Are Slow Streets Shared Streets?

An Analysis of Communities Served by San Francisco's Slow Streets Program

A thesis submitted by

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Abstract

Driven by a need for safe open space in urban areas during the COVID-19 pandemic, municipalities instituted programs to reallocate street space for active transportation and recreation. While the roll-out of these policies varied across cities, it is critical to understand how ongoing programs, such as San Francisco's Slow Streets program, are serving different populations within a city. Ensuring fair access to active transportation infrastructure and open spaces for vulnerable populations can help offset the disproportionate health and safety burdens placed on disadvantaged communities from existing transportation systems.

This thesis examines the distribution of Slow Streets in relation to demographic, environmental, and economic indicators. Using a Service Area analysis and multicriteria vulnerability indexes, I evaluate the distributional equity of the program and identify populations and neighborhoods lacking coverage. Quantifying differences in access across communities shows that Slow Streets serve whiter, more affluent block groups while predominantly Black, Asian, and low-income block groups are underserved. Multicriteria overlay indexes reveal that the most vulnerable areas of San Francisco have less coverage than the least vulnerable areas, with maps highlighting which neighborhoods could benefit the most from interventions. As the program looks to expand, prioritizing equity in placement decisions can help guide placement of future corridors. Expansion into neighborhoods such as Bayview-Hunters Point and Excelsior could help alleviate equity concerns but must be done with a robust community engagement process.

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Chapter 1: Introduction

The COVID-19 pandemic highlighted a need for outdoor public spaces that were accessible to pedestrians and cyclists. With a reduction in cars on the road due to COVID-related lockdowns and remote work, municipalities across the United States began to encourage active transportation and recreation through the reallocation of road space. The implementation of street reallocation programs in cities during the COVID-19 pandemic resulted in one of the largest and swiftest redistributions of street space since the advent of automobiles. While programs went by a variety of names including Slow Streets, Open Streets, and Shared Streets, one unifying theme was the reclamation of public street spaces. Over 500 cities globally implemented active transportation policies or programs in response to shifting realities of daily life brought on by the pandemic (Combs & Pardo, 2021).

While many of these programs did not result in fully pedestrianized streets, the reduction of vehicle volumes or speeds due to traffic calming measures employed by cities has been shown to reduce pedestrian and cyclist injury and fatalities in treated corridors (SFMTA, 2023). Creating human-scale streets that deprioritize auto-centric design can make cities safer, healthier, and more desirable places to live (Soni & Soni, 2016). Dedicated public space for active transportation encourages adoption of healthier lifestyles, with walking and cycling linked to numerous health benefits (Slater, 2020). With urban areas often lacking space for residents to recreate and socialize outdoors, it became increasingly important for cities to reclaim space from cars during periods of isolation and lockdowns due to the pandemic.

San Francisco was an early adopter of street reallocation practices during the pandemic, implementing the first phase of their Slow Streets program in May 2020, focusing expanding access to active transportation and recreation in residential areas. With 18 corridors as of 2023, the program looks to promote low-carbon travel modes for all ages and abilities. Following initial success, the program became permanent in 2022, with goals to expand the network and improve upon the original design standards.

However, the rapid and often top-down introduction of these programs (Combs & Pardo, 2021) raises questions of where in cities were streets closed to motor vehicles. While the roll-out of these policies varied across cities, it is critical to understand how ongoing programs, such as San Francisco's Slow Streets, are serving different populations within a city. As the Slow Streets program becomes permanent and expands, it becomes necessary to examine who is already being served by it and what populations are underserved. Such analysis will allow for targeted expansion to improve the distributional equity of the program.

This thesis will address the following question: who lives near streets participating in San Francisco's Slow Streets program? Spatial techniques are employed in conjunction with demographic data to examine the distribution of participating streets amongst different communities in San Francisco. A Service Area analysis and regression conducted within ArcGIS will identify populations served and any statistically significant relationships between access to Slow Streets corridors and different demographic variables. Quantifying differences in access provides insight into the distributional equity of the program. To understand which neighborhoods are not being served by Slow Streets, I constructed weighted and unweighted vulnerability indexes composed of different environmental justice and equity indicators to identify gaps in Slow Streets access in relation to disadvantaged communities. These indexes will show the cumulative effect of different risk factors to identify areas that could benefit from interventions. Such research highlights the importance of incorporating equity considerations into siting of active transportation infrastructure.

The thesis summarizes this research as follows: Chapter 2 explores the impacts of street reallocation with a literature review. Chapter 3 then explains the methodology and data utilized for research. Chapter 4 provides the findings and Chapter 5 serves as a space to discuss results and implications.

Chapter 2: Background and Literature Review

The following literature review will provide an overview of equity-related concerns in active transportation followed by a brief history of San Francisco's Slow Streets program. The public health, safety, and community impacts of street reallocation programs will also be examined with special consideration of how these programs affect disadvantaged communities.

Defining Equity

With the recent expansion of bike and pedestrian infrastructure across the United States, there has been a proliferation of literature examining equity in active transportation planning and programs. Lee et al. (2017) define active transportation equity as "the equitable distribution of active transportation costs and benefits across space and between social groups" (220). However, active transportation projects often fail to integrate considerations of equity in planning and implementation processes (Agyeman & Doran, 2021; Lee et al., 2017). As a result, the benefits of active transportation infrastructure in many cities are not equitably distributed (Ermagun et al., 2023; Hosford & Winters, 2018). This phenomenon is well studied in recent active transportation literature, particularly concerning access to bike lanes and bike share stations. The geographic coverage of bike share stations is identified as a barrier to uptake for disadvantaged populations (Hosford & Winters, 2018).

Ensuring all people have sufficient levels of accessibility is a critical component of an equitable transportation system as a resource's value to a user decreases with distance (Martens, 2016; Talen 1998). However, investment in cycling infrastructure in American cities is biased towards areas with privileged populations (Flanagan et al., 2016). Comprehensive reviews across multiple U.S. cities have found disparities in bike lane and bike share access between affluent, White communities and low-income and BIPOC communities (Braun et al., 2019; Ursaki & Aultman-Hall, 2016).

In a similar vein, studies have also found that access to urban green space disproportionately favors whiter and wealthier neighborhoods (Wolch et al., 2005). Histories of systemic racial oppression and discriminatory land use patterns contribute to the inequitable distribution of public resources (Lindsey et al., 2001; Wolch et al., 2005). These spatial incongruities deepen the divide between communities. Talen (1998) considers the equity in the distribution of public amenities a critical objective for planners to strive for.

Understanding the challenges faced by disadvantaged communities in the space of active transportation planning provides the foundation for why it is important to consider, plan for, and include such communities in these processes. While it is important to acknowledge unique circumstances faced by different groups, for succinctness, I will use the term 'disadvantaged communities' throughout this thesis to refer to underserved or vulnerable peoples who experience structural or physical barriers to mobility, including BIPOC and low-income communities.

With traditionally disadvantaged populations more vulnerable to the health, safety, and accessibility-related risks of transportation systems (Adkins et al., 2017), lacking access to active transportation infrastructure can exacerbate these risks. As disadvantaged individuals are less likely to own cars, they are more reliant on walking or biking, even when infrastructure is unsafe or lacking (Sandt et al., 2016). These conditions and other societal, cultural, and economic barriers result in a disproportionate burden being placed on disadvantaged communities. Creating fair access to active transportation opportunities for low-income and BIPOC populations helps ensure distributive justice (Lee et al., 2017). In order to reduce risk exposure and advance distributive justice, it is critical for active transportation planning and policy to explicitly incorporate considerations of equity to improve both spatial and social access to such infrastructure.

However, guidance and standards on how to achieve equitable outcomes are lacking. In a review of equity in active transportation plans, Lee et al. (2017) find that equity is often vaguely defined, leading to inconsistent application and varying degrees of prioritization in planning processes. A similar study of transportation plans also identified that definitions of equity were lacking or inconsistent (Manaugh et al., 2015). Within the context of a plan, an actionable definition of equity should include considerations of how the distribution will be measured and how equity is interconnected with the other components of the plan (Berg & Newmark, 2020). Even when equity is emphasized during the goal setting phase, the translation of these goals into plans with concrete objectives and measurable outcomes is often inadequate (Manaugh et al., 2015). In an analysis of fifteen pedestrian master plans, Berg and Newmark (2020) find that only 40% of these plans included measures of accountability as a step towards achieving equitable outcomes. Such limited and inconsistent coverage of equity in plans suggests there is room for growth in ensuring procedural equity. Concrete definitions with measurable goals are needed to plan for and assess equity.

Measuring Equity

Multiple approaches can be used to understand how equitable a program is. Previous infrastructure-focused equity analyses mostly fall into two main categories: process studies and outcome studies (Nicholls, 2001). Process studies seek the reasons behind a distribution of resources from a program by focusing on the process by which the program was created

(Nicholls, 2001). Considerations of equity must be embedded into processes to achieve equitable outcomes (Sandt et al., 2016). Actionable items such as goal setting, public involvement, and data analysis help to identify gaps and opportunities in planning stages. However, traditional planning processes can act as a barrier for disadvantaged communities, leading to exclusionary outcomes (Agyeman & Doran, 2021). Such process studies look to understand these planning processes and why a program serves different populations.

Conversely, outcome studies focus on the results of a program to evaluate the program's equity. Evaluating the demographics served based on the geographic distribution of a program or plan provides a more comprehensive picture of equity (Lee et al., 2017). Talen's (1998) paper on "equity mapping" provides the foundation for analyzing resource distribution in relation to a population's socioeconomic characteristics. Employing Geographic Information Systems (GIS) allows for the visualization of variation in access to a resource across space. Several widely cited studies have since been conducted on urban public park access using Talen's approach to understand if a resource is distributed equitably (Lindsey et al., 2001; Nicholls, 2001; Wolch et al., 2005; Boone et al., 2009). Adding a spatial lens invites a comparison of the relationship between populations who are served by a resource versus those that are not to better understand the distributive effects of said resource.

Nicholls (2001) demonstrated a simplified approach to combining accessibility and equity drawing from a more complex theoretical framework that Talen and Anselin (1998) proposed. Accessibility is first determined with buffers around infrastructure to create a service area. Then, using service areas as a proxy for access, the demographic characteristics of residents within the service area of a resource can be compared against those outside the service area. A two-sample statistical test can then determine if the differences between populations are statistically significant (Nicholls, 2001).

In more recent analyses about equity in access to bike infrastructure, Nicholl's (2001) approach has been iterated upon by incorporating network analysis-based service areas, different definitions of accessibility, and more advanced statistical methods (Braun et al., 2021; Hosford & Winters, 2018; Ursaki & Aultman-Hall, 2016). Service areas from network analysis delineate an accessible region based on the distance or time from a point on an existing road network. These service areas provide a more nuanced results than a general buffer, as street layouts and available infrastructure may limit access to a resource that a general buffer cannot capture. However, using spatial accessibility as a proxy for distributional equity remains a common technique as accessibility is a key tenet of equitable and just transportation systems (Martens 2016).

GIS is frequently used to measure accessibility to the resources, usually through a service area or other street network analysis, which assess proximity based on actual travel paths. These levels of accessibility have been overlaid with socioeconomic characteristics of neighborhoods to draw inferences about the spatial equity and distributional impacts of the program (Braun et al., 2019; Hosford & Winters, 2018).

These analyses use different combinations of socioeconomic characteristics to quantify equity, although race and income are consistently included across studies. Age, zero-car households, and education-level were also utilized. Environmental measures such as pollution burden or $PM_{2.5}$ concentration were not heavily emphasized in studies assessing equitable active transportation access. However, equity literature concerning environmental justice or climate resilience does include these and other similar measures (Heckert & Rosan, 2016). Recent studies have also included more advanced statistical methods such as bivariate correlation and regression models to further demonstrate relationships across space (Braun et al., 2019; Braun et al., 2021; Hosford & Winters, 2018).

Existing research on equitable access highlights important complexities that need to be accounted for to truly understand access, including contextual & relational specificity and quality of services accessed. A person's accessibility is relative and context-specific due to environment, demographic attributes, and personal preferences (Arranz-Lopez et al., 2019). The cycling gender gap is one such example, with higher rates of men riding bicycles than women (Shaw et al., 2019). As such, separating groups based on advantages or constraints provides a more comprehensive picture of relative accessibility. Another drawback with using accessibility is an assumption that the facilities being studied are equal in quality and resources offered. Offering a distinction between the quality of the resources could add further depth to accessibility-focused studies.

While assessing a program's equity can take a variety of approaches, the reviewed literature employed GIS-based spatial techniques to draw inferences about which populations a program is serving. In the context of active transportation and open space, accessibility is used as a spatial measure to compare the socio-economic characteristics of those with access against those without access.

Street Reallocation Programs

Driven by a need for safe spaces in urban areas to support active recreation during the onset of the COVID-19 pandemic, municipalities instituted programs to reallocate street space for walking and cycling (Dean et al., 2023). Expanding the public arena to include streets provided space for everyday recreation and socializing that dense urban areas needed during lockdowns. Adding space for recreation and active transportation were the motivating factors for street reallocations (Fischer & Winters, 2021; Dean et al., 2023). Forms of reallocation varied, as some cities opted for traffic calming measures while others entirely removed cars from participating streets. A review of 51 US cities found that 45% reallocated space from cars for recreation or active transportation infrastructure (Dean et al., 2023).

A common theme across programs was the encouragement of active transportation modes through the construction of low-cost and quickly constructed measures (Combs & Pardo, 2021). Changing mobility demands allowed cities to seize the opportunity to push active transportation agendas (Oluyede et al., 2024). These programs are viewed as an experimental means to redefine mobility, taking advantage of tactical and easily implemented approaches to transform public street space (Combs & Pardo, 2021; Glaser & Krizek, 2021). Interventions allowed cities to prioritize public life through retrofits and reclamation of streets. However, the tactical nature and swift rollout of these programs meant that some lacked the comprehensive public outreach process that is often necessary to further equity (Kim, 2022). Community feedback was only used by 35% of 51 U.S. cities when deciding on placement of interventions (Dean et al., 2023). Additionally, sustaining initial success from temporary programs can be difficult. Many COVID-era street reallocation programs have been scaled back or eliminated (Dean et al., 2023).

Impacts of Street Reallocation Programs

While the literature on the health and safety impacts of COVID-era reallocation programs is somewhat limited due to the recency of the pandemic, the social, health, and safety benefits of active transportation infrastructure, pedestrianized streets, and urban recreational spaces have been well documented. Special consideration of equity-related issues and impacts on disadvantaged communities will be given in the following review.

Social Benefits of Street Reallocation

Access to open space in a dense urban environment can provide a multitude of community benefits. Offering the opportunity to recreate and relax can improve the connectedness of a local community by promoting human interactions (Soni & Soni, 2016; Nieuwenhuijsen & Khreis, 2016). Public space previously reserved for cars can now be utilized for social activities and outdoor recreation. Studies have found that residents of low-traffic streets consistently had more social interactions and friendly relationships with neighbors when compared with to those on high-traffic streets (Appleyard, 1982; Hart & Parkhurst, 2011). Considering the important role that streets play in shaping the character of a neighborhood, the polluted and dangerous nature of many urban streets creates a hostile environment for non-car-users. On the contrary, open space where community members can spend time improves the livability of an area. In the context of the pandemic, being quarantined has been linked with increased rates of depression, isolation, and other negative mental health outcomes (Hwang et al., 2020, Slater et al., 2020). Improving social cohesion through reclaimed street space could help counteract these increased feelings of isolation during pandemic health mandates and lockdowns.

Health Benefits of Street Reallocation

Encouraging physical activity and discouraging car use leads to positive environmental and health outcomes. The following section demonstrates ways that street reallocation programs provide a way to do both simultaneously.

Cars are a significant emitter of localized air pollution and greenhouse gases. Various studies link air pollution from cars to increased rates of chronic obstructive pulmonary disease, cardiovascular diseases, respiratory infections and lung cancer (Bhalla et al., 2014; Lelieveld et al., 2015). According to one estimate, vehicle-based emissions are the cause of 184,000 deaths globally (Bhalla et al., 2014). Moving away from auto-centric infrastructure and reducing reliance on cars helps curb localized air pollution from traffic. Modeled scenarios show that increased rates of walking and cycling leads to reduced rates of diseases related to $PM_{2.5}$ (Woodcock et al., 2013; Rojas-Rueda et al., 2013). Air quality monitoring results on fully pedestrianized streets have shown up to 40% less emissions when compared to non-pedestrianized streets (Soni & Soni, 2016). Due to exposure to higher concentrations of pollutants and crash risks, health-related risks of cycling are disproportionally high in disadvantaged communities (Braun et al., 2021). San Francisco's Slow Street program looks to reduce vehicle volumes on participating streets, which could lead to reductions in local air pollution.

Encouraging active transportation is also associated with positive health outcomes. Physical inactivity is a major risk factor for mortality, with insufficient physical activity being attributed to 3.2 million deaths annually (World Health Organization, n.d.). Walking and biking regularly have been shown to reduce anxiety, blood pressure, and rates of chronic disease (US Department of Health and Human Services, 2019). While White adults reported increased levels of physical activity during the pandemic, Black or Hispanic adults experienced decreased levels of physical activity (Watson et al., 2021). In addition, communities of color are less likely to have access to recreational spaces like urban greenways and public parks (Lindsey et al., 2001; Slater et al., 2020). This lack of park and greenspace coverage exacerbated inequities faced by disadvantaged communities during the pandemic. With a stated goal of encouraging active transportation modes, San Francisco's Slow Streets program could provide a way to bridge that gap in physical activity.

Previous research indicates that environmental factors influence levels of physical activity (Humpel et al., 2004; Owen et al., 2004). Attributes of walkable infrastructure such as accessibility, convenience, and aesthetics were strongly associated with physical activity of residents in studied areas (Humpel et al., 2004). In Lisbon, Portugal, volumes of pedestrians increased following interventions to make a street more walkable, with the magnitude of the intervention influencing the degree to which walking behaviors change (Cambra & Moura, 2020). However, many studies examining the relationship between active transportation interventions and health outcomes remain cross-sectional (Creatore et al., 2016; Owen et al., 2004), resulting in associations of correlation rather than causation. Considering the number of factors that affect an individual's health, it is difficult to establish a causal relationship between interventions, associated behavioral change, and health outcomes. However, Slow Streets create spaces for safe active transportation that was not previously available.

Safety Benefits of Street Reallocation

The safety risks that automobiles pose to pedestrians and cyclists are significant, especially in disadvantaged communities. Street reallocation programs create safe spaces for these groups, allowing them to access public street space without the threat of automobiles.

One of the most tangible impacts of pedestrianized streets and traffic calming measures is a reduction in motor vehicle-related incidents. Cars resulted in 46,980 deaths in the United States in 2021 (National Safety Council, n.d.) From 2000 to 2022, 152,000 pedestrians have been killed by cars in the U.S. (National Safety Council, n.d.). However, the burden of risk is not equally spread across road users. Not only are pedestrians and cyclists more likely to be involved in fatal crashes, but disadvantaged neighborhoods also have higher rates of crashes and fatal incidents (Barajas, 2018; Braun et al., 2021). San Francisco communities with high poverty rates experience disproportionate amounts of injuries stemming from cars. Half of all streets in San Francisco's High Injury Network are in "Equity Priority" communities, despite the network only making up 12% of streets in San Francisco. (Vision Zero SF, 2021). The CDC estimated that from 2009-2018, pedestrian fatality rates were twice as high for Black and Hispanic men when compared to White men after controlling for variables (CDC 2021).

