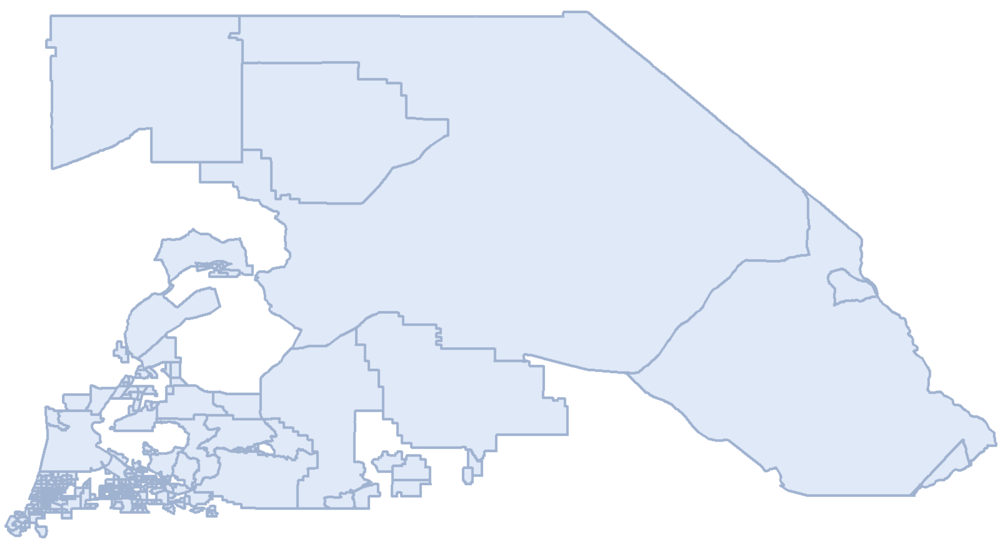
San Bernardino Council of Governments (SBCOG)

Regional Equity Study



San Bernardino County Census Tracts

Analysis Prepared by the Center for Social Innovation at the University of California, Riverside

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Executive Summary

Mapping is essential for understanding equity — the ways in which it manifests, and how it informs the way individuals and communities experience the world. The maps presented in the report show us the current landscape, with context provided by what happened in the past, using data that will ultimately inform and guide decisions for the future.

The San Bernardino Council of Governments (SBCOG), commissioned a region-wide study as the starting point for determining communities within jurisdictions that are affected by inequities. By drilling down to the Census tract level and identifying disadvantaged communities demographically, geospatially, and via varying types of investments, SBCOG can better understand challenges faced by specific disadvantaged communities. The intent is for this information to help SBCOG and its related policymakers to have a clearer understanding of existing conditions and what available data indicates, toward recommendations and options to address various challenges.

The intent of this analysis is to identify barriers to equity within the built environment faced by disadvantaged communities, from both a county-wide as well as at the sub-regional level. To do this, we used a modification of the SB1000 three-method cut to identify tracts which met certain criteria. Method 1 focuses on the environmental burden in San Bernardino County, Method 2 focuses on household income level combined with an environmental burden/environmental justice aspect, and Method 3 looks into various aspects in detail, combining regression analysis and spatial analysis. In San Bernardino County by tract level, we study economic mobility, commuting time to work, life expectancy, warehouse proximity, health factors, food desert proximity, and residential demographics, among others. Based on this approach, we isolate disadvantaged communities in San Bernardino County for individually by method, and also via combined approaches (i.e., Method 1 & 2, and then Method 1, 2 & 3)

Regression analysis provides six key indicators: household income, life expectancy, California environmental score, asthma rate, poverty rate, linguistic isolation, and education attainment related to the housing burden. Childhood poverty and income mobility show the univariate correlation across zip code areas in San Bernardino between upward income mobility and measures of social capital constructed. Economic connectedness is strongly positively correlated with income mobility, and the correlation is 0.66. In addition, we used spatial analysis and explored several possibilities regarding the residential environment, network access, catchment areas, and proximity based on land use designations.

We hope that the maps and data included in this report can efficiently and effectively inform SBCOG and aid in important decision making, ultimately leading to a more equitable landscape for communities in our region. While there are limitations to this data and the data that is currently available, we believe these maps help to lay out an important starting point which will help guide discussions on policy interventions. As more data is collected and mapping technology becomes more sophisticated, mapping equity in the region will become increasingly salient. Future research should build on and continue this important endeavor for our region. As San Bernardino County continues to grow and become increasingly diverse, these mapping tools will become more important and a central tool for decision makers in the region.

Introduction

Background & Study Rationale

The idea of “disadvantage” has multiple dimensions. On the one hand, it is often thought of as a lack of access to things like capital and opportunities that more prosperous and successful groups have. But it can also be extended to mean things like undue burden, who bears the brunt of negative externalities of certain policy decisions, and the impacts of a broader social, historical, and structural context, among others.

Within the environmental and environmental justice literature, the focus tends to be on disproportionate burdens and exposure to harmful environmental conditions, or environmentally-related (and by extension health-related) byproducts of policy and often specifically economic decisions. On the other hand, much of the socio-economic status approach examines aspects such as education, poverty, unemployment, access to “good jobs”, upward mobility, food access and security, and access to other basic services.

Municipalities, similarly, have identified varying definitions of what constitutes “disadvantage”, ranging from specifically looking at it through an environmental justice lens, to more of a focus on economic opportunity, though more often than not the language generically referred to identifying disadvantage without defining it.

Within the context of this project, UCR was tasked with embarking on a region-wide study of San Bernardino County to identify communities (identified at the tract level) affected by inequities. The intent was to better understand the specific challenges faced by varying communities, including variations in disadvantage (if any), and help inform SBCOG and other regional policymakers about the current status of various challenges. In order for all San Bernardino County residents to have the opportunity to achieve their full potential and for all San Bernardino County communities to thrive and prosper, it is critical to address imbalances and disparities. In general, disadvantaged communities refers to areas that suffer most from a combination of health, environmental, and economic burdens, which can manifest themselves as high poverty rates, high unemployment rates, and high incidences of asthma and heart disease. As California’s Environmental Protection Agency has created an analytical tool, CalEnviroScreen, to help identify disadvantaged communities at the tract level, this was largely used to form the baseline cuts of the available data.

Study Context

As part of the discovery phase of this project, UCR explored several different approaches to start to identify specific variables of interest in identifying disadvantaged communities, and understanding the characteristics of the disadvantage.

Outside of the typical variables associated with disadvantage - e.g., poverty, unemployment, household income, low educational attainment, among others - we wanted to get a more nuanced understanding of the existing barriers - structural, historical, physical - that communities faced. As part of this analysis, we identified several variables to include in addition to the CalEnviroScreen 4.0 dataset used as the baseline initial cutoff for the SB1000 methods (explained in more detail below):

- *Childhood poverty*: related to intergenerational mobility, and overall mobility; studies have shown that it is increasingly difficult to escape poverty at all stages of life, but particularly when a child grows up in poverty.[1] Research by Chetty et al. (2014) has shown that the ability of children to do better than their parents/prior generations has declined over the past few decades in the US.[2] Additionally, recent research by Chetty et al. (2022) has found that one way to increase childhood mobility is to attend schools where there is a mix of incomes.[3] While the ability to analyze school enrollment location choice is beyond the scope of this project, we felt it was important to highlight the potential impact of external socio-economic forces on childhood circumstances into adulthood outcomes.
- *Food access*: related to housing cost burden; impact of unemployment, income, basic needs expenses. Kirkpatrick and Tarasuk (2011) highlight the impact of housing costs on food costs, as they find that families tend to view housing costs as set, whereas food costs are viewed as more variable[4]
- *Proximity to industrial land uses*: Environmental justice-oriented research has highlighted the impact of proximity of industrial land uses to residential areas.[5]
- *Proximity to high throughput roads*: public health research has found that proximity to high throughput roads has increased likelihood of adverse health outcomes[6]
- *Housing cost burden, availability of a range of housing stock options*: emphasis on single family homes can create undue housing cost burden for low-income families or those who have smaller household sizes; HUD typically defines housing as costing no more than 30% of income, but the tight housing market in California generally, and Southern California in particular, has created a situation where the lowest earners end up spending a disproportionate amount of their income on housing, leaving less money for other necessities such as food and transportation. Research has highlighted the impact

[1] https://www.jstor.org/stable/2657556#metadata_info_tab_contents
[2] https://academic.oup.com/qje/article/129/4/1553/1853754
[3] https://www.nature.com/articles/s41586-022-04996-4
[4] https://link.springer.com/article/10.1007/s11524-010-9535-4
[5] https://ajph.aphapublications.org/doi/full/10.2105/AJPH.2011.300183
[6] https://ehp.niehs.nih.gov/doi/pdf/10.1289/ehp.6566

of housing on physical and mental health,[7] indicating the policy has a major role to play in addressing housing burden toward improving overall health and well-being[8]

- *Social determinants of health factors*: there is increasing and mounting evidence that both social and environmental factors impact overall health and well-being.[9] This can take a variety of forms, but in the context of this study, we chose to include it as a way to acknowledge that there are more impacts due to disadvantages than the typical set of physical and mental health variables.

Methodology

We took several things into consideration when exploring the different ways that we could both identify disadvantaged communities, but also create a dataset that would be usable for policymakers.

First, we used the SB1000 approach as a baseline (see Figure 1), but due to the desire to broaden the scope beyond the specific environmental focus of SB1000, opted to utilize the Method 1 and 2 cuts, and then create a series of Method 3 cuts to create different outcome datasets and visualizations. Part of the motivation was that by creating one single dataset, which would effectively end up acting like an index measure, we felt that we would inevitably lose a fair amount of nuance. Index measures are very helpful in taking a lot of information and packaging it all in a way that helps the reader quickly understand what the main takeaway is, but the sacrifice is that certain variables end up getting less attention than they may otherwise get by creating several variable cuts.

A note: while we viewed the SB1000 method cuts as a cumulative approach, we also felt that it was important to create the cuts as standalone datasets. Meaning, we wanted to make sure that we were able to capture dynamics that appeared outside of the tracts selected through the Method 1, and then Method 2 process. For instance, because the Method 1 cut is purely based on California Environmental score and Method 2 cut is based on an income threshold plus an environmental threshold cut (PM2.5 and diesel[10]), there are likely areas that are not flagged by the Method 1 cut that may have a high percentage of linguistic isolation, and it is also possible that there are areas not captured by a Method 1 cut that have a high housing cost burden. Because the policymakers that are the intended audience of this dataset may not all cover areas flagged by either a Method 1, Method 2, or cumulative Method 1 & 2 cut, we wanted to make sure that they would still be able to understand what the data says about the geographic areas they represent. Additionally, because the Method 3 cut included built environment/spatial

[7] https://www.annualreviews.org/doi/pdf/10.1146/annurev.publhealth.25.101802.123036
[8] https://www.sciencedirect.com/science/article/pii/S0140673608616906
[9] https://journals.sagepub.com/doi/abs/10.1177/002214650404500303 & https://ajph.aphapublications.org/doi/full/10.2105/AJPH.2014.302200
[10] Note that SB1000 doesn't require the environmental indicators used to be specifically PM2.3 and diesel these were selected as representative for this particular analysis, but other environmental factors are equally useful and appropriate for this type of analysis.

aspects, we wanted to make sure that the data was also not limited to the areas identified through the Method 1, Method 2, and Methods 1 & 2 cuts, particularly because while some spatial aspects do align with socio-economic trends and also environmental aspects, due to the way aspects such as physical infrastructure are implemented they may not exactly correlate the same way (e.g., an area may have had sidewalks for many years, prior to neighborhood and land use change).

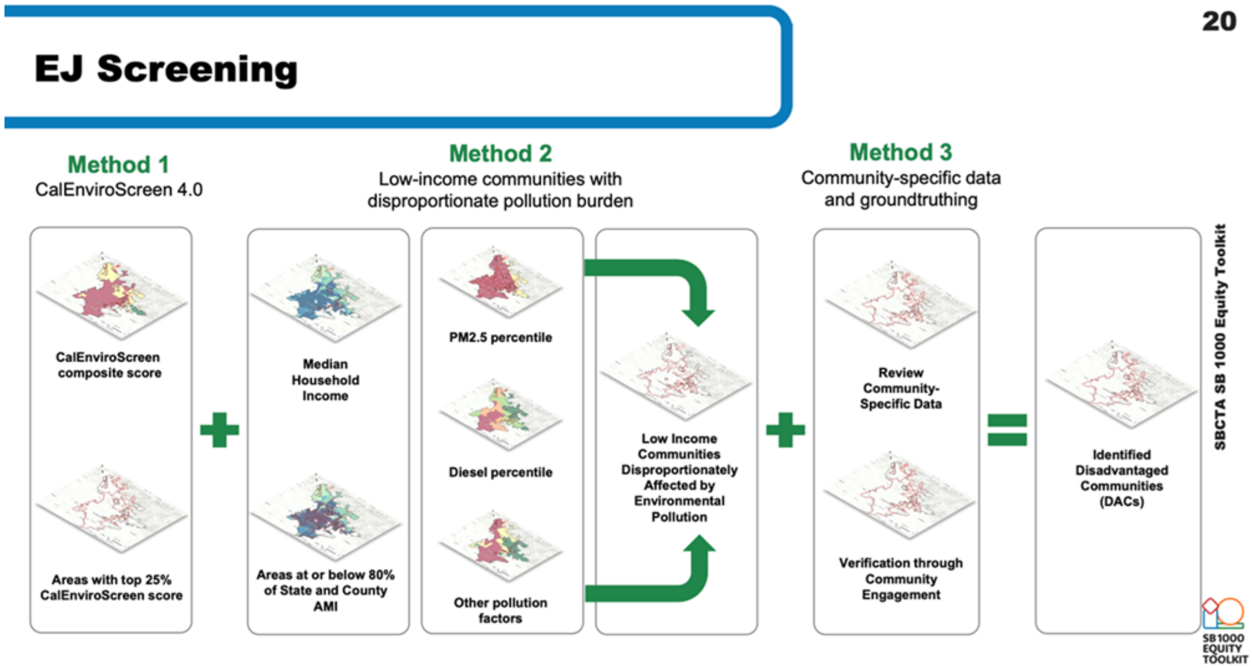
In addition, we use regression analysis and build a correlation matrix in Method 3 to better understand indicators' performance. The dendrogram (tree-like structure) links the correlation between variables, such as housing cost burden, food deserts, linguistic isolation, child poverty, low education, life expectancy, health issues, and commuting to work, and clusters high correlation variables. We have an overview of how these variables impact at the tract level in San Bernardino. However, an equity analysis has multiple aspects and is very complicated, particularly when addressing the spatial component, making it difficult to create an accurate cut that could be used as a “standard” Method 3. Based on the regression analysis, we select six indicators, such as poverty, education, commuting time to work, asthma, and life expectancy variables which have more impact on housing burden cost and health factors. In particular, the regression analysis was done on housing cost burden as housing cost is an increasing issue in the area, is a physical investment by the region, but is also related to non-physical aspects like impact on amount of income left for non-housing expenditures.

Another issue that came up was that many environmental disparities end up manifesting themselves into health disparities, but that health disparities are often narrowly defined into typical physical outcomes. We wanted to broaden the scope along the lines of the social determinants of health literature, which expands the typical definition of health outcomes to include the influence of forces such as economic, social, and physical surroundings.

We chose to adopt a modification of the SB1000 Equity Toolkit approach, in that we utilize the standard Method 1 (see image below) and Method 2 approach, and then employed a regression analysis of several variables, including some variables taken from SCAG’s PEPA approach.

Final note: as this is a data project, CSI created all figures used in this report using publicly available datasets, except where specifically indicated.

Figure 1: SB1000 Methods 1, 2, & 3

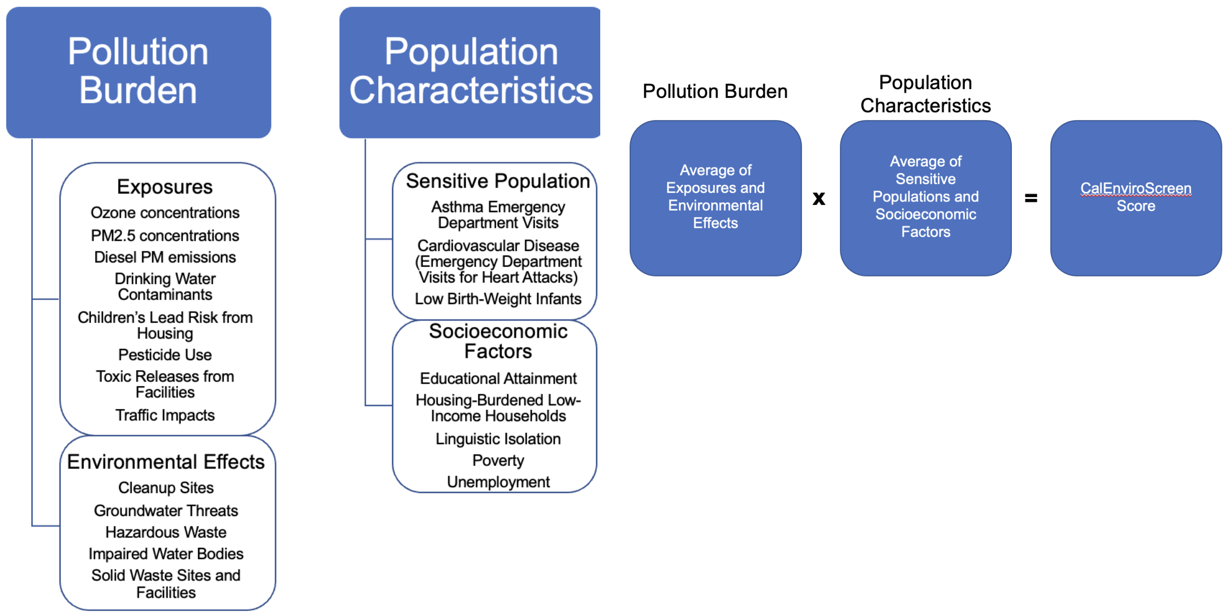


Source: SCAG presentation, SB1000 equity toolkit

Method 1

The Method 1 cut utilized the CalEnviroScreen 4.0 dataset, and isolated tracts with the top 25% score. Method 1 identified 131 tracts (34.5% of total).

Figure 2. CalEnviroScreen 4.0 Calculation

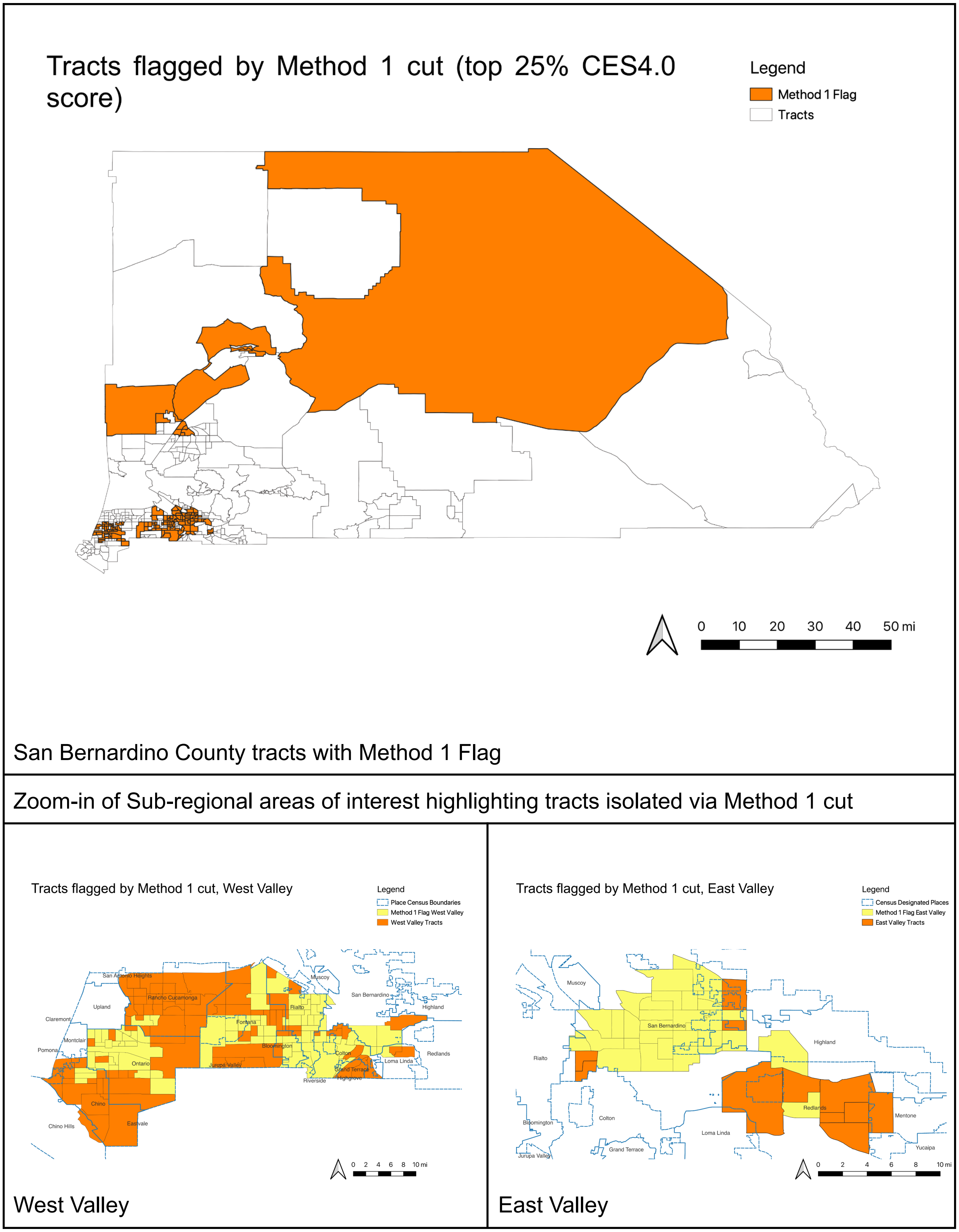


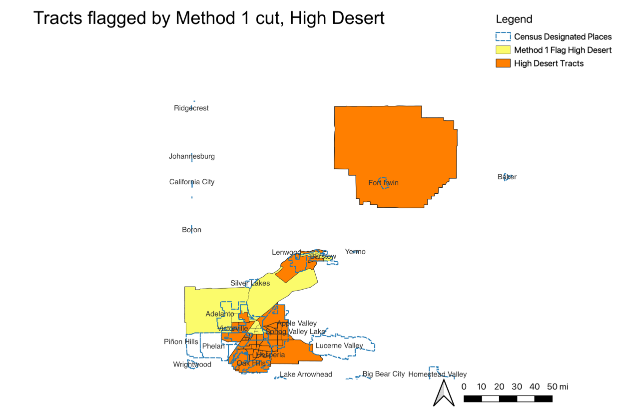
To get the CalEnviroScreen score we multiply the Pollution Burden score by the Population Characteristics Score.

Source: CalEnviroScreen 4.0 documentation

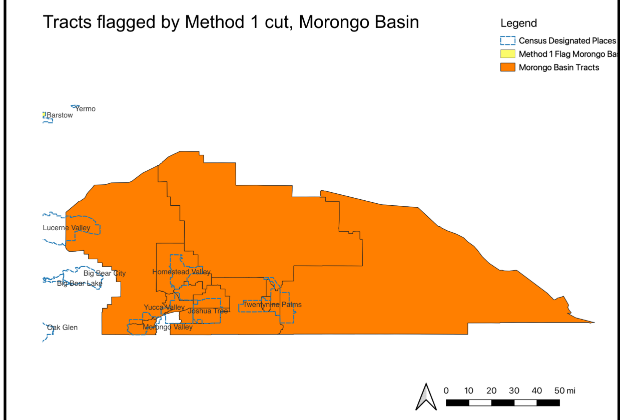
A higher CalEnviroScreen 4.0 score means a higher pollution burden. We isolated the top 25% score to determine which areas are heavily burdened at the tract level in San Bernardino County.

Figure 3. Geographic breakdown of San Bernardino County by Method 1 flags and regional areas of interest





High Desert

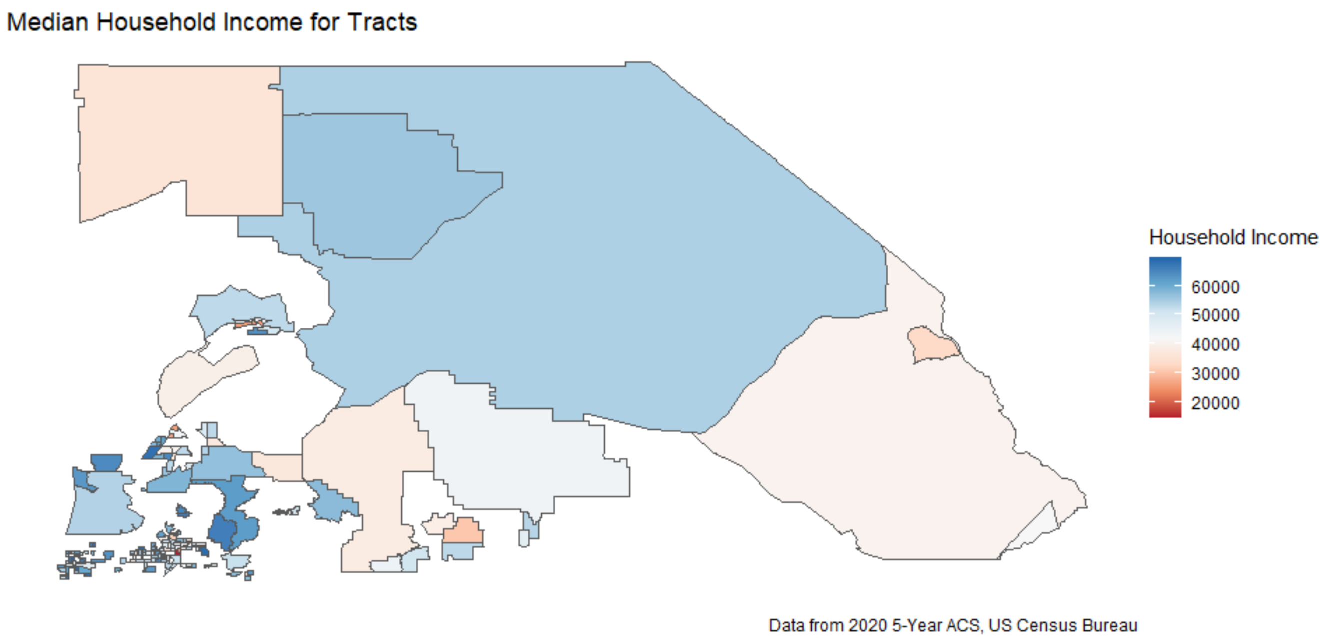


Morongo Basin

Method 2

Method 2 isolated tracts where the countywide area median household income (AMI) level is below 80%, and further isolated those tracts that had greater than 75% exposure to PM2.5 and also greater than 75% exposure to diesel particulate matter. The San Bernardino AMI is $61,200 for 1 person, $69,900 for 2 persons, $78,650 for three persons, and $87,400 for a 4 person household. We use a baseline of a 4 member household for the Method 2 AMI threshold cutoff.

Figure 4. Median household income level below 80%



https://drive.google.com/drive/folders/1K7DHvQpM-2eU-wh8-ZegFBodtGEewu5d

The median household income in the northwest and southeast parts, such as Searles Valley, Twentynine Palms-Yucca Valley, and Needles in San Bernardino, has lower income levels, around $35,000.[11] The median household income level in the southwest part, such as Ontario and Mount Baldy-Wrightwood, has a higher income level above $60,000. We isolated 174 (45.9%) tract areas for Method 2, in which the Median Household Income level below 80%. We isolated 63 (16.62%) tract areas where the median household income level is below 80% and

[11] https://statisticalatlas.com/county/California/San-Bernardino-County/Household-Income

PM2.5 is above 75%. We isolated 49 (12.93%) tract areas for median household income level below 80% and diesel above 75%.

Figure 5. Method 2 Median household income level below 80% and PM2.5 above 75%

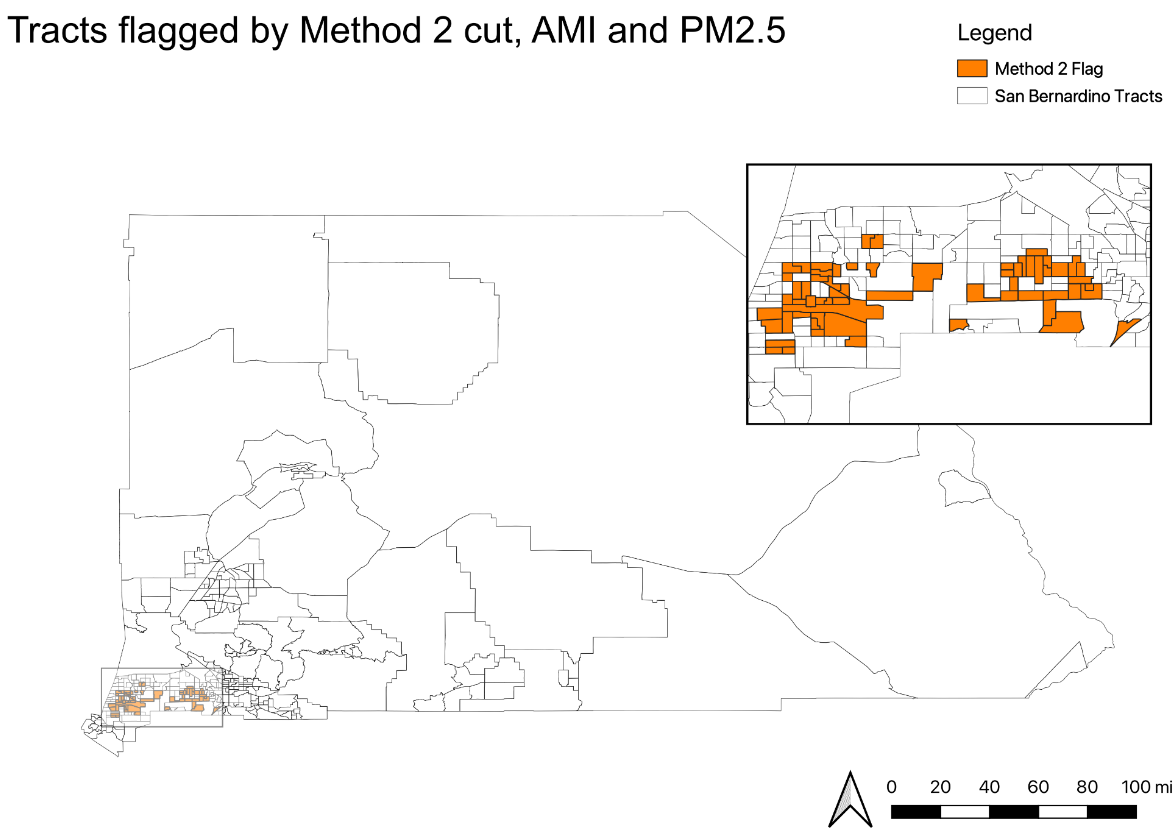
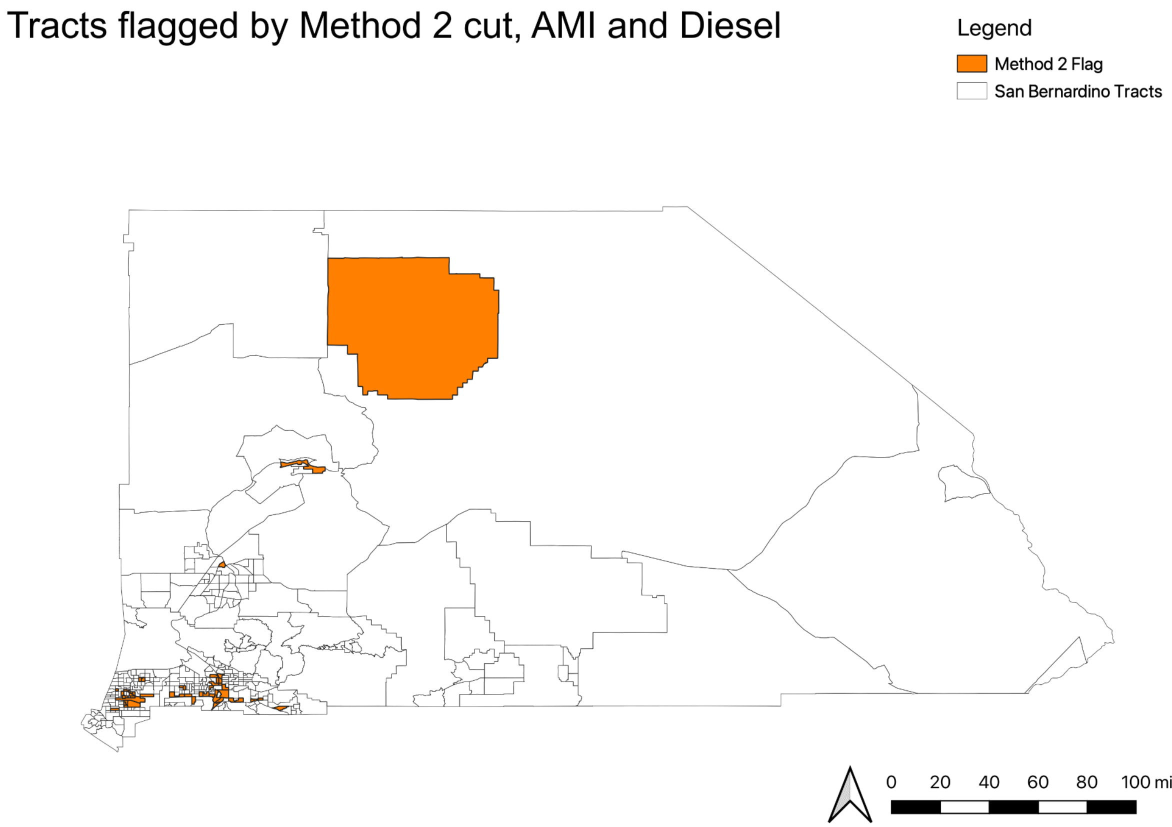


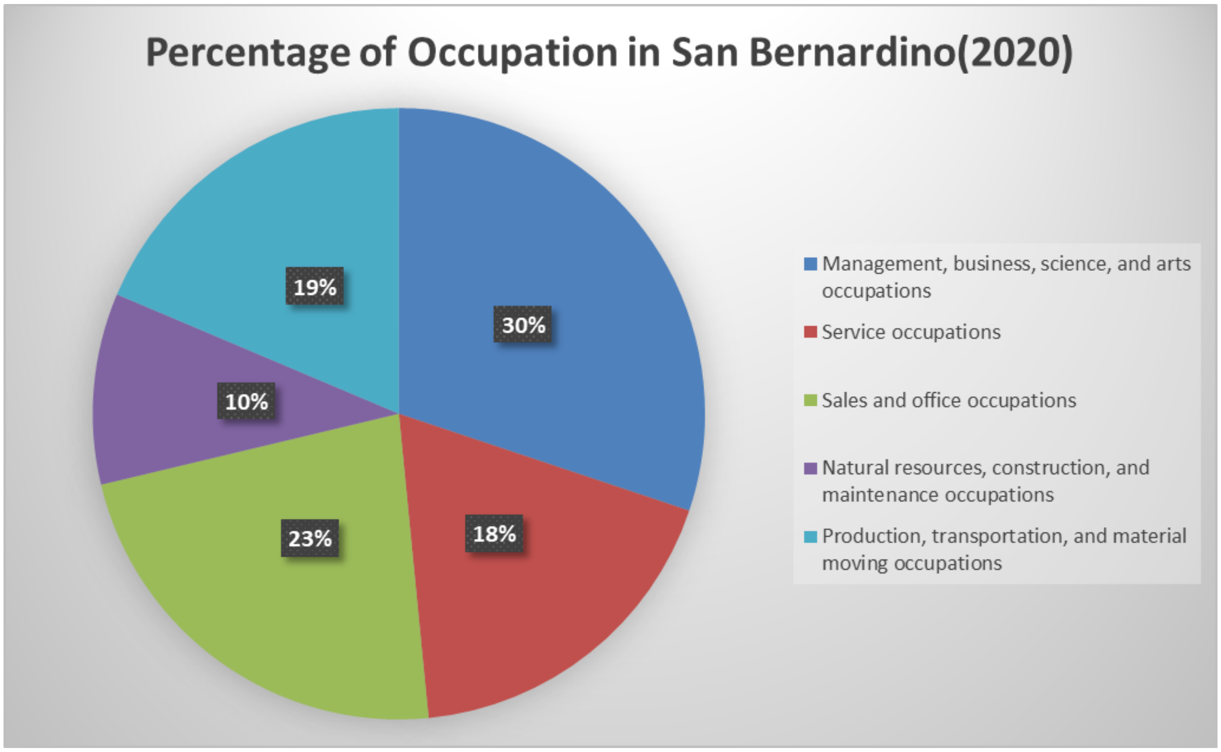
Figure 6. Method 2 Median household income level below 80% and Diesel above 75%



Data Link: https://drive.google.com/drive/folders/1u3FbY6GYVHrcfS1oJJY6X_V3yC1oTCfH
Method2_cut.csv

Occupation

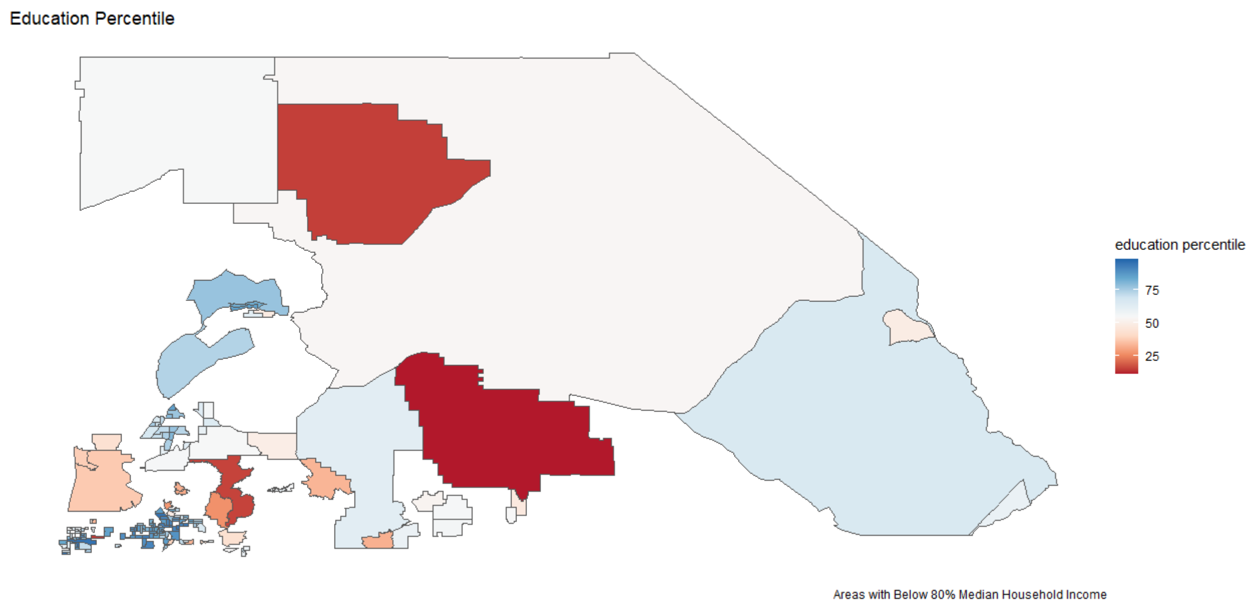
Figure 7. Percentage breakdown by occupation, 2020



In San Bernardino, management, business, science, and arts occupations have the highest percentage at 30%. The second highest category is sales and office occupations at 23%. The last one is natural resources, construction, and maintenance occupations at 10%.

