Urban Transportation Infrastructure and Cyclist and Pedestrian Safety

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Overview

- Problem Statement
- Data and Methods
- Some Results
- Severe Pedestrian/Bicyclist Injury Areas (SPIAs and SBIAs)
- Suggested Countermeasures

Problem Statement

- Over 75,000 pedestrians are injured in motor vehicle crashes every year in the US
- Over 6,000 pedestrians are killed every year
- Over 47,000 bicyclists are injured every year
- Over 840 bicyclists are killed every year

Problem Statement

- In 2019, 5,975 pedestrian crashes occurred in Texas, resulting in 669 deaths, a 5% increase in fatalities over the previous year
- 1,317 people were seriously injured
- From 2015 to 2019, traffic crashes claimed the lives of 3,150 pedestrians in Texas

Problem Statement

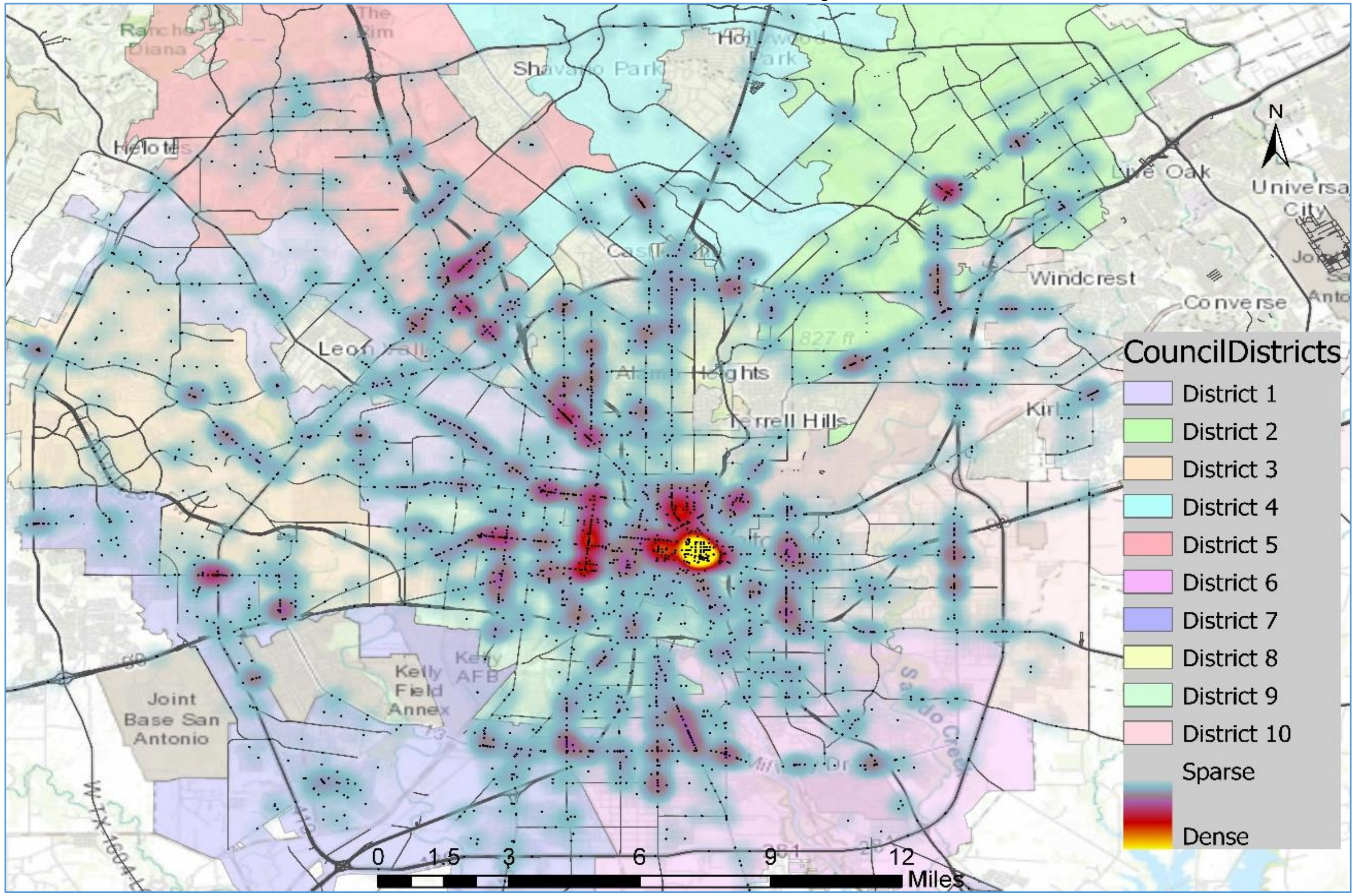
- The vast majority of these injuries and fatalities occur in urban areas
- San Antonio is one of the US cities witnessing an increase in pedestrian and bicyclist severe injuries
- There is a need to understand the characteristics and causes of these crashes and develop appropriate countermeasures

Data and Methods

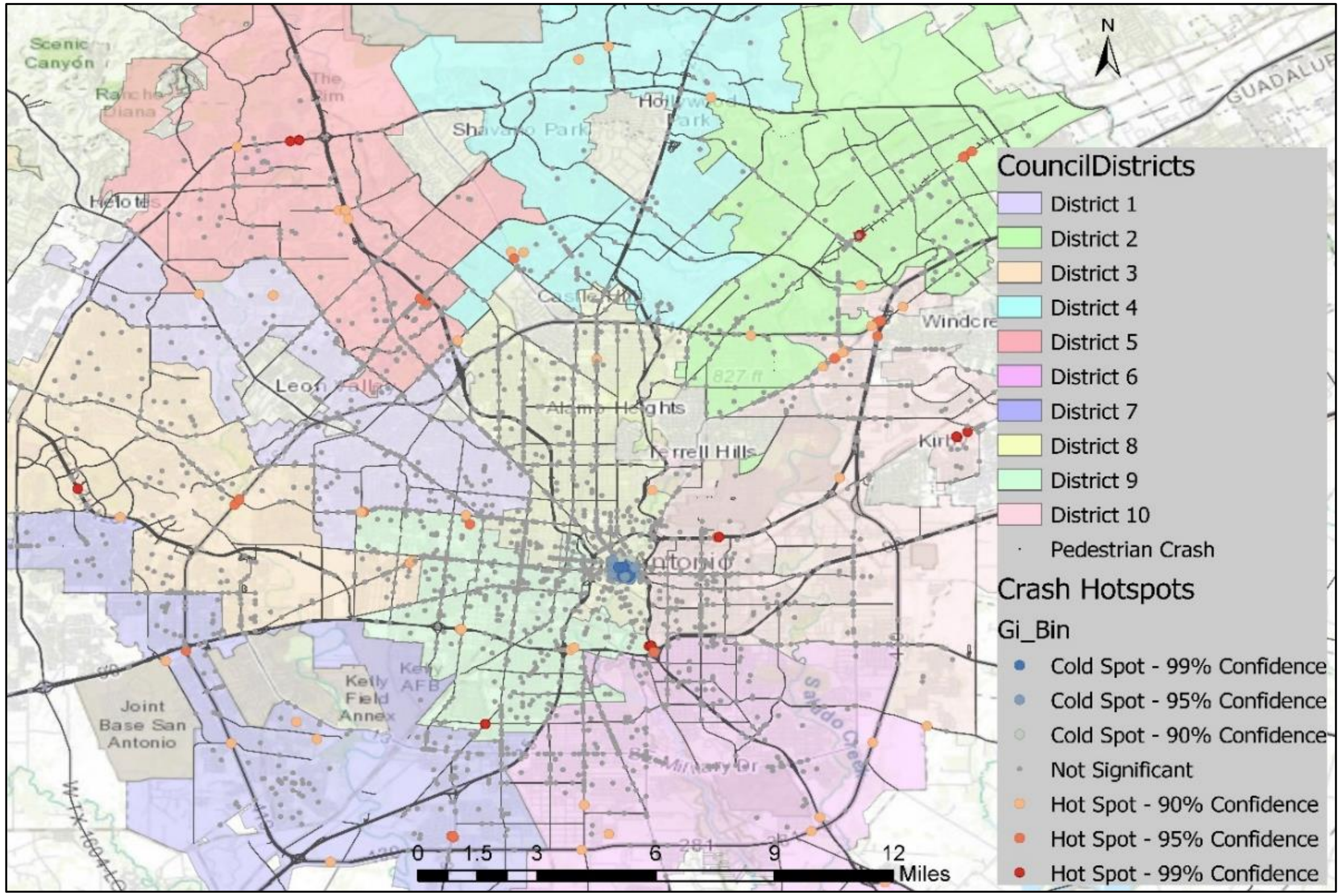
- The crash data for the period of January 2013 to December 2018 were acquired from the Texas Department of Transportation's (TxDOT) Crash Records Information System (CRIS)
- High-risk locations were identified through heat maps and hotspot analysis
- Bivariate analysis and logistic regression were used to identify the most significant predictors of severe pedestrian/bicyclist crashes

Results- Pedestrian Crashes 2013-2018

Heat map of pedestrian crashes in San Antonio based on crash density

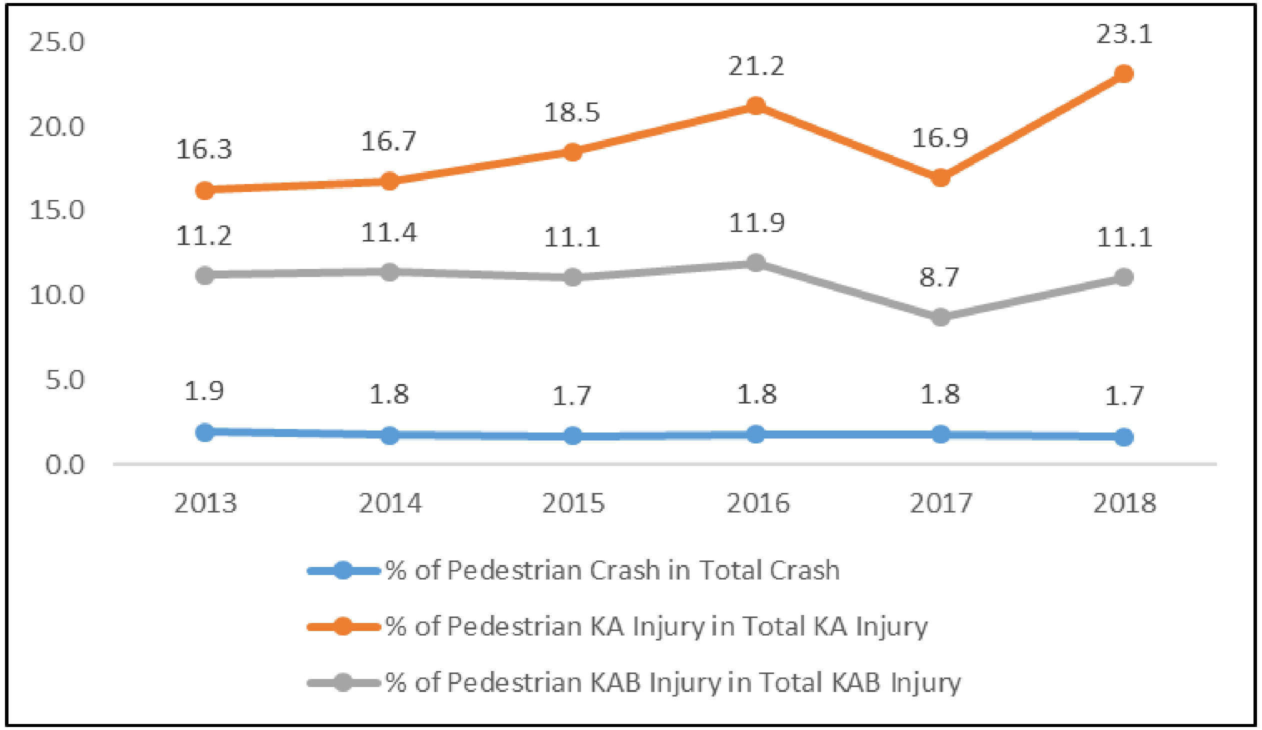


Hotspots of pedestrian crashes in San Antonio based on crash severity



How serious are pedestrian crashes?

Pedestrian crashes and injuries as proportions of the total traffic crashes and injuries



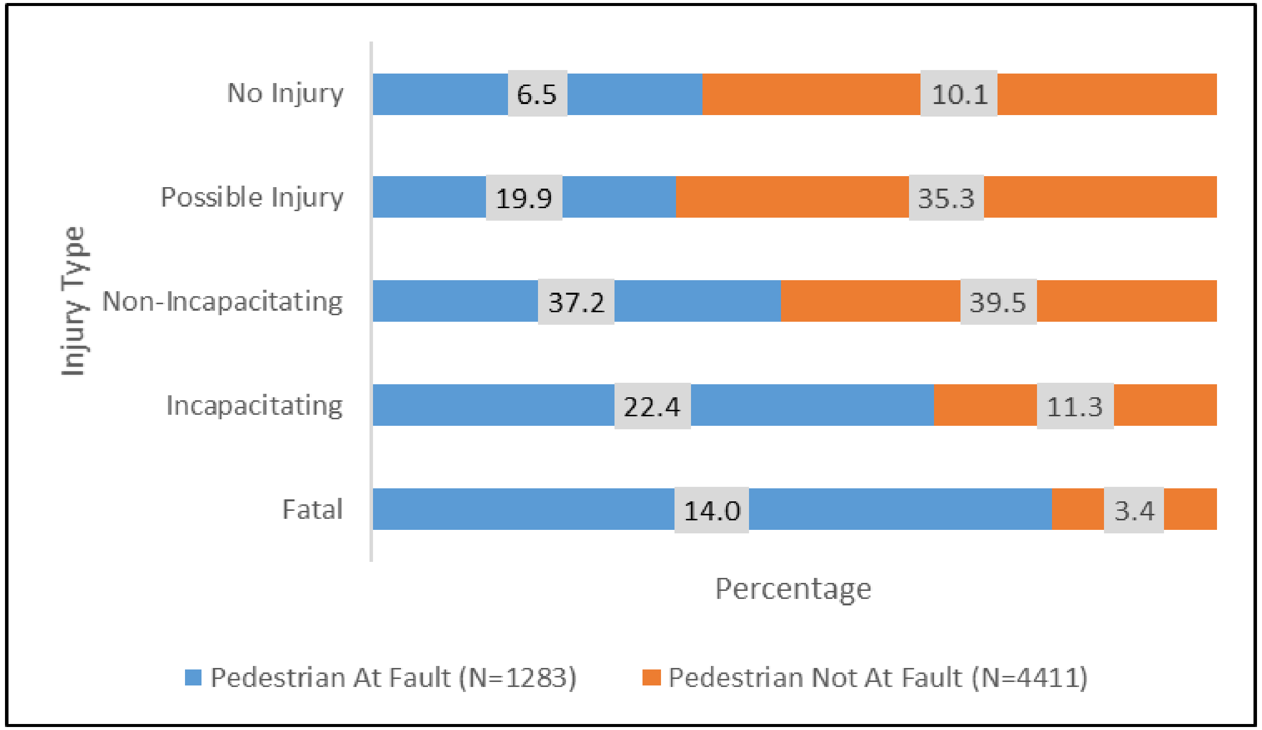
Statistical Analysis

- Pedestrian crashes were divided into two sub-groups based on the party at fault in the crash
- For each sub-group, the relationship between different human-, environment-, and vehicle-related factors and the proportions of pedestrian crashes with two different injury severity levels (KA and KAB) were examined
- Bivariate analysis and logistic regression modeling were used

