10th St	211,007
Webster St & 10th St	209,636

Figure 6: Estimated Weekly Pedestrian Volume



In addition to estimated pedestrian volumes, Table 7 and Table 8 offer summary statistics for the built environment characteristics included in the regression. Oakland's street network is primarily comprised of local streets with two lanes and a speed limit of 25 miles per hour.

Table 7: Oakland Street Network by Functional Classification (Excluding Freeways)

Functional Classification	Number of Miles	% of Oakland Street Network
Arterials	188	19%
Collectors	107	11%
Local streets	670	70%
Total street network	965	100%

Table 8: Summary Statistics for Regression Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Posted speed limit	26.03	2.54	25.00	50.00
Weekly pedestrian crossings (thousands) per segment	110.01	185.65	-14.45	2,256.95
Number of traffic signals per segment	0.66	1.33	0.00	10.00
Number of lanes	2.21	0.71	1.00	8.00

Table 9 shows the results of the OLS regression investigating the relationship between built environment characteristics, weekly pedestrian volumes, and pedestrian collisions weighted for severity.

Table 9: Relationship Between Built Environment Characteristics/Pedestrian Volumes and Weighted Pedestrian Collisions, 2012-2021

Variable	Coefficient	*p*-value	Robust *p*-value	VIF
Posted speed limit	-0.117	0.000*	0.000*	1.539
Weekly pedestrian crossings (thousands) per segment	0.007	0.000*	0.000*	1.885
Number of traffic signals per segment	2.449	0.000*	0.000*	2.310
Arterial (dummy)	0.958	0.000*	0.000*	2.053
Collector (dummy)	-0.240	0.001*	0.000*	1.087
3-6 lanes (dummy)	0.615	0.000*	0.000*	1.643
Intercept	2.950	0.000*	0.000*	-

**=Statistically significant at a 99% confidence interval*

Number of Observations: 27,972 street segments
Multiple R2: .506
Adjusted R2: .506

When using solely the model to create an HIN, the model overestimates pedestrian crashes in downtown and underestimates them elsewhere in Oakland, particularly in East Oakland. Figure 7 shows the HIN created with a threshold of 10 or more weighted collisions — the same threshold used to create the other HINs presented in this paper. The result is an HIN comprised almost exclusively of downtown streets, which does not reflect collision risk across the city. Figure 8 shows the HIN created if the threshold is adjusted to 7 or more weighted collisions, which encompasses a higher proportion of the street network. While this HIN includes longer segments of International Boulevard and Telegraph Avenue, it still excludes key corridors such as Bancroft Avenue and Foothill Boulevard in East Oakland in favor of downtown corridors.

The model violates the assumption of normally-distributed standardized residuals, indicating that there are key predictive factors missing from the explanatory variables, or that the current variables need to be transformed to account for this. However, the signs of the coefficients confirm that the relationships between built environment characteristics and collision risk established in existing literature apply to the City of Oakland's context. Weekly pedestrian crossings, arterials, traffic signals, and roads with 3 to 6 travel lanes are positively associated with pedestrian crashes, while posted speed limit and collectors are negatively associated with pedestrian crashes. While prior research says that speed is associated with higher collision severity, high posted speed limits in Oakland are typically on low pedestrian activity roads such as Doolittle Drive and Hegenberger Road, resulting in a negative relationship with crash frequency.

The coefficient for weekly thousands of pedestrian crossings may be larger than the observed coefficient (0.007) because the Schneider model produces an overestimate of pedestrian volumes. I compare estimated volumes to annual pedestrian counts conducted at 36 Oakland intersections by OakDOT's Bicycle and Pedestrian Program.[xli] This comparison showed that when compared to 2019 pre-pandemic counts, the model overestimates absolute pedestrian volumes by an average factor of 15.2. When compared to 2022 post-pandemic counts, the model overestimates volumes by an average factor of 15.7. The methods used to assign tract-level employment and population data to individual street intersections in GIS may also contribute to this overestimate. However, the model may still be valuable in determining an intersection's pedestrian activity relative to other intersections.