Education percentile

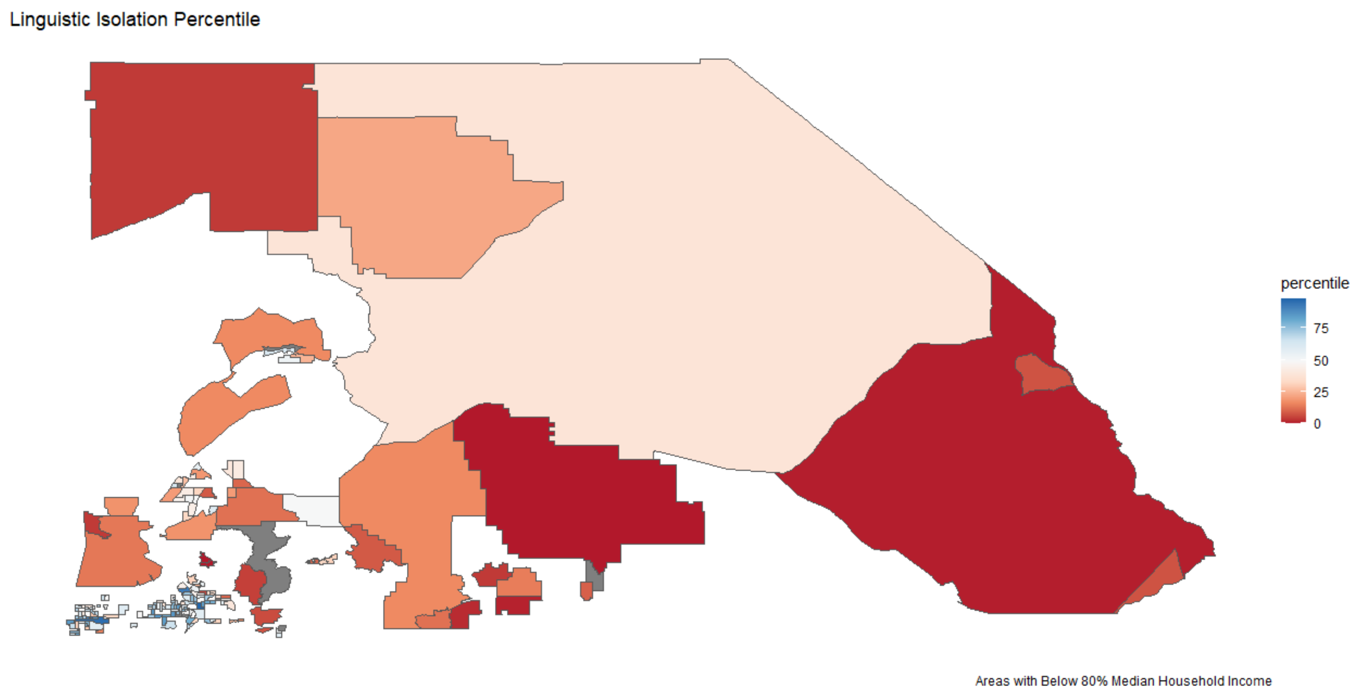
Figure 8. AMI below 80% and Educational attainment percentile - over 25 and less than a high school diploma



The education percentile plot shows the distribution of the percent of the population over 25 with less than a high school education.

Linguistic isolation

Figure 9. AMI below 80% and Linguistic Isolation



Linguistic percentiles show percent of limited English-speaking households. The southwest region has percentages above 70%.

Method 1 & 2 - Intersect

While there is reason to keep the various methods separate to better understand the impact of the data threshold filters on the resultant identified areas, we want to run an intersection of where variables flagged in Method 1 overlapped with those of Method 2. The flagged areas represent the CES 4.0 Score with the top 25% and median household income level below 80%. As seen in the figure below, the areas are largely in the northeast corner of the county (the High Desert) and in the southwestern portion of the county.

Figure 10. Areas where flags for methods 1 & 2 intersect

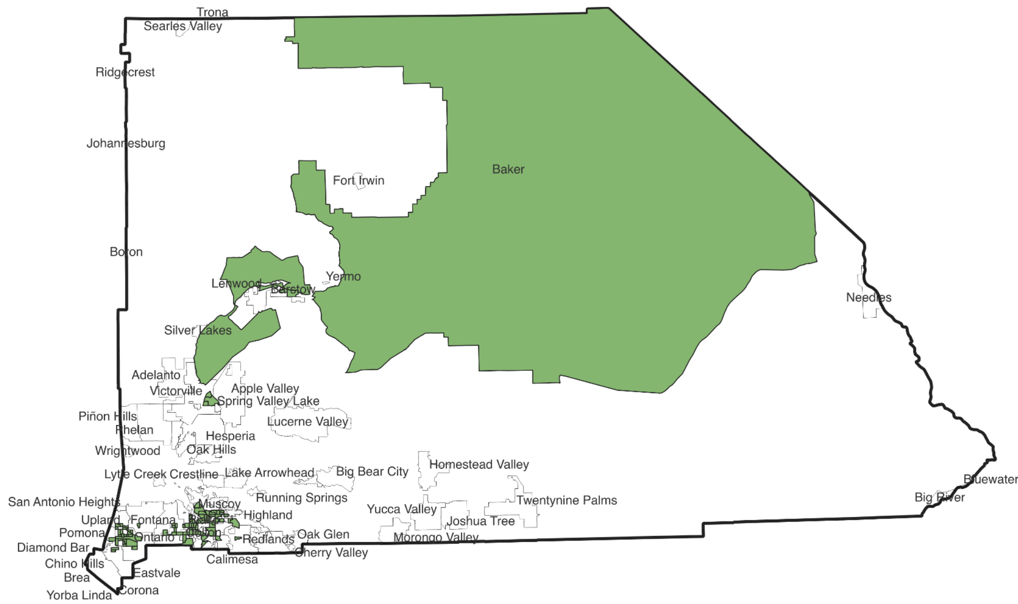
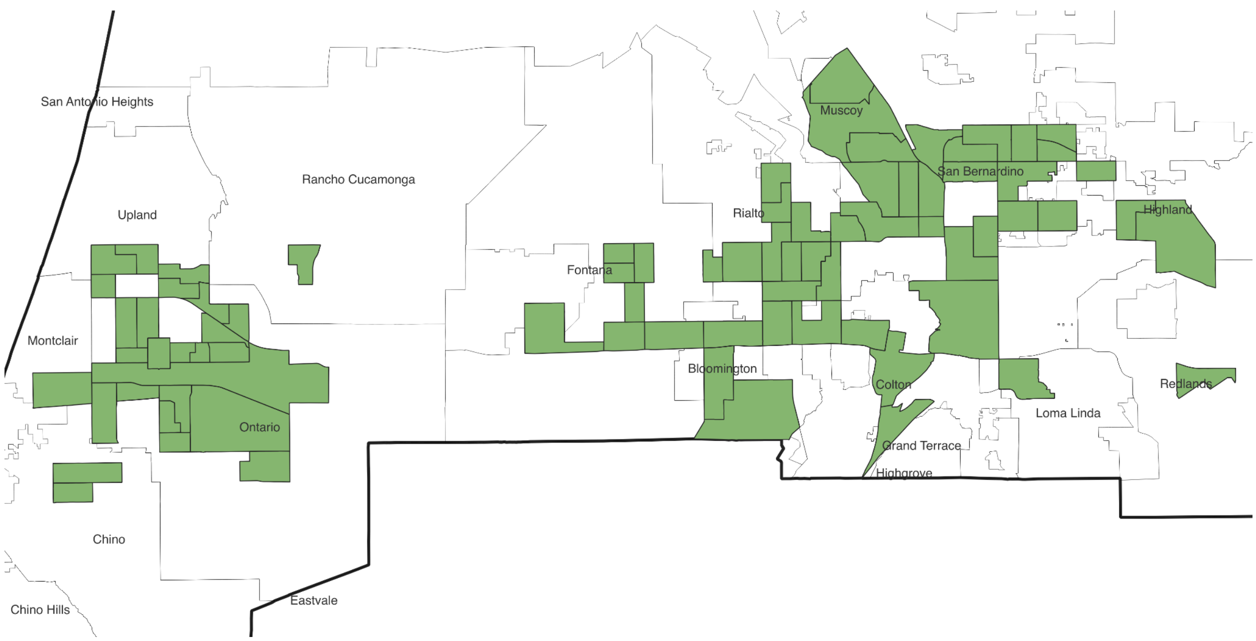


Figure 11. Areas flagged in the southwest corner of the county



The associated land use designations for these parcels ranged greatly, as seen in Table 1.

Table 1. Land uses associated with the tracts that were an overlap of Methods 1 and 2 cuts

Communication Facilities	Mixed Commercial and Industrial	Senior High Schools	Trade Schools and Professional Training Facilities	Pre-Schools/Day Care Centers
Duplexes, Triplexes and 2- or 3-Unit Condominiums and Townhouses	Older Strip Development	Regional Shopping Center	Fire Stations	Cropland and Improved Pasture Land
High Density Single Family Residential	Other Special Use Facilities	Trailer Parks and Mobile Home Courts, High-Density	Police and Sheriff Stations	Truck Terminals
Railroads	Electrical Power Facilities	Other Open Space and Recreation	Medium Density Single Family Residential	Correctional Facilities
Government Offices	Retail Centers	Commercial and Services	Non-Irrigated Cropland and Improved Pasture Land	Vacant Area
Elementary Schools	Low-Rise Apartments, Condominiums, and Townhouses	Mixed Transportation	Water Transfer Facilities	Natural Gas and Petroleum Facilities
Freeways and Major Roads	Mineral Extraction - Other Than Oil and Gas	Liquid Waste Disposal Facilities	Regional Parks and Recreation	Rural Residential High Density
Low Density Single Family Residential	Wholesaling and Warehousing	Water Storage Facilities	Solid Waste Disposal Facilities	Mineral Extraction - Oil and Gas
Manufacturing, Assembly, and Industrial Services	Water, Undifferentiated	High-Rise Major Office Use	Major Metal Processing	Mixed Transportation and Utility
Orchards and Vineyards	Under Construction	Mobile Home Courts and Subdivisions, Low-Density	Major Medical Health Care Facilities	
Urban Vacant	Mixed Residential	Irrigated Cropland and Improved Pasture Land	Base (Built-up Area)	
Open Storage	Colleges and	Horse Ranches	Unknown	

	Universities		
Improved Flood Waterways and Structures	Nurseries	Special Use Facilities	Rural Residential Low Density
Local Parks and Recreation	Commercial Recreation	Junior or Intermediate High Schools	Rural Residential
Low- and Medium-Rise Major Office Use	Golf Courses	Cemeteries	Dairy, Intensive Livestock, and Associated Facilities
Other Public Facilities	Commercial Storage	Light Industrial	Poultry Operations
Retail Strip Development	Vacant Undifferentiated	Maintenance Yards	Airports
Religious Facilities	Hotels and Motels	Mixed Multi-Family Residential	Abandoned Orchards and Vineyards
Public Parking Facilities	Other Agriculture	Vacant With Limited Improvements	Industrial
Manufacturing	Medium-Rise Apartments and Condominiums	Bus Terminals and Yards	Mixed Residential and Commercial

Source: SBCOG land use file

Method 3

Regression analysis

Regression analysis is a basic approach in which researchers study the values of several independent variables to predict or describe the values of outcome. A few models that were considered include:

Decision Tree Regression
The decision tree model breaks down a data set into subsets by splitting results into a tree with decision and leaf nodes. The main idea is to plot a value for any new data point connecting the problem. The parameters and algorithm determine the kind of way in which the split is conducted, and the split is stopped when the minimal number of information to be added reaches. Decision trees often yield good results, but even if any slight change in data occurs, the whole structure changes, making the models unstable.

Quantile regression (semi-parametric method)
Quantile regression has two main advantages. One is that it makes no assumptions about the distribution of the variables we want to analyze. Another is that it tends to endure the influence of an outside option. A **quantile regression model was ultimately chosen as it analyzes the**

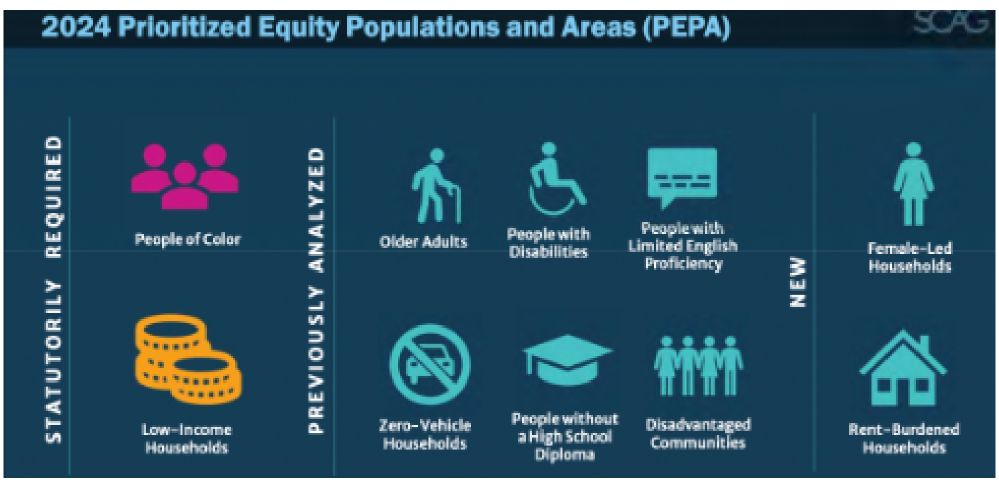
relationship between a set of independent variables and specific quantiles(median) of dependent variables.

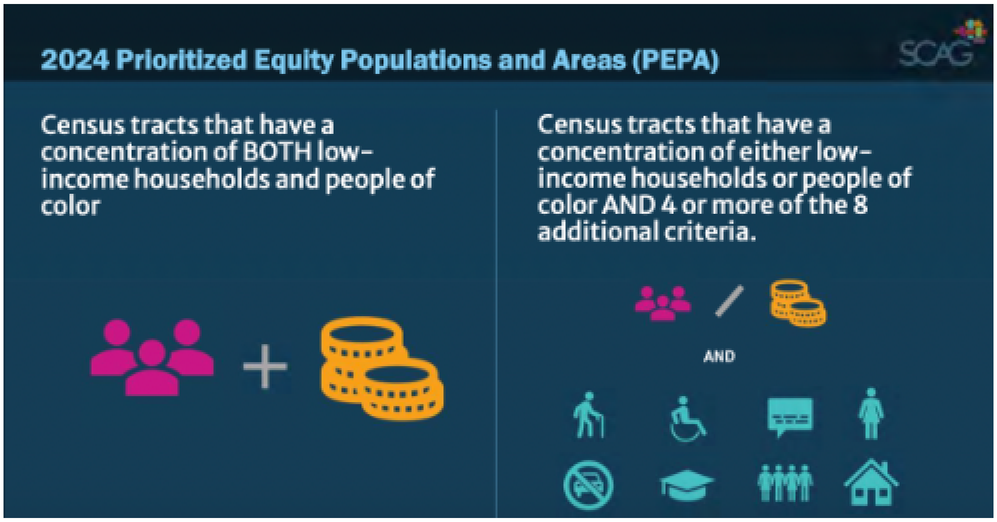
Quantile regression criteria:
The target variable needs to be continuous. The predictors can be continuous variables or dummy variables for categorical forecasters. Either the intercept term or predictor is required to run an analysis. When selected, this quantile regression setting assumes that error terms are independently and identically distributed. Quantile regression has limitations because the parameters are more complicated to estimate than Gaussian or generalized regression.

Method 3: Housing Cost Burden

Because housing burden accounts for a large portion of household expenses, we chose that as one measure to identify disadvantaged communities. The first regression table focuses on what factors have a strong impact on the housing burden variable. Housing burden is measured percent housing-burdened low-income households. We selected variables from CalEnviroScreen 4.0, 2020 ACS (5-year estimate) household income, life expectancy, and health outcome dataset.

Figure 12. SCAG Prioritized Equity Populations and Areas approach





Source: SCAG presentation

Based on SCAG's proposed 2024 Prioritized Equity Populations and Areas (PEPA) analysis, we include 15 variables that may affect the housing burden variable at tract level in San Bernardino. The 15 variables are total population, CalEnviroScreen 4.0 score, traffic (traffic density in vehicle-kilometers per hour per road length, within 150 meters of the census tract boundary), cleanup sites (sum of weighted EnviroStor cleanup sites within buffered distances to populated blocks of census tracts), asthma (age-adjusted rate of emergency department visits for asthma), low birth weight (percent low weight birth), education (percent of population over 25 with less than a high school education), linguistic isolation (percent limited English speaking households), poverty (percent of population living below two times the federal poverty level), unemployment (percent of population over the age of 16 that is unemployed and eligible for the labor force), population characteristic (average of percentiles from the population characteristics indicator), household income, mean travel time to work, and life expectancy.

Figure 13. Regression analysis

	housing burden		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	45.01	5.98 – 84.05	**0.026**
total population	0.00	-0.00 – 0.00	0.306
ces 4 0 score	0.25	0.08 – 0.41	**0.004**
traffic	-0.00	-0.01 – 0.00	0.148
cleanup sites	-0.10	-0.26 – 0.06	0.228
asthma	-0.07	-0.10 – -0.04	**<0.001**
low birth weight	-0.85	-1.97 – 0.26	0.136
education	-0.32	-0.51 – -0.14	**0.001**
linguistic isolation	0.27	0.03 – 0.50	**0.031**
poverty	0.09	-0.06 – 0.24	0.259
unemployment	-0.21	-0.56 – 0.14	0.251
pop char	0.27	0.06 – 0.47	**0.012**
householdincome	-0.00	-0.00 – 0.00	0.268
mean travel time	0.07	-0.09 – 0.24	0.364
life expectancy	-0.49	-0.96 – -0.02	**0.045**

Source: CSI

From the quantile regression table, we can find that the most critical factors related to housing burden variables are CalEnviroScreen.4.0. score, asthma, education, linguistic isolation, population characteristics, and life expectancy.

Ces.4.0.score: the coefficient estimate of 0.246 means that the 0.5 quantile of housing burden increases by about 0.246 for every one unit increase in ces.4.0.score. P-value is smaller than 0.05, and the coefficient is statistically significant at 95% confidence intervals.

Asthma: the coefficient estimate of -0.072 means that the 0.5 quantile of housing burden decreases by about 0.072 for every one unit increase in asthma. P-value is smaller than 0.05, and the coefficient is statistically significant at 95% confidence intervals.

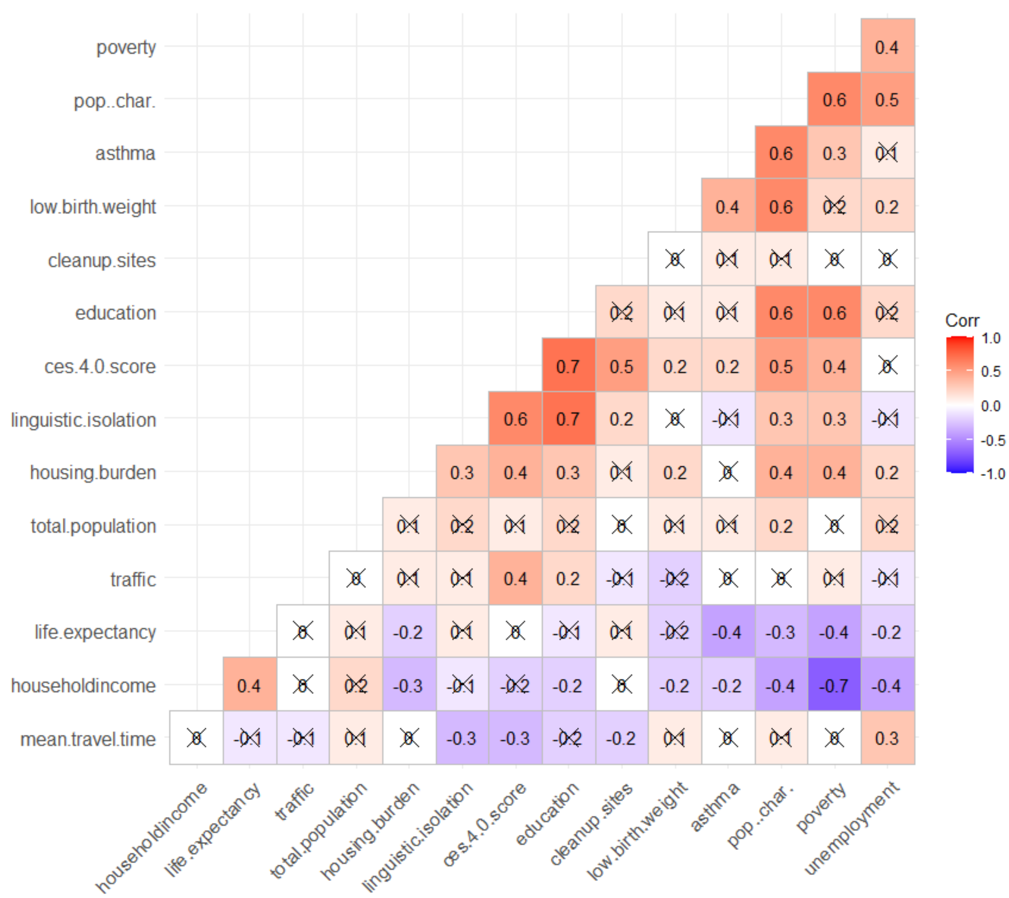
Education: the coefficient estimate of -0.324 means that the 0.5 quantile of housing burden decreases by about 0.324 for every one unit increase in education. P-value is smaller than 0.05, the coefficient is statistically significant at 95% confidence intervals.

Linguistic isolation: the coefficient estimate is 0.265 means that the 0.5 quantile of housing burden increases by about 0.265 for every one unit increase in linguistic isolation(percent limited English speaking households). P-value is smaller than 0.1, the coefficient is statistically significant at 0.1 level.

Population characteristics: the coefficient estimate is 0.266 means that the 0.5 quantile of housing burden increases by about 0.266 for every one unit increase in population characteristics. P-value is smaller than 0.1, the coefficient is statistically significant at 0.1 level.

Life Expectancy: the coefficient estimate is -0.489 means that the 0.5 quantile of housing burden decreases by about 0.489 for every one unit increase in life expectancy. P-value is smaller than 0.1, the coefficient is statistically significant at 0.1 level.

Figure 14. Correlation Heatmap Analysis



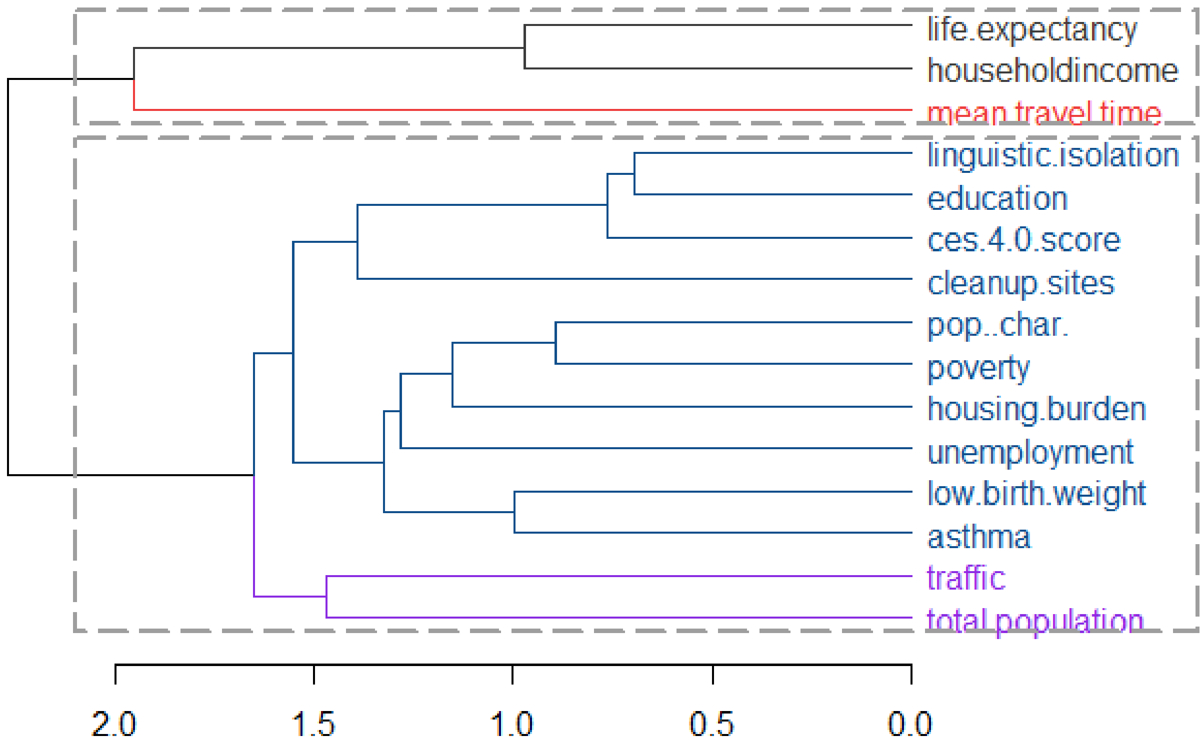
Source: CSI analysis of CalEnviroScreen 4.0 data and ACS 2020 5-year file

Correlation analysis studies how variables are related. Correlation analysis is helpful for testing relationships between categorical variables and continuous variables. Correlations are functional because if you detect what relationship variables have, you can make predictions about future behavior. Knowing the link between different variables and future behavior is critical in the social sciences, such as government policy, education, and healthcare.

A correlation coefficient measures the degree and puts a value to the relationship. Correlation coefficients have a value of between -1 and 1. The magnitude represents the strength of the correlation, and the sign indicates the direction of the correlation. A low degree of correlation close to 0 means no relationship between the variables. In contrast, a high degree of correlation closer to -1 or 1 indicates a perfect negative or positive correlation.

From the correlation matrix, we notice a high positive correlation between ces4.0 score, education, and linguistic isolation (0.7). Similarly, the poverty rate has a high negative correlation with household income (-0.7). Generally, areas with a higher level of household income have a lower level of poverty rate. Population characteristics also show a moderate correlation with asthma, low birth weight, education, and ces4.0 score.

Figure 15. Hierarchical Correlation Plot

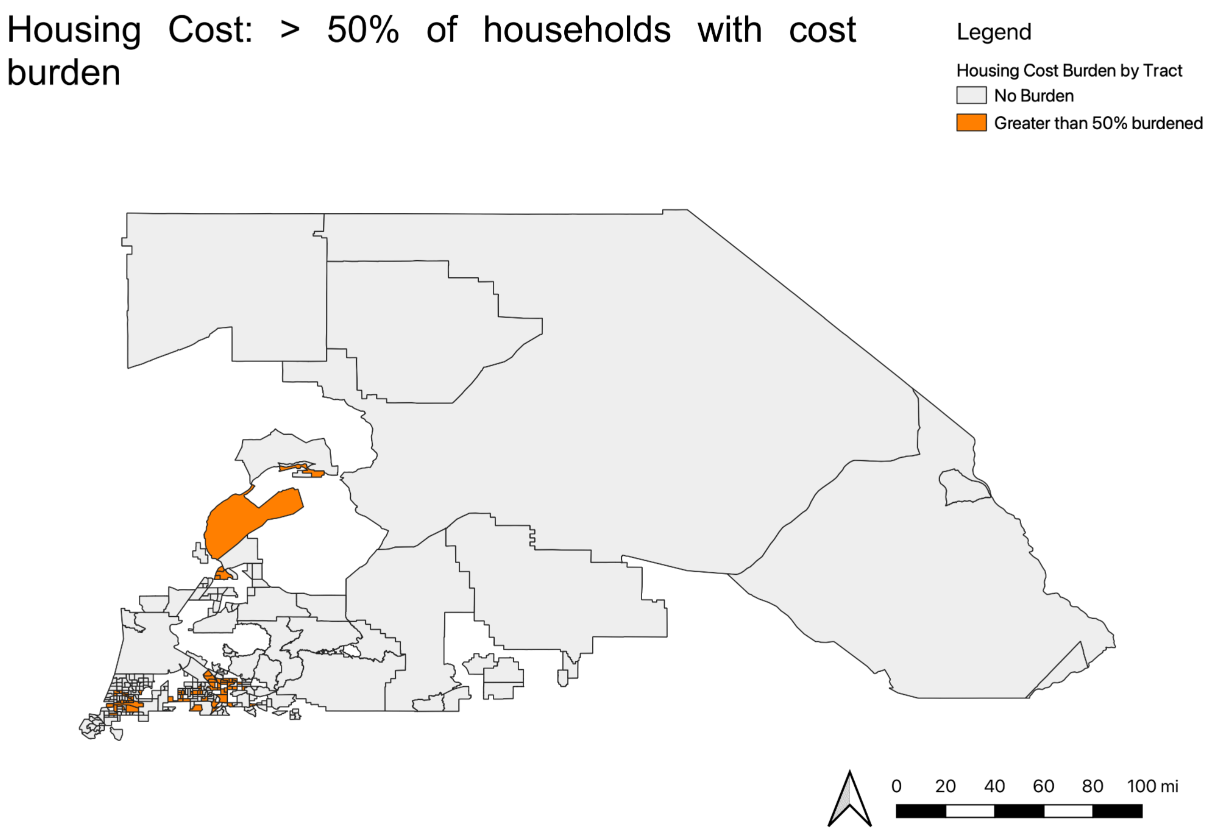


Source: CSI analysis of CalEnviroScreen 4.0 data

The plot provides an overview of the correlation between 15 variables using a dendrogram, a tree-like structure. The plot lists the variables at the tree structure's end as the right column. The variables are then linked together in the dendrogram according to how well they are correlated. The x-axis measures the height within the dendrogram ranging from 0 to 2. The heights (lengths of the lines within the dendrogram) indicate the level of correlation between variables, with shorter sizes showing stronger correlations.

We can observe that linguistic isolation and education are pretty closely correlated and have a correlation of 0.7. Population characteristics and poverty rates are closely correlated with a correlation of 0.6. Similarly, low birth weight and asthma are moderately correlated (0.4). The group of variables, including population characteristics, poverty rate, housing burden, unemployment, low birth weight, and asthma, expectedly, have a higher level of correlation among themselves than they do with other variables. This result also matches the quantile regression model analysis.

