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MINETA TRANSPORTATION INSTITUTE

Are California's Local Jurisdictions Disproportionately Directing Growth Toward Existing Disadvantaged Communities? Evidence from the Southern California and San Francisco Bay Area Regions

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MINETA TRANSPORTATION INSTITUTE

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16. Abstract

Communities across the United States are striving to promote smart urban growth through compact urban infill residential development. They are doing so to mitigate sprawl's negative fiscal, environmental, social, and physical impacts, strengthen land use-housing-transportation linkages, and develop at densities needed for well-functioning public transit. Some states, such as California, have gone a step further by linking compact urban infill development as critical to meeting greenhouse gas (GHG) reduction targets. Anecdotal evidence suggests some California local jurisdictions are planning disproportionately large amounts of new urban development in disadvantaged communities (DACs). However, empirical evidence is lacking. This study aims to fill this gap. Using the two most populated regions of the state—the San Francisco Bay Area (S.F. Bay Area) and Southern California (SoCal)—as case studies, this research finds that the new housing is disproportionately planned in DACs in both the case study regions. Specifically, of the areas earmarked for future growth, close to a quarter (22%) are disadvantaged in the S.F. Bay Area region and close to half (48%) in the SoCal region. Meanwhile, the total area of the region that is disadvantaged is only 14% and 26%, respectively. These findings are critical for equity implications in policy and planning in these areas and beyond.

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Background

Communities across the United States (US) are striving to promote smart urban growth through compact urban infill residential development (EPA, 2015). They are doing so to mitigate sprawl's negative fiscal, environmental, social, and physical impacts, strengthen land-use-housing-transportation linkages, and develop at densities needed for well-functioning public transit.

Some states, such as California, have gone a step further by making compact urban infill development a critical tool for meeting their greenhouse gas (GHG) reduction targets. Several pieces of California's state-level legislation, such as the Global Warming Solutions Act, 2006 [Senate Bill (SB)/Assembly Bill (AB) 32] and the Sustainable Communities and Climate Protection Act (SB 375), are driving its efforts to reduce GHG emissions, 30% of which come from tailpipe emission generated by cars and light-duty trucks (ILG, 2015). While fuel efficiency and other technological advancements are forecast to contribute to the most emissions reduction, the State recognizes the critical need for reducing vehicle miles traveled (VMT) to achieve the state's GHG emission reduction goals (CARB, 2017). Furthermore, the literature calls for reducing sprawl, growing more compactly, and strengthening housing-transportation linkages to reduce VMT (Boarnet et al., 2017; Stevens, 2017). Accordingly, in partnership with the local jurisdictions, California's 18 metropolitan planning organizations (MPOs) have been including a new element in their regional transportation plans called Sustainable Community Strategy (SCS). Pursuant to SB 375, an MPO's SCS seeks to better align the region's transportation, housing, and land-use plans, policies, and investments. In doing so, SCSs aim to reduce GHG emissions and foster healthy, equitable communities (CARB, 2018).

Several pieces of recent state legislation, such as SB 35, SB 9, and SB 10, seek to promote housing in transit-rich areas. Despite these efforts, California communities struggle to reduce VMT (Shepherd IV, 2021; CARB, 2018). This struggle has prompted several MPOs to redouble their efforts to help their regions accommodate most of their new housing in already urbanized areas, often as infill transit-oriented housing. While necessary for VMT reduction, such urban developments could have unintended negative consequences if planned in already distressed, underserved (i.e., disadvantaged) communities, or DACs, that already have high concentrations of low-income and minority populations, low-quality schools, poor transportation access, and high pollution levels. Anecdotal evidence suggests that some local jurisdictions are planning to focus new residential development in DACs, but empirical evidence is lacking. This research aims to fill this gap.

Research Questions

Using the two most populous California regions—the San Francisco Bay Area (represented by Metropolitan Transportation Commission-Association of Bay Area Governments, MTC-ABAG) and the Los Angeles Metropolitan Area (represented by Southern California Association of Government, SCAG)—as case studies, this research examines the extent to which new housing is being planned in DACs. Specifically, this research asks the following research questions (RQs):

- RQ1: At which locations is new housing being planned in the DACs of the San Francisco Bay Area (S.F. Bay Area) and the Southern California (SoCal) regions?
- RQ2: Is new housing being disproportionately planned in DACs?
- RQ3: What are the top four jurisdictions in each region where DACs are planned to take new housing?

Findings

An in-depth literature review was conducted to identify the dimensions and sub-dimensions of disadvantage and the variables that operationalize them. The dimensions included demographic, economic, educational, environmental, and transportation. Disadvantages were then combined across these dimensions to develop an overall measure of disadvantage called the DAC Index. Geographic information system (GIS) was used to show the spatial location of the DACs in both case study regions. The GIS was then used to display the areas where new housing is planned in the DACs. These areas are called Priority Development Areas (PDAs) in the S.F. Bay Area region and Priority Growth Areas (PGAs) and Spheres of Influence (SOIs) in the SoCal region. Plan Bay Area 2050 and Connect SoCal serve as the sustainable community strategies for the S.F. Bay Area and the SoCal regions, respectively, and serve as their regional transportation plans. These plans identify PDAs as areas for targeted future growth for the S.F. Bay Area region and PGAs and SOIs for the SoCal region. By overlaying the location of the PDAs (for the S.F. Bay Area region) and PGAs and SOIs (for the SoCal region) on the location of DACs, it was found that new housing is disproportionately planned in DACs in both the case study regions. Specifically, close to a quarter (22%) of the area within the S.F. Bay Area's PDAs and close to half (48%) of SoCal's PGAs and SOIs are disadvantaged. Meanwhile, the total area of the region that is disadvantaged is only 14% and 26%, respectively, showing that the areas targeted for growth are more disadvantaged than the region as a whole.

Similarly, the areas targeted for growth that are not disadvantaged as a percentage of total non-disadvantaged areas of the region are 2.5% and 6.1%, respectively. In comparison, the areas targeted for growth that are disadvantaged as a percentage of total disadvantaged areas of the region are much higher, 4.3% and 16.1%, respectively, showing that areas targeted for growth that are disadvantaged comprise a larger proportion of the DACs in these regions, compared to similar non-disadvantaged areas.

Finally, the top four jurisdictions in each region planning to accommodate new housing in DACs were identified. They are (in decreasing order of disadvantage) Pittsburg, Oakland, unincorporated Contra Costa County, and Fairfield in the S.F. Bay Area region and unincorporated San Bernardino County, unincorporated Los Angeles County, unincorporated Riverside County, and the city of Los Angeles for the SoCal region.

Conclusions

Notably, four of the eight top disadvantaged jurisdictions are unincorporated counties—one in the S.F. Bay Area region and three in the SoCal region. To the extent county governments might not be well-equipped to mitigate some of the ill effects of concentrating new housing in DACs (such as the burden on already poor transportation accessibility, low-quality schools, and environmental pollution), this finding is concerning. Furthermore, to the extent that the top four jurisdictions in each region might not be the wealthiest (for example, Oakland, Pittsburg, and Fairfield in the S.F. Bay Area region and the city of Los Angeles in SoCal), these jurisdictions' ability to mitigate negative impacts of this housing concentration is questionable.