Figure 7: Regression-Based 2017-2021 Pedestrian High Injury Network (10 or More Predicted Weighted Crashes)

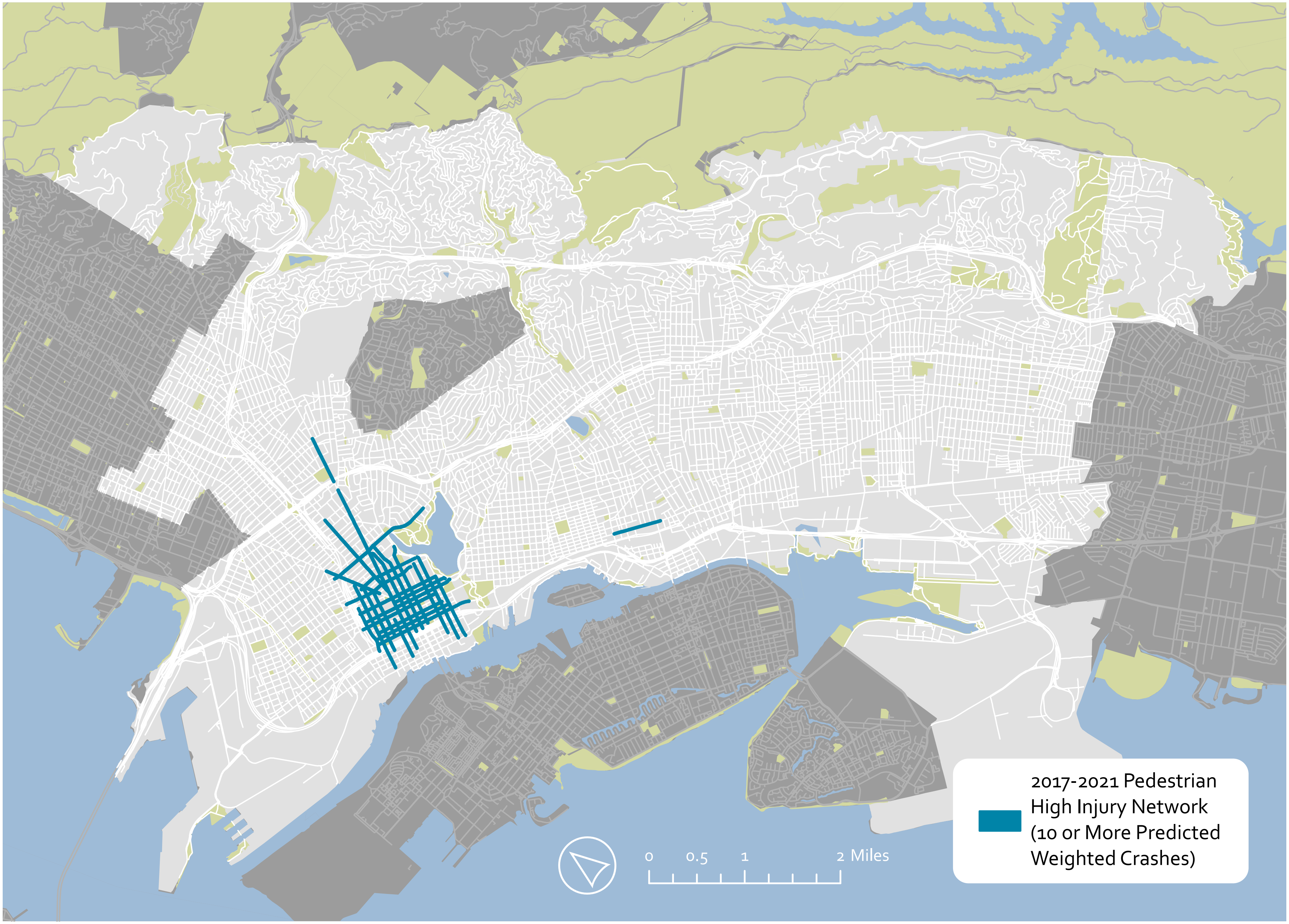
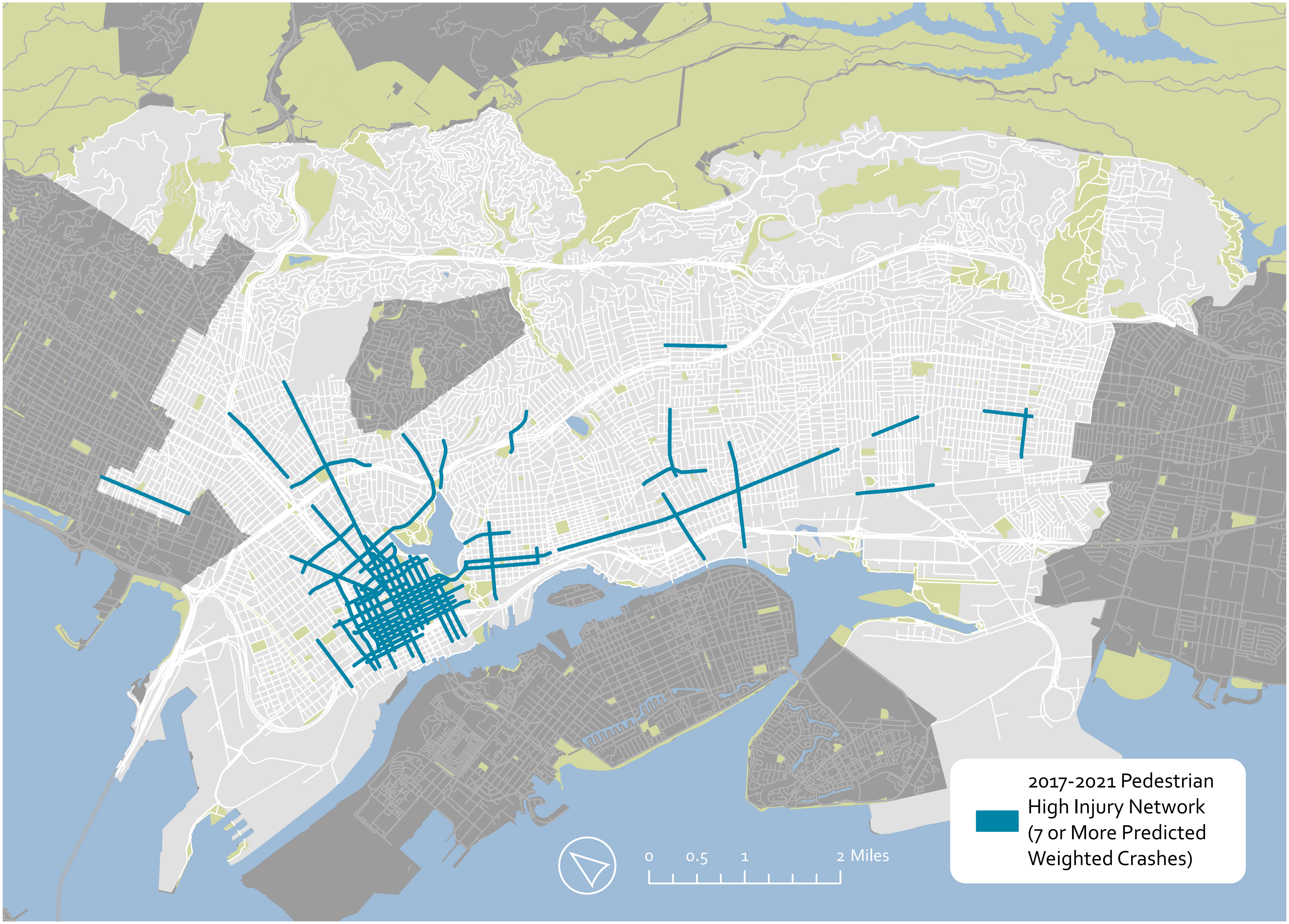