Figure 16. Tracts with greater than 50% of households with housing cost burden



Method 3: Proximity to food deserts

Inequitable access to affordable foods in some US communities may be one reason for observed economic and social disparities. A food desert describes a situation where low-income neighborhoods have limited access to full-service supermarkets. Because supermarkets generally offer a variety of healthy foods at reasonable cost, food access is defined by proximity to a supermarket. Food access has typically been measured as the physical distance between the centroids of spatial units of analysis (e.g., census tracts), or between the closest supermarket and the centroids of spatial units housing the population. Various distance thresholds have been used for residents: 1 mile, 10 miles, and 20 miles.

In San Bernardino, approximately 14.5 percent of residents live in poverty. According to Feeding America (a non-profit with a national network of 200 food banks and 60,000 food pantries and meal programs) more than 85,000 children across San Bernardino County experienced food insecurity in 2019. About 30 percent of San Bernardino residents are eligible to receive SNAP, which provides nutrition benefits to supplement the food budget of needy families so they can purchase healthy food and underscore the county's extent of poverty.

Qualitative data from focus groups related to the larger SB1000 project also highlighted similar concerns from the community:

"Participants also expressed concern with a lack of access to healthy food in low-income communities. Fast food restaurants, liquor stores, and lower-quality grocery stores tend to concentrate in low-income communities, while higher resource communities enjoy access to healthy food at full-service grocery stores (Hilmers, Hilmers, and Dave 2012). A lack of access to fresh and healthy food is linked to a host of health complications, including diabetes, obesity, and high calorie diets."

Figure 17. Low-income more than 1 mile from a supermarket

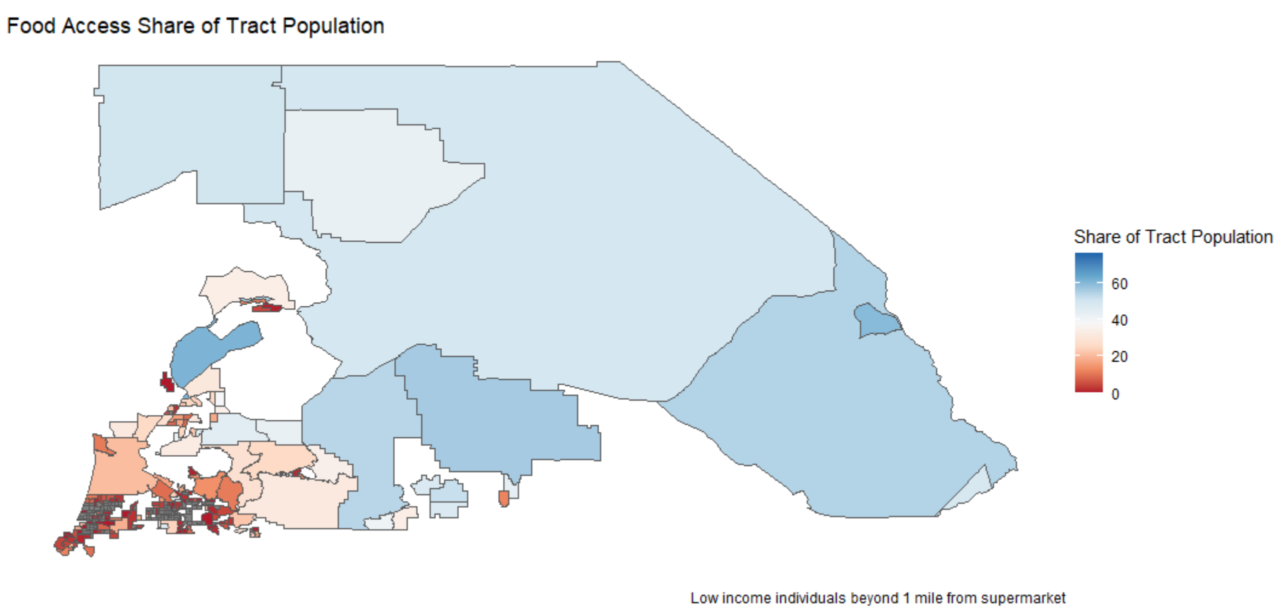


Figure 18. Low-income greater than 10 miles from a supermarket

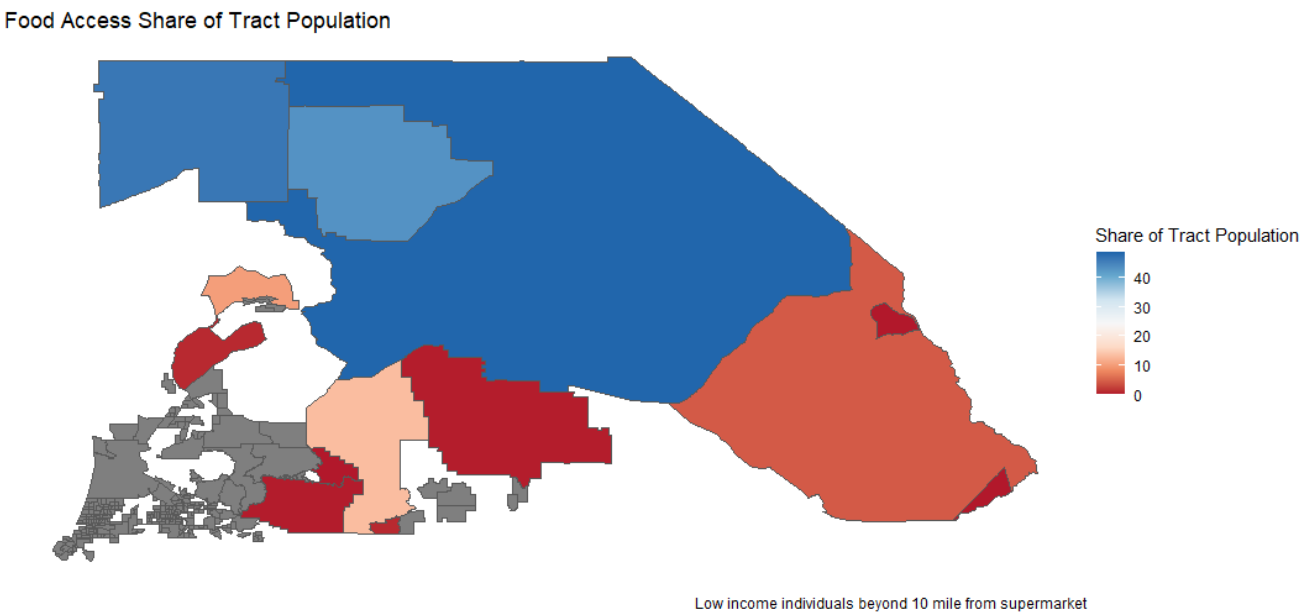
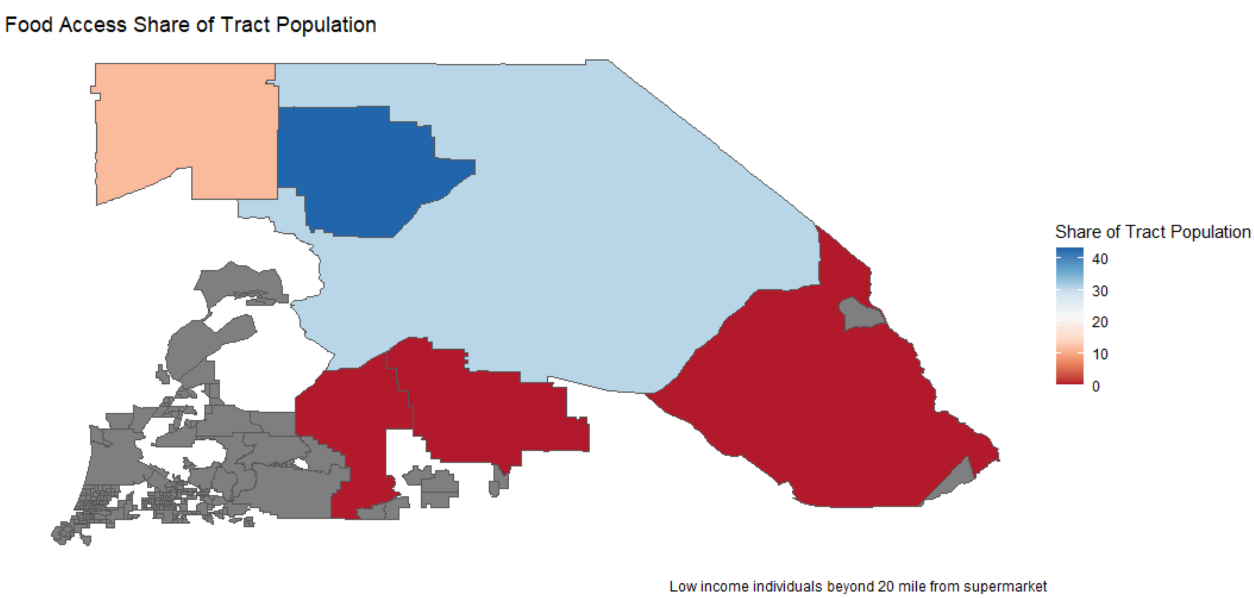
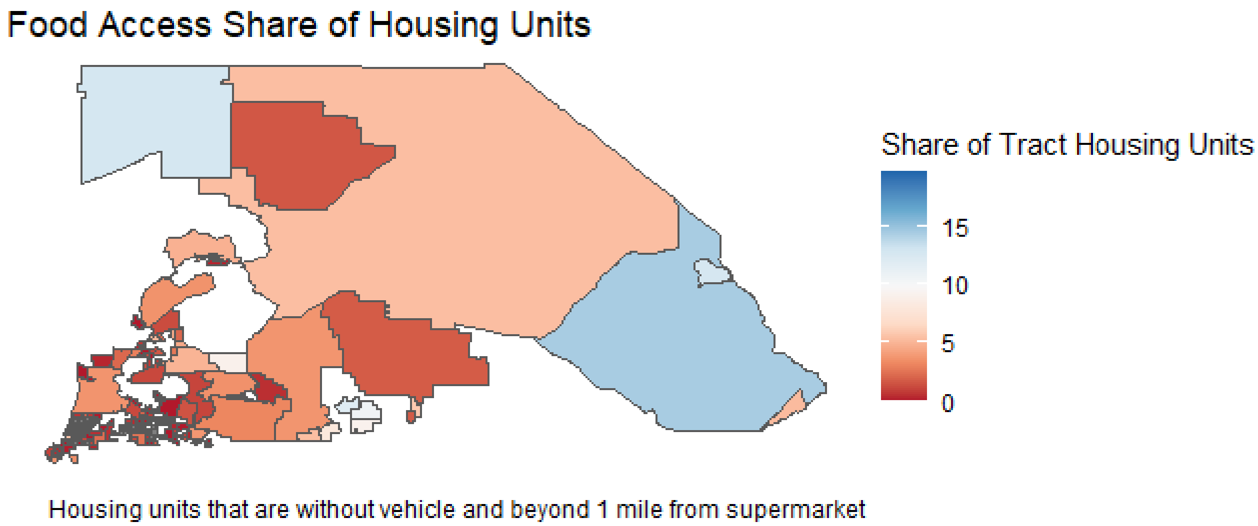


Figure 19. Low-income greater than 20 miles from a supermarket



https://drive.google.com/drive/folders/1ykQ1dpHDCYD0ht6lz8hmU1WtT-Lg6Wt5

Figure 20. Percentage of housing units without a vehicle and greater than 1 mile from a supermarket



The figure above illustrates the percentage of housing units by tract that are without a vehicle and beyond 1 mile from a supermarket. Areas in red have a lower percentage, meaning that these tracts have fewer housing units without access to a vehicle, and are further than 1 mile away from a supermarket.

The following figures provide a similar analysis, though done for greater than 10 miles, and greater than 20 miles from a supermarket.

Figure 21. Percentage of housing units without a vehicle and greater than 10 miles from a supermarket

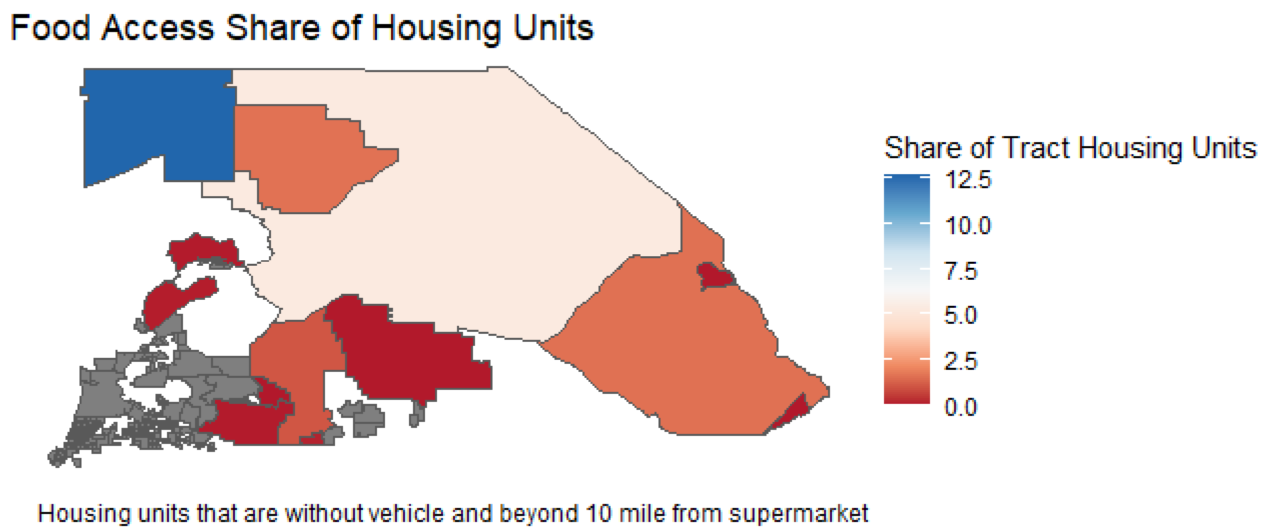
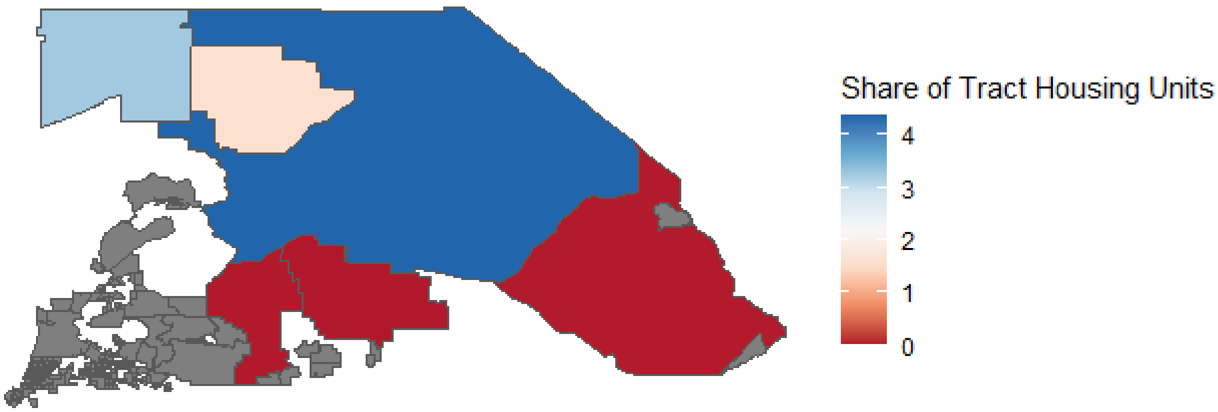


Figure 22. Percentage of housing units without a vehicle and greater than 20 miles from a supermarket

Food Access Share of Housing Units



Housing units that are without vehicle and beyond 20 mile from supermarket

Data link: https://drive.google.com/drive/folders/1ykQ1dpHDCYD0ht6lz8hmU1WtT-Lg6Wt5

Figure 23. Percentage of housing units receiving SNAP benefits, greater than 1 mile from a supermarket

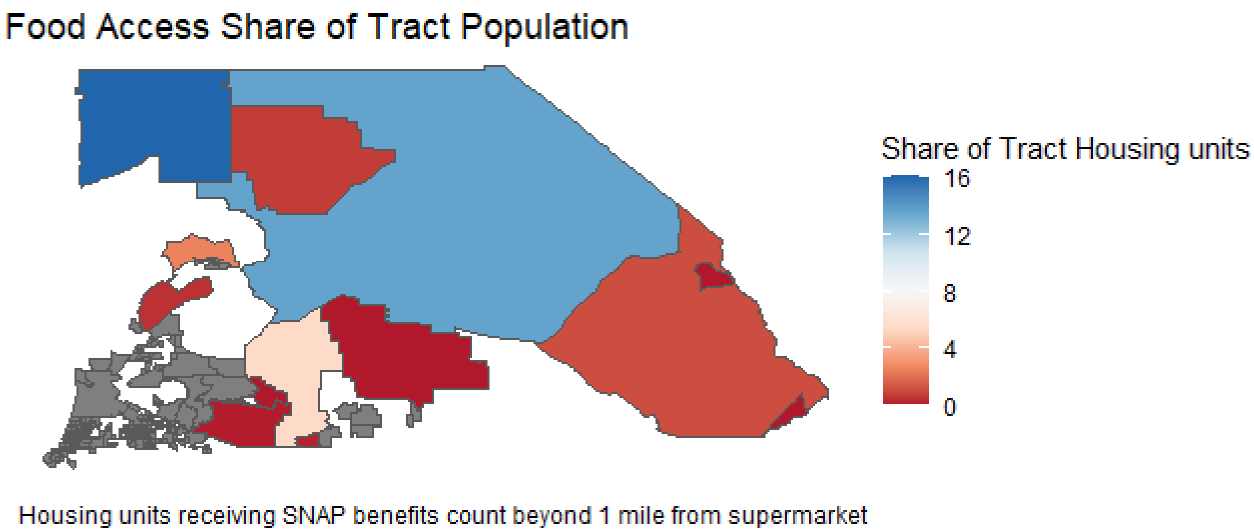


Figure 24. Percentage of housing units receiving SNAP benefits, greater than 10 miles from a supermarket

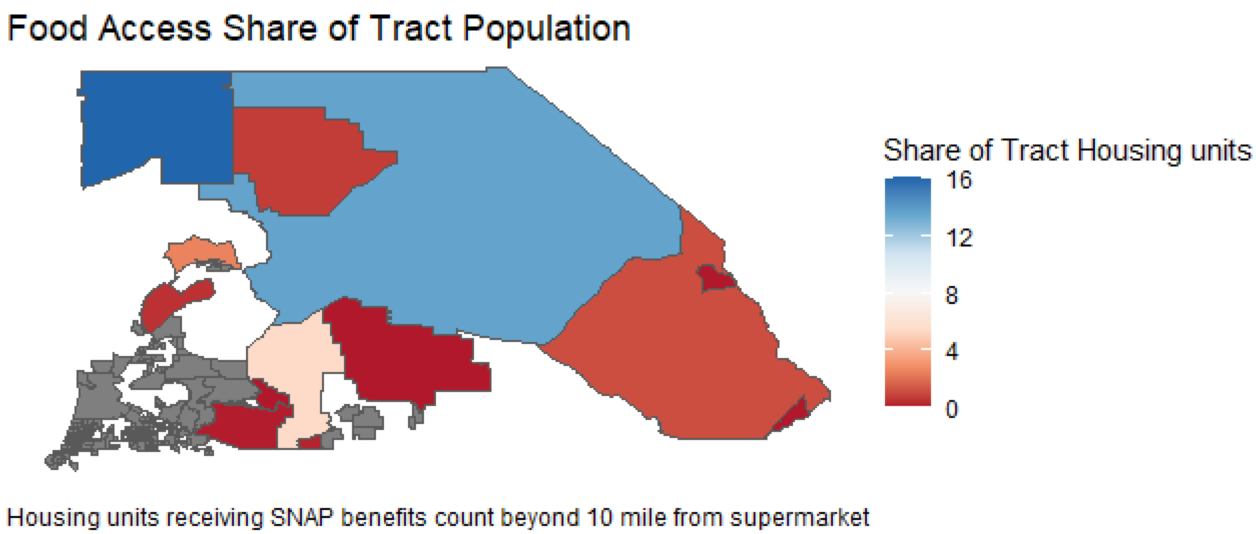
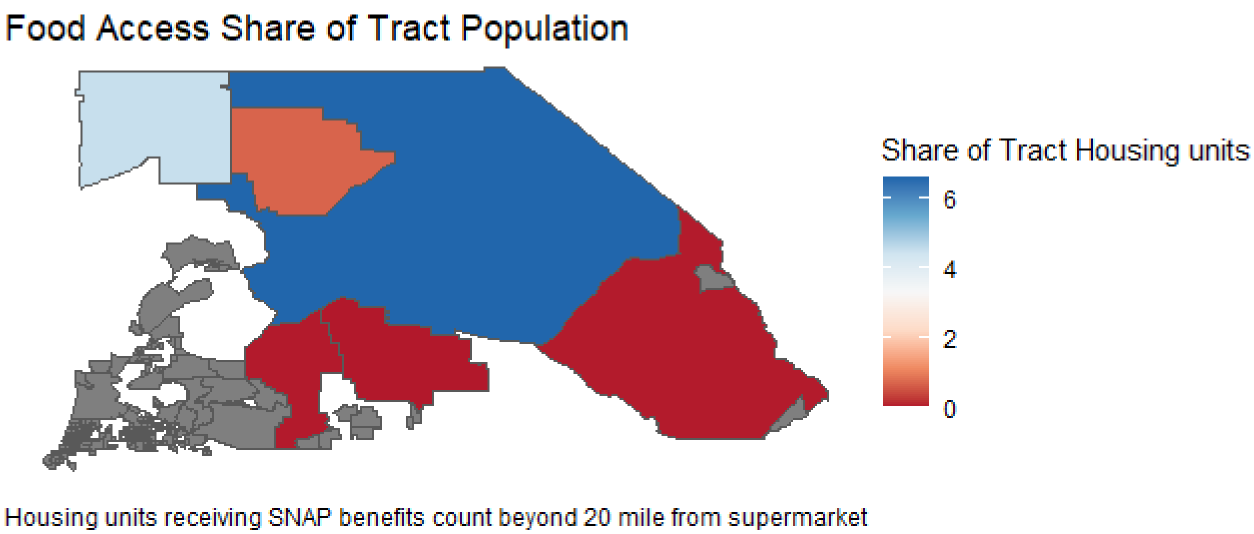


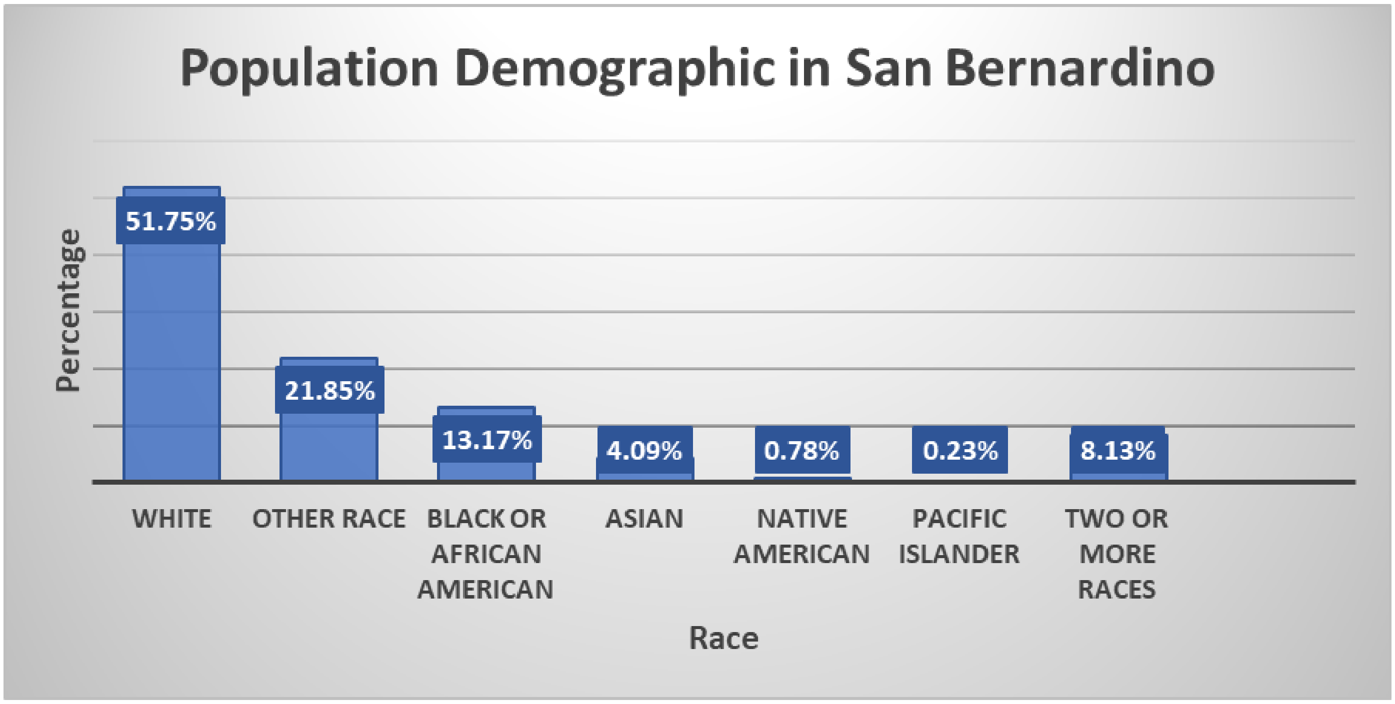
Figure 25. Percentage of housing units receiving SNAP benefits, greater than 20 miles from a supermarket



Data link: https://drive.google.com/drive/folders/1ykQ1dpHDCYD0ht6lz8hmU1WtT-Lg6Wt5

Supplemental Nutrition Assistance Program (SNAP) is for low-income people who satisfy federal income eligibility rules and issue monthly electronic benefits to add to their budget to buy more healthy and nutritious foods at many markets and food stores. These three figures show housing units receiving SNAP benefits at the tract level in San Bernardino.

Figure 26. Population count by tract



In 2020, the largest racial group in the county is White residents (51.75%, or 81k) and Other (21.85%, or 46.8k) The smallest racial group is Native Hawaiian or Pacific Islander at 0.23%.

Figure 27. Access to supermarkets within a 0.5, 1, 10, and 20 mile radius, by race

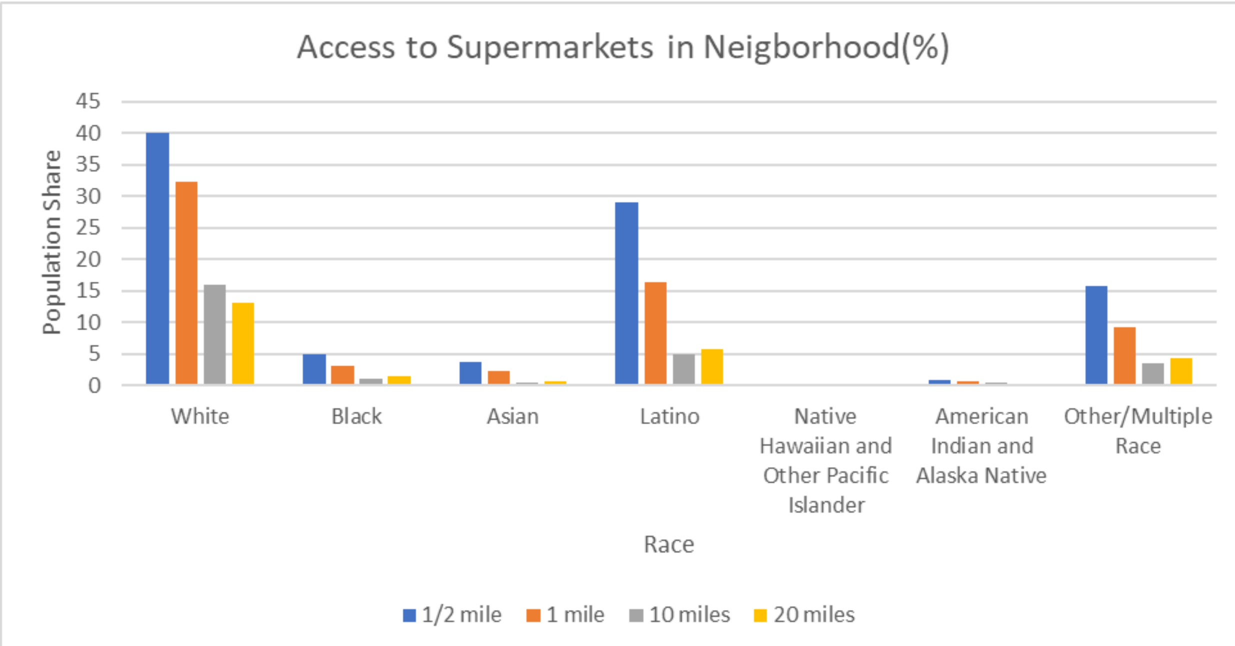
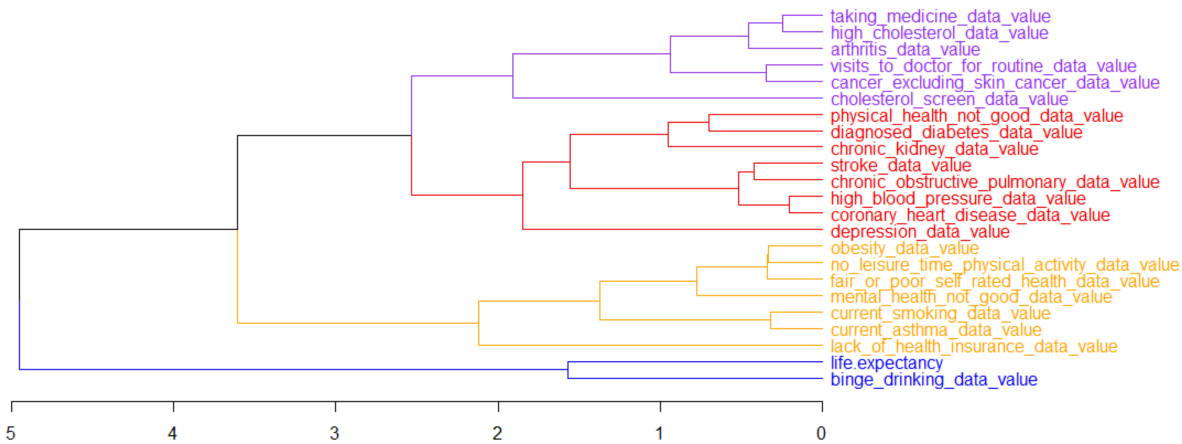


Figure 27 breaks down access to supermarkets within 0.5,1, 10, and 20 miles by race. Whites make up the largest share of the region's population, with the majority falling within ½ mile of a supermarket. Latinos make up the next largest population share, with the majority falling within ½ mile of a supermarket, though with a slightly greater share at the 20 mile distance cut than 10 miles.

Method 3: Life expectancy

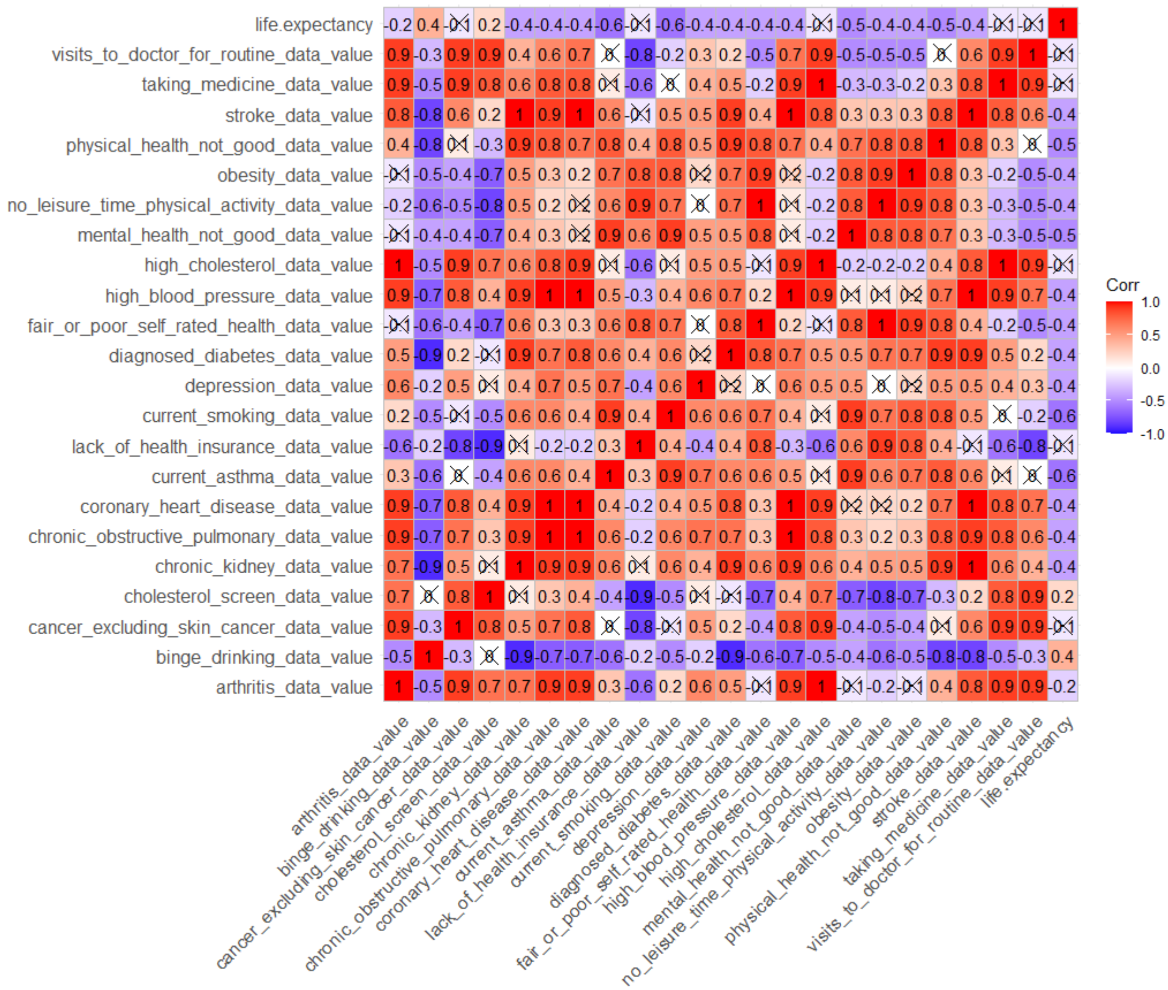
Data from the Centers for Disease Control and Prevention shows that US life expectancy is an average of 77.3 years - 74.5 years for men and 80.2 for women. Based on this information, we worked to understand what correlation - if any - there was between various health issues and how long an individual lived.