More research is needed to assess the effects of the concentration of new housing on the DACs of these top-impacted jurisdictions. The first step in this direction is to do a closer, jurisdiction-level examination to document the negative impacts of housing concentration. It is also important to know if plans, policies, and funding programs are being developed, or are already in place at the local, regional and state levels to mitigate these impacts, how effective are they, or how effective are they likely to be?

1. Introduction

Communities across the United States (US) are striving to promote smart urban growth through compact urban infill residential development (EPA, 2015). They are doing so to mitigate sprawl's negative fiscal, environmental, social, and physical impacts, strengthen land-use-housing-transportation linkages, and develop at densities needed for a well-functioning public transit.

States such as California have gone a step further making compact urban infill development a critical tool for meeting its greenhouse gas (GHG) reduction targets. Several pieces of its state-level legislation, such as the Global Warming Solutions Act, 2006 (SB/AB, 32) and the Sustainable Communities and Climate Protection Act (SB, 375), are driving California's efforts to reduce GHG emissions, 30% of which come from tailpipe emission generated by cars and light trucks (ILG, 2015). While fuel efficiency and other technological advancements are forecast to contribute the most to emissions reduction, reducing vehicle miles traveled (VMT) is also key to reducing the state's GHG emissions (CARB, 2017). Furthermore, the literature calls for reducing sprawl, growing more compactly, and strengthening housing-transportation linkages to reduce VMT (Boarnet et al., 2017; Stevens, 2017). Accordingly, in partnership with the local jurisdictions, California's 18 largest metropolitan planning organizations (MPOs) have included a new element to their regional transportation plans called Sustainable Community Strategies (SCSs). Under the SCSs, regions seek to align their transportation, housing, and land-use plans, policies, and investments. In doing so, SCSs aim to reduce GHG emissions and foster healthy, equitable communities (CARB, 2018).

Several pieces of recent state legislation, such as SB 35, SB 9, and SB 10, seek to promote housing in transit-rich areas. Despite these efforts, California communities struggle to reduce VMT (Shepherd IV, 2021; CARB, 2018). This struggle has prompted several MPOs to redouble their efforts to accommodate most new housing in already urbanized areas, often as infill transit-oriented housing. While necessary for VMT reduction, such urban developments could have unintended negative consequences if planned in already distressed, underserved (i.e., disadvantaged) communities that already have high concentrations of low-income and minority populations, low-quality schools, poor transportation access, and high pollution levels.

A lawsuit against the California Air Resource Board (CARB) contends that the focus on developing housing in existing urban areas is unlikely to affect white, wealthy, and elderly homeowners; while disproportionally negatively impacting minority aspiring homeowners since in the absence of public subsidies, infill housing is likely to be prohibitively expensive (The Two Hundred et al. v. CARB et al. 2018).

A nascent stream of literature has found empirical evidence of the negative impacts of housing development in disadvantaged communities (DACs), specifically those related to housing affordability and displacement in transit-oriented developments (TODs). For example, Chapple et al.'s (2017) study of the S.F. Bay Area and Los Angeles regions found that TODs around fixed-rail stations increased house prices and the displacement of existing low-income households. Similarly, Verma et al. (2019) found that increases in house prices between 2005 and 2015 displaced many S.F. Bay Area minority communities and reduced their access to high-resource neighborhoods. Recent research following this line of inquiry has also assessed the effectiveness of anti-displacement strategies (Chapple & Loukaitou-Sideris, 2021).

In summary, the existing research indicates that urban infill development could lead to gentrification and displacement, reducing minority communities' access to high-resource areas. This research extends this line of inquiry by estimating the extent to which "planned" efforts (including, but not limited to TODs) are concentrating new housing in DACs. For example, while there is significant anecdotal evidence and conjecture that such a concentration is occurring in many urbanized regions of California, robust empirical evidence is lacking. The first step toward gathering such evidence is to develop the methods and metrics needed to identify DACs, especially metrics that could be developed using existing readily available data instead of those that might need resource-prohibitive location-specific primary data. The second step is to use such metrics to identify the location of DACs for a few regions and, finally, to overlay the areas of planned urban infill residential growth to estimate the extent to which such growth areas overlap with the locations of DACs.

Identifying the magnitude of this overlap would help all levels of government focus on areas of significant overlap to examine whether DACs located in these areas are witnessing localized negative unintended consequences of new residential development (including displacement and the deterioration in the quality of infrastructure and services). If yes, what tools (i.e., plans, policies, strategies, and funding) are available to mitigate these impacts, and what additional tools are needed? The answers to these questions are valuable for developing and revising transportation, housing, and land use plans and policies, as well as prioritizing state, regional, and local funds, including revisions to the state low-income housing tax credit (LIHTC) allocation criteria, and in the case of California, its cap-and-trade revenues disbursement criteria under the California Climate Investments Program. Finally, the theoretical and methodological frameworks and metrics developed for this study will benefit transportation professionals and state, regional, and local agencies nationwide.

1.1 Research Objective and Questions

Using two of the most populous California regions—S.F. Bay Area (represented by Metropolitan Transportation Commission-Association of Bay Area Governments, MTC-ABAG) and Los Angeles Metropolitan Area (represented by the Southern California Association of Government, SCAG)—as case studies, this research examines the location and extent to which new housing is being planned in DACs. Specifically, this research asks the following research questions (RQs):

- RQ1: At which locations is new housing being planned in the DACs of the S.F. Bay Area and the Southern California (SoCal) regions?
- RQ2: Is new housing being disproportionately planned in DACs?
- RQ3: What are the top four jurisdictions in each region where DACs are planned to take new housing?

2. Literature Review

2.1 How Disadvantage is Defined in the Literature

There is a long history of researchers and policy analysts measuring disadvantaged communities, equity, and environmental justice. Consequently, there is a great diversity of perspectives on what constitutes disadvantage and how to measure it. These definitions, and the consequent metrics used to measure them vary considerably, due to several factors including the type or purpose of the research or policy analysis being performed; local market, geographic, and socioeconomic conditions; and the demographic characteristics of residents.

Concepts of neighborhood disadvantage in the US have been influenced by the equity definitions and associated measurement systems developed in response to Title VI of the 1964 Civil Rights Act (Karner & Niemeier, 2013). Title VI prohibits any federally funded program or assistance to discriminate based on race, color, and national origin (USGPO, n.d.).

President Clinton's 1994 Executive Order (EO) 12898, focused on Environmental Justice and played a complementary role to Title VI. While Title VI focused on the disproportionate and discriminatory effects of federal funding, EO 12898 broadened the list of potential impacts to specify that the benefits of federally funded projects to a community should not be "purchased through the disproportionate allocation of its adverse environmental and health burdens on the community's minority" (USGPO, n.d.). This EO thereby expanded Title VI's definition of equity beyond the consideration of the disproportionate and discriminatory allocation of benefits from a project, program, or activity to include adverse impacts as well (USGPO, n.d.).

Motivated by the equity-related concerns that are central to the above-mentioned federal statutes, socio-economic disadvantage is central to the DAC-focused scholarly literature. Additionally, it is common for researchers to add other dimensions, based on their research purpose and discipline. For example, public health researchers typically focus their definitions of disadvantage in terms of socio-economic and environmental conditions that lead to health impacts (Singh, 2003; Su et al., 2009; Sadd et al., 2011).