Results

- Pedestrian gender, road type, road speed limit are strong predictors of pedestrian injury irrespective of the severity of injury
- Driver alcohol influence and nighttime substantially increased severe pedestrian injury risk irrespective of party at fault
- Pedestrian-at-fault crashes resulted in a substantially higher proportion of severe pedestrian injuries compared to crashes where pedestrians were not at fault

Injury severity in pedestrian crashes by party at fault



Results

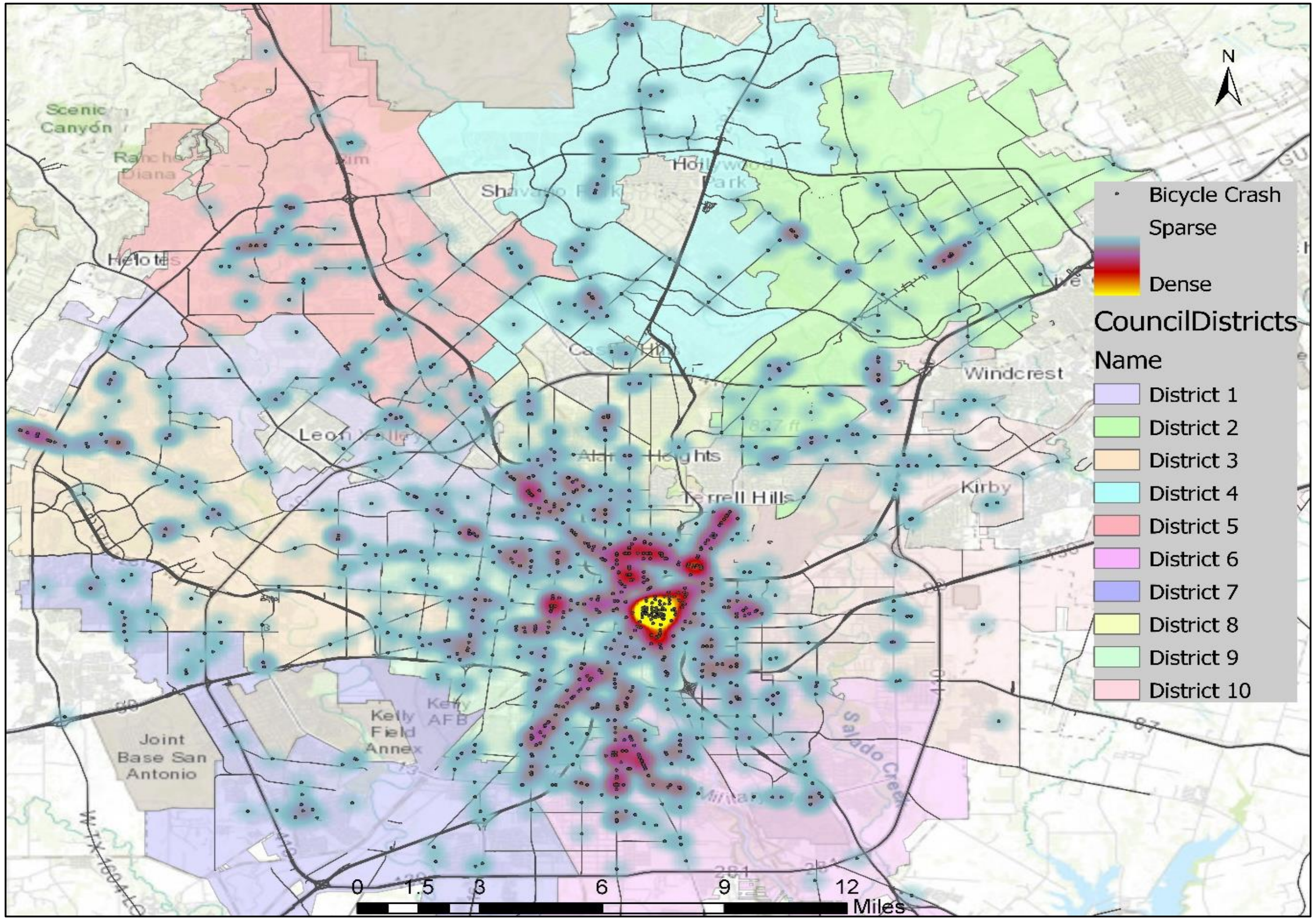
- Variables affecting driver reaction time such as lighting condition, traffic control, and vehicle type were generally strong predictors of severe pedestrian injury in crashes when pedestrians were the party at fault
- On the other hand, road environment characteristics related variables such as road type, speed limit, and alignment along with type of collision were better predictors of crashes when pedestrians were not at fault

Results

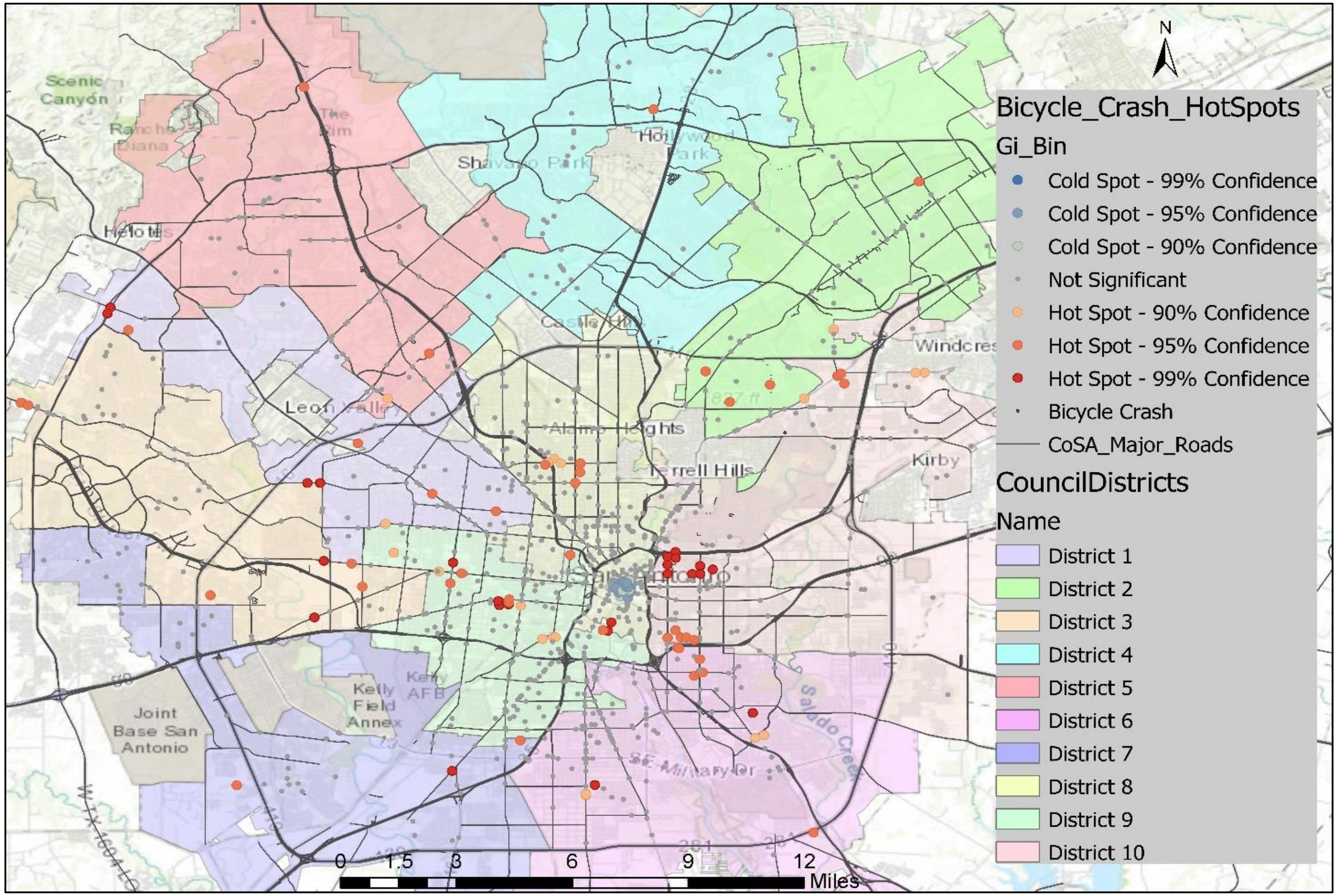
- The influence of alcohol on drivers and nighttime conditions (8 p.m.–6 a.m.) substantially increased the risk of severe pedestrian injury irrespective of the party at fault
- The day of the week was a significant predictor only for pedestrian-not-at-fault crashes with the odds of severe pedestrian injury increasing during the weekend
- In addition to emergency vehicles, which expectedly travel at high speeds, pickup trucks had relatively higher odds of severe injury, probably due to their rigid body structures

Results- Bicyclist Crashes (2014-2018)

Heat map of bicyclist crashes in San Antonio based on crash density



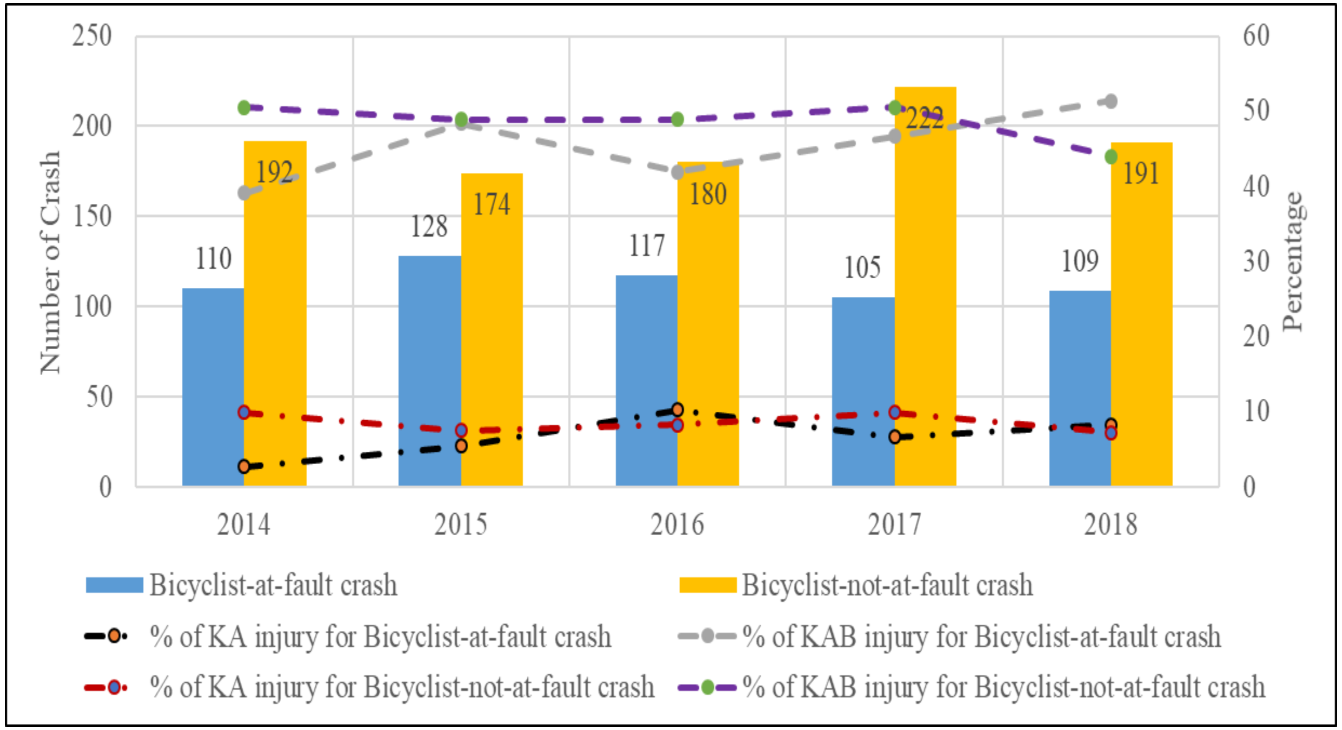
Hotspots of bicyclist crashes in San Antonio based on crash severity



Results

- The primary contributing factors of bicycle-motor vehicle crashes were driver inattention and disregard of stop sign/light for both bicyclists and vehicle drivers
- The strongest predictors of injury severity include lighting condition, road class, time of occurrence, day of week, bicyclist age, and bicyclist ethnicity
- Bicycle crashes, especially on-facility, occurred mostly at intersections
- Crash severity risk is lower at intersections, but relatively higher when bicyclists were not at fault