The connection between city-scale transportation systems and neighborhood-level socioeconomic characteristics can be seen in safety outcomes across local communities. This becomes especially important as lower income people are more dependent on lower-cost modes of travel such as walking and cycling (Sandt et al., 2016). As such, individuals may have to walk or cycle regardless of whether existing infrastructure allows for safe mobility. A study of over 7,000 bicycle crashes in the San Francisco Bay Area revealed that Black bicyclists are more at risk from crashes in low-income neighborhoods (Barajas, 2018). Members of disadvantaged communities represent some of the highest risk street users. Addressing the intersection of safety, mobility, and vulnerability requires a review of the spatial inequities of the built environment across a city's neighborhoods. While Slow Streets programs provide an opportunity to address this issue, explicit consideration and prioritization of disadvantaged communities is needed when siting interventions.

Traffic deaths also rose sharply during the pandemic, making it even more important to create safe spaces for pedestrians and cyclists (Buss, 2022). Reducing vehicular volumes and speed is strongly linked with safety benefits. Vehicular speed is a critical factor in determining the outcome of a crash. If a vehicle is traveling 20 mph when it hits a pedestrian, the pedestrian has a 90% chance of survival. When that speed is increased to 40 mph, that rate of survival decreases to just 40% (Vision Zero SF, 2021). In 2020, 40% of San Francisco's vehicle-related deaths were pedestrians (Vision Zero SF, 2021). While the context and type of intervention varies widely across cities, most assessments of traffic calming measures conclude they are effective in reducing traffic collisions and vehicle speeds (Bunn et al., 2003; Distefano & Leonardi, 2019; Elvik, 2001; Nieuwenhuijsen & Khreis, 2016). Slow Streets provide another traffic calming tool to reform transportation systems that traditionally prioritized vehicular mobility over safety.

Critiques of Street Reallocation Programs

Many of the processes that resulted in street reallocations during COVID-19 circumvented traditional planning processes in the name of emergency planning, leading to questions regarding the equity of such programs. The rapid roll-out of such programs has led to a backlash in some communities, particularly those that feel they weren't given a voice in planning processes (Combs & Pardo, 2021). Due to the pressing nature of the public health crisis, these quick-build programs sacrificed a robust public feedback process, eschewing a critical step in building community support. Oakland, one of the first cities to implement a COVID-era street reform program, scaled back the size of the program following community outcry regarding the lack of outreach conducted by city officials (Thebault, 2023). While the benefits of active transportation infrastructure and outdoor recreation are well documented, many of these programs were the outcome of exclusionary and top-down planning processes. Equity must be considered in planning processes to ensure equitable outcomes (Sandt et al., 2016).

It is important to center equity when evaluating these programs because equity cannot be assumed. These programs were implemented during a pandemic that disproportionately impacted low-income communities and people of color and adapted a transportation system that was not designed to serve them (Watson et al., 2021; Agyeman & Doran, 2021). A review of 51 US cities' COVID-era street reallocation programs found that only 35% of cities incorporated geographic equity into decisions regarding reallocated spaces (Dean et al., 2023). Early studies on the distribution of reallocated streets reveal that differences in served populations are program and context specific, with some programs serving disadvantaged populations more than others (Firth et al., 2021; Fischer & Winters, 2021).

As street reallocations cater to pedestrians and bicyclists, those living near streets with interventions are the most likely to utilize it due to distance constraints associated with those modes of mobility. The farther a facility is from a user, the lower its value due to travel and distance-related costs (Lindsey et al., 2001; Ottensmann, 1994). The populations served by a Slow Streets corridor would be dominated by those living in neighborhoods that are accessible by foot or bike. As a result, the program is devoting resources to a specific set of users. These amenities are only accessible to certain neighborhoods. An analysis of census data revealed that the median income was $81,000 on streets that participated in New York City's Open Streets program compared to a median income of $60,000 in the rest of the city (Cuba, 2020). Streets distributed in such a manner disproportionately benefit the wealthy, making the program inaccessible to disadvantaged communities. Street reallocations could be a tool to address inequities in active transportation and urban open space with deliberate and thoughtful siting.

With stated goals of providing space for recreation, Slow Streets interventions also devoted resources to a specific set of uses over other needs and services during a pandemic (Schmidt, 2022). Slow Streets inhibits the mobility of those reliant upon cars for transportation, as a portion of the street network has been rendered inaccessible or lower speed. Individuals who are unable take advantage of active transportation infrastructure, whether due to travel distance or impediments to individual mobility, would have to take more circuitous routes. Such programs represent a trade-off, reflecting cities' shifting priorities towards active transportation and away from car-based modes of transportation.

Some activists have called into question the time and resources devoted to these programs during a pandemic (Walker, 2020; Thomas, 2020). Following Oakland's initial rollback of their Slow Streets program due to public outcry, city officials decided to prioritize safe access to COVID testing centers and other essential services (Thebault, 2023). Health disparities between White and BIPOC communities have been well documented over the years (Maness et al., 2020; Zavala et al., 2019). During the pandemic, these incongruities deepened. Black, Indigenous, and Hispanic Americans experienced higher COVID mortality rates than White Americans after adjusting for age distributions amongst groups (Maness et al., 2020, National Center for Health Statistics, 2023). In addition, essential workers that needed to come into work during the pandemic were disproportionately from disadvantaged communities, increasing their possibility of exposure to COVID-19 (Rogers et al., 2020).

Other structural inequities should also be considered. The threat of structural racism and violence in spaces leads BIPOC communities to experience these spaces differently than White residents (Thomas, 2020). The contrast between these programs and the 2020 Black Lives Matter movement that was occurring simultaneously on some of the same streets underscores these differences in experiencing public space. Over-policing can discourage disadvantaged communities from fully utilizing public space (Agyeman & Doran, 2021). Racial profiling results in a disproportionate number of citations issued to Black cyclists and pedestrians in cities across the United States (Agyeman & Doran, 2021). Rather than encouraging BIPOC communities to take agency over public space in their own neighborhoods, New York City initially opted for heavy police presence. NYPD-run Open Streets have not been as successful as those run by community groups, with residents reporting inconsistent enforcement, a lack of maintenance, and over-policing (Cuba, 2020). Of the 40 arrests made in Brooklyn for social distancing violations between March 17, 2020 and May 4, 2020, 35 were Black residents and four were Hispanic (Southall, 2020). In 2015, 80% of Tampa, Florida’s bicycle citations were issued to Black people despite only 25% of Tampa’s population being Black. (Mitchell & Ridgeway, 2018). Moreover, San Francisco’s Vision Zero plan acknowledges that “people of color are disproportionately stopped for traffic stops in SF” (Vision Zero SF, 2021).

Public space is not passive, but rather an arena where the creation and contestation of identities takes place (Lindsey et al., 2001). Racism and disparities in police enforcement manifest in public spaces, inhibiting the use and enjoyment of these spaces by BIPOC communities. Gender, race, and class all function to encourage or discourage participation in public space (Ruddick, 1996). Slow Streets should provide spaces that BIPOC residents feel comfortable navigating.

The threat of gentrification associated with urban infrastructure improvements is another potential downside of street reallocations. Complete Streets movements and other active transportation infrastructure such as bike lanes have come to signify impending gentrification and displacement (Agyeman & Doran, 2021). While there is limited research quantifying the impact of Slow Streets on housing values and rates of displacement, similar street infrastructure interventions have been well studied in the context of gentrification. Investments and interventions in neighborhoods play an important role in reshaping the urban space and character of the neighborhood. Increased demand for space in urban cores of the city by affluent adults (Ehrenhalt, 2013) is spurred on by recent pushes by municipalities to improve the livability of urban spaces. Higher land values and housing costs in a neighborhood resulting from new amenities result in the displacement of preexisting low- and moderate-income residents (Immergluck & Balan, 2017; Morrison 2021). As a result, disadvantaged communities see bike lanes as “a symbol of gentrification” and rising rents, rather than an infrastructure improvement with health and safety benefits (Zimmerman et al. 2015, 35).

Curbing motor vehicle use while creating space for outdoor recreation and active transportation modes can provide significant benefits to communities. Reduced vehicle accidents and volumes, lower pollution, and more communal space are outcomes all cities should strive for. However, given the disproportionate negative health and safety impacts of both COVID-19 and existing transportation infrastructure on disadvantaged communities, it is critical to understand which populations are being served by street reallocation programs.

San Francisco Slow Streets Program Background

The San Francisco Municipal Transportation Agency (SFMTA) introduced the Slow Streets program as an emergency response to the COVID-19 pandemic. The program was rolled out in April 2020 with support from city residents (Rogow. 2021). Participating streets were closed to through traffic, with traffic calming measures used to create safe low-stress corridors for all ages and abilities. At its height during the pandemic, the program had 25 corridors (SFMTA, n.d.). By early 2024, the number of corridors has been reduced to 18 corridors of varying lengths. Post-pandemic, streets need to be reauthorized and complete a public outreach process. The SFMTA surveyed residents on each Slow Street to gauge their support before a street was renewed after the expiration of the State of Emergency. Following a series of public hearings, the SFMTA Board made the program permeant in December 2022.

While Slow Streets initially arose as a response to pandemic-related issues, the program's goals have evolved over time. The SFMTA now views the program as a means to build and connect San Francisco's active transportation network and expand use of non-car, low-carbon mobility by residents. The Slow Streets program has been integrated into many larger city plans, including Vision Zero SF, the Climate Action Plan, and the Active Communities Plan (ACP). Encouraging low-carbon modes of transit, building the city's active transportation network, and reducing vehicle speeds work in parallel with many of San Francisco's long-term goals.

After it was made permanent in 2022, the program implemented new targets for vehicle volumes and speeds on participating streets. These targets (under 1,000 vehicles/day and speeds under 15 mph) are based on guidance from National Association of City Transportation officials for low-stress corridors. The SFMTA relies on speed and volume data to assess performance of different streets in the program. Designs and interventions are adjusted accordingly based on performance data to meet targets. SFMTA data shows that Slow Streets experienced a 48% reduction in collisions compared to a citywide 14% decrease over the same period. As seen in Figure 1, following program implementation, vehicular volumes decreased by 61%, with twelve of the sixteen studied corridors meeting the volume target. Median vehicular speeds fell by 18% on streets, but only four of sixteen studied Slow Streets meet the speed target of 15 mph or less. The SFMTA concluded in their 2023 Evaluation Report that Slow Streets are safer than the average street in San Francisco. Some corridors such as Sanchez have over 1,000 pedestrians on weekend days (SFMTA n.d.).

The infrastructure associated with Slow Streets has evolved over time. Temporary signs and barriers that demarcated Slow Streets corridors at the program's start are slowly being replaced with more permanent or robust interventions such as speed cushions, concrete islands, traffic circles, and pavement markings. It should be noted that the level of intervention varies from street to street, with some streets' interventions limited to small signs. A mural pilot program was introduced in 2023 to create a sense of community on Slow Streets. The murals are designed and painted by community members, encouraging placemaking (SFMTA, n.d.).

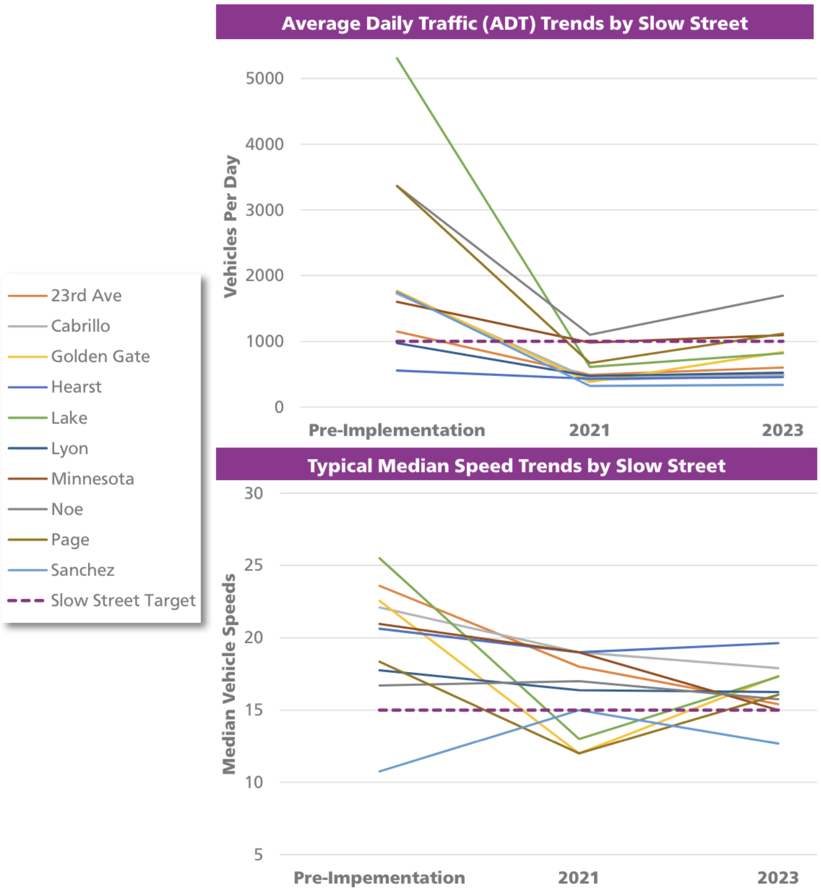
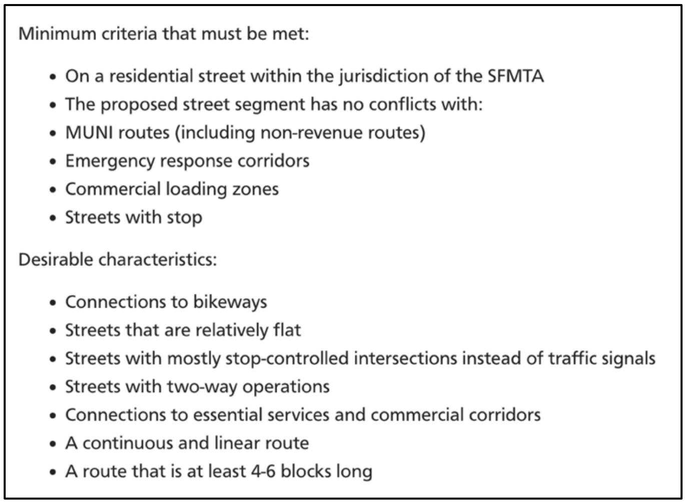


Figure 1. SFMTA tracking data for average daily traffic and median speed on Slow Streets. Source: SFMTA 2023 Slow Streets Evaluation Report

Figure 2. Slow Street. Source: SFMTA

With regards to street selection criteria, the SFMTA chose flat, straight residential streets with stop-controlled intersections (SFMTA, n.d.). Streets with bus routes and emergency response corridors were excluded from the search. A list of SFMTA criteria can be found in Figure 3. A street's gradient plays an important role in its walkability, especially considering San Francisco's notoriously hilly geography and steep streets. While some COVID-era street reallocation programs included interventions such as outdoor dining in business and commercial districts, San Francisco's focused on residential corridors. Outdoor dining was permitted through San Francisco's Shared Spaces program.

As of early 2024, program expansion is planned, with new corridors being identified through community outreach during development of SFMTA's long-term active transportation network plan, the ACP. Advancing equity is a key goal of the ACP. Outreach during the ACP's planning process includes targeted engagement in disadvantaged neighborhoods such as Bayview-Hunters Point, the Mission, SoMa, and the Tenderloin.



Minimum criteria that must be met:

- On a residential street within the jurisdiction of the SFMTA
- The proposed street segment has no conflicts with:
- MUNI routes (including non-revenue routes)
- Emergency response corridors
- Commercial loading zones
- Streets with stop

Desirable characteristics:

- Connections to bikeways
- Streets that are relatively flat
- Streets with mostly stop-controlled intersections instead of traffic signals
- Streets with two-way operations
- Connections to essential services and commercial corridors
- A continuous and linear route
- A route that is at least 4-6 blocks long

Figure 3. List of SFMTA used to select Slow Streets corridors

Three months after it began, the program had an 80% approval rating based on an online survey conducted by the SFMTA (Barnett, 2020). Similar survey-based research also confirmed strong support for the program (Rogow, 2021). An email analysis revealed that only 24% of emails to the SFMTA about Slow Streets were in direct opposition to the entire program, with most emails expressing corridor-specific concerns or requests (Rogow, 2021). However, communities of color and low-income neighborhoods in the southern portions of the city were largely absent from survey responses (Rogow, 2021). The health and safety inequities of modern transportation systems and the COVID-19 pandemic make it especially important to include such communities in outreach. Considerations of equity must be embedded into processes to achieve equitable outcomes (Sandt et al., 2016). Consulting disadvantaged communities when evaluating a program is one such way to integrate equity into these processes.

Some residents critiqued gaps in Slow Streets coverage in denser areas of San Francisco, such as the Tenderloin (Graf 2020). Compared to the rest of San Francisco, the Tenderloin experiences higher rates of poverty, COVID-19 cases and traffic-related injuries (Rogow, 2021). However, the Tenderloin's hills and high-volume streets make it unsuitable for Slow Streets based on SFMTA's criteria for corridors. In response to feedback, the SFMTA implemented neighborhood specific safety improvement corridors in the Tenderloin and Bayview (SFMTA n.d.).

The pandemic that was the impetus for the creation of the Slow Streets initiative may have passed, but the need for recreational space in dense urban areas remains. As this program continues to evolve, understanding who the program is currently serving allows for targeted outreach and growth in underserved communities.

Chapter 3: Methodology

In the following chapter, I outline my approach to evaluating the distributional equity of San Francisco's Slow Streets program. Drawing from previous research in the field of equity and active transportation programs, I employ spatial analysis tools from ArcGIS to better understand the distribution of infrastructure in relation to demographic characteristics of the populations it serves. To capture a more comprehensive picture of the distributional equity of the program, three separate techniques will be used: service area analysis, composite vulnerability index, and regression analysis.

In Chapter 2, I detailed how previous distributional equity analyses were conducted with a particular focus on GIS-based studies. Due to the recent implementation of the COVID-era street reallocation programs, the body of research assessing the spatial distribution of reallocated streets through the lens of equity is relatively nascent. As a result, pre-existing spatial methodologies for assessing equity in spatial access to active transportation and green space infrastructure will be adapted to be used in the context of Slow Streets.

Data

Demographic data for San Francisco County was downloaded from the American Community Survey (ACS) 2017-2021 and joined with Tiger/Line block group polygons. While block group level data is susceptible to large margins of error, block groups offer a more granular level of analysis and are commonly used in vulnerability indexes and equity analyses (Bhuyan et al., 2019; Heckert & Rosan 2016; Rygel et al., 2006). The variable used to characterize race, percent non-white, is defined as the percent of respondents that did not select White alone, non-Hispanic. Slow Streets layers, neighborhood boundaries, and crash data were sourced from DataSF, San Francisco's open data portal. Slow Streets locations were downloaded on December 28th, 2023.