Transportation researchers add the transportation dimension (Field, 2000; Currie, 2004; Aman & Smith-Colin, 2020; Rowangould et al., 2016). For example, Aman and Smith-Colin (2020) identified neighborhoods in Dallas, Texas, that are transit deserts, defined as census tracts where there is an elevated level of transit need (transit dependent population) and a low level of transit supply. Rowangould et al. (2016) defined DACs as a combination of low-income status, low-income minorities, and low vehicle ownership.

Urban form/land use researchers lean towards definitions of disadvantage that emphasize the social vulnerability of different land use configurations (Heckert & Rosan, 2016; Hughey et al., 2016;

Foote & Walter, 2017; Nicoletti et al., 2022). For example, Hughey et al. (2016) developed a socioeconomic disadvantage index to identify the links between neighborhood park access, park quality, socio-economic status (SES), and racial and ethnic composition. Foote and Walter (2017) defined SES disadvantage as neighborhoods with high levels of unemployment, poverty, renter-occupied housing, and low levels of education.

Housing researchers often define disadvantage in terms of a community's access to affordable and high-quality shelter (Deng, 2007; Galster & Tatian, 2009; Wan & Su, 2016; Goetz et al., 2019). Specifically, Deng (2007) studied the effects of LIHTC and housing voucher funding on integration and school performance using an income-related definition of disadvantage. Wan and Su (2016) developed a neighborhood housing deprivation index by combining six domains of variables that reflect the housing disadvantage (internal facilities, living space, physical form and structure, attached facilities, affiliated natural amenities, and affordability).

2.2 Literature Search Methodology

Google Scholar was used to search for literature about DAC measurement techniques, varying the search term keywords to account for differences in nomenclature across disciplines. First, we searched Google Scholar with the phrase "disadvantaged communities metrics." Second, we replaced each word of the phrase with its variants, including "distressed," "underserved," and "marginalized" representing "disadvantaged"; substituting "neighborhoods," "populations," and "localities" for "communities"; and "criteria," "indicators," "measures," "scale," "index," and "benchmarks" for "metrics". Third, the word "accessibility" and its variants were added to "disadvantaged communities metrics" and its variants. The literature identified through this first round of searches was studied to refine and add further keywords. Reference lists of the articles were also reviewed to identify other sources. These steps produced 223 pieces of literature.

Literature was classified into high, medium, and low groups, based on their relevance to the study objectives. For example, studies that merely mentioned disadvantaged communities were rated low, while studies that developed disadvantaged community metrics were rated high. Fifty-three studies were rated low, leaving the remaining 164 with high or medium ratings. US-focused and recent studies were prioritized, leaving 107 studies for in-depth review.

Literature Synthesis

While reviewing the literature, close attention was given to determine (a) whether the studies belonged to a specific discipline (for example, public health or housing) or if they were cross-disciplinary; (b) whether the variables used by the studies to operationalize DACs could be grouped into a few categories; and (c) the empirical methods used to estimate disadvantage.

It was found that the body of the literature primarily fell in or across the following four research disciplines: (1) public health, (2) transportation, (3) urban form/land use, and (4) housing. The public health studies (50) accounted for half of the sources. Many studies were cross-disciplinary, falling under two or more research disciplines. Next, the variables operationalizing DACs could be categorized into the following groups: income and poverty, employment, education and language proficiency, race/ethnicity, other (non-race/ethnicity) demographic, transportation, and in the case of public health literature, other variables. These groups of variables are discussed in the next section under each research discipline if they are used by 30% or more of the studies in that discipline. Sources where some form of composite index or scale was created to represent disadvantage (or some aspect of it) were also identified.

2.3 Use of Variables in Disadvantaged Communities Research

Table 1 summarizes the variables commonly used across various research disciplines. A detailed description is provided below.

Income/poverty

Typically, income/poverty variables either measure household income in relation to the federal poverty level (HCD/CTCAC, 2023; Fede et al., 2016; Hughey et al., 2016; SANDAG, 2021), some absolute measure of income such as median household income (Meltzer & Schuetz, 2012; Goetz et al., 2019), a relative measure, such as household income as a percentage of the jurisdiction or region's median household income (Deng, 2007; Bhatia & Maizlish, 2016), or housing cost burden (SANDAG, 2021). Some studies used proxy measures such as percentage of families on welfare (Foote & Walter, 2017; Sealy-Jefferson et al., 2016).

Employment

The most used employment variables included variants of employment or unemployment rates, such as percentage of unemployment among men (South, 2001), percentage of employed in the civilian labor force (Foote & Walter, 2017), percentage of blue collar/service workers (South, 2001), percentage of unemployed workforce (Aman & Smith-Colin, 2020), and percentage of unemployed (SANDAG, 2021).

Education and language proficiency

In the case of education/language proficiency variables, language proficiency is primarily assessed as the percentage of people with limited proficiency in English (Di & Murdoch, 2013). Many variables are used to assess education quality. Many studies focused on the quality of K-12 education (HCD/CTCAC, 2023; Deng, 2007; Ellen et al., 2018), while others focused on the level of education completed, for example, the percentage of adults who had not completed high school (Heckert & Rosan, 2016), percentage of population with a high school diploma (Archibald & Putnam Rankin, 2010), percentage of those who attended high school (Foote & Walter, 2017), percentage with a high school diploma or below (Ermagun & Tilahun, 2020), percentage with a college degree or more (HCD/CTCAC, 2023; Foote & Walter, 2017), percentage with master's degree and above (Ermagun & Tilahun, 2020). Many studies used variables that combined age and education. For example, King and Clarke (2015) used percentage of population aged 25 and older with less than 12 years of education, and percentage of population aged 25 and older with more than 16 years of education. Similarly, Owen and Levinson (2015) used percentage of population 25 years and older with B.A./B.S. or higher. Another stream of literature in the field of housing used proxy variables to assess education quality. These measures included student-teacher ratio, and percentage of students by race (Di & Murdoch, 2013).

Race/ethnicity

The percentage of a neighborhood's total population that is of a specific race or ethnicity is the most common variable used to operationalize this dimension (Aman et al., 2021; Ermagun & Tilahun, 2020; King & Clarke, 2015; Lian et al., 2014; Owen & Levinson, 2015; Sadd et al., 2011; Su et al., 2009). A small number of studies measured racial/ethnic concentration. For example, the percentage of Black population in a census tract compared to the metropolitan average (Glaeser & Vigdor, 2001). HCD/CTCAC (2023) developed methods to identify high-opportunity neighborhoods for low-income people in the state using variables of racial segregation, such as tracts with a racial location quotient of higher than 1.25 for Black, Hispanic, and Asian, or all people of color in comparison to the county.

Other demographic variables

Other (non-race) demographic variables often measured the percentage of people in various age groups (Carleton & Porter, 2018; Currie, 2004; Horner et al., 2015; Hughey et al., 2016; Schuetz et al., 2012), or in a specific age group, such as the percentage of the elderly (Ermagun & Tilhaun, 2020). Some studies focused on variables such as percentage of adults divorced and percentage of adults who never married (Salari et al., 2021), or percentage of single-parent households (Archibald & Rankin, 2010; Field, 2000). Some examined the percentage of female-headed households (Sealey-Jefferson et al., 2016; Wang & Arnold, 2018), and the percentage of female-headed households with dependent children (Lian et al., 2014). The percentage of recent immigrants (El-Geneidy et al., 2016), percentage of adult females living alone, and percentage of older people living alone (Li & Liu, 2016) were also studied.