Figure 8: Regression-Based 2017-2021 Pedestrian High Injury Network (7 or More Predicted Weighted Crashes)



Recommendations

Proposed Methodology for Finalizing High Injury Network Segment Extents

I propose a methodology for determining HIN extents that is primarily based on segment characteristics (number of lanes, posted speed limit, and functional classification), and secondarily based on intersection characteristics (traffic signal presence and estimated pedestrian intersection crossings). The three-step process for smoothing and cleaning an HIN after the initial collision analysis is outlined below:

1. Determining whether to connect noncontiguous segments
2. Determining whether to extend or shorten a segment
3. Determining whether to remove a segment

In order to prepare the data, I dissolve the Oakland street network by street name, number of lanes, speed limit, and functional classification to create corridors with identical characteristics. I then overlay the street network with the point feature layers for traffic signals and pedestrian crossings. Estimated pedestrian crossings are used to categorize intersections as lowest, low, medium-low, medium, medium-high, high, and highest pedestrian activity, as previously shown in Figure 6. In this section, I test the methodology on the 2021 pedestrian HIN raw output.

Step 1: Connecting Noncontiguous Segments

Some jurisdictions, such as the City of Sacramento, already have a protocol in their HIN process to connect noncontiguous segments if they are less than a certain distance apart.[xlii] I propose that noncontiguous segments on an HIN be connected if the gap between the segments has the same roadway characteristics and similar pedestrian volumes as either one of the segments. The segments should also be connected if the gap has a higher speed limit or more travel lanes, and therefore a higher potential for collisions, than either of the segments. In Figure 9, the highlighted segments are on Martin Luther King Jr. Way, a 2021 HIN corridor.

Figure 9: Martin Luther King Jr. Way on the 2021 High Injury Network

Taking this corridor as an example, the northern segment has mostly medium-low pedestrian volumes, while the southern segment has medium-low pedestrian volumes at the northern end and medium-high volumes at the southern end. Both segments have two lanes, a posted speed limit of 30, and a functional classification of minor arterial. The gap between the segments has medium-low pedestrian volumes, two lanes, a posted speed limit of 30, and a functional classification of minor arterial — the same characteristics as both segments. Connecting these segments creates a longer HIN corridor, capturing one additional serious injury collision and two injury collisions that occurred in the gap between the noncontiguous segments.

Step 2: Extending or Shortening a Segment

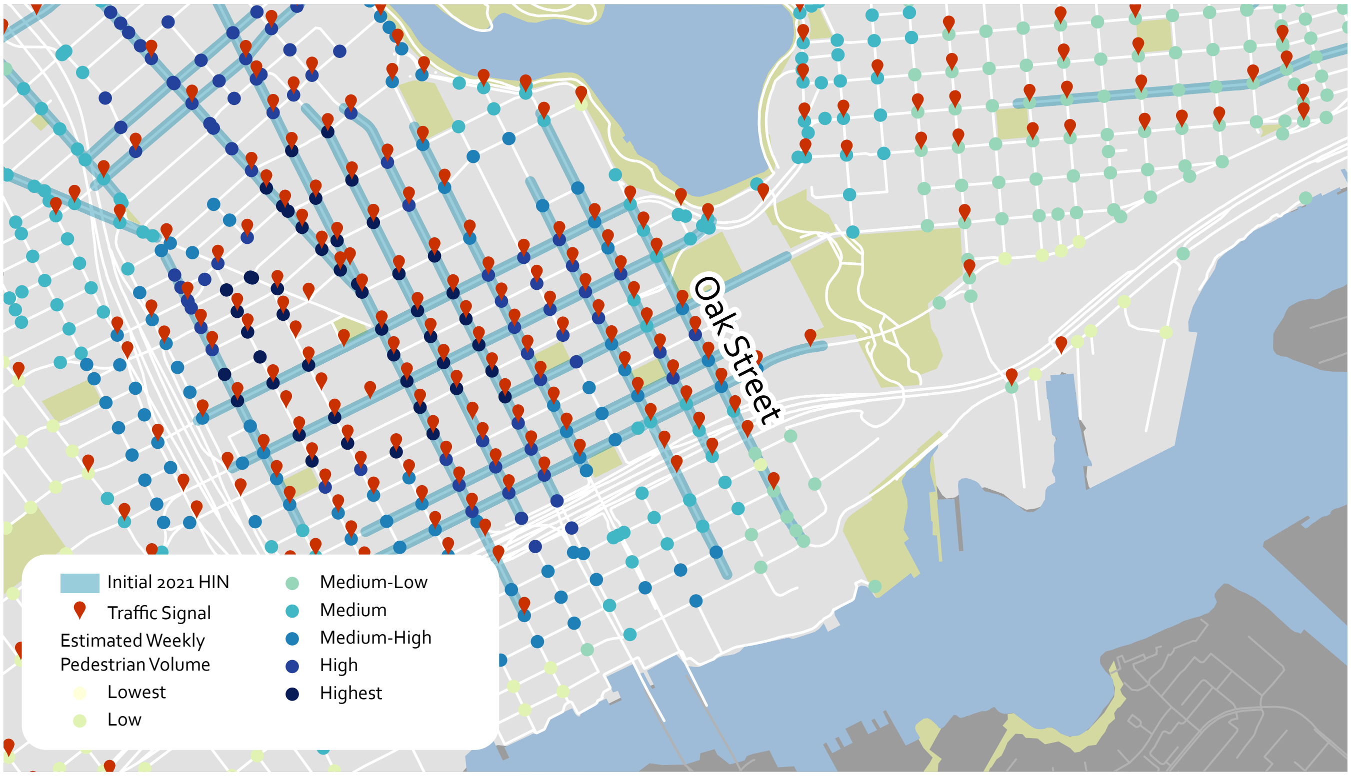
An HIN segment should be extended based on the underlying roadway characteristics and pedestrian volumes. Extensions can also be utilized to connect the corridor with an intersecting principal arterial, where intersection crashes are more likely to happen. For this step, I use Piedmont Avenue as an example (Figure 10). This segment on the HIN has low to medium-low pedestrian volumes, two lanes, a posted speed limit of 25, and a functional classification of minor arterial. The portion of Piedmont

