MOUNTAIN-PLAINS CONSORTIUM

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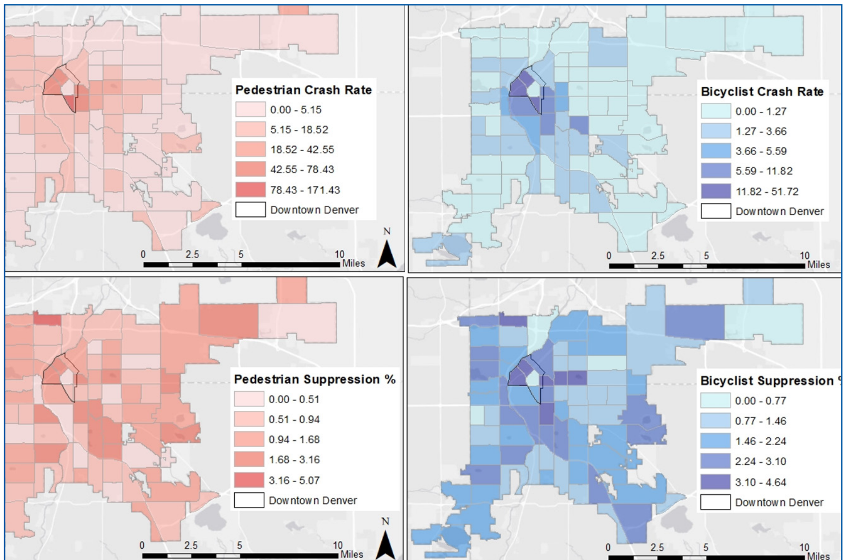
Reassessing Child Pedestrian Mode Choice and Safety via Perceived Parental Risk



Choropleth comparison of crash-based reactive analyses and proactive analysis

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16. Abstract

Traditional pedestrian and bicyclist safety analyses typically examine crashes, injuries, or fatalities. However, this reactive approach only accounts for the places where people are currently walking or biking and those that are doing so. Would a proactive approach – examining areas where pedestrian and bicyclist activity is being suppressed because of safety concerns – illuminate other previously neglected safety issues?

The goal of the first section is to compare results from reactive and proactive pedestrian and bicyclist safety analyses. To accomplish this, we focus on child pedestrians and bicyclists because of the structured characteristics of their travel behavior regarding trips to school. We complete a reactive crash cluster analysis and a proactive safety analysis that is based on trip suppression due to traffic safety concerns for Denver, CO. A parental perception survey informs the mode choice model we create for the proactive safety analysis. Findings suggest that reactive approaches identify downtown Denver and major corridors as unsafe, while the proactive analysis also identifies neighborhoods in west, east, and northeast Denver. Due to an absence of crashes, the majority of these areas would not normally be considered unsafe for pedestrians and bicyclists based on conventional reactive approaches. The fact that they are perceived as unsafe may be limiting usage and thereby limiting the number of crashes. In order to improve safety where children are currently walking and bicycling – as well as where they want to walk or bike – traditional analyses would benefit from augmentation by such a proactive safety approach.

The second section looks at the question: which populations are most impacted by traffic safety issues neglected by traditional crash analyses? Results suggest that negative impacts are borne disproportionately by low-income, low-education, Hispanic, and black neighborhoods. Proactive analysis results specifically identify perceived safety issues in neighborhoods in north and northeast Denver that were neglected by results from the reactive analyses. Findings suggest that the inequitable distribution of traffic safety issues identified in past crash-based literature – and confirmed in this work – is graver than a conventional reactive analysis would lead one to believe.

The last section presents a GIS tool intended to help cities better focus their Vision Zero efforts on the cities' most vulnerable users, kids.

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Reassessing Child Pedestrian Mode Choice and Safety via Perceived Parental Risk

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Disclaimer

ABSTRACT

Traditional pedestrian and bicyclist safety analyses typically examine crashes, injuries, or fatalities. However, this reactive approach only accounts for the places where people are currently walking or biking and those that are doing so. Would a proactive approach – examining areas where pedestrian and bicyclist activity is being suppressed because of safety concerns – illuminate other previously neglected safety issues?

The goal of the first chapter is to compare results from reactive and proactive pedestrian and bicyclist safety analyses. To accomplish this, we focus on child pedestrians and bicyclists because of the structured characteristics of their travel behavior regarding trips to school. We complete a reactive crash cluster analysis and a proactive safety analysis that is based on trip suppression due to traffic safety concerns for Denver, CO. A parental perception survey informs the mode choice model we create for the proactive safety analysis. Findings suggest that reactive approaches identify downtown Denver and major corridors as unsafe, while the proactive analysis also identifies neighborhoods in west, east, and northeast Denver. Due to an absence of crashes, the majority of these areas would not normally be considered unsafe for pedestrians and bicyclists based on conventional reactive approaches. The fact that they are perceived as unsafe may be limiting usage and thereby limiting the number of crashes. In order to improve safety where children are currently walking and bicycling – as well as where they want to walk or bike – traditional analyses would benefit from augmentation by such a proactive safety approach.

The second chapter looks at the question: which populations are most impacted by traffic safety issues neglected by traditional crash analyses? Results suggest that negative impacts are borne disproportionately by low-income, low-education, Hispanic, and black neighborhoods. Proactive analysis results specifically identify perceived safety issues in neighborhoods in north and northeast Denver that were neglected by results from the reactive analyses. Findings suggest that the inequitable distribution of traffic safety issues identified in past crash-based literature – and confirmed in this work – is graver than a conventional reactive analysis would lead one to believe.

The last chapter presents a GIS tool intended to help cities better focus their Vision Zero efforts on the cities' most vulnerable users, kids.

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1. INTRODUCTION

Researchers traditionally analyze crashes, injuries, or fatalities when examining traffic safety of walking and bicycling trips (Administration, 2006; Zegeer, Nabors, Gelinne, Lefler, & Bushell, 2010). However, the only people that are accounted for in this reactive approach to safety are those who are already walking or biking – the people who have decided that those activities are safe enough to pursue. What about the people who – because of traffic safety concerns – have decided to not walk or bike in the first place? Furthermore, the only locations that are identified in reactive approaches are the locations that have pedestrians and bicyclists present. What about the places where people have decided not to walk or bike? How would we proactively identify these places as unsafe before a crash occurs or even before any walking or biking occurs?

Past research has investigated how perceptions of traffic safety impact the choice to walk or bike (Cho, Rodriguez, & Khattak, 2009; Nevelsteen, Steenberghen, Van Rompaey, & Uyttersprot, 2012a; Schneider, Ryznar, & Khattak, 2004). We propose building upon this work by quantifying walking and bicycling trip suppression due to traffic safety concerns and using active transportation trip suppression as an indicator of traffic safety risk. If high levels of pedestrian and bicycle trips are being suppressed due to traffic safety concerns, this suggests that there are traffic safety issues present, regardless of whether crashes are occurring. We then compare results from our proactive safety analysis to results from a traditional reactive analysis.

To accomplish these objectives, we reactively and proactively analyze the safety of children's walking and biking trips to and from school in Denver, Colorado. Children are some of the most vulnerable road users and depend on walking and biking if they wish to have independent mobility. Their trips to school are also highly structured, making this an ideal group to study. For the reactive approach, we complete a crash cluster analysis specific to child pedestrians and bicyclists. For the proactive approach, we weigh shortest path distances with suppression proportions from a parental perceptions survey to derive the level of child school trip suppression associated with traffic safety concerns. Finally, we compare results from this proactive analysis to results from the traditional reactive crash analysis. If our goals include promoting walking and biking activity instead of simply reducing existing pedestrian and bicycle crashes, such a proactive safety analysis may represent an important new perspective on pedestrian and bicyclist safety.

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[1] This portion of the report has been peer-reviewed and is scheduled for publication: Ferenchak, N. and Marshall, W. Suppressed Child Pedestrian and Bicycle Trips as an Indicator of Safety: Adopting a Proactive Safety Approach in Denver, Colorado. *Transportation Research – Part A*.

2. THEORY

Traditional safety analyses rely on crashes, injuries, or fatalities to identify unsafe roadways (Board, 2001; Waldheim, Wemple, & Fish, 2015). This approach is utilized for safety studies of vehicles as well as for pedestrians and bicyclists (Administration, 2006; Zegeer et al., 2010). Ideally, these crash-based safety analyses account for exposure – a pedestrian or bicyclist's proximity to potentially harmful situations involving motor vehicles – in the form of distance or time traveled, user counts, times crossing a street, or the product of pedestrian or bicyclist and vehicle volumes (Molino et al., 2012). However, the lack of reliable pedestrian and bicyclist exposure data makes such comparisons difficult (Turner et al., 2017). In the absence of appropriate exposure data, cluster analyses of crashes are a common approach used to identify areas of safety concern (Blackburn, Zegeer, & Brookshire, 2017).

The four pedestrian and bicyclist safety analyses for Denver, Colorado that were most recently completed by local and regional transportation agencies consisted of traditional crash-based analyses that did not account for exposure (Governments, 2012, 2017; Works, 2016, 2017). While such a focus on crashes can allow for the successful identification and reduction of those crashes, it is by nature a reactive approach that requires a crash to occur before any safety issues can be identified. Because a pedestrian or bicyclist crash cannot take place unless there is a pedestrian or bicyclist present, this conventional approach only accounts for people who are currently walking or biking and the places where they are doing so.

A proactive approach to safety is one that identifies areas that are likely to experience crashes before those crashes occur. It could also be an approach that identifies areas where safety concerns have caused low levels of pedestrian and bicyclist activity and have therefore effectively hidden safety issues from the objective eye. For instance, proactive approaches can be effective when exposure levels – and therefore crash levels – are so low that traditional indicators do not provide an accurate representation of risk (Cho et al., 2009; Schneider et al., 2004). Perceptions of safety have been shown to correlate with exposure levels and may therefore proactively indicate safety issues (NOLAND, 1995; Pucher, Dill, & Handy, 2010). In other words, while a road perceived as unsafe may suppress walking and biking trips, and therefore reduce or preclude pedestrian and bicycle crashes, these same negative safety perceptions can be used as an indicator that safety issues – albeit hidden from conventional, objective analyses – are present.

Past researchers have taken several approaches when using perceptions of safety to proactively identify pedestrian and bicyclist safety issues. An early attempt surveyed pedestrians and drivers on the campus of the University of North Carolina at Chapel Hill, asking them to identify locations that posed safety issues to pedestrians (Schneider et al., 2004). When the researchers compared these subjective perceptions to objective outcomes, it became apparent that there were areas perceived as unsafe that had no crashes occurring. Researchers determined that, while these areas were otherwise desirable to pedestrians, the perception of these areas as 'accidents waiting to happen' was reducing levels of exposure. While these results provide a theoretical foundation for our work, the method of identifying unique hotspots is not scalable. In other words, because the perceptions were not tied to specific characteristics of the built environment, the survey would need to be re-administered for every new area that may be studied in the future. We seek a methodology that can be generalized and applied to other areas.

Cho et al. (2009) improved upon this scalability issue by creating a risk estimate based on built environment characteristics such as land use mix and street connectivity (Cho et al., 2009). They found that increased perceptions of risk for pedestrians and bicyclists reduced crash rates because of decreased usage. However, the methods did not account for street-level risk factors such as roadway width, vehicle speeds, and vehicle volumes, which could have an impact on behavior. This approach and its results have relatively limited implications for built environment improvements as road network connectivity and land use mixes are not as easily addressed as vehicle volumes, vehicle speeds, or sidewalk gaps.

Nevelsteen et al. (2012) built upon these trip suppression studies by examining the relationship between perceptions of street-level risk factors and pedestrian and bicyclist trip allowance for children traveling to school (Nevelsteen, Steenberghen, Van Rompaey, & Uyttersprot, 2012b). However, the researchers only examined two factors: the presence of pedestrian and bicycle facilities and vehicle speeds. Furthermore, the study was performed in a Belgian context that reports 40% of 11 and 12-year olds cycling to school – a transportation culture that is vastly different from much of the world.

All of the studies examining safety perceptions showed that perceptions of safety and trip suppression differ from objective safety outcomes such as crashes. Specifically, Cho et al. (2009) and Schneider et al. (2003) found that perceptions of unsafe conditions lowered use and therefore exposure, which improved objective safety outcomes, thereby hiding the safety issues (Cho et al., 2009; Nevelsteen et al., 2012b). However, these past proactive analyses – while providing a strong foundation for the research at hand – were either focused on small areas, included few roadway variables, or were in unfamiliar contexts. We therefore create a new proactive model that quantifies trip suppression for children's trips to and from school with additional roadway risk factors and then compare results to those from more conventional reactive crash-based analyses. We hypothesize that the reactive and proactive analyses will illuminate different safety concerns, thereby successfully complementing one another.

3. DATA

We utilized the City and County of Denver for our analysis. Denver has a population of 663,303 according to the 2016 American Community Survey. Because Denver has detailed crash data available and high enough population, pedestrian, and bicyclist levels to obtain significant samples, it was an ideal location for our study.

While there are suitable levels of walking and biking, there are also pedestrian and bicyclist safety issues present. According to DPW reports and data from DRCOG – the local metropolitan planning organization – there were 1,508 pedestrians and 1,083 bicyclists hit by motor vehicles in Denver between 2011 and 2014 (Works, 2017). These collisions resulted in injuries for 918 pedestrians and 791 bicyclists, with 72 pedestrians and seven bicyclists killed (Works, 2016, 2017).

3.1 Reactive Analysis

We performed our own crash cluster analysis of pedestrian and bicyclist crashes in Denver that was specific to children. Crashes were pulled from DRCOG's Regional Data Catalog in GIS point format for the years 2010-2014. We included any crash involving a pedestrian or bicyclist under the age of 14 in our analysis in order to match the proactive analysis. Similar to the agency-produced reports, we did not account for exposure as reliable counts of child pedestrians and bicyclists were not available.

3.2 Proactive Analysis

The goal of the proactive safety analysis was to quantify the level of child pedestrian and bicyclist trip suppression caused by traffic safety concerns and utilize that as an indicator of safety. There were two aspects of the proactive safety analysis: 1) suppression rates based on survey-derived parental perceptions of roadway characteristics; and 2) routes to school based on a GIS closest facility network analysis.

For the suppression rates, we administered a survey to parents of children enrolled in pre-kindegarten through 8th grade in Denver, Colorado, asking them which roadway characteristics they would allow their child to walk or bike on. Roadway characteristics included number of lanes, posted vehicle speed limits, vehicle volumes, and the presence of sidewalks and bike lanes. We will expand further on the survey methods in Section 4. For a more exhaustive review, please refer to (Ferenchak, 2018; Ferenchak & Marshall, 2018).

To derive the shortest path distances to schools, we utilized a closest facility GIS network analysis with child home locations as origins and schools as destinations. We approximated child home locations on the block group level by creating a random point for each child based on population numbers from the 2015 American Community Survey. The National Historical Geographic Information System (NHGIS) provided us with this population dataset (Manson, Schroeder, Van Riper, & Ruggles, 2017). We clustered origin points according to residential building footprints provided by the City and County of Denver's Open Data Catalog in polygon shapefile format. School destinations were in point shapefile format from DRCOG's Regional Data Catalog. The analysis considered only public elementary and middle schools.

Data for Denver's street network came from the Denver Open Data Catalog in GIS polyline shapefile format. This layer included posted speed limits and the number of lanes for each road segment. We utilized vehicle volumes provided by DRCOG, considering any roadway with more than 1,000 vehicles per day as high volume (Program, 2014). We noted the presence of sidewalks based on the DRCOG Regional Data Catalog's GIS sidewalk layer, which was provided in polyline shapefile format. We accounted for bike lanes based on their location per Google Maps, satellite imagery, and Google Street View and accounted for the off-road multi-use path network based on a layer provided by the Denver Open Data Catalog.

4. METHODS

4.1 Reactive Analysis

The Optimized Hotspot Analysis tool in Esri's ArcMap allowed us to identify statistically significant clusters of child pedestrian and bicyclist crashes. The tool functions to identify both hotspots and cold spots in incident data. When inputting the data, we considered each crash point as a single equally-weighted incident. The tool automatically aggregates all incidents found to be clustered into a mean centroid point and outputs the Getis-Ord Gi* statistic in the form of a confidence level bin for each identified cluster. We utilized clusters that were in the 95% confidence bin (two standard deviations for normally-distributed data) and had at least three crashes. Once these aggregated clusters were identified, we returned to the original crash point layer and assigned each crash to its appropriate cluster.

4.2 Proactive Analysis

We first administered a parental survey to quantify how perceptions of roadway characteristics influence suppression of children's pedestrian and bicycle trips. We then completed a GIS network analysis to find the shortest path distance between the estimated home location of each child in Denver and their closest school. We next applied the trip suppression rates to the road network and ran the network analysis once again. This allowed us to measure the additional walking or biking distance required to avoid traffic safety issues. Finally, we used distance decay functions to estimate the levels of trip suppression.