Transportation

Household vehicle availability was a common variable used to measure transportation disadvantage, as it was often found in public health and transportation literature (Butler et al., 2013; Lian et al., 2014; Fede et al., 2016; Field, 2000; Ken, 2000; Knighton et al., 2016; Rowangould et al., 2016; Singh, 2003). A few studies measured the availability of transportation infrastructure, such as percentage of the neighborhood with access to bus services, population-weighted density of bus stops per hectare, and percentage of the population-weighted neighborhood area within 100 meters of a foot or bicycle path (Field, 2000; Ken, 2000; Richardson et al., 2017; McLennan et al., 2011; Hegerty, 2016). Others measured transportation access to various amenities and disamenities. For example, Acevedo-Garcia et al. (2014) used several key destination variables—proximity to high-quality early childhood education centers, proximity to health care facilities, retail healthy food environment index, proximity to toxic waste release sites, volume of nearby toxic waste release, proximity to parks and open spaces, and proximity to employment—to develop their Child Opportunity Index. Still fewer studies used sophisticated transportation accessibility measures derived from travel demand models (Ferguson et al., 2012; Horner & Wood, 2014; Stokes & Seto, 2018; Widener et al., 2013).

Housing-focused research also varied in the sophistication of variables used, ranging from simple measures such as the distance to the nearest transit station (Galster & Tatian, 2009; Chapple et al., 2017) to access to jobs by transit operationalized by the number of low wage jobs contained within a transit stop service area (Zhong et al., 2017). Finally, Ellen et al. (2018) used the HUD Low Transportation Cost Index, which comprises estimates of census tract auto ownership costs, automobile use costs, and transit costs.

Table 1. Commonly Used Variables to Operationalize DAC

	Research discipline			
	Public Health	**Transportation**	**Urban form/land use**	**Housing**
Commonly used variables				
Income/Poverty	• % people on welfare; • % below poverty level; • median household income; • % non-institutionalized population below federal poverty level (FPL)	• % of households in poverty; • % households spending > 30% of income on housing	• median individual income; • % of residents below $30k per year; • % in poverty; • % residents on public assistance; • % population under 125% of FPL; • % population people not on public assistance (welfare); • average household income of those w/ high school degree or more; • median household income	• median family income as a proportion of the region's median family income; • % population above 200% FPL; • median household income
Employment	• % adult men who are either unemployed or out of labor force; • % blue collar/service workers	• % workforce unemployed; • % unemployed	• % in civilian labor force and employed; • % not in armed forces in the labor force	Not discussed because they are included in less than 30% of the studies.
Education and Language Proficiency	• % proficient in English; • % adults who have not	• % population 25+ with B.A./B.S. or higher; • % population with high school degree & below; • % illiterate population	• % less than high school education; • % high school degree or more; • % college degree or more; • % attended high school; • % with university degree;	• elementary school test scores; • HUD School Proficiency Index; • student-teacher ratio;

	Research discipline			
	Public Health	**Transportation**	**Urban form/land use**	**Housing**
	completed high school; • % with high school diploma		• % 4th graders who meet or exceed math proficiency standards; • % 4th graders who meet or exceed literacy standards; • % high school cohort that graduated on time; • % students not receiving free or reduced-price lunch.	• % students by race, % students with limited English proficiency; • % adults with a bachelor's degree or above
Race/ethnicity	• % population of a specific race—e.g., % non-Hispanic white and % non-Hispanic Black	• % population of a specific race—e.g., % non-Hispanic Black, % Hispanic; % non-Hispanic Asian/Pacific Islander/Native American; and % non-Hispanic other	• % population of a specific race—e.g., % non-white	• % Black residents compared to metropolitan average; • % students of various races/ethnicities; • tracts with racial location quotient > 1.25 for Black, Hispanic, Asian, or all people of color in comparison to county
Other demographics	• % single parent households; • % female-headed households; • average residential tenure in the neighborhood	• % aged 65+; • % foreign-born; • % female; • % recent immigrants	• % in various age cohorts—e.g., % under 18 years; • % 65+; • % foreign born; • median age; • % adult females living alone; • % of older people living alone; • average disposable income for householders of age between 15 and 24; • marital status; • median age of householder;	Not discussed because they are included in less than 30% of the studies.

	Research discipline			
	Public Health	**Transportation**	**Urban form/land use**	**Housing**
			• median age of children; • % adults divorced; • % adults never married	
Transportation	• household vehicle availability; • % of neighborhood with access to bus services; • population-weighted density of bus stops per hectare; • % of population-weighted neighborhood area w/in 100 meters of foot or bicycle path; • accessibility to key destinations	• % households without access to a car; • % neighborhood with access to bus services	• % households without access to a car; • % neighborhood with access to bus services	• distance between a census tract's centroid & nearest transit station; • % land used for transportation in a neighborhood; • access to jobs by transit; • census tracts within ½-mile of transit station; • HUD Low Transportation Cost Index (combination of a census tract auto ownership costs, automobile use costs, and transit costs)

2.4 Choice of Geographic Scale of Analysis

DAC-related research has used a variety of approaches to measure a neighborhood. Data availability often leads researchers to approach this question in similar ways. In the US, census/American Community Survey (ACS) data are by far the best and most widely available data available at the neighborhood level, with several choices of geographical size to choose from, including zip code, census tract, block group, and block levels. Others, such as the county, election district, or transportation analysis zone (TAZ) levels are also used, but often because of other data requirements or specific uses for the research that require these choices (Fede et al., 2016; Bejleri et al., 2018; Siler et al., 2020).

Research does not definitively suggest the most appropriate geographic scale to identify a DAC. For example, Krieger et al. (2002) developed a diverse set of single-variable and composite area-based socioeconomic measures at the census tract, block group, and zip code levels to investigate the associations between different measurement approaches and mortality rates in these states. Their findings suggest that block group and tract socioeconomic measures performed similarly, but zip code either did not detect gradients, or found gradients that were inconsistent with those found at the tract and block-group level measures, suggesting zip code-level analysis may not be ideal.

Similarly, Singh (2003) created an area deprivation index (i.e., a weighted scale) to look at the changes in mortality within DACs over time, comparing the performance of the scale at the census tract, zip code, and county geographical levels of analysis. However, the study did not find meaningful differences between different geographic units of analysis, since the factor analysis used to create the scales for each of these three geographical levels produced similar factor loadings in magnitude and relative explanatory importance.

Overall, census tracts (Lisabeth et al., 2006; Dubowitz et al., 2011; Lian et al., 2014; Acevedo-Garcia et al., 2014; Bhatia & Maizlish, 2016; Niedzielski & Boschmann, 2014; Goetz et al., 2019; Aman et al., 2021) and census block groups (Platt et al., 2009; Kind et al., 2014; Qian & Niemeier, 2019; Heckert & Rosan, 2016; Hughey et al., 2016; Knighton et al., 2016; Roux et al., 2001) are used more often, with the latter providing an opportunity to conduct more in-depth analysis.