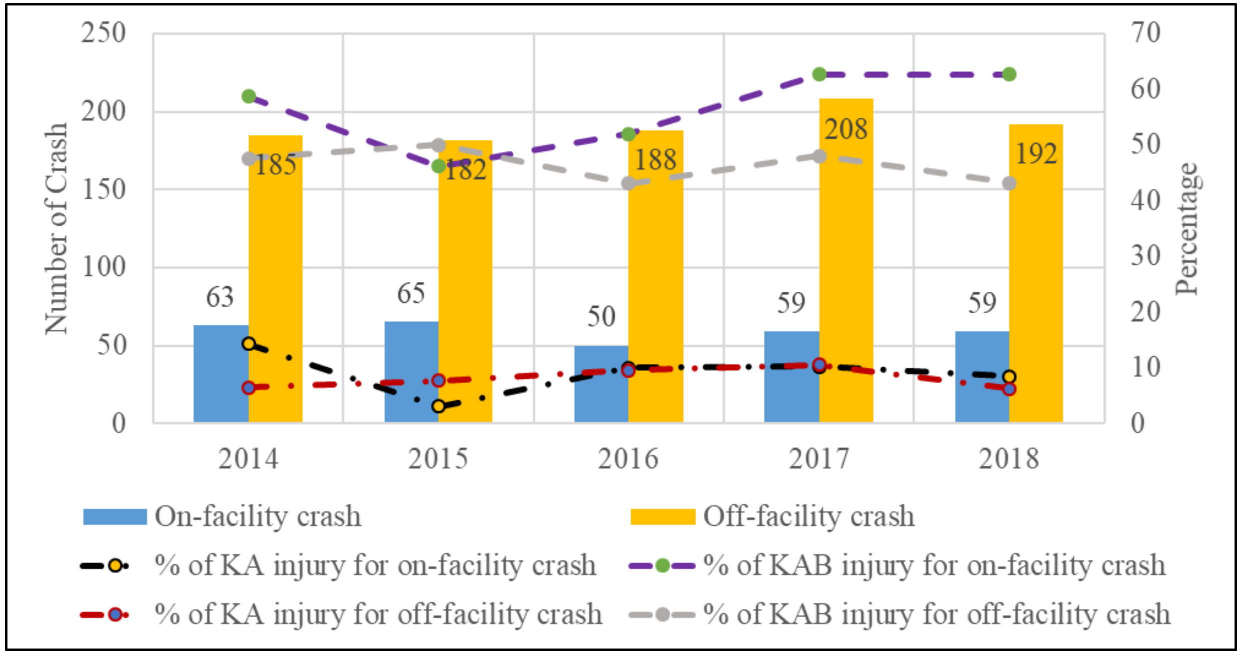
Annual frequencies and percentages of KA and KAB injury of bicyclists based on the party at fault



Results

- Existence of bicycle facilities on roads made no statistically significant difference in crash frequency and severity (this is very complicated)
- Off-facility severe bicycle crashes had several strong predictors (bicyclist age and ethnicity, intersection presence, temporal variables) while on-facility severe bicycle crashes had almost none
- Dark lighting condition increased both severe and non-severe injury risk (especially for bicyclist-not-at-fault crashes)

Annual frequencies and proportions of K and A bicyclist crashes based on presence of facility



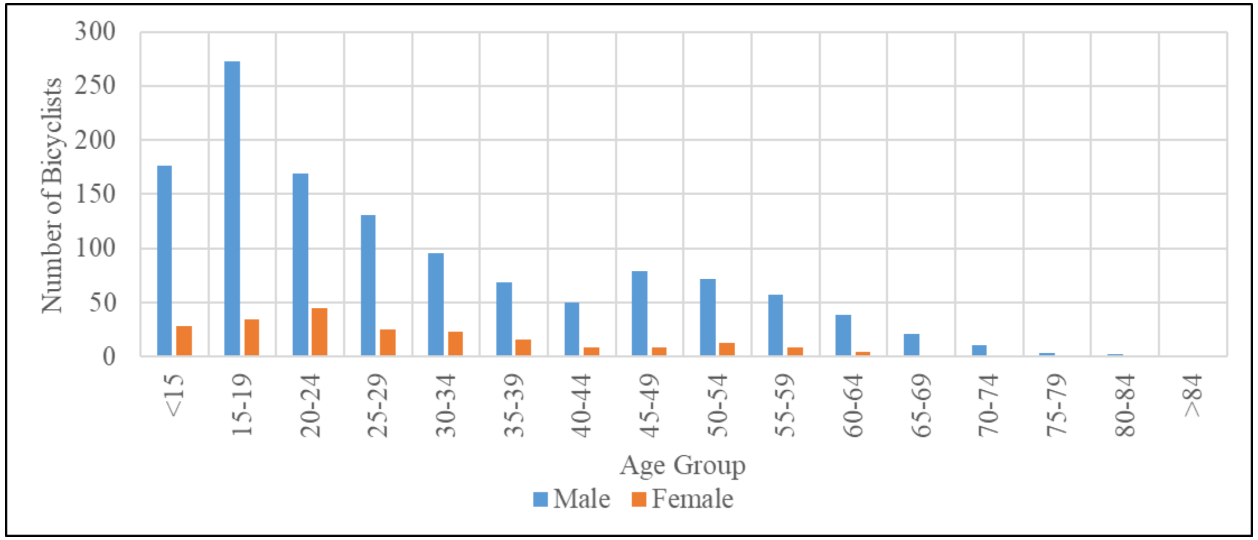
Results

- Both severe and non-severe injury risk of bicyclists were highest in the summer and lowest in the winter
- The weekend period has lower bicycle crash counts but higher KA injury proportions
- During weekend, bicyclist-not-at-fault and on-facility crashes were more susceptible to injury compared to their counterparts
- Weekend nights have substantially higher severe injury risk due to higher frequency of DWI and distracted drivers

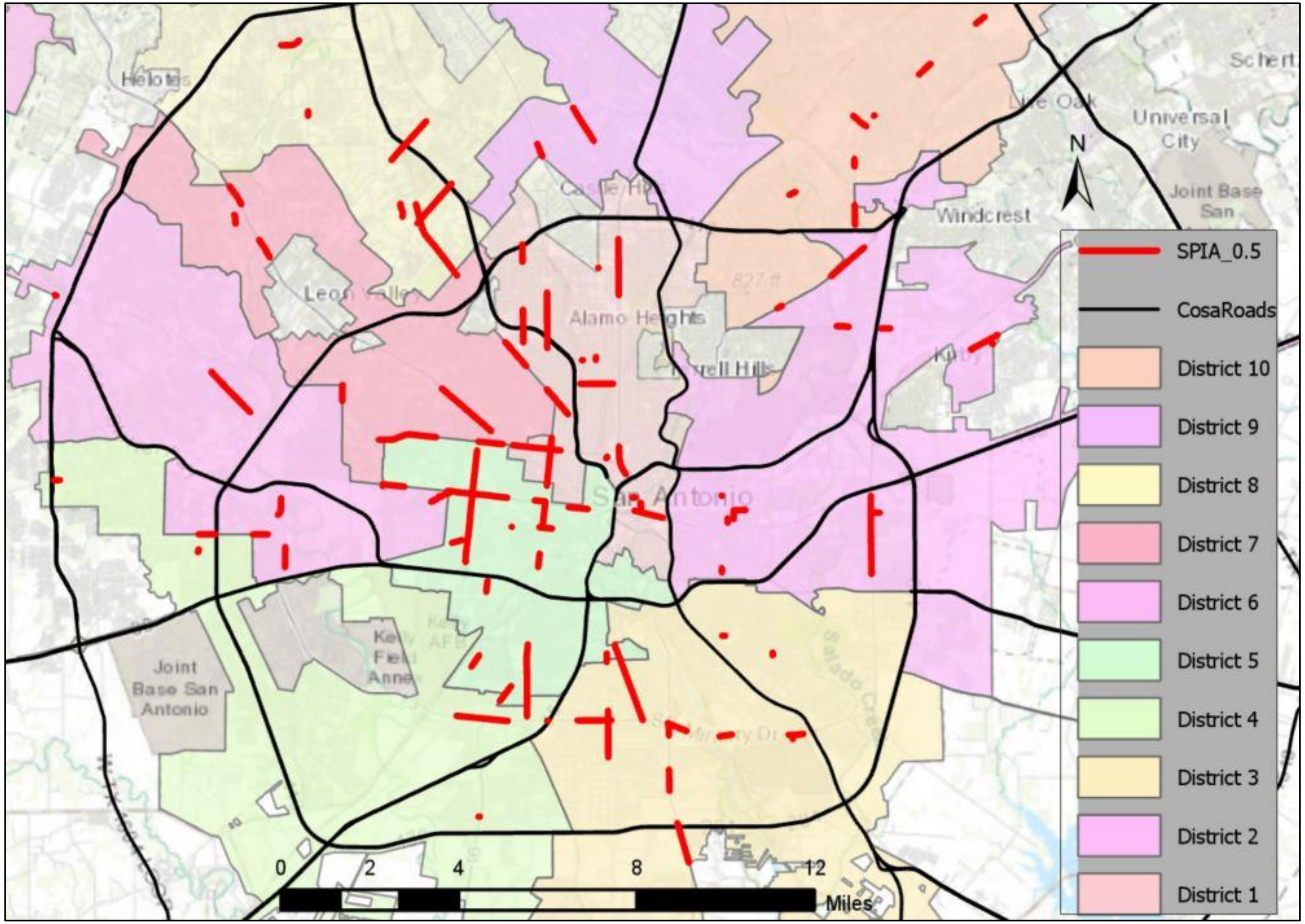
Results

- Male bicyclists were more likely to be involved in severe crashes and female bicyclists were more likely to be involved in non-severe crashes
- All severe injury crashes related to older bicyclists occurred on roads without bicycle facilities
- Bicycle crashes on highways and FM roads are more likely to result in severe injury

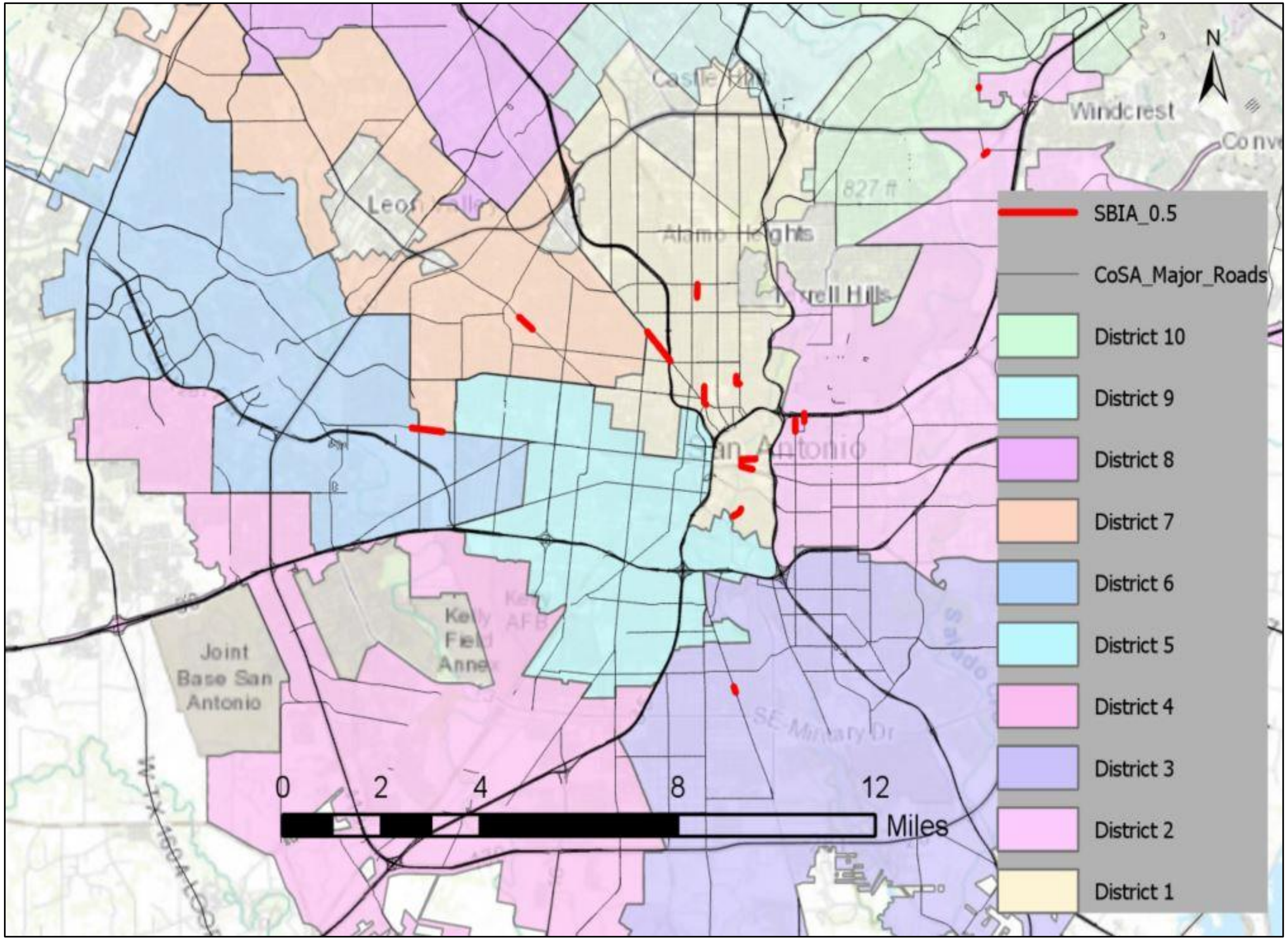
Age and gender distribution of bicyclists involved in crashes



Severe Pedestrian/Bicyclist Injury Areas (SPIAs and SBIAs)



Severe Pedestrian Injury Areas (SPIAs) with 0.5 mile Center-to-Center Crash Distance



Severe Bicyclist Injury Areas (SBIAs) with 0.5 mile Center-to-Center Crash Distance

Some Countermeasures

Countermeasures Related to Infrastructures

- Protected Left-Turn Phase
- Right Turn on Red Restrictions
- Illuminated Crossing Marking
- High Visibility Crosswalk
- Rectangular Rapid Flash Beacon
- Push Button with Voice and Visual
- Crossing Islands and Medians
- Mid-block Crosswalks and Signals
- Curb Extension
- Small Curb Radius

For Motorist Safety

- Always use seat belts
- Perform periodic 360 degree vehicle safety check
- Heed posted speed limits
- Practice situational awareness
- When turning, yield the right of way to pedestrians
- Stop for pedestrians at crosswalks
- A void drunk, careless, fatigued, and inattentive
- Inattention: at sixty miles per hour, your vehicle travels almost a football field in three seconds “Do I know what is in my path right now?”