A survey of parents of children in elementary and middle school provided us with the proportion of children's pedestrian and bicyclist trips that are suppressed because of safety concerns. The survey excluded parents of high school students because those students have more independence than younger students and would be more likely to drive themselves or carpool with a friend. The survey was offered exclusively online and was marketed through newsletters, fliers, social media by Denver Public Schools and the City and County of Denver, parent-teacher organizations, and local advocacy groups. The survey was open in 2017 during the month of October in both English and Spanish. The 1,298 survey respondents provided us with 924 complete responses accounting for 1,331 children.

Parents first provided information regarding child age, gender, and physical activity levels. The survey then presented parents with a variety of scenarios consisting of varying roadway design characteristics and asked whether they would allow their child to walk or bike to school on each roadway (Figure 4.1). Each scenario included a corresponding picture from a road in Denver. Scenarios contain4.ed consistent aesthetics and residential land use contexts. Parents were able to answer "No", "Yes, with trusted adult supervision", or "Yes, without adult supervision". Each survey included five randomly selected walking questions and five randomly selected bicycling questions from a pool of twenty walking questions and twenty bicycling questions. Roadway design characteristics included number of lanes (2, 3, or 4 lanes), posted speed limits (25 mph, 35 mph, or 45 mph), the presence of sidewalks and bike lanes (none or on one or both sides of the road), and vehicle volumes (low or high volumes). Parent responses were converted into proportions of disallowance (also referred to as the suppression rate) for each of the forty roadway scenarios. We calculated suppression rates by dividing the total number of responses by the number of parents responding "No." Therefore, for the sake of this report, we treated "Yes, with trusted adult supervision" and "Yes, without adult supervision" responses the same.

Figure 4.1 Example of Survey Questions

Since the number of roadway scenarios in Denver exceeded the number of scenarios that we could feasibly include on the survey, we developed a beta regression general linear model (GLM) to derive a suppression rate for each roadway scenario in Denver (Table 4.1). The betareg package in R provided us with the ability to create this beta regression with a logit link function. The beta regression GLM is superior to a standard linear regression when the dependent variable is in the form of a proportion bounded between zero and one and when – as was present in our data – normality is weak (Hayter, 2007). We formed the beta regression GLM by taking the twenty walking scenarios and twenty biking scenarios included in the survey and coding the four predictor variables as dummy variables. This allowed for standardization of the regression results. The 25 mph and two-lane variables were removed from the model to avoid multi-collinearity. We designated the outcome variable as the proportion of parents that would not allow their children to use each roadway scenario.

Table 4.1 Predictors of the Proportion of Parents Who Would Not Allow Their Child to Walk or Bicycle

		Walk $R^2 = 0.977$; n =20	Bike $R^2 = 0.9509$; n = 20
Intercept		-0.260*	-0.703***
Speed	35 mph	0.995***	0.644***
	45 mph	1.868***	0.901***
Lanes	3 lanes	0.495***	0.618***
	4 lanes	0.597***	1.166***
Facilities		-2.584***	-0.819***
Volume		0.770***	1.111***

*** *p<0.001*
** *p<0.05*
* *p<0.01*

With these beta regression results, we then derived the corresponding suppression rate for each Denver roadway scenario that was not featured in the survey. Road attributes found throughout Denver included speeds of 15 mph, 25 mph, 30 mph, 35 mph, 40 mph, 45 mph, and 55 mph, number of lanes from one to nine, non-motorized facilities on zero, one, or two sides of the road, and low or high vehicle volumes. There were 138 roadway scenarios for walking and 78 scenarios for biking.

We then derived the level of trip suppression for each child. We accomplished this by determining the shortest path distance between each child's estimated home location and their closest school and then computing how much distance would be added to those trips if the children avoided roads perceived as unsafe. To avoid edge issues, we included children outside of Denver if their closest school was located in Denver. Because of privacy issues, we approximated the location of children's homes on the block group level by creating one random point for each child living in each block group. We clustered random points to residential building footprints so that trips would originate in realistic patterns. While the assumption that each child will attend their closest school is known to be faulty because of the Colorado Open Enrollment program that allows children to attend schools other than their originally assigned neighborhood school, privacy issues precluded us from knowing which school each child actually attends. Even if these children were not attending their closest school, the areas near their homes would be where we would expect the majority of children's trips, assuming that many children's walking and biking trips originate from their home.

After determining the shortest path distance from each child's estimated home to their closest school, we then reran the network analysis with each road segment weighted according to safety-perception-based suppression rates. In this scenario, routes became a balance of travel costs associated with distance and safety perceptions. We therefore needed to standardize these two variables. Distance decay functions allowed us to standardize the variables in a probabilistic manner (Iacono, K. Krizek, & El-Geneidy, 2008). Distance decay functions are inverse power functions that use distance or time as a proxy for travel costs. Those used in our survey were developed based on data from travel surveys, joint-use facility user surveys, and a Non-Motorized Pilot Program (NMPP) survey from the Twin Cities region (Iacono et al., 2008). The functions were specific to children walking and biking to school. The distance decay function for walking to school had a dependent variable of percent of school and school-based trips made by walking and an independent variable of travel time in minutes (Equation 1). Because we needed to standardize the variables into a distance so that we could perform a closest facility analysis, we used an assumption of 25 minutes per mile for pedestrian speed (a rough conversion of the standard 3.5 feet per second used in the Manual on Uniform Traffic Control Devices).

$$y = 0.523\mathrm{e}^{-0.10x} \qquad (1)$$

where:

y = percent of school or school-related trips made by walking
x = travel time (minutes)

The distance decay function for biking to school (Equation 2) had a dependent variable of percent of school and school-based trips made by biking and an independent variable of travel distance in kilometers. We converted the function to feet to coincide with the foot-based network analysis. We also transformed both distance decay functions so that a value of 100% of trips correlated with a distance of zero. This avoided any negative distance outcomes, which would not have been acceptable in the network analysis.

$$y = 0.4651\mathrm{e}^{-0.1236x} \qquad (2)$$

where:

y = percent school or school-related trips made by biking
x = distance (km)

Because the GIS network analysis was based on trip distance, we used the distance decay functions to translate safety perceptions into distance values, and then used those distance values as our weights. This method is justified because distance decay functions can be interpreted as both measuring the impedance to travel through a network as well as willingness of individuals to travel various distances to access opportunities (Iacono et al., 2008). As an example of this method, a road segment with a pedestrian disallowance rate of 25% was given a weight of approximately 711 feet while a segment with a pedestrian disallowance rate of 95% was given a weight of approximately 7,400 feet. We applied these additional distances as added-cost barriers in point format. We assigned the point barriers at the midpoint of each segment. Therefore, when we ran the weighted network analysis, we accounted for both distance and perceptions in units of feet. In this way, model agents were able to decide between a short, unsafe route and a long, safe route.

Since roadways had different suppression rates for walking and biking, we ran this weighted network analysis twice, once for each mode. We then determined the difference between the original shortest path distance and the weighted distance. The distance decay functions allowed us to derive a probabilistic estimate of trip suppression for each child. By inputting into our distance decay functions the additional distance added to each trip in the weighted network analysis, we converted the additional distance to a percentage of suppression. In other words, if a child's walking trip increased by 711 feet when we accounted for safety perceptions, that child's trip was considered 25% suppressed. If a child's trip increased by 7,400 feet, that child's trip was considered 95% suppressed.

Once we estimated levels of suppression for each trip, we interpolated suppression values for all of Denver through an Empirical Bayesian kriging (EBK) tool in GIS. EBK uses known point values to interpolate values for cells in a raster layer. EBK is superior to standard kriging approaches because it accounts for uncertainty introduced with the estimation of the semivariogram. We used a power semivariogram with no transformation. This analysis allowed us to estimate levels of trip suppression while not yet accounting for the number of possible users.

We were then interested in combining levels of trip suppression with the number of possible users. In other words, one neighborhood might have high levels of trip suppression but only one possible user, while another neighborhood might have slightly less trip suppression but many possible users. Kernel density analysis in GIS enabled us to simultaneously account for levels suppression and users by estimating a magnitude-per-unit area for cells in a raster layer. Child points were the base layer and trip suppression rates (as proportions) were the population variable. We employed a planar method.

This kernel density analysis also allowed us to perform a spatial comparison of our reactive and proactive analyses by overlaying child pedestrian and bicyclist crash clusters on top of our kernel density outputs in GIS. We then confirmed these spatial observations with statistical analysis. Spearman's rank order correlations from the cor.test package in R (at a 95% confidence level) enabled us to statistically explore the relationship between trip suppression and crashes. This was an appropriate test to use because – as the two datasets had different distributions – the rank order allowed us to transform the data into a standard format for comparative analysis. Furthermore, the transformation into ordinal data allows for less sensitivity to outliers in the datasets. We performed this analysis on the block group level by deriving the average amount of trip suppression and the number of crashes for each block group in Denver. We completed this task with spatial joins in GIS. A buffer of fifty feet allowed for edge issues to be avoided.

5. RESULTS

5.1 Reactive Analysis

Between 2010 and 2014, 342 child pedestrian crashes and 208 child bicyclist crashes occurred in Denver. For the 342 child pedestrian crashes, there were fifty-two clusters identified consisting of a total of 219 crashes. Of these fifty-two identified clusters, eight clusters were significant at 95% confidence and consisted of at least three crashes. These eight clusters contained a total of 31 child pedestrian crashes. The largest cluster used in the analysis had six crashes, and the smallest had three. For the 208 child bicyclist crashes, there were thirty-two clusters identified consisting of a total of 150 crashes. Of these thirty-two identified clusters, eleven clusters were significant at 95% confidence and consisted of at least three crashes. These eleven clusters contained a total of 67 child bicyclist crashes. The largest cluster used in the analysis had twelve crashes and the smallest had three.

Pedestrian crash clusters are focused in an area around South Federal Boulevard and just outside of downtown Denver (Figure 5.1). The bicyclist crash clusters are primarily focused in the area proximate to and south of downtown Denver (Figure 5.1). The rest of the residential neighborhoods that largely comprise Denver have few identified clusters. The majority of un-clustered crashes occur near downtown and in west Denver as well.

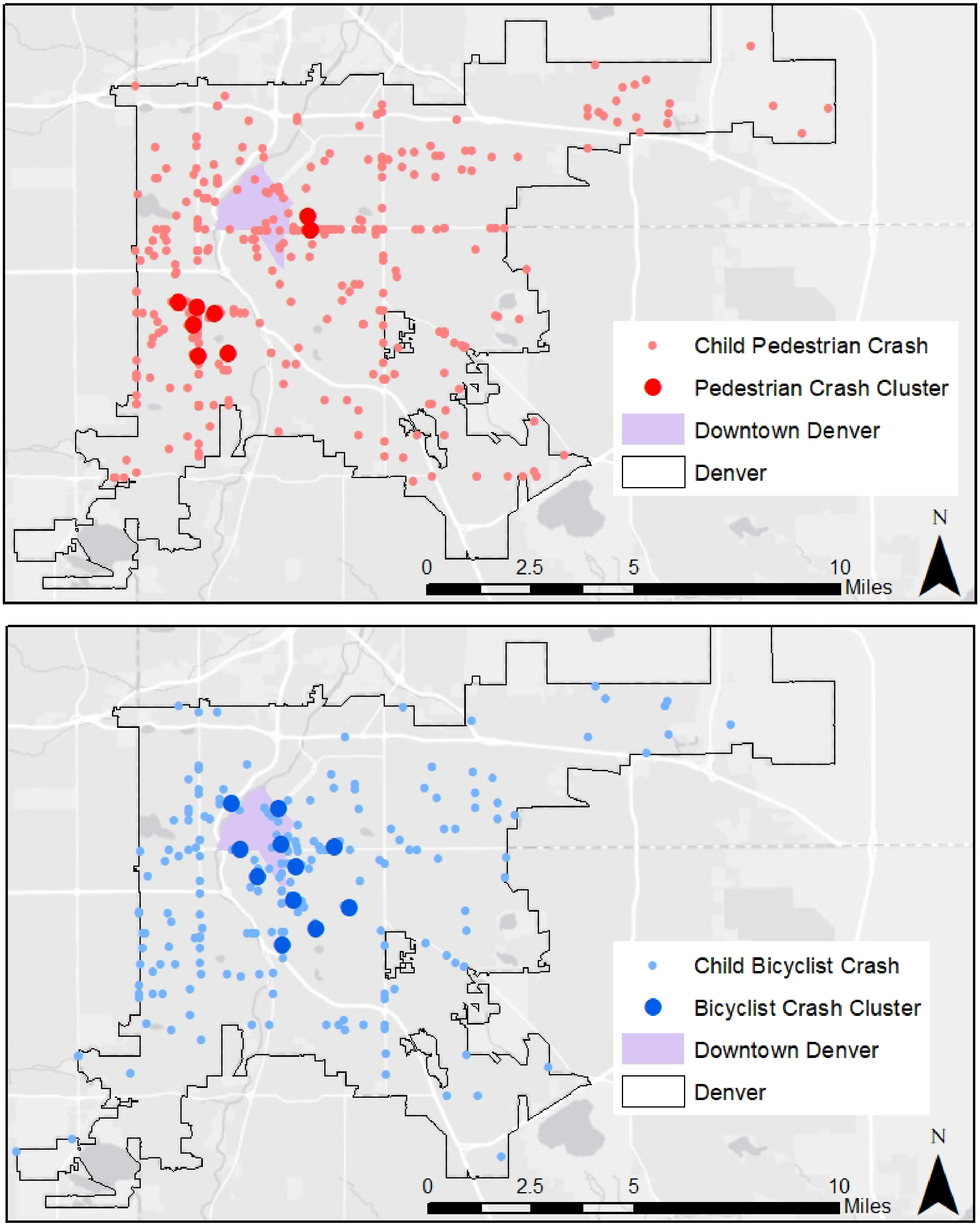

Figure 5.1 Child Crash Clusters for Pedestrians (Above) and Bicyclist (Below), 2010-2014
(Data Source: DRCOG Regional Data Catalog)

5.2 Proactive Analysis

Based on survey results from parents, the most important roadway characteristic in terms of walking trip suppression was the presence of sidewalks (Table 4.1). There are limited sidewalk gaps in central Denver but larger concentrations of sidewalk gaps present in east and north Denver (Figure 5.2). The most important roadway characteristic in terms of bicycling trip suppression was vehicle volumes (approximately equivalent to adding two additional lanes to a two-lane road) with the presence of bike lanes being slightly less important (Table 4.1). Wide, high volume roadways are found throughout Denver while bike lanes are primarily located downtown and in an east-west orientation to the northeast of downtown Denver (Figure 5.2).

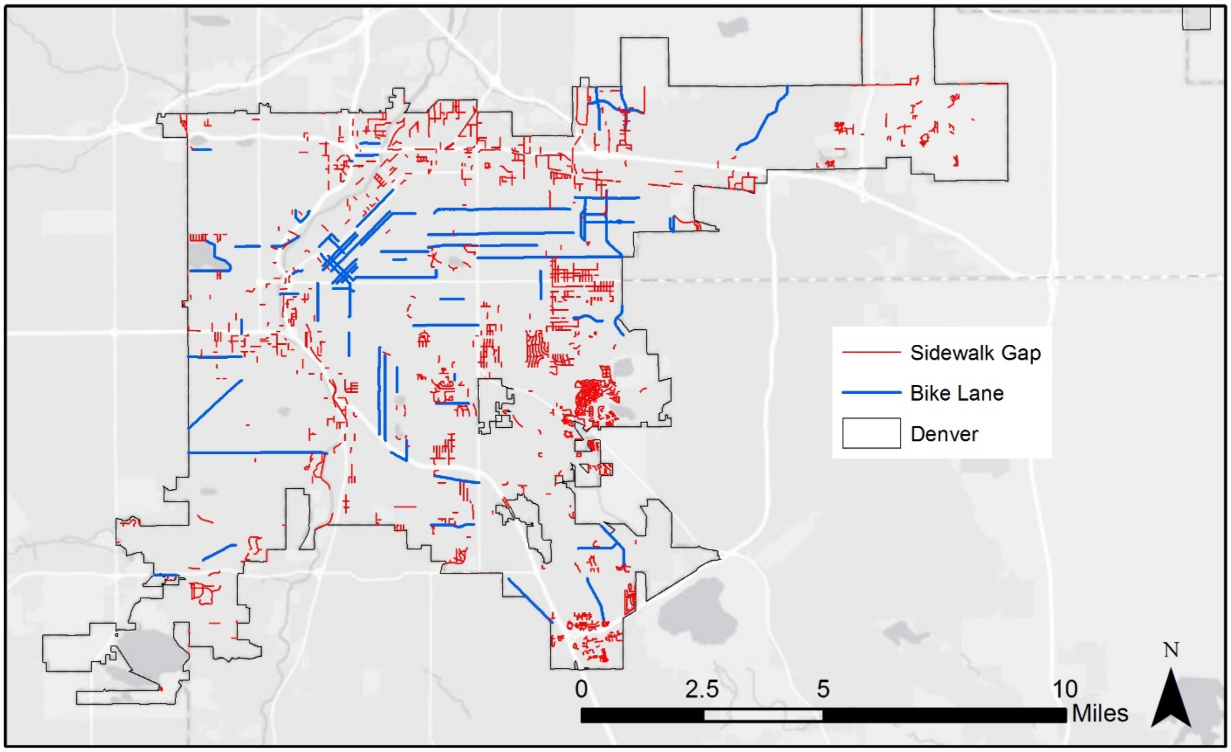

Figure 5.2 Location of Pertinent Roadway Characteristics in Denver
(Data Source: Denver Data Catalog and DRCOG Regional Data Catalog)

There were 136,138 children included in the proactive analysis with 112,648 children living in Denver and 23,490 children living in municipalities directly bordering Denver. The highest concentrations of children are found in the residential areas in west and northeast Denver (Figure 5.3). We included 217 public elementary and middle schools – both inside and outside Denver – in the analysis (Figure 5.3).