Among other geographic scales, TAZs are often used in transportation-focused studies (Miller & Shaw, 2001; Widener et al., 2015; Carleton & Porter, 2018; Karner, 2018). Only a small minority of research studies also use census block-level data (Qian & Jaller, 2021), due to the paucity of data at this level.

2.5 Use of Composite Disadvantaged Community Indices and Scales in Disadvantaged Communities Research

Neighborhood disadvantage is a subjective concept open to interpretation, potentially composed of many valid components and dependent not only on the contribution of each of those individual variables but also on the combined effects of those components that are often greater than the sum of their parts. Therefore, Lou et al. (2023) note that researchers and analysts have sought the means to standardize and simplify these measurements while also capturing the complexities inherent in neighborhood disadvantage measurement. To address these challenges, some researchers have combined multiple contributing variables into a unified index or scale score, thereby simplifying interpretation of the results and capturing the interactions between individual variables.

Using an index to represent such a numerous and diverse, but also, inherently related (i.e., correlated) set of indicators allows analysts to develop a single or small set of index scores that better represent the interrelated, combined effects of its constituent variables (Babbie, 1998). Neighborhood disadvantage indices have the benefit of providing a single or small set of scores that combine and summarize the scores of multiple variables representing diverse domains of neighborhood conditions such as income, poverty, education, employment, housing conditions, transportation availability, and access to services (PHASC, 2015).

Indices do have several limitations, including (1) different criteria used by different researchers for testing validity; (2) differences in the configuration of study area boundaries (e.g., neighborhoods) and scale of geographies at which the analysis is conducted; and (3) application of different measures within the same index, such as data describing individuals combined with variables describing neighborhood (aggregate) conditions can lead to ecological fallacies where false conclusions are drawn based on neighborhood data (Philips at el., 2016).

Noting the lack of consensus over how to measure neighborhood disadvantage, Krieger et al. (2002) assessed the robustness and validity of various methods, including (1) a two-factor analysis-derived scale using the maximum likelihood approach, and (2) a z-score-based index, using inputs identified by factor analysis. They found few differences in terms of performance between the composite (index or scale) methods for measuring neighborhood socioeconomic status and single-variable methods. In fact, single-variable poverty indicators performed well compared to composite methods, detecting the same gradients of socioeconomic inequality across neighborhoods. Eibner and Strum (2006) came to similar conclusions, giving a warning that by grouping all metrics into a single factor score index, analysts may mask heterogeneous influences of input factors on neighborhood health outcomes.

A clear majority of health studies researching disadvantaged neighborhoods employed complex indices or scales, followed by housing studies. However, only one-quarter of the transportation research (and even fewer urban form studies) reviewed here used this approach.

The literature employs a variety of methods to combine individual indicators into disadvantaged neighborhood indices and scales, though most use a variation of one of three techniques. The most complex is factor analysis (data reduction). Simpler standardization methods (e.g., z-scores and percentiles) are also used, along with a mix of these techniques.

Lian et al. (2014) utilized factor analysis to construct a census tract data-based index of neighborhood socioeconomic deprivation that suggested six domains of variables: education, occupation, housing conditions, income and poverty, racial composition, and residential stability. Factor (principal components) analysis reduced the 21 census variables included in their analysis to a factor score using seven variables that served as the basis for their neighborhood deprivation index. The variables were standardized and weighed by factor loading coefficients and then included in their statistical analysis by computing a neighborhood socioeconomic deprivation index and identifying the associations between deprivation and breast cancer-related deaths. Similarly, Fede et al. (2016) developed an index of small-area deprivation (ZIP Code Tabulation Area—ZCTA—level) and compared its performance at predicting the chronic disease burden for Medicare recipients to other existing indices. They then used factor analysis using these three standardized indicators, and since they found that the factor loadings for each were nearly identical, they did not use weightings and simply summed the three to yield their final index score.

Researchers using the z-score technique include Lisabeth et al. (2006), who used six neighborhood-level census tract variables combined into a z-score-based index focusing on various aspects of neighborhood wealth and income to identify the relationships between neighborhood SES and the occurrence of strokes. These included: (1) median annual household income; (2) median value of occupied housing units; (3) percentage of households receiving interest, dividend, or net rental income; (4) percentage of adults who completed high school; (5) percentage of adults who completed college; and (6) percentage of those in managerial or professional occupations.

Acevedo-Garcia et al. (2014) developed the Child Opportunity Index to measure the extent of racial and ethnic inequity for children in neighborhoods (census tracts) within the 100 largest US metropolitan areas using multiple variables for each of the three indicator domains (or "Categories"): educational; health and environmental; and social and economic opportunities. Acevedo-Garcia et al. first converted each individual variable's value into a z-score and then averaged all z-scores within each category to yield a composite z-score for each. However, following this initial category-level averaging, the research team then averaged all three domain scores into a final, composite Child Opportunity Index score for each neighborhood.

El-Geneidy et al. (2016) developed an index of social vulnerability and transit cost and time accessibility for census tracts in Montreal, Canada. This index used census measures of median household income, percentage of recent immigrants, percentage of the workforce that is unemployed, and percentage of those with education at the level of only a high school diploma (25-64 years old), all weighted equally. To ensure all variables included in the index were describing the same population, the researchers ran Pearson correlation coefficients, where a value of over 0.5

indicated sufficient correlation between them. They then normalized each variable as z-scores against the regional average, then summed them to give a total index score of social disadvantage.

HCD/CTCAC (2013) created a regionally derived index score using twenty-one indicators, making it possible to sort each tract or rural block group into opportunity categories according to the index ranking within its region or rural county. The z-score indicators represent three domains: economic, environmental, and education. These tract-level z-scores were averaged together by domain (with equal weighting), and then these three domain scores were averaged together to create the final overall index score.

Finally, Dubowitz et al. (2011) employed a mixed-method technique, using exploratory factor analysis to select variables and z-scores to standardize and combine them into a combined index score of neighborhood SES.

3. Research Methodology and Findings

The following six-step methodology was adopted to answer the research questions.

3.1 Step 1: Identify Case Study MPOs

Data tables from CARB's year 2018 progress report were used to identify one to two case study regions for in-depth analysis. This report was prepared to assess the progress made under SB 375 (CARB, 2018, Appendix A). These tables provide information for all 18 metropolitan planning organizations (MPOs), including the total new single- and multi-family housing units planned for 2020 and 2030 and the average increase in urbanized land between the SCS base year and 2020. Since this research focuses on the concentration of new housing in existing DACs—housing likely to be in the form of infill, multi-family developments—the top-two MPOs were identified (MTC-ABAG for the S.F. Bay Area and SCAG for the greater Los Angeles region) using the following criteria: (a) the numbers of new housing units planned, (b) multi-family housing as a proportion of total housing, and (c) the least amount of new urbanized land added for each housing unit planned for 2020.

Prima facie, the San Diego Association of Governments (SANDAG)—the MPO for the San Diego region—should have been a good choice, but SANDAG planned for or developed a large amount of new urbanized land in recent years, indicating a sprawling growth pattern. Specifically, it added approximately 14,000 acres every two years between 2015 and 2020 and planned for about 85,000 new housing units until 2020—or 17 acres for every 100 housing units. In comparison, SCAG's two-year average is approximately 5,000 acres for around 500,000 units (one acre for every 100 housing units), and MTC-ABAG's two-year average is about 3,000 acres for about 225,000 units (1.3 acres for every 100 units). California's smaller MPOs showed a similar pattern of sprawl to that seen for SANDAG (CARB, 2018). Therefore, it was determined that while including smaller MPOs in these case studies may have been valuable, time and resource constraints necessitated concentrating research efforts on the state's two largest MPOs, where new housing is more likely to be infill and have the negative consequences that motivated this study.