Neighborhood boundaries were created by the San Francisco Planning Department, Department of Public Health, and Mayor's Office of Housing and Community Development by aggregating Census tracts and resident definitions. Due to a lack of official codified statistical boundaries and definitions for San Francisco neighborhoods, these boundaries are the best approximation of generally accepted neighborhoods. The scale of analysis shifts from block groups to neighborhoods for certain methods to aid in the interpretation of results. Rather than referring to general geographic areas in San Francisco, neighborhoods provide familiar place names for reference. The SFMTA also has adopted a list of Equity Strategy Neighborhoods to assess Muni performance in low-income and high-minority areas. The boundaries for these nine neighborhoods differ from the neighborhood layer discussed above but are utilized to evaluate results of methods in official SFMTA-identified high vulnerability areas.

Crash data from the SF Department of Public Health was limited to the same five-year time frame as the ACS data. Traffic crashes that resulted in injuries were utilized due to data availability. The crash point data was joined with block group level data, resulting in crash counts from 2017 to 2021 for each block group. If a crash occurred on a border between two block groups, it was counted in each block group. While this results in certain crashes being double counted, the goal of the crash data was to quantify the presence of traffic-related risk in each block group rather than rank block groups by total crashes. Variables selected to be analyzed were identified based on a review of relevant literature. The reasoning behind the socioeconomic and built environment variables chosen in the construction of the vulnerability index is expanded upon in Table 2.

Table 1. Data Sources

Agency	Layer	Format	Year	Source
ArcGIS Online	San Francisco Network Dataset	Network	2023	-
California Office of Environmental Health Hazard Assessment	Pollution Burden	Shapefile	2023	CalEnviroScreen
San Francisco Department of Public Health	Traffic Crashes Resulting in Injury	Point	2017-2021	DataSF
San Francisco Municipal Transportation Agency	San Francisco Equity Strategy Communities	Shapefile	2017	DataSF
San Francisco Municipal Transportation Agency	Slow Streets	Polyline	2023	DataSF
San Francisco Planning Department	San Francisco Neighborhood Map	Shapefile	2023	DataSF
US Census	ACS 2017-2021 5-Year Estimates	Table	2017-2021	US Census
US Census	2021 TIGER/Line Shapefiles: Block Groups	Shapefile	2021	US Census

Service Area Analysis

To determine if the Slow Streets program is serving different populations, a Service Area Analysis was conducted. In the robust body of literature on spatial analyses of equitable infrastructure distribution, spatial accessibility is often used with demographic data as a proxy for distributional equity. Quantifying inequality across socioeconomic groups in access to opportunities can indicate whether a program's infrastructure is equitably distributed. A host of studies researching accessibility to public resources provides the foundation for this approach: using a buffer area to judge accessibility and then comparing populations in the served areas to those not in served areas (Talen 1998; Linsdey et al., 2001; Nicholls, 2001; Wolch et al., 2005). While these studies mostly used Euclidean buffers around the resource, I conducted a Service Area Analysis to provide a more refined region of accessibility to match the ways that people could travel to access the Slow Streets area.

The ArcGIS Online Network Dataset was utilized as the road network for San Francisco. Slow Streets line data was converted to points to prep for service area analysis. To create the service area polygon for each Slow Street, the travel mode was set to walking with a cutoff to 0.25 miles. The 0.25-mile cutoff is a generally accepted range of distance to determine walking accessibility in literature (Aultman-Hall et al., 1997; Figueroa, 2023). While some studies have found that people are willing to walk further than 0.25 miles to a transit stop or green space (Yang & Diez-Roux, 2012), the range was kept to 0.25 miles to account for those who are mobility-impaired. Additionally, block groups were often only partially intersected by a service area. As a result, some of the population considered “served” lives outside the 0.25-mile service area. For this thesis, population is assumed to be evenly distributed across census block groups.

Block groups were selected that intersected a Slow Street service area. Block groups with less than 5% of their total area in a Slow Street Service Area were removed from this selection, as the vast majority of the population of these block groups would not live within a 0.25-mile walk of a Slow Street. Averages were then calculated for demographic variables in intersected block groups. The process was repeated to calculate averages for block groups that did not intersect with a service area. To compare the populations, a two-sample t test was conducted, confirming that the differences between populations were statistically significant ($p<0.05$).

Percent coverage calculations based on service area were conducted using the Tabulate Intersection tool with neighborhood boundaries from the SFMTA and the San Francisco Planning Department.

To further understand the relationship between socioeconomic status, race, and Slow Streets access, I used the Multivariate Clustering tool from ArcGIS. The tool utilizes unsupervised machine learning to group features with similarities into clusters. Values are standardized to put attributes on the same scale and minimize the impact of large variances. Race and income are typically highly correlated (Akee et al., 2019), allowing for natural clusters to form. The tool maximizes the similarities within clusters and the differences between clusters. Three clusters of block groups were created with the percent White and median household income variables: low income-high BIPOC population, medium income-middle BIPOC population, and high income-low BIPOC population. The proportions of block groups with Slow Streets access for each cluster was then calculated.

Vulnerability Index

An index was constructed to help identify communities that were particularly susceptible to risks and vulnerabilities. This index aggregates both underlying socioeconomic characteristics and the built environment into one composite measure, as many factors influence a community's risk and needs (Cutter et al, 2003; Emrich, 2005). Combining different conditions and characteristics shows the cumulative effect of different vulnerability and risk factors (Flanagan et al., 2011). While the subjectivity involved in constructing a vulnerability index will be explored later as a limitation of this study, this index is meant as starting point for conversations about Slow Streets coverage in more vulnerable communities of San Francisco. GIS-based indexes are a visual tool for planners and residents to compare different areas, especially to highlight which neighborhoods could benefit the most from interventions (Heckert & Rosan, 2013).

It is widely acknowledged that there is no one accepted set of factors to include in a vulnerability index, as variables used to quantify equity vary across studies and contexts (Mah et al., 2023; Tate, 2013). The factors chosen to quantify vulnerability were determined based on repeated inclusion in literature and the specific context of this study. Slow Streets aim to create safe spaces for residents to partake in recreation and active transportation. Thus, characteristics were selected to capture at-risk populations who have been shown to be disproportionately impacted by negative outcomes of transportation systems.

Selected variables were organized into two categories: socioeconomic characteristics and the built environment. Socioeconomic characteristics included median income, percent non-White, percent households below poverty line, zero-car households, and elderly population. As demonstrated in Chapter 2, these variables are often used in traditional equity and social vulnerability analyses to signify at-risk populations. Pollution burden and crashes were used to represent the built environment. While not as consistently used in studies as the socioeconomic variables above, these indicators incorporate environmental risks that contribute to an area's vulnerability. The California EnviroScreen Pollution Burden score is an average of a number of pollution-related variables, providing an overall measure of pollution for a given area. While environmental justice focused studies typically separate variables such as $PM_{2.5}$ and Ozone levels, this index uses one composite indicator of pollution.

Table 2 provides an overview of the rationale and literature supporting these variables' inclusion. This is not an exhaustive list of factors that could be included, but rather a representation of commonly used indicators in studies that were pertinent to this context.

Table 2. Results of a review of 16 equity analyses and social vulnerability index studies. The Appendix contains a full list of studies reviewed.

Variable	**Reasoning**	**Studies Used In**
Percent non-White	Certain racial and ethnic groups experience discrimination, marginalization, and other disadvantages that make them particularly susceptible to risk (Cutter et al., 2003). Considerations of race and ethnicity are nearly universally included in reviewed literature. The specific variable used varies, with some studies using individual race and ethnicity categories.	14
Median income	Poor individuals are less likely to own cars and are more reliant on walking and biking (Sandt et al., 2016). Poorer neighborhoods experience higher rates of crashes and fatal incidents (Barajas, 2018).	12
Elderly population	Mobility constraints and other health sensitivities lead to increased vulnerability to poor pedestrian and bike infrastructure (Sandt et al., 2016). Elderly pedestrians involved in car crashes have the highest mortality rate of pedestrian injury victims (Sklar et al., 1989).	13
Children	Child pedestrians experience higher rates of fatalities in car-related collisions, with car crashes being a leading cause of childhood deaths (Malek, et al., 1990). Children from lower income areas are most vulnerable (Elias & Shiftan, 2014)	11
Zero-car households	These households are more reliant upon walking and biking, even when infrastructure is unsafe (Sandt et al., 2016)	7
Households below poverty line	24% of Americans living in poverty do not own a vehicle (Sandt et al., 2016). Many people could benefit from improved access to enhanced pedestrian and biking facilities.	8
Pollution burden	Captures the overall measure of pollution in a given area. Airborne toxins are linked to a variety of negative health outcomes (Bhalla et al., 2014). Studies that included pollution levels were typically analyzing environmental justice.	4
Crashes	High crash block groups pose high risk to residents and are disproportionately located in disadvantaged areas (Vision Zero SF, 2021). The Slow Streets program looks to provide safe streets that can be used by all.	2

This index's intent is to reveal areas of vulnerability, as opposed to indicating suitable areas for new Slow Streets. As such, operational variables considered by the SFMTA when selecting Slow Street locations such as slope and street length were not included. Percents were utilized for these indicators rather than absolute size of block group population. By using relative proportions, bias towards block groups with larger populations can be avoided (Tate, 2013).

When constructing a vulnerability index, weights can be assigned to variables based on their relative importance. Assigning weights is a highly subjective process (Rygel et al., 2006). While equal weighting may be viewed as "a recognition that there is insufficient understanding of underlying processes to assign meaningful weights," it remains a subjective decision (Tate, 2013, p. 530). Additionally, many of these indicators are correlated, as relationships between these variables are highly complex and interrelated due to larger structural forces and histories (Schmidtlein et al., 2008), causing implicit weighting to occur.

For this study's purposes, two indexes were created: one simple overlay with equal weights and one weighted overlay. Given the lack of consensus on a set of methods or weights to construct such composite measures, comparing the results between a weighted and unweighted index can provide insight on the consistency of outputs between these two methods. In an evaluation of the Social Vulnerability Index, Spielman et al. (2020) stresses the importance of achieving consistent results for a vulnerability index. For the weighted overlay, ranks were assigned to each variable based on common themes across literature. While their exact definitions varied from study to study, variables for percent non-White and median income were consistently included and prioritized in both equity and vulnerability-focused indexes. As a result, these two variables were weighted the heaviest in the ranking system. Other ranks were determined based on prevalence in similar studies (see Table 2).

Drawing from a previous study evaluating the equity of Complete Streets (Tustin, 2022), the Analytic Hierarchy Process (AHP) Priority Calculator was utilized to create more specific weights for each variable. The AHP process calculates priorities and assigns percentage weights based on relative rankings. The race and ethnicity variable received a weighting of 30%, roughly 10% more than the median income variable. However, with the addition of the poverty variable, which was weighted 9%, income could be considered equally weighted to race and ethnicity. Poverty and median income are intrinsically related, with income being a primary factor when calculating poverty levels. Based on the inclusion of a poverty variable by some studies, I included it as well, understanding that poverty can better capture at risk populations. As a result, poverty and income are implicitly weighted more in the unweighted index due to its additive nature.

For both indexes, all variables were standardized on a scale from 1 to 10 with the Reclassify tool, with higher scores representing higher risk. The Raster Calculator was used to aggregate the variable scores for the unweighted index. The weights assigned by the AHP calculator were input into the Weighted Overlay tool to create the weighted index. Lower composite index scores indicate less vulnerable areas, while higher scores indicate high vulnerability. To quantify the difference in vulnerability in areas served by Slow Streets against those not served, the Zonal Statistics tool was used to find the average index value inside and outside of service areas. To provide more granular insight on vulnerable neighborhoods and compare differences between the two resulting indexes, the mean index value was calculated for neighborhoods defined by the San Francisco Planning Department. Neighborhoods were then ranked by averaging the two index scores to arrive at a list of most to least vulnerable neighborhoods. The percent area served in the top 20% of neighborhoods (most vulnerable) was compared to the area served in the bottom 20% of neighborhoods (least vulnerable) to draw insights on the program's performance.

Regression

A Geographically Weighted Regression (GWR) was also conducted in ArcGIS to examine the relationship between Slow Streets locations and demographic variables. The regression demonstrates how changes in explanatory variables affect a block group's distance to Slow Streets. An Exploratory Regression was first run to find the best combination of candidate independent variables. Variables added to the Exploratory Regression were those included in the vulnerability indexes. Based on the Exploratory Regression, percent White, median income, and number of crashes were identified as significant variables. All had negative relationships, meaning that distance to a Slow Street decreased as the independent variable increased. No models passed with ArcGIS's default criteria selected, indicating that a global equation wouldn't be suitable. As a result, the GWR's local modelling was selected, which accounts for fluctuations in space between variables by building a regression equation for each block group. This local model differs from the global model of a general linear regression. The GWR also incorporates geographical weighting to features in each local regression equation, meaning that features that are farther away from a particular feature have less influence on results (Esri, n.d.).

The Near tool was used to create the dependent variable of distance from the nearest Slow Street, allowing for a Continuous model. Number of Neighbors was selected at the Neighborhood Type with a Golden Search to minimize the value of the Akaike Information Criterion (AICc). Different versions of the model were run with different variables included to assess the best fit and observe how results changed with the inclusion or exclusion of certain variables. To restrict analysis to statistically significant results, only block groups with variable pseudo-T scores less than –1.96 or greater than 1.96 were chosen.

Chapter 4: Results and Analysis

In the following chapter, I provide an overview of the results of my service area analysis, multicriteria overlay, and geographically weighted regression. I'll first summarize service area coverage relative to demographic indicators. Then I'll assess the weighted and unweighted composite vulnerability indexes at the neighborhood level. Finally, I'll use a geographically weighted regression to identify whether and where there are measurable correlations between slow streets and outcome measure.

Figure 4. Map of Slow Streets service area network analysis

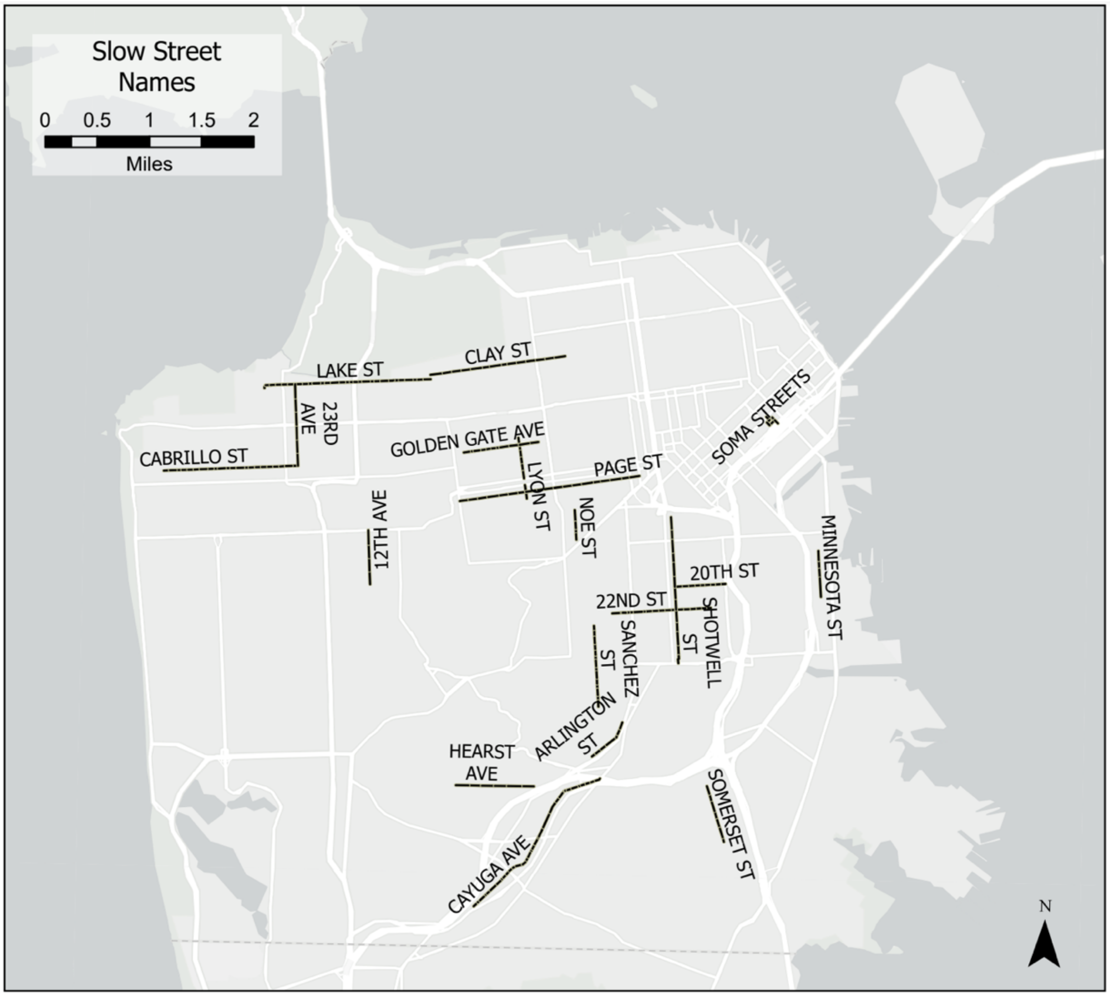


Figure 5. Names of Slow Street corridors

Service Area

The service area analysis identified that 8.28 miles of San Francisco, or 18% of the city's total area, are within 0.25 miles of a Slow Street, as seen in Figure 4. Table 3 provides an overview of the general results of the service area analysis. The 0.25-mile walking distance around each of the 18 Slow Streets corridors intersects with 233 of San Francisco's 680 block groups. There are 305,000 residents that live in the 233 served block groups, representing 35% of San Francisco's population. The difference between the percentage of total area covered and the percentage of residents served can likely be attributed to the program's focus on residential zones, where more people are likely to live.