Avenue that has the same characteristics extends about seven blocks south to the freeway. Extending the HIN segment to this endpoint would capture one additional serious injury collision and six injury collisions.

Figure 10: Piedmont Avenue on the 2021 High Injury Network

Shortening an HIN segment should be done with caution. In the example of Oak Street (Figure 11), the street narrows from three to two lanes south of the freeway. Pedestrian volumes and traffic signal density also drop off, and consulting the mapped crash data shows that zero pedestrian crashes occurred south of the freeway in the last ten years. This is an instance where the sliding window segment methodology resulted in a longer HIN corridor than necessary, and shortening the segment results in a more focused HIN without excluding any crashes. In summary, a segment should only be shortened if the excluded portion has a lower speed limit or number of lanes than the rest of the segment, and if shortening the segment does not exclude any fatal or serious injury crashes.

Figure 11: Oak Street on the 2021 High Injury Network



Step 3: Removing a Segment

Some cleaning is necessary to remove streets that only end up on the HIN because they intersect with a street with a high number of crashes. This is a typical data cleaning process that already occurs in HIN development.[xliii] Short segments of local streets with low pedestrian volumes that intersect with high-volume arterials are prime candidates for double checking. For example, this segment of 64th Street (Figure 12) is only about 1,200 feet long, and it is a local street with two lanes and low pedestrian volume. Referencing mapped crashes shows that all of the crashes on this "high injury" corridor happened at the intersection of International Boulevard and 64th — no crashes occurred on the rest of the segment. We can conclude that this segment was erroneously included in the HIN, and can be removed.