3.2 Step 2: Develop Metrics to Identify DACs

Existing literature across several disciplines was reviewed to identify the variables used to operationalize community-level disadvantage. These disciplines included public health, transportation, urban form/land use, and housing. The variables or indices used by the existing literature fell under the following major dimensions: environment/health, transportation/urban form/land use, housing/economic, race/ethnicity/demographic, and education.

Next, existing off-the-shelf metrics and tools that used the variables employed by the literature or included additional variables not identified in the literature were reviewed. These metrics and tools included the US Department of Housing and Urban Development's (HUD) School Proficiency Index, Low Poverty Index, Low Transportation Cost Index, and Environmental Health Index; the metrics developed by the California Department of Housing and Community Development (HCD) and the California Tax Credit Allocation Committee (CTCAC) to create opportunity maps; the latest version of the California Communities Environmental Health Screening Tool, called CalEnviroScreen 4.0, developed by the California Office of Environmental Health Hazard Assessment; and the US Environment Protection Agency's (EPA) Smart Location Database (SLD).

The US Census tables that provided the data to operationalize the variables employed by the literature but not included in these off-the-shelf tools or measured in these tools at higher levels of geographies were then identified. The focus was on identifying robust data at the most fine-grained level possible, usually a census block group. Each off-the-shelf metric was examined to determine the suitability of one over the other. For example, while HUD's Environmental Health Index and CalEnviroScreen 4.0 measure environmental pollution, the former only measures air pollution, while the latter measures air, ground, and water pollution.

In some cases, census-tract-level data were used because either the information was unavailable at the block-group level or was not robust (i.e., margins of error exceeded the variables' values). Percentages of single-parent households and all the variables used to operationalize the environmental dimension (which are from CalEnviroScreen 4.0) were measured at the census-tract level. Median gross rent as a percentage of household income is another example.

Finally, a DAC index was developed that comprised five major dimensions to mirror those seen in the literature. These dimensions included demographic, economic, educational, environmental, and transportation. These dimensions were subdivided into two or more sub-dimensions, with one or a combination of two or more variables operationalizing each sub-dimension. See Tables 2 and 3 for the major and sub-dimensions, the variables comprising them, the geographic scale at which they were measured, and the data source.

The variables for the sub-dimensions were either those used by the literature or their variants. Variants were developed if it was believed they were an advance over the variables used in the literature. For example, the literature often used an absolute measure of income to operationalize the economic dimension, such as household income above 200% of the federal poverty line (HCD/CTCAC, 2023). Such measures do not capture regional differences. For example, a household above 200% of the federal poverty level in a high-cost region might be considered extremely low-income. In contrast, in a low-cost region, it could be moderate income. Therefore, methods were utilized that directly measured the cost of living (median rent as a percentage of household income is an appropriate measure of housing affordability) or measured economic wellbeing in the context of the region (a block group's median income as a proportion of the county's area median income).

Such sub-dimensions allowed metrics to reduce aggregation bias and maintain the multi-faceted nature of each dimension. For example, HCD/CTCAC Opportunity Maps group eleven environmental variables under one dimension, using the average scores for these variables as the score for that dimension. Therefore, a census tract that does poorly on three or four variables but is average on the remaining was likely to be reported as doing well on the environmental dimension, thereby masking the potentially significant environmental hazards present in the community. To address this "masking effect," the environmental dimension was divided into three sub-dimensions, reducing the aggregation bias while allowing analysis of the effect of several types of environmental impacts. For example, while the S.F. Bay Area region had no environmental disadvantage, several census tracts were disadvantaged on the sub-dimension Env 3: Children's lead risk from housing. Similarly, the transportation dimension was divided into three sub-dimensions, with Transp 2 and Transp 3 operationalizing local and regional transportation accessibility, respectively.

The measurement methodology also included, to the extent possible, using relative, not absolute, thresholds to measure disadvantage. An example of such a threshold is the Transp 5 sub-dimension (see Table 3), which measured a block group's regional transportation accessibility relative to other block groups in that region. However, absolute thresholds were used in a few cases where they made better theoretical sense than the relative thresholds. For example, since the literature (Kuby et al., 2004; O'Neill et al., 1992; Zhao et al., 2003) suggests three quarters of a mile as the outer threshold for walking to a transit stop, this value was used instead of a relative threshold.

To the extent possible, disadvantage was measured in the context of the region, not the state and the nation. For example, the disadvantage for both the demographic sub-dimensions. However, in a few cases, the threshold did not need to be relative or in the context of the region. For example, the threshold for disadvantage on the Econ 1 sub-dimension—a household spending more than 50% of income on rent—is uniform across the US.

In a few cases, data were not available at the regional level (e.g., the Educ 2 sub-dimension), or it made more sense to develop thresholds for disadvantage relative to the state. This was the case for all the Env sub-dimensions where if the entire region is highly polluted, then just identifying the top quartile of polluted block groups in that region would under-report environmental disadvantage. Therefore, the thresholds for the Env sub-dimensions were relative to the state.

Certain variables were highly correlated with each other. In that case, the variables most often used in the literature were used. For example, the percentage of white alone population (included in the analysis) was highly correlated with the percentage of the population not proficient in English (excluded), and the percentage of households with zero vehicles (included) was highly correlated with the percentage of people using non-auto modes of transport to work (excluded).

Table 2. Dimensions of DAC Index

Dimension	Sub-dimension	Variable	Disadvantage for the sub-dimension	Disadvantage for the dimension	Overall disadvantage
Demographic	Dem1	% white alone population	If the block group is in the bottom quartile for the region	Both Dem1 and Dem 2 are disadvantaged	If two or more dimensions are disadvantaged
	Dem 2	% single-parent households	If the census tract is in the top quartile for the region		
Economic	Econ 1	Median gross rent as % of household income	If the % is equal to or more than 50%	Either Econ 1 or Econ 2 is disadvantaged	
	Econ 2	Median household income as a % of the county's area median income	If the % is less than or equal to 50%		
Educational	Educ 1	% of adults over 25 years of age with a high school diploma or above	If the block group is in the bottom quartile for the region	Both Educ 1 and Educ 2 are disadvantaged	
	Educ 2	HUD School Proficiency Index	If the block group is in the bottom quartile for the nation		
Environmental	Env 1	Average of the percentile of concentrations of Ozone, PM2.5, Diesel Particulate Matter, and toxic releases to air from industrial facilities	If the census tract is in the top quartile for the state	Disadvantage on two out of three sub-dimensions	
	Env 2	2/3 of the average of the percentiles of exposure to drinking water contaminants and use of certain high-hazard, high-volatility pesticides AND 1/3 of the average of the percentiles of environmental effects of toxic cleanup sites, ground water threats from	If the census tract is in the top quartile for the state		