Table 3. Area, population, and block groups in 0.25-mile Slow Street service area

	Number of Block Groups	Block Groups (%)	Area (sq mi)	Area (%)	Population	Population (%)
Inside Service Area	233	34.3	8.3	17.7	305,504	35.3
Outside Service Area	447	65.7	38.5	82.3	560,081	64.7
Total	680		46.8		865,585	

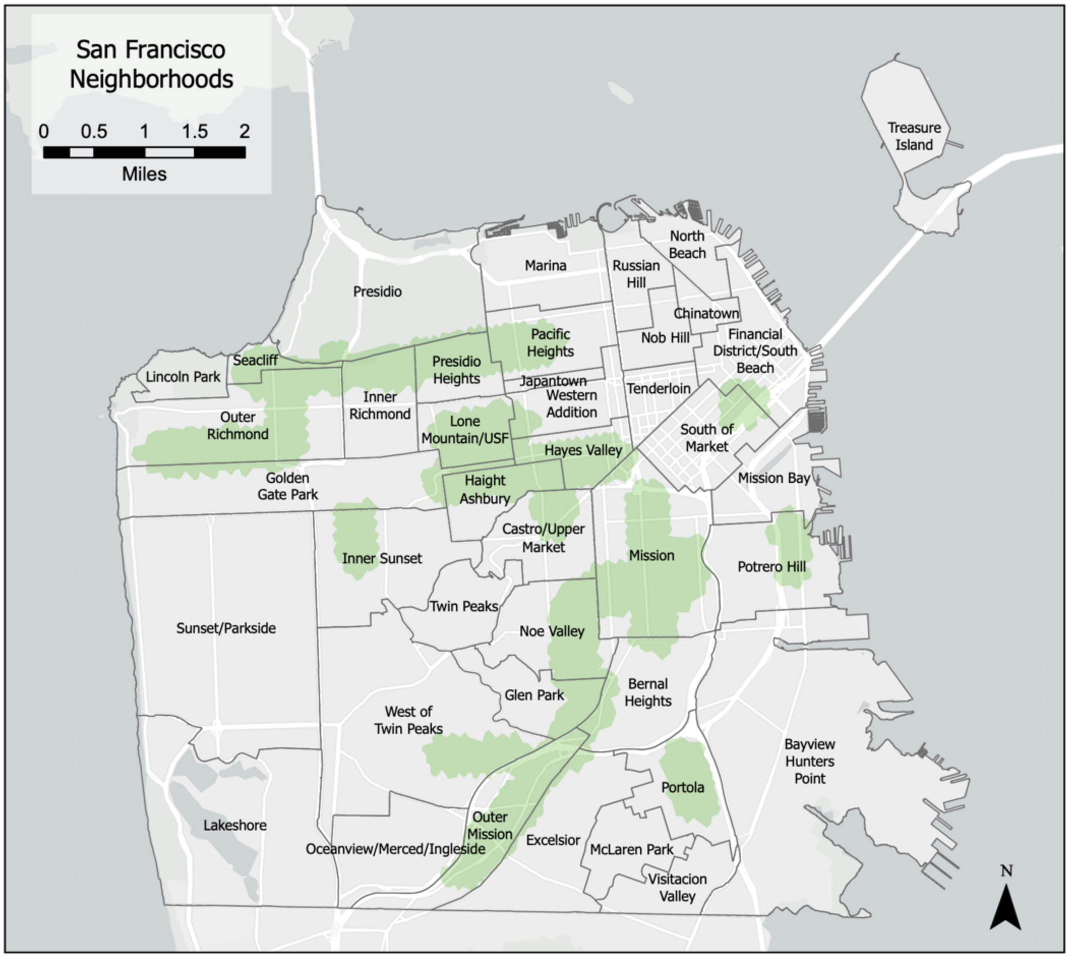


Figure 6. Map of San Francisco Neighborhoods with Slow Streets Service Area overlay

Neighborhood Level

Calculating percent coverage based on neighborhoods defined by the San Francisco Planning Department offers more granular information regarding Slow Streets access across neighborhoods. Seacliff, Hayes Valley, Lone Mountain/USF, and the Outer Mission neighborhoods all have above 70% of their respective areas within walking distance of a Slow Street. Other notable neighborhoods that are well-covered by service areas include Haight Ashbury (64%), Presidio Heights (63%), and the Mission (60%).

The Sunset, Bayview Hunters Point, Excelsior, and Oceanside have little-to-no Slow Street coverage, despite most of these neighborhoods being primarily residential. Additionally, much of northeast San Francisco is not within walking distance of a Slow Street, including the Tenderloin, Nob Hill, Russian Hill, the Marina, and North Beach. This region of San Francisco is known for its hills, disqualifying large portions of it from Slow Street eligibility. The SFMTA avoided selecting streets with steep gradients, as hills can discourage active transportation users. A full list of service coverage area by neighborhood can be found in the Appendix. Insight into which neighborhoods have less access to Slow Streets than others provides a starting point to address spatial gaps in coverage.

The SFMTA adopted a list of nine Muni Service Equity Strategy Neighborhoods to assess Muni performance in low-income and high-minority areas. Using this list as a proxy for official SFMTA-identified high vulnerability areas reveals significant gaps in coverage in some of these neighborhoods. These neighborhood definitions and boundaries differ from the San Francisco Planning Department neighborhoods discussed above. As seen in Table 4, overall Slow Streets coverage in these areas is 14%, below the city-wide average of 18%. This average coverage in Equity Strategy Neighborhood is 4% less than the city-wide average, indicating a discrepancy in access to Slow Streets between Equity Strategy and non-Equity strategy neighborhoods. The Mission is the Equity Strategy neighborhood with the most coverage, with 62% of the Mission within walking distance of Slow Streets. Removing the outlier of the Mission from the percent coverage calculation reduces the mean coverage to just 8% in the remaining Equity Strategy neighborhoods. Access to Slow Streets is lacking in the majority of neighborhoods that the SFMTA identified as historically marginalized communities.

Table 4. Percent area in walking distance of a Slow Distance in SFMTA Equity Strategy Neighborhoods

Neighborhood	Percent Coverage
Mission	62.16
Western Addition	32.95
Excelsior/Outer Mission	23.41
Downtown/Civic Center	4.7
Visitacion Valley	2.04
Ocean View/Ingleside	0.39
Bayview/Hunter's Point	0
Chinatown	0
Treasure Island	0
Average	**13.96**

Race and Ethnicity

Figure 7 provides a visual representation of the spatial distribution of the non-White population in San Francisco overlaid with a service area layer. In the 176 block groups with over two-thirds White residents, 36% of the area is within walking distance of a Slow Street. In the 192 block groups with over two-thirds non-White residents, 11% of the area is within walking distance of a Slow Street. Neighborhoods with a high percentage of non-White residents, such as the Sunset District, Excelsior, Bayview-Hunters Point, lack any access to Slow Streets corridors.

Majority White block groups have more coverage than block groups with majority non-White residents.

The Somerset and Cayuga corridors serve some of the highest percentages of BIPOC residents. The Somerset Street corridor in the Portola serves block groups that are 81% non-White on average. The Cayuga Avenue corridor in Excelsior is also located in a district with a high percentage of non-White residents. However, this street was only implemented in late 2023, nearly two and a half years after the program begun.

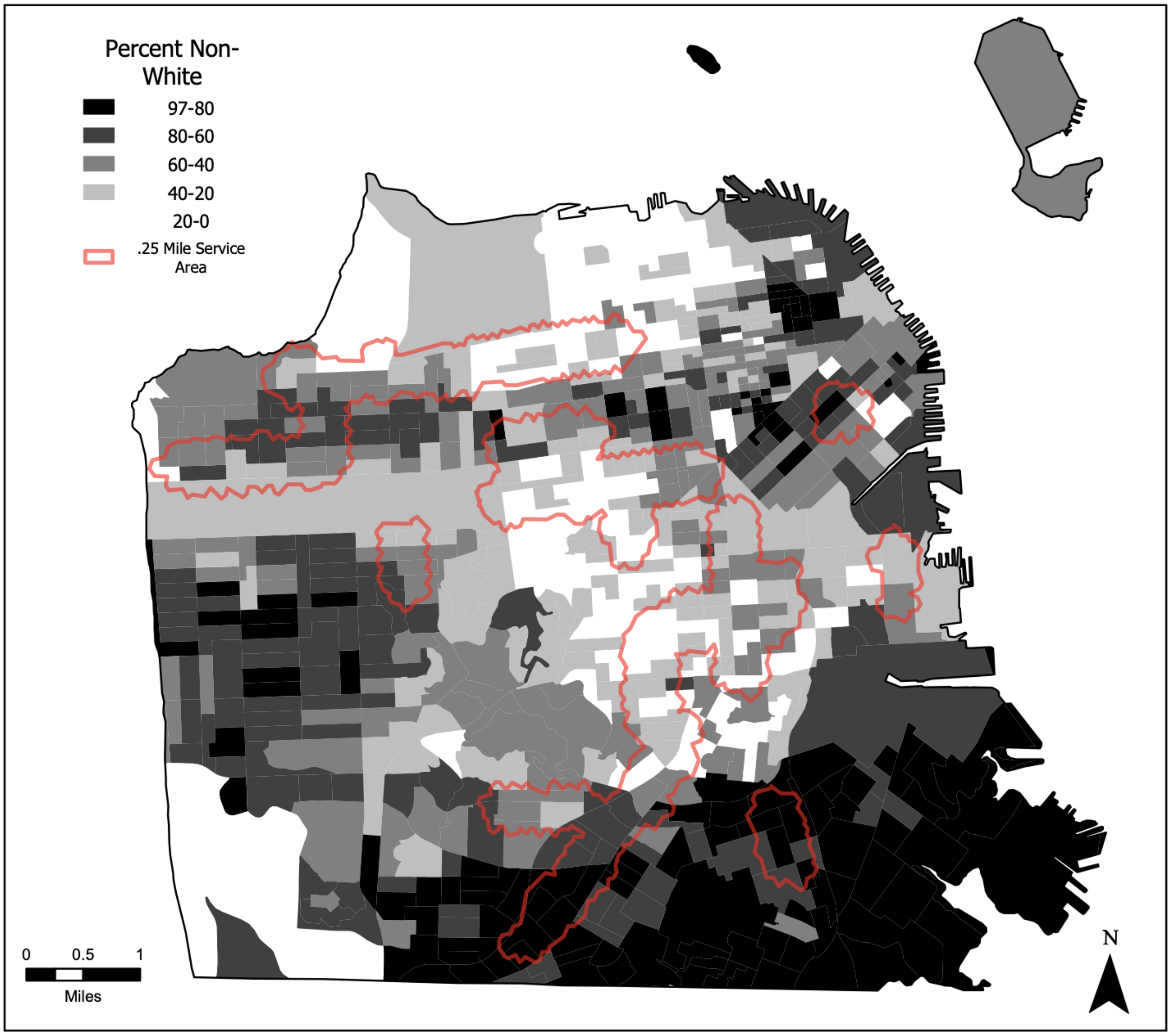


Figure 7. Percent non-White map with Slow Streets service area

Total population and relative percentages by block group were used to examine the distribution of Slow Streets in relation to race and ethnicity. Most of the people living within 0.25 miles of a Slow Street are White, with 137,000 living in served block groups. However, White residents are also the largest demographic group in San Francisco, accounting for 46% of San Francisco's total population. Roughly 40% of Latino and White San Franciscans have access to a Slow Street. With 35% of San Francisco's total population living within walking distance to a Slow Street, Latino and White residents are overrepresented in network service areas. Asian and Black residents are underrepresented, with only 30% of Asian and Black San Franciscans living in a service area. Total population in service areas broken down by race and ethnicity can be seen in Table 5.

Table 5. Total population by block group organized by service area and race and ethnicity

	Inside Service Area	**Outside Service Area**	**Total**
Asian Total	88,398	206,948	295,346
Asian (%)	29.9	70.1	
Black Total	11,840	30,670	42,510
Black (%)	27.5	72.5	
Hispanic or Latino Total	55,010	78,149	133,159
Hispanic or Latino (%)	42.6	57.4	
White Total	137,746	201,261	339,007
White (%)	41.2	48.8	

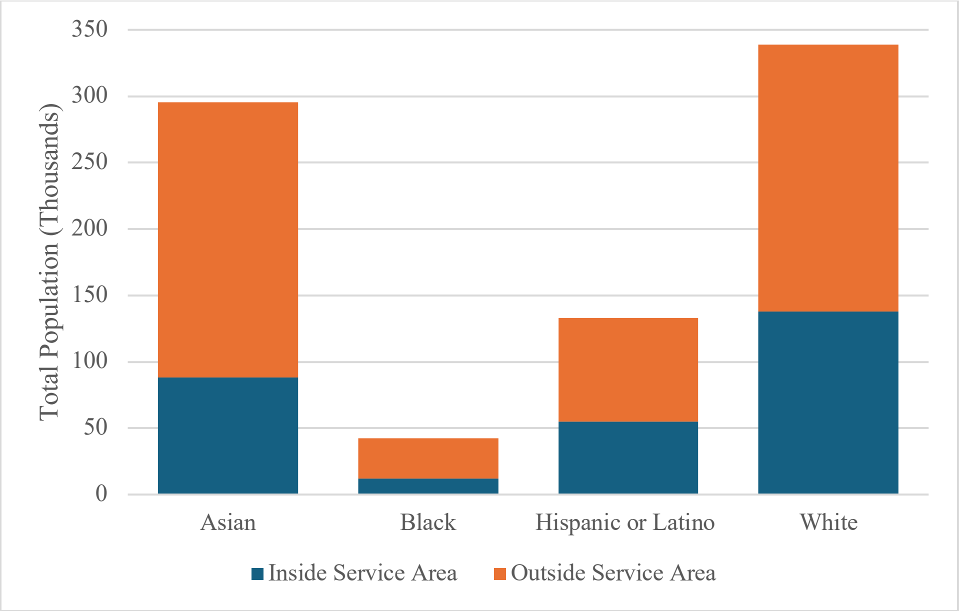


Figure 8. Total populations inside and outside of 0.25-mile Slow Street service area block groups by race and ethnicity

Table 6. compares proportions of race and ethnicity in served versus unserved block groups. Served block groups were 11% more White than non-served block groups and 8% more White than an average block group in San Francisco. While White residents represent 46% of San Francisco's total population, block groups with access to Slow Streets were 54% White on average. Hispanic or Latino residents also made up a larger percentage of the population in served block groups when compared to non-served block groups and the citywide average. This can in part be explained by the ample service area coverage in the Mission, where there are higher percentages of Hispanic or Latino residents.

On the other hand, Asian and Black residents represented a smaller proportion of served block groups when compared to non-served and average block groups. Served block groups were 11% less Asian than unserved block groups. Only a small portion of the Sunset, a neighborhood with a high density of Asian residents, has access to a Slow Streets corridor, despite being a heavily residential area. On average in served areas, White residents are heavily overrepresented, Hispanic or Latino residents are slightly overrepresented while Asian residents are heavily underrepresented and Black residents are slightly underrepresented. These findings are consistent with the differences in rates of inclusion by total population discussed above.

Table 6. Percentage of average race and ethnicity inside and outside of 0.25-mile Slow Street service area block groups

	Inside Service Area	**Outside Service Area**	**Citywide Average**
Asian (%)*	29.7	41.3	34.6
Black (%)*	4.5	6.4	5.7
Hispanic or Latino (%)*	16.2	13	14.6
White (%)*	54.1	42.9	45.8
*Statistically significant difference between populations ($p<0.05$) based on unpaired two sample t-test			

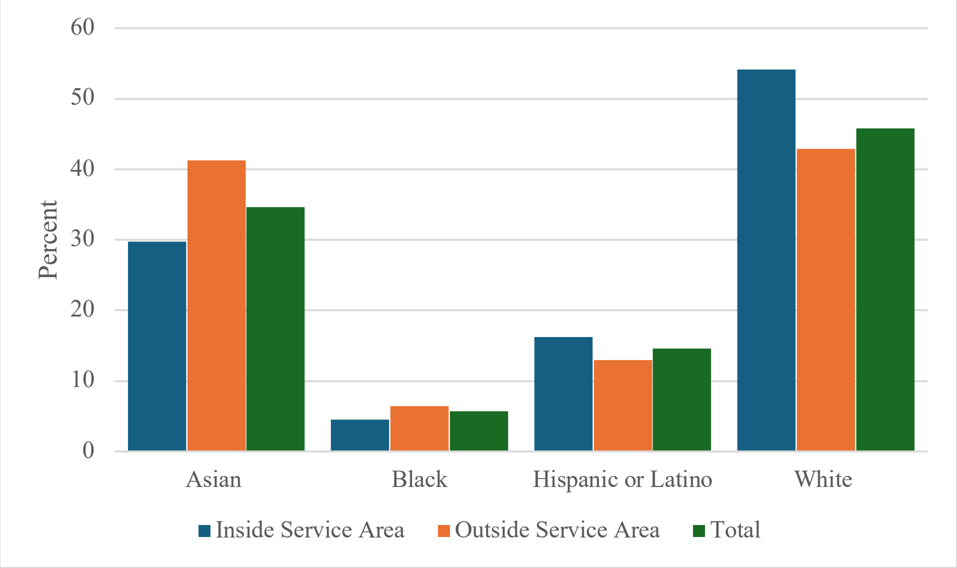


Figure 9. Percentage of average race and ethnicity inside and outside of 0.25-mile Slow Street service area block groups. Total percentage represents total percentage citywide.

Income

Figure 11 shows the spatial distribution of median household income by block group overlaid with the Slow Streets service area. Areas with lower incomes such as the Tenderloin and Hunters Point-Bayview lack access to Slow Streets corridors. Meanwhile, higher-income neighborhoods such as Presidio Heights and Noe Valley have large areas within walking distance of a Slow Street corridor. As a result, served block groups average a median household income of $143,000, while non-served block groups average a median household income of $119,000. When analyzed using a two-sample t-test, this $24,000 difference is statistically significant ($p<0.05$). Block groups with Slow Streets coverage are more affluent than those without access.

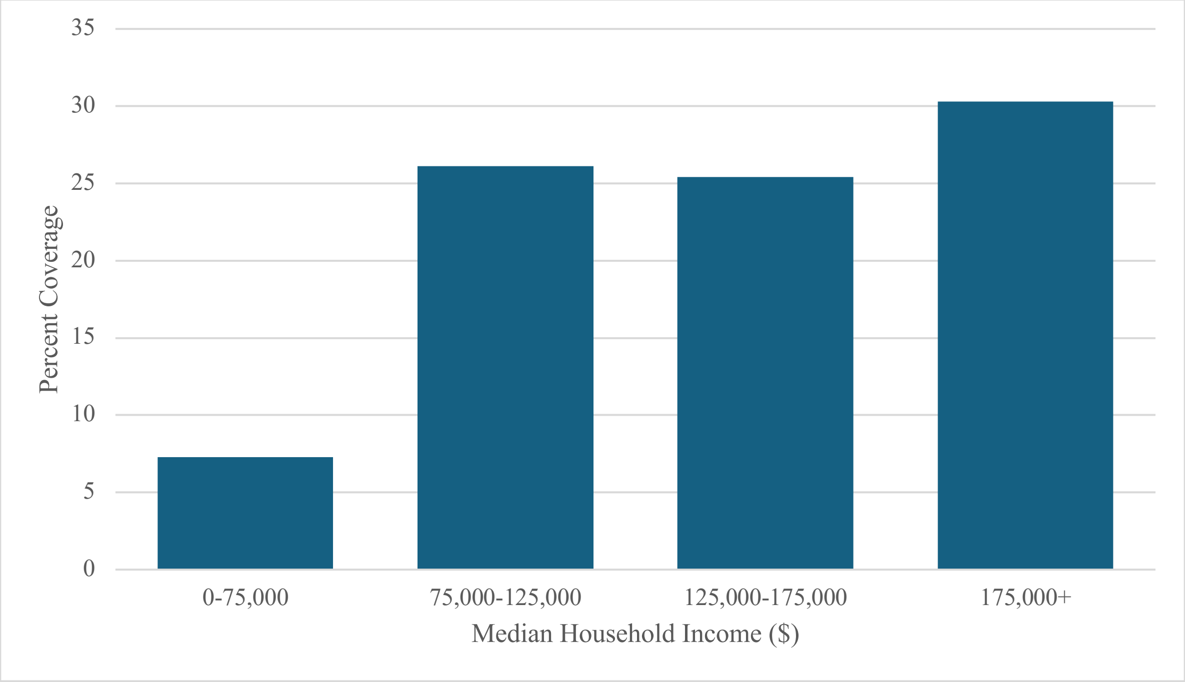


Figure 10. Chart of Slow Streets coverage in block groups by median household income

Examining the distribution of Slow Street coverage area in relation to income further highlights the difference in coverage across income brackets. In the 254 block groups with a median household income above $150,000, 28% of the area is covered by service areas. In the 125 block groups with a median household income under $75,000, only 7% of the area is covered by service areas. Such results indicate that extremely poor areas are severely lacking in access to Slow Streets.