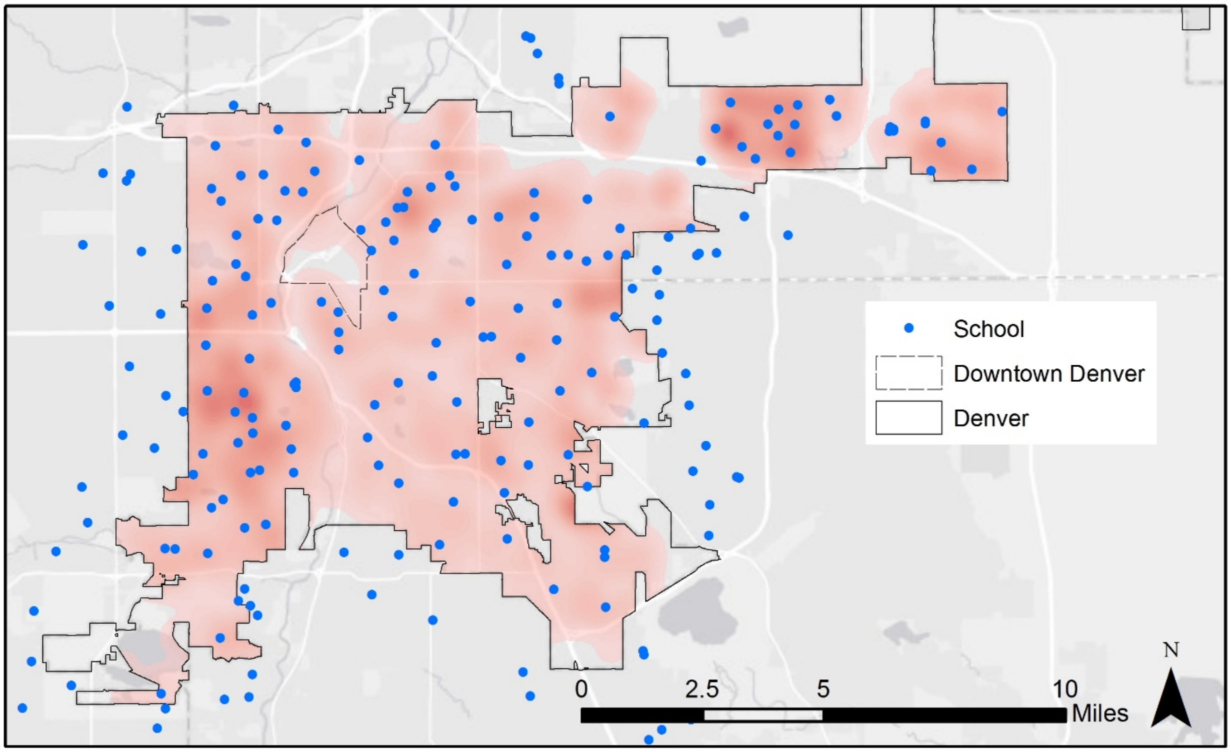

Figure 5.3 Child Population Concentrations (Red = Higher Concentration) and School Locations in Denver (Data Source: U.S. Census Bureau)

Within GIS, the network analysis tool was able to derive a pathway to each child's closest school. Of the children considered in the proactive analysis, 56.8% of children had a shortest path of 0.5 miles or less to their closest school (via network distance as opposed to Euclidian distance), and 93.1% of children had a shortest path of one mile or less (Figure 5.4).

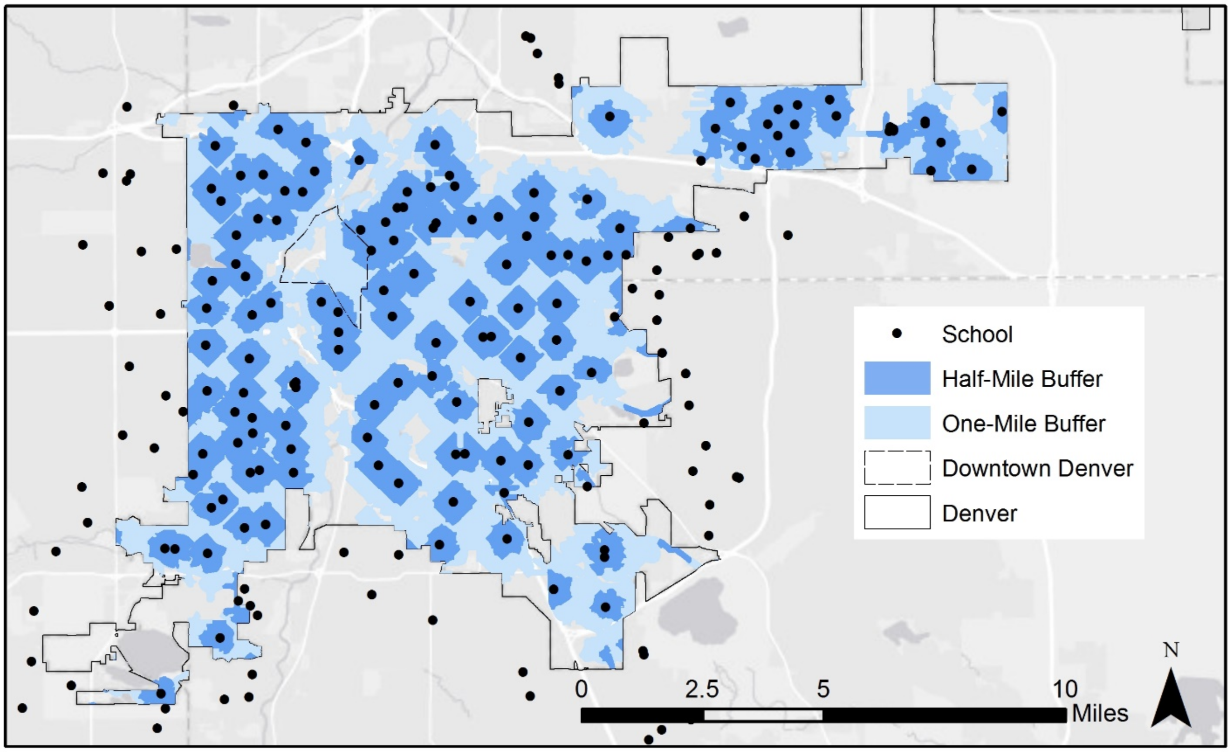

Figure 5.4 Half-mile (walkshed) and One-mile (Bikeshed) Network Buffers around Schools in Denver

Next, we weighted the network analysis with trip suppression rates and re-ran the analysis for both walking and bicycling trips. Trip lengths increased for both walking and biking trips once barriers were added into the network analysis (Table 5.1). Trip lengths for bicyclists increased more, reflecting the fact that parents found bicycling less safe than walking. The average shortest path distance for pedestrians and bicyclists was approximately one-half mile. Average trip lengths increased by 294 feet for walking and 481 feet for biking after barriers were added to the network analysis. However, those increases were averages for the entire city and spatial clustering was present in parts of Denver (Ferenchak & Marshall, 2018).

Table 5.1 Child Pedestrian and Bicycling Trip Lengths in feet

	Walk	Bike
Shortest Path		
Shortest	5.2	5.2
Average	2,681.1	2,681.1
Longest	9,710.9	9,710.9
Std. Dev.	1,465.6	1,465.6
Weighted Path		
Shortest	5.2	5.2
Average	2,974.6	3,162.3
Longest	13,354.9	14,917.4
Std. Dev.	1,792.7	2,029.3

Empirical Bayesian kriging shows that clustering of elevated levels of trip suppression are found throughout several neighborhoods in Denver (Figure 5.5). These results interpolate and extrapolate suppression levels without accounting for population concentrations. We resampled the raster layer with cubic convolution.

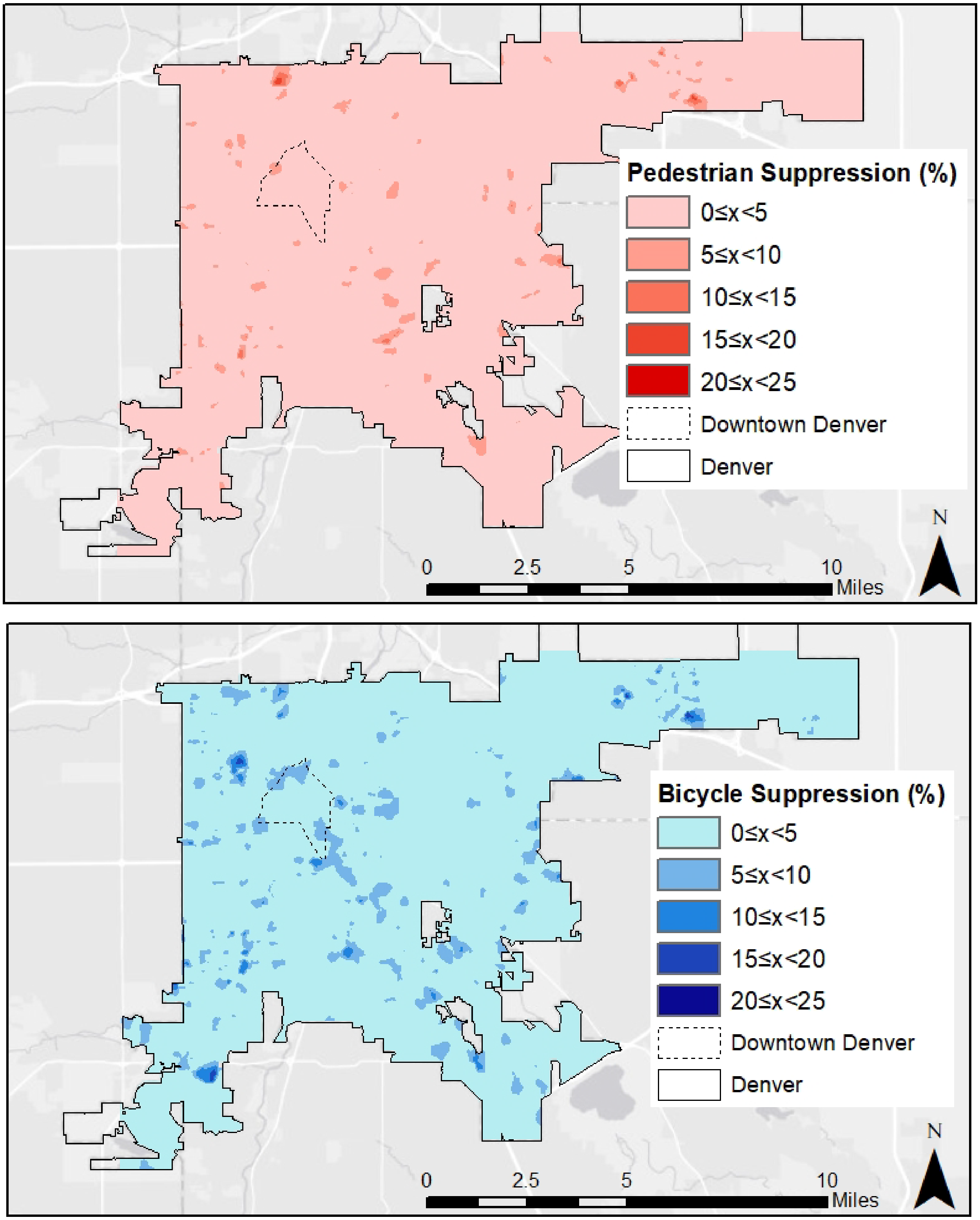

Figure 5.5 Trip Suppression for Child Pedestrian (Above) and Bicyclist (Below) Trips

We then accounted for population concentrations in our suppression analysis. Kernel density results suggest that there are suppression-population concentrations in west, east, and northeast Denver, but few concentrations in central Denver (Figure 5.6). These trends are most likely related to the lower concentrations of children and fewer perceived safety issues (there are few sidewalk gaps and many bike lanes) found in central Denver. The large concentration of walking suppression in east Denver coincides with high concentrations of children and sidewalk gaps while concentrations in west Denver primarily correspond with Federal Boulevard, a wide, busy, and higher-speed road (Figure 5.6). The concentration in northeast Denver coincides with a neighborhood that includes a curvilinear tributary network, where all trips are forced to funnel onto larger, higher-volume roads.

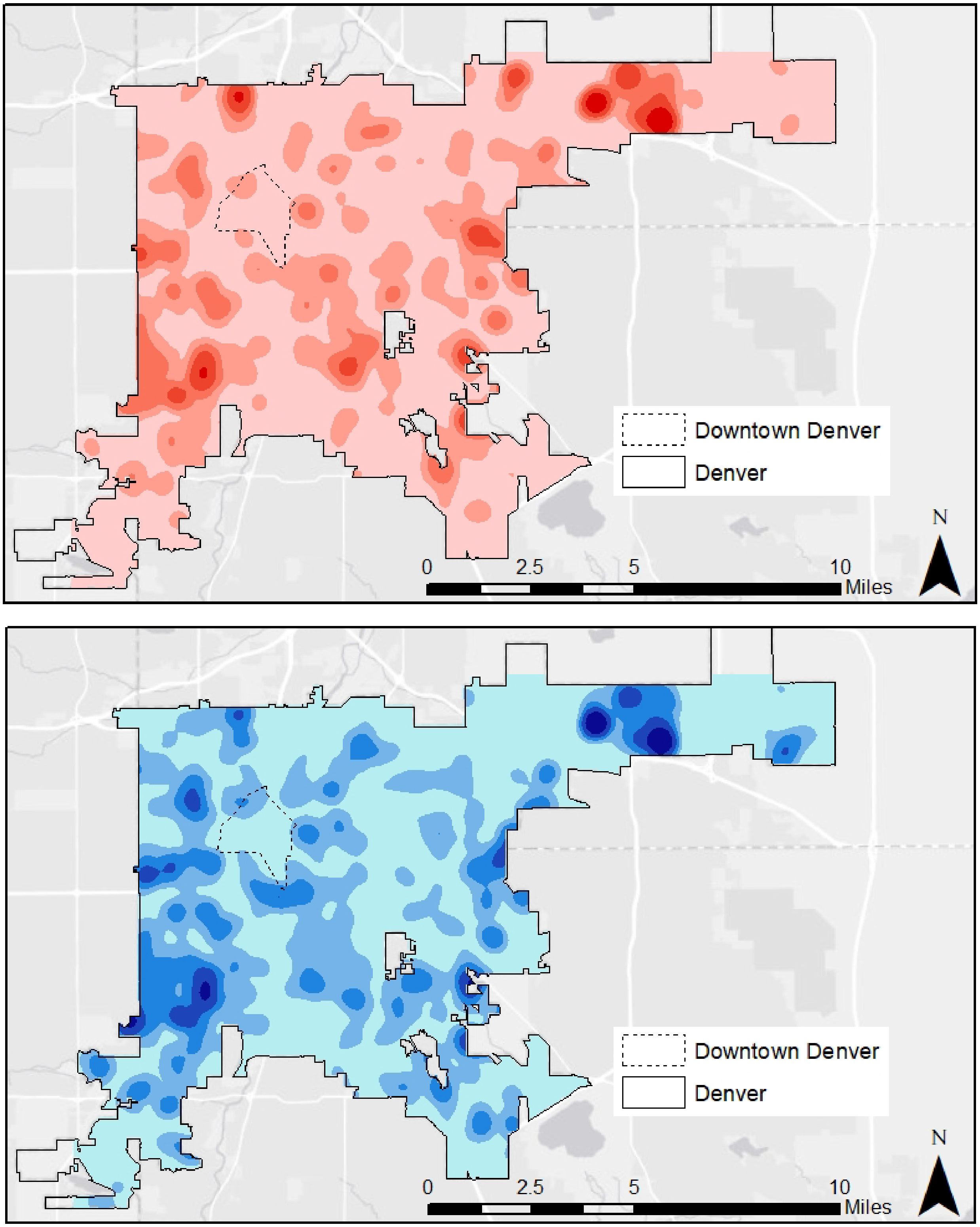

Figure 5.6 Trip Suppression Weighted by Child Populations (Dark = Higher Concentration) for Child Pedestrian (Above) and Bicyclist (Below) Trips

5.3 Comparison

The reactive pedestrian and bicyclist safety analyses identify areas near downtown and central Denver as well as S. Federal Boulevard (for pedestrians) as the areas of most concern. Safety issues in these areas have manifested in the form of high levels of crashes. However, Figure 5.7 shows that – in addition to the proactive pedestrian analysis identifying S. Federal Boulevard – the proactive analyses alternatively identify areas in east, northeast, and west Denver as having perceived traffic safety issues. These safety concerns may be hidden by a lack of non-motorized activity (despite the high concentrations of children) resulting from trip suppression. This trip suppression precludes crashes from occurring in the first place and, therefore, from being visible in a conventional reactive analysis.