For Bicyclists Safety

- Same rules of the road as motorists; obey traffic signs, signals, and lane markings
- Wear a properly fitted helmet
- Be visible—don’t ride in the “gutter” and use lights at night
- Five foot overtaking law also applies to you
- If riding on the sidewalk, pass pedestrians slowly and warn them before overtaking (leave enough room); look for cars before crossing driveways and at intersections
- If you haven’t, take a bike safety class
- Be cautious when passing stopped buses or other vehicles
- Pay attention and put your phone away—pedestrians may enter your path suddenly
- Obey the speed limit and drive to conditions

For Pedestrians Safety

- Use designated crossings where/when provided
- Watch for cars even if you have the right-of-way and watch for bicyclists on sidewalks
- Be visible and pay attention
- Pay attention to potential “right on red” violation at a crosswalk
- Cross the street only at intersections and crosswalks. Look left, right, then left again before crossing.
- Make eye contact with drivers before crossing - don’t assume drivers see you
- Obey all traffic and crosswalks signals
- Use the sidewalk. If there isn’t one, walk on the left side of the road, facing oncoming traffic
- When walking, put away electronic devices that take your eyes and ears off the road
- Wear bright clothing during the day, and wear reflective materials or use a flashlight at night

Publications

- Billah, K., H. O. Sharif, and S. Dessouky, 2021: Analysis of Pedestrian–Motor Vehicle Crashes in San Antonio, Texas. *Sustainability*. 2021, 13, 6610; DOI: 10.3390/su13126610.

- Billah, K., H. O. Sharif, and S. Dessouky, 2021: Analysis of Bicyclist Safety in the City of San Antonio, Texas, 2014-2018. *In Submission*.

Thank you for your ATTENTION!!!

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Systemic analysis of bicycle & pedestrian safety in Utah

Patrick Singleton
Utah State University

Tran-SET Webinar

17 June 2021

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- Funding
  - Utah Department of Transportation
  - 19.318 "Systemic analysis of bicycle and pedestrian safety in Utah"
  - 19.316 "Safety in numbers? Developing improved safety predictive methods for pedestrian crashes at signalized intersections in Utah using push button-based measures of exposure"

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Source: Singleton, Mekker, & Islam, 2021, report on 19.316 for Utah DOT, https://drive.google.com/file/d/1Z1oF9d2-qtI9Z38PTnOY_Z_txADIaWer/view

Outline

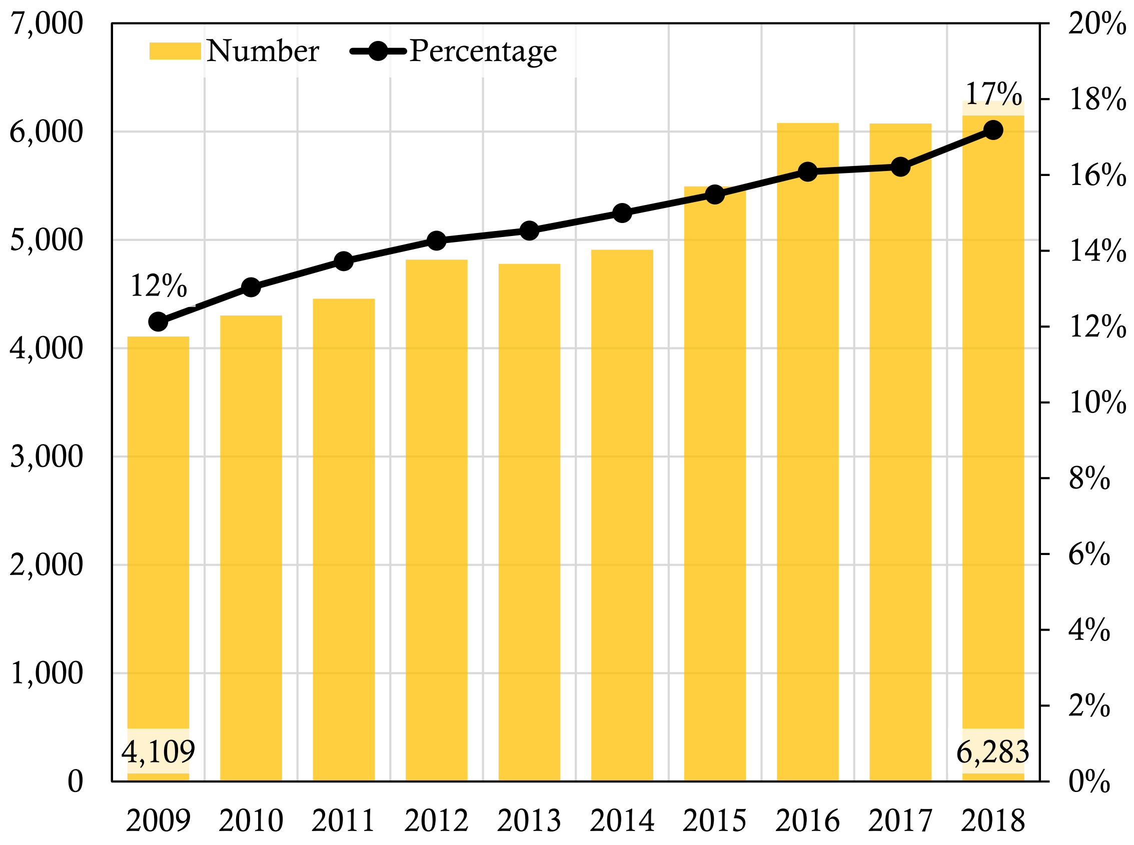
- Motivation
- Approach
- Key findings
- Future work

Systemic safety analysis

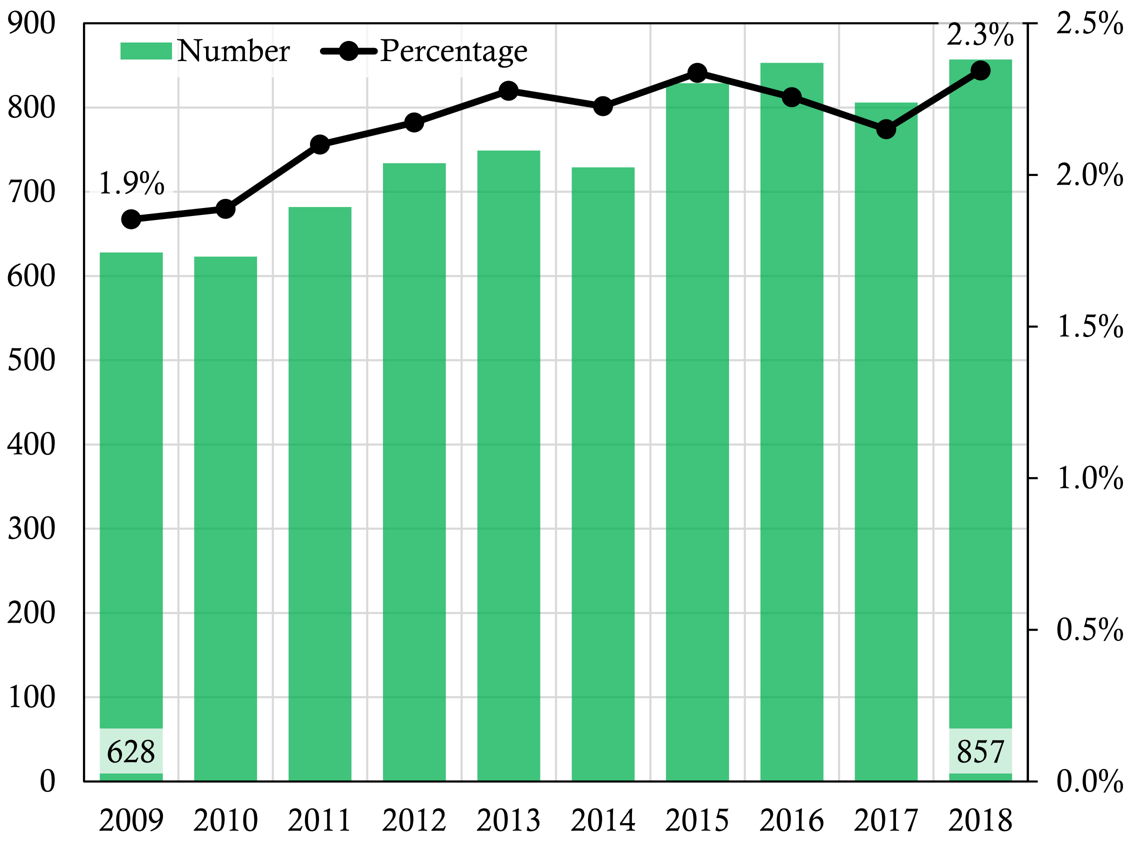
1. Define scope
2. Compile data
   - Crash data
   - Exposure data
   - Segment/intersection
   - Neighborhood/built environment data
3. Determine risk factors
   - Negative binomial
   - Gradient boosting

Motivation

Pedestrian fatalities (US)



Bicycle fatalities (US)



Source 1: NHTSA (2020), Traffic Safety Facts: Pedestrians, https://crashstats.nhtsa.dot.gov/Api/Public/Publication/812850
Source 2: NHTSA (2020), Traffic Safety Facts: Bicyclists and Other Cyclists, https://crashstats.nhtsa.dot.gov/Api/Public/Publication/812884

The traditional approach

- Roadway Safety Management Process

- Site-level focus
- Screening network for "hot-spots" using site-based crash histories
- Requires high crash frequencies and concentrations
- Analyzing specific crash types

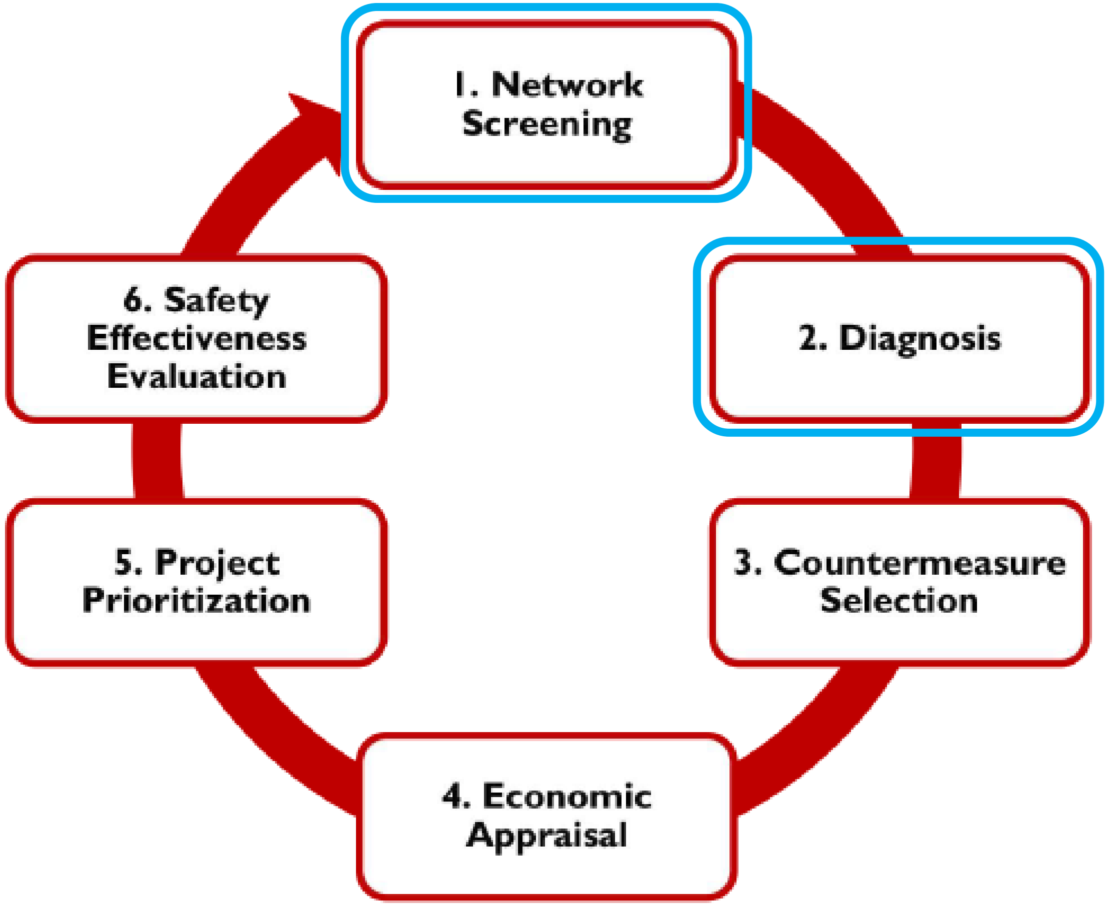
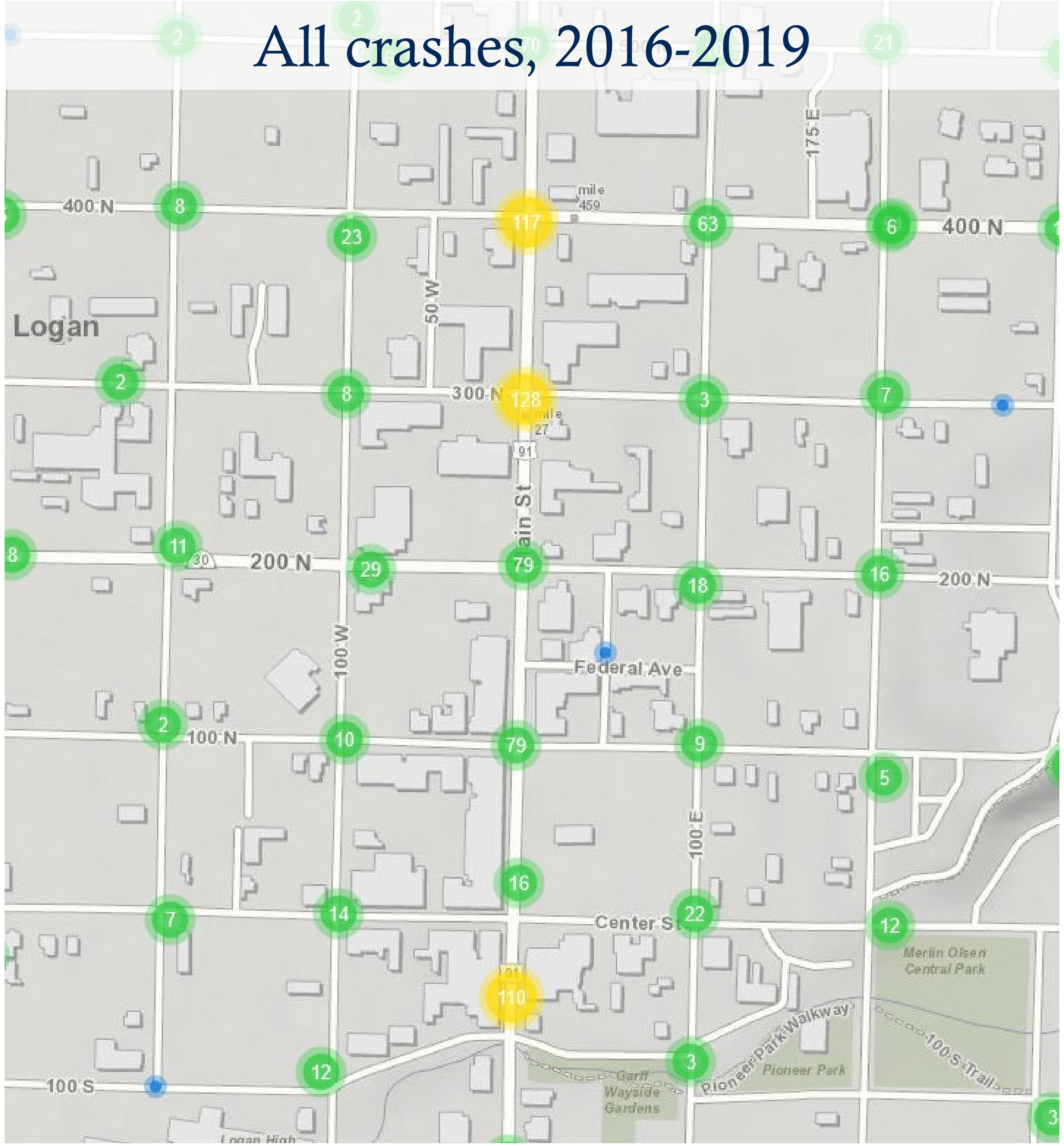
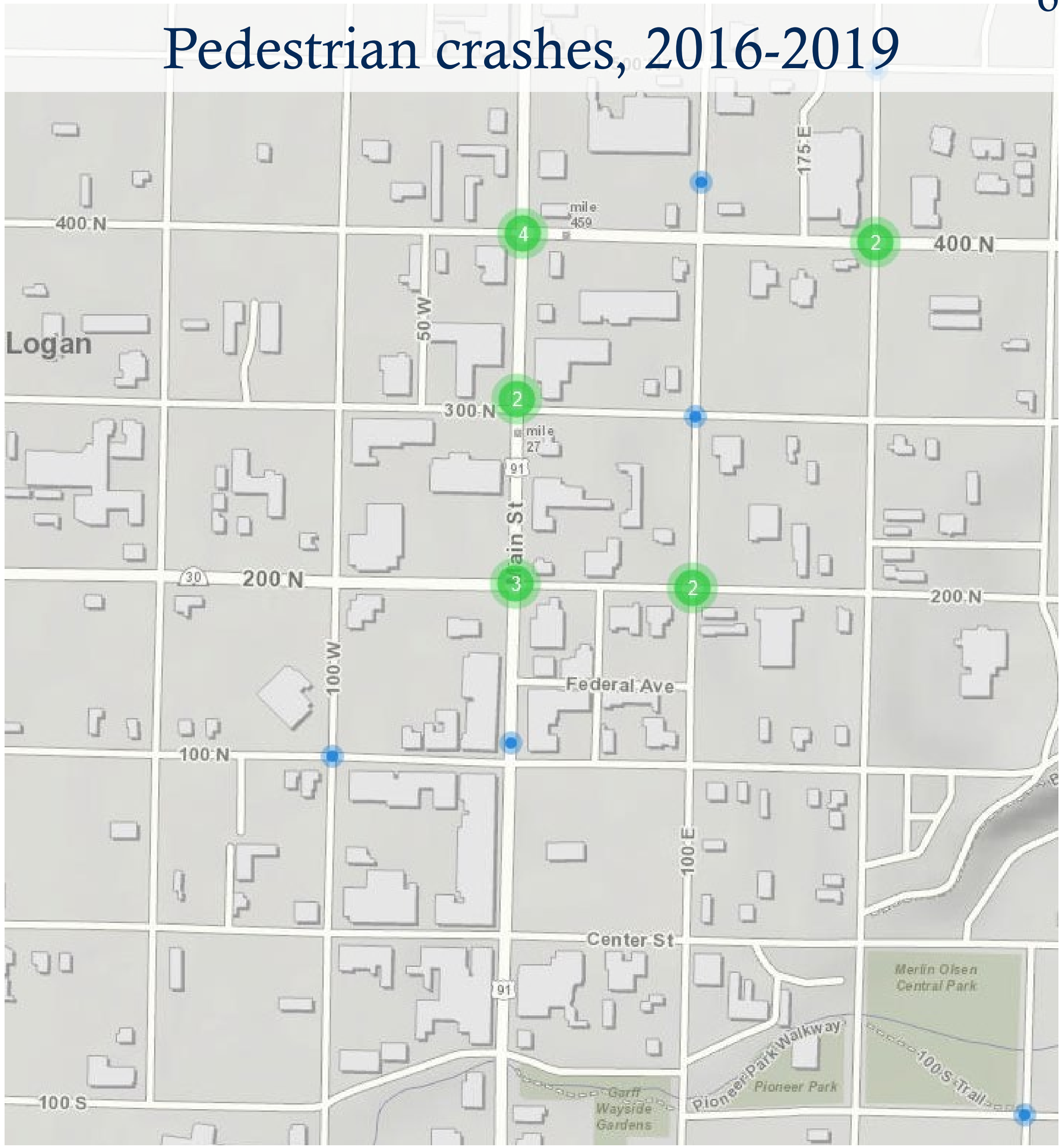