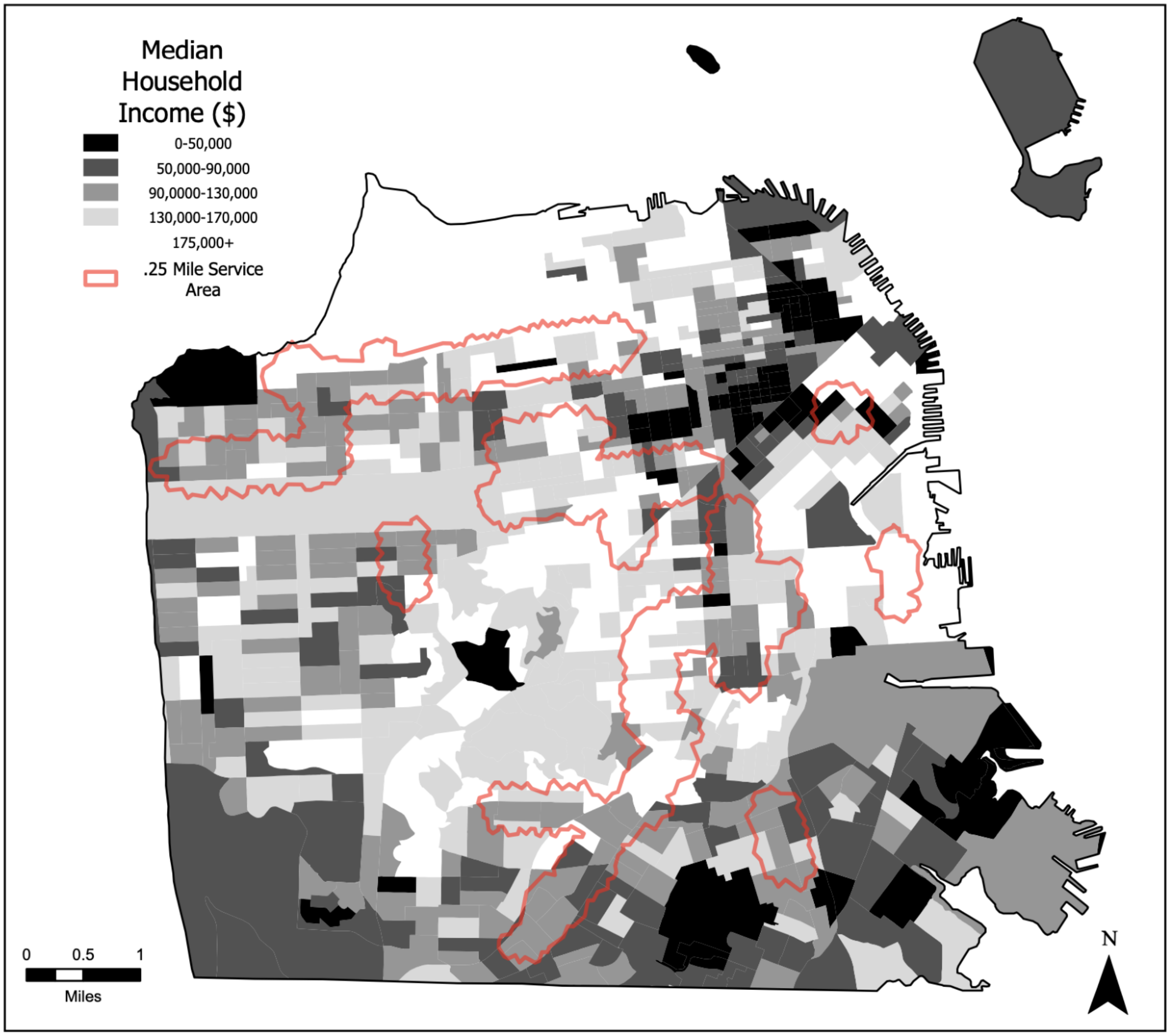


Figure 11. Median income with Slow Streets service area

Multivariate Clustering

To further demonstrate the differences in Slow Streets coverage in neighborhoods with different demographics and socioeconomic statuses, I conducted a multivariate clustering analysis in GIS. The variables for percentage White and median household income are often correlated (Akee et al., 2019). The results of this cluster analysis indicate that high income, majority White neighborhoods have significantly more access to Slow Streets than low income, high BIPOC neighborhoods. The Multivariate Clustering Tool identified 240 high income and majority White block groups in San Francisco, 50% of which are served by a Slow Street. Only 16% of the 132 low income and majority BIPOC neighborhoods are served by a Slow Street. Figure 12 provides a visual guide for low-income neighborhoods with high BIPOC populations lacking in Slow Streets coverage.

Table 7. Results of the multivariate cluster analysis by block group

	In Slow Streets Service Area	**Outside Slow Streets Service Area**	**Total Block Groups**	**Percentage Served by Slow Street**
Low Income-Majority BIPOC	21	111	132	15.9
Medium Income-Medium Race	122	184	306	39.8
High Income-Majority White	121	119	240	50.4

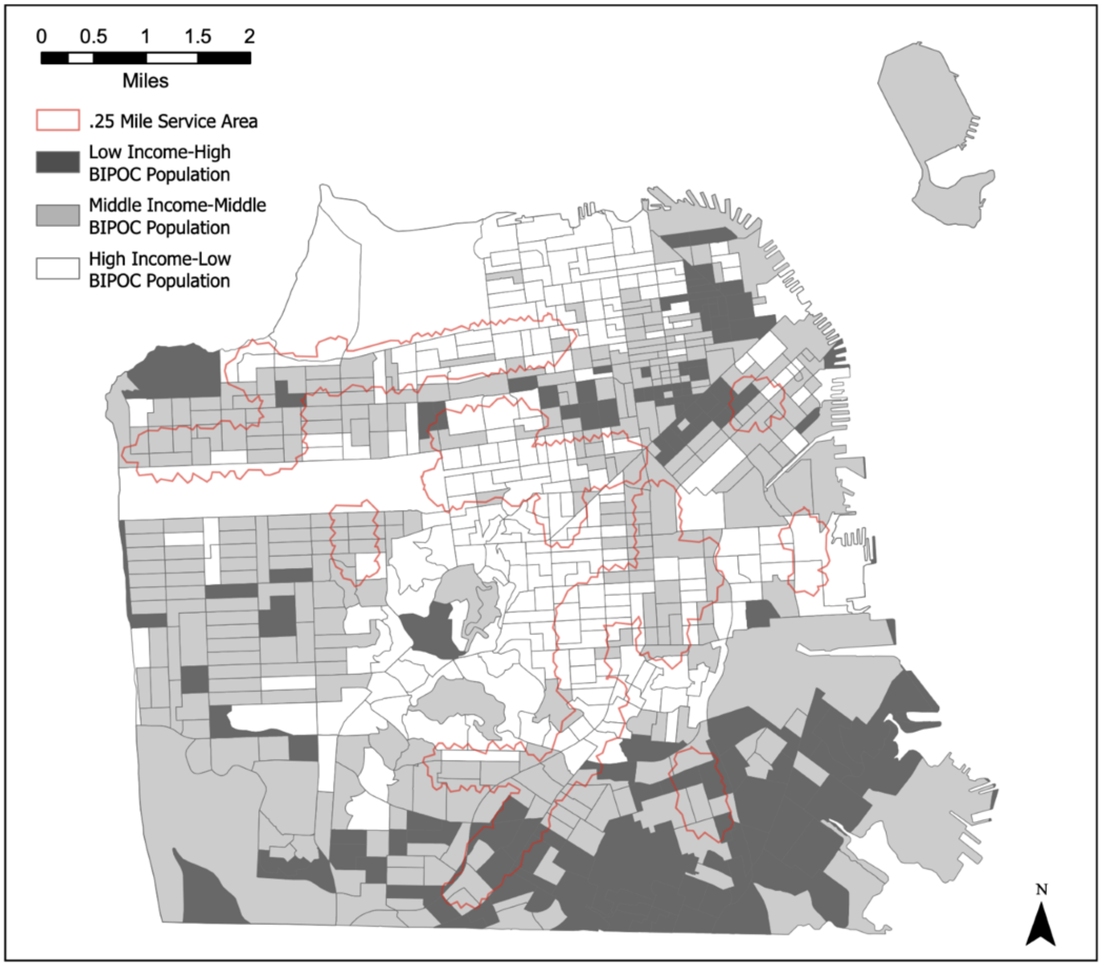


Figure 12. Map of the multivariate cluster analysis

Other Indicators

Other indicators of vulnerability had smaller discrepancies between served and non-served block groups. The respective differences for zero-car households, people over the age of 65, children under the age of 5, and pollution burden all were separated by a few percentage points, as seen in Table 8. While each of these indicators tended to have higher rates (indicating higher vulnerability) outside service areas, the differences were not statistically significant at the $p < 0.05$ level (except for pollution burden). Visual examination of maps (see Appendix) reveals that these indicators are not as spatially clustered as income and race or ethnicity. More dispersed geographic distribution of such indicators leads to smaller differences between served and unserved block groups. Maps for each variable can be found in the Appendix. One the other hand, the results of a Global and Local Moran's I indicate Slow Streets locations are clustered, mostly through the center of San Francisco. Spatial autocorrelation of race and income was also confirmed by a Global and Local Moran's I. Maps of the Local Moran's I can be seen in the Appendix. Clusters of high income and majority White block groups coincide with high-high clusters of Slow Street access.

Table 8. Socioeconomic and environmental variables inside and outside service areas

	Inside Service Area	**Outside Service Area**	**Average**
Total Median Household Income ($)*	142,600	119,400	126,700
Zero Car Households (%)	11.5	13.1	12.3
Pollution Burden (%)*	33.9	36.7	35.8
Age 65+ (%)	28.4	29.8	28.6
Age 0-5 (%)	4.3	4	4.2
*Statistically significant difference between populations (p<0.05) based on unpaired two sample t-test			

Vulnerability

Overview

By combining multiple risk indicators, these indexes provide a composite measure of vulnerability at the neighborhood-level. Overlaid with the Slow Streets service area, these indexes help to assess the distributional equity of the program and identify neighborhoods in need of special consideration for community engagement and targeted expansion.

As seen in Table 9, the unweighted vulnerability index resulted in a mean value of 4.29 for the entire city with a range between 2 and 8. The mean value within a 0.25-mile walking distance to a Slow Street was 4.1, while the mean value outside a service area was 4.34. Higher values indicate higher vulnerability. To assess whether this index aligns with known vulnerable neighborhoods, the mean value for SFMTA Equity Strategy neighborhoods was calculated. The average value for the nine Equity Strategy neighborhoods was 4.93, 0.64 higher than the mean value for the city. SFMTA-identified vulnerable neighborhoods receiving higher vulnerability scores than city average provides assurance that the index is generally identifying more vulnerable areas correctly.

The weighted vulnerability index resulted in a mean value of 4.67 across the entirety of San Francisco with a range between 1 and 8. The mean value within a 0.25-mile walking distance to a Slow Street was 4.26, while the mean value outside a service area was 4.79. The mean weighted value for the nine SFMTA Equity Strategy neighborhoods was 5.8, 1.13 higher than the city's value. Like the unweighted index, this indicates general alignment between the weighted index and SFMTA-identified vulnerable areas.

Table 9. Average vulnerability index values

	Unweighted	**Weighted**
San Francisco	4.29	4.67
Inside Service Area	4.1	4.26
Outside Service Area	4.34	4.79
Equity Strategy Neighborhoods	4.93	5.8

The mean score for service areas around specific Slow Streets was calculated to provide insight on which corridors are serving the most vulnerable populations. Somerset, Cayuga, and SoMa streets all received both weighted and unweighted scores above 5, meaning they served higher vulnerability block groups. Meanwhile, the Sanchez, Clay, Minnesota, and Noe Street service areas all received both weighted and unweighted scores below 3.2. Comparing these high and low vulnerability corridors to the overall unweighted (4.1) and weighted (4.26) average in all service areas reveals that there are significant differences in populations served by different corridors.

Citywide, weighted scores were higher on average than unweighted scores. Both the unweighted and weighted indexes had higher average values outside service areas when compared to the citywide and served area averages. This indicates that Slow Streets locations in early 2024 tend to be in less vulnerable areas. These results are consistent with the findings for independent socioeconomic variables such as income and race, as Slow Streets were in higher income, whiter block groups on average. Figure 13 provides the distribution of values for each index organized by the Jenks natural breaks classification method. These maps highlight the spatial distribution of vulnerability within SF in relation to Slow Streets.

Figure 13. Unweighted and weighted vulnerability indexes based on the results of a multicriteria overlay.

Differences Between Weighted and Unweighted Indexes

To better understand the differences between the weighted and unweighted indexes, I analyzed neighborhood-level data with San Francisco Planning Department neighborhood boundaries. Not only does this provide rankings of vulnerability by neighborhood, but one can also see discrepancies in rankings between the two indexes. Table 10 shows a breakdown of each neighborhood's vulnerability score. Each neighborhood was ranked by weighted and unweighted scores. The resulting ranks were then averaged for an overall ranking, with higher rankings indicating higher vulnerability. Bayview-Hunters Point has the highest average ranking, followed by Chinatown, Portola, Excelsior, and South of Market. Three of the five highest vulnerability neighborhoods correspond with Equity Strategy neighborhoods. Castro, Haight Ashbury, Noe Valley, and Presidio Heights were the lowest ranked, indicating lower vulnerability. These neighborhoods have higher proportions of White residents and high incomes than the rest of the city.

Evaluating consistency between the two indexes can be accomplished by calculating the difference in rankings for each neighborhood. Of the 39 neighborhoods 26, or 66%, had a difference in ranking of five or under. On the contrary, five of the 39 neighborhoods, or 12%, had a difference in ranking of ten or greater.

Visitacion Valley had the highest discrepancy of 19 spots, with a weighted rank of 4th and an unweighted rank of 23rd. Visitacion Valley is an Equity Strategy designated area, indicating that the weighted rank is more closely aligned with the SFMTA's definition of equity priority. Analysis of the rank order of neighborhoods between the weighted and unweighted index suggests that the weighted index is better aligned with known vulnerable neighborhoods.

In the weighted index, the percent non-White variable was heavily weighted, resulting in a greater emphasis on race and ethnicity. The population of Visitacion Valley is 91% non-White, which likely resulted in the high ranking by weighted index. Other neighborhoods with large discrepancies in rank such as SoMa, the Financial District, and Oceanview/Merced/ Ingleside, were also either heavily White or non-White or on the extreme ends of the income bracket. The greater weight placed on race and income variables in the weighted index means that resulting scores for those areas with extreme values would be skewed. In the unweighted index, variables were additive, meaning extreme values for race and income might not be reflected in the overall score if other variables' scores were lower.

Table 10. List of San Francisco neighborhoods organized by their average ranked index score

Neighborhood	Unweighted Average Score	Unweighted Rank	Weighted Average Score	Weighted Rank	Difference in Ranking	Average Ranking	Slow Streets Coverage (%)
Bayview Hunters Point	5.35	4	6.45	1	3	2.5	0
Chinatown	5.72	2	6.1	5	-3	3.5	0
Portola	5.1	6	6.44	2	4	4	43.5
Excelsior	4.89	10	6.39	3	7	6.5	7.4
South of Market	5.84	1	5.33	12	-11	6.5	16.4
Tenderloin	5.67	3	5.38	11	-8	7	0.4
Treasure Island	5.01	8	5.9	7	1	7.5	0
North Beach	5.1	7	5.45	10	-3	8.5	0
Outer Mission	4.71	13	5.83	8	5	10.5	71.8
Financial District/South Beach	5.3	5	5.02	17	-12	11	6.5
Oceanview/Merced/ Ingleside	4.52	16	5.99	6	10	11	1.9
Nob Hill	4.89	11	5.25	13	-2	12	0
Western Addition	4.96	9	5.15	15	-6	12	13.5
Japantown	4.43	17	5.63	9	8	13	0
Visitacion Valley	4.05	23	6.33	4	19	13.5	0
Outer Richmond	4.71	14	5.25	14	0	14	53.4
Mission Bay	4.72	12	4.61	19	-7	15.5	1.3

Neighborhood	Unweighted Average Score	Unweighted Rank	Weighted Average Score	Weighted Rank	Difference in Ranking	Average Ranking	Slow Streets Coverage (%)
Mission	4.66	15	4.36	21	-6	18	60.4
Lakeshore	4.29	19	4.75	18	1	18.5	0
Inner Richmond	4.31	18	4.55	20	-2	19	34.9
Sunset/Parkside	4.06	22	5.13	16	6	19	0
Bernal Heights	4.27	20	4.24	22	-2	21	17.9
Hayes Valley	4.13	21	4.15	25	-4	23	78.2
Lone Mountain/USF	3.9	25	4.2	23	2	24	76.3
Inner Sunset	3.74	26	4.18	24	2	25	18.5
West of Twin Peaks	3.65	28	4.12	26	2	27	11.8
Russian Hill	3.7	27	3.62	28	-1	27.5	0
Twin Peaks	3.51	30	3.69	27	3	28.5	0
Lincoln Park	3.99	24	3.02	34	-10	29	0
Pacific Heights	3.51	31	3.44	30	1	30.5	39.5
Glen Park	3.26	34	3.45	29	5	31.5	30.3
Marina	3.56	29	2.89	37	-8	33	0
Potrero Hill	3.2	35	3.28	31	4	33	22.6
Seacliff	3.32	33	3.11	33	0	33	80.4
Presidio	3.36	32	3	36	-4	34	6.5
Presidio Heights	2.98	37	3.15	32	5	34.5	63.6
Noe Valley	2.93	38	3.01	35	3	36.5	48.4
Haight Ashbury	3.01	36	2.78	39	-3	37.5	64.1
Castro/Upper Market	2.75	39	2.84	38	1	38.5	26.2

Percent Coverage by Neighborhood

Percent coverage calculations were used to further highlight the discrepancy in coverage between high and low vulnerability areas. The scale of analysis was shifted from block groups to neighborhoods for ease of interpreting results. Rather than referring to general geographic areas, neighborhoods provide familiar place names for reference. The top 20% most vulnerable neighborhoods by ranked index score have an average coverage of 8.46% while the 20% least vulnerable neighborhoods by the same measure have an average coverage of 38.97%. Table 10 provides the exact percent coverage numbers by neighborhood organized from most to least vulnerable. Five of the top eight most vulnerable neighborhoods are not served by any Slow Streets while only one of the eight least vulnerable neighborhoods do not have coverage.