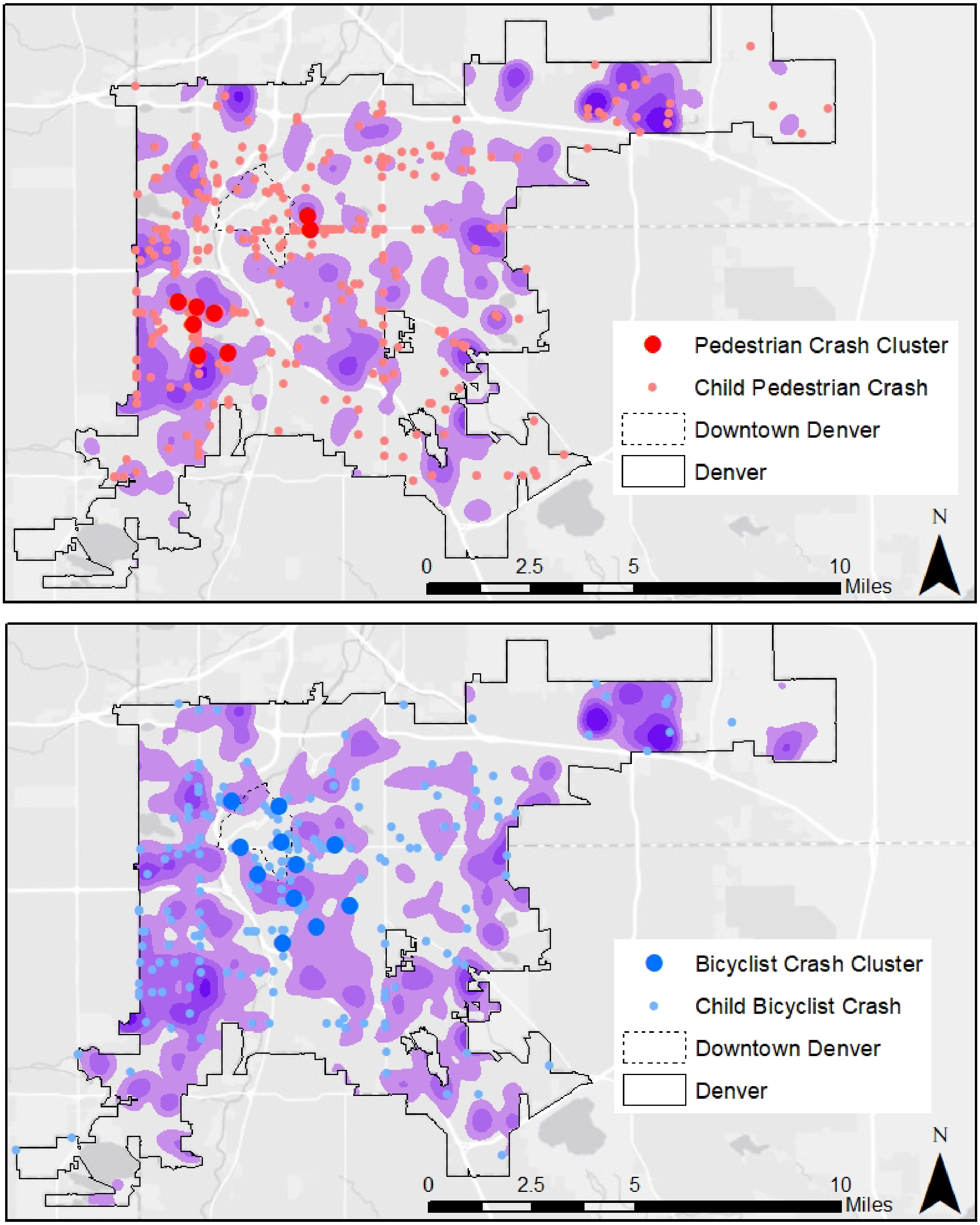

Figure 5.7 Spatial Comparison of Crash-Based Reactive Analyses and Proactive Analysis (Pedestrian On Top; Bicycle On Bottom; Dark = Higher Concentration)

In addition to the above spatial analysis, Spearman's rho indicates that the correlation between reactive and proactive outcomes is statistically negligible (Table 5.2). Even though there is statistical significance for pedestrians, the correlation is weak enough to be considered negligible (Hinkle, Wiersma, & Jurs, 2003). There is no significant relationship for bicyclists. This indicates what the spatial analysis showed before: there are areas in Denver with few crashes but high suppression and areas with many crashes but low suppression. These findings suggest that had we only examined the location of crashes, we would have neglected other safety issues that are only identified by considering trip suppression.

Table 5.2 Spearman's Rank Order Correlation of Trip Suppression and Crashes

	Walk (n=481)	Bike (n=481)
rho	0.1817	0.0496
p-value	<0.001	0.2772
S	1.52e7	1.76e7

Taking a closer look at the results, we can see that – along with identifying hidden safety issues – the proactive analysis can present fine-grained traffic safety results. By identifying a single point as a crash hotspot through a reactive analysis, we cannot understand the larger context of the issue. Similarly, by identifying a lengthy high-crash corridor, we cannot know exactly where the issue is or what is causing it. With the proactive analysis, however, an analyst can observe where trips should be occurring and what might be blocking them. Figure 5.8 shows that there are distinct clusters of suppressed trips throughout neighborhoods in Denver that do not necessarily fall on a major corridor or at a major intersection. One single gap in a sidewalk could possibly suppress children over a three-block area (Figure 5.8). While a single missing sidewalk does not constitute a major safety issue from a crash-based perspective, it is a major safety issue for this particular neighborhood and can be effectively identified through a proactive analysis. Not only do the results of the proactive analysis present new and important findings, but the associated output presents a more practical way of considering and addressing pedestrian and bicyclist safety.

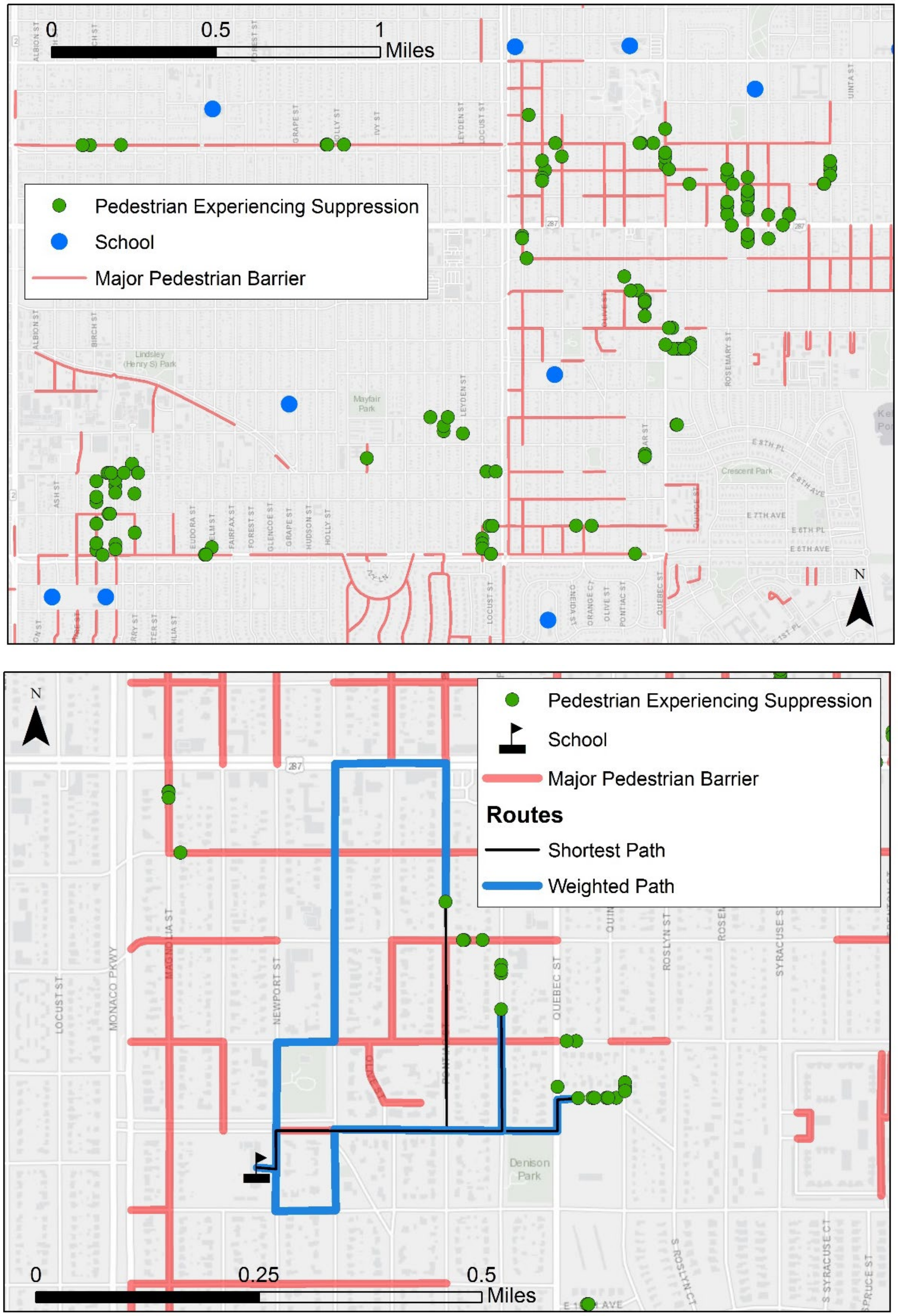

Figure 5.8 Example of Pedestrian Trips Experiencing Suppression

6. DISCUSSION

This research went through several iterations before arriving at its current state. Our first approach applied barriers to the street network binarily defined as those roadways with greater than 50% disallowance. The first approach also used a binary definition of trip suppression, assuming ½ mile walksheds and one-mile bikesheds. We found that moving to a probabilistic approach using distance decay functions provided for a more realistic suppression model. Also, we had originally performed a linear regression to interpolate and extrapolate suppression rates for roadway scenarios not on the survey. After experimenting with a Gaussian GLM, we determined that the model was not suitable because the data had weak normality. We used a beta regression GLM for our final model as it is ideal for dependent variables that are proportions bounded between zero and one.

While the existing iteration provides a methodology to develop a proactive safety analysis tool, the methodology does employ some assumptions that can be improved through future work. Excluding levels of non-motorized exposure was a limitation. Including exposure would provide a clearer picture, especially by allowing for crash rates in the reactive analysis. However, non-motorized exposure is difficult to obtain and was not used in the existing agency-produced reports either. Future work would benefit from user counts or volumes to better understand where trips are occurring and the accuracy of the trip suppression estimations.

Furthermore, pedestrian and bicyclist trip purpose may have been inconsistent among the different analyses. All analyses, however, were for users of the same age. Because of the concentration of children in Denver and the location of roadway characteristics perceived as unsafe, we believe that suppressed child trips would be similarly clustered regardless of trip purpose. Future work will hopefully move toward a more holistic model for all ages and trip purposes. Additionally, we would gain a better understanding of trip suppression by accounting for the characteristics of crossings (e.g. signalization, phasing, turning movements, crosswalks, refuge islands, etc.) as well as other levels of the current variables that we did not test in the present iteration. Further exploring the impact of vehicle volumes beyond the current binary low/high definition would be beneficial to subsequent work. Finally, there were other factors – such as crime and socioeconomics – that influence trip suppression and would be worthy to examine in future analyses.

7. CONCLUSION

Conventional crash-based analyses help identify areas with active transportation safety problems. However, these reactive analyses can only find locations where walking and bicycling levels are high enough to enable safety issues to manifest themselves. The proactive analysis that we propose in this chapter can identify active transportation safety concerns that a crash-based, reactive analysis may miss. By recognizing places where perceived safety concerns have lowered walking and bicycling trips – enough to effectively reduce crashes and hide safety issues from sight – we furnish ourselves with a new lens through which we can better understand latent active transportation safety issues.

Findings suggest that proactive safety analyses can effectively complement traditional reactive approaches. Cities that wish to obtain a holistic perspective of their streets' safety would be prudent to consider both manifested and latent pedestrian and bicyclist safety issues. While we recommend that other cities administer their own survey to account for city-specific traffic safety perceptions, this chapter provides a framework to accomplish more holistic traffic safety analyses. The research fills a critical gap in the literature by showing the importance of proactive safety analyses and providing methods to accomplish such analyses.

Both reactive and proactive safety analyses provide unique and important perspectives on traffic safety. If our goal is to enable more people to safely walk and bike as opposed to simply reducing crashes, then it is imperative to consider active transportation traffic safety proactively.

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PART 2: An Equity Analysis of Proactively- vs. Reactively-Identified Traffic Safety Issues[2]

9. INTRODUCTION

A primary barrier to walking and bicycling – and to the benefits thereof – is the threat of unsafe traffic conditions (Carver, Timperio, & Crawford, 2008; Dellinger, Staunton, & CDC, 2002). Traditional approaches to improving traffic safety for active transportation focus on locations of pedestrian and bicyclist crashes, injuries, or fatalities (Administration, 2006; Zegeer, Nabors, Gelinne, Lefler, & Bushell, 2010). However, such a reactive approach only considers threats posed to people that are currently walking and bicycling. Neglected are those who perceive their road environment to be so unsafe that they choose not to walk or bike in the first place (thereby precluding them from appearing in traditional crash statistics). Such neglected traffic safety issues are abundant in some urban areas (N. N. Ferenchak, 2018); better understanding them may help us to better enable more active transport. Towards this end, we seek to answer the following question: which populations are being hindered by traffic safety concerns missing from traditional reactive crash-based analyses?

In this chapter, we develop a metric to proactively identify perceived pedestrian and bicyclist traffic safety issues. The number of children that would encounter a road perceived as unsafe on their walking or bicycling trip to school serves as a proactive indicator of traffic safety. Based on results derived from the proactive methodology and those from a traditional crash analysis, we then explore which residents are impacted by both perceived and extant traffic safety issues in order to identify whether there are equity concerns at play.

To accomplish these goals, we explore child pedestrian and bicycle trips to and from school in Denver, Colorado. This is a useful set of trips to examine because children's trips to and from school are relatively structured and predictable. Parental surveys first provide us with a method to estimate trip suppression rates based on street design characteristics. We then weight a GIS closest facility network analysis with these suppression rates and determine the relative level of trip suppression. Finally, educational, income, ethnic, and racial compositions on the Census tract level allow us to perform statistical and spatial socio-demographic analyses via linear regressions and bivariate choropleth mapping. Bivariate choropleth maps illustrate two variables simultaneously, allowing for those variables to be spatially analyzed relative to one another. We first perform these socio-demographic analyses on reactively-identified traffic safety issues (i.e. crashes) and subsequently on proactively-identified issues. When these proactive results are combined with those from traditional traffic safety methods, we acquire a more holistic view of pedestrian and bicyclist safety and the equity impacts of these issues.

[2] This portion of the report has been peer-reviewed and is scheduled for publication: Ferenchak, N. and Marshall, W. An Equity Analysis of Proactively- vs. Reactively-Identified Traffic Safety Issues. *Transportation Research Record*.

10. THEORY

Researchers typically utilize crashes, injuries, or fatalities – ideally normalized to levels of user exposure – to analyze transportation safety of both motorized (Board, 2001; Waldheim, Wemple, & Fish, 2015) and non-motorized users (Administration, 2006; Zegeer et al., 2010). However, reactively accounting for only those users involved in a crash neglects people who do not undertake a trip due to traffic safety concerns. Proactively accounting for people who choose not to undertake a trip is especially vital for pedestrian and bicycle safety analyses, where latent demand is often impeded by traffic safety concerns (Schneider, Ryznar, & Khattak, 2004).

Prior proactive traffic safety studies have used traffic safety perceptions as a proactive indicator of traffic safety (Bellemans, van Bladel, Janssens, Wets, & Timmermans, 2009; Cho, Rodriguez, & Khattak, 2009; Nevelsteen, Steenberghen, Van Rompaey, & Uyttersprot, 2012; Schneider et al., 2004). However, these analyses either anecdotally examined specific areas – an approach that is not scalable – or only accounted for a limited number of roadway characteristics when estimating trip suppression rates. In an effort to increase applicability of proactive safety analyses across geographic extents, we developed a more holistic method of measuring pedestrian and bicycle trip suppression rates (N. N. Ferenchak, 2018). This method uses GIS to identify which neighborhoods are most affected and relies on the perceived safety of such roadway characteristics as vehicle speeds, vehicle volumes, roadway width, and the presence of non-motorized facilities.