Image: Gross et al. (2016), https://safety.fhwa.dot.gov/rsdp/downloads/fhwasa16041.pdf

All crashes, 2016-2019



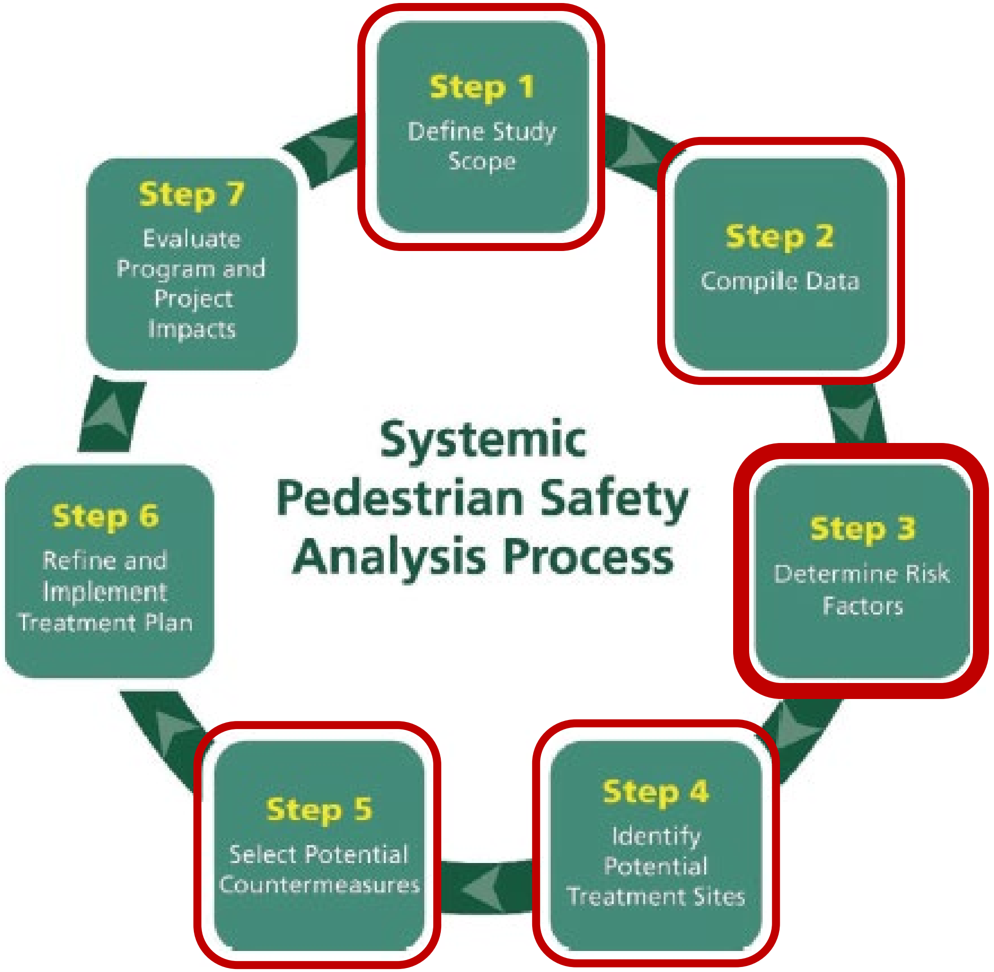
Pedestrian crashes, 2016-2019



Images: Utah Vehicle Collisions, https://crashmapping.utah.gov/

Crash data are protected under 23 USC 409.

The systemic approach



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Systemic Pedestrian Safety Analysis

- System-level focus
- Appropriate for low-frequency, highly-dispersed crashes
- Proactive identification of risk factors before hot-spots emerge
- Focus on low-cost proven treatments and countermeasures

Image: Thomas et al. (2018), https://doi.org/10.17226/25255

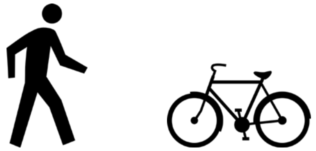
Our approach

- Conduct a systemic analysis of **bicycle and pedestrian safety** in Utah, in order to identify *risk factors*, potential treatment sites, and potential countermeasures

1. Define scope (crash types, locations)
2. Compile data (crashes, exposure, segment/intersection, neighborhood)
   a. Pedestrian exposure ← model using push-button data + social/built environment
3. Determine risk factors (crash models)
   a. Negative binomial regression models
   b. Gradient boosting decision trees
   c. Existing literature

① Define scope

- Crash types
  - "Pedestrian-involved"
  - "Bicycle-involved"
  - All crash types & severity levels



- Locations
  - State highway network only
  - Segments ("mid-block")
  - Intersections, signalized
  - Intersections, not signalized

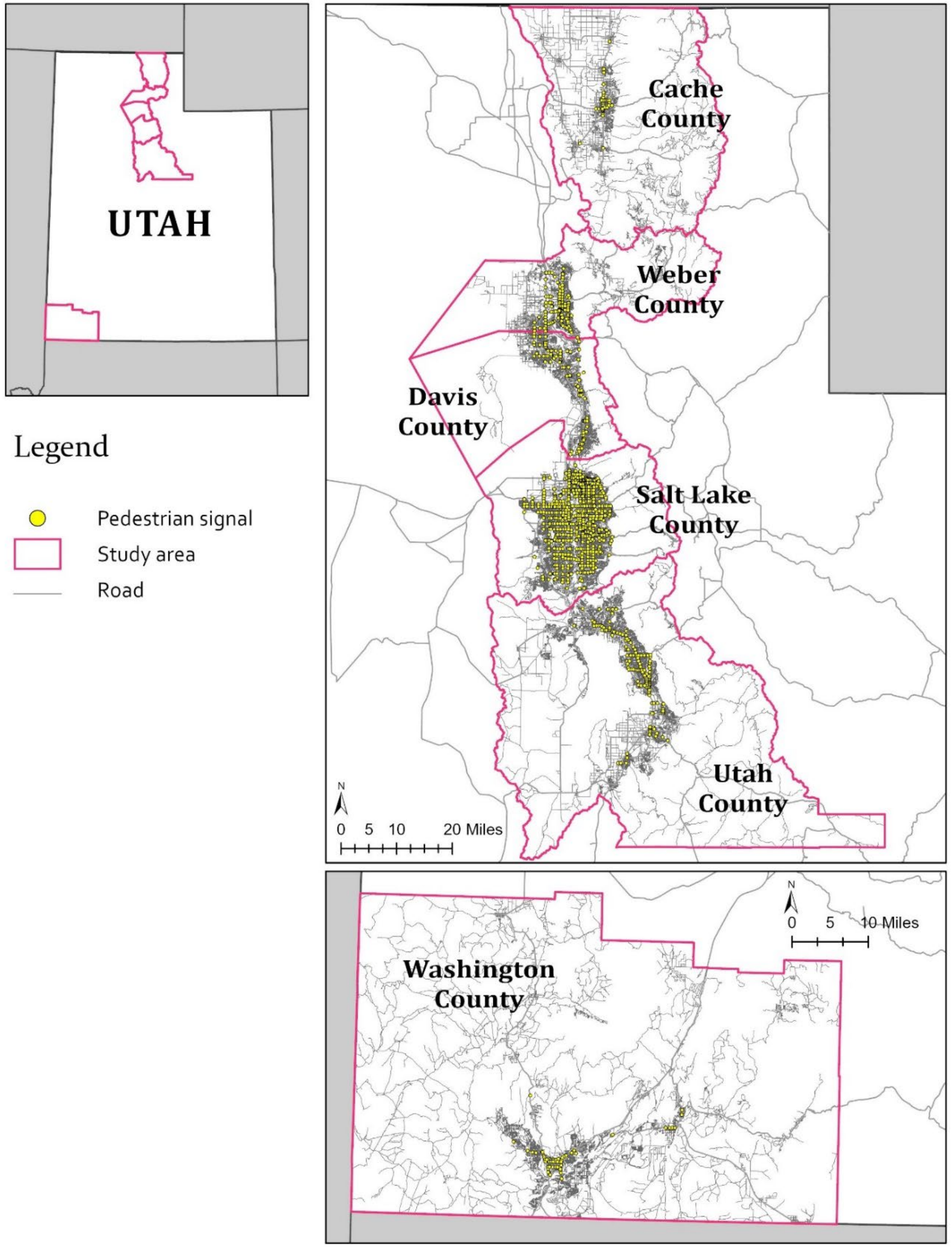
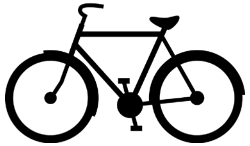