Figure 28. Dendrogram Correlation Plot of health variables



Data source: National Center for Health Statistics, USALEEP

Figure 29. Hierarchical correlation plot of health variables

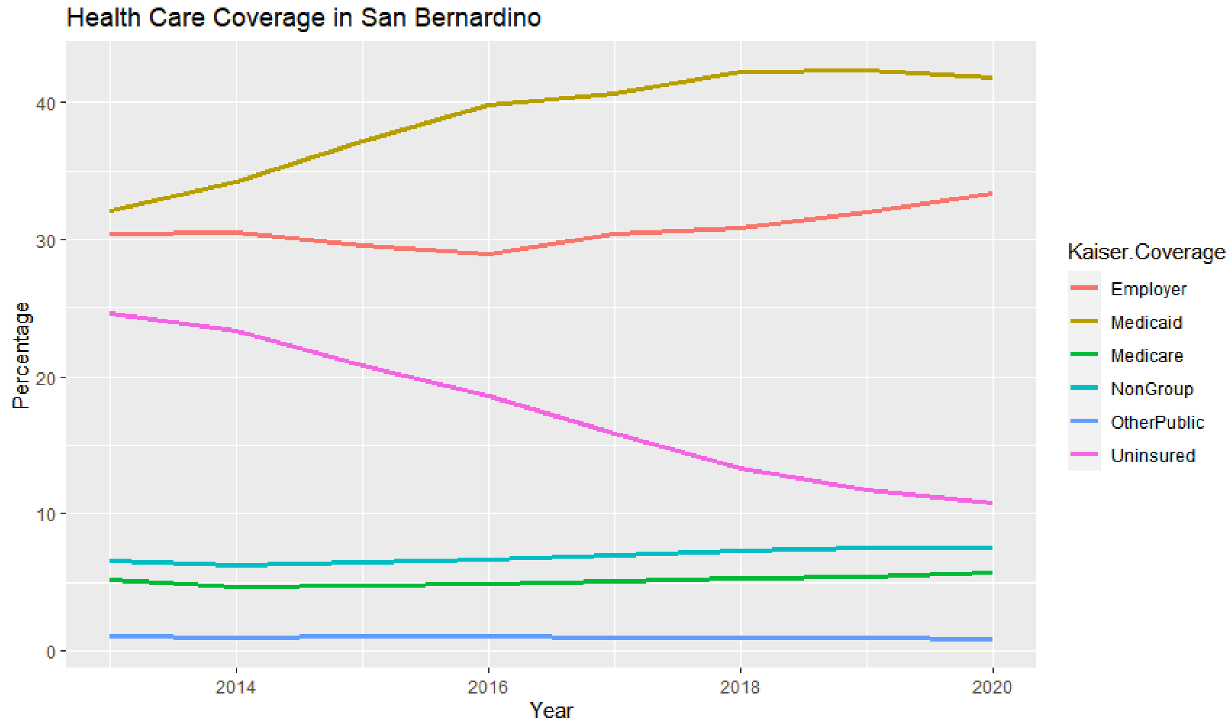


Data source: National Center for Health Statistics, USALEEP

This hierarchical correlation plot provides the correlation between life expectancy with 22 health issues at the tract level. The various health problems are linked in the dendrogram according to how well they correlate. The x-axis measures the height within the dendrogram ranging from 0 to 5. The heights indicate the correlation level between these variables, and shorter heights imply a stronger correlation.

We can observe that the current smoking data value correlates highly with asthma rates, and high blood pressure strongly correlates with coronary heart disease. The correlation between chronic kidney and arthritis is strong (0.7). The numeric correlation matrix heatmap provides whether the health issues have a strong positive correlation, strong negative correlation, or weak correlation. Life expectancy strongly correlates negatively with asthma and mental health issues (-0.6) and positively correlates with binge drinking rates (0.4).

Figure 30. Health care by coverage source

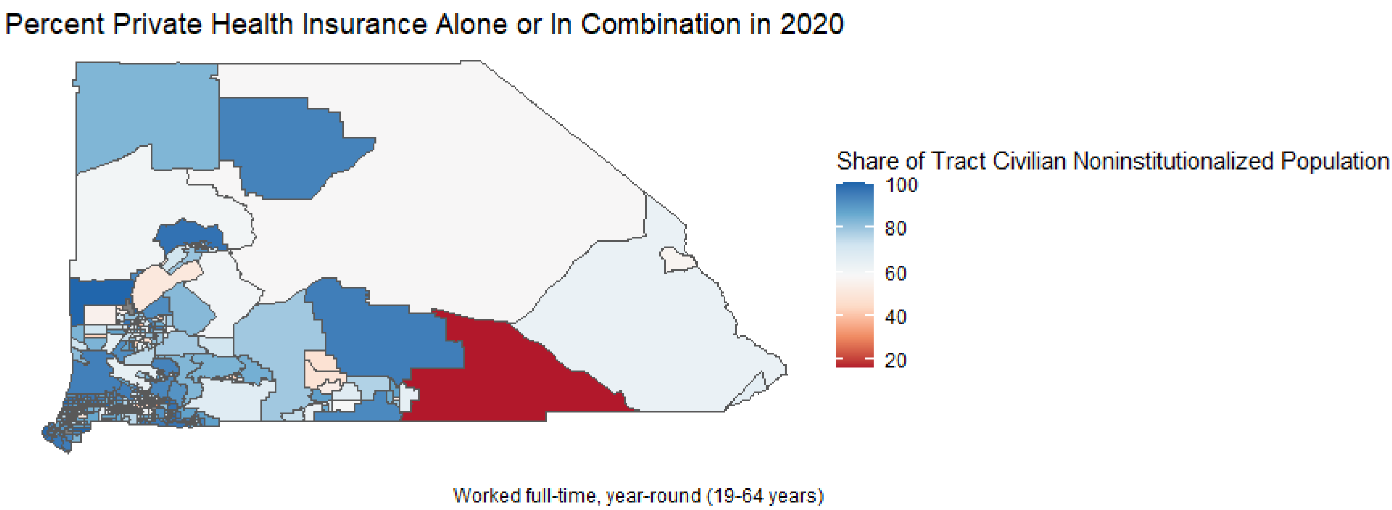


https://datausa.io/profile/geo/san-bernardino-ca/
And Census Bureau ACS 5-year Estimate.

Data set: https://drive.google.com/drive/folders/1t3u0uJL2fU1oDMr7GrFf9sfSz0AXBAdh

The percentage of uninsured households in San Bernardino has decreased by 8.7% during the COVID-19 pandemic. The graph shows various types of health care coverage changes over five years.

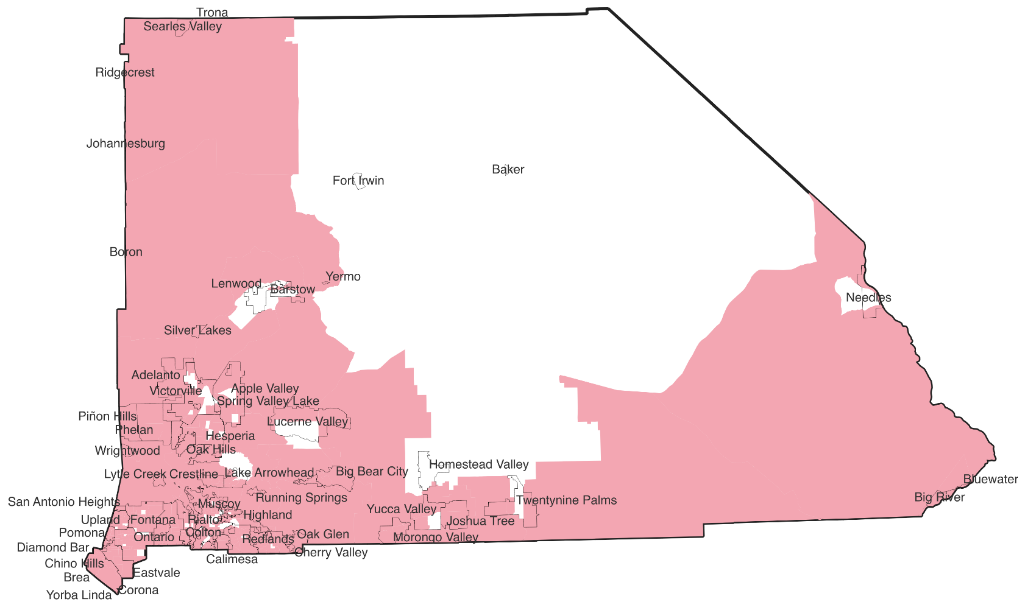
Figure 31. Percent private health insurance alone or in combination, 2020



Data source: ACS 2020 5-year Estimate

Figure 31 shows the percent private coverage for the civilian noninstitutionalized population, where private coverage is defined as for private health insurance alone or in combination. The universe is the population who worked full-time, year-round (19-64 years), civilian noninstitutionalized population with private health coverage percentage at the tract level.

Figure 32. Areas with 74.5 years or greater life expectancy



Data Source: USA LEEP

Method 3: Childhood poverty

Figure 33. Poverty Rate by Age

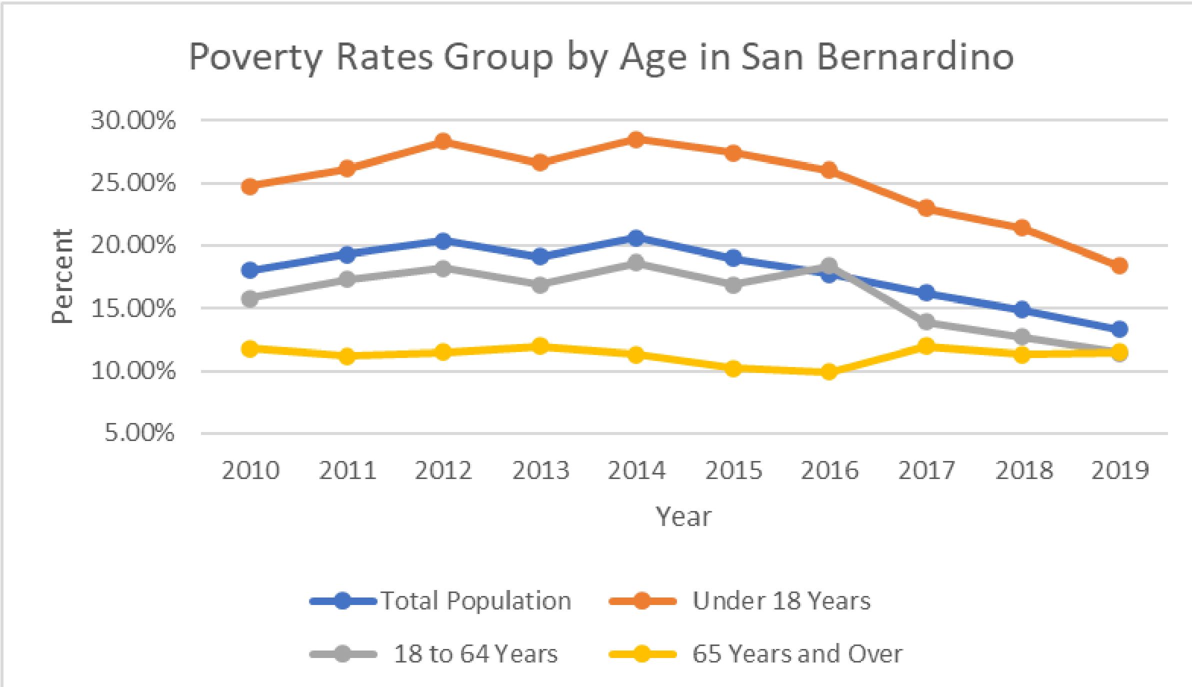
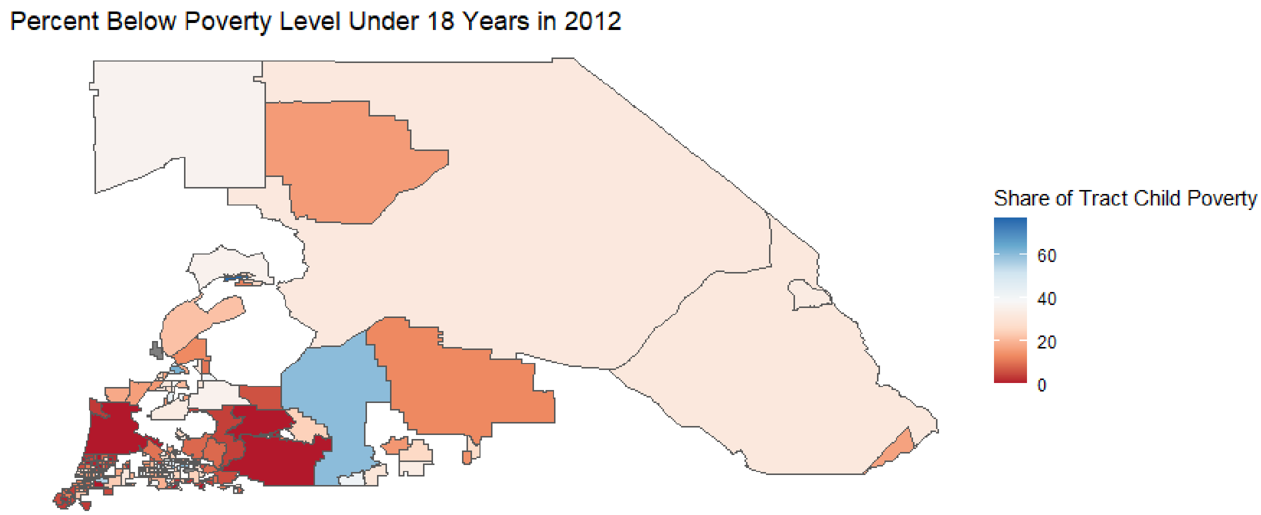


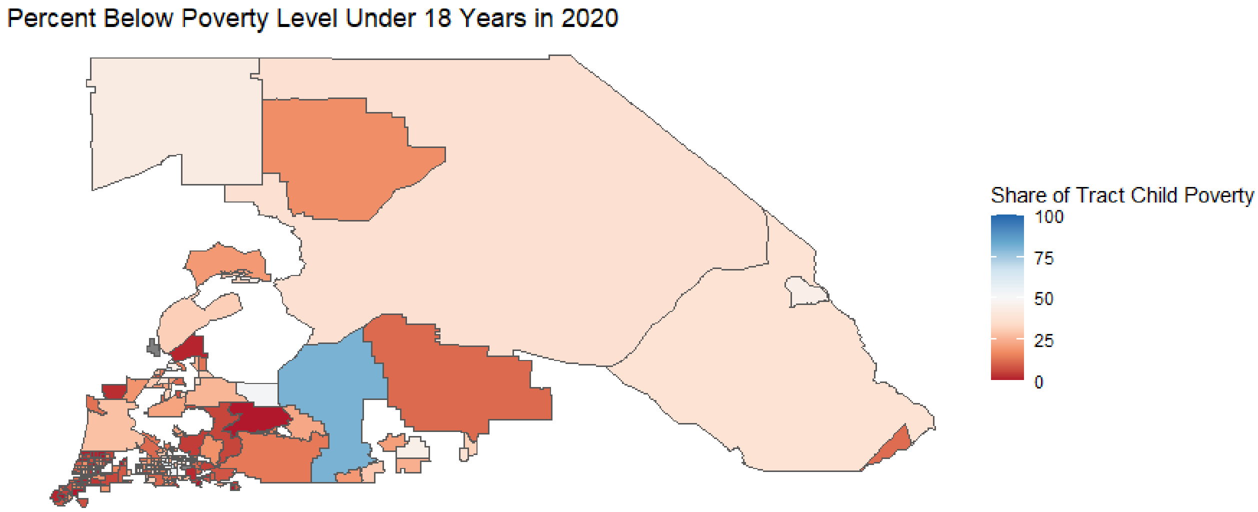
Figure 33 shows that poverty rates declined for most age groups over the past ten years. The percentage of households living in poverty decreased from 18% in 2010 to 13.3% in 2019. The poverty rate of those under 18 in San Bernardino County dropped from 24.7% in 2010 to 18.7% in 2019. Adult poverty rates declined four percentage points over the past ten years. Seniors aged 65 years and over show a slight change over the period 2010 - 2019.

Figure 34. Percent under 18 years below poverty level, 2012



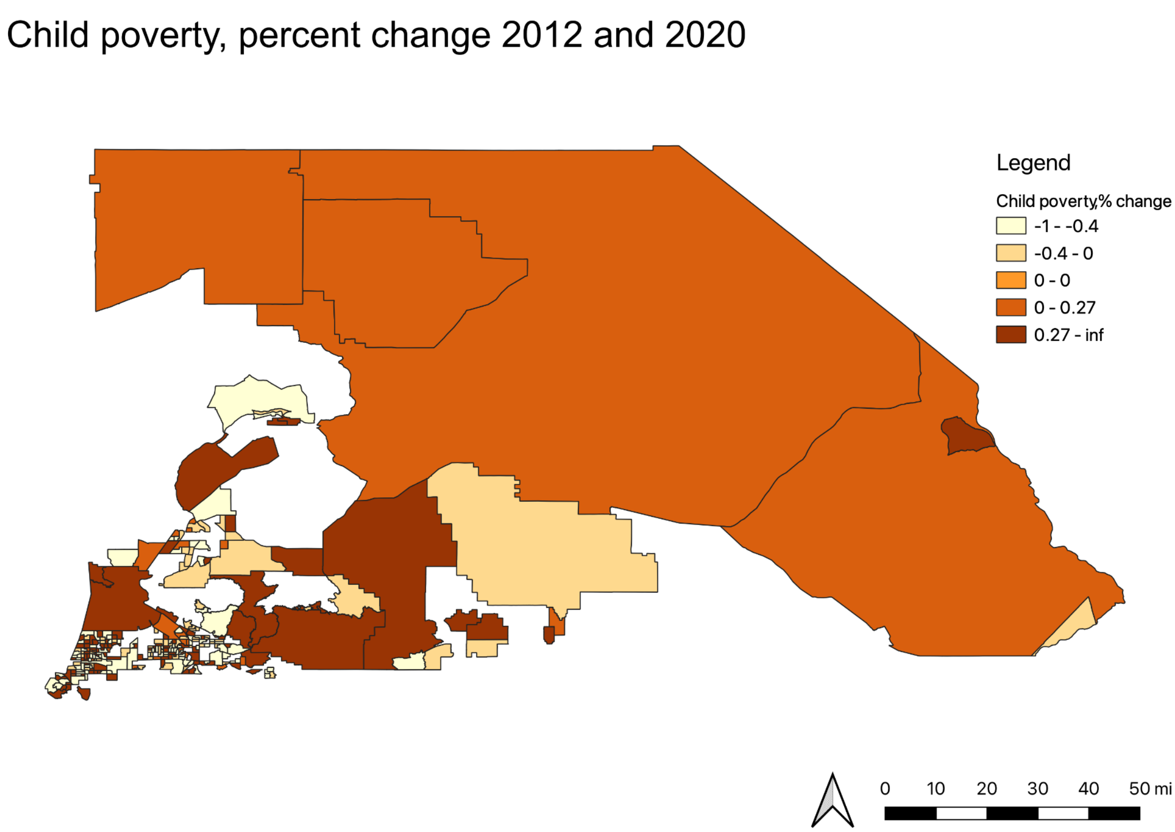
This figure identifies children under 18 years who were below the poverty level in 2012 in San Bernardino County at the tract level. The blue tract areas have higher childhood poverty rates above 60%, in the south near Twentynine Palms of San Bernardino County. The northwest part near Searles Valley shows tracts where children's poverty rates are around 40%.

Figure 35. Percent under 18 years below poverty level, 2020



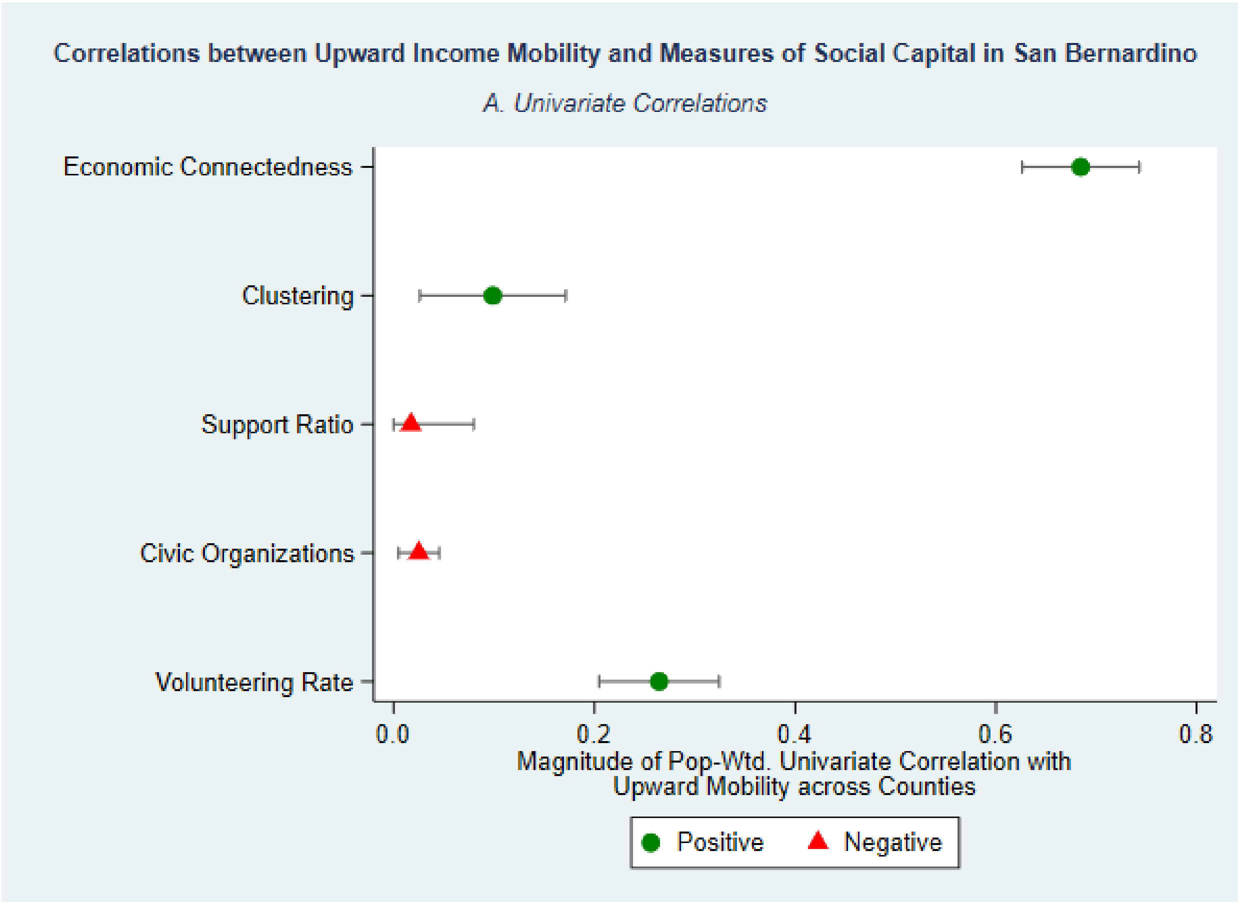
The percentage under 19 years below the poverty level declines from 2010 to 2020 in many tract areas. In the northwest and southwest parts of San Bernardino, children's poverty rates have been reduced by about five percent.

Figure 36. Percent change in poverty for those under 18 years of age, 2012 & 2020



Method 3: Childhood Poverty and Income Mobility

Figure 37. Correlation between upward mobility and measures of social capital



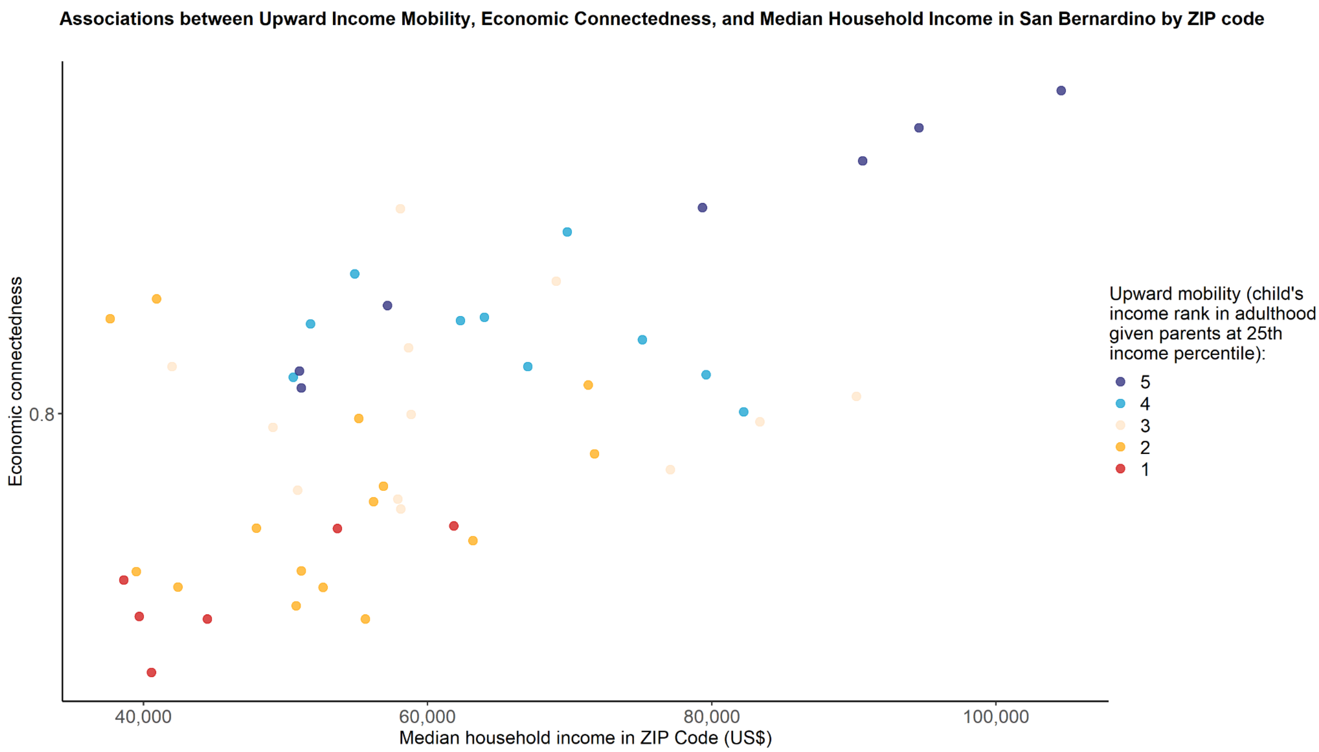
Data source:
https://www.socialcapital.org/?dimension=EconomicConnectednessIndividual&dim1=EconomicConnectednessIndividual&dim2=CohesivenessClustering&dim3=CivicEngagementVolunteeringRates&geoLevel=county&selectedId=06037

This figure shows the univariate correlation across zip code areas in San Bernardino between upward income mobility and measures of social capital constructed, such as economic connectedness, clustering, support ratio, civic organization, and volunteering rate.

Chetty (2022) defines economic connectedness as two times the share of high socioeconomic status (SES) friends among low-SES individuals, averaged over all low-SES individuals in a zip code. Clustering means the average fraction of an individual's friend pairs who are also friends with each other. Support ratio is the proportion of within-zip code friendships where the pair of friends share a third mutual friend within the same area. Volunteering shows the percentage of Facebook users who are members of a group predicted to be 'volunteering' or 'activism.' Civic organization describes the number of Facebook pages expected to be "Public Good" based on the page title, category, and other page characteristics, per 1000 users in the zip code. The average income percentile rank defines upward income mobility in San Bernardino in adulthood of children in the 1978-1983 birth cohorts who grew up in the zip code area with parents at the 25th percentile of the national parental household income distribution.

From the figure, we can see that economic connectedness is strongly positively correlated with income mobility, and the correlation is 0.66. However, all the other measures of social capital are not strongly correlated to upward income mobility in San Bernardino.

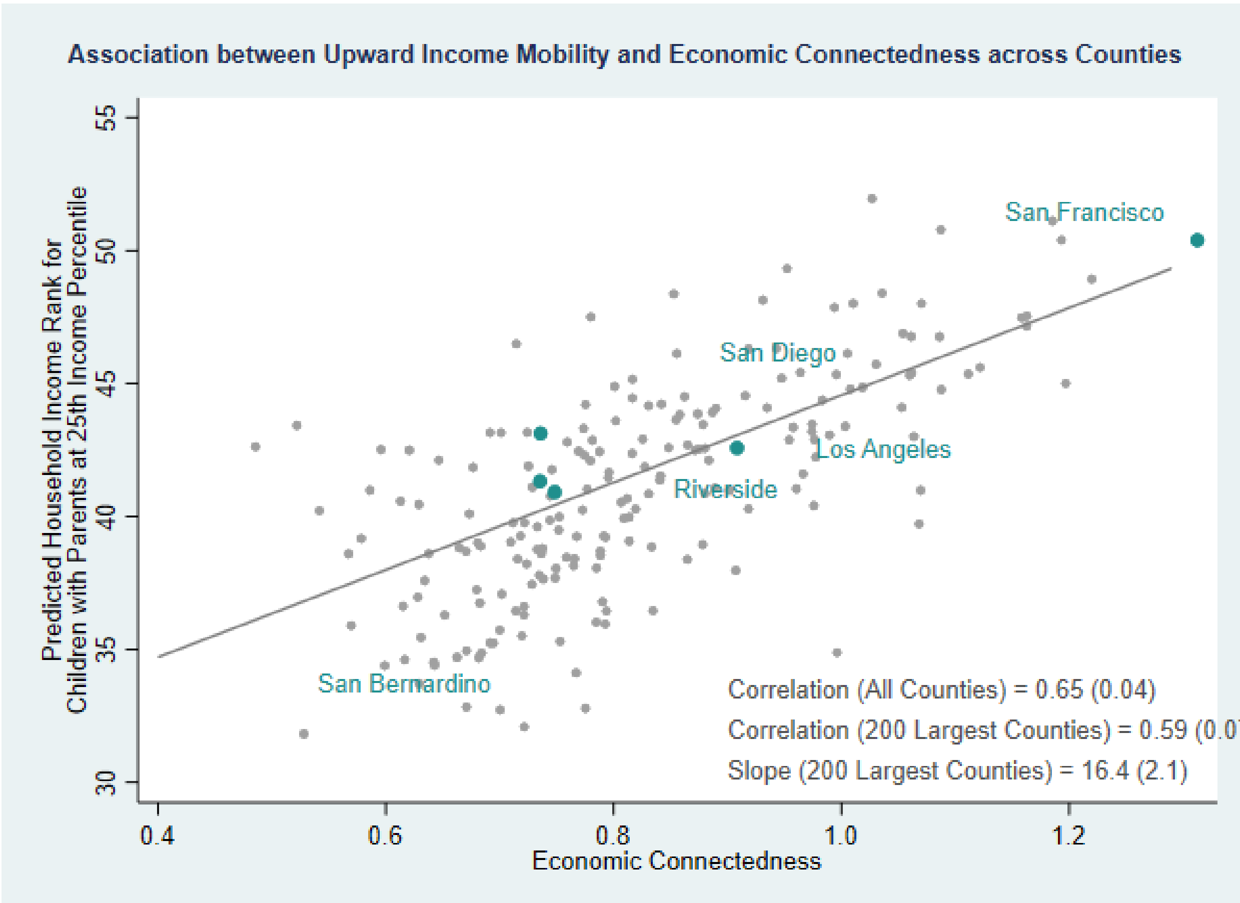
Figure 38. Associations between upward mobility, income connectedness, and median household income by Zip code



Data source:
https://www.socialcapital.org/?dimension=EconomicConnectednessIndividual&dim1=EconomicConnectednessIndividual&dim2=CohesivenessClustering&dim3=CivicEngagementVolunteeringRates&geoLevel=county&selectedId=06037

The scatter plot shows the relationship between economic connectedness, median household income (based on 2014- 2018 ACS), and upward income mobility by zip code in San Bernardino. The difference in color indicates the level of upward income mobility for children who grew up in low-income families by zip code in San Bernardino. The red dots show areas with lower levels of mobility, and the blue dots show higher levels of upward income mobility. The results tend to show that children who grew up in an area with high economic connectedness give rise to better prospects for upward income mobility than just around high-income households.