With this enhanced understanding of the areas impacted by neglected traffic safety issues, we can better understand the populations that are affected. This will aid in the formulation of appropriate solutions to our traffic safety issues. While socio-demographic analyses of proactively-identified traffic safety issues have not been performed in the past, prior studies have defined which populations are most impacted by traffic crashes of varying degrees of severity (Braver, 2003; Campos-Outcalt, Bay, Dellapena, & Cota, 2003; Harper, Marine, Garrett, Lezotte, & Lowenstein, 2000; Marshall & Ferenchak, 2017; McAndrews, Beyer, Guse, & Layde, 2013; Schiff & Becker, 1996). These studies have generally shown that black, Hispanic, lower-socioeconomic, and lower-education populations are at higher risk for traffic fatalities and injuries (Table 10.1). Can we expect similar relationships when proactively looking at perceived traffic safety issues?

Table 10.1 Studies Examining the Relation between Traffic Injuries/Fatalities and Socio-Demographics

Reference	Location & Time	Safety Metric	Demographic	Relation
Schiff & Becker, 1996	New Mexico 1958-1990	Traffic Fatalities	Native American Hispanic Males	+ +
Harper et al., 2000	Colorado 1991-1995	Traffic Fatalities	Hispanic	+
Braver, 2003	Nationwide 1995	Traffic Fatalities	Black Hispanic Educ. Attainment Socioeconomic Status	+ + - -
Campos-Outcalt et al., 2003	Arizona 1990-1996	Traffic Fatalities	Native American	+
Marshall & Ferenchak, 2017	Nationwide 1989-2012	Traffic Fatalities	Black Hispanic	+ +
McAndrews et al., 2013	Wisconsin 2001-2009	Traffic Injuries	Black Native American	+ +

11. DATA

The reactive traffic safety analysis that we completed in this study relied upon data from police-reported pedestrian and bicyclist crashes. To conduct the proactive analysis, we first derived roadway characteristic-based trip suppression rates from a parental perceptions survey. We applied these suppression rates to the roadways of Denver using GIS and roadway data provided by city and regional government organizations. For results from both the reactive and proactive analyses, we overlaid socioeconomic data obtained from the US Census (on the Census tract level) in the form of race, ethnicity, educational attainment, and median household income (MMHI) in order to understand which populations are most impacted.

We chose Denver, Colorado for our study because of the availability of data and the willingness of Denver Public Schools (DPS) and the City and County of Denver to collaborate on the survey. Denver is the heart of Colorado's Front Range region with a 2016 population of 663,303 residents (119,395 under 15 years of age) spread out over the city's 155 square miles. The dense downtown is surrounded by medium-density neighborhoods laid out in predominantly gridded street networks. According to DPS, there are 92,331 children enrolled in DPS's 207 schools throughout the city.

11.1 Reactive Analysis: Crash Data

For our reactive analysis, we obtained motor vehicle crash data for the years 2010-2014 in GIS point shapefile format from the Denver Regional Council of Governments (DRCOG). All motor vehicle crashes involving a pedestrian or bicyclist under the age of 14 that occurred within the City and County of Denver were included in the reactive analysis. It was appropriate to use only those child pedestrian and bicyclist crashes that involved a motor vehicle because we were specifically concerned with on-road traffic safety issues. We identified pedestrian crashes based on reported pedestrian actions combined with user age as provided by police reports. We identified bicycle crashes based on reported vehicle types and user age. The crashes were originally geocoded by DRCOG, and DRCOG reports that they were subsequently verified by the Colorado Department of Transportation (CDOT).

Since counts of child pedestrians and bicyclists were not available citywide, we accounted for exposure using a population-based approach by calculating the number of crashes per 100 children living in each tract. Age-based population counts on the Census tract level were obtained from the 2015 American Community Survey (ACS). Such population-based exposure metrics have been shown to be effective for analyzing the safety of child active transport (DiMaggio & Li, 2013; N. Ferenchak & Marshall, 2017) and are an indicator of public health (Marshall & Ferenchak, 2017).

11.2 Proactive Analysis: Population and Built Environment Data

We collected age-based population data on the block group level from the 2015 ACS via the National Historical Geographic Information System (NHGIS) (Manson, Schroeder, Van Riper, & Ruggles, 2017). We used GIS-generated random points derived from these populations as origins for our closest facility network analysis. The City and County of Denver's Open Data Catalog provided us with the sidewalk network, roadway network, and off-road trail network in polyline shapefile format. We cleaned the layers by removing any duplicate segments and ensured that schools' access points reflected actual conditions. We then combined the roadway and trail networks to perform a closest facility network analysis. After confirming accuracy with Google StreetView and satellite imagery, we utilized the values for speed limits and number of lanes that were provided in these shapefiles when estimating trip suppression.

DRCOG's Regional Data Catalog provided traffic volumes and school locations in point shapefile format. We transferred traffic volumes from the point shapefile to our roadway network via spatial joins. Google Maps, satellite imagery, and Google StreetView informed our manual update of the bike lane network (originally provided in polyline shapefile format by DRCOG). The analysis included protected, buffered, and standard bike lanes.

11.3 Proactive Analysis: Parental Perceptions Data

To understand which situations parents will allow their children to walk or bike (in order to derive trip suppression rates), we surveyed parents of children in pre-kindergarten through 8th grade. The survey was available online and was open during October 2017. We provided surveys and promotional materials in English and Spanish and advertised through DPS and the City and County of Denver.

Respondents first provided the grade level and gender of each child. Then, parents answered eight travel behavior questions. As a model for the travel behavior questions on the survey, we used the Leuven Travel Behavior of Children to Primary School Survey (Nevelsteen et al., 2012). Parents answered whether they would allow their child to either walk or bike along eight different roadway scenarios on the child's trip to school (four pedestrian scenarios and four bicycle scenarios). We provided a picture for each of these scenarios and identified four different roadway characteristics for the parents: the speed limit of the roadway, the number of lanes, the presence of active transportation facilities (a sidewalk for walking scenarios and a bike lane for bicycling scenarios), and the vehicular volume of the roadway (Figure 11.1). Past researchers have found these characteristics to be important determinants of children's travel behavior (Larsen, Buliung, & Faulkner, 2013). Each of the scenarios had a unique combination of roadway characteristics.

Three of the roadway characteristics had three levels (speed limit: 25 mph, 35 mph, or 45 mph; number of lanes: 2 lanes, 3 lanes, or 4 lanes; presence of non-motorized facilities on: 0 sides, 1 side, or 2 sides of the roadway). One of the factors had two levels (volume of the roadway: low or high). We designated any roadway having more than 1,000 vehicles per day as high volume (Program, 2014).

After being asked whether they would allow their child/children to walk or bike to school along the roadway, parents were able to respond either "No", "Yes, with trusted adult supervision", or "Yes, without adult supervision". Parents were able to answer for up to four children on the same screen and were given the option to leave comments at the end of the survey.

Of the 1,298 survey respondents, 924 provided complete responses. These 924 complete parent responses accounted for 1,331 children. There was a representative distribution of responses across grade levels (Figure 11.2) and genders (50.2% male, 49.5% female, 0.3% other). Most surveys were completed for one (52.2% of surveys) or two children (40.0%). A more expansive discussion of the survey methodology and results can be found in the original study (N. N. Ferenchak, 2018).

For the proactive analysis in this chapter, we utilized the number of times children encounter roads that are perceived as unsafe as our outcome variable. For our analysis, we counted this outcome variable on the Census tract level and then controlled for the number of children living in each Census tract in the same manner as the reactive outcome variable. Since children could encounter more than one unsafe road on their trip to school, some Census tracts averaged more than one encounter per child.

7. Would you allow your children to use this roadway **on foot** to get to school?

35 mph Speed Limit
2 Lanes
Sidewalks
Low Vehicle Volume

13. Would you allow your children to use this roadway **on bike** to get to school?

35 mph Speed Limit
3 Lanes
Bike Lanes
High Vehicle Volume

Figure 11.1 Roadway Scenarios from the Parental Survey

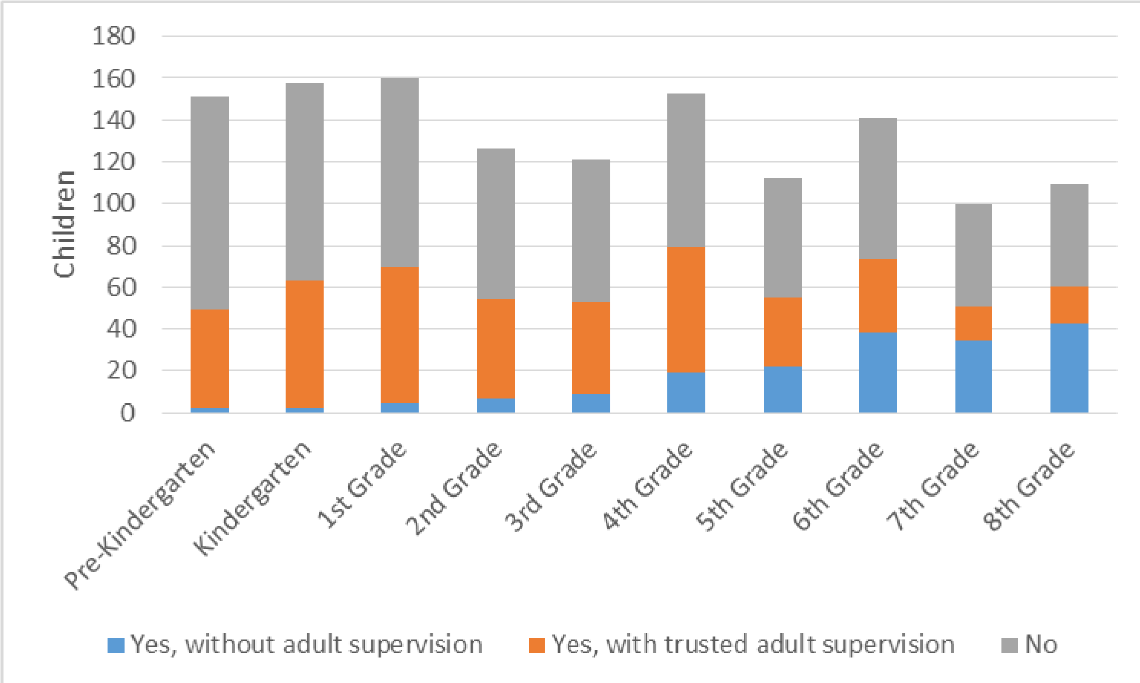


Figure 11.2 Parental Allowance by Grade Level

11.4 Demographic Data

We collected data pertaining to median household income, educational attainment, ethnicity, and race on the Census tract level from the 2015 ACS via the NHGIS (Manson et al., 2017). Educational attainment took the form of the percentage of the population that has a high school degree, ethnicity took the form of the percentage of the population that identified as Hispanic, and race took the form of the percentage of the population that identified as black. Because we wished to examine minority races, we included black (9.8% of population) but did not include other races because of low representation in Denver. In terms of ethnicity, we included Hispanic as a variable; 30.8% of Denver's population identifies as Hispanic.

12. METHODS

We began by conducting a reactive analysis using pedestrian and bicyclist crashes. To undertake a proactive analysis, we connected children with their closest schools and then integrated barriers – based on results from the parental survey – into the network analysis to determine the number of children that encounter roads perceived as unsafe. Finally, we utilized socio-demographic data to identify affected populations for both the reactively- and proactively-identified traffic safety issues.

12.1 Reactive Analysis

After querying child pedestrian and bicyclist crashes from the motor vehicle crash layer provided by DRCOG, we counted the number of crashes that occurred in each Census tract using a spatial join in GIS. To avoid edge issues, we used a 50-foot buffer around each Census tract when completing the counts. Since our traffic safety outcomes were in count form, we needed to normalize for exposure. Because pedestrian and bicyclist counts on a citywide level were not feasible, we controlled for the number of children living in each Census tract. While past research has used this approach when analyzing the safety of child active transport (DiMaggio & Li, 2013; N. Ferenchak & Marshall, 2017), population-based exposure metrics do not account for differences in trips occurring within and across Census tracts. In other words, some Census tracts may contain many schools that are well-connected with child origins while other Census tracts may contain few schools or few well-connected schools. Using population as an exposure metric does not differentiate between these different types of Census tracts. Our outcome variable took the form of child pedestrian and bicyclist crashes per 100 child residents of each Census tract. We used these outcome variables in the socio-demographic analysis.

12.2 Proactive Analysis

We utilized a closest facility GIS network analysis to measure the number of children encountering roads perceived as unsafe, defining child homes as origins and their closest school as destinations. All children were designated by a random point on the block group level. Because of Colorado's Open Enrollment policies (and to avoid edge issues), we included children in neighboring municipalities if their closest school was in Denver. All public elementary and middle schools in Denver were included in the analysis.

The closest facility methodology started at an origin (i.e. child) and found the shortest route distance to their respective destination (i.e. school). While pedestrians and bicyclists often do not use the shortest available path because of safety and comfort concerns, the fact that we wished to measure these safety and comfort concerns justified this method (Krizek, El-Geneidy, & Thompson, 2007).

All public roads and off-road trails were included in the roadway network. We integrated the impact of roadway network connectivity on active transportation levels into the analysis by accounting for intersection density per factors determined by past research (Schlossberg, Greene, Phillips, Johnson, & Parker, 2006). In other words, since children living among denser roadway networks have been found to be more likely to pursue active transport, we accounted for those differences in travel behavior in our model (Schlossberg et al., 2006). We did not account for crime because of mixed findings in terms of the relationship between crime and walking levels, mainly due to more walkable environments attracting different types of crime (Foster et al., 2014).

Once we identified our pedestrian and bicyclist routes, we needed to determine how many children were encountering roads perceived as unsafe. While we used trip suppression rates provided directly by parents for those roadway scenarios that were featured on the survey, we needed to interpolate or extrapolate suppression rates for roadway scenarios that were not on the survey (e.g. one-lane roads, six-lane roads, 55 mph roads, etc.).

To interpolate and extrapolate suppression rates, we created a linear regression model using the four roadway characteristics as predictor variables and the percentage of disallowance as the outcome variable (Table 12.1). Additional details regarding this analysis are available in the original research (N. N. Ferenchak, 2018). We did not find evidence of non-linearity, which suggests that this technique is appropriate. The most important factor suppressing walking trips was a lack of sidewalks, while the most important factor suppressing biking trips was vehicle volumes. Each roadway segment in our network analysis now had a set of roadway characteristics and a corresponding percentage of parents that would not allow their child to walk or bike on that segment.

Table 12.1 Direction of Linear Regression Results for Trip Disallowance

	Walk	Bike
Speed (mph)	+ ***	+ ***
Lanes	+ *	+ ***
Facilities	- ***	- ***
Volume	+ ***	+ ***

* *p<0.10*
** *p<0.05*
*** *p<0.01*

If a segment had a suppression rate of 50% or higher, we considered that segment as one to be avoided by child pedestrians and bicyclists and therefore designated it as a barrier (Figure 12.1). We did not account for age when determining barrier weights because we did not know the exact age of any specific child (for privacy reasons). The number of children who encounter a road with a suppression rate of 50% or higher was our proactive indicator of traffic safety and represented an average child in terms of age. A spatial join provided counts of children encountering roads perceived to be unsafe for each Census tract. Child population counts then allowed us to control our outcome variable for exposure, resulting in the number of children encountering roads perceived to be unsafe per 100 child residents in each Census tract.