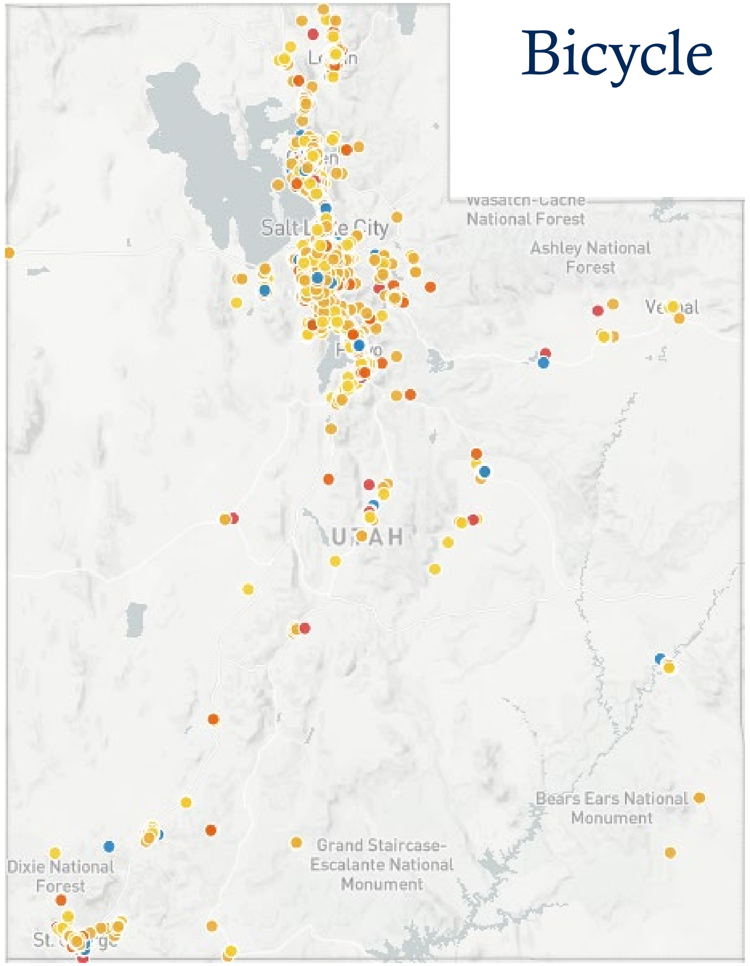
Image: Singleton et al. (2021), https://doi.org/10.1016/j.jtrangeo.2021.103067

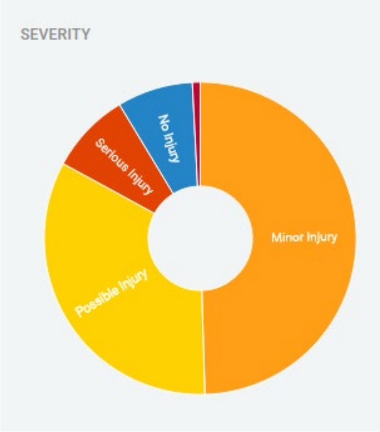
② Crash data

Reported crashes, 2010-2019

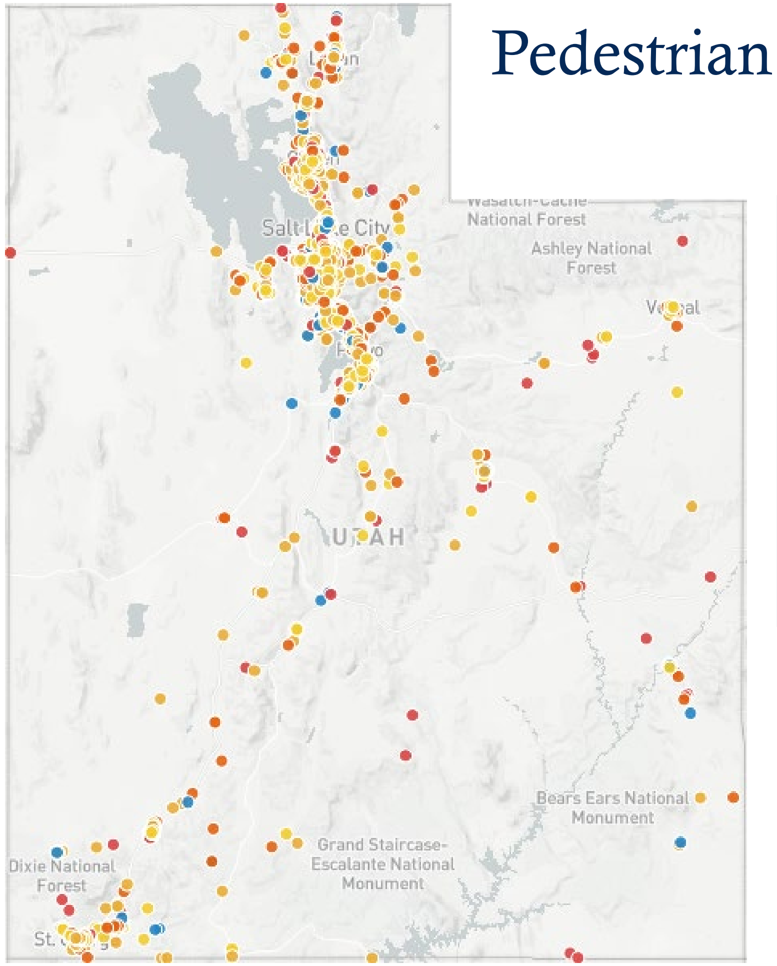
Bicycle

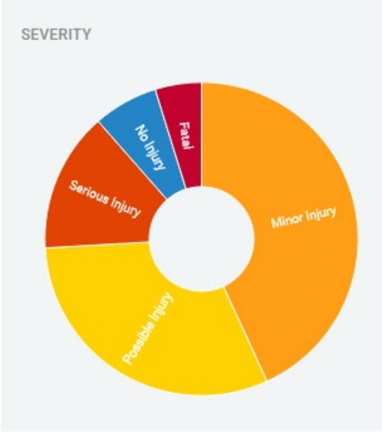






Pedestrian



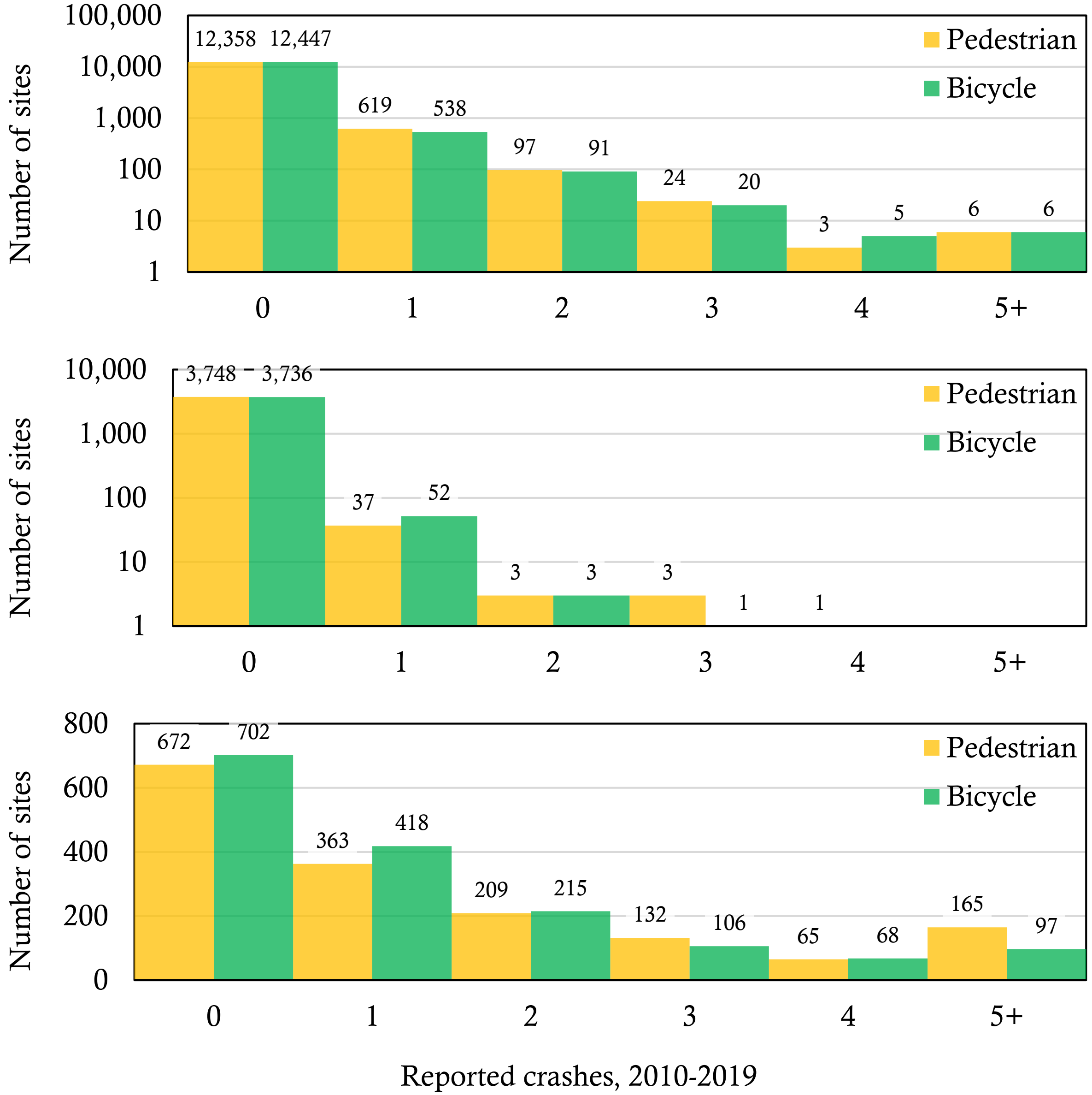


Images: Numetric map (2019), https://udot.numetric.com/roads/crash-query

Crash data are protected under 23 USC 409.

② Crash data

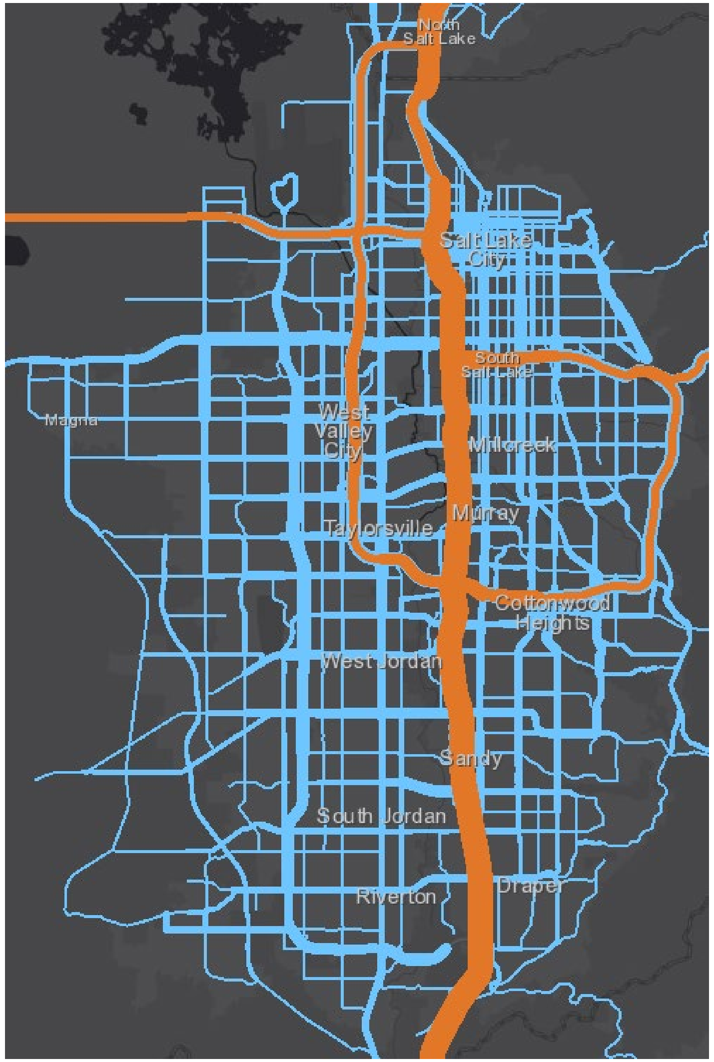
- 13,107 segments (mid-block)
  - 940 pedestrian crashes
  - 831 bicycle crashes
- 3,792 intersections, not signalized
  - 56 pedestrian crashes
  - 61 bicycle crashes
- 1,606 intersections, signalized
  - 2,598 pedestrian crashes
  - 2,046 bicycle crashes



Data: Numetric (2019), https://udot.numetric.com/roads/crash-query

Crash data are protected under 23 USC 409.

② Exposure (volume) data



- Motor vehicle traffic volumes
  - ← AADT from UDOT Data Portal
- Bicycle volumes
  - Bicycle counts from STRAVA Metro
- Pedestrian volumes
  - Pedestrian push-button presses from ATSPM (Automated Traffic Signal Performance Measures)
  - Converted into estimated pedestrian volumes using prior research sponsored by UDOT (Keeping Utah Moving)

Image: UDOT Traffic Count map (2019), https://www.arcgis.com/home/item.html?id=c48bd876d49c4fe39c3517eea24461d1

② Pedestrian exposure data

1. Push-button presses → Estimated pedestrian crossing volumes at signals

- Recorded videos
  - UDOT traffic cameras
  - 90 signals, 320 crosswalks
  - 24,085 crossing-hours of video
  - January to December, 2019
  - Different hours, weekdays, seasons
- Counted pedestrians
  - 174,923 people walking

Source 1: Singleton & Runa, 2021, article in *Transportation Research Record*, https://doi.org/10.1177/0361198121994126
Source 2: Singleton, Runa, & Humagain, 2020, report for Utah DOT, https://drive.google.com/file/d/1Z1oF9d2-qtI9Z38PTnOY_Z_txADIaWer/view