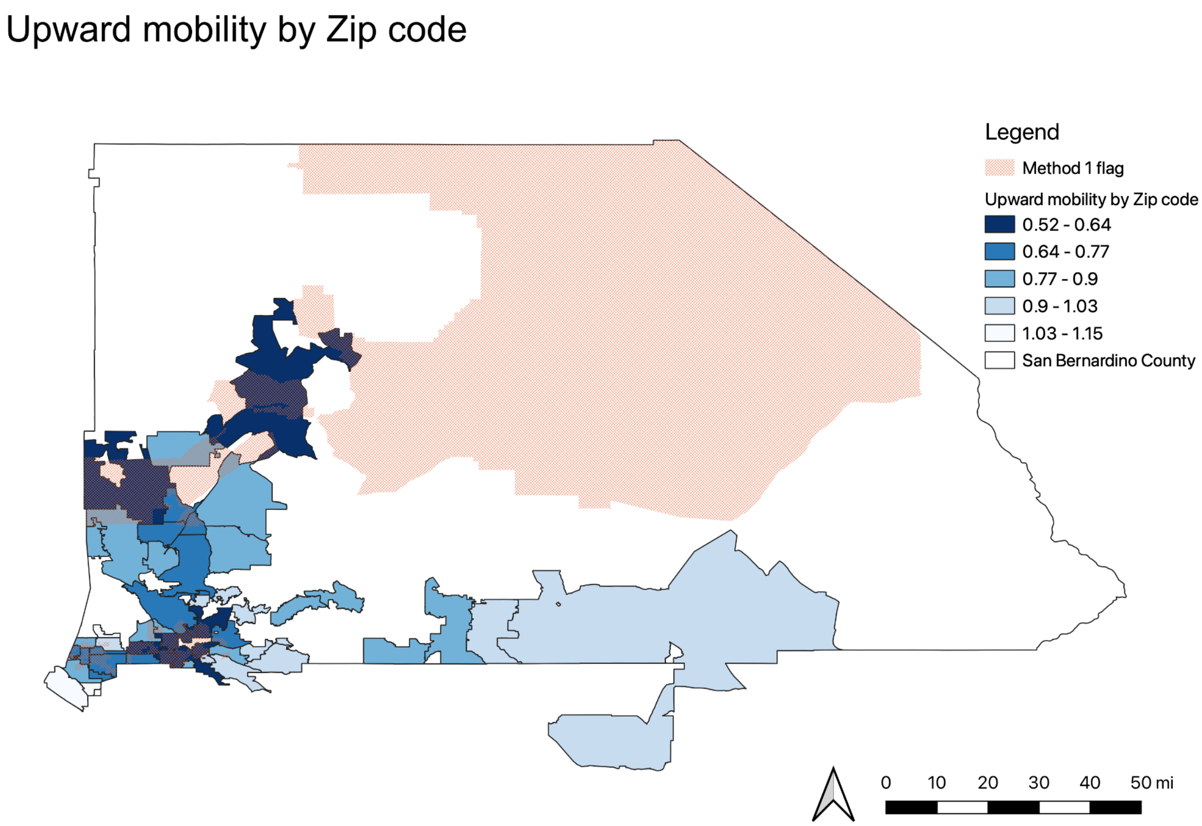
Figure 39. Association between upward income mobility and economic connectedness by selected counties



Data source:
https://www.socialcapital.org/?dimension=EconomicConnectednessIndividual&dim1=EconomicConnectednessIndividual&dim2=CohesivenessClustering&dim3=CivicEngagementVolunteeringRates&geoLevel=county&selectedId=06037

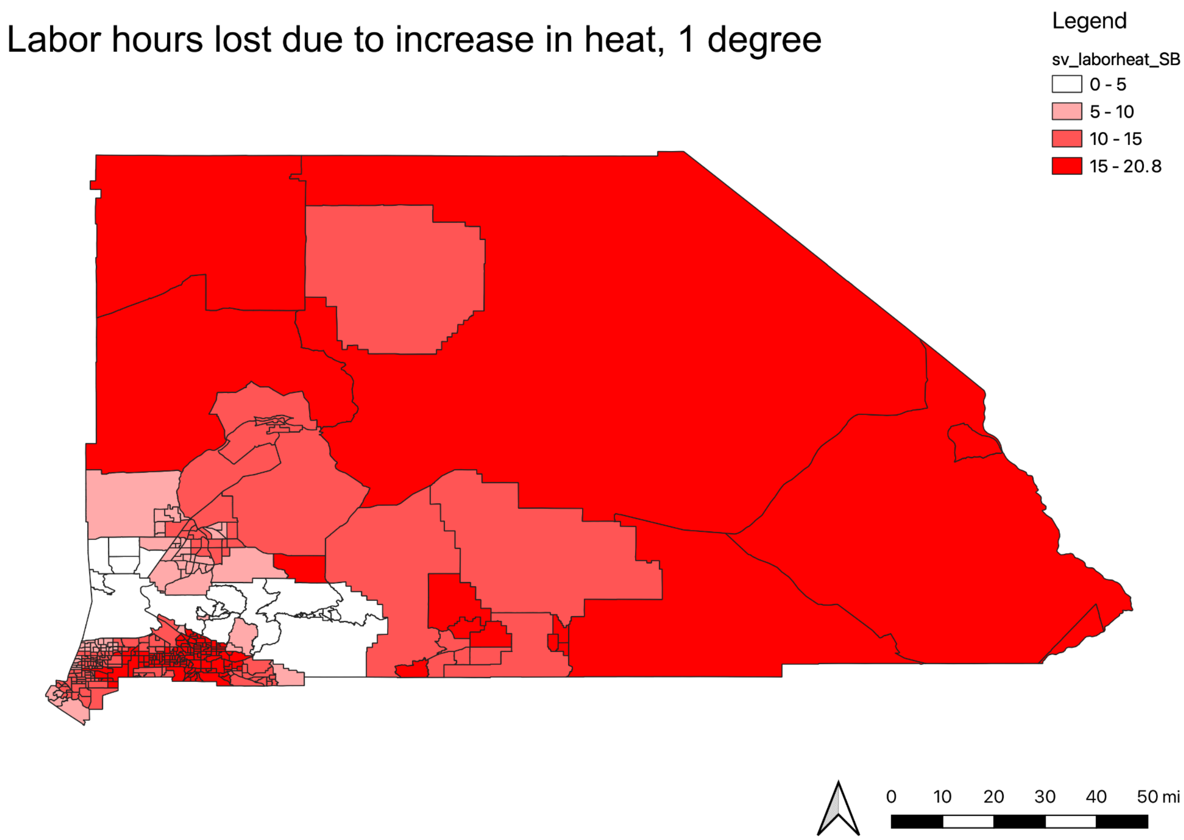
This figure presents the relationship between economic connectedness and income mobility non-parametrically through a scatter plot for the 200 counties in the U.S. Children who grow up in counties where low-SES individuals have more high-SES friends are inclined to have much higher rates of upward income mobility. We employed Chetty's (2022) method to run an OLS regression on the 200 largest U.S. counties by population, and standard errors are clustered by commuting zone in parenthesis. We select five counties (San Bernardino, Riverside, San Diego, Los Angeles, and San Francisco) in California.

Figure 40. Upward mobility by Zip code overlaid with Method 1



Method 3: Relationship to extreme heat

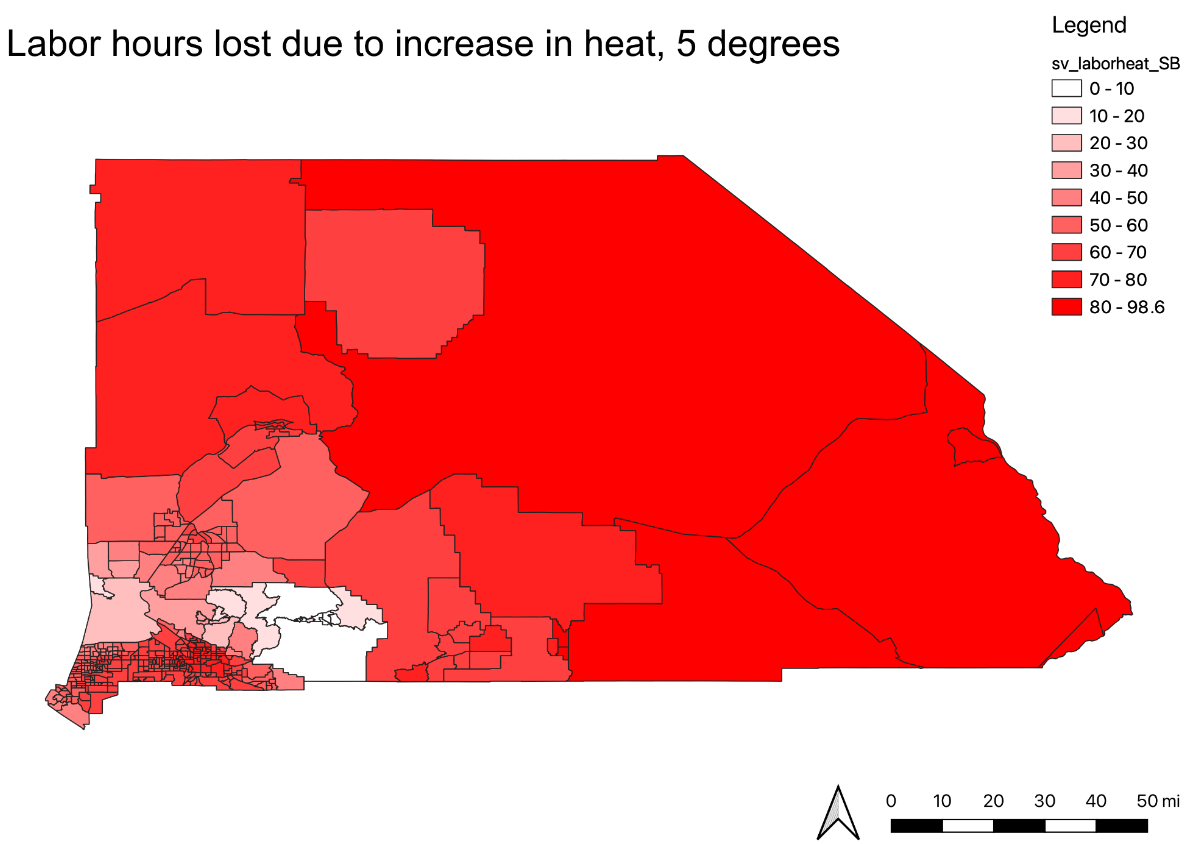
Figure 41. Hours lost per climate exposed worker per year, 1 degree



Source: Source: https://www.epa.gov/cira/technical-appendices-and-data

Extreme heat is becoming a greater issue in the region, which impacts daily life as well as worker conditions. The EPA has calculated hours of work lost per climate exposed worker for 1-degree increments of increased temperature, going up to 5 degrees.

Figure 42. Hours lost per climate exposed worker per year, 5 degrees



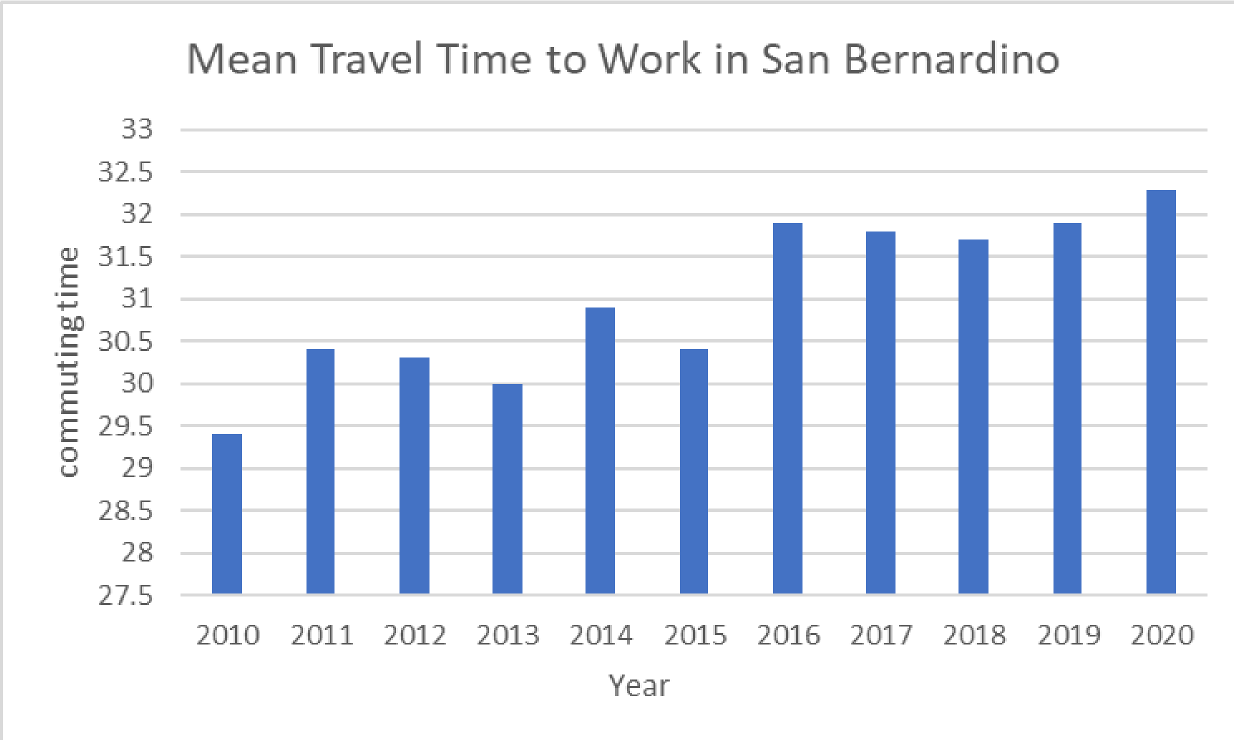
Large portions of the county face significant amounts of hours lost due to extreme heat, with up to half a full week of work lost with a 1 degree increase, and over two full weeks of work lost with a 5 degree increase.

Method 3: Travel time to work & mode of commute to work

San Bernardino County residents' average travel time to work was 32.3 minutes in 2020 and has increased slightly, compared with the average of 29.4 minutes in 2010.

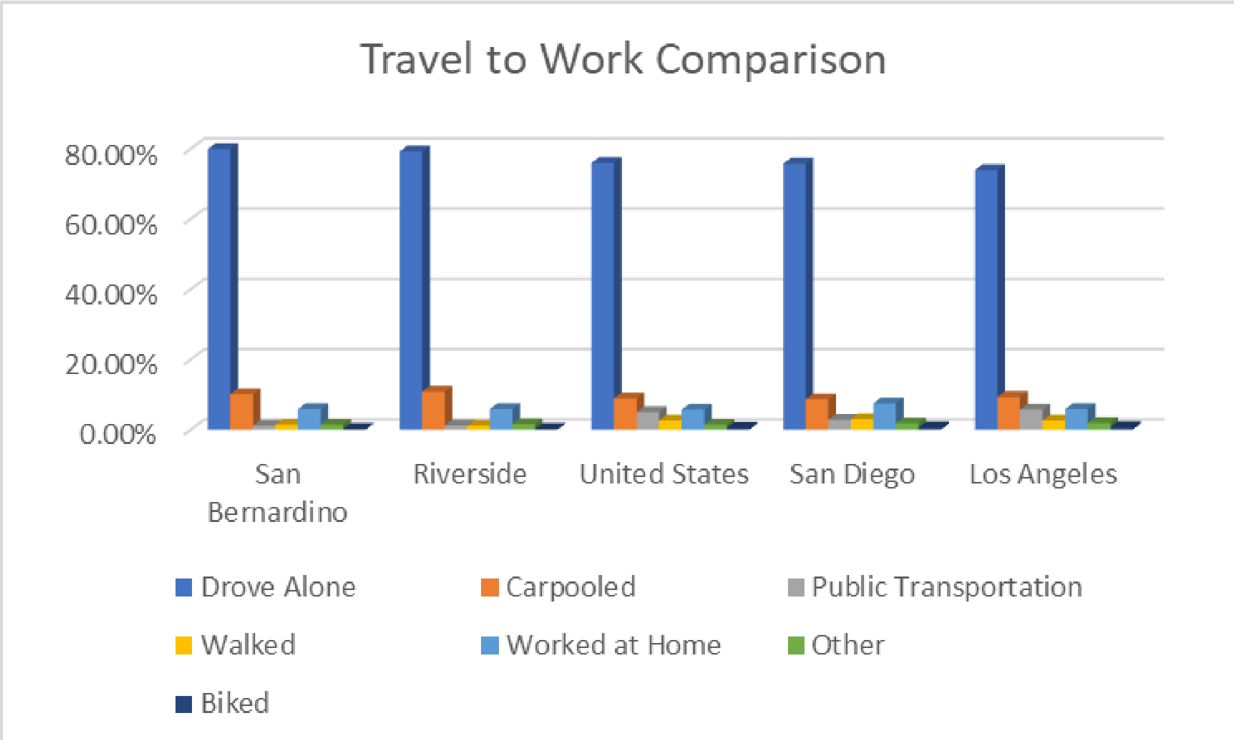
The majority of San Bernardino County commuters drove alone at 79.9% in 2019. This level has increased by 6.2% from 2010 to 2019. The second most popular common way of commuting is carpooling (10.1%), which has declined by 7.3% since 2010, when commuters were more likely to drive to work with someone else. Commuters working at home have steadily increased from 3.5% to 5.9% over the years.

Figure 43. Mean travel time to work



The average commuting time in San Bernardino takes a longer period (32.2 minutes) than the average US worker (26.9 minutes) in 2020. The mean travel time to work also shows an increasing trend from 2010 to 2020. In addition, based on the ACS 5-year estimate data, 5.75% of the labor pool commutes in excess of 90 minutes.

Figure 44. Travel to time to work by mode, comparison by other Southern California regions



The figure above shows the number of residents using each mode of transportation over time in 5 different areas in 2020. 77.1% of workers choose to drive alone to work in San Bernardino. Compared with Riverside, San Diego, Los Angeles, and the U.S., more people in San Bernardino drive alone to work.

Figure 45. Mean travel time to work, 2010

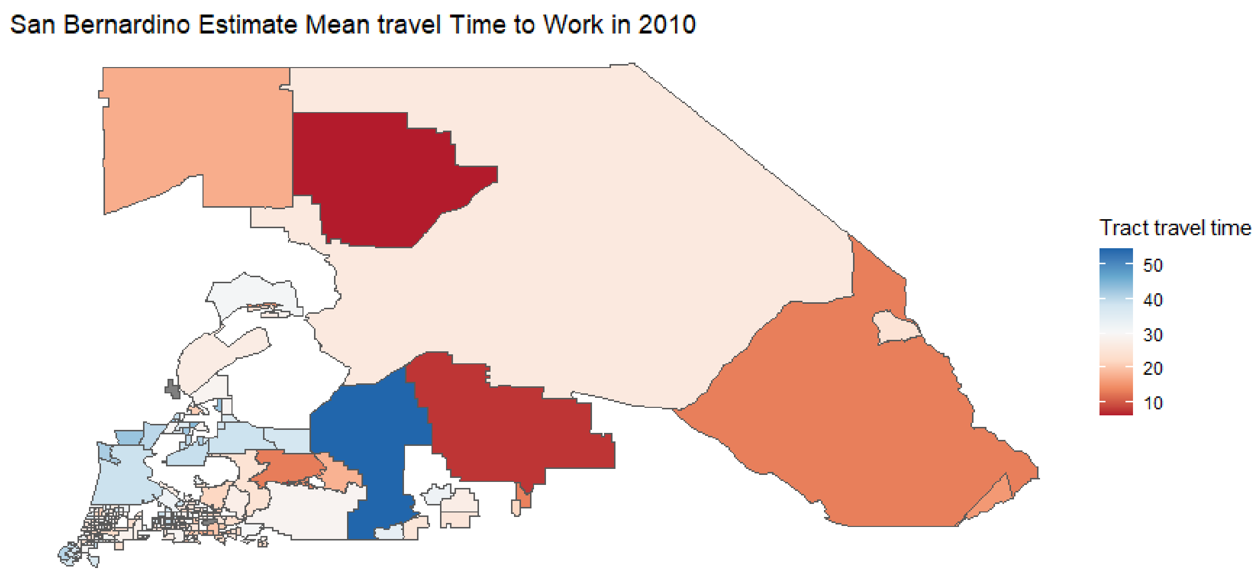


Figure 46. Mean travel time to work, 2020

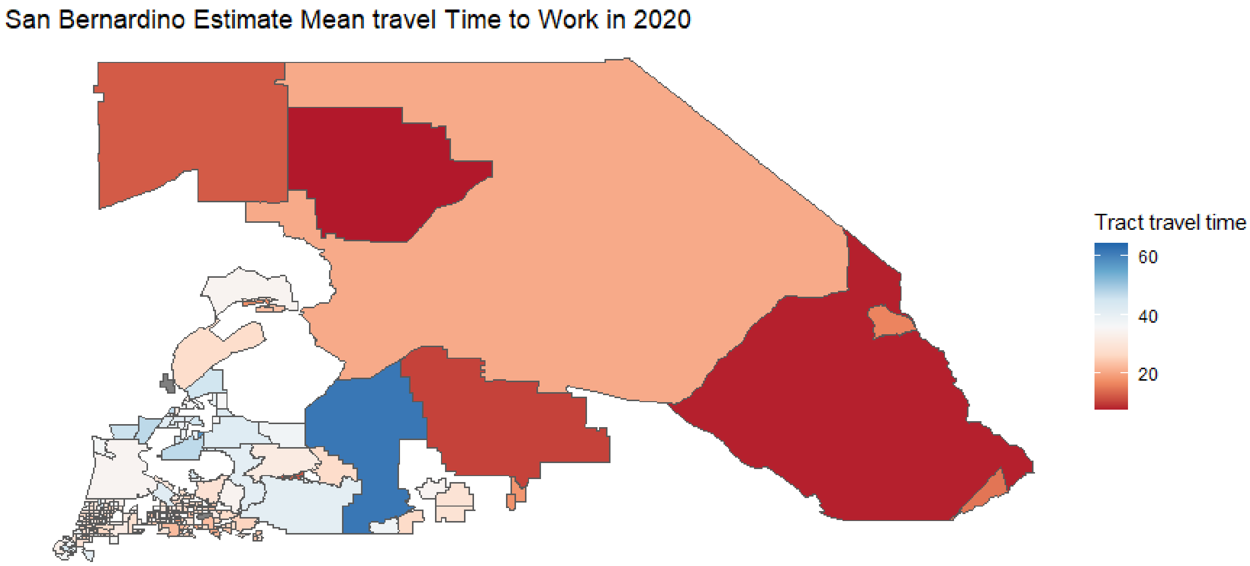
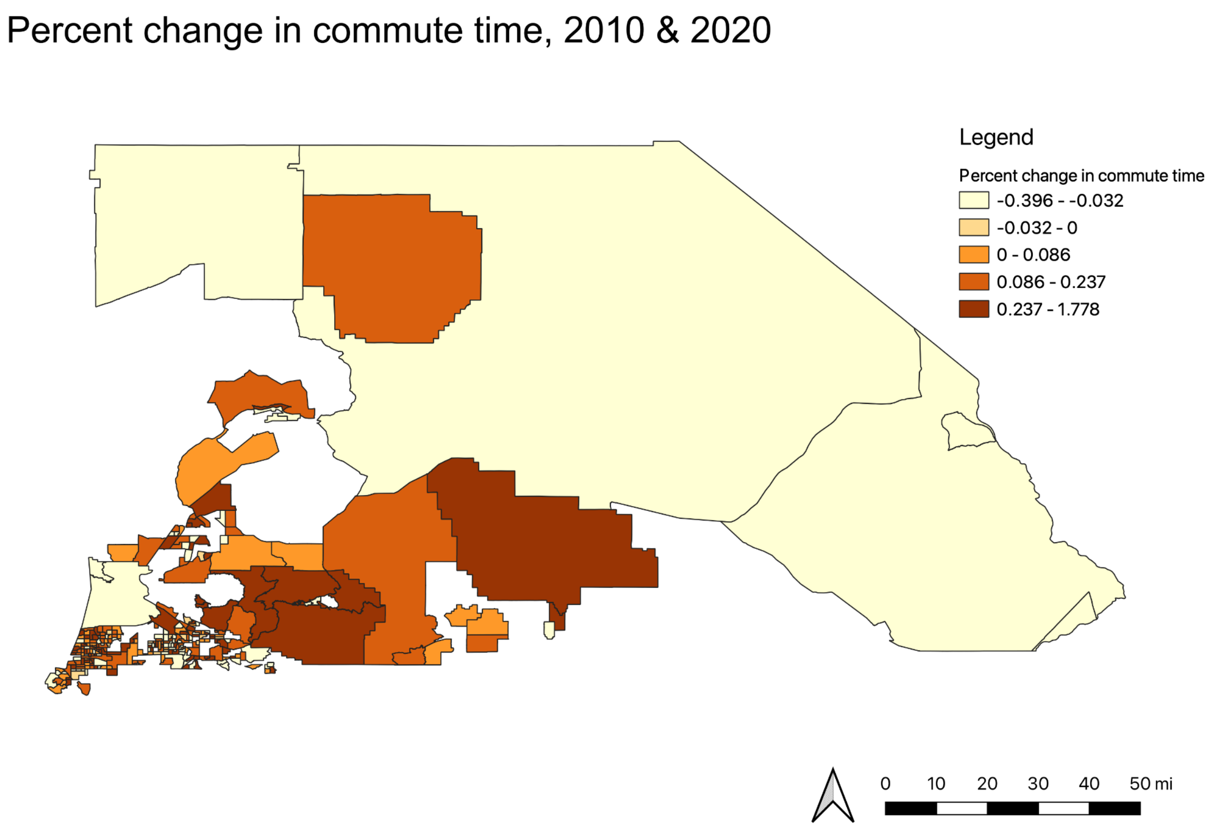


Figure 47. Commuting time percent change, 2010 & 2020

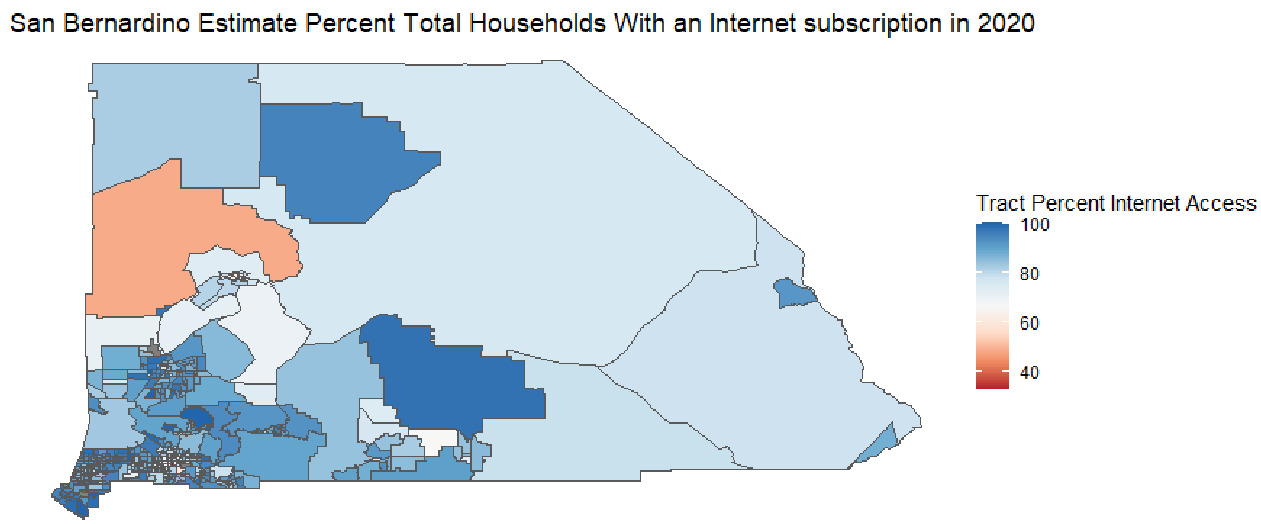


Method 3: Type of Internet Access

Access to reliable, high-speed broadband internet enhances access to employment, education, and healthcare. It is associated with increased economic development. Broadband access is necessary to support adequate employment opportunities, workforce development, education, healthcare, and access to federal programs (e.g., SNAP). It can foster social connectedness, particularly among the older population, reducing the burden of social isolation, strengthening community support, and decrementing solitude. Broadband Internet access has the potential to improve loneliness, strengthen community support, and alleviate the burden of social isolation, particularly among the elderly population.

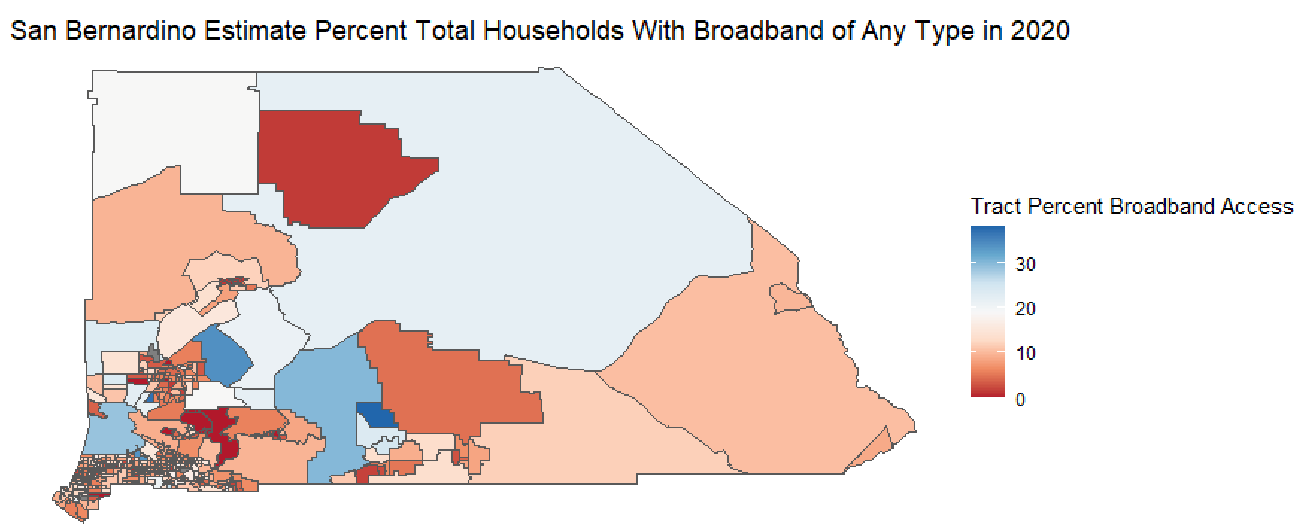
Low-income areas are linked with lower broad internet access in San Bernardino. The distribution of internet access is distinct in different tract areas. Especially for the western parts, the internet access rate is below 50%, and the estimated percentage of households with broadband of any type is around 10%.

Figure 48. Percent of total households with an internet subscription, 2020



Data source: 2020 ACS 5-year

Figure 49. Percentage of households with broadband, 2020



Method 3: Spatial analysis

Part of UCR's task was to also evaluate to the extent possible the impact and relationship of the built environment to creating disadvantage. As part of this work, we explored several possibilities regarding network access, catchment areas, and proximity based on land use designations.

There are several limitations and caveats that need to be mentioned. First, while we hoped to do a land use change assessment (e.g., illustrate how industrial land use has changed over the last decade to understand the context of various measures of impacts), the land use parcel data we received lacked the level of consistency over each year of data provided needed to accurately understand the actual change over time. In the future, it would be helpful to start collecting land use data in a way that can be tracked longitudinally in order to be able to more accurately understand what types of land uses are changing and where, and what the potential spatial impacts may be on adjacent land uses.

Second, the spatial network proximity analysis relied heavily on the line geometry provided. This causes some inherent problems, as the network and spatial models run can only be as accurate as the relationship between the various lines and polygons. While we believe that this analysis still provides a basis for some general takeaways about proximity, location, and access, it should not be taken as a completely accurate and comprehensive representation. Additionally, line geometry is a representation of a point in time, and so its accuracy is highly dependent on how often the dataset is updated, which is notably a time-consuming and expensive process.

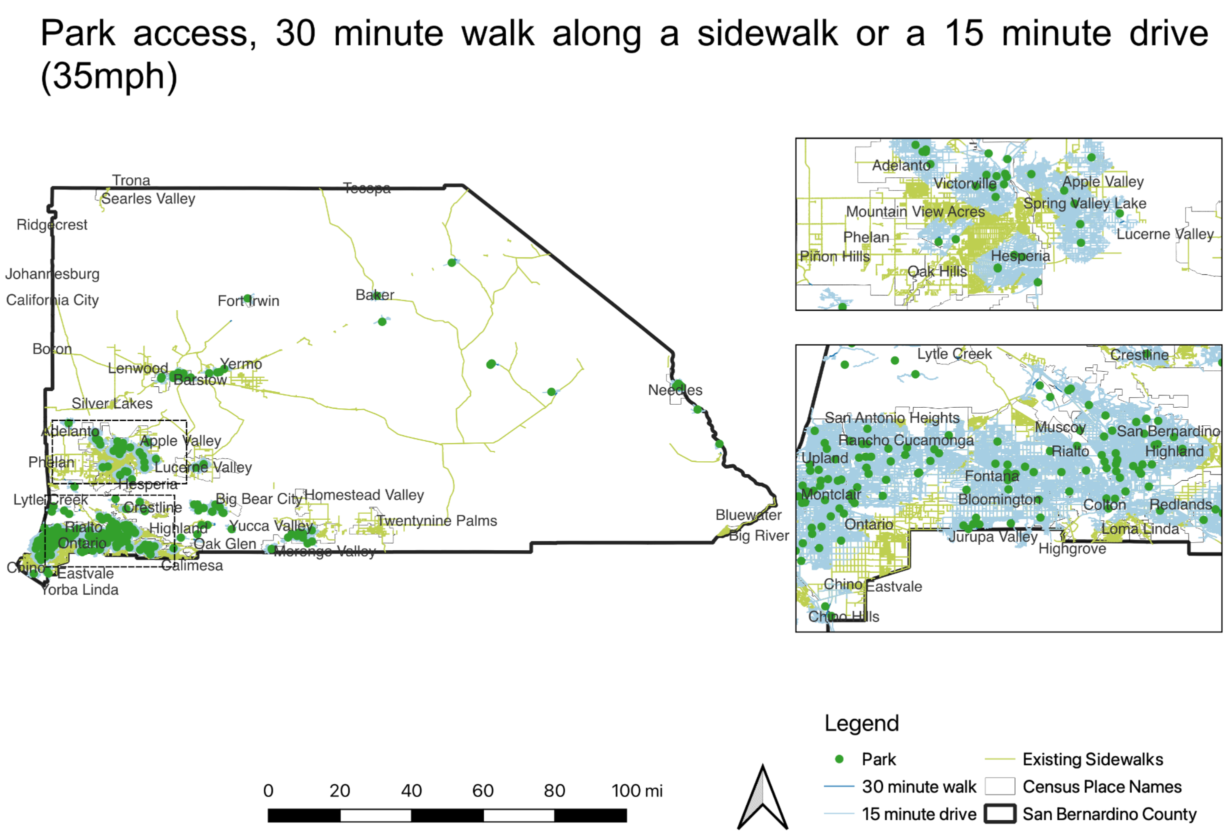
Third, while part of the intent of this project was to better understand disadvantage within San Bernardino County, the spatial data does not necessarily lend itself to understanding causality. For instance, the land use data only captures what the land use designation is, not what the particular parcel is actually being used for, and also does not capture what it might be in the process of being used for (e.g., small deviation (possibly just at the applicable, associated zoning level) or a larger deviation from what is currently indicated as the land use designation). While some of this data undoubtedly exists at the municipal level, including specific detailed business-related data, it was determined that acquiring this data would take significantly longer than the study period to complete, and it was also not clear to what extent we would be able to offer meaningful conclusions. Additionally, the spatial data we were able to access does not include specifics about zoning, just land use designations. While zoning data would be especially useful, particularly if it spanned multiple years, inconsistencies in labeling across jurisdictions also poses a large practical challenge in terms of creating a baseline for comparison.

The majority of the figures below focus on the southwest section of San Bernardino County, as the other regions that are flagged by the overlap in Methods 1 & 2 data cuts are larger, less-densely populated areas of the county in the desert, and pose different circumstances and challenges.

Method 3: Access to parks

As part of this analysis, we sought to understand how accessible parks were to the larger community. We ran a network analysis based on the sidewalk line geography and road network geography to understand how accessible parks were from other land uses, using either walking or driving as mode share.