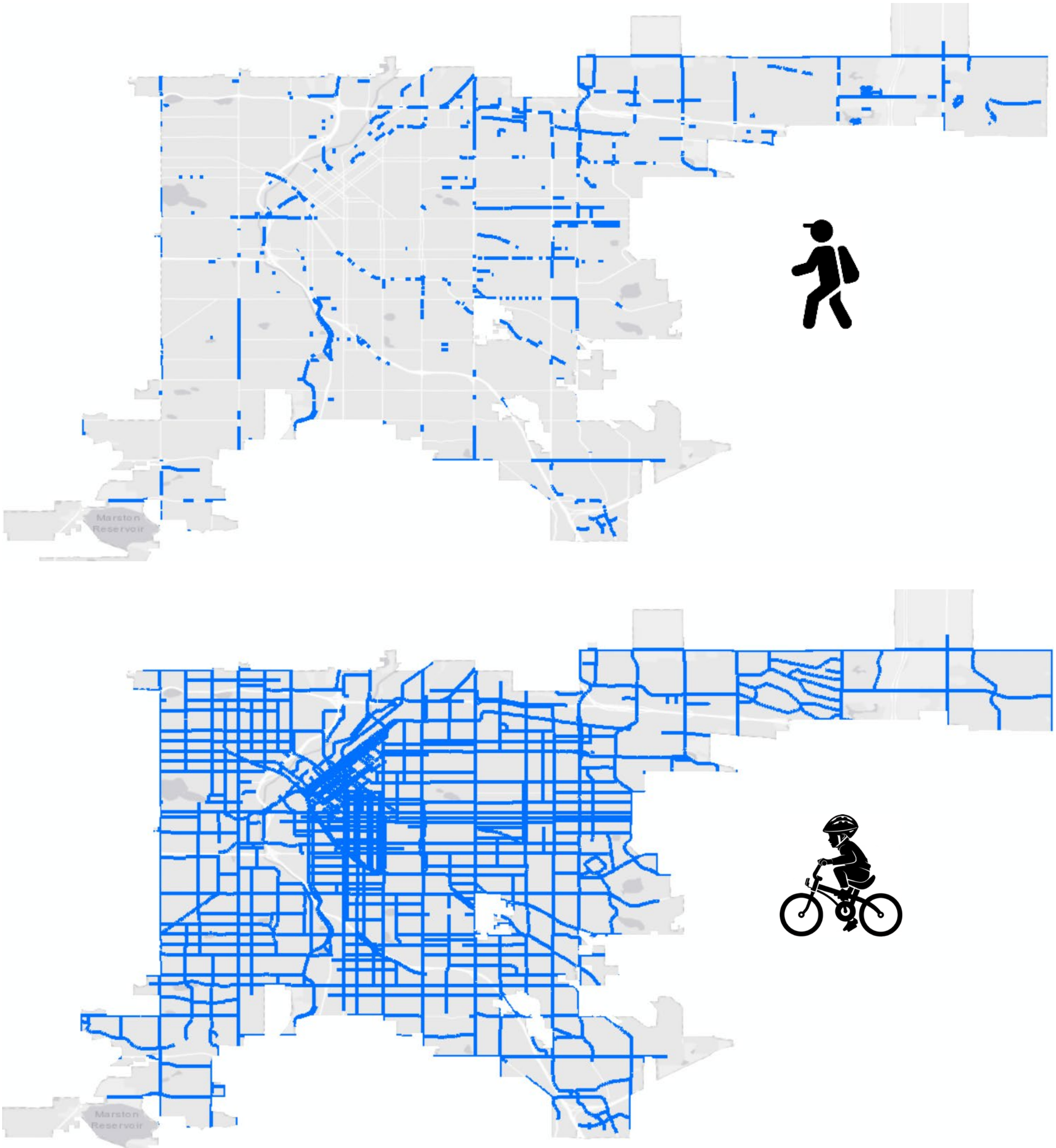


Figure 12.1 Location of Barriers Identified by Parents for Pedestrians (Top) and Bicyclists (Bottom)

12.3 Demographic Analysis

After completing our proactive and reactive analyses, we then examined the socio-demographics of the populations being affected. We first completed a statistical analysis on the Census tract level using linear regressions. A linear regression predicts the change in a dependent variable (i.e. traffic safety outcomes in the form of crashes or children encountering roads perceived as unsafe) per unit of predictor variable (i.e. median household income, educational attainment, race, and ethnicity) in the form:

$$Y = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n$$

Where:
Y = dependent variable (traffic safety outcomes)
X = independent variable (socio-demographics)
b = coefficient

Because of the straight-line function for all the variables, the coefficients, b, show the change in the dependent variable per change in the independent variable, all other things being held equal. Errors are assumed to be normally distributed. In our model, all dependent variables were continuous. Because the Hispanic, black, and education variables were proportions between zero and one while the median household income variable was not, we transformed the income variable into a proportion to standardize the regression analyses. Our dependent variables took the form of crashes per 100 child residents and children encountering roads perceived as unsafe per 100 child residents; our predictor variables took the form of the percentage of the population in each tract that self-identified as Hispanic, self-identified as black, had attained a high school degree, and the median household income for each tract.

Since the independent variables were found to exhibit linear correlation (Table 12.2), we used separate linear regression models for each independent variable to avoid collinearity issues.

Table 12.2 Pearson Product-Moment Correlation Coefficients between Socio-Demographic Variables on the Census Tract Level

	Income	Education	Hispanic
Income	-		
Education	0.55	-	
Hispanic	-0.52	-0.93	-
Black	-0.28	-0.19	0.04

In order to more clearly understand how these traffic safety trends were distributed across the city, we supplemented our statistical analysis with spatial analysis in GIS. We completed this spatial analysis on the Census tract level with bivariate choropleth maps by dividing each variable into ternary quantiles and creating one map for every combination of traffic safety outcome and socio-demographic variables.

13. RESULTS

13.1 Reactive Analysis

During the study period, there were 342 child pedestrian crashes and 208 child bicyclist crashes that occurred in Denver. Other descriptive statistics for dependent and independent variables on the level of the Census tract can be found in Table 13.1.

Table 13.1 Descriptive Statistics on the Census Tract Level

	Definition		Mean	Min.	Max.	Std. Dev.
Crashes	Per 100 child residents	Ped	1.30	0	8.18	1.33
		Bike	0.77	0	4.34	0.88
Encounters	Per 100 child residents	Ped	21.4	0	137.93	28.56
		Bike	87.3	0	314.23	62.35
Income	Median household income ($)		61,320	11,410	175,313	26,445
Education	% no high school diploma		14.4	0	51.5	13.8
Hispanic	%		28.9	1.7	85.6	23.8
Black	%		9.2	0	49.2	10.3

Child pedestrian and bicycle crashes were concentrated in west Denver, as shown by per-capita univariate choropleth maps divided into five quantiles (Figure 13.1).

Figure 13.1 Per-capita Distribution of Child Pedestrian (Left) and Bicyclist (Right) Crashes (Red = High Concentration)

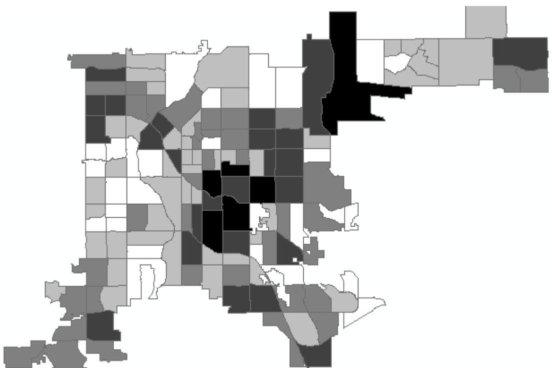
13.2 Proactive Analyses

According to survey results, parents perceive the roadway environment of Denver as less safe for bicycling than for walking. Approximately 12.2% of children walking to school in Denver would encounter a road with 50% disallowance or greater assuming that the child takes their shortest route to school. However, 61.4% of children in Denver would encounter a similar barrier for bicycling. These percentages translate to tens of thousands of active transport trips that encounter roads perceived as unsafe every day, showing that negative perceptions of traffic safety issues are relatively widespread in Denver. We found children that encounter roads perceived as unsafe for walking were concentrated in northeast Denver while children that encounter roads perceived as unsafe for bicycling are more evenly distributed throughout the city, as shown by per-capita univariate choropleth maps divided into five quantiles (Figure 13.2).

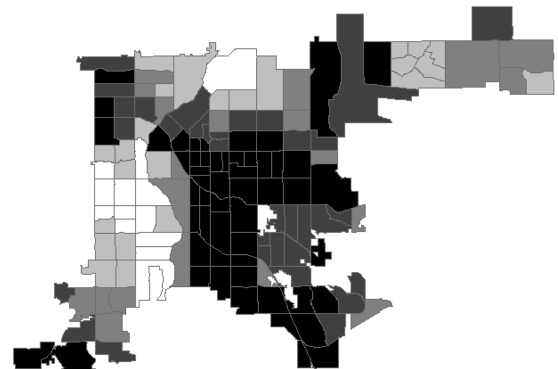
Figure 13.2 Per-Capita Distribution of Child Pedestrians (Left) and Bicyclists (Right) that Encounter Roads Perceived as Unsafe (Black = High Concentration)

13.3 Demographic Analysis

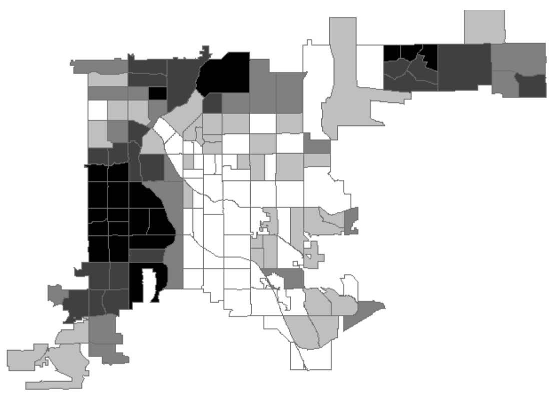
Spatial analysis indicates concentrations of low-income populations in west, north, and northeast Denver, concentrations of low-education and Hispanic populations in west Denver, and concentrations of black populations in northeast Denver, as shown by per-capita univariate choropleths divided into five quantiles (Figure 13.3). How do these socio-demographics align with traffic safety outcomes?



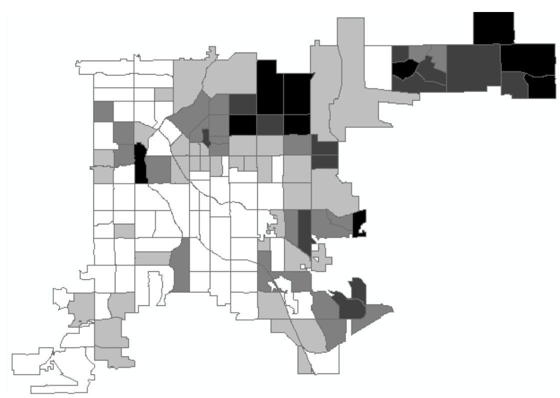
Income *(white = low-income)*



Education *(white = low-education)*



Hispanic *(black = high concentration)*



Black *(black = high concentration)*

Figure 13.3 Per-Capita Distribution of Socio-Demographic Populations

Results from linear regression models indicate that both proactively- and reactively-identified traffic safety issues in Denver are concentrated in neighborhoods with high levels of Hispanic, black, low-education, and low-income populations, with crashes being more strongly so (Table 13.2). For example, negative relationships indicate that Census tracts with lower educational attainment and lower household incomes experience more child pedestrian and bicyclist crashes. Positive relationships indicate that Census tracts with higher proportions of Hispanic and black populations experience more child pedestrian and bicyclist crashes (except for black populations and bicyclist crashes). All these relationships are in the expected – albeit inequitable – direction, with the exception of black populations and bicyclist crashes. Similarly, inequitable distributions of crashes have also been found in past research (Braver, 2003; Campos-Outcalt et al., 2003; Harper et al., 2000; Marshall & Ferenchak, 2017; McAndrews et al., 2013; Schiff & Becker, 1996). Because we transformed the income variable into a proportion, comparison can be made between the independent variables. Results indicate that education has the strongest relationship with pedestrian crashes while the black variable has the strongest relationship with bicycle crashes.

Tracts that contain children who encounter roads perceived as unsafe for walking and bicycling have similar socio-demographic compositions. Except for low-income populations and pedestrian encounters, all relationships are in an inequitable direction. Half of these inequitable relationships reach statistical significance. Results indicate that the black variable has the strongest relationship with pedestrian encounters while education has the strongest relationship with bicycle encounters. These results suggest that while our reactively-identified traffic safety issues are inequitably distributed, our proactively-identified traffic safety issues – those that may be unrecognized by traditional methods in the first place – are also inequitably distributed.

Table 13.2 Socio-Demographic Analysis Linear Regression Results
Pedestrian (n=144)

	Child Crashes				Children Encountering Roads Perceived as Unsafe			
	Coeff.	R^2	Std. Error	Intercept	Coeff.	R^2	Std. Error	Intercept
Income	-2.25***	0.06	0.00	0.02	8.79	0.00	0.29	0.18
Education	-3.38***	0.12	0.01	0.01	-23.45	0.02	0.28	0.18
Hispanic	1.40***	0.06	0.01	0.01	19.17**	0.03	0.28	0.16
Black	0.15	0.00	0.01	0.01	62.28***	0.05	0.28	0.16

Bicycle (n=144)

	Child Crashes				Children Encountering Roads Perceived as Unsafe			
	Coeff.	R^2	Std. Error	Intercept	Coeff.	R^2	Std. Error	Intercept
Income	-1.13**	0.04	0.01	0.01	-54.59	0.02	0.62	1.06
Education	-0.56	0.01	0.01	0.01	-216.43***	0.23	0.55	0.56
Hispanic	0.16	0.00	0.01	0.01	132.27***	0.25	0.54	0.49
Black	-1.28*	0.02	0.01	0.01	68.72	0.01	0.62	0.81

* *p<0.10*
** *p<0.05*
*** *p<0.01*

To understand the distribution of these relationships and whether any clustering exists, we pursued spatial analysis with bivariate choropleth maps. Spatial analysis results mirror results from the statistical analyses (Figure 13.4). For income and education, dark pink signifies Census tracts with low income or low education and high levels of crashes or encounters. Therefore, for maps involving income and education, dark pink indicates equity issues. For Hispanic and black variables, dark blue signifies Census tracts that have high levels of Hispanic or black populations and high levels of crashes or encounters. Therefore, for maps involving Hispanic or black variables, dark blue indicates equity issues.

The bivariate choropleth reactive (i.e. crash) analysis identifies income, education, and Hispanic equity issues in west Denver for both pedestrians and bicyclists (Figure 13.4). Black populations do not display prominent concentrations of identified equity issues on the bivariate choropleth maps.

Bivariate choropleth maps of the proactive (i.e. children that encounter roads perceived to be unsafe) analysis not only identify similar equity issues in west Denver, but also identify equity issues in north and northeast Denver for education, Hispanic, and black variables for both pedestrians and bicyclists. Income – which was not found to have a strong, significant relationship with perceived issues – displays a concentration in north Denver that was largely neglected by the reactive approach but does not display the concentration in west Denver as clearly.

Findings show that north and north-east Denver – which consist of predominantly black, Hispanic, and low-income neighborhoods – have few crashes. Why is this? The proactive analysis indicates that children face many roads that parents perceive as unsafe in these areas of the city. If parents do not let their children walk or bike in these areas, then crashes will be precluded, and these issues will therefore be hidden from the traditional analysis. The proactive methodology allows Denver (and other communities) to see where walking and biking may be suppressed due to safety concerns before those safety concerns manifest themselves. In Denver, these perceived traffic safety issues are inequitably impacting low-income, low-education, black, and Hispanic populations.

The equity issues in north and northeast Denver that are proactively-identified but not reactively-identified are found in areas containing tributary roadway networks. These networks do not provide adequate local road connectivity, forcing pedestrians and bicyclists to funnel onto wider and faster roads that are perceived as less safe. While few child pedestrian and bicyclist crashes occur in these neighborhoods, there are roadway conditions that have been identified as unsafe by parents, there are many children living there, and there are high levels of low-income, low-education, Hispanic, and black populations present, resulting in neglected traffic safety equity issues.

Reactive
Proactive
Income
Education
Hispanic
Black
Low
High
Safety Outcomes
Low
High
Demographics

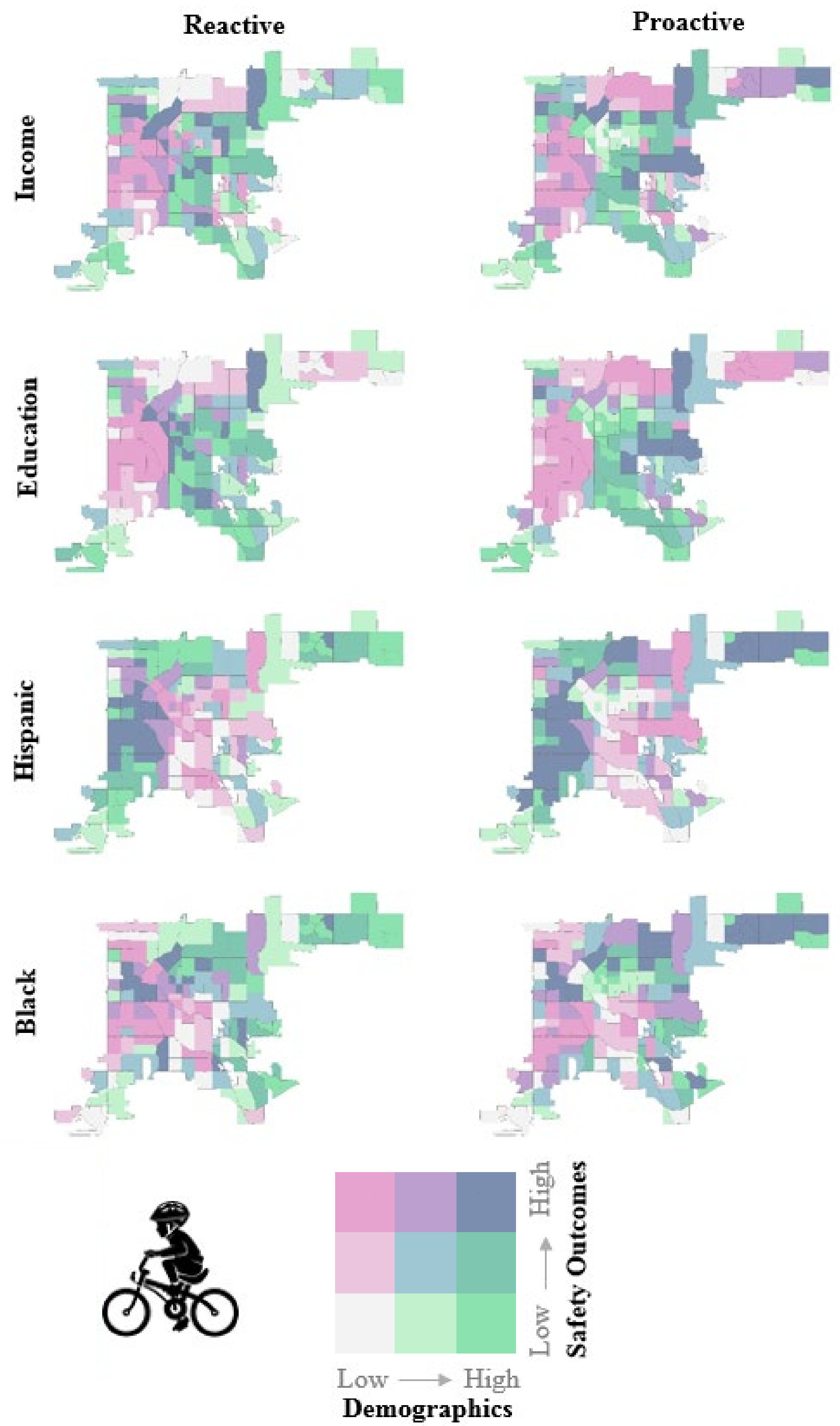


Figure 13.4 Bivariate Choropleth Maps Showing Relation between Socio-Demographics and Traffic Safety Outcomes for Pedestrians (Top) and Bicyclists (Bottom)

14. CONCLUSION

Findings suggest that both reactively- and proactively-identified traffic safety issues are positively associated with Hispanic, black, low-education, and low-income populations. These results indicate that the equity issues identified by past crash-based studies may be more serious than those studies identified. In addition, proactive indicators can identify neglected equity issues, such as those found in north and northeast Denver in this analysis. If we can more holistically identify the populations that are being impacted, then we can begin to approach traffic safety in a more targeted and effective manner. By concentrating safety improvements in the neighborhoods highlighted by the bivariate choropleth maps, we can work towards fixing perceived traffic safety equity issues currently neglected by reactive approaches.