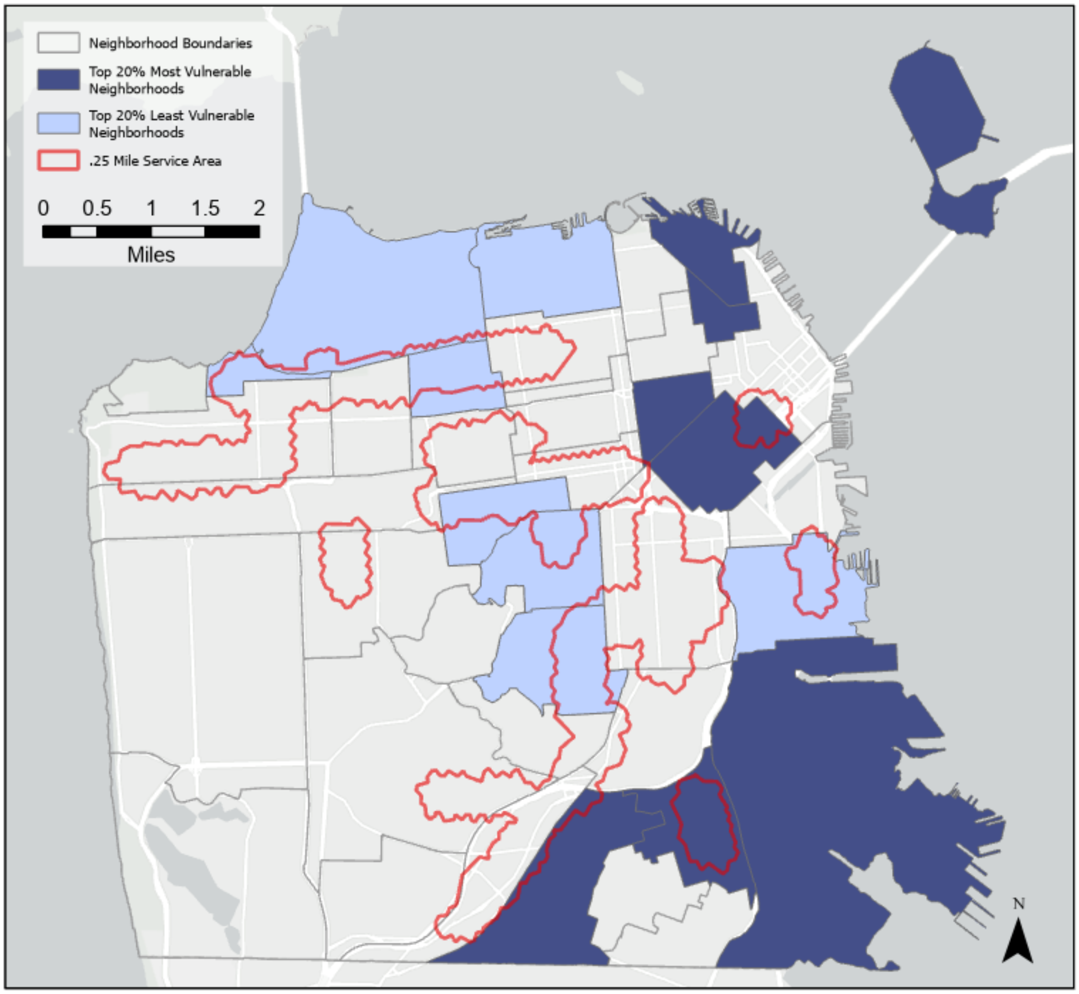


Figure 14. Most and least vulnerable neighborhoods in San Francisco by index ranking. Ranking was derived by averaging the results of the weighted and unweighted indexes.

Regression Analyses

Multiple regression models were run using tools in the ArcGIS Spatial Statistics Toolbox to identify a model and variables that best explain the relationship between explanatory variables and distance to Slow Streets. An Exploratory Regression identified percent White, median household income, and crashes as statistically significant. All had negative relationships with the dependent variable, indicating that as the independent variable increased (percent White, median household income, and crashes) the distance to a Slow Street decreased all else remaining the same. The variables all had Variance Inflation Factors (VIF) under 3, indicating a lower risk for multicollinearity. However, no models passed all of the Exploratory Regression's requirements and tests based on the default criteria set by ArcGIS. In particular, low R-Squared values and failed Jarque-Bera and spatial autocorrelation tests indicate a poorly fitted model with sources of potential bias. The highest R-Squared value of the potential models was 0.1. This low R-Squared value indicates that a global model does not adequately explain variation in the dependent variable. The Jarque Bera p-value did not meet the cutoff of greater than 0.1, indicating either nonlinear relationships or data outliers.

A General Linear Regression (GLR) run with the model with the lowest AICc value from the Exploratory regression returned similar results. A low VIF and statistically significant variables indicates some potential explanatory power and low risk of global multicollinearity. However, the model had a low R-Squared of 0.09 and did not pass the Jarque-Bera and spatial autocorrelation tests, further confirming that a global model likely cannot capture the full relationship between explanatory variables and distances to Slow Streets. The GLR's poor performance indicates that relationships between the explanatory and dependent variables likely vary spatially across San Francisco.

To account for relationships that fluctuate geographically, a Geographically Weighted Regression (GWR) was run with the significant variables from the Exploratory Regression. With a regression equation being fit to each block group, adjusted R-Squared values were much higher, resulting in an overall adjusted R-Squared value of 0.9. See Figure 15 for a map of local R-Squared values across San Francisco, showing the model's ability to explain variation in

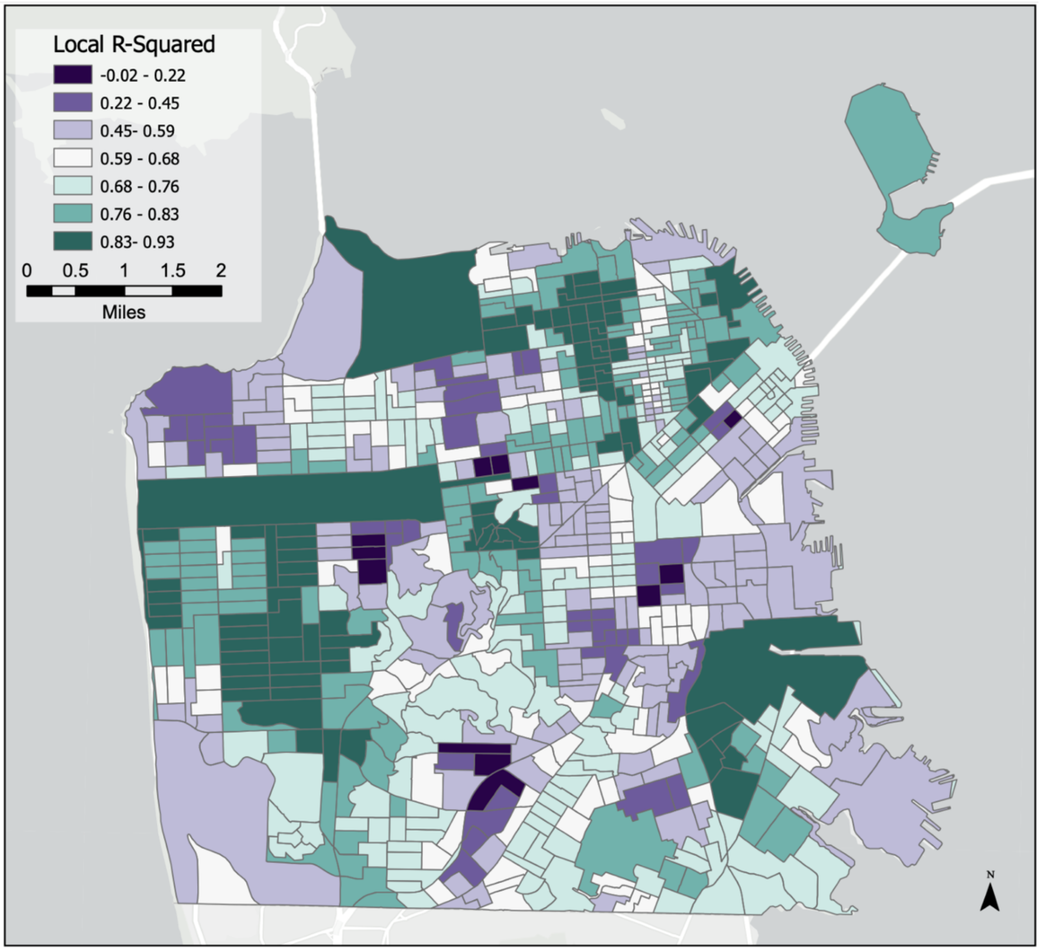
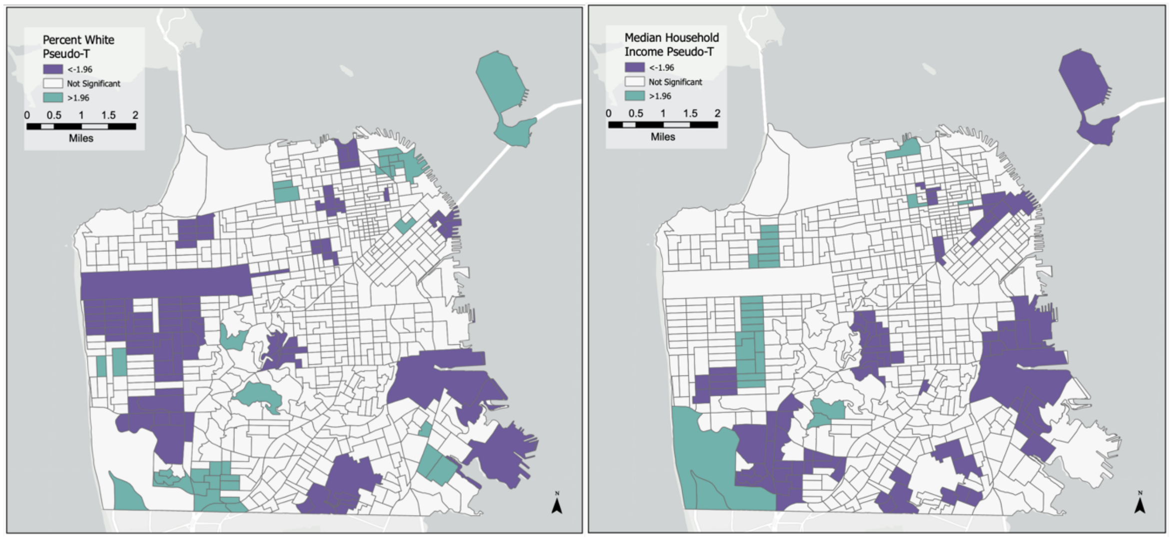


Figure 15. Map of Local R-Squared values from the GWR

distance to Slow Streets over space. The range of local R-Squared values indicates spatial differences in the explanatory power of the model. The highest R-Squared values were clustered in the Sunset and Marina neighborhoods. The residuals were small and normally distributed, indicative of good model fit. The Sigma-Squared MLE, or maximum likelihood estimation of the variance, value was 0, a desired outcome. However, the condition numbers for features were large, indicating results are influenced by local multicollinearity. The results of a Global and Local Moran's I showed the spatial clustering of race and median income, which likely introduces this error in model design. Additionally, the correlation between income and race as discussed in Chapter 3 also provides a source of error. Running other iterations of a GWR with different combinations of variables did not return lower condition numbers. While the results of the GWR offered more explanatory value than the GLR, the strong probability of local multicollinearity indicates that the model could be further refined.

To identify areas where coefficients would be interpretable, the Pseudo-t statistic for each variable was filtered to less than –1.96 and greater than 1.96. This results in a map that only shows block groups where the Pseudo-T stat is statistically significant for different variables at the 95% confidence level. As seen in Figure 16, green block groups indicate a positive relationship between the dependent and explanatory variables whereas purple indicates a negative correlation. For crashes, negative relationships can be observed in the high crash areas around the southern and eastern edges of San Francisco, where Slow Street coverage is low. For the percent White variable, there is a negative relationship for much of the Sunset district, where there is a large Asian community and little Slow Street coverage.

The results for most of the area in San Francisco are not significant, indicating that there is not a statistically significant relationship between these variables and distances to Slow Streets for large portions of San Francisco. Notably, there are few significant results across all tested variables in most of the areas near Slow Streets, especially in the center and northwest portions of San Francisco. It is difficult to infer whether Slow Streets themselves would have had an impact on the absence of significant results as the income and race variables were a five-year estimate from 2017-2021, meaning Slow Streets were only in place for just over year-and-a-half at the time of data collection. Crash data was from the same period. Future studies could divide data before and after Slow Streets implementation to better understand the impact of Slow Streets on relationships. However, such maps indicate that relationships between variables and distance to Slow Streets vary across San Francisco.



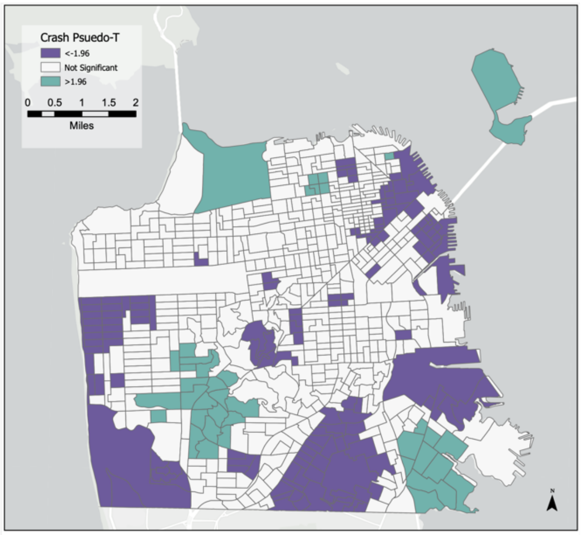


Figure 16. Pseudo-T values for variables. Green indicates a significant positive relationship and purple indicates a significant negative relationship.

Summary

A service area analysis, vulnerability index, and GWR were conducted to assess how Slow Streets are serving different populations spatially across San Francisco. Based on the service area analysis, Slow Street access was concentrated in whiter and wealthier neighborhoods. Differences in race and income between served and non-served populations were statistically significant. Served block groups were an average of 11% more White and had a median household income $24,000 greater than non-served block groups. A multivariate cluster also confirmed there is less coverage in low income-high BIPOC population block groups than high income-high White population block groups.

The vulnerability indexes provided insight into the program's distributional equity by identifying high-vulnerability areas in relation to Slow Streets coverage. Both mean scores of the weighted and unweighted indexes were higher outside of service areas than inside. Differences in vulnerability scores by Slow Streets corridor show that corridors serve different populations. To provide neighborhood-level analysis, this composite measure of multiple risk factors was also used to identify disadvantaged communities in San Francisco. The highest vulnerability neighborhoods had less Slow Streets service area coverage than lower vulnerability neighborhoods.

While inferences from the regression analysis may be limited due to the lack of fine-grained data and high likelihood of local multicollinearity, the relative success of the GWR when compared to a GLR suggests the influence of space across relationships between variables and distances to Slow Streets. Race, income, and number of crashes per block group were identified as significant variables with negative relationships globally. However, the GWR suggested relationships between individual variables and distance to Slow Streets varied across San Francisco. For each variable, there were areas with significant positive or negative relationships, while other neighborhoods lacked statistically significant relationships.

Chapter 5: Conclusions

The purpose of this thesis was to assess how San Francisco's Slow Streets program was serving different populations. Programs should strive to achieve an equitable distribution of public resources. The results of a service area analysis show that White and affluent residents are disproportionately served by the program, while Asian and Black San Franciscan's are underrepresented. Neighborhood-level differences in access were explored with multicriteria overlays. The most vulnerable areas of San Francisco have less coverage than the least vulnerable areas. Tables showing percent coverage by neighborhood highlight which communities could benefit the most from interventions. This discrepancy in access between disadvantaged and privileged communities reflects a larger trend: disadvantaged communities shoulder a disproportionate amount of the health and safety risks stemming from our transportation systems. Creating fair access to active transportation and recreation resources for at-risk populations is of the utmost importance to help offset these burdens.

This thesis focused on the distributional outcomes of a program, but considerations of the procedural equity are equally important. One of the first steps towards addressing historical injustices and structural inequities in our transportation systems is embedding equity into planning processes. Goal setting, public involvement, and concrete definitions of equity help to move to more equitable outcomes. As the program looks to expand, prioritizing equity in placement decisions can help guide placement of future corridors. Expansion into neighborhoods such as Bayview-Hunters Point and Excelsior could help alleviate equity concerns but must be done with a robust community engagement process. Slow Streets represent an opportunity to reclaim public space for people. However, implementing programs without centering equity can lead to disempowered communities being excluded from the program. Public pushback and criticism against street reallocation efforts in other cities such as Oakland highlights the importance of community engagement and participation in planning processes.

Limitations

Some limitations of this study include subjectivity in the creation of the vulnerability index and assuming distance-based accessibility is a proxy for distributional equity. The construction of a vulnerability index introduces subjectivity to the results. While I justified my decisions for the inclusion, exclusion, and weighting of indicators based on existing literature and the context of this study, it is widely accepted that there is no one accepted set of factors to include in a vulnerability index. As Tate (2013) notes: while subjectivity in modeling is not necessarily bad, it is a source of uncertainty in vulnerability indexes. Tate suggests employing uncertainty analyses to better understand the effects of subjective decisions. The choice of whether to weight or not to weight variables was addressed by constructing and then comparing two indexes. However, the amount of weight for each variable, or lack thereof, influenced the resulting scores. The additive nature of the non-weighted index means that extreme values for some variables could be nullified. For example, a block group that is extremely poor but mostly White would not end up with a high vulnerability score. Implicit weighting is also liable to occur due to the complex and interrelated relationships of socioeconomic and demographic variables (Schmidtlein et al., 2008).

Another limitation of this thesis is using accessibility as a proxy for distributional equity. While a robust body of literature has previously employed such techniques, it is not without drawbacks. As touched upon in Chapter 2, accessibility is a complex concept that requires contextual and relational specificity. This thesis uses a relatively simple understanding of access with a 0.25-mile walking service area based on a network provided by ArcGIS. In reality, each person's accessibility is highly relative due to environment, demographic attributes, and personal preferences. (Arranz-Lopez et al., 2019). More nuanced analyses might separate groups and geographies by mobility advantages or constraints. Additionally, this thesis assumes that all Slow Streets corridors are equal in quality. However, not all streets perform similarly. SFMTA tracking shows that some corridors have not met vehicle speed reduction goals. Distinguishing between the quality and desirability of Slow Streets could provide further depth.