Figure 50. 30-minute walk-shed along an existing sidewalk route or 15 minute drive-shed at 35mph

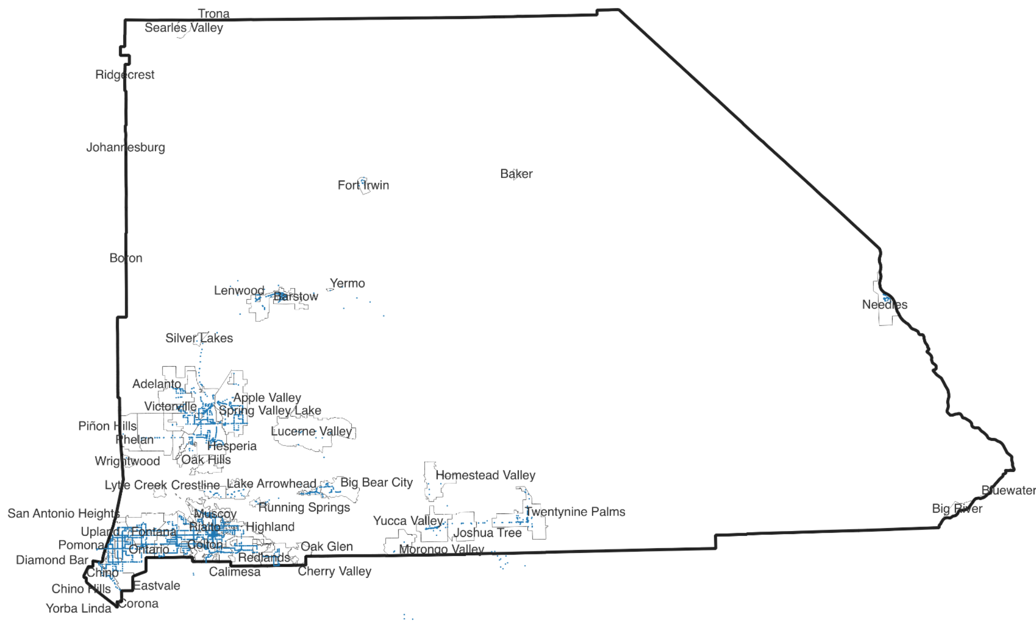


Method 3: Public Transportation

The densest public transit network of bus stops are located in southwest San Bernardino County. In this region, the places with the greatest concentrations of stops are Chino Hills, Chino, Montclair, Ontario, Upland, Rancho Cucamonga, Fontana, Bloomington, Rialto, Colton, Grand Terrace, Muscoy, San Bernardino, Loma Linda, Highland, Redlands, Monotone, and Yucaipa.

There are significantly smaller concentrations of bus stops in the Hesperia - Victorville area, Yucca Valley - Joshua Tree - Twentynine Palms area, and Barstow area.

Figure 51. Bus stops



This difference in coverage density is important because in practical terms, it creates barriers to being able to actually rely on public transportation for one's daily transportation needs.

From the focus groups:

"In addition to neighborhood-scale concerns, participants cited existing transportation infrastructure as an issue impacting the built environment and public health, particularly in remote areas of the County (e.g., high desert and tribal communities). Participants noted that public transportation infrastructure is either non-existent or not accessible for remote communities. Local organizations have piloted alternative transportation models (e.g., carpools, van shares, etc.), ensuring access to critical services (e.g., medical care, grocery stores, mental health services) with success and recommend supporting these models with public funding. Additionally, the lack of active transportation infrastructure across the region reinforces dependence on GHG-emitting vehicles, resulting in poor air quality and negative health outcomes (SBAG and SCAG 2015)."

Granted, from a policy perspective, the lower density in the remote areas of the County creates practical barriers in terms of funding and resources to be able to fund, maintain, and sustain a robust public transportation infrastructure.

Method 3: Residential land use designations in proximity to industrial and industrial-adjacent land use designations, within a 15 minute walk (along a sidewalk) of a bus stop

In large part, one of the biggest goals of the spatial analysis portion of this project was to better understand the impact of industrial and industrial-adjacent land use designations on the immediate and surrounding community. While it is impossible to make any causal statements, we wanted to better understand the proximity between residential land use designations and industrial and industrial-adjacent land use designations. In this particular case, we wanted to understand the catchment area of a 15 minute walk radius along a sidewalk from a bus stop, as this may capture those residents who are most reliant on public transportation and may also be particularly cost-burdened.

From the focus group data:

"Across all focus groups, participants expressed concern with environmental justice issues in the built environment and public health impacts in San Bernardino County, particularly for low-income communities and people of color. Participants cited disproportionate exposure to unhealthy and polluting land uses, resulting in poor air quality and negative health outcomes. A report on racial equity conditions across the Southern California Associated Governments (SCAG) region, explains that a "disproportionate share of people of color and low-income communities live near freeways and industry, exposing communities to higher rates of exposure to all sources of air pollution." High levels of air pollution are linked to serious health issues, including asthma, heart disease, cancer, and premature death (SCAG 2021).

The logistics and distribution industry was prominently cited by participants as a main driver of poor air quality. Warehousing and distribution centers, often located in industrial zones, contribute to air pollution with truck traffic, truck idling, and warehousing construction operations (CA DOT 2009). The logistics industry can also create negative noise and traffic impacts to communities surrounding these sites. Participants noted that a lack of access to green infrastructure, such as solar technology and electric vehicles, compounds air quality issues in low-income communities and communities of color."

Table 2. Residential and industrial land use and industrial land use-adjacent designations, within 15 minutes of a bus stop along a sidewalk

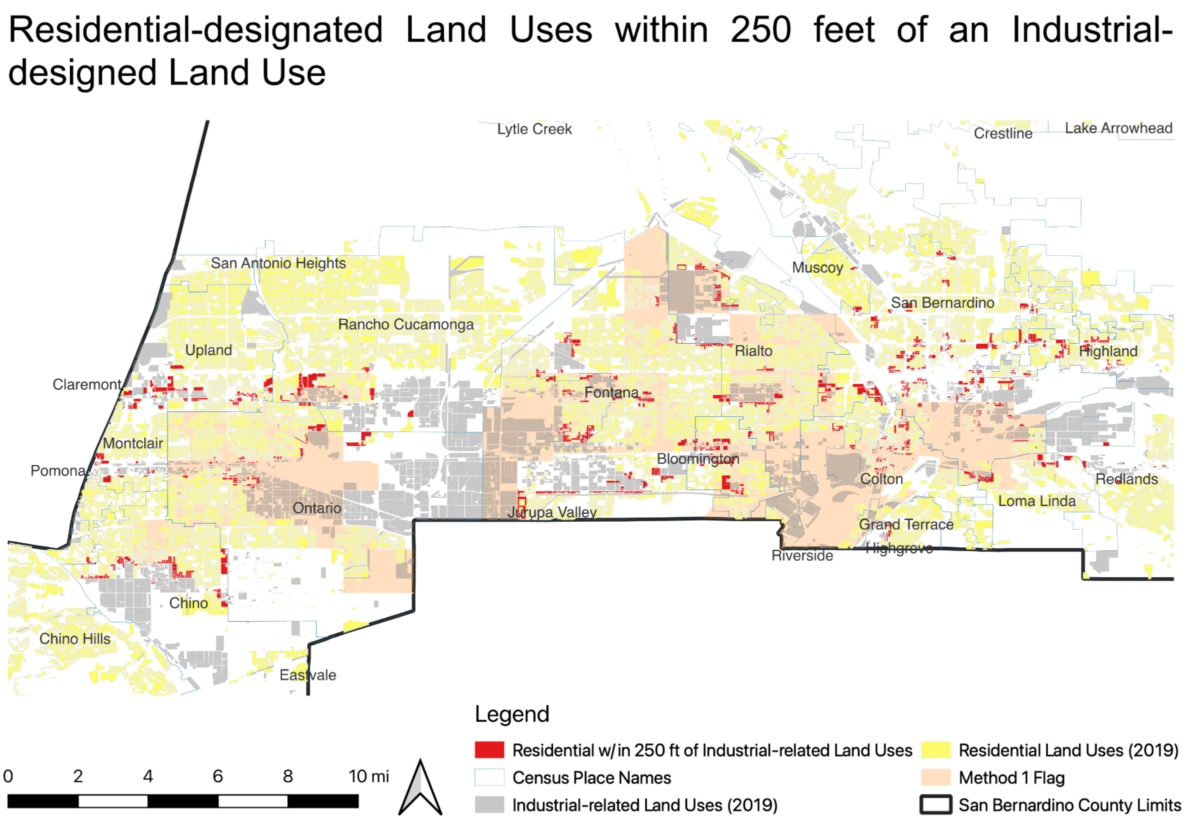
Residential LU designations	Industrial and related LU designations
Duplexes, Triplexes and 2- or 3-Unit Condominiums and Townhouses	Industrial Light Industrial

High Density Single Family Residential Low Density Single Family Residential Low-Rise Apartments, Condominiums, and Townhouses Medium Density Single Family Residential Medium-Rise Apartments and Condominiums Mixed Multi-Family Residential Mixed Residential Mixed Residential and Commercial Mobile Home Courts and Subdivisions, Low-Density Rural Residential Rural Residential High Density Rural Residential Low Density Trailer Parks and Mobile Home Courts, High-Density	Liquid Waste Disposal Facilities Major Metal Processing Manufacturing Manufacturing, Assembly, and Industrial Services Mineral Extraction - Other Than Oil and Gas Mixed Commercial and Industrial Natural Gas and Petroleum Facilities Solid Waste Disposal Facilities Wholesaling and Warehousing

As part of this Method 3 analysis, we aimed to identify residential land use designations that fell within a 15-minute walking distance of a bus stop as well as within close proximity to industrial designated land uses.

This was done in part for two reasons. First, we wanted to understand how many residential areas were within a reasonable distance of a bus stop to better understand accessibility for those who may not have access to a car. Second, we wanted to identify those residential areas that are also within close proximity of an industrially-designated land use. While we cannot identify which of these land uses are currently occupied by actual, active industrial uses, because their land use designation is for industrial and industrial-type uses, it can be reasonably assumed that these locations are prime spots for any type of new industrial and/or industrial-adjacent uses that may be proposed and/or approved in the future.

Figure 52. Any type of designated residential land use that is within a 250 foot buffer of any type of designated industrial, manufacturing, or warehouse land use.

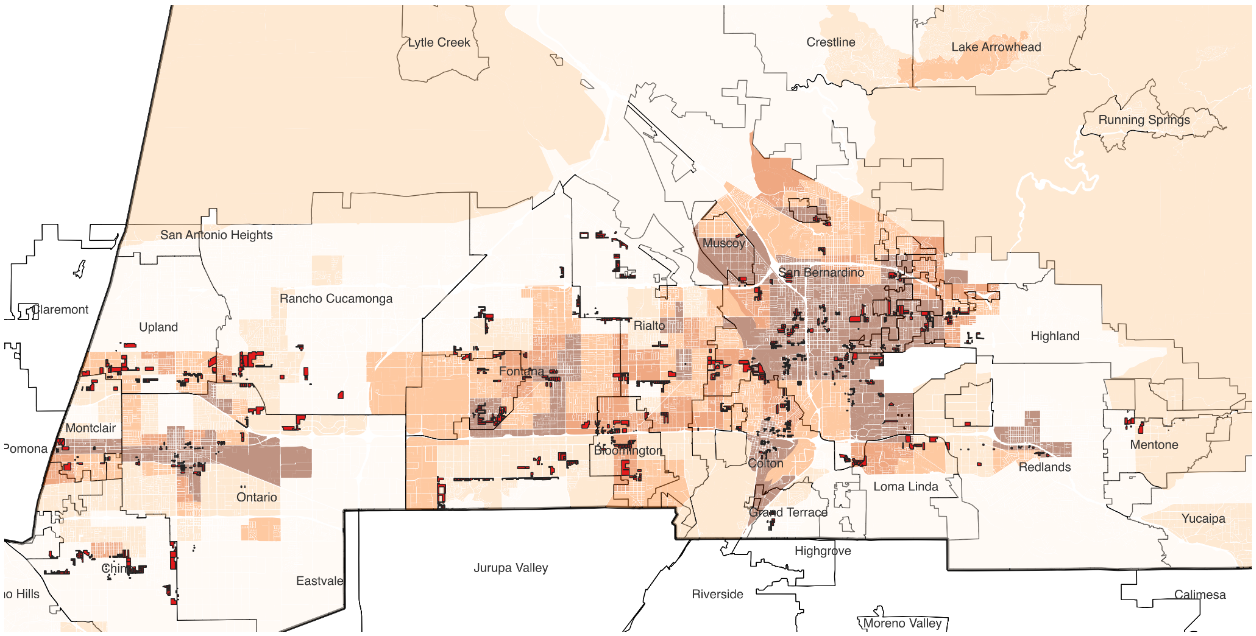


Much of southwestern San Bernardino county has parcels that fall within this catchment area, and include the Census Places: Chino, Montclair, Upland, Rancho Cucamonga, Ontario, Fontana, Bloomington, Rialto, Muscoy, San Bernardino, Colton, Grand Terrace, Loma Linda, Highlands, Redlands, and Mentone. Other areas in the county include Hesperia, Apple Valley, Victorville, Adelanto, Lenwood, and Barstow. There are several other areas, but they have significantly smaller densities of these parcels.

We merged the parcel level data with the CalEnviroScreen 4.0 data at the tract level to get an approximation of what potential disadvantage-related variables corresponded with each parcel.[12] Layering this information with poverty rates using the CalEnviroScreen 4.0 dataset, we see that many of these communities are also areas with high poverty rates.

[12] Note that this is only an approximation; CalEnviroScreen 4.0 (CES) data uses the 2010 tract vintage, where the parcel level data is from San Bernardino County COG's parcel level file. There are likely several geometries that did not merge completely, and as such these takeaways should only be used to get a general indication of what some of the associated CES variables may be for each of the parcel level geometries.

Figure 53. Residential land use designations that fell within a 15-minute walking distance of a bus stop as well as within close proximity to industrial designated land uses, overlaid with CES 4.0 poverty rates



Method 3: Residential land use designated areas in proximity to freight truck routes

As part of the qualitative analysis done by the larger SB1000 team, focus groups were asked to identify top concerns regarding environmental justice and equity. Respondents identified the logistics and distribution industry as a top concern, and a key contributor to the region's poor air quality.

From the focus group:

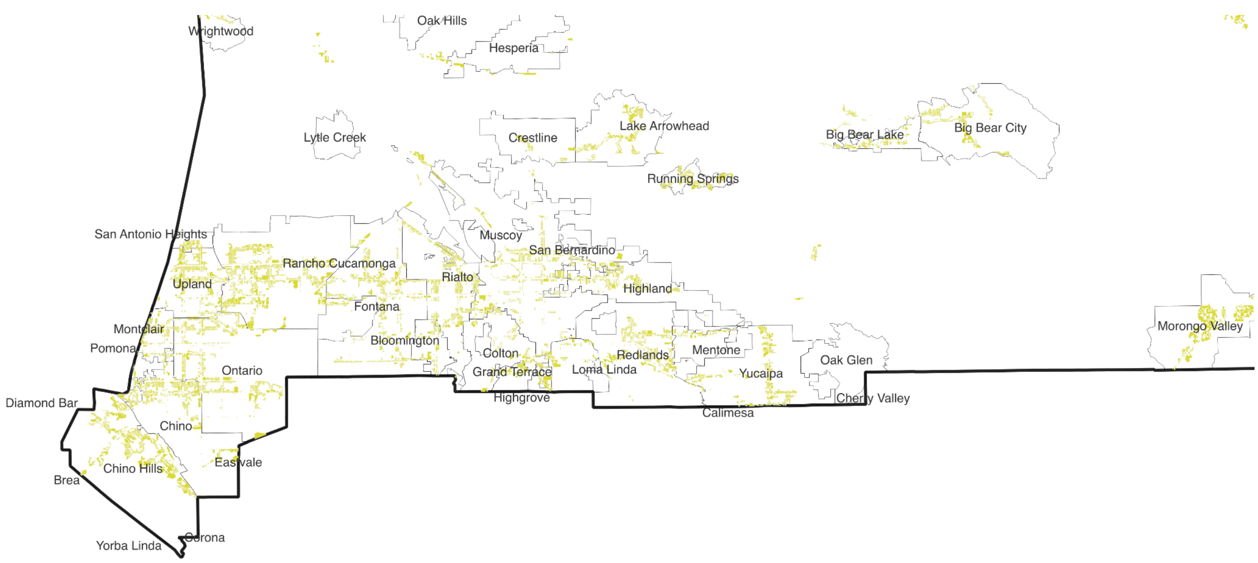
"The logistics and distribution industry was prominently cited by participants as a main driver of poor air quality. Warehousing and distribution centers, often located in industrial zones, contribute to air pollution with truck traffic, truck idling, and warehousing construction operations (CA DOT 2009). The logistics industry can also create negative noise and traffic impacts to communities surrounding these sites. Participants noted that a lack of access to green infrastructure, such as solar technology and electric vehicles, compounds air quality issues in low-income communities and communities of color."

As part of this analysis, we sought to isolate residential land uses that were in close proximity to freight truck routes. Note that we used freight truck routes instead of the basic road network as we wanted to ensure that we picked up large freight vehicles which typically can primarily only operate on certain thoroughfares, as opposed to the smaller trucks that do not necessarily have the same restrictions.

Freight Line geometry:
https://data-usdot.opendata.arcgis.com/datasets/usdot::freight-analysis-framework-faf5-network-links/about

While the range of surrounding residential area whose air quality may be impacted by freight traffic is difficult to generalize (e.g., particulate matter trajectories are highly dependent on a range of factors, including atmospheric conditions, the modeling of which is outside the scope of this project), because most large freight vehicles must primarily travel on designated routes we instead opted to capture all residential designated land uses within proximity of these designated routes.

Figure 54. Residential land use designation within proximity of a truck freight route



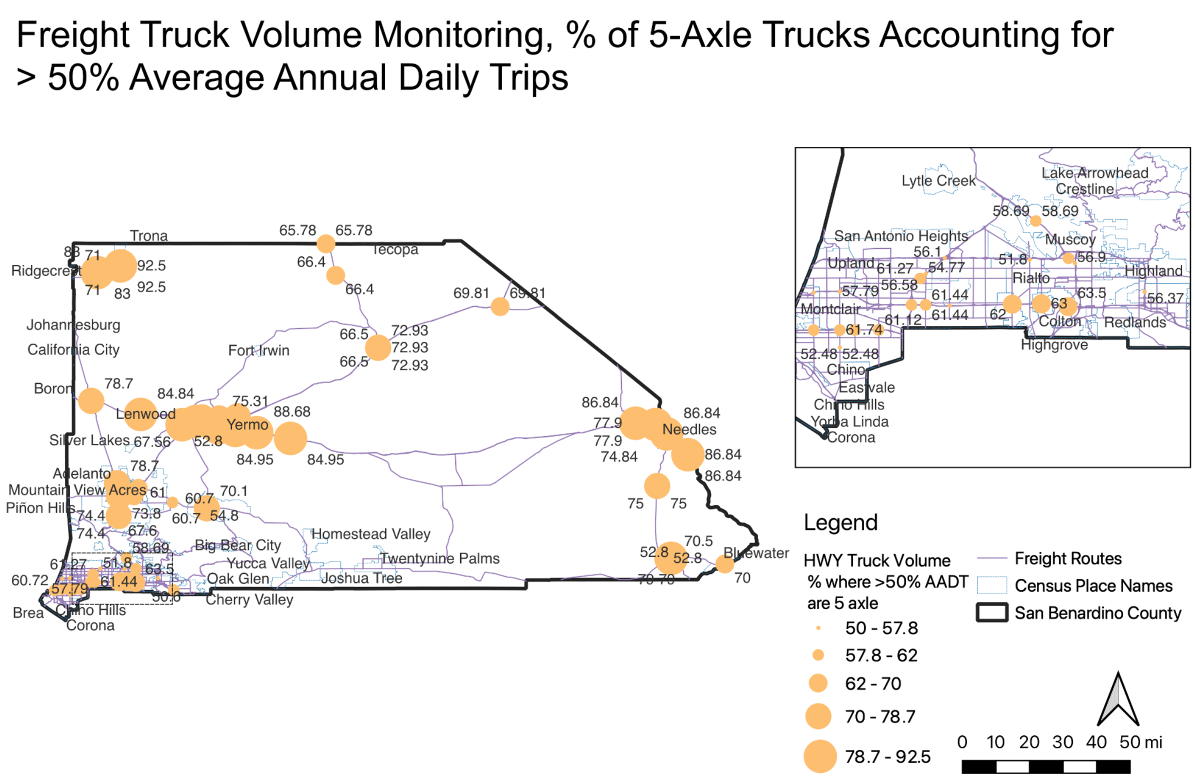
However, we also wanted to understand who lives in these residentially-designated areas. As an important caveat, the residential parcels indicated above in olive green are those that are designated as residential on the land use file - the land use dataset does not indicate what use is actually on a particular parcel.

Additionally, as noted earlier, there are limitations to further analysis based on this data. The following two figures rely on the merging of parcel-level data with tract-level data. This was primarily done to get an idea of the potential demographics that may be impacted by freight movement along these designated corridors. However, due to the nature of combining two different line geometries from two different sets of year vintages, there are limitations to the accuracy of the data merge, and any comparisons that can be made using it.

Method 3: Freight truck volumes, locations

Freight truck volumes are also particularly high in this region, with many counting stations recording over 20,000 daily trips, and with many of the counting stations recording over 40% of the trips attributed to 5-axle truck trips (labels on map are percentages of total share of recorded trips).

Figure 55. Freight truck volume monitoring locations



The following table lists monitoring locations that have greater than 50% of the Annual Average Daily Traffic attributed to 5 axle trucks as of August 2022.

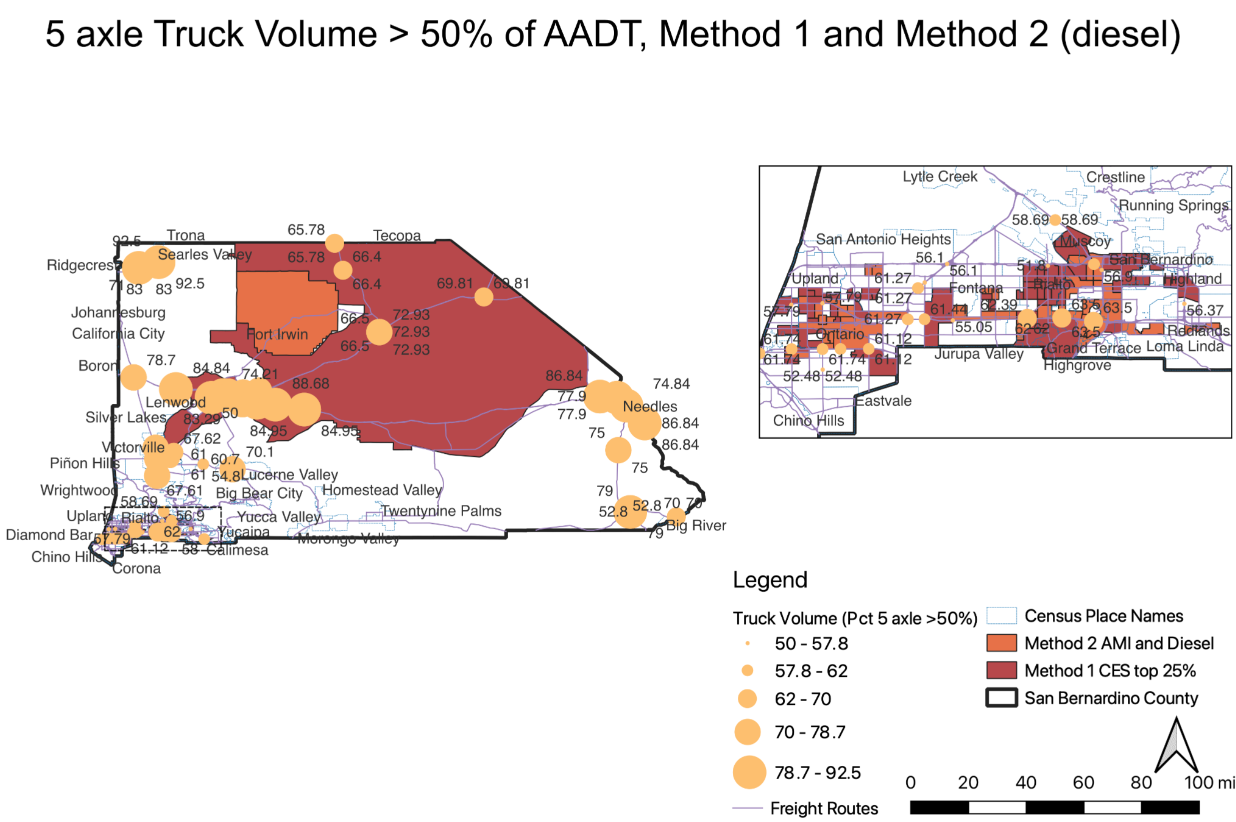
Table 3. Monitoring locations with greater than 50% of its annual average daily truck traffic attributed to 5 axle trucks

MONTCLAIR, CENTRAL AVENUE	BAKER, JCT. RTE. 127	JCT. RTE. 95
UPLAND, JCT. RTE. 83	NIPTON ROAD	SCHAEFER AVE
ONTARIO, JCT. RTE. 15	LUCERNE VALLEY, JCT. RTE. 247	JCT. RTE. 62
ETIWANDA AVENUE	BEAR VALLEY CUTOFF	HAVASU LAKE ROAD
FONTANA, CHERRY AVENUE	BARSTOW, JCT. RTE. 15	EAST JCT. RTE. 40
BLOOMINGTON, CEDAR AVENUE	A STREET	WEST JCT. RTE. 40
PEPPER AVENUE	AIRPORT ROAD	SARATOGA SPRINGS ROAD
COLTON, MOUNT VERNON AVENUE	WEST NEWBERRY ROAD	SAN BERNARDINO/INYO COUNTY LINE
YUCAIPA BOULEVARD	E/O DESERT OASIS ROADSIDE REST	TRONA ROAD
JCT. RTE. 10	JCT. RTE. 95 NORTH	RIALTO, RIVERSIDE AVENUE
JCT. RTE. 66	PARK ROAD	JCT RTE 15
RANCHO CUCAMONGA, MILLER AVENUE	JCT. RTE. 95 SOUTH	E/O SANTA ANA RIVER BRIDGE
JCT. RTE. 395 NORTH	ARIZONA STATE LINE	SAN BERNARDINO, JCT. RTE. 259 NORTH
JCT. RTE. 18 SOUTH	IRON WASH BRIDGE	SAN BERNARDINO, HIGHLAND AVENUE
VICTORVILLE, JCT. RTE. 18 SOUTHEAST	JCT. RTE. 15	SAN BERNARDINO, JCT RTE 206
BARSTOW, LENWOOD ROAD	LOS ANGELES/SAN BERNARDINO COUNTY LINE	JCT. RTE. 18
BARSTOW, JCT. RTE. 40 EAST	CENTRAL AVENUE	STODDARD WELLS ROAD
JCT. RTE. 58 WEST	ONTARIO, JCT. RTE. 83	PALMDALE ROAD; JCT. RTE. 18

GHOST TOWN ROAD	GROVE AVENUE	GEORGE AIR FORCE BASE ROAD
YERMO INSPECTION STATION	ARCHIBALD AVENUE INTERCHANGE	TWENTY MULE TEAM RD

While the largest share of monitoring stations that picked up greater than 50% of AADT for 5-axle trucks were located in southwest San Bernardino, there were also clusters located in the Barstow area as well as in the Hesperia - Victorville area. Many of these areas (particularly in southwest San Bernardino) are also either within or adjacent to tracts identified as within the top 25% of CalEnviroScreen 4.0 scores, which is one measure of significant disadvantage.

Figure 56. CES 4.0 top 25% scores, and percentage of diesel particulate matter



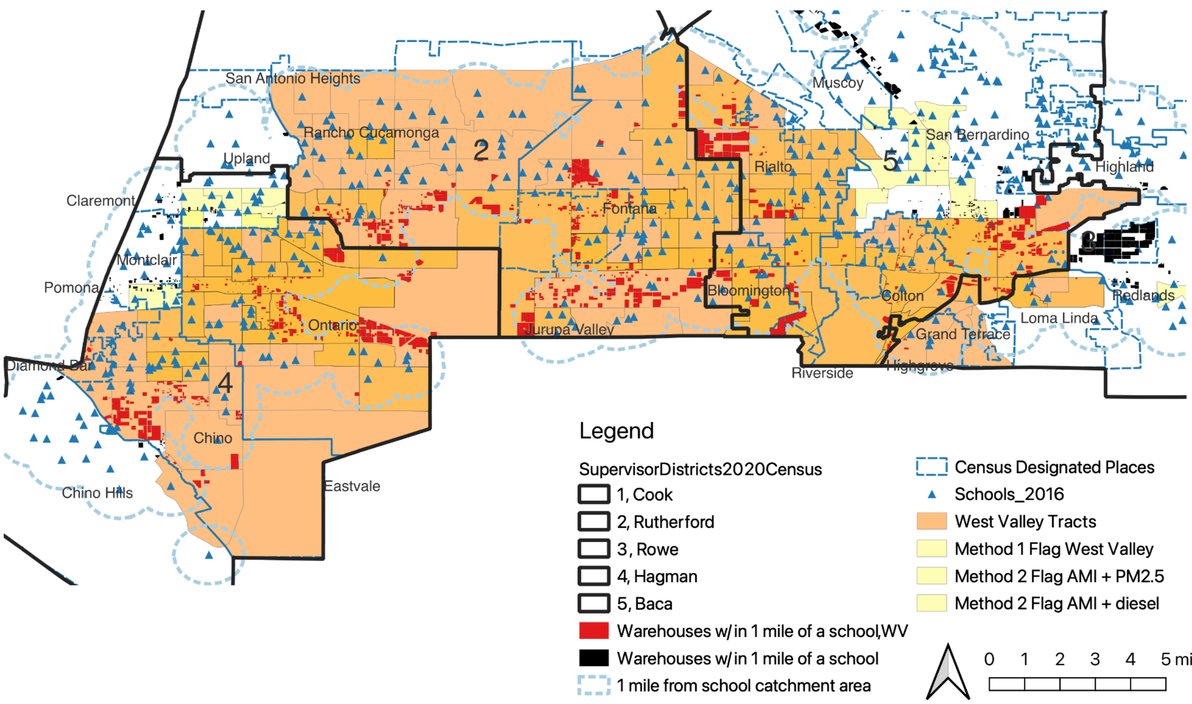
Ideally we would have been able to analyze historical data to help identify potential trends in AADT, which would be an important variable to track down for further analysis.

Method 3: Proximity to warehouses and warehouse-adjacent zoning assessed designations

One area of concern was the relationship between land uses and environmental justice aspects. This particular analysis looked at the proximity of schools to warehouses. While we were able to identify over 2,000 warehouses and warehouse-related uses (as identified on Assessor parcel data) that were within 1 mile of a school, of which over 1,000 were in the West Valley area, it should be noted that there may be more or fewer warehouses that are close to a school, depending on the actual land use.

Figure 57. Schools in proximity to warehouses, warehouse distribution centers, and warehouse-adjacent zoning assessed designations

Warehouses within 1 mile of a school (overlaid with Method 1 & 2)

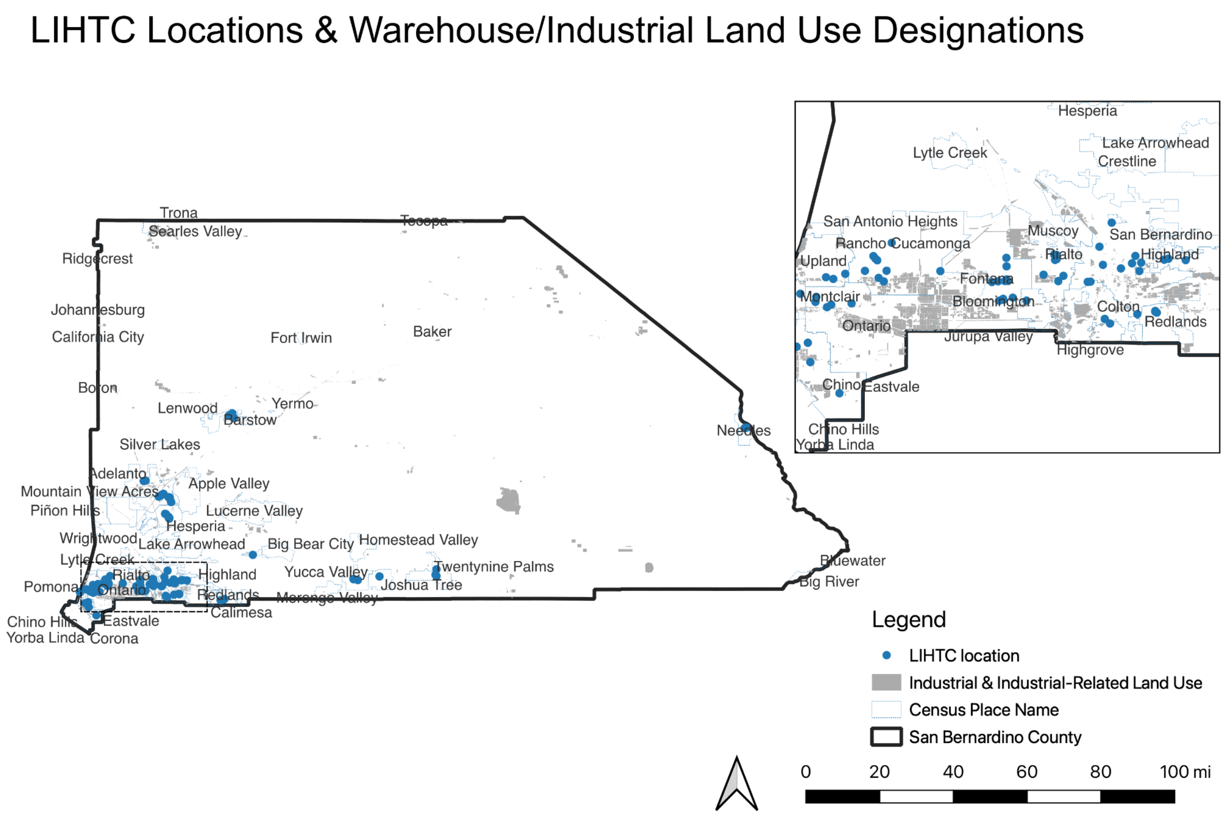


Parcel data source:
https://open.sbcounty.gov/datasets/sbcounty::sbco-parcel-polygons/explore?location=33.410376%2C-118.648044%2C22.99

We also wanted to understand what, if any, spatial burden low-income individuals have with relation to proximity to warehouses and warehouse-related land uses. Based on the same

Assessor data, we mapped out low-income housing tax credit housing production in relation to warehouses and other industrial land use designations. Similar to the caveat identified above, this analysis does not take into account what the actual land use is. However, it does provide information on what the land use designation is, which does factor into what the actual use of a particular parcel is.