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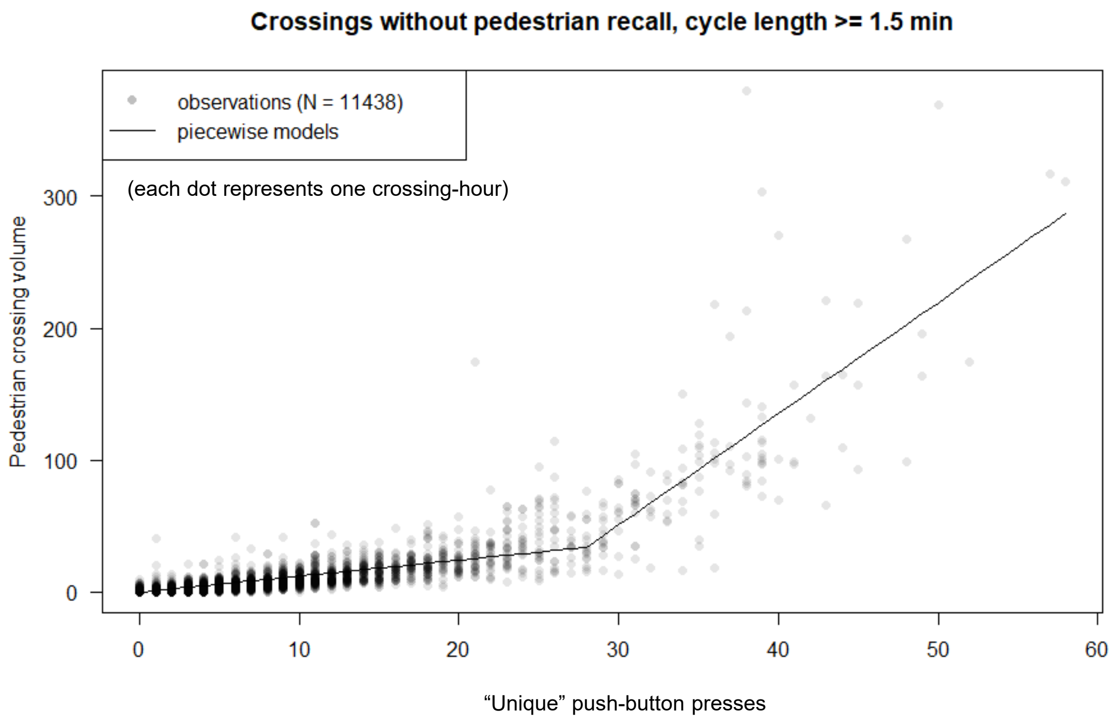

- Developed regression models*
  - *Outcome*: ped crossing volume
  - *Input*: "unique" push-button presses (15 sec filter), or ped calls registered
  - Non-linear (piecewise or quadratic)
- Overall, very good model fits
  - Correlation = 0.85
  - Mean error = ± 3 peds/hour

- *Five models for different situations: pedestrian hybrid beacons (PHBs/HAWKs), crossings on pedestrian recall at high-activity vs. low-activity signals, crossings not on pedestrian recall at signals with short vs. long cycle lengths

Source 1: Singleton & Runa, 2021, article in *Transportation Research Record*, https://doi.org/10.1177/0361198121994126
Source 2: Singleton, Runa, & Humagain, 2020, report for Utah DOT, https://drive.google.com/file/d/1Z1oF9d2-qtI9Z38PTnOY_Z_txADIaWer/view

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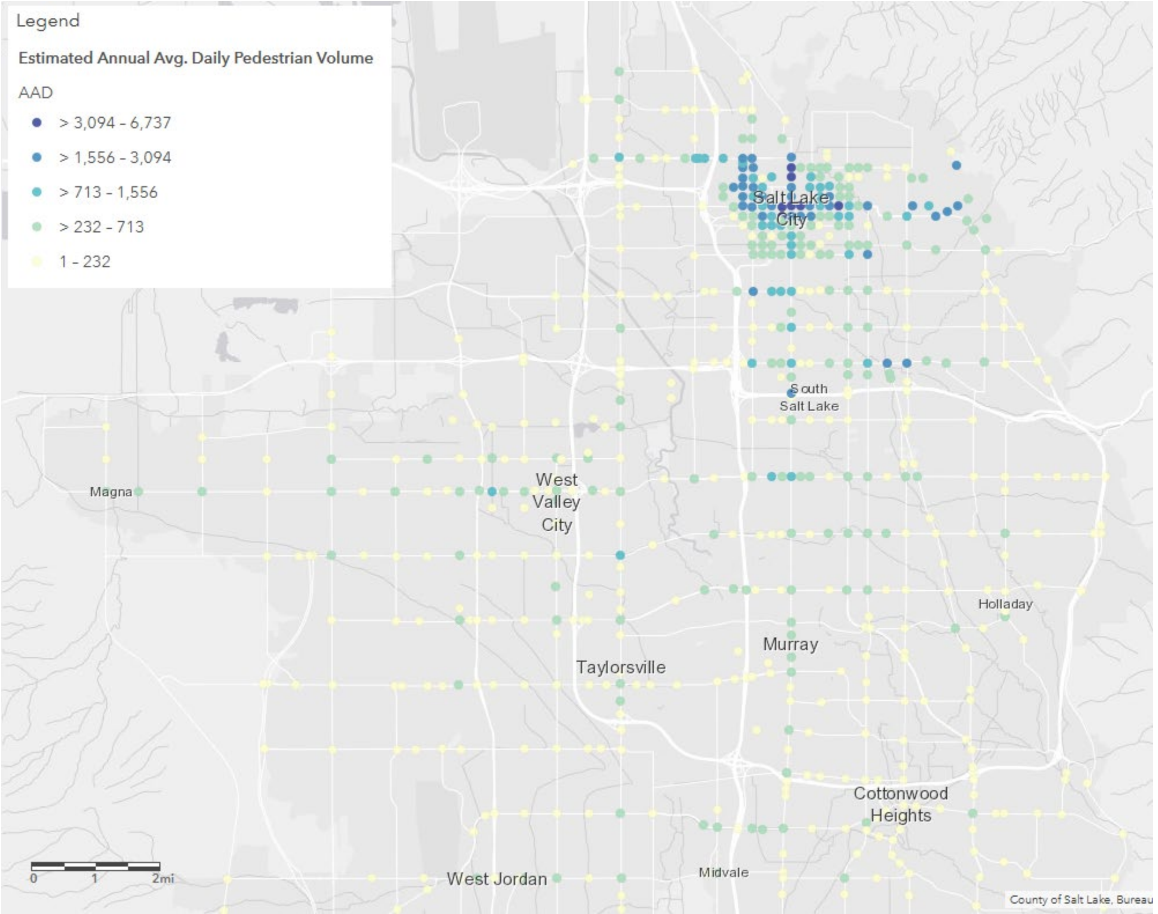

- Applied regression models
  - Assembled signal data from ATSPM
  - 1,494 signals in Utah
  - July 2017 – June 2018
- Calculated annual average daily pedestrian (AADP) crossing volume estimates

Source 1: Singleton, Park, & Lee, 2020, map for Utah DOT, https://arcg.is/0S84Wf
Source 2: Singleton, Runa, & Humagain, 2020, report for Utah DOT, https://drive.google.com/file/d/1Z1oF9d2-qtI9Z38PTnOY_Z_txADIaWer/view

② Pedestrian exposure data

2. Ped volumes at signals → Estimated ped volumes at other intersections/segments

- Pedestrian activity explained by:
  - Built environment (BE)
  - Land use (LU)
  - Sociodemographics (SD)

- Estimated direct demand model
  - *Outcome*: ln(AADP) for signals
  - *Inputs*: BE/LU/SD variables
  - Log-linear, spatial error model
  - 10-fold cross-validation

Source 1: Singleton, Park, & Lee, 2021, article in *Journal of Transport Geography*, https://doi.org/10.1016/j.jtrangeo.2021.103067
Source 2: Singleton, Park, & Lee, 2021, report for Utah DOT, under review and available from the authors

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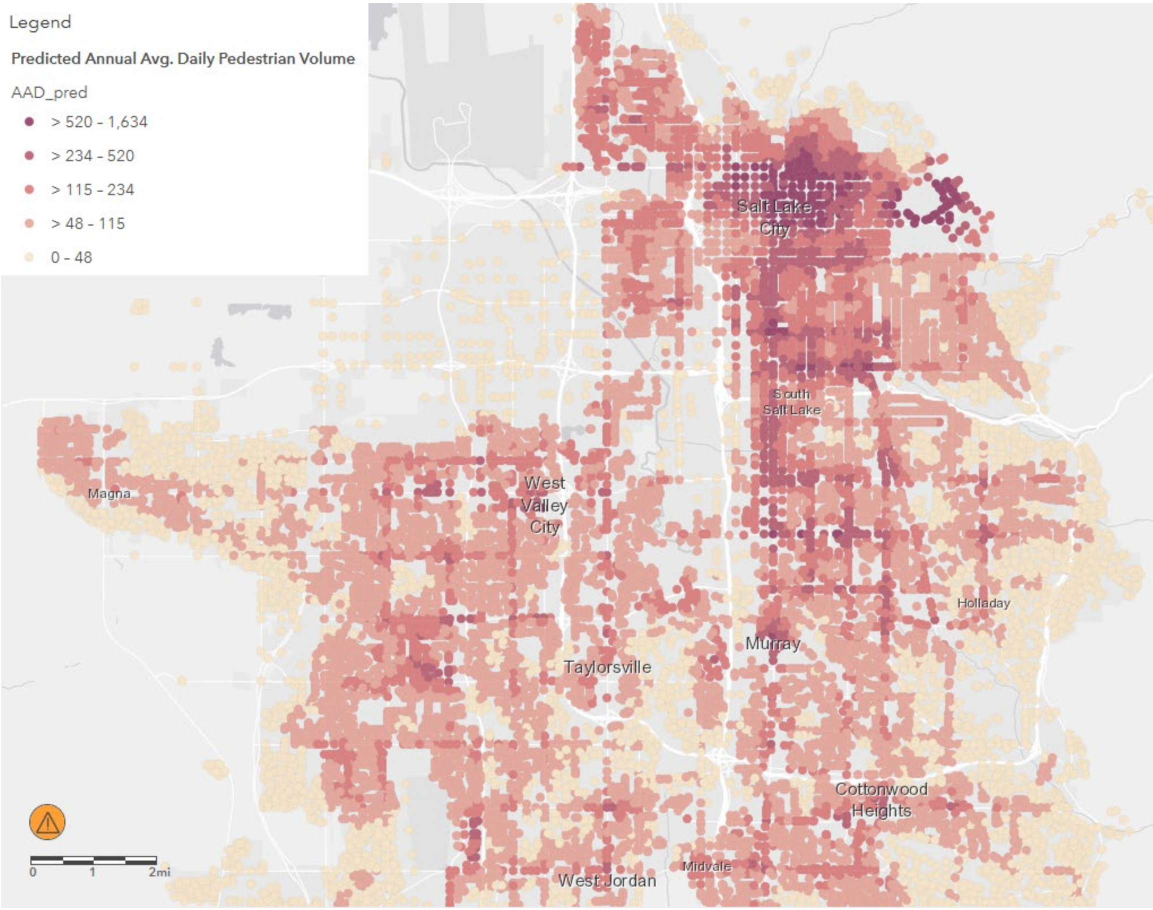
② Pedestrian exposure data

2. Ped volumes at signals → Estimated ped volumes at other intersections/segments



- Applied direct demand model
  - Assembled sociodemographic, built environment, & land use data
  - 62,336 intersections
- Calculated AADP estimates
  - For non-signalized intersections: directly from model
  - For segments: interpolated, 50% of average of adjacent intersections

Source 1: Singleton, Park, & Lee, 2020, map for Utah DOT, https://arcg.is/0O8bOG
Source 2: Singleton, Park, & Lee, 2021, report for Utah DOT, under review and available from the authors

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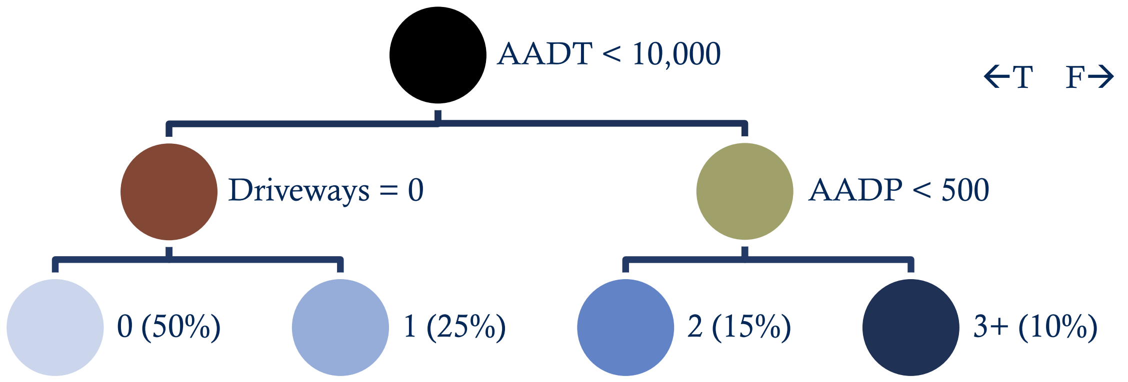
② Other data

- Segment characteristics
  - Lanes, shoulders, barriers, medians, islands, rumble strips
  - Speed limit, grade, driveways
- Signalized intersection characteristics
  - Intersection type (# legs)
  - Crosswalk length, marking type
  - RTOR prohibited, channelized
  - Bus stops, bike lanes on approaches
- Other intersection characteristics
  - Adjacent segment characteristics

- Land use / built environment data
  - Population, employment densities
  - Land uses, parks, schools, etc.
  - Intersection density, transit stops
- Neighborhood sociodemographics
  - Household income, size, vehicle ownership
  - Race/ethnicity, disability status

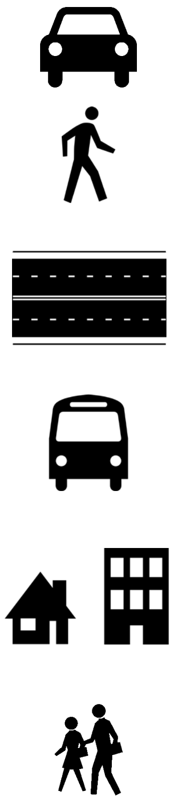
③ Determine risk factors

- Negative binomial (NB) regression *
  - # crashes = *f*(motor vehicle & pedestrian/bicycle exposure, segment/intersection characteristics, land use / built environment data, neighborhood sociodemographics)
  - Accounts for overdispersion (variance > mean) of crash frequency distribution
  - Same method to develop Safety Performance Functions (SPFs)
- Gradient boosting (GB) decision trees *
  - Efficient machine learning technique
  - Based on ensembles of decision trees
  - "Importance" based on how much each variable contributes to the splitting
- Existing literature



* Implemented in R using the MASS and XGBoost packages.