Future Research

This thesis can serve as guide for future studies and planners to assess how a program is serving different populations. Due to the recent implementation of COVID-era street reallocation programs, research assessing the spatial distribution of reallocated streets through the lens of equity is relatively limited. Iterating on techniques from previous literature evaluating equity in active transportation infrastructure and parks, GIS was used to visualize the variation in access to a resource in relation to the demographic characteristics of a population. Applying this framework to other cities can offer insight into street reallocation programs' larger impacts and provide a platform to compare and contrast outcomes. It should be acknowledged that a framework needs to be adapted to each city's local context. The assumptions and variables used for San Francisco do not apply universally. As such, it is important to engage and be familiar with the community the framework is used in (Heckert & Rosan, 2016).

As time progresses, more data will become available about the ramifications of a reallocated street on health, safety, and livability of a neighborhood. Such data should be incorporated into decisions about variable choice and weighting. Having this information also furthers our understanding on the impacts of such a program. The threat of gentrification and ensuing displacement associated with infrastructure additions or improvements (Immergluck & Balan, 2017; Morrison 2021) also should be further explored.

As previously mentioned, this thesis focuses on the distributional outcomes of Slow Streets. A more in-depth analysis of procedural equity is necessary to understand how these outcomes came to be. Additional assessment of community response and feedback to the program, particularly in disadvantaged areas, can also shed light on the program's impact and perception in local communities. The relative success of community-run Open Streets versus NYPD-run Open Streets in New York City (Cuba 2020) also provides an interesting avenue to further explore. These insights would allow the SFMTA to continue to adapt and improve the program's accessibility and performance.

Finally, a suitability overlay could be performed to identify specific streets for expansion. Contrasted with a vulnerability index, a suitability analysis could incorporate SFMTA criteria for Slow Streets corridors. This thesis did not account for such criteria, as I looked to understand differences in currently served populations to assess the program's equity. The areas identified by the vulnerability index are certainly areas that could be targeted for expansion. However, the index and maps were intended as an exploratory tool to identify neighborhoods that could benefit from interventions. A suitability analysis could take this a step further by allowing us to combine equity considerations with SFMTA criteria for corridors. Such an overlay would also provide insight into the existing spatial distribution of Slow Streets. Criteria such as slope and street length would have influenced decisions in initial placement of streets, resulting in some areas being excluded from participation in the program. Future regression analyses could also include such criteria.

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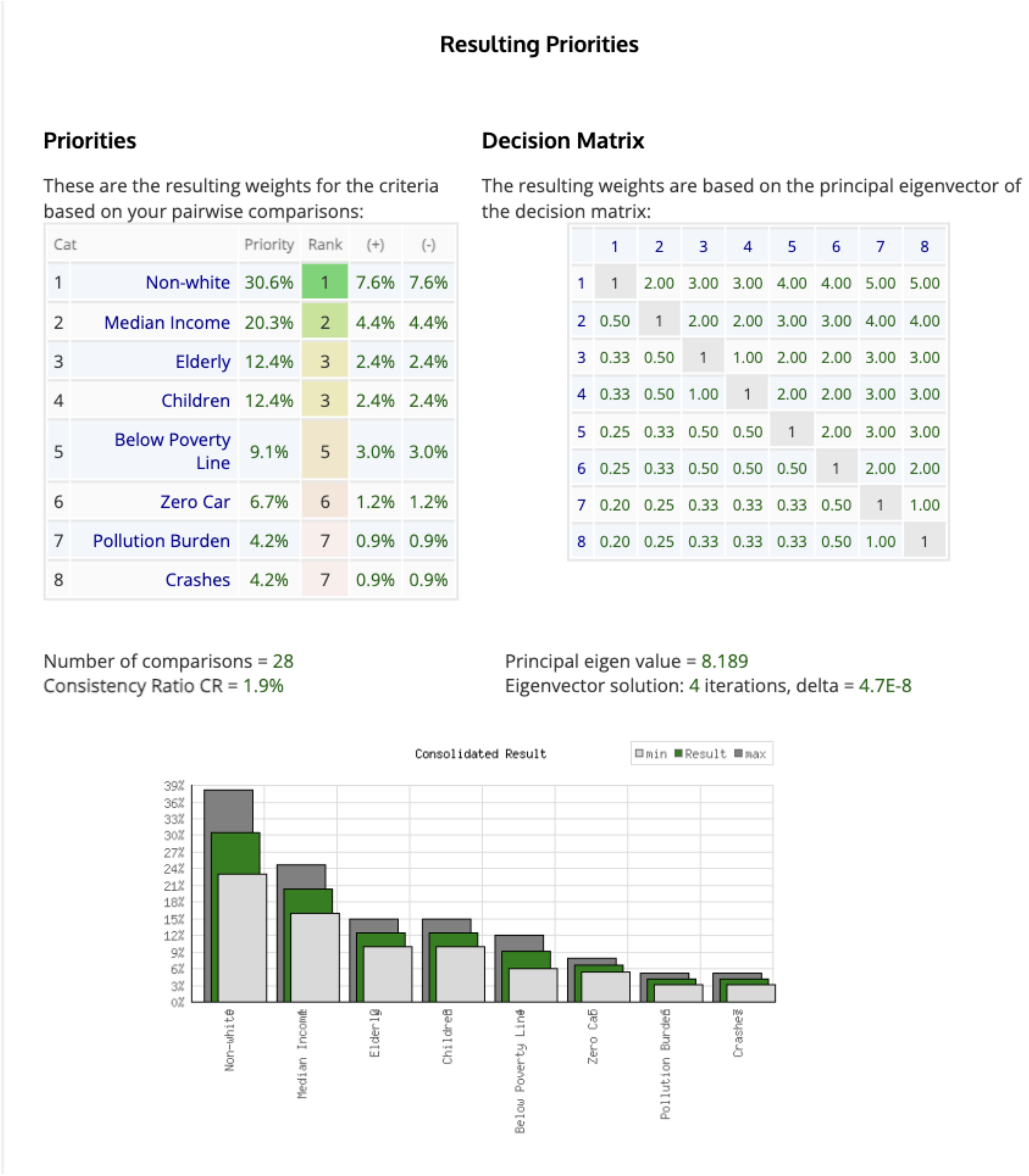
Appendix

AHP Calculator



Resulting Priorities

Priorities

These are the resulting weights for the criteria based on your pairwise comparisons:

Cat		Priority	Rank	(+)	(-)
1	Non-white	30.6%	1	7.6%	7.6%
2	Median Income	20.3%	2	4.4%	4.4%
3	Elderly	12.4%	3	2.4%	2.4%
4	Children	12.4%	3	2.4%	2.4%
5	Below Poverty Line	9.1%	5	3.0%	3.0%
6	Zero Car	6.7%	6	1.2%	1.2%
7	Pollution Burden	4.2%	7	0.9%	0.9%
8	Crashes	4.2%	7	0.9%	0.9%

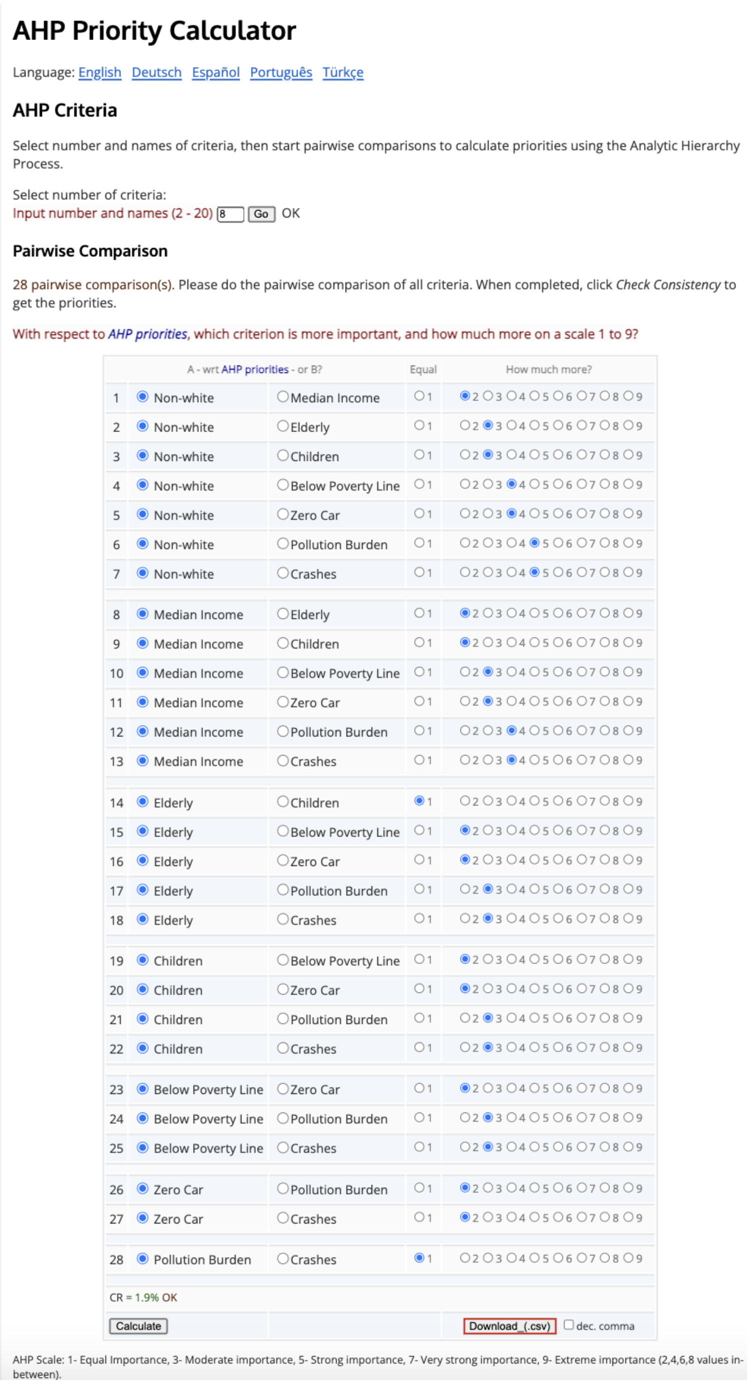
Decision Matrix

The resulting weights are based on the principal eigenvector of the decision matrix:

	1	2	3	4	5	6	7	8
1	1	2.00	3.00	3.00	4.00	4.00	5.00	5.00
2	0.50	1	2.00	2.00	3.00	3.00	4.00	4.00
3	0.33	0.50	1	1.00	2.00	2.00	3.00	3.00
4	0.33	0.50	1.00	1	2.00	2.00	3.00	3.00
5	0.25	0.33	0.50	0.50	1	2.00	3.00	3.00
6	0.25	0.33	0.50	0.50	0.50	1	2.00	2.00
7	0.20	0.25	0.33	0.33	0.33	0.50	1	1.00
8	0.20	0.25	0.33	0.33	0.33	0.50	1.00	1

Number of comparisons = 28
Consistency Ratio CR = 1.9%

Principal eigen value = 8.189
Eigenvector solution: 4 iterations, delta = 4.7E-8



AHP Priority Calculator

Language: English Deutsch Español Português Türkçe

AHP Criteria

Select number and names of criteria, then start pairwise comparisons to calculate priorities using the Analytic Hierarchy Process.

Select number of criteria:
Input number and names (2 - 20) 8 Go OK

Pairwise Comparison

28 pairwise comparison(s). Please do the pairwise comparison of all criteria. When completed, click *Check Consistency* to get the priorities.

With respect to *AHP priorities*, which criterion is more important, and how much more on a scale 1 to 9?

	A - wrt AHP priorities - or B?		Equal	How much more?
1	● Non-white	○ Median Income	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
2	● Non-white	○ Elderly	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
3	● Non-white	○ Children	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
4	● Non-white	○ Below Poverty Line	○ 1	○ 2 ○ 3 ● 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
5	● Non-white	○ Zero Car	○ 1	○ 2 ○ 3 ● 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
6	● Non-white	○ Pollution Burden	○ 1	○ 2 ○ 3 ○ 4 ● 5 ○ 6 ○ 7 ○ 8 ○ 9
7	● Non-white	○ Crashes	○ 1	○ 2 ○ 3 ○ 4 ● 5 ○ 6 ○ 7 ○ 8 ○ 9
8	● Median Income	○ Elderly	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
9	● Median Income	○ Children	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
10	● Median Income	○ Below Poverty Line	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
11	● Median Income	○ Zero Car	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
12	● Median Income	○ Pollution Burden	○ 1	○ 2 ○ 3 ● 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
13	● Median Income	○ Crashes	○ 1	○ 2 ○ 3 ● 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
14	● Elderly	○ Children	● 1	○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
15	● Elderly	○ Below Poverty Line	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
16	● Elderly	○ Zero Car	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
17	● Elderly	○ Pollution Burden	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
18	● Elderly	○ Crashes	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
19	● Children	○ Below Poverty Line	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
20	● Children	○ Zero Car	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
21	● Children	○ Pollution Burden	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
22	● Children	○ Crashes	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
23	● Below Poverty Line	○ Zero Car	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
24	● Below Poverty Line	○ Pollution Burden	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
25	● Below Poverty Line	○ Crashes	○ 1	○ 2 ● 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
26	● Zero Car	○ Pollution Burden	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
27	● Zero Car	○ Crashes	○ 1	● 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9
28	● Pollution Burden	○ Crashes	● 1	○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

CR = 1.9% OK

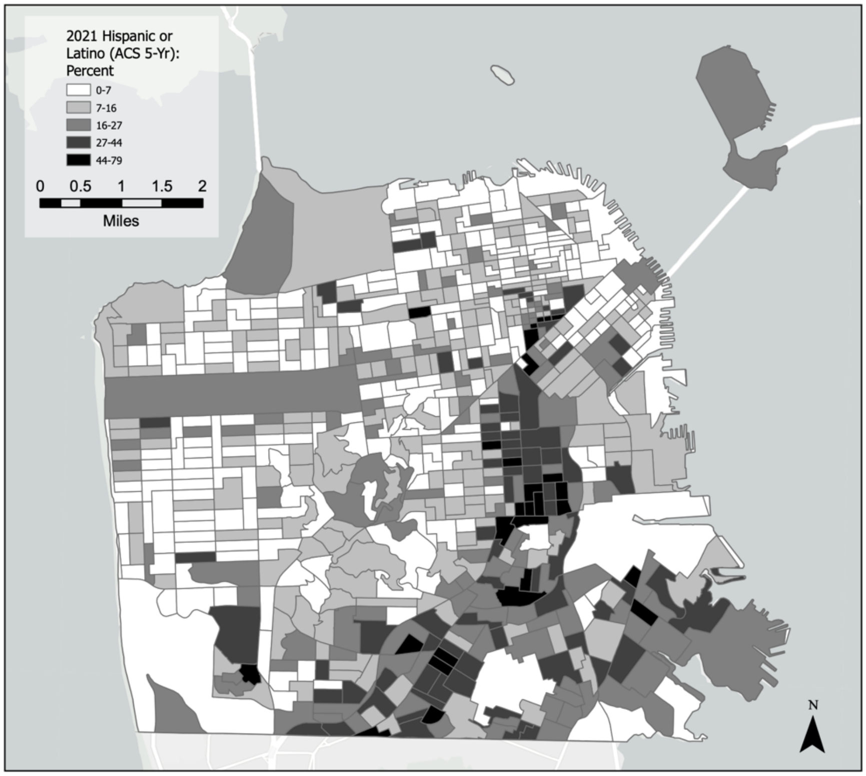
AHP Scale: 1- Equal Importance, 3- Moderate importance, 5- Strong importance, 7- Very strong importance, 9- Extreme importance (2,4,6,8 values in-between).