Figure 58. LIHTC residential areas in proximity to warehouses, warehouse distribution centers, and warehouse-adjacent zoning assessed designations



Data source: https://lihtc.huduser.gov

Method 3: Access to alternative fueling stations

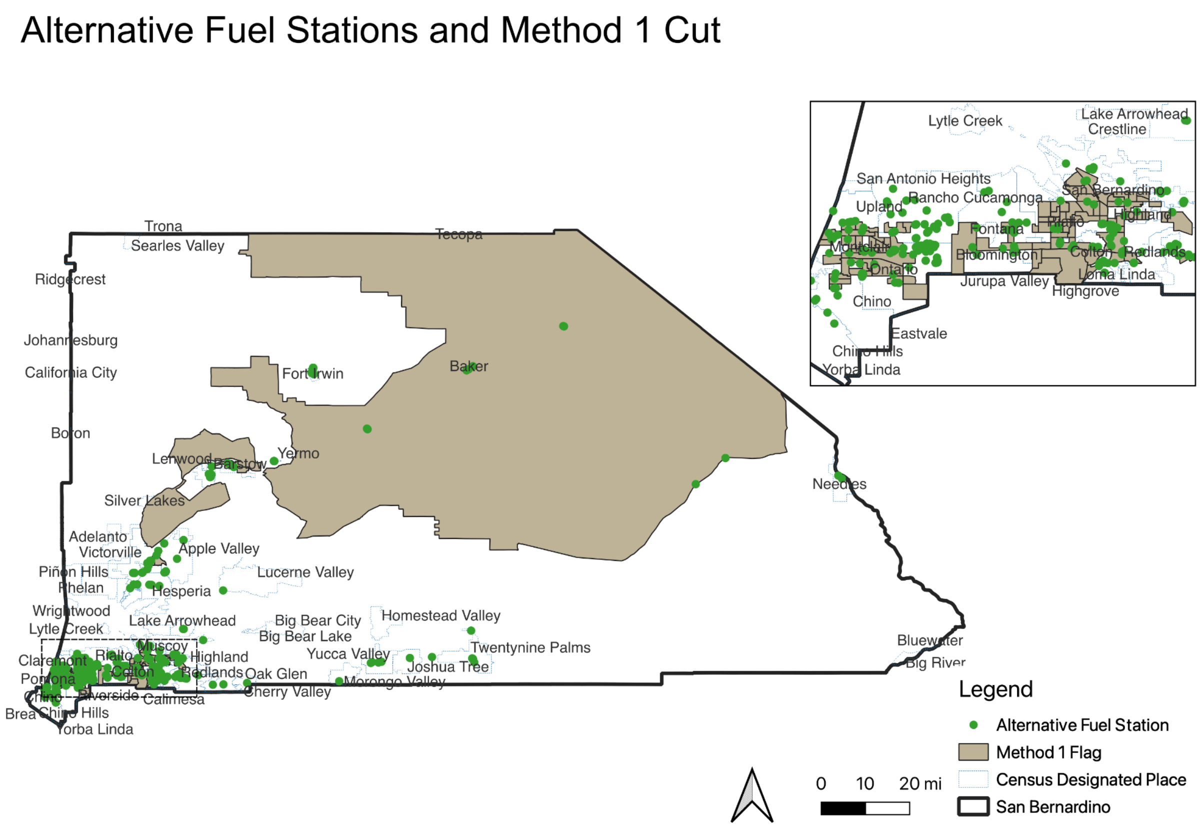
Alternative fuel sources have been identified as one way to address pressing air quality issues. As part of the policy push to address global warming and climate change, both the state and federal level have been pushing vehicle manufacturers to adopt alternative fuel technology for consumer-type motor vehicles, offering significant incentives to help increase demand. However, a major barrier to greater increases in purchases of these types of vehicles is availability of alternative fueling stations - be they in residential or commercial type settings.

From focus group:

"The logistics and distribution industry was prominently cited by participants as a main driver of poor air quality. Warehousing and distribution centers, often located in industrial zones, contribute to air pollution with truck traffic, truck idling, and warehousing construction operations (CA DOT 2009). The logistics industry can also create negative noise and traffic impacts to communities surrounding these sites. Participants noted that a lack of access to green infrastructure, such as solar technology and electric vehicles, compounds air quality issues in low-income communities and communities of color."

Lack of access to alternative fueling stations also impacts the ability of communities to fully take advantage of alternative fuel vehicles such as electric vehicles. Particularly for those who live in multi-unit housing, such as apartment complexes, having access to infrastructure like publicly-accessible electric charging stations becomes key to enabling communities to leverage the environmental benefits of alternative fuel vehicles as well as take advantage of the many state- and federal-level incentives tied to owning an alternative fuel vehicle.

Figure 59. Public alternative fuel stations, overlaid by Method 1 (CES 4.0 top 25%)



Data source:
https://data-usdot.opendata.arcgis.com/datasets/usdot::alternative-fueling-stations/about

Groupings of public alternative fuel stations are predominantly located in the southwest corner of San Bernardino, with smaller clusters in the Hesperia - Victorville area and the Barstow area. Otherwise there are a handful in the northeastern half of the county, primarily located at travel centers.

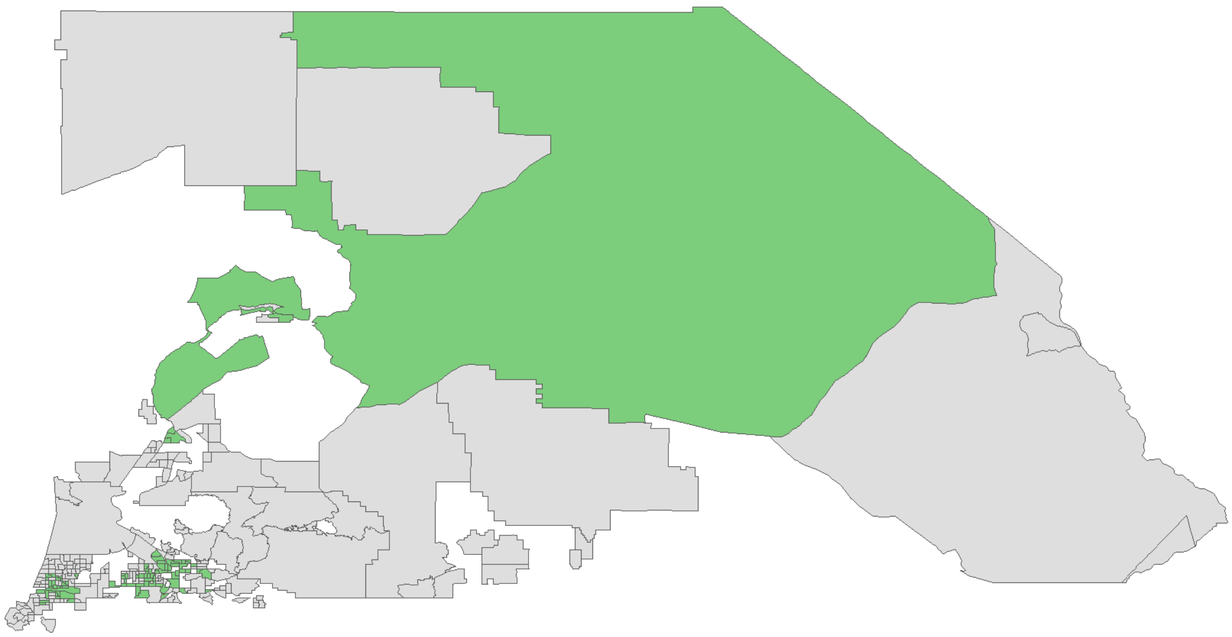
Discussion & Suggested Next Steps

Summary discussion

The Method 1 cut isolated areas with tracts that had the top 25% scores via the CalEnviroScreen 4.0 dataset. The areas flagged were concentrated in the southwest corner of San Bernardino County as well as parts of the Barstow-Victorville area, and then a substantial portion of the northeast segment of the county (note: the tracts here are geographically very large as the population density is very low). Through this approach we isolated 129 tracts (35% of total).

The Method 2 cut further drilled down on various aspects of disadvantage, initially isolating areas with an area median income of less than 80%. Some other options that were considered as part of this cut were PM2.5 percentile and diesel percentile as per the same CalEnviroScreen 4.0 dataset. Because of the nature of the SB1000 proposed Method 2 cuts, which then suggest using other measures of disadvantage, we opted to evaluate some options from SCAG's PEPA approach (illustrated in Figure 13). However, we could not use all of the variables as including all of them would have flagged a majority of tracts within the County, reducing the utility of this particular analysis. Because of this, we opted to isolate several variables based on knowledge of the policy process as well as what the literature has identified as important to understanding disadvantage (both in the present as well as contributing to generational disadvantage). A few things should be noted here. First, while we conducted a regression analysis to better understand which variables were most highly correlated with disadvantage - and ideally to isolate which ones should be used for the method cuts - the reality is that this particular set of decisions was more of an 'art' approach than a 'science' approach. For instance, while we used SCAG's PEPA approach to help inform our consideration of variables that might make sense for a Method 2 cut (see Figure 13 for SCAG's proposed PEPA variables), variables such as older populations were excluded since there are areas that tend to skew older, but are not necessarily disadvantaged (e.g., while it is in Riverside County, the Palm Springs area is an example of a community that skews older but is also affluent). Additionally, the variable households that do not have access to an automobile was also excluded since technically many policy approaches are working to steer people away from using vehicles and instead toward using mass transit and active transportation options. Finally, we also opted to omit the variable female-led households because that then removes male-led households (while less frequent, there are households that are single parent and not female-led) as well as households where either a grandparent or another family member/guardian are the primary caregivers. Through this approach we then isolated 173 tracts (46.8% of total). By combining Method 1 and Method 2, we isolated 87 tracts (23.5% of total).

Figure 60. San Bernardino County tracts with Method 1 and 2 Flag



The Method 3 cut aimed to address spatial aspects of the built environment, as well as feedback that was gathered from some of the qualitative data collection conducted as part of the larger SB1000 process conducted by the overall SB1000 team (note: UCR was not an active part of this particular process due to several external issues beyond the team's control). Aspects that were considered included walkability, access to parks/open space, access to bicycle lanes, proximity to sidewalks, land uses (e.g., schools, residential) that were within a specified distance of a warehouse, land uses within proximity of public bus stops, racial breakdown of proximity to major freight thoroughfares, proximity to publicly accessible electric vehicle charging stations, among others.

For this particular assessment, a few things should be noted. First, population density throughout the county varies considerably, and as a practical measure does factor into aspects such as the existence and/or extensiveness of public transportation networks, the frequency of public parks, and the relative usefulness of mapping out proximity/adjacency of land uses. Second, infrastructure investments also vary widely, and often correspond to the type of development in an area - i.e., urban areas will inherently look different than very rural areas. While sidewalks may be common in densely populated urban areas (granted this isn't always the case, particularly in areas that are also heavily populated by industrial uses, or older neighborhoods, or lower-income), they often are not a part of the landscape in rural areas, and sometimes are only sparsely deployed in very suburban areas. The same can be said of bike lanes and for newer infrastructure amenities such as electric vehicle charging stations.

A few major takeaways can be noted. First, the sidewalk infrastructure in the southwest portion of the county - which is also the location of some of the highest population densities in the county - is fairly comprehensive. As a caveat, this analysis is based on the current line geometry available for use by the study team, and may not be fully updated and/or may not fully be indicative of the current condition of the sidewalk (e.g., incomplete, broken sections, unusable sections). Second, the amount and distribution of parks is fairly high for the southwest portion of the county - again where there is the highest population density. Granted this is dependent on available data, but further analysis could look at trends related to health outcomes, including variables such as frequency of exercise that is not related to work.

When looking at the breakdown of residential uses by race, the southwest portion of the county is heavily Hispanic/Latino, with much smaller frequencies of Black/African American residents.

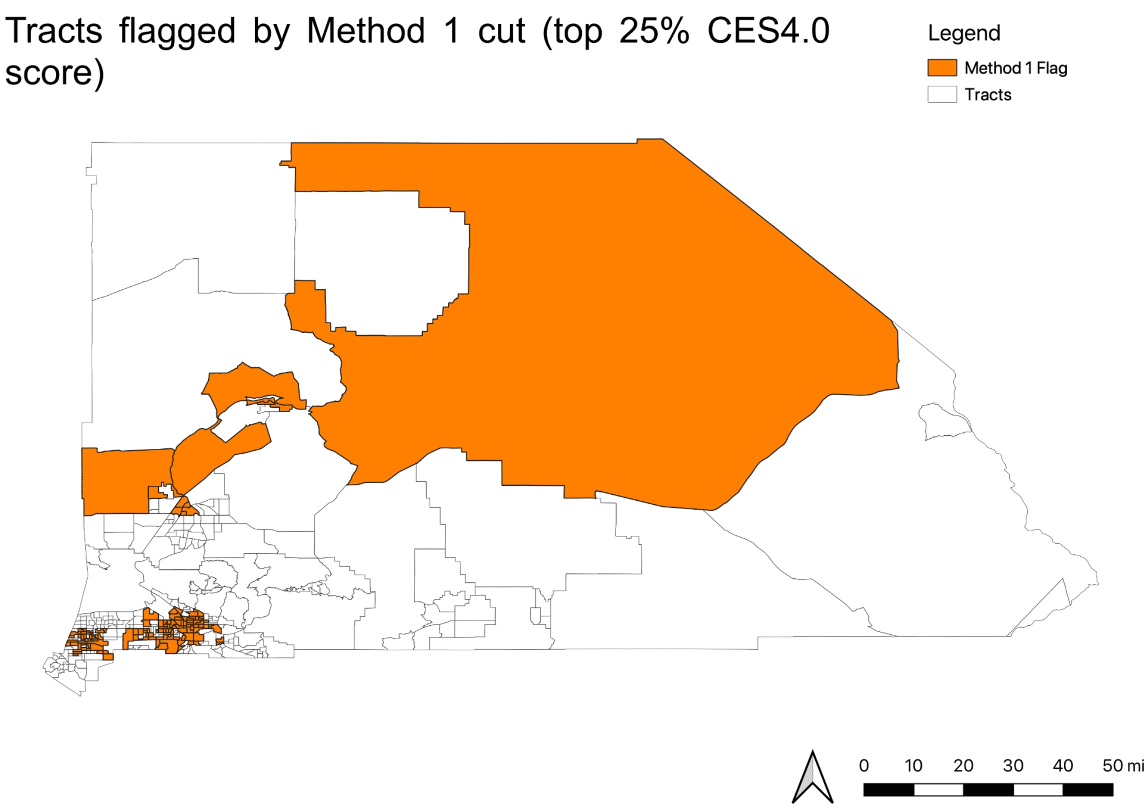
The following are some major takeaways:

- The southwest corner of the county /West Valley has significant environmental disadvantage
- For some spatial metrics (e.g., park access, availability of sidewalks, public transportation access) disadvantage in the SW corner of the county/West Valley is less than in other parts of the county (note: this region has greatest population density and greatest clusters of urban areas)
- Existing data raises some questions about land use designations and decisions (e.g., relationship between siting of LIHTC production, schools, warehouses, truck routes and volumes)
- Emerging technologies that may impact future environmental burden scores like CalEnviroScreen, such as electric vehicle charging infrastructure, are becoming more common and are increasingly found outside of major urban centers, but still skew heavily toward more urbanized areas and/or areas that are heavily trafficked
- Food access is a significant concern, with tracts throughout the county where households that do not have access to a vehicle also live more than ½ mile from a grocery store; in rural areas food access shows 9 tract areas representing low income greater than 20 miles from supermarket, and 18 tract areas representing low income greater than 10 miles from a supermarket.
- Regression analysis identifies the following key indicators relevant to housing cost burden: household income, life expectancy, CES 4.0 score, asthma rate, poverty rate, linguistic isolation, and educational attainment
- Childhood poverty and upward income mobility analysis shows the correlation between upward mobility and social capital

Regional profiles

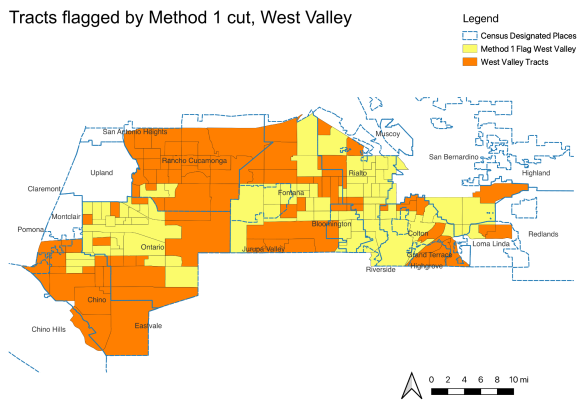
As part of this analysis, we were asked to also zero in on four sub-regional areas: West Valley, East Valley, the High Desert, and the Morongo Basin.

Figure 61. San Bernardino County sub-regions of focus

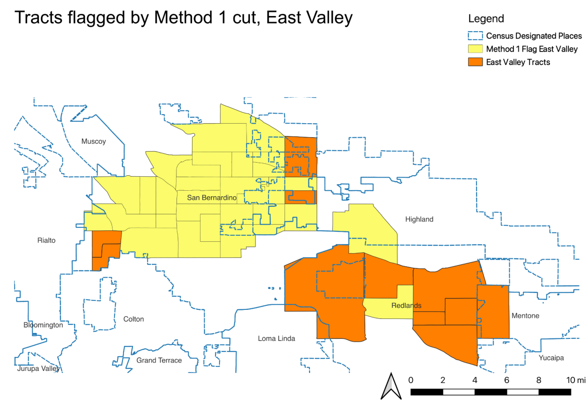


San Bernardino County tracts with Method 1 Flag

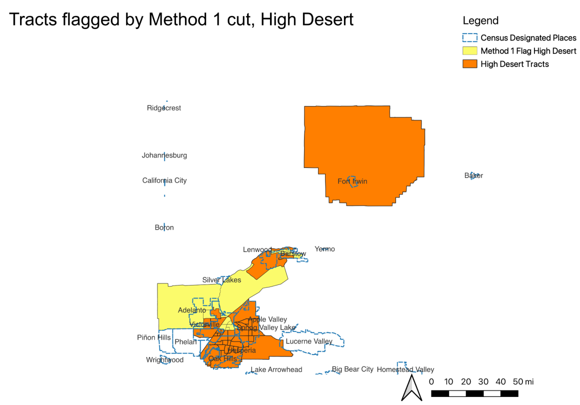
Zoom-in of isolated areas via Method 1 cut



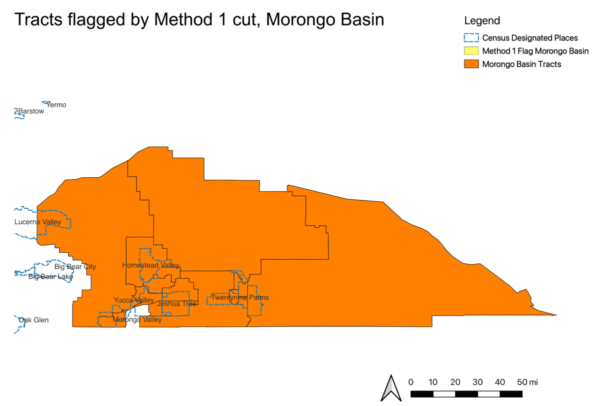
West Valley



East Valley



High Desert



Morongo Basin

East Valley is in San Bernardino County, including San Bernardino, Loma Linda, Bryn Mawr, Grand Terrace, Redlands Colton, and Rialto. The average household income is $57,392, below the San Bernardino area median income of $61,200, and the poverty percentile is 72.20%. The average CES 4.0 score percentile is also above 75%. Around 52% of residents choose to rent their homes.

West Valley is mainly located in the cities of Rancho Cucamonga and Chino. The average household income is $86,012, above the San Bernardino area median income, and the poverty percentile (38.81%) is the lowest compared with East Valley, High Desert, and Morongo Basin. The Education percentile (percent of the population over 25 with less than a high school education) is 45.06%, lower than the other three regions.

High Desert areas include Victorville, Hesperia, and Barstow cities. It usually turns extremely hotter in the summer and much colder in the winter than in the lower valleys. The average household income is $51,081 which is below the median income level in San Bernardino

County, and the poverty rate is the highest (79.44%) compared to the other three regions. In addition, the asthma rate (79.66%) is also higher than in East Valley, West Valley, and Morongo Basin.

Morongo Basin is a valley region and an endorheic basin, including Joshua Tree, Morongo Valley, Copper Mountain Mesa, Wonder Valley, Pioneertown, Johnson Valley, Homestead Valley, Yucca Mesa, and Desert Heights, located in San Bernardino County in Southern California. The total population is 22,315, which is the lowest compared to the other three regions. In addition, the average household income is $42,185, which is much lower than the median income level, and the poverty rate is above 75%. The CES 4.0 percentile is 33.97%, which means the pollution burden in Morongo Basin is comparatively low. The linguistic isolation percentile is 9.51%, which is lower than the other three regions, though the area also has a low population density and so this lower percentage needs to be taken within context.

Table 4. Analyzing Characteristics in East Valley, West Valley, High Desert, and Morongo Basin

Characteristics	East Valley	West Valley	High Desert	Morongo Basin
Average Household Income	57,392	86,012	51,081	42,185
Ces.4.0. Percentile*	77.47%	51.06%	56.54%	33.97%
Asthma Percentile**	75.08%	30.88%	79.66%	56.49%
Low Birth Weight Percentile	68.35%	44.77%	67.82%	46.91%
Education Percentile***	73.73%	45.06%	68%	52.58%
Linguistic Isolation Percentile	52.70%	45.86%	37.73%	9.51%
Poverty Percentile	72.20%	38.81%	79.44%	77.74%
Child Poverty Percentile	24.79%	8.47%	28.15%	37.98%
Housing Burden Percentile	54.77%	40.29%	53.40%	53.42%
Total Population	288546	179313	124373	22315
Population Density (pp/sq. m.)	0.001579	0.0015601	0.0000439	0.0000113
Population Density (ppl/sq. mi)	6.48e-10	1.74e-11	6.25e-10	2.811e-12

Notes: none of the data reported above reflects any of the method cuts described earlier

* Average percentile
** Average Age-adjusted rate of emergency department visits for asthma
*** Average Percent of population over 25 with less than a high school education

Table 5. Analyzing Estimated Total Population Group by Race and Education in East Valley, West Valley, High Desert, and Morongo Basin (ACS 2020 5-year estimate)

Region	East Valley	High Desert	Morongo Basin	West Valley
White	52.13%	68.70%	80.95%	56.34%
Black or African American	10.12%	9.41%	1.47%	6.21%
American Indian and Alaska Native	0.60%	1.22%	0.62%	0.86%
Asian	4.87%	3.14%	2.30%	12.08%
Native Hawaiian and Other Pacific Islander	0.21%	0.60%	0.80%	0.22%
Some Other races	22.81%	8.34%	3.98%	13.79%
Two or more races	9.27%	8.61%	9.92%	10.49%
Hispanic or Latino	66.94%	54.25%	20.50%	45.68%
Estimate Percent Below High School Graduate	27.43%	13.20%	21.61%	14.28%
Estimate Percent High school graduate or higher (population 25 years and over)	72.57%	78.39%	85.72%	86.80%
Estimate Percent Bachelor's degree or higher (population 25 years and over)	16.15%	9.62%	19.85%	29.17%
Estimate Percent High school graduate	29.34%	33.05%	24.10%	22.76%
Estimate Percent Bachelor's degree	10.23%	6.59%	12.73%	19.49%

Estimate Percent Graduate or professional degree	5.92%	3.03%	7.17%	9.66%

Figure 62. Estimated percent of population by educational attainment

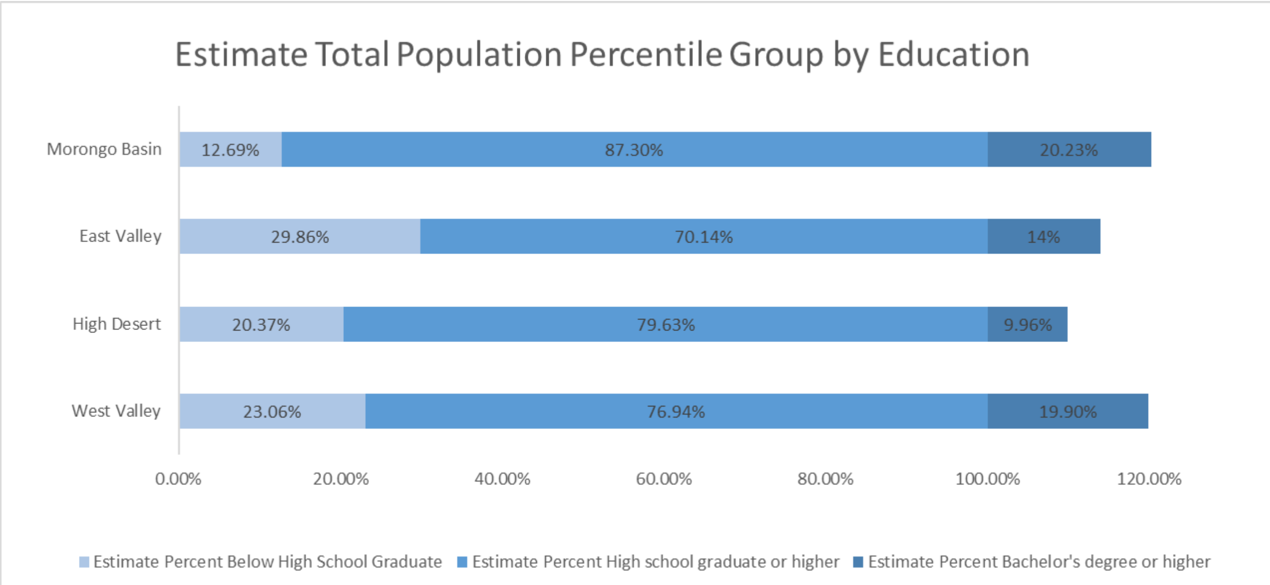
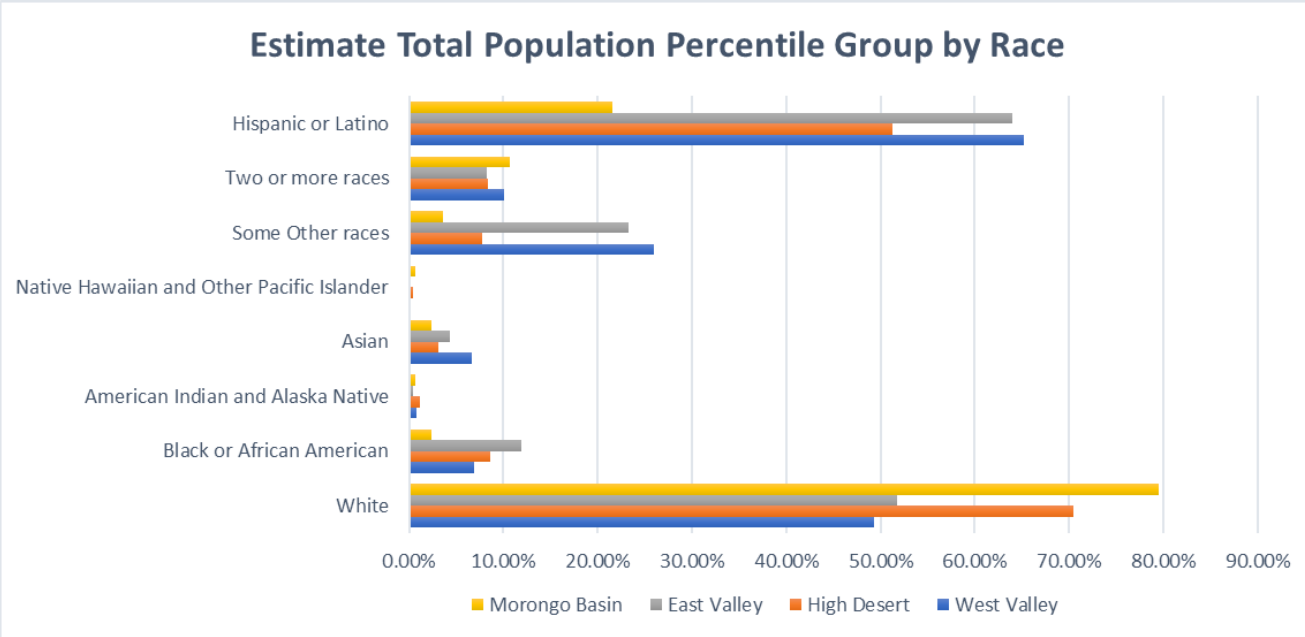


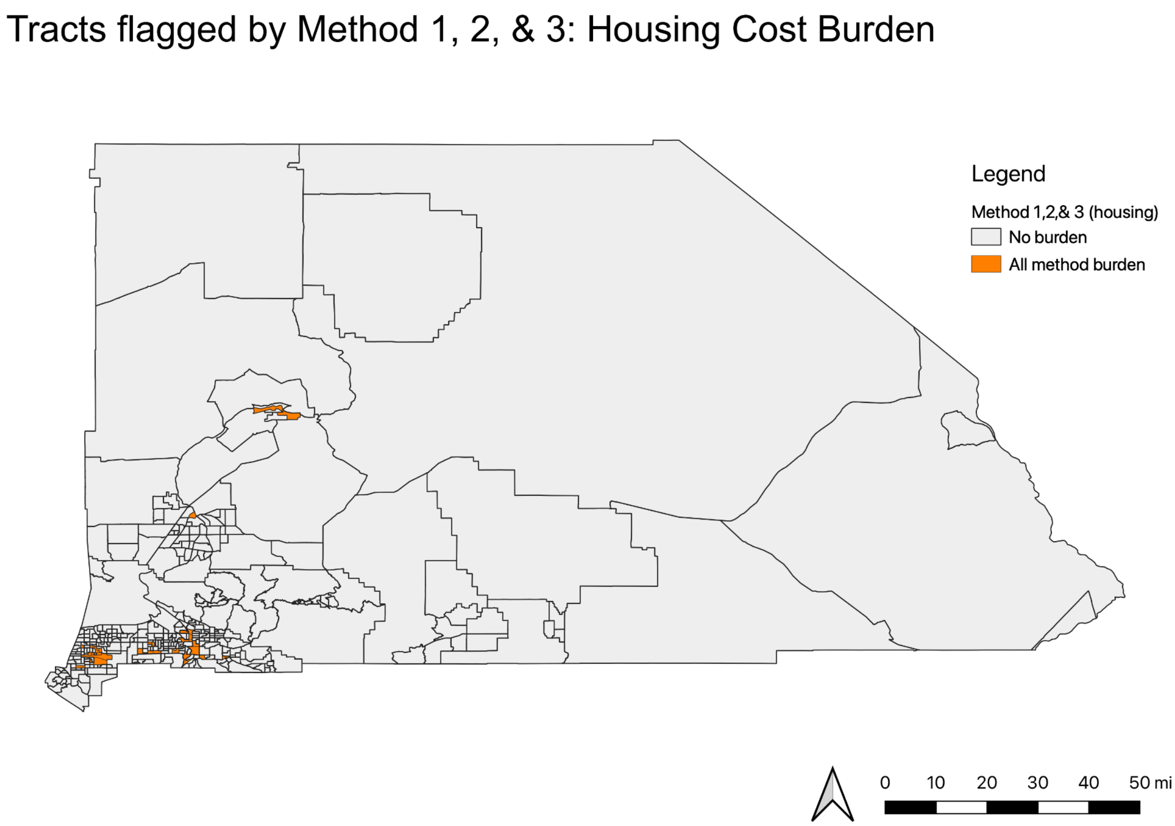
Figure 63. Estimate total percentage of population by race



Method 1, 2, and 3: Housing

Areas with top 25% Composite CalEnviroScreen 4.0 Score
Below 80% Median Household Income
Diesel in the 75th Percentile or higher
Housing Burden in the 50 percentile or higher

Figure 64. Tracts flagged by Method 1, 2, & 3: housing cost burden



Note: Method 2 uses < 80 % AMI and Diesel >= 75%

Table 6. Method 1, 2, and 3 (Housing Burden Cost) Tract Areas for Four Regions

Tract	Region	Approximate Location
6071012500	West Valley	Colton
6071012400	West Valley	San Bernardino
6071005701	East Valley	San Bernardino
6071001812	West Valley	Ontario
6071012002	High Desert	Barstow
6071001600	West Valley	Ontario
6071001803	West Valley	Ontario
6071001400	West Valley	Ontario

6071000604	West Valley	Chino
6071002501	West Valley	Unincorporated San Bernardino County area
6071001504	West Valley	Ontario
6071007303	West Valley	Loma Linda
6071004604	East Valley	San Bernardino
6071007107	West Valley	Grand Terrace
6071004302	East Valley	San Bernardino
6071003000	West Valley	Fontana
6071003612	West Valley	Colton
6071003302	West Valley	Fontana
6071003301	West Valley	Fontana
6071002803	West Valley	Fontana
6071004700	East Valley	San Bernardino
6071004800	East Valley	San Bernardino
6071009800	High Desert	Victorville
6071001501	West Valley	Ontario
6071001305	West Valley	Ontario
6071001309	West Valley	Ontario
6071001308	West Valley	Ontario
6071009400	High Desert	Barstow

Method 1, 2, and 3: Child poverty

Areas with top 25% Composite CalEnviroScreen 4.0 Score
Below 80% Median Household Income
Diesel in the 75th Percentile or higher
Child Poverty 20th Percentile or Higher

Figure 65. Tracts flagged by Method 1, 2, & 3: child poverty

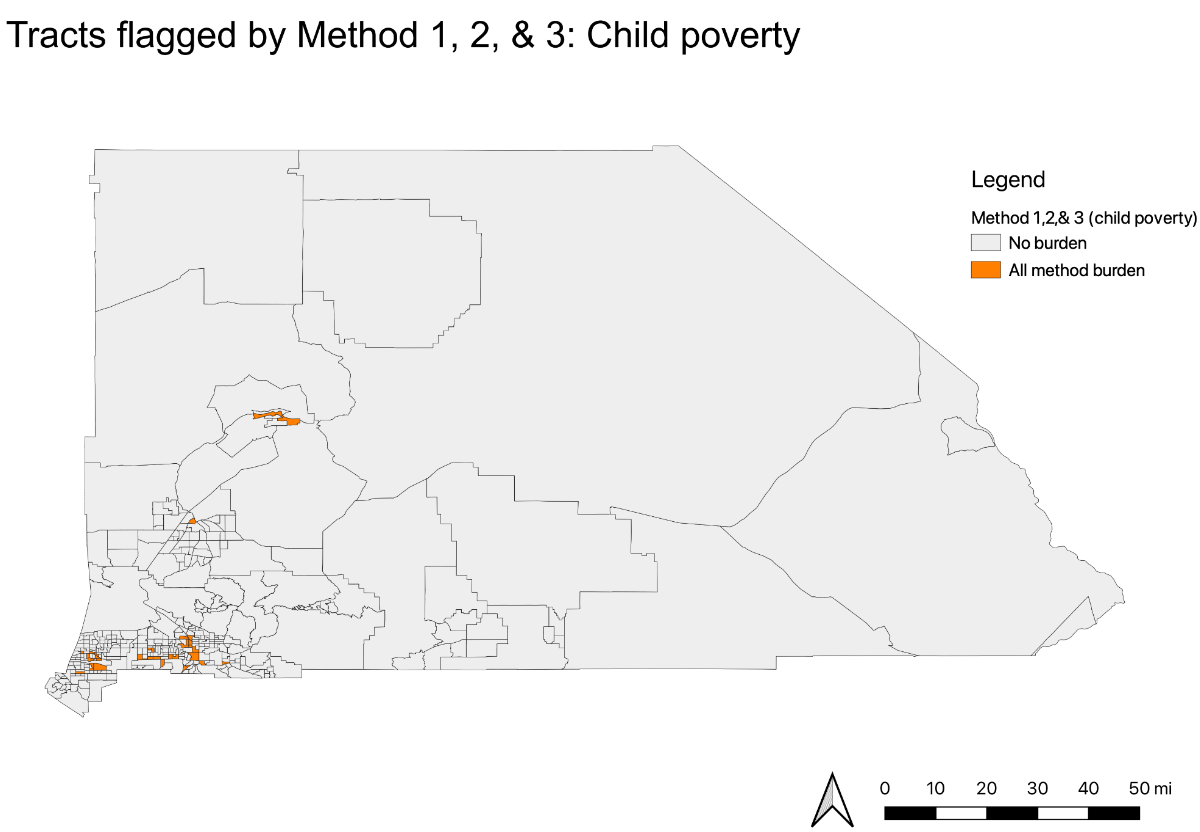


Table 7. Method 1, 2, and 3 (Child Poverty) Tract Areas for Four Regions

Tract	Region	Approximate Location
6071012400	West Valley	San Bernardino
6071005701	East Valley	San Bernardino
6071003609	West Valley	Rialto
6071001810	West Valley	Ontario
6071012002	High Desert	Barstow
6071001803	West Valley	Ontario
6071001400	West Valley	Ontario
6071000604	West Valley	Chino