3 Crash models (NB): Pedestrian



Variable	Segments (mid-block) [a]	Intersections, not signalized [b]	Intersections, signalized [c]
Motor vehicle traffic volume	+	n.s.	+
Pedestrian volume	+	+	+
Number of legs at intersections	n/a	+	+
Crosswalk length	n/a	n/a	+
Presence of a bike route/lane	n.s.	n.s.	–
Transit stops/stations	+	n.s.	+
Density of driveways	+	n/a	n/a
Residential or employment density	–	+	–
% Hispanic or non-White race/ethnicity	+	n.s.	+
% with a disability	+	n.s.	+

Not significant in any model: truck percentage, speed limit, percentage grade, two-way left-turn lane, roadway with wide medians

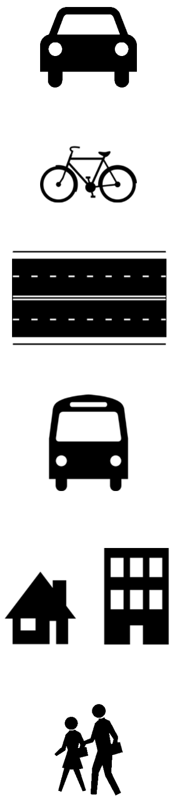
[a] N = 4,979. Also sig.: number of left-turn lanes (–), presence of barrier / rumble strips (–), % zero-vehicle households (+)

[b] N = 1,152. Also sig.: none

[c] N = 1,441. Also sig.: high-viz crosswalk markings (+), no right-turns-on-red (–), % land use vacant (+), schools/places of worship (–)

+ = positive association (more crashes)
– = negative association (fewer crashes)
n.s. = not significant ($p > 0.10$)
n/a = not applicable (not included in model)

3 Crash models (NB): Bicycle



Variable	Segments (mid-block) [a]	Intersections, not signalized [b]	Intersections, signalized [c]
Motor vehicle traffic volume	+	+	+
Bicycle volume	+	n.s.	+
Number of legs at intersections	n/a	+	+
Crosswalk length	n/a	n/a	+
Percentage grade	+	–	n/a
Transit stops/stations	+	+	+
Density of driveways	+	n/a	n/a
Residential or employment density	+	+	+
% Hispanic or non-White race/ethnicity	+	n.s.	+
% with a disability	n.s.	n.s.	+

Not significant in any model: truck percentage, speed limit, presence of a bike route/lane

[a] N = 11,910. Also sig.: number of left-turn lanes (+), presence of barrier / rumble strips (–)

[b] N = 3,192. Also sig.: two-way left-turn lane (+), roadway with wide medians (–)

[c] N = 1,441. Also sig.: channelized right-turns (–), places of worship (–), household income (–)

+ = positive association (more crashes)

– = negative association (fewer crashes)

n.s. = not significant ($p > 0.10$)

n/a = not applicable (not included in model)

③ Crash models (GB): Pedestrian

Variable (ordered by importance*)	Segments (mid-block) [a]
Pedestrian volume	+
Motor vehicle traffic volume	+
Density of (minor) driveways	−
Percentage grade	+ overall, n.m. (− to +)
Household income	− overall, n.m. (− to +)
Density of (major) driveways	−
% Hispanic or non-White race/ethnicity	+
Transit stops	+

Variable (ordered by importance*)	Intersections, not signalized [b]
Residential density	+
Median width (major)	−
Number of legs at intersections	+
Pedestrian volume	+
Distance to nearest signal	n.m. (+, −)
Percentage grade	+

[a] N = 13,107. [b] N = 4,555. 70% used for training, 30% used for testing.
* Importance measured by "gain" statistic. Only variables with gain ≥ 0.05 are shown.

+ = positive association (more crashes)
− = negative association (fewer crashes)
n.m. = non-monotonic (change in direction)

③ Crash models (GB): Bicycle

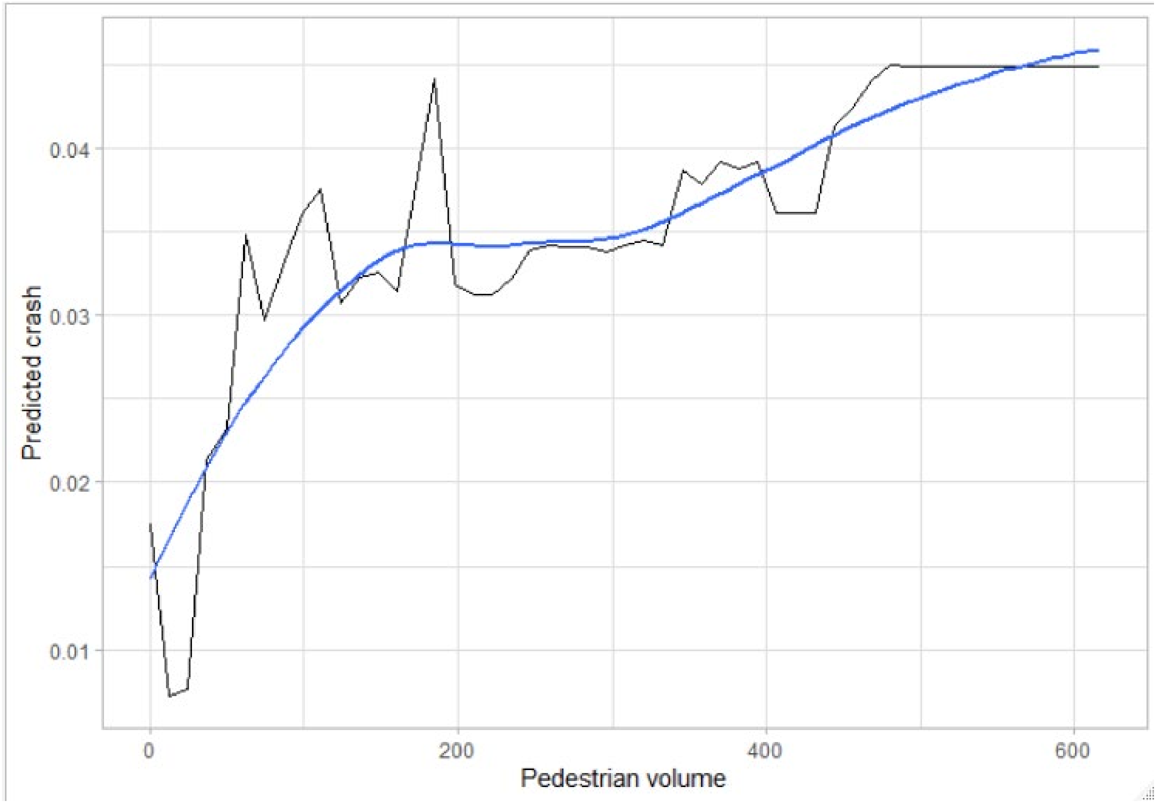
Variable (ordered by importance*)	Segments (mid-block) [a]
Motor vehicle traffic volume	+
Employment density	+
Density of (major) driveways	–
Density of (minor) driveways	+
Bicycle volume	+
Household income	– overall, n.m. (+ to –)
% Hispanic or non-White race/ethnicity	+
Residential density	–

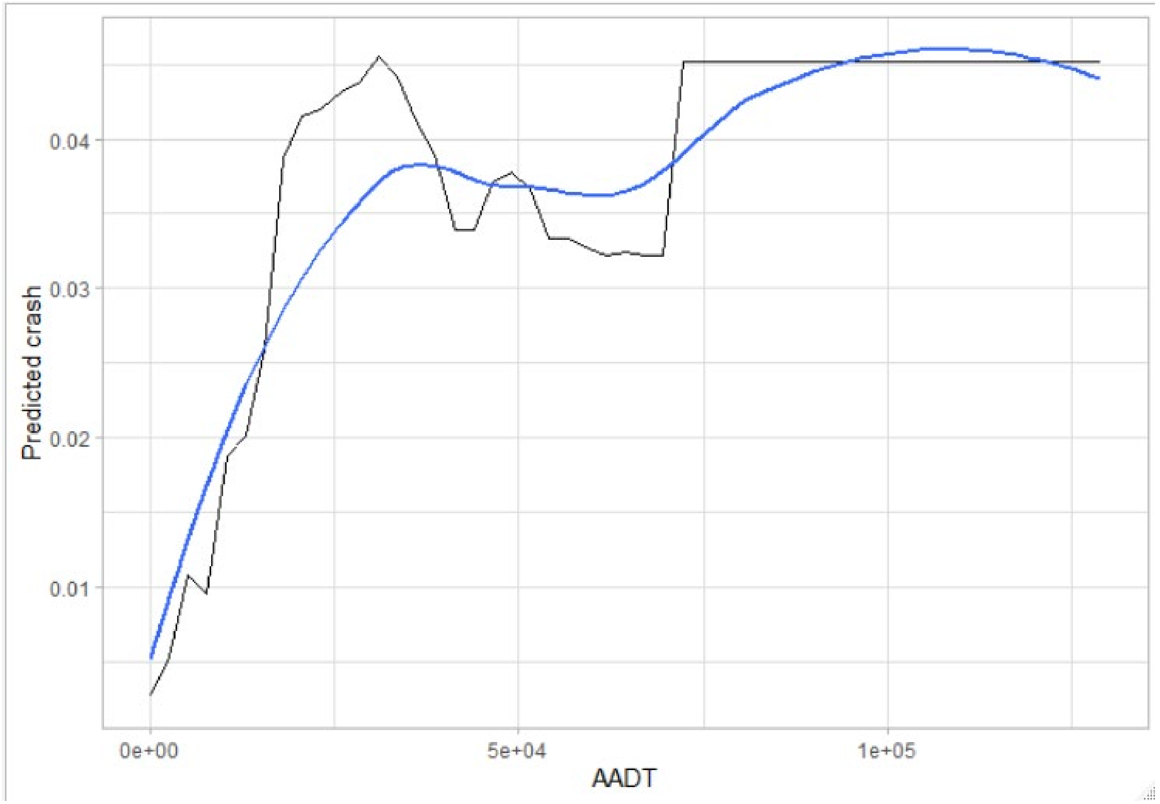
Variable (ordered by importance*)	Intersections, not signalized [b]
Median width (major)	–
Residential density	+
Number of legs at intersections	+
Motor vehicle traffic volume	+
Distance to nearest intersection	+
Percentage grade	–
Household income	– overall, n.m. (– to +)

[a] N = 13,107. [b] N = 4,555. 70% used for training, 30% used for testing.
* Importance measured by "gain" statistic. Only variables with gain ≥ 0.05 are shown.

+ = positive association (more crashes)
– = negative association (fewer crashes)
n.m. = non-monotonic (change in direction)

③ Crash models (GB): Non-linearities



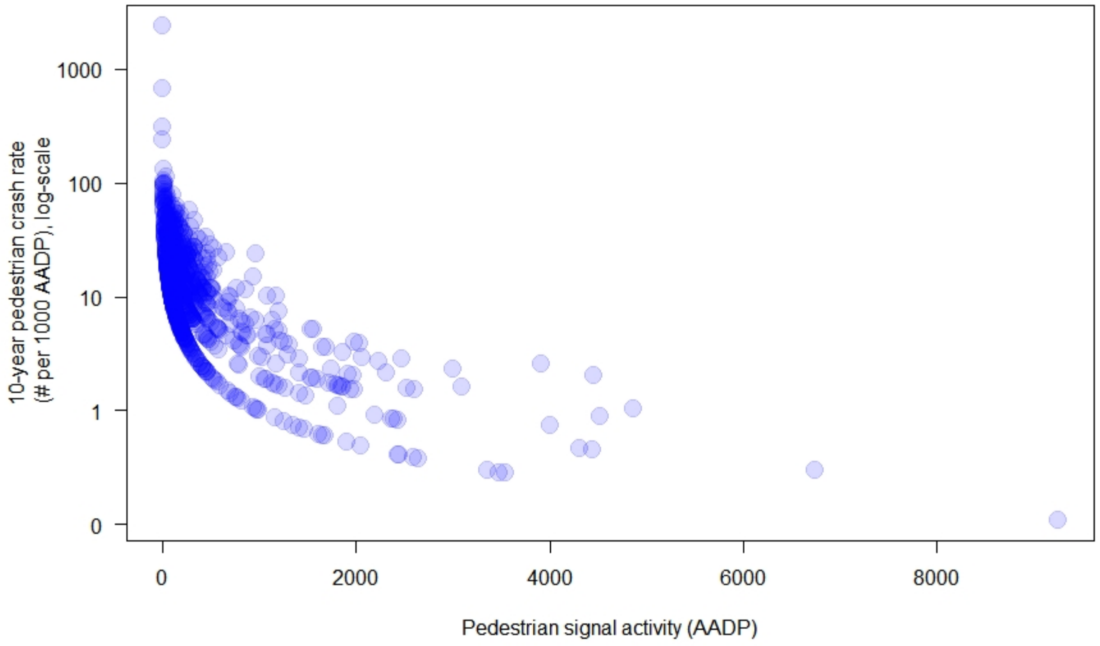


Partial dependence plots: Marginal effect of variable on predicted outcome.

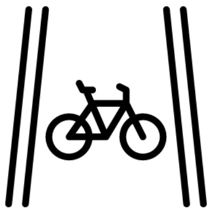
Results for pedestrian volume and motor vehicle traffic volume for Pedestrian Segments model.

Key findings

- “Safety in numbers” for 
  - 10% increase in walking → 4.1–4.4% increase in ped crashes



- Potential strategies
  - Complete streets
  - Access management


- Focus efforts in “at-risk” communities
  - Lower income
  - Non-white and/or Hispanic
  - Disabilities

Source: Singleton, Mekker, & Islam, 2021, report for Utah DOT, https://drive.google.com/file/d/1Z1oF9d2-qtI9Z38PTnOY_Z_txADIaWer/view

Future work

- Systemic safety analysis
  - Identify potential treatment sites

Table 10. Example 1: Identification of potential sites using risk factors.

Risk Factor	Number of Sites	Total Prior Observed Crashes (8 years)	Total SPF-Predicted Crashes (8 years)	Range of SPF Rankings (of ~23,000 segments)
1. Presence of midblock crosswalk (1 or more)	196	50	50.1	4–20,870
2. Plus, 4 or 5+ through lanes	26	24	19.2	4–2,228
3. Plus, on-street parking	12	10	14.6	9–2,228

  - Recommend countermeasures

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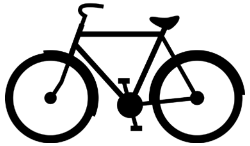
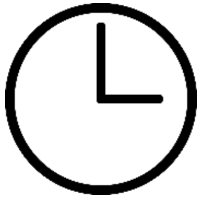
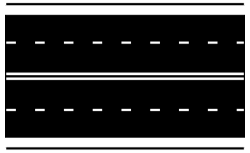
- Potential improvements
  - Bicycle volumes



  - Temporal alignment of crash data and other data (10 years vs. one point)



  - Consistency/completeness of roadway attribute data



  - Accounting for spatial dependence

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Images: Thomas et al., (2018), https://doi.org/10.17226/25255. CMF Clearinghouse, http://www.cmfclearinghouse.org/. PEDBIKESAFE, http://www.pedbikesafe.org/.

Questions?

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