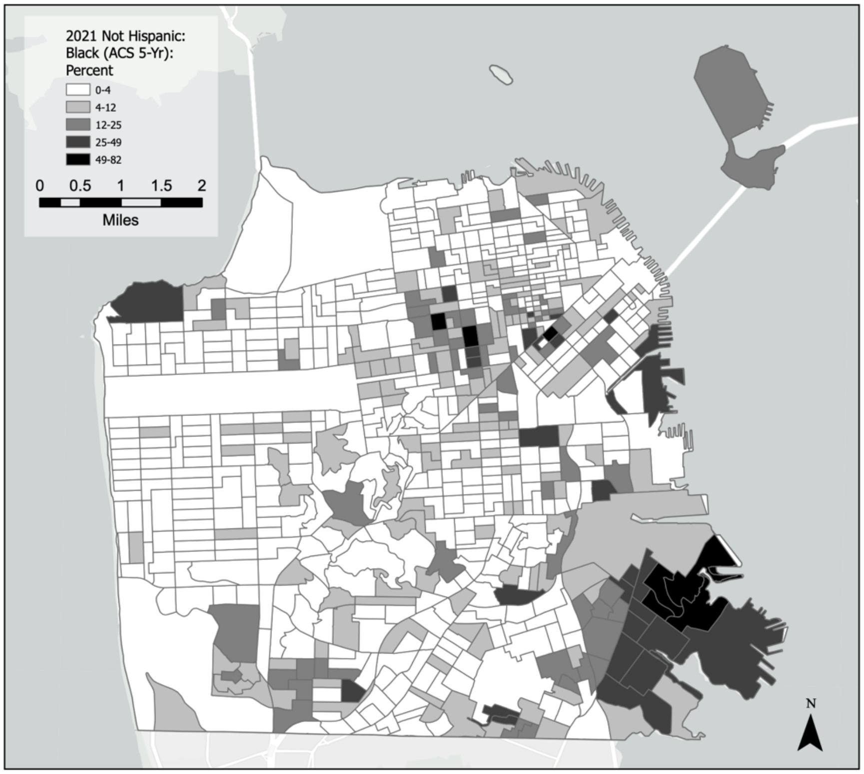
Variable Ranking Table

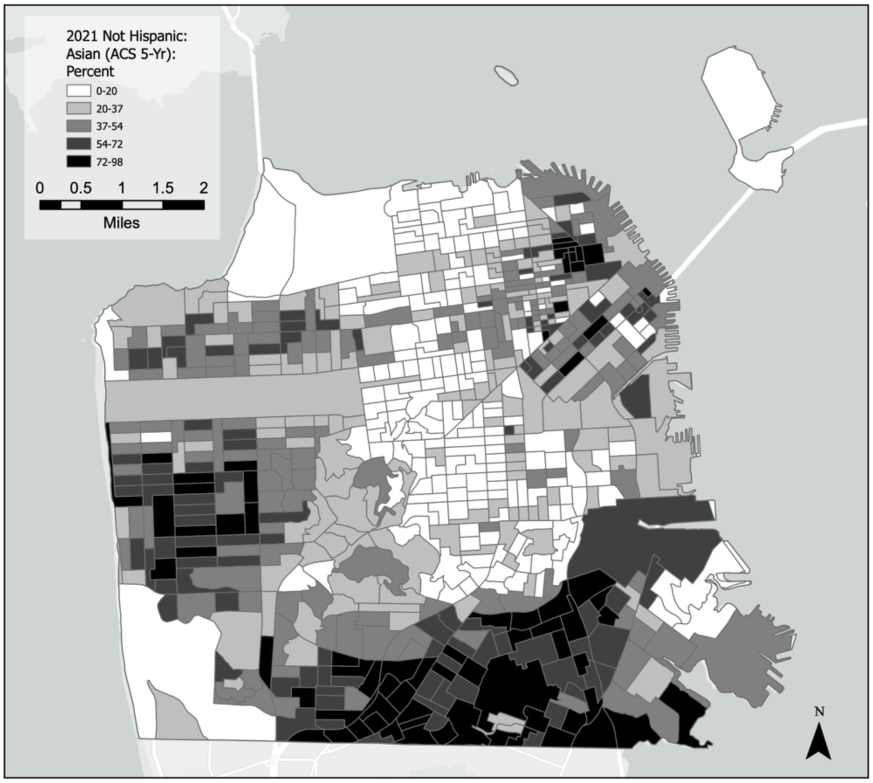
Variable	Studies Used In
Percent non-White	Heckert & Rosan, 2016; Tate, 2013; EPA EJ Index; CDC Social Vulnerability Index; Rygel et al., 2006; Flanagan et al., 2011; Emrich, 2005; Tustin 2022; Cutter et al, 2003; Nicholls, 2001; Bhuyan et al., 2019; Prelog, 2015; Ursaki & Aultman-Hall, 2016; Braun et al., 2021; Braun et al., 2019
Median income	Heckert & Rosan, 2016; Tate, 2013; Flanagan et al., 2011; Emrich, 2005; Tustin 2022; Cutter et al., 2003; Nicholls, 2001; Ursaki & Aultman-Hall, 2016; Winters et al., 2018; Hosford & Winters, 2018; Braun et al., 2021; Braun et al., 2019
Elderly population	Heckert & Rosan, 2016; Tate, 2013; Flanagan et al., 2011; CDC Social Vulnerability Index; Emrich, 2005; EPA EJ Index; Tustin 2022; Rygel et al., 2006; Cutter et al, 2003; Nicholls, 2001; Bhuyan et al., 2019; Prelog, 2015; Ursaki & Aultman-Hall, 2016;
Children	Heckert & Rosan, 2016; Tate, 2013; EPA EJ Index; CDC Social Vulnerability Index; Rygel et al., 2006; Flanagan et al., 2011; Emrich, 2005; Cutter et al, 2003; Nicholls, 2001; Bhuyan et al., 2019; Prelog, 2015
Zero-car households	Tate, 2013; Flanagan et al., 2011; CDC Social Vulnerability Index; Tustin 2022; Bhuyan et al., 2019; Prelog, 2015; Braun et al., 2021;
Households below poverty line	Tate, 2013; CDC Social Vulnerability Index; Emrich, 2005; EPA EJ Index; Rygel et al., 2006; Bhuyan et al., 2019; Prelog, 2015; Braun et al., 2021; Braun et al., 2019
Pollution burden	Heckert & Rosan, 2016; Emrich, 2005; EPA EJ Index; Braun et al., 2021
Crashes	Tustin 2022; Braun et al., 2021

Maps

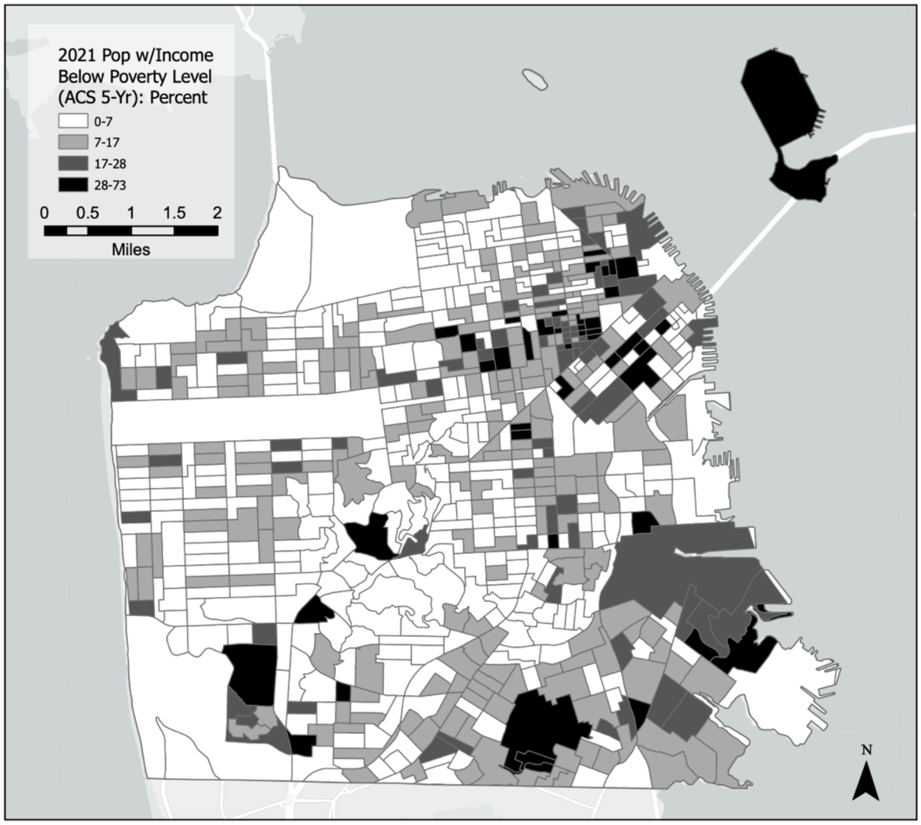
Overlay Variable Maps

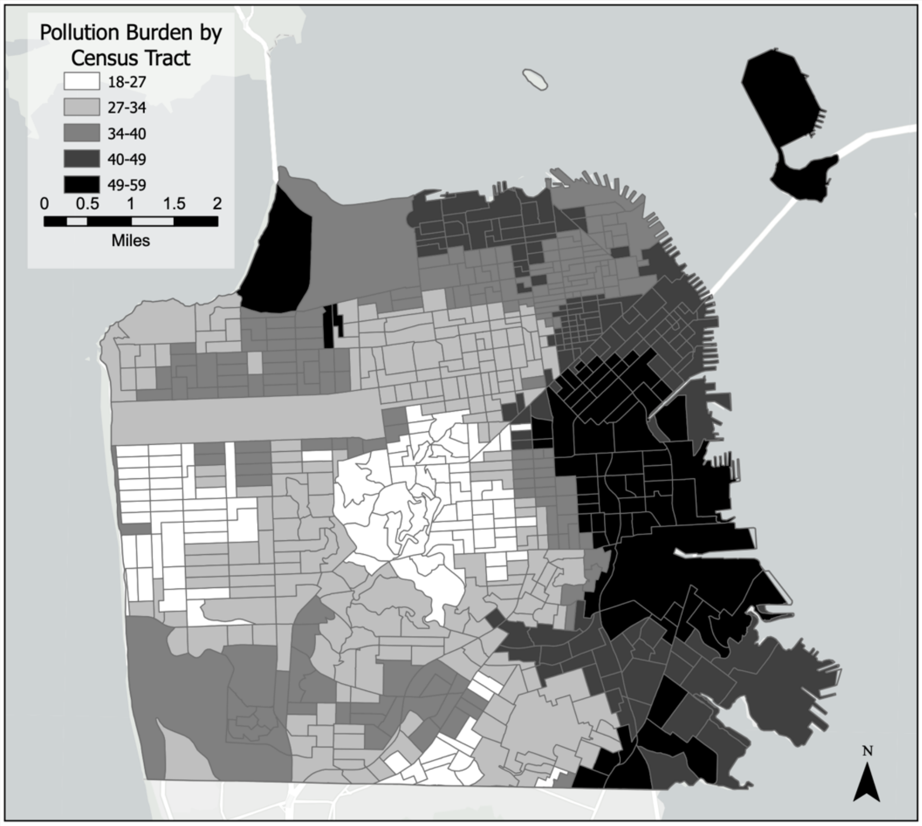


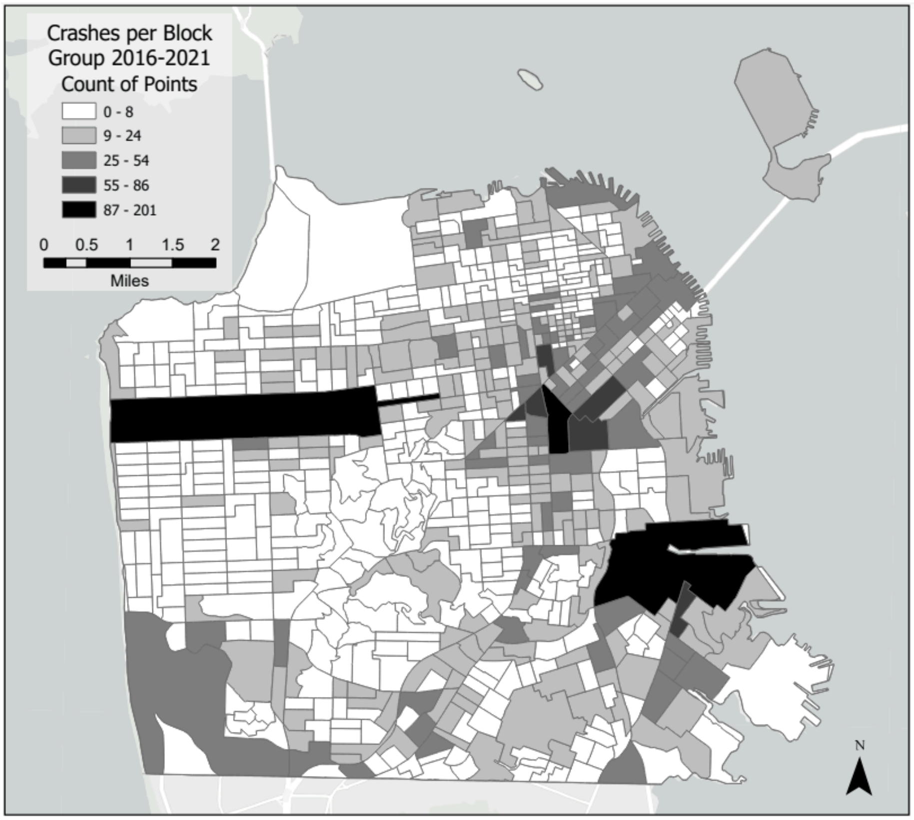


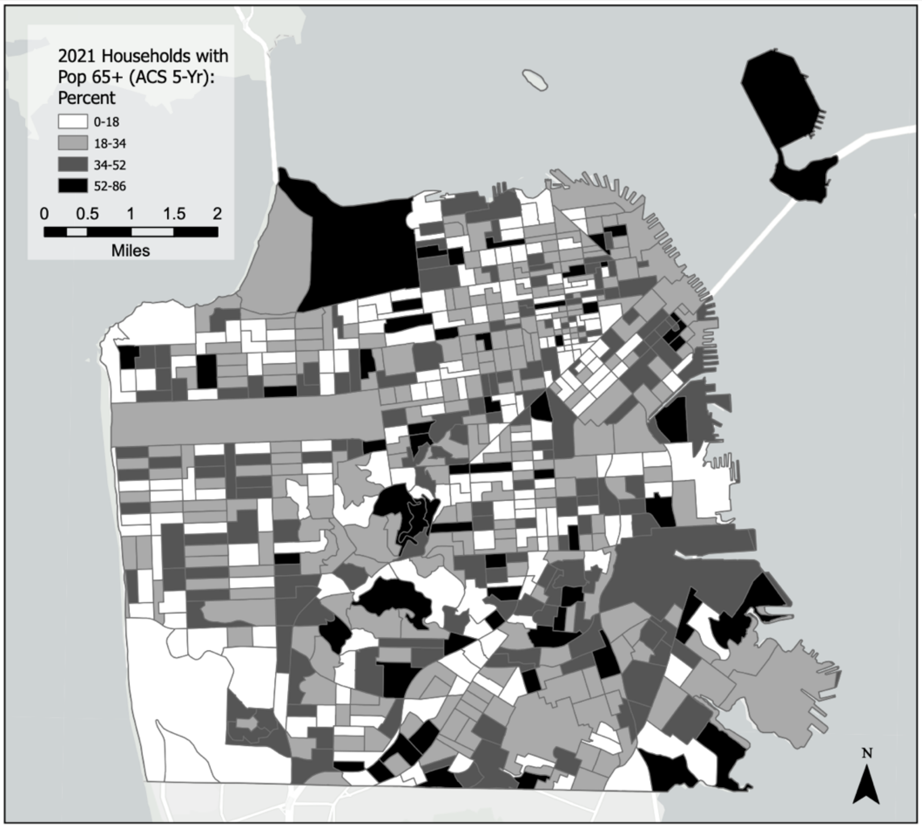

2021 Not Hispanic: Asian (ACS 5-Yr): Percent
0-20
20-37
37-54
54-72
72-98
0
0.5
1
1.5
2
Miles
N

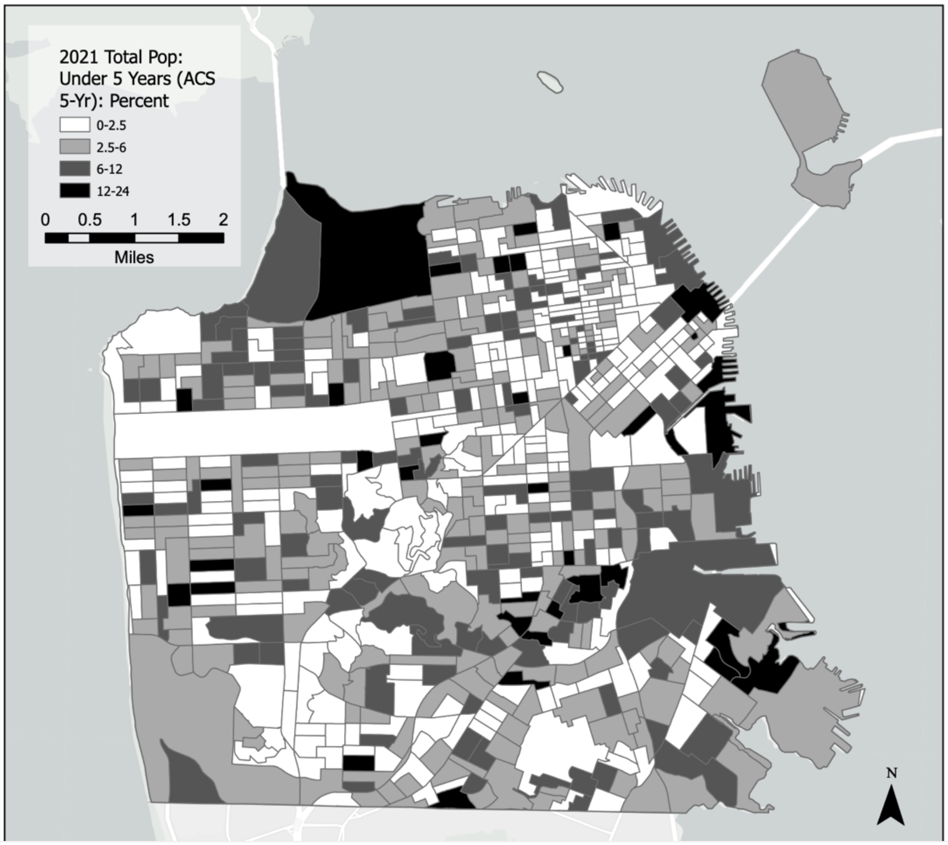

2021 Not Hispanic: White (ACS 5-Yr): Percent
0-21
21-40
40-57
57-73
73-98
0
0.5
1
1.5
2
Miles
N

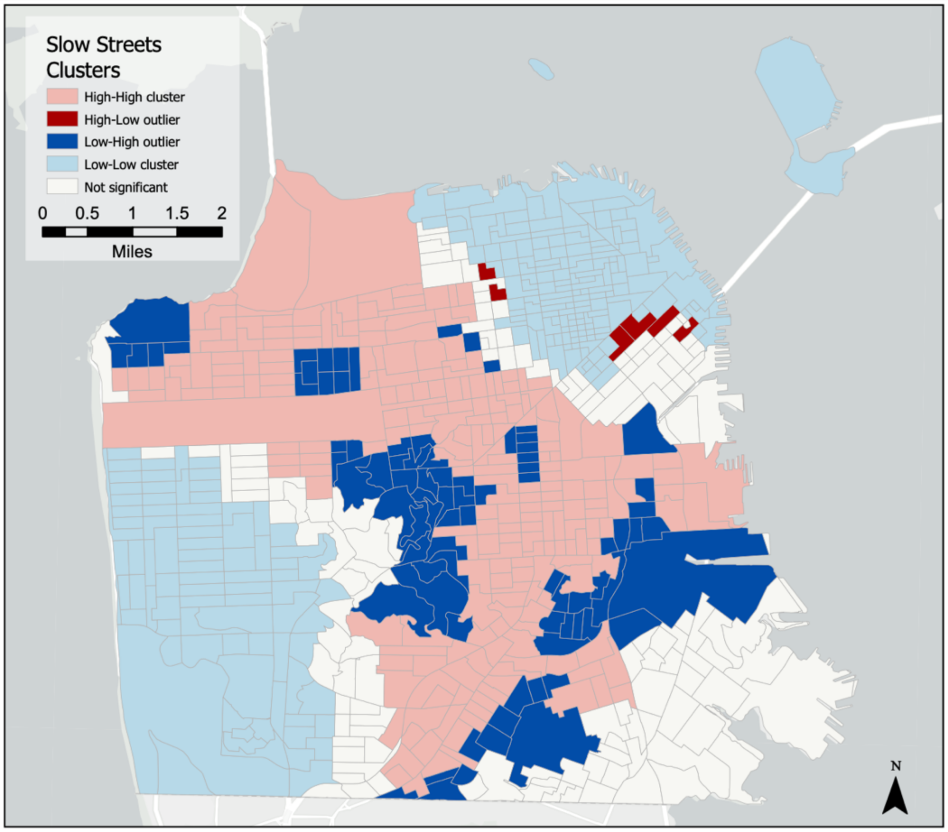

2021 Pop w/Income Below Poverty Level (ACS 5-Yr): Percent
0-7
7-17
17-28
28-73
0
0.5
1
1.5
2
Miles
N


Pollution Burden by Census Tract
18-27
27-34
34-40
40-49
49-59
0
0.5
1
1.5
2
Miles
N


Crashes per Block Group 2016-2021 Count of Points
0 - 8
9 - 24
25 - 54
55 - 86
87 - 201
0 0.5 1 1.5 2
Miles
N


2021 Households with Pop 65+ (ACS 5-Yr): Percent
0-18
18-34
34-52
52-86
0 0.5 1 1.5 2
Miles
N


2021 Total Pop: Under 5 Years (ACS 5-Yr): Percent
0-2.5
2.5-6
6-12
12-24
0
0.5
1
1.5
2
Miles
N


Slow Streets Clusters
High-High cluster
High-Low outlier
Low-High outlier
Low-Low cluster
Not significant
0
0.5
1
1.5
2
Miles
N