6071002501	West Valley	Unincorporated San Bernardino County area
6071001504	West Valley	Ontario
6071007303	West Valley	Loma Linda
6071004604	East Valley	San Bernardino
6071007107	West Valley	Grand Terrace
6071004302	East Valley	San Bernardino
6071004001	West Valley	Bloomington
6071003000	West Valley	Fontana
6071003612	West Valley	Colton
6071003302	West Valley	Fontana
6071003301	West Valley	Fontana
6071002803	West Valley	Fontana
6071004202	East Valley	San Bernardino
6071004700	East Valley	San Bernardino
6071004800	East Valley	San Bernardino
6071009800	High Desert	Victorville
6071001813	West Valley	Ontario
6071001103	West Valley	Ontario
6071001501	West Valley	Ontario
6071001305	West Valley	Ontario
6071001309	West Valley	Ontario
6071009400	High Desert	Barstow

Method 1, 2, and 3: Linguistic isolation

Areas with top 25% Composite CalEnviroScreen 4.0 Score
Below 80% Median Household Income
Diesel in the 75th Percentile or higher
Linguistic Isolation in the 50th Percentile or Higher

Figure 66. Tracts flagged by Method 1, 2, & 3: linguistic isolation

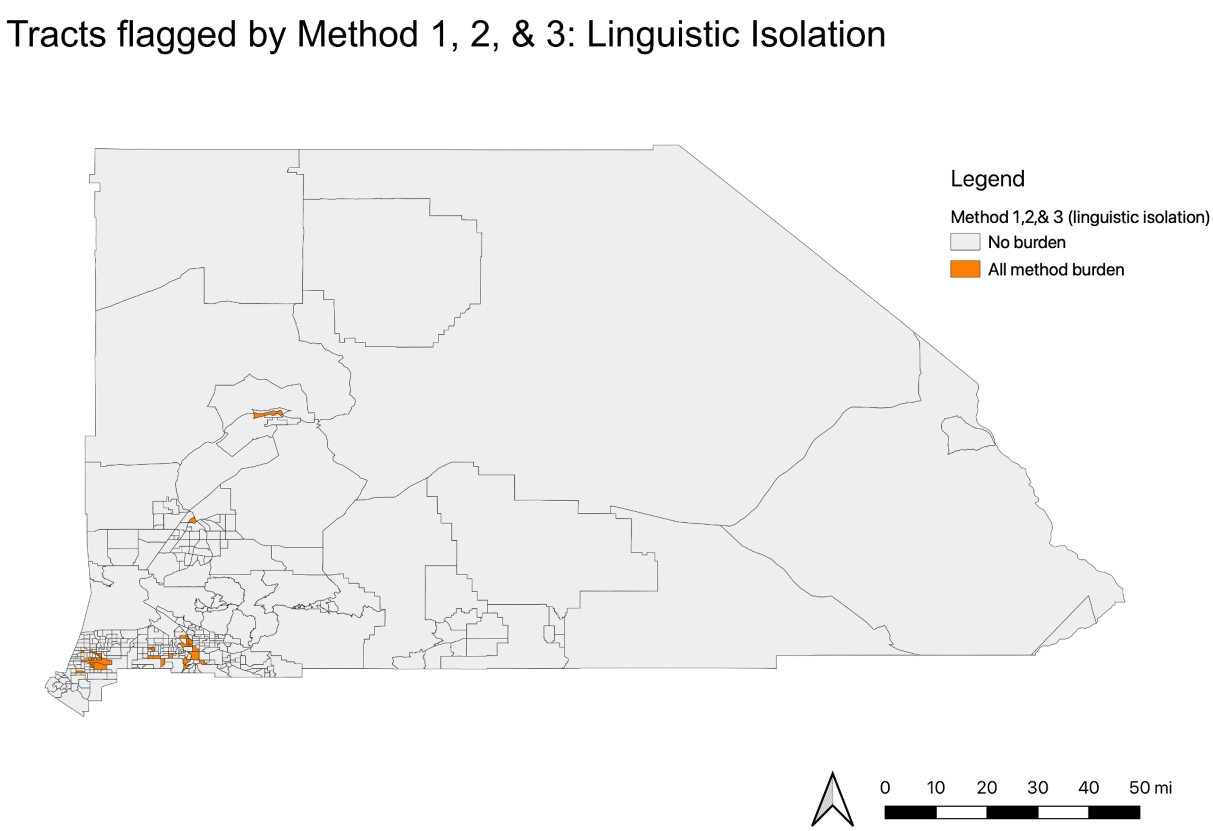


Table 8. Method 1, 2, and 3 (Linguistic Isolation) Tract Areas for Four Regions

Tract	Region	Approximate Location
6071012500	West Valley	Colton
6071012400	West Valley	San Bernardino
6071005701	East Valley	San Bernardino
6071003609	West Valley	Rialto
6071001812	West Valley	Ontario
6071001600	West Valley	Ontario
6071001803	West Valley	Ontario
6071001400	West Valley	Ontario
6071000604	West Valley	Chino

6071001504	West Valley	Ontario
6071007303	West Valley	Loma Linda
6071007107	West Valley	Grand Terrace
6071004302	East Valley	San Bernardino
6071004001	West Valley	Bloomington
6071003000	West Valley	Fontana
6071003302	West Valley	Fontana
6071003301	West Valley	Fontana
6071002803	West Valley	Fontana
6071004202	East Valley	San Bernardino
6071004700	East Valley	San Bernardino
6071004800	East Valley	San Bernardino
6071009800	High Desert	Victorville
6071001813	West Valley	Ontario
6071001501	West Valley	Ontario
6071001305	West Valley	Ontario
6071001308	West Valley	Ontario
6071009400	High Desert	Barstow

Method 1, 2, and 3: Travel to work

Areas with top 25% Composite CalEnviroScreen 4.0 Score
Below 80% Median Household Income
Diesel in the 75th Percentile or higher
Mean Travel Time to Work Longer or Equal Than 30 min are 173 tracts (46.8%)

Figure 67. Tracts flagged by Method 1, 2, & 3: travel time to work (> 30 minutes)

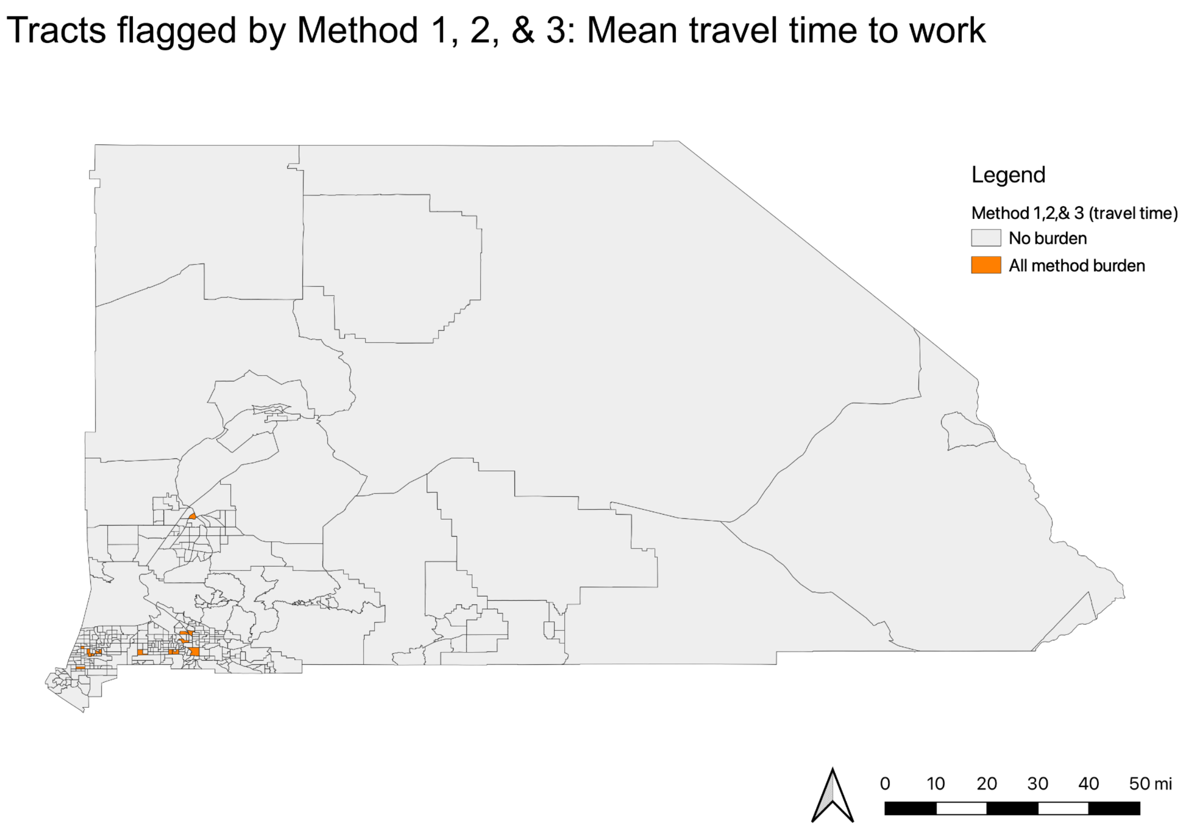


Table 9. Method 1, 2, and 3 (Mean Travel Time to Work) Tract Areas for Four Regions

Tract	**Region**	**Approximate Location**
6071012400	West Valley	San Bernardino
6071003609	West Valley	Rialto
6071001400	West Valley	Ontario
6071000604	West Valley	Chino
6071002501	West Valley	Unincorporated San Bernardino County area
6071004604	East Valley	San Bernardino
6071004302	East Valley	San Bernardino
6071003612	West Valley	Colton

6071009800	High Desert	Victorville
6071001103	West Valley	Ontario
6071001501	West Valley	Ontario
6071001309	West Valley	Ontario
6071001308	West Valley	Ontario

Method 1,2, and 3: Asthma

Areas with top 25% Composite CalEnviroScreen Score
Below 80% Median Household Income
Diesel in the 75th Percentile or higher
Areas with Asthma rate in 75% or higher are 137(37.1%)

Figure 68. Tracts flagged by Method 1, 2, & 3: asthma rate > 75%

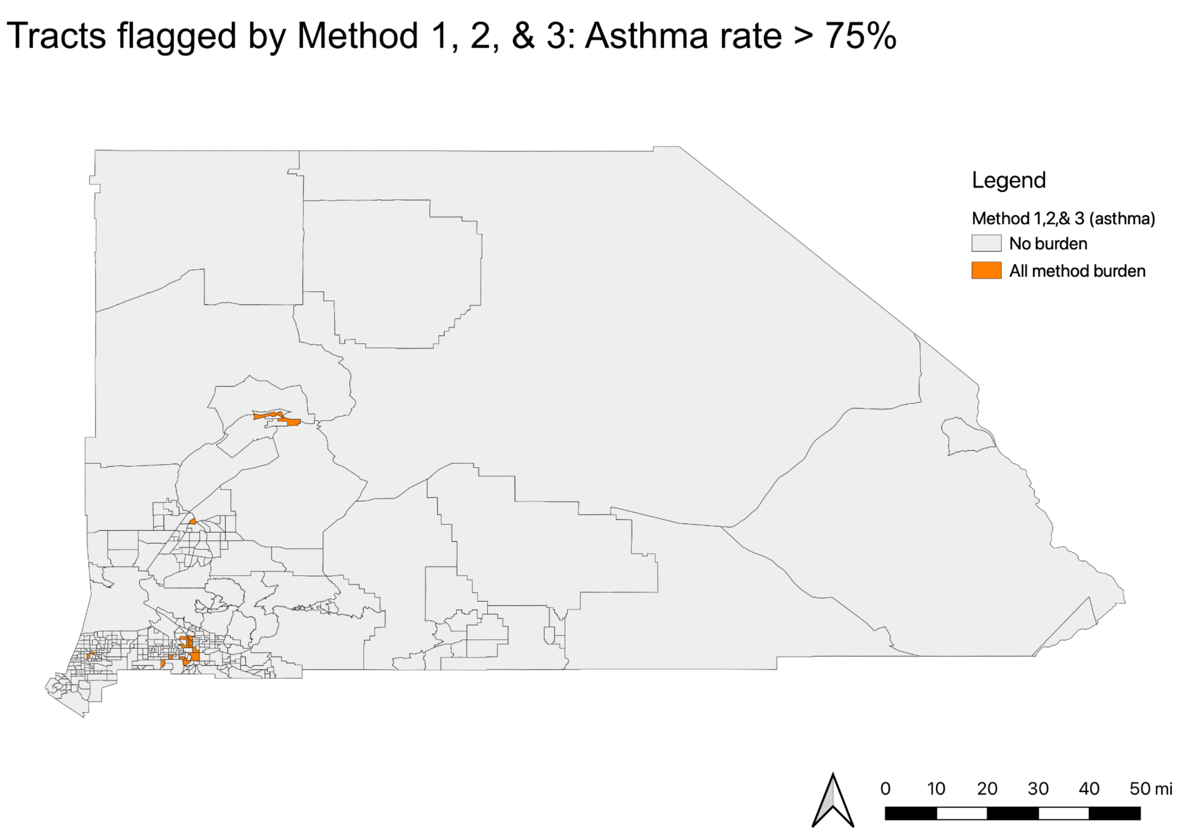


Table 10. Method 1, 2, and 3 (Asthma) Tract Areas for Four Regions

Tract	Region	Approximate Location
6071012500	West Valley	Colton
6071012400	West Valley	San Bernardino
6071005701	East Valley	San Bernardino
6071003609	West Valley	Rialto
6071012002	High Desert	Barstow
6071006601	West Valley	Colton
6071004604	East Valley	San Bernardino
6071004302	East Valley	San Bernardino
6071004001	West Valley	Bloomington
6071004202	East Valley	San Bernardino
6071004700	East Valley	San Bernardino
6071004800	East Valley	San Bernardino
6071009800	High Desert	Victorville
6071001103	West Valley	Ontario
6071009400	High Desert	Barstow

Method 1, 2, and 3: Educational attainment

Areas with top 25% Composite CalEnviroScreen Score
Below 80% Median Household Income
Diesel in the 75th Percentile or higher
Areas with Estimate Percent Less than High School Graduate greater or equal than 20% are 140 (37%)

Figure 69. Tracts flagged by Method 1, 2, & 3: educational attainment (>20% with less than a high school diploma)

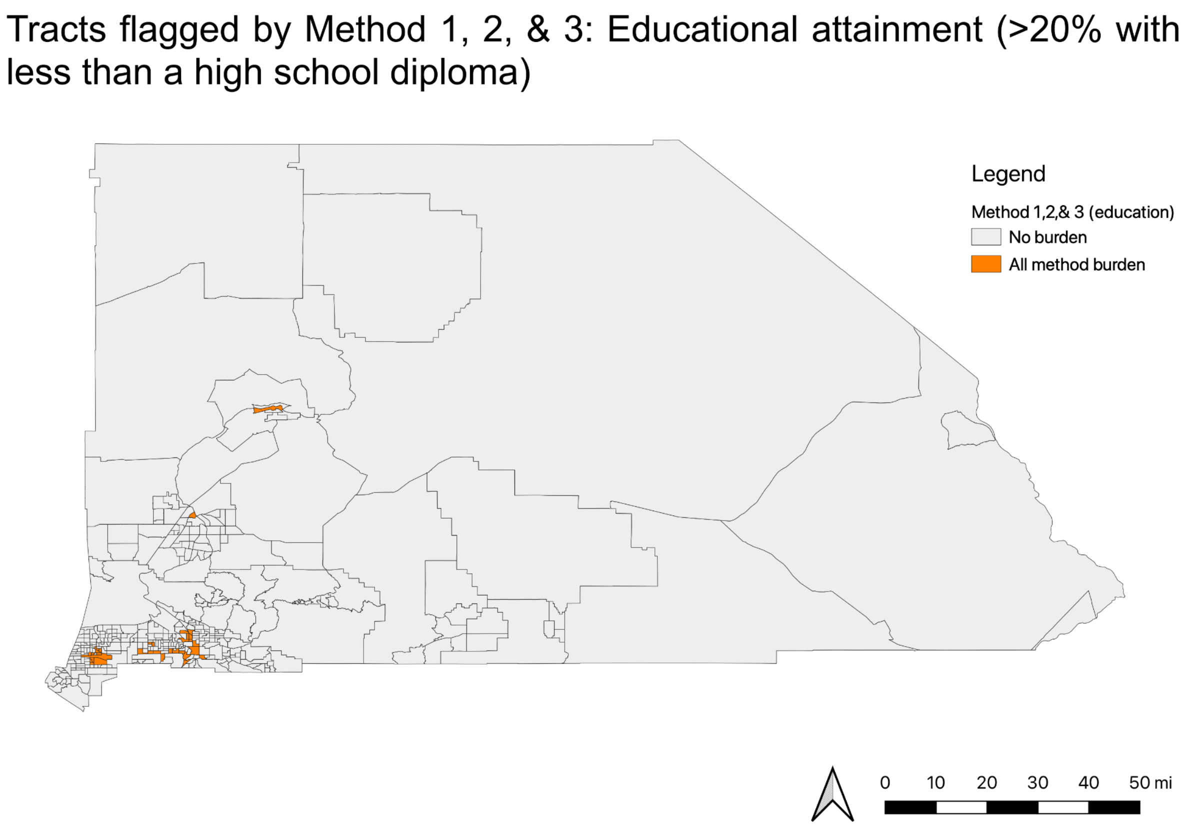


Table 11. Method 1, 2, and 3 (Low Education Attainment) Tract Areas for Four Regions

Tract	Region	Approximate Location
6071012500	West Valley	Colton
6071012400	West Valley	San Bernardino
6071005701	East Valley	San Bernardino
6071003609	West Valley	Rialto
6071001812	West Valley	Ontario
6071001810	West Valley	Ontario
6071001600	West Valley	Ontario
6071001803	West Valley	Ontario

6071001400	West Valley	Ontario
6071002501	West Valley	Unincorporated San Bernardino County area
6071006601	West Valley	Colton
6071001504	West Valley	Ontario
6071007303	West Valley	Loma Linda
6071004604	East Valley	San Bernardino
6071007107	West Valley	Grand Terrace
6071004302	East Valley	San Bernardino
6071004001	West Valley	Bloomington
6071003000	West Valley	Fontana
6071003612	West Valley	Colton
6071003302	West Valley	Fontana
6071003301	West Valley	Fontana
6071002803	West Valley	Fontana
6071004202	East Valley	San Bernardino
6071004700	East Valley	San Bernardino
6071004800	East Valley	San Bernardino
6071009800	High Desert	Victorville
6071001813	West Valley	Ontario
6071001501	West Valley	Ontario
6071001305	West Valley	Ontario
6071001309	West Valley	Ontario
6071001308	West Valley	Ontario
6071009400	High Desert	Barstow

Method 1, 2, & 3: all six indicators combined

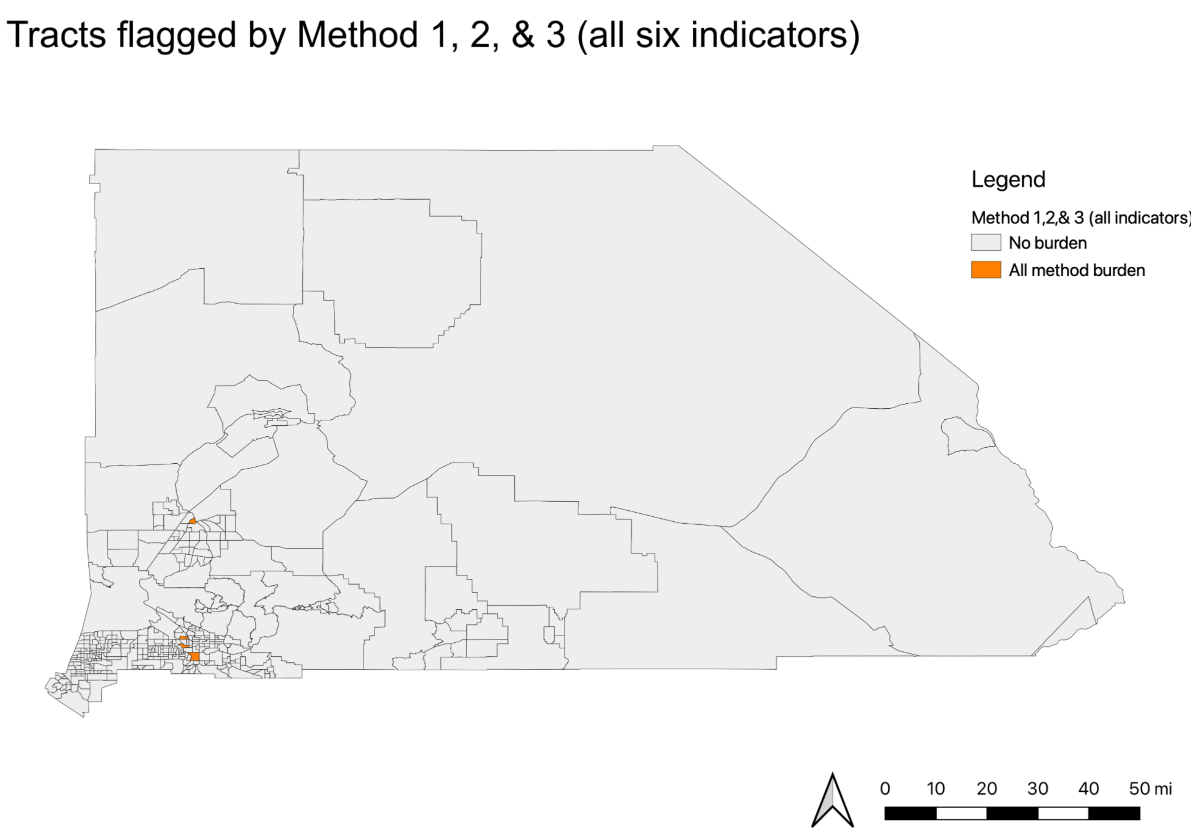
Table 12. Method 1, 2, and 3 Disadvantaged Tract Areas

Census Tract	Region	Approximate Location
6071004302	East Valley	San Bernardino
6071009800	High Desert	Victorville
6071004103	Other Region	Muscoy
6071012400	West Valley	San Bernardino

Note: Method 2 here uses diesel

This table shows a combination of Methods 1, 2, and 3 (six indicators) flagged tract areas (note: this does not address the spatial analysis done for method 3). The six indicators include household burden cost percentile above 50%, child poverty rate above 20%, linguistic isolation above 50%, mean travel time to work longer than 30 minutes, asthma above 75%, and estimated percent with less than a high school diploma greater than 20%.

Figure 70. Tracts flagged by Method 1, 2, & 3



Next Steps & Future Research

Because of the nature of the data that are available, not all trends could be tracked longitudinally. If data on, for example, land uses were periodically collected in a way that was comparable across time (i.e., coded the same way), that could be very informative to policymakers, so they can understand what the changes look like, across what time periods, and the spatial distribution (if any). While this would take some pre-planning and would likely require a few iterations of trial and error, having data that can be compared across 5, 10, 15, and even 20 years would likely help planners and policymakers be able to visualize the impacts of policy decisions that cannot always be seen in the silos of what is realistically routine every-day decision making.

For example, the following datasets cannot be tracked now, but could be tracked moving forward:

- Average daily truck traffic - because Caltrans keeps updating their dataset, if this could be downloaded periodically (e.g., annually, bi-annually) then we can do an analysis of trends over time

- Land use and zoning changes - if this could be standardized and then updated periodically then it would be possible to get an idea of built environment changes over time
- Changes in EV/alternative fueling infrastructure - periodically check the data, compare changes over time

Thus, the following are suggestions:

to understand *trends*:
- collect consistent data on land use and zoning designations
- collect longitudinal data on truck traffic volume, traffic volume, journey to work/mode share
- if possible, collect consistent data on actual parcel usage

to further understand *disadvantage*:
- collect data on typical and non-typical variables; e.g., EV charging infrastructure
- collect data on various social determinants of health indicators
- if possible, collect data on formal vs informal economy
- if possible, collect data on remote work
- if possible, collect data on other health metrics such as physical activity, healthcare coverage and access, service utilization/identified barriers
- if possible, collect data on social service utilization/identified barriers to utilization

to *create a more dynamic tool*:
- consider looking into an interface that can automatically update with new data (e.g., income)

These types of additional longitudinal data would be very helpful in terms of better understanding the overall experience of communities living in the region, highlighting both the challenges they face and possible opportunities and solutions. Mapping inequities in this way not only allows us to better understand the indicators we have presented in this report, but it also lifts up the real life experiences of underserved and historically excluded populations. Understanding each specific community's circumstances and needs are essential as we aim for a more equitable future. As San Bernardino County continues to grow and become increasingly diverse, these mapping tools will become more important and a central repository for data for decision makers in the region to refer to.

Appendix A: dataset sources and notes

Variable	Data source	Notes (if applicable)
Household Income	ACS 2020 5-year	
Area Median Income (County)	ACS 2020 5-year	Used 2020 data
Childhood poverty	ACS 2020 5-year	Federal poverty line
Poverty	CES 4.0	
PM2.5	CES 4.0	
Diesel	CES 4.0	
CalEnviroScreen 4.0 (CES 4.0)	https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40	2010 and 2020 tract vintage, depending
Educational Attainment	CES 4.0	
Linguistic Isolation	CES 4.0	
Total Population	CES 4.0	
Asthma	CES 4.0	
Housing Cost Burden	CES 4.0	
Travel time to work	ACS 2020 5-year file	
Mode share to work	ACS 2020 5-year file	
Extreme heat	https://www.epa.gov/cira/technical-appendices-and-data	Used 2012 tract vintage as per documentation
Internet access	ACS 2020 5-year file	
Income Mobility	https://www.nature.com/articles/s41586-022-04996-4 https://www.nature.com/articles/s41586-022-04997-3#data-availability https://www.socialcapital.org/?dimension=EconomicConne	Analysis done by zip code

	ctednessIndividual&dim1=EconomicConnectednessIndividual&dim2=CohesivenessClustering&dim3=CivicEngagementVolunteeringRates&geoLevel=county&selectedId=06037	
Life expectancy	National Center for Health Statistics USALEEP https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html	U.S._Life_Expectancy_at_Birth_by_State_and_Census_Tract_-_2010-2015.csv
Land use	San Bernardino County COG	2019 data
Assessor Data by Parcel	San Bernardino County https://open.sbcounty.gov/datasets/sbcounty::sbco-parcel-polygons/explore?location=33.410376%2C-118.648044%2C22.99	
Freight traffic	https://gisdata-caltrans.opendata.arcgis.com/datasets/c079bdd6a2c54aec84b6b2f7d6570f6d_0/about	Continuously updated; used data from fall 2022
LIHTC	https://lihtc.huduser.gov	Geocoded by UCR
Schools	San Bernardino County COG	
Bus stops	San Bernardino County COG	
Sidewalks	San Bernardino County COG	
Parks	San Bernardino County COG	
Roads	San Bernardino County COG	

Appendix B: Codebook

CalEnviroScreen 4.0

Variable Name	Description

Census Tract	Census Tract ID from 2010 Census
Total Population	2019 ACS population estimates in census tracts
California County	California county that the census tract falls within
ZIP	Postal ZIP Code that the census tract falls within
Approximate Location	Approximate city, town, or area where each census tract is located based on US Census Incorporated Places (2020, Cities), US Census Designated Places, (2020, Designated Places), and the CA Department of Tax and Fees City and County Boundaries and City Annexations (2021, Unincorporated Areas) boundary files. All tracts that did not fall within one of these boundaries were assigned "unincorporated county area" based on that tract's county. This is for reference purposes only and should not be used to determine whether a census tract falls within a city or town boundary.
CES 4.0 Score	CalEnviroScreen Score, Pollution Score multiplied by Population Characteristics Score
CES 4.0 Percentile	Percentile of the CalEnviroScreen score
PM2.5	Annual mean PM2.5 concentrations
PM2.5 Pctl	PM2.5 percentile
Diesel PM	Diesel PM emissions from on-road and non-road sources
Diesel PM Pctl	Diesel PM percentile
Asthma	Age-adjusted rate of emergency department visits for asthma
Asthma Pctl	Asthma percentile
Low Birth Weight	Percent low birth weight
Low Birth Weight Pctl	Low birth weight percentile
Education	Percent of population over 25 with less than a high school education
Education Pctl	Education percentile
Linguistic Isolation	Percent limited English speaking households
Linguistic Isolation Pctl	Linguistic isolation percentile
Poverty	Percent of population living below two times the federal poverty level
Housing Burden	Percent housing-burdened low-income households
Housing Burden Pctl	Housing burden percentile
Pop. Char.	Average of percentiles from the Population Characteristics indicators

2020 ACS 5-year estimate

Variable	Description	original codebook name	Source

HouseholdIncome	Household Income	S1903_C03_001E	
geometry	2020 tract level		
mean.travel.time	Total Estimate Travel Time To Work Mean travel time to work (minutes)	s0801_c01_046e	ACSST5Y2020.S0801_data_with_overlays_2022-08-10T005442.csv
poverty2012	Percent below poverty level!!Estimate! AGE Under 18 years in 2012	S1701_C03_002E	ACSST5Y2012.S1701.csv/Child_poverty.csv
poverty2020	Percent below poverty level!!Estimate! AGE Under 18 years in 2020	S1701_C03_002E	ACSST5Y2020.S1701.csv/Child_poverty.csv
pct_change	Child poverty percentage change from 2012 to 2020.		
population_density	Total population/ALAND10		tl_2010_06071.csv

Food Access Research Atlas Data 2019

Variable	Long Name	Description
CensusTract	Census Tract Number	Census Tract Number
lalowi1share	Low access, low-income population at 1 mile, share	Share of tract population that are low income individuals beyond 1 mile from supermarket
lalowi10share	Low access, low-income population at 10 miles, share	Share of tract population that are low income individuals beyond 10 miles from supermarket
lalowi20share	Low access, low-income population at 20 miles, share	Share of tract population that are low income individuals beyond 20 miles from supermarket
lahunv1share	Vehicle access, housing units without and low access at 1 mile, share	Share of tract housing units that are without vehicle and beyond 1 mile from supermarket
lahunv10share	Vehicle access, housing units without and low access at 10 miles, share	Share of tract housing units that are without vehicle and beyond 10 miles from supermarket
lahunv20share	Vehicle access, housing units without and low access at 20 miles, share	Share of tract housing units that are without vehicle and beyond 20 miles from supermarket
lasnap1share	Low access, housing units receiving SNAP benefits at 1 mile, share	Share of tract housing units receiving SNAP benefits count beyond 1 mile from supermarket
lasnap10share	Low access,housing units receiving SNAP benefits at 10 miles, share	Share of tract housing units receiving SNAP benefits count beyond 10 miles from supermarket
lasnap20share	Low access, housing units receiving SNAP benefits at 20 miles, share	Share of tract housing units receiving SNAP benefits count beyond 20 miles from

		supermarket
lawhite1share	Low access, White population at 1 mile, share	Share of tract population that are white beyond 1 mile from supermarket
lawhite10share	Low access, White population at 10 miles, share	Share of tract population that are white beyond 10 miles from supermarket
lawhite20share	Low access, White population at 20 miles, share	Share of tract population that are white beyond 20 miles from supermarket
lablack1share	Low access, Black or African American population at 1 mile, share	Share of tract population that are Black or African American beyond 1 mile from supermarket
lablack10share	Low access, Black or African American population at 10 miles, share	Share of tract population that are Black or African American beyond 10 miles from supermarket
lablack20share	Low access, Black or African American population at 20 miles, share	Share of tract population that are Black or African American beyond 20 miles from supermarket
laasian1share	Low access, Asian population at 1 mile, share	Share of tract population that are Asian beyond 1 mile from supermarket
laasian10share	Low access, Asian population at 10 miles, share	Share of tract population that are Asian beyond 10 miles from supermarket
laasian20share	Low access, Asian population at 20 miles, share	Share of tract population that are Asian beyond 20 miles from supermarket
lanhopi1share	Low access, Native Hawaiian and Other Pacific Islander population at 1 mile, share	Share of tract population that are Native Hawaiian or Other Pacific Islander beyond 1 mile from supermarket
lanhopi10share	Low access, Native Hawaiian and Other Pacific Islander population at 10 miles, share	Share of tract population that are Native Hawaiian or Other Pacific Islander beyond 10 miles from supermarket
lanhopi20share	Low access, Native Hawaiian and Other Pacific Islander population at 20 miles, share	Share of tract population that are Native Hawaiian or Other Pacific Islander beyond 20 miles from supermarket
laaian1share	Low access, American Indian and Alaska Native population at 1 mile, share	Share of tract population that are American Indian or Alaska Native beyond 1 mile from supermarket
laaian10share	Low access, American Indian and Alaska Native population at 10 miles, share	Share of tract population that are American Indian or Alaska Native beyond 10 miles from supermarket
laaian20share	Low access, American Indian and Alaska Native population at 20 miles, share	Share of tract population that are American Indian or Alaska Native beyond 20 miles from supermarket
laomultir1shar	Low access, Other/Multiple race	Share of tract population that are Other/Multiple

e	population at 1 mile, share	race beyond 1 mile from supermarket
laomultir10share	Low access, Other/Multiple race population at 10 miles, share	Share of tract population that are Other/Multiple race beyond 10 miles from supermarket
laomultir20share	Low access, Other/Multiple race population at 20 miles, share	Share of tract population that are Other/Multiple race beyond 20 miles from supermarket
lahisp1share	Low access, Hispanic or Latino population at 1 mile, share	Share of tract population that are of Hispanic or Latino ethnicity beyond 1 mile from supermarket
lahisp10share	Low access, Hispanic or Latino population at 10 miles, share	Share of tract population that are of Hispanic or Latino ethnicity beyond 10 miles from supermarket
lahisp20share	Low access, Hispanic or Latino population at 20 miles, share	Share of tract population that are of Hispanic or Latino ethnicity beyond 20 miles from supermarket