Dimension	Sub-dimension	Variable	Disadvantage for the sub-dimension	Disadvantage for the dimension	Overall disadvantage
		leaking underground storage sites and cleanups, hazardous waste facilities and generators, impaired water bodies, and solid waste sites and facilities			
	Env 3	Children's lead risk from housing	If the census tract is in the top quartile for the state		
Transportation	Transp 1	Percent of households with zero vehicles	If the block group is in the top quartile for the region	Disadvantage on two out of three for Transp 2, 3 and 4; additionally, one of Transp 1 and 5	
	Transp 2	Intersection density in terms of pedestrian-oriented intersections having four or more legs per square mile	0-15 intersections/sq. mi.		
	Transp 3	Distance from the population-weighted centroid to nearest transit stop (meters)	If the distance is greater than 800 meters (3/4 mile)		
	Transp 4	Gross activity density (employment + housing units) on unprotected land (that is, land available for development)	Density less than 18/acre		
	Transp 5	Jobs within 45-minute transit commute, distance decay weighted (walk network travel time, GTFS schedules)	If the block group is in the bottom quartile for the region		

3.3 Step 3: Collect Census and Other Spatial Data to Operationalize the Metrics

Table 3 shows that data were obtained to operationalize the variables from various sources, including the US Census, HUD, EPA SLD, and CalEnviroScreen 4.0. See Table 3, Column 5 for the specific data sources, such as US Census table numbers and the exact EPA SLD variables. The 2010 and 2020 block groups and census tract GIS files were downloaded from the US Census Tiger/Lines Shapefiles website (US Census, 2022). Several of these data came with GIS files that were merged into an ArcGIS project—one for each region.

Table 3. Data Sources and Year

Dimension	**Sub-dimension**	**Variable**	**Geographic-level of data**	**Specific Data Sources and Year**
Demographic	Dem1	% white alone population	Block group	US Census: Decennial Census 2020, Table P1
	Dem 2	% single-parent households	Census tract	US Census: American Community Survey (ACS) 2010: 5-Year Estimate, Table DP02
Economic	Econ 1	Median gross rent as % of household income	Census Tract	US Census: American Community Survey (ACS) 2020: 5-Year Estimate, Table B25071
	Econ 2	Median household income as a % of the county's area median income	Median Household Income: Block group Area Median Income: County	For Median Household Income: US Census: ACS 2020 5-year Estimate, Table B19013. ACS 2018, 2019, or 2021 data for missing 2020 data For County's Area Median Income: HUD

Dimension	Sub-dimension	Variable	Geographic-level of data	Specific Data Sources and Year
Educational	Educ 1	% of adults over 25 years of age with a high school diploma or above	Block group	US Census: ACS 2020 5-year Estimate, Table B15003
	Educ 2	HUD School Proficiency Index	Block group	HUD School Proficiency Index Great Schools (proficiency data, 2013-14)
Environmental	Env 1	Average of the percentile of concentrations of Ozone, PM2.5, Diesel Particulate Matter, and toxic releases to air from industrial facilities	Census tract	CalEnviroScreen 4.0: Various years and data sources
	Env 2	2/3 of the average of the percentiles of exposure to drinking water contaminants and use of certain high-hazard, high-volatility pesticides AND 1/3 of the average of the percentiles of environmental effects of toxic cleanup sites, ground water threats from leaking underground storage sites and cleanups, hazardous waste facilities and generators, impaired water bodies, and solid waste sites and facilities	Census tract	
	Env 3	Children's lead risk from housing	Census tract	
Transportation	Transp 1	Percent of households with zero vehicles	Block group	US Census: ACS 2020 5-year Estimate, Table DP04
	Transp 2	Intersection density in terms of pedestrian-oriented intersections having four or more legs per square mile	Block group	EPA SLD, field D3BP04. Source: 2018 HERE Maps NAVSTREETS

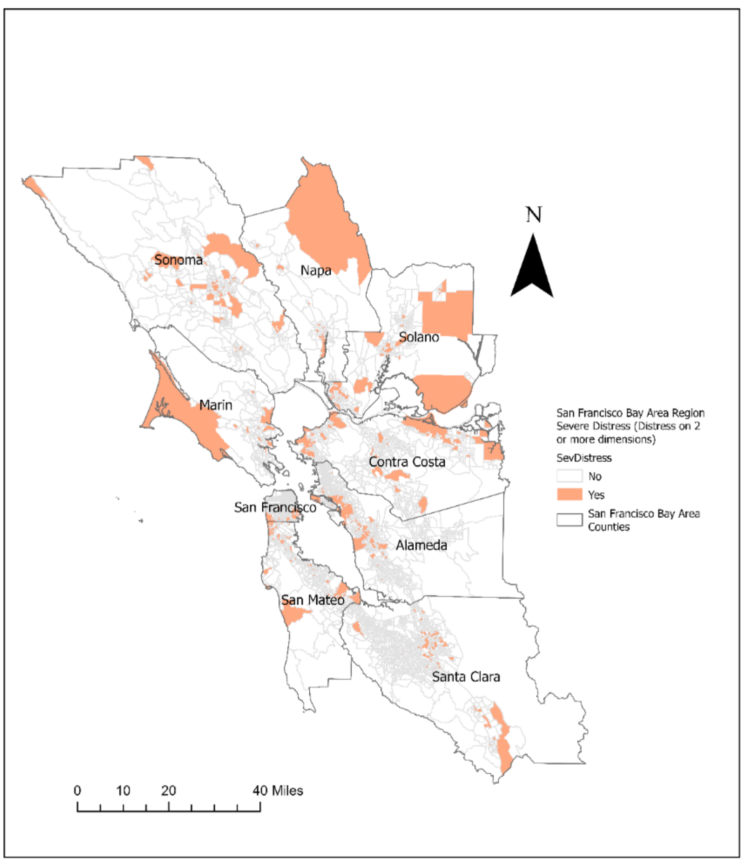
Dimension	Sub-dimension	Variable	Geographic-level of data	Specific Data Sources and Year
	Transp 3	Distance from the population-weighted centroid to nearest transit stop (meters)	Block group	EPA SLD, field D4a. Source: 2020 General Transit Feed Specification (GTFS) files, 2020 Center for Transit Oriented Development (CTOD) database
	Transp 4	Gross activity density (employment + housing units) on unprotected land	Block group	EPA SLD, field D1d. Source: Derived from other EPA SLD variables
	Transp 5	Jobs within 45-minute transit commute, distance decay weighted (walk network travel time, GTFS schedules)	Block group	EPA SLD, field D5br. Source: 2020 TravelTime API, 2017 Census Longitudinal Employer-Household Dynamics (LEHD) data, 2020 GTFS files

3.4 Step 4: Spatially Locate DACs

Rather than use more computationally challenging approaches (e.g., principal component analysis or factor analysis) to develop disadvantaged community metrics, it was decided to use a simpler methodology—an unweighted sum of the dimensions and sub-dimensions. Notably, a substantial proportion of the off-the-shelf metrics that measure disadvantage adopt such simpler methodologies, including the HUD's School Proficiency Index, CalEnviroScreen 4.0, and HCD/CTCAC's metrics for Opportunity Maps.