Primary limitations of this work are related to the fact that only children were examined. Once a more robust proactive indicator has been developed, future work would benefit from examining pedestrian and bicycle outcomes for all ages and all trip purposes. An arbitrary threshold of 50% suppression rate to designate barriers was another limitation of the work. A more robust integration of suppression rates into the network analysis could better inform future work. Furthermore, we cannot be sure whether the socio-demographic characteristics of those involved in crashes reflect the general characteristics of low-income, low-education, Hispanic, and black system users or neighborhoods. It may very well be that the crashes occurring in these Census tracts did not involve residents of those Census tracts or residents from the minority groups. Future work might also explore to what extent the race and ethnicity variables are simply indicators of socioeconomic status, as past work has suggested (McAndrews et al., 2013).

Similarly, future work would benefit from exploring whether there is confounding between socio-demographics and perceptions and how those differing perceptions relate to differences in travel behavior. It may be that low-income, low-education, black or Hispanic residents perceive walking and biking as more or less safe and are therefore more or less willing to walk or bike. This would result in them being more or less likely to encounter roads perceived as unsafe. Future work could address these issues.

Furthermore, people's perceptions may change from place to place. We recommend administering a survey specific to each locale that wishes to pursue a proactive safety analysis instead of adopting the models used in this work.

Crash outcomes have been shown to be the result of a combination of factors including behavior (e.g. seat belt use, impaired driving, speeding, and number of vehicle occupants) and the availability of protective travel environments and vehicles (Braver, 2003; Campos-Outcalt et al., 2003; Marshall & Ferenchak, 2017; McAndrews et al., 2013). Alternatively, the proactively-identified indicators are based solely on infrastructure. The fact that crashes result from a combination of factors – some of which may also be related to socio-demographics – may have resulted in stronger relationships with the socio-demographic variables. Future work would also benefit from proactively accounting for different behaviors, vehicles, environments, social norms, and time affluence of the socio-demographic groups. Believing that street design is responsible for all school travel decisions would be taking an overly environmental deterministic perspective on the problem.

Walking and bicycling are important modes of travel. However, many traffic safety issues – which act as barriers to walkability and bikability – remain unrecognized. By identifying low-income, low-education, black, and Hispanic populations as being particularly impacted by proactively-identified traffic safety issues, we can begin to understand how to more appropriately amend these issues, thereby enabling walking and biking for all.

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PART 3: Implementing Vision Zero: A Proactive Approach to Building Cities for Kids

16. INTRODUCTION

So your city has finally come to realize that safety on our streets is not as much about reducing the number of fender benders as it is about eliminating fatalities and severe injuries. Now, city officials are even working on a Vision Zero plan that will propose some protected bike lanes, increase police enforcement of all modes, and establish an education program about distracted driving and walking. If and when those things come to fruition, your city may become a little bit safer. Will you be any closer to eliminating fatalities and severe injuries? Probably not significantly.

In a perfect world, your city would set about making each and every street and intersection safer. To make a significant dent in the problem, they'd also need to entirely change their mindset about what transportation is for. This, regretfully, is too high of a hurdle – both economically and politically – for almost every US city at this point.

While we acknowledge the need for a comprehensive overhaul of the way that cities conduct the business of transportation, this chapter gives them a more definitive place to start. We do so by changing the client. Instead of conventional design that attempts to account for a wide variety of road users, we first focus on one type of road user: kids.

Children under 18 represent almost 23% of the US population, but rarely do we engineer our streets for them other than to put up a sign that attempts to limit speeds around schools at certain times of the day and certain times of the year. Even then, cities such as Denver only lower school zone speed limits to 35 mph when the adjacent street is considered important for moving traffic (see Figure 16.1). This is the antithesis of the Vision Zero philosophy.

Figure 16.1 35 mph "School Zone" in Denver, CO

If we want to make our cities safer – and healthier and more vibrant – let's stop focusing on traffic demand 30 years down the road and start trying to make our cities safe for kids to walk, bike, scooter, hop, roller skate, and however else they might want to get around right now. To realize this goal, the conventional approach begins with trying to figure out where kids pursue active transport and then trying to make those places safer. This chapter proposes a subtle, but critical, change to that line of thinking. Instead of asking where kids walk and bike and trying to make those places safer, we look to where they don't walk bike. In other words, we intend to first figure out where kids *should* be using active transport. Then, we look to see how many of those kid walking trips are being *suppressed* by the existing transportation system.

Past research suggests that young children tend to have poor gap and speed assessment and often overestimate their abilities (Connelly, Conaglen, Parsonson, & Isler, 1998; Plumert, Kearney, & Cremer, 2004). Children also have limited peripheral vision and trouble locating sounds (S. David, Foot, Chapman, & Sheehy, 1986). These traits are not that different from our older populations, which are expected to increase from 15% of the population to more than 23% over the next few decades. If we design our streets so that children can safely walk – and include ADA accessibility – then our designs will accommodate just about everyone. The chapter presents a new, data-driven, spatial approach to prioritizing Vision Zero transportation investments towards the creation of kid-friendly cities. While we focus on Denver, CO, for the sake of this chapter, the approach can be applied to any city.

17. BACKGROUND

The state of transportation planning has long been described as ‘predict and provide’ (Goulden, Ryley, & Dingwall, 2014; Owens, 1995). Foremost in transportation planners and engineers’ minds is providing enough capacity to reach a satisfactory level of service (LOS) after traffic growth has been extrapolated to some future date. Accommodating future traffic that will not exist for another 30 years often comes at the cost of not accommodating pedestrians and bicyclists with safe and comfortable facilities today. Even when we try to account for active transportation safety, we end up with narrow sidewalks next to fast, high-traffic roads (see Figure 16.1), pedestrian bridges over wide arterials, or shared lane markings (i.e. sharrows) where they do more harm than good. The prioritization of safety interventions commonly resembles a triage, with only the most critical intersections receiving attention after enough crashes have precipitated.

A new approach to traffic safety has recently gained momentum in the US. Since 2014, approximately thirty-five cities, two states, and the District of Columbia have made commitments to pursue the goals of Vision Zero. According to the Vision Zero Network, the goals of Vision Zero are to “eliminate all traffic fatalities and severe injuries, while increasing safe, healthy, equitable mobility for all” (Network, 2018). Instead of treating them as accidents, Vision Zero posits that traffic crashes are preventable and accounts for human failing by endeavoring to reduce speeding, distraction, and aggressive driving behavior.

New York City – which was the first major US city to commit to Vision Zero – has pursued interventions that include bus and taxi driver training, leading pedestrian intervals, speeding enforcement, protected bike lanes, truck sideguards, speed humps, and left-turn calming treatments, among others (York & Operations, 2018). While preliminary results are somewhat promising, New York City still has a long way to go (Figure 17.1). Fatalities have dropped since implementation, but it is too early to distinguish whether this was part of a wider trend or a result of Vision Zero efforts (York & Operations, 2018).

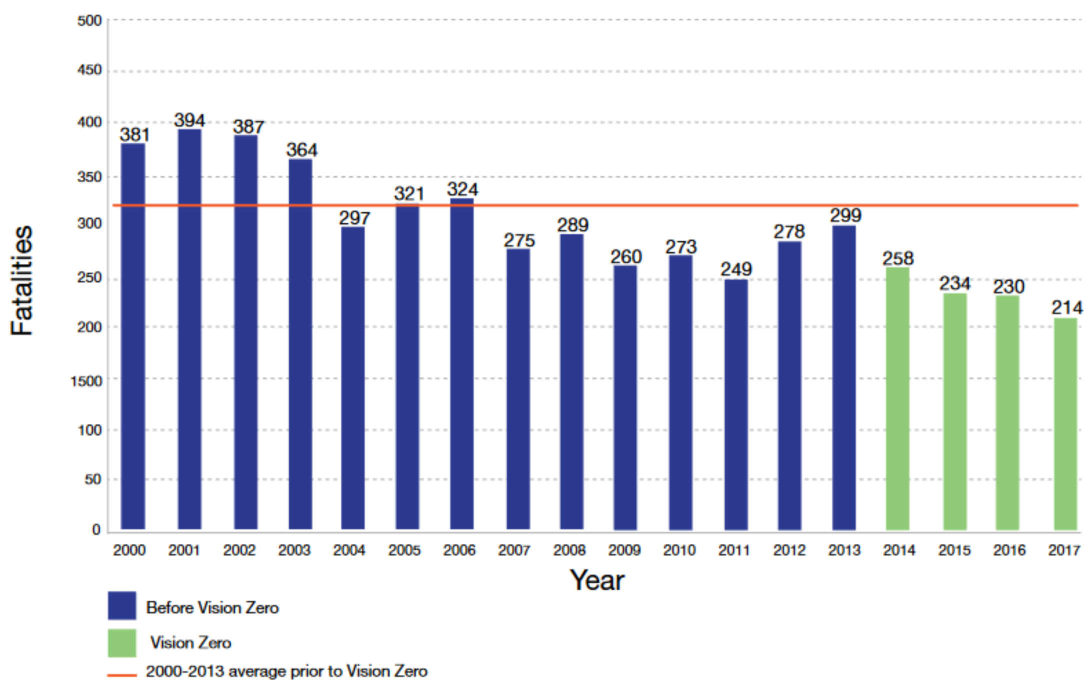

Figure 17.1 New York City Traffic Fatalities, 2000-2017 (data source: NYC DOT & NYPD)

Another burgeoning traffic safety movement asserts that to design cities that are safe for everyone, we must design them so that they are safe for kids. This movement evolved from the Safe Routes to School (SRTS) program that began in the 1990s and taught us several important lessons. First, we recognized that kids need special accommodations in the transportation system. Second, we confirmed that when we focus resources on known traffic safety issues, we can get more kids walking and biking while concurrently improving safety outcomes (DiMaggio & Li, 2013; Dumbaugh & Frank, 2007; Orenstein, Gutierrez, N, & Rice, 2007). While progress was made through SRTS, efforts were narrowly focused around schools.

Recent efforts have built off this SRTS momentum by calling for entire cities that are designed to accommodate kids. The National Association of City Transportation Officials (NACTO) recently announced Streets for Kids, a program that will develop design guidance for public spaces that allow kids of all ages to learn, play, and move around a city (National & Officials, 2018). Arup, a large multinational engineering firm, recently released a report that details how to design cities for urban childhoods (Arup, 2017). Their findings show that – not only do we need more playgrounds and parks – we need to provide child-friendly infrastructure for children's independent, safe, and comfortable mobility. The World Health Organization also released a report that focuses on designing age-friendly cities (Organization, 2007). While their primary focus is on the elderly, they assert that true age-friendly designs serve both older populations and children simultaneously. Finally, 8 80 Cities is a non-profit organization founded by Gil Penalosa aimed at enhancing mobility for people of all ages, from 8-year-olds to 80-year-olds. They have worked with 250 communities on six continents to further child-friendly designs. These organizations all believe that if we can make our cities safe for kids – some of the most vulnerable users of our streets – we can surely make them safe for all.

Those serious about Vision Zero should take note of these recent movements and begin looking into how they can better design our cities for kids. Consider New York City's Vision Zero treatments we mentioned before: taxi driver training, leading pedestrian intervals, and truck sideguards. These are all good things but are probably most appreciated by the strong and fearless pedestrians and bicyclists that are on the road today. They are not nearly enough to ensure that New York City's streets are safe for their most vulnerable users. Now consider the second half of the Vision Zero credo: "…while increasing safe, healthy, equitable mobility for all" (Network, 2018). Right now, because of the "Zero" in the name and the visceral relationship we have with injuries and fatalities, the first part of the credo gets most of the attention. However, the final part is an ideology that is just as important, and – by interpreting it as designing for child pedestrians, some of our most vulnerable users – we can better define a framework for how to accomplish the first part of the Vision Zero credo. Making our streets safe for kids to walk and bike should be considered as the most fundamental building block of urban design.

Vision Zero efforts in North America have largely used conventional, reactive approaches to improving road safety by focusing on where pedestrians are involved in crashes. Unfortunately, these data only tell us about the users that are currently out there walking. To unfortunately become a crash statistic, the street needs to be perceived as safe enough to walk in the first place. As is, we completely ignore: i) users who deem the road too unsafe to use in the first place; and ii) the places where these people might want to walk or bike. Instead of waiting for crashes to happen, we need a proactive approach – focused on kids – that embraces the second half of the Vision Zero credo: "…while increasing safe, healthy, equitable mobility for all" (Network, 2018). This chapter presents a more comprehensive approach to Vision Zero efforts via a method that proactively accounts for the latent demand of childhood pedestrian and bicyclist trips and identifies locations where these trips are being suppressed by perceived safety issues.

18. THE PROACTIVE CHILDHOOD SAFETY ASSESSMENT RESEARCH

Before we discuss how to use our proactive approach, this section describes the underlying research, including the survey and network analysis methodologies. Additional information beyond the scope of this chapter can be found in Ferenchak & Marshall (Ferenchak & Marshall, 2018a, 2018b).

The goal of this research is to proactively identify traffic safety issues for child pedestrians and bicyclists. Instead of examining crashes, we use perceptions as a proactive indicator of safety issues. Through a parental survey, we determine which roadway characteristics are suppressing the most child pedestrian and biking trips. We then combine this suppression with locations where trips could be occurring to proactively identify which safety issues should be prioritized.

To derive suppression rates, we administered a survey to parents of children in elementary and middle schools in Denver, Colorado. Our survey was offered exclusively online – in both English and Spanish – and was open in 2017 for the month of October. Information regarding child age and gender was provided by parents first. The survey then presented parents with scenarios consisting of varying roadway design characteristics in consistent land use and residential contexts (Figure 18.1). Each scenario included a corresponding picture from a road in Denver. Parents were able to answer "No", "Yes, with trusted adult supervision", or "Yes, without adult supervision" when asked whether they would allow their child to walk to school on each roadway. Each survey included five randomly selected walking questions and five randomly selected bicycling questions from a pool of twenty walking questions and twenty bicycling questions. Roadway design characteristics on the survey included number of lanes (2, 3, or 4 lanes), posted speed limits (25 mph, 35 mph, or 45 mph), the presence of sidewalks (none or on one or both sides of the road), and vehicle volumes (low or high volumes).

924 complete responses from 1,298 survey respondents provided us with information on 1,331 children. We converted parent responses into suppression rates for each of the forty roadway scenarios by dividing the total number of responses by the number of parents responding "No."

6. Would you allow your child to use this roadway **on foot** to get to school?

25 mph Speed Limit
2 Lanes
Sidewalks
Low Vehicle Volume

Figure 18.1 Example of Survey Questions

Since there are more roadway scenarios than can feasibly be included in a parent survey, we interpolated suppression rates for other possible scenarios. For example, while the survey garnered perceptions regarding streets signed at 35 and 45 mph, we interpolate for 40 mph. Because the dependent variable was in the form of a proportion (of parents not allowing their child to walk), we developed a beta regression general linear model (GLM) with a logit link function using the betareg package in R. The beta regression GLM is appropriate when the dependent variable is in the form of a proportion bounded between zero and one. We formed the beta regression GLM by taking results from the twenty walking scenarios included in the survey and coding the four predictor variables as dummy variables. This standardized the regression results, allowing for comparison between the different variables. We removed the 25 mph and two-lane variables from the model to avoid multi-collinearity.