Figure 12: 64th Street on the 2021 High Injury Network

Results of Applying the Methodology to the 2021 High Injury Network

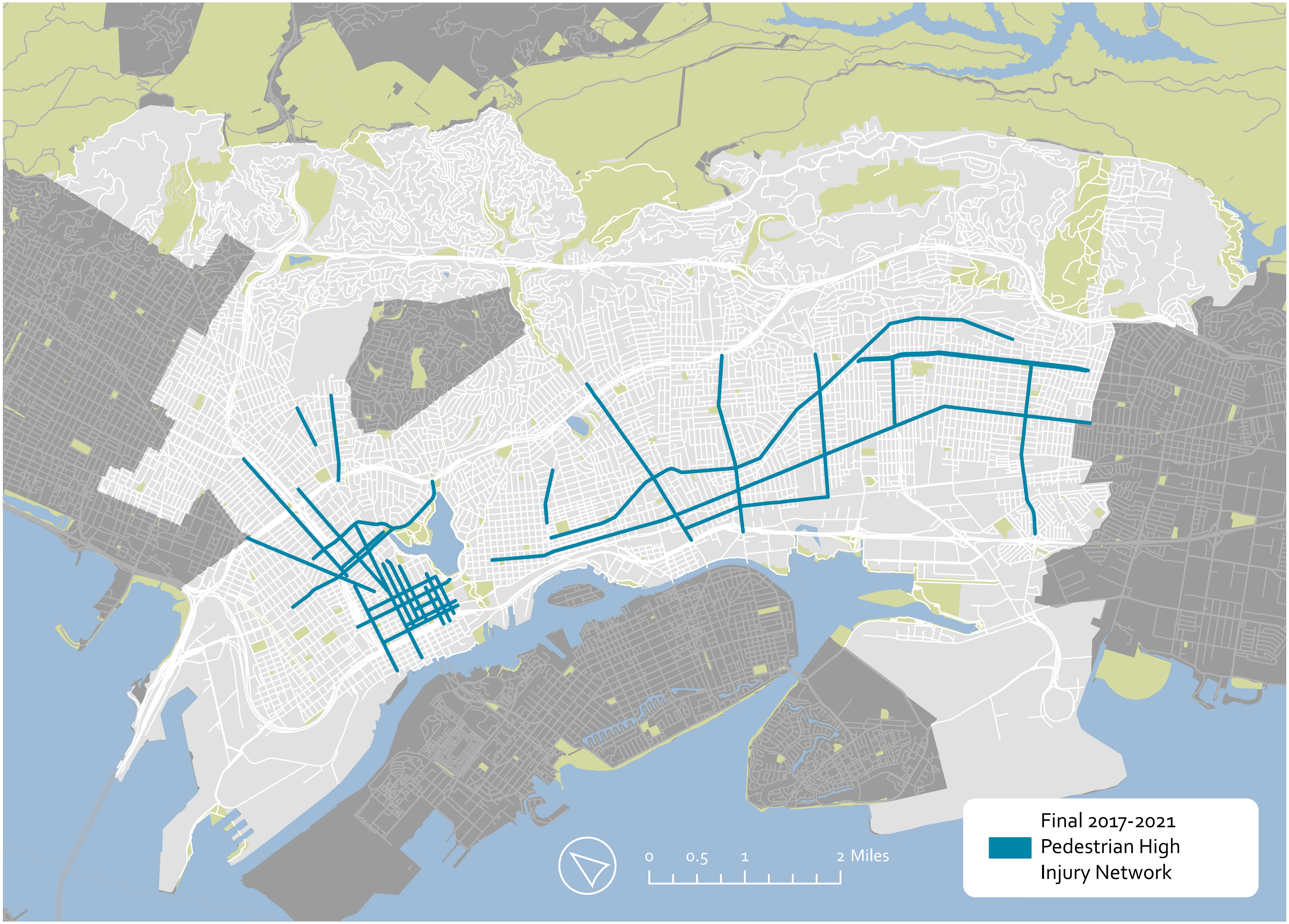
Applying the methodology detailed above to the initial 2021 HIN results in a final HIN that is 2 miles shorter, yet captures a higher proportion of fatal and serious injury crashes from 2017-2021 (Table 10). The cleaned HIN also shows improved performance in capturing crashes that happened in the previous five years (51% of all crashes compared to 46% in the raw output, and 56% of fatal and serious injury crashes compared to 50%). Considering that 2012-2016 crash data was not used in the development of this HIN, this may show that incorporating roadway characteristics results in a more stable HIN over time and reduces the effects of crash data variation.

Compared to the combined HIN (which was created by merging the 2016 HIN and 2021 HIN raw outputs), the cleaned 2021 HIN captures a slightly smaller percentage of crashes but is 17 miles shorter, which makes it more useful for prioritizing limited resources. Compared to the overlap HIN (which consists only of segments that are on both the 2016 and 2021 HIN raw outputs), the cleaned 2021 HIN performs significantly better in capturing all types of crashes. Lastly, the final HIN is more focused on long, connected segments on arterial streets, which may align better with grant opportunities and capital improvement project scopes.

Table 10: Descriptive Statistics for Proposed 2021 Pedestrian High Injury Network versus Initial Networks

	Proposed 2021 HIN	2021 Initial HIN	2016 and 2021 Initial HINs Combined	Segments in Both 2016 and 2021 HINs
Length (Miles)	46.1	48.1	63.6	42.3
% of Oakland Street Network	4%	4%	5%	4%
% of 2012-2016 Crashes Captured	51%	46%	58%	40%
% of 2017-2021 Crashes Captured	56%	57%	59%	40%
% of 2012-2016 KSI Crashes Captured	56%	50%	63%	45%
% of 2017-2021 KSI Crashes Captured	60%	57%	61%	43%
% Arterial Streets	97%	77%	79%	79%

Figure 13: Final Proposed 2021 High Injury Network



Additional Recommendations for Updating and Utilizing a High Injury Network

HINs are used in different ways by different stakeholders. In the City of Oakland, the HIN is one criterion used to prioritize corridors for improvements via major capital projects, the paving plan, the Bicycle Plan and Pedestrian Plan, and neighborhood traffic safety requests.[xliv] At the county level, the Alameda County Transportation Commission is proposing to use local HINs and the Countywide HIN as prioritization criteria in the forthcoming Countywide Active Transportation Plan.[xlv] At the regional level, the Metropolitan Transportation Commission uses HINs to guide One Bay Area Grant (OBAG) funding decisions and has recommended the use of HINs to advance the Regional Vision Zero Policy, a key strategy in the Draft Plan Bay Area 2050+ Transportation Element.[xlvi]

Based on the finding that the current HIN methodologies do not consistently identify corridor start and end points, regional agencies should integrate flexibility relating to this in scoring grant applications. For example, projects should not be penalized for only partially being on the HIN. Furthermore, local agencies should not use HINs to scope a project's extent, either for grant applications or for project implementation. Instead, this should be done using a more holistic approach that takes roadway characteristics and adjacent land uses into consideration. Alternatively, local agencies can develop a methodology for their HIN that aligns with parallel processes such as their paving plan or capital improvement plan. This can improve the effectiveness of the HIN and ensure that HIN analysis is integrated into all aspects of the agency's infrastructure planning.

When updating an adopted HIN, jurisdictions will need to reconcile the differences between the adopted and updated network. Agencies should exercise caution when deciding to remove a segment from a previous HIN. This decision should be justified by either a completed safety project along the corridor or a significant change in land use or travel patterns. If there is no reason to believe that the underlying collision risk on the corridor has changed, the prior crash history identified in the previous HIN should be carried over into the updated HIN. This ensures that the segment remains eligible for safety improvements and grant funding moving forward.

Limitations and Future Work

The proposed methodology for determining HIN segment extents requires complete, up-to-date, and accurate data on roadway characteristics, which some agencies may not have access to. The City of Oakland data used in this paper is complete, but has some issues such as off-street paths marked as local streets, and information on number of lanes not being regularly updated in recent years. Data availability is a major barrier to more rigorous geospatial analysis in smaller and lower-resource jurisdictions. Paradoxically, smaller cities may benefit more from an HIN methodology that incorporates roadway characteristics, since they are more likely to encounter issues with collision data sample size. The recommendations for statewide HIN guidance state, "In cases where a jurisdiction experiences few collisions due to its size, systemic methodologies, which rely on prioritization based on high-risk roadway characteristics or other contextual factors (e.g., professional judgment from city staff recognizing that a certain intersection may have safety issues), may be appropriate to include in the development of an HIN."[xlvii] County governments and regional metropolitan planning organizations such as the Metropolitan Transportation Commission can play an important role in providing consolidated, publicly-available datasets.

There are also limitations in the methods used for pedestrian volumes. Assigning intersection-level pedestrian volumes to segments may overestimate volumes on local streets that intersect with high-volume arterials. Furthermore, an updated pedestrian crossing volume model may be needed for post-COVID years with the rise of remote work affecting pedestrian activity in downtowns.

This paper focuses on pedestrian HINs. The application of this approach to all-mode HINs is more complicated, as it would require bicyclist and traffic volume data (or the development of a model to estimate volumes). Other mode-specific data would need to be incorporated, such as the presence and type of bikeway facility on a segment.

Lastly, this paper adds to the vast range of HIN methodologies used across California. Statewide guidance on HIN development is still needed to offer some level of standardization across jurisdictions, which is necessary if HINs are used as a criterion for statewide transportation funding allocations. In addition to the recommendations detailed in the 2021 report, "Recommendations for

California Statewide Guidance on High Injury Networks," guidance on determining HIN extents can ensure that funding decisions take underlying roadway characteristics into consideration.[xlviii]

Conclusion

HINs are valuable tools, and developing one is an important first step that jurisdictions still need to take to address road safety. However, changes in HINs over time have implications on resource prioritization that must be addressed. HINs affected by crash data biases may not accurately indicate where capital improvements are most needed, particularly if agencies are not updating their HINs on a regular basis. Furthermore, traditional HINs are in a gray area between rapid response and long-range planning. Their reliance on retrospective data makes HINs unideal to be the sole tool used in long-range planning, but implementation and development does not happen fast enough to constitute rapid response. Since HINs are nevertheless increasingly being used as a long-range planning tool, there is an opportunity to incorporate more proactive measures into their development. I find that due to variations in the exact locations of crashes along a corridor from year to year, HINs may not consistently identify segment start and end points. This raises concerns about the use of HINs to scope project extents or score grant applications, and demonstrates the need to integrate more flexibility into these processes. The proposed methodology improves the accuracy of segment extents based on literature on the effects of roadway characteristics and pedestrian volumes on collision risk. This integrates a Safe System Approach into HIN development, which has the potential to improve HIN stability over time, smooth over errors in crash reporting, and reduce the frequency of network updates needed.

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