For walking, a lack of sidewalks resulted in the most suppression (Table 18.1). Parents are then concerned about vehicle speeds and vehicle volumes.

Table 18.1 Predictors of the Proportion of Parents Who Would Not Allow Their Child to Walk or Bike

		Walk $R^2 = 0.977$; n =20	Bike $R^2 = 0.9509$; n = 20
Intercept		-0.260*	-0.703***
Speed	35 mph	0.995***	0.644***
	45 mph	1.868***	0.901***
Lanes	3 lanes	0.495***	0.618***
	4 lanes	0.597***	1.166***
Facilities		-2.584***	-0.819***
Volume		0.770***	1.111***

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Volume		0.770***	1.111***

*** *p<0.001*
** *p<0.05*
* *p<0.01*

Using these beta regression results, we then derive the suppression rate for each roadway scenario. After a spatial join, every road segment in the city will have a corresponding rate of walking and biking trip suppression.

In order to understand trip suppression, we then need to determine how much distance would be added to children's shortest-path trips if the children were to try to avoid roads perceived as unsafe. If trip length does not increase significantly, we do not consider the trip highly suppressed. If in avoiding safety issues, trip length increases greatly, then the trip is highly suppressed.

To accomplish this, we first determine the shortest path distance from each child's estimated home to their closest school (or park or whatever destinations the user provides) using a closest facility network analysis in GIS. We then rerun the network analysis with each road segment weighted according to its suppression rate. In the weighted analysis, trip choices are a balance between distance and safety perceptions. In other words, what are the chances that the child will choose a short, unsafe trip or a longer but safer trip? Distance decay functions allow us to standardize distance and safety variables. Distance decay functions are inverse power functions that use distance or time as a proxy for travel costs. We developed ours based upon data from travel surveys, joint-use facility user surveys, and a Non-Motorized Pilot Program (NMPP) survey from the Twin Cities region (Iacono, K. Krizek, & El-Geneidy, 2008).

The distance decay functions for walking to school has an output variable for the percent of school and school-based trips made by walking and an independent variable of travel time in minutes (Equation 1). To standardize travel time into a distance so that we can perform a closest facility analysis, we used an assumption of 25 minutes per mile for pedestrian speed (a rough conversion of the standard 3.5 feet per second used in the Manual on Uniform Traffic Control Devices). This pedestrian speed assumption has shown to be appropriate for kids (K. S. David & Sullivan, 2005). We input the proportion of children allowed to walk to school (the inverse of the suppression rate) into this equation and derived an equivalent distance, which we then used to weight the network analysis. For example, a road segment with a pedestrian disallowance rate of 25% had a weight of approximately 711 feet, while a segment with a pedestrian disallowance rate of 95% had a weight of approximately 7,400 feet. We also transformed the distance decay function so that a value of 100% of trips correlates with a distance of zero. This avoids any negative distance outcomes, which would not be acceptable in the network analysis.

$$y = 0.523\mathrm{e}^{-0.10x} \tag{1}$$

where:

y = percent of school or school-related trips made by walking
x = travel time (minutes)

The distance decay function for biking to school (Equation 2) had a dependent variable of percent of school and school-based trips made by biking and an independent variable of travel distance in kilometers. We converted the function to feet to coincide with the foot-based network analysis. We also transformed both distance decay functions so that a value of 100% of trips correlates with a distance of zero. This avoids any negative distance outcomes, which would not be acceptable in the network analysis.

$$y = 0.4651\mathrm{e}^{-0.1236x} \tag{2}$$

where:

y = percent school or school-related trips made by biking
x = distance (km)

We join these results to your road layer so that each of the street segments has an additional weight (in feet). This weight functions as an added-cost barrier that is assigned at the midpoint of each segment. Therefore, when the weighted network analysis is run, it will account for both distance and perceptions in units of feet, allowing model participants to choose between a short, unsafe route and a longer, safer route.

We then compare the weighted distance to the original shortest path distance. The distance decay functions allow us to convert the added distance back to a percentage of suppression. In other words, if a child's walking trip increased by 711 feet when we accounted for safety perceptions, that child's trip was considered 25% suppressed. If a child's trip increased by 7,400 feet, that child's trip was considered 95% suppressed.

Kernel density analysis in GIS then facilitates simultaneously accounting for levels of suppression and the number of possible users by estimating a magnitude-per-unit area for cells in a raster layer. In other words, one neighborhood might have high levels of trip suppression but only one possible user while another neighborhood might have slightly less trip suppression but many possible users. Basing our output on the number of potential users helps protect us from the opportunity costs of focusing too much of our attention on, for example, industrial parks where few children would want or need to walk or bike. Child origin points are the base layer and trip suppression rates (as proportions) are the population variable for the kernel density. We employ a planar method as the analysis takes place on a relatively localized area.

19. APPLYING THE PROACTIVE APPROACH

This section provides instructions so that users can run a proactive child pedestrian and bicyclist safety analysis of their own city. Users will need a few pieces of data for this iteration (Table 19.1) that are likely to be free and relatively easily-accessible from either their city or metropolitan planning organization.

Table 19.1 Necessary Data that Users Need to Compile (*optional data in italics*)

		Format	Name
	Study Area	GIS Polygon	'StudyArea'
Destinations	Schools	GIS point	'Schools'
	Parks, playgrounds, recreation centers, etc.	In schools layer	
Transport Network	Roads	GIS line	'Roads'
	Speed Limits	In road layer	'Speed'
	Number of Lanes	In road layer	'Lanes
	Sidewalks	In road layer	'Sidewalk'
	Vehicle Volumes	In road layer	'Volume'

19.1 Survey Data

It will be easiest for users to use the suppression rates derived from our survey of Denver, Colorado, for their city. The suppression rates for pedestrians are already in the form of added distance weights in 'P.csv' in the 'Default_Data' folder.

19.2 Network Data

To understand how many child pedestrian trips are suppressed, the PAKS Tool will run a GIS closest-facility network analysis connecting children with their closest schools via the transport network. The PAKS Tool will first estimate trip origins by creating random points representing child home locations. These random points will be within the study area and will be based on child populations from the 2016 American Community Survey by block group (Manson, Schroeder, Van Riper, & Ruggles, 2017). Areas covered by water are not included in the block group layer so that random points will only be placed over land. The study area can be anywhere in the United States and should be defined by the user and saved as a polygon layer named 'StudyArea' in the 'Your_Data' folder. The analysis includes children between the ages of four and fourteen years to match our survey responses. To avoid edge issues, the PAKS Tool will include children living in the block groups just outside of the city and account for them in the analysis if their closest school is in the study area.

For destinations, users must provide a GIS point layer of elementary and middle schools named 'Schools' in the 'Your_Data' folder. Users can optionally provide data (in the same GIS point layer) for other child destinations such as parks, playgrounds, community centers, etc.

Users will also need road network GIS data that accounts for the roadway factors used in the survey. Combine all road and off-road trail segments that you would like to include in the analysis into one layer and name it 'Roads' in the 'Your_Data' folder. Add connections directly to school points (Figure 19.1). If connections are not added, all trips will end at a single point. Use the 'Feature to Line' tool to break the road segments at each intersection.

Figure 19.1 Example of a School Connection

Populate all segments with the roadway characteristics listed in Table 19.1, using the field names specified in the table. Posted speed limits should be in increments of 5 mph and range from 5 mph through 85 mph. The number of lanes should be between 1 and 12. Include lanes in both directions as well as turn lanes in the lane count. Values for sidewalks should indicate how many sides of the road the facility can be found on (either on 0 sides, 1 side, or 2 sides of the road). Vehicle volumes should be considered high for any roadway with more than 1,000 vehicles per day and marked with a value of '1' (Program, 2014). The remaining roadways should be considered low volume and marked with a value of '0'. Local roads for which traffic volumes are not provided should be considered low volume. Make sure that every segment has all attributes identified. Make sure that the road layer is projected in US feet in a projected coordinate system that is appropriate for your location. Off-road trails included in the analysis should have attributes coded as '0'.

Next, create a network dataset using the 'Roads' layer. Right click on the 'Roads' layer and select 'New Network Dataset'. On the first screen, name the network dataset 'Roads_ND'. On the next screen, specify that the network dataset not model turns. Accept all other commands as default (no connectivity, no elevation, keep only the distance attribute, do not add any travel modes, and no driving directions). Finish the network dataset and add all its components to the map.

After the ‘Roads’ layer and the corresponding network dataset are complete, add all layers to the map (starting with Roads_ND, then Schools, StudyArea, BlockGroups, and P.csv). Right click on the model inside the Proactive Pedestrian Safety Toolbox and click ‘Edit’. Make sure that all file paths have been updated for their appropriate location on your machine. This includes outputs for any ‘Feature to Vertices Points’, ‘Create Random Points’, ‘Copy Features’, ‘Spatial Join’, and ‘Kernel Density’ commands and the ‘Schools.shp’ layer. Keep the same layer names but save them to the appropriate folder. Then validate the model and fix any errors. Ensure that the Network Analyst and Spatial Analyst extensions are on. Finally, run the model.

20. TOOL OUTPUT

The PAKS Tool produces kernel density maps representing trip suppression for child pedestrians, thereby proactively identifying child pedestrian safety issues. Proactive identification of safety issues can help with prioritization in areas that have such low existing exposure, reactive crash-based prioritization is not feasible. The kernel density maps can be found in the 'Results' folder under 'Network_Analysis'. The kernel density maps show where there are both: 1) many children living; and 2) roadway characteristics that are perceived as unsafe. The kernel density maps are based on the origins of the trips (where the children live) as opposed to their actual routes or their destinations. The line shapefiles in 'Network_Analysis' are the shortest path and the weighted path routes.

Outputs for your city should look similar to the outputs from the case study in Denver detailed below (Figure 20.1). There are safety issues found throughout Denver, mostly consisting of localized hotspots within neighborhoods. These hotspots can be interpreted as traffic safety issues that have been identified by parents and that are impacting many children. However, the hotspots differ considerably from where child pedestrian crashes are occurring and show that we need to supplement our reactive analyses with proactive approaches to identify suppressed traffic safety issues in our cities (Ferenchak & Marshall, 2018b).

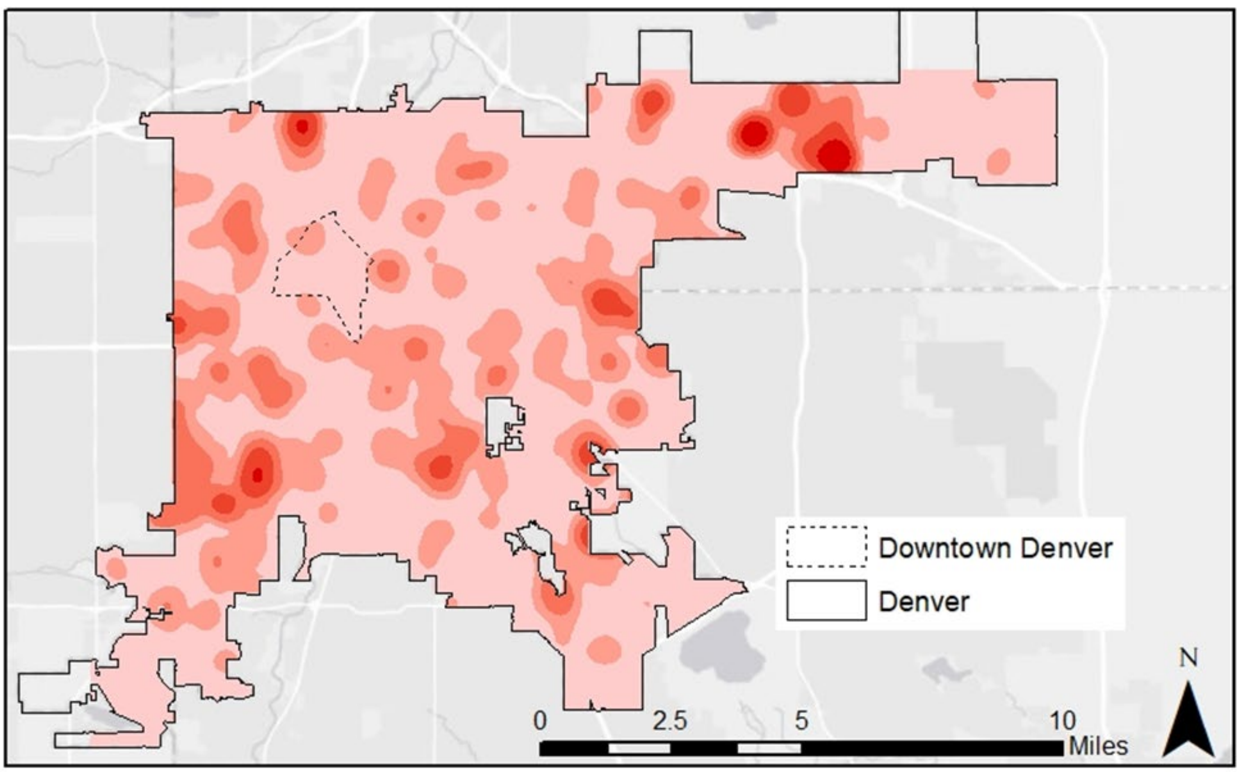

Figure 20.1 Suppressed Child Pedestrian Trips throughout Denver

The most useful benefit of the PAKS Tool becomes apparent when we take a finer-grained look at the output (Figure 20.2). Although we would ideally design every street to be safe for kids to walk, that is a lofty goal that is currently unrealistic for most cities. However, by using the PAKS Tool output, we can begin to identify which streets should be prioritized. We can also identify specific issues (whether they are sidewalk gaps, high vehicle volumes, or unsafe crossings) that are suppressing large clusters of children. Even though there may not be any pedestrian crashes occurring at these identified issues (precisely because the trips have been suppressed), we can now proactively see hidden safety issues that should be addressed. This gives us a place to start to proactively prioritize our traffic safety issues with children in mind. For example, at the bottom of Figure 20.2, we can see how one sidewalk gap is causing considerable trip suppression for many child pedestrians. While other sidewalk gaps in the area may not have the same influence on trip suppression, the sidewalk gap directly adjacent to the school is a clear candidate for prioritization. This would not have been detected with a traditional reactive analysis.

Figure 20.2 Proactive Pedestrian Traffic Safety Issue Identification and Prioritization

21. CONCLUSIONS

Eliminating all fatalities and serious injuries is an admirable goal for Vision Zero cities. To begin to work toward that goal, we can start by designing for our most vulnerable users: kids. Doing so will also help ensure the second part of the Vision Zero mission: "…while increasing safe, healthy, equitable mobility for all." The PAKS Tool detailed in this chapter enables planners, engineers, and city officials to proactively identify and prioritize safety issues that may have been neglected by past crash-based studies. It provides cities with a starting point for the substantial journey of redesigning cities so they work safely for child pedestrians.

Some cities that have already promoted children's mobility are finding success. Vienna, Austria, recently completed a pilot project that banned cars on a primary school's access road during the beginning of the school day (Köllinger, 2018). Vienna's pedestrian officer Petra Jens reported that the program made the area safer for children, with many kids starting to walk or bike and vehicle volumes decreasing not just on the access road, but throughout the surrounding area. The pilot recently transitioned into a permanent project, and twenty other schools are requesting similar treatments. The city of Pontevedra, Spain, has similarly experimented with kid-based traffic restrictions (Velazquez, 2018). They found that – in addition to making the streets safer for children, resulting in more children walking, biking, and playing – their new streets program also attracted families from throughout the region to move to the city. The "Children's Fountain" square – an intersection that once accommodated 25,000 vehicles per day – now accommodates small children independently playing. These are great examples of cities that value safe mobility for all.

While we provide a tool to allow cities to be designed for kids, the methodology does employ some assumptions that can be improved through future work. The current iteration of the PAKS Tool uses perceptions of parents in Denver. However, parent perceptions may vary in different communities. Performing additional surveys may provide better results.

Excluding levels of non-motorized exposure was a further limitation. While non-motorized exposure is difficult to obtain, future work would benefit from user counts or volumes to better understand where trips are occurring and where they are being suppressed. Additionally, there are other factors – such as crime and socioeconomics – that may be influencing trip suppression and would be worthy to examine in future analyses. We would like to also account for the characteristics of crossings (e.g. signalization, phasing, turning movements, crosswalks, refuge islands, etc.) as well as other levels of the current variables that were not tested in the current iteration.

Finally, while we consider making our streets safe for kids to walk as the most fundamental building block of urban design, future work should also consider biking – another mode of transportation that children rely on for independent mobility. Future versions of the PAKS Tool will account for child bicyclist suppression as well.

Vision Zero has brought needed attention and resources to the road safety arena. Preliminary results are promising. To truly make streets that are safe for everyone, however, we need to begin designing our cities for kids. Through the tool – and design mindset – introduced in this chapter, cities can now start doing exactly that.

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