Using the methodology noted in Table 2, Column 4, disadvantage was calculated for each block group for each sub-dimension. Next, the methodology in Table 2, Column 5, was used to calculate the disadvantage along each of the five dimensions. Finally, if a block group was disadvantaged on two or more dimensions, that is, the DAC Index (DACI) score was two or more, it was considered disadvantaged overall. A separate GIS layer comprising such disadvantaged block groups was created. See Figure 1 for the location of DACs in the S.F. Bay Area region and Figure 2 for the SoCal region.

Figure 1. DACs in the S.F. Bay Area Region



As Figure 1 shows, many of the disadvantaged areas of the region are in Solano, Napa, and Marin counties (mainly in the unincorporated areas), followed by Contra Costa County and Alameda, San Mateo, and San Francisco counties, especially areas that are along the bay. Finally, a smattering of these areas are in central Santa Clara County (in the city of San José) and the southern tip of the county.

Figures A1 through A7 in the Appendix show the location of DACs for each dimension. Notably, the largest areas are under transportation disadvantage (see Figure A3). Finally, as noted above, while the region is not disadvantaged on the environmental dimension (see Figure A6), it is on one of its sub-dimensions—Env3—that measures children's lead risk from housing (see Figure A7).

Figure 2. DACs in the SoCal Region

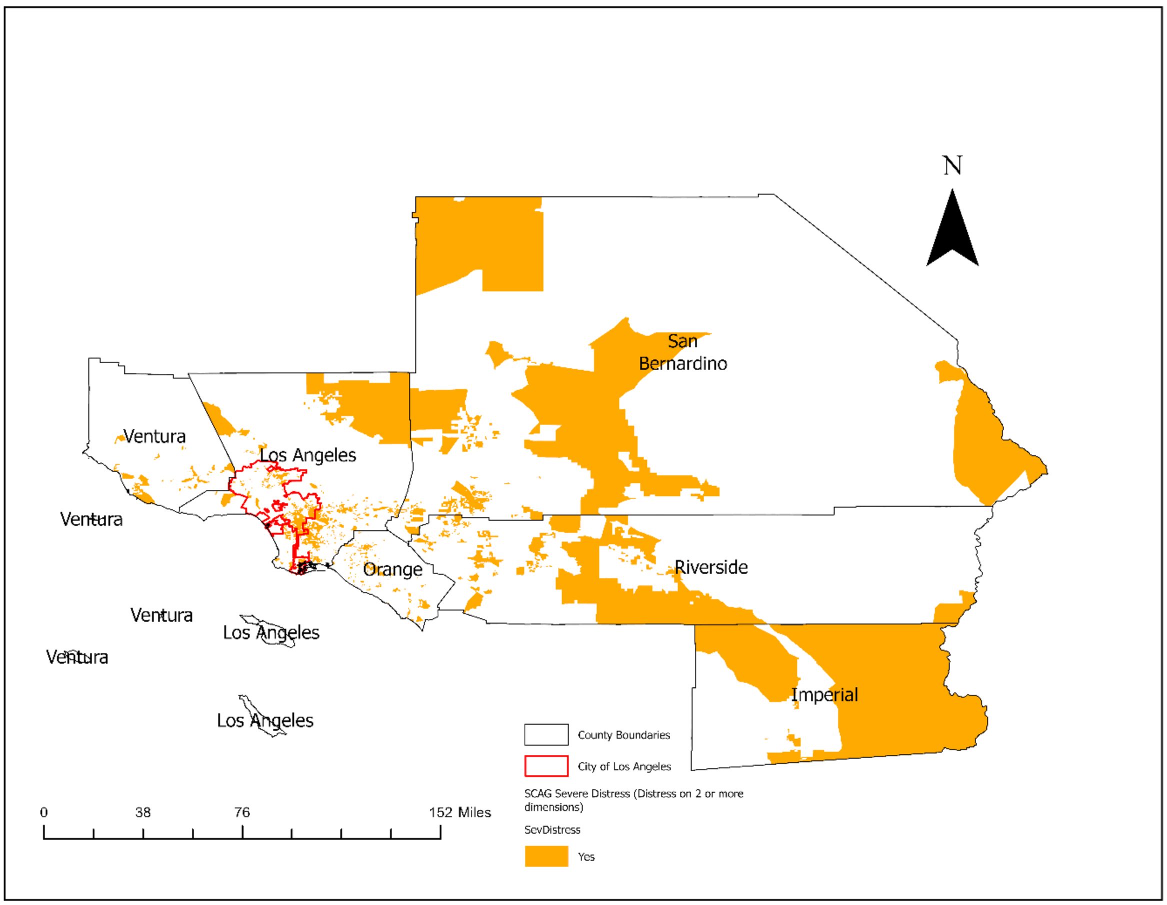


Figure 2 shows that large swathes of San Bernardino, Riverside, and Imperial counties are severely disadvantaged. Los Angeles, Orange, and Ventura counties follow them. The disadvantaged areas largely fall in the unincorporated parts of the San Bernardino, Riverside, Imperial, and Los Angeles counties. Finally, they are also in the cities of Los Angeles County, especially the city of Los

Angeles, where they are concentrated mainly in the southern and eastern sections of the city, followed by the cities in Orange and Ventura counties.

A review of the various dimensions of disadvantage (see Figures B1 to B5 in the Appendix) reveals that, like the S.F. Bay Area region, transportation distress is most widespread (see Figure B3), followed by economic disadvantage (see Figure B1). Furthermore, unlike the S.F. Bay Area region, several parts of the SoCal region experience environmental disadvantage, especially areas in around the southern and eastern parts of the city of Los Angeles and those at the confluence of Los Angeles, Orange, and Riverside counties (see Figure B5).

3.5 Step 5: Identify Locations of Planned New Housing

All of California's 18 MPOs must develop SCSs to guide their GHG reduction efforts. The Plan Bay Area 2050 and Connect SoCal serve as the SCSs for the ABAG-MTC and SCAG, respectively, and serve as these regions' regional transportation plans. These plans identify areas for targeted future growth, called Priory Development Areas (PDAs), Transit Rich Areas (TRAs) and High Resource Areas (HRAs) in the S.F. Bay Area region and Priority Growth Areas (PGAs) in the SoCal region. Connect SoCal notes:

> Connect SoCal's PGAs—Job Centers, TPAs, HQTAs, Neighborhood Mobility Areas (NMAs), Livable Corridors and Spheres of Influence (SOIs)—account for only four percent of the region's total land area, but implementation of SCAG's recommended growth strategies will help these areas accommodate 64 percent of forecasted household growth and 74 percent of forecasted employment growth between 2016 and 2045 (SCAG 2020, p. 50).

The PGAs are called Spheres of Influence (SOI) in the unincorporated areas of SoCal counties. To complicate matters further, some SOIs are outside the PGAs. Therefore, the GIS files for the S.F. Bay Area region PDAs and the PGAs and SOIs for the SoCal region were obtained. At the time these GIS files were obtained for this study, files for TRAs and HRAs were not available. Hence this study only includes PDAs for the S.F. Bay Area region. See Figure 3 for the location of PDAs and Figure 4 for PGAs and SOIs. As Figure 3 shows, a substantial proportion of the area under PDAs is around the bay in San Francisco, San Mateo, Santa Clara, and Alameda counties, with a fair bit sprinkled across Contra Cosa County. Except for the unincorporated Contra Costa County, most PDA areas lie within city boundaries.

Figure 3. PDA Locations in the S.F. Bay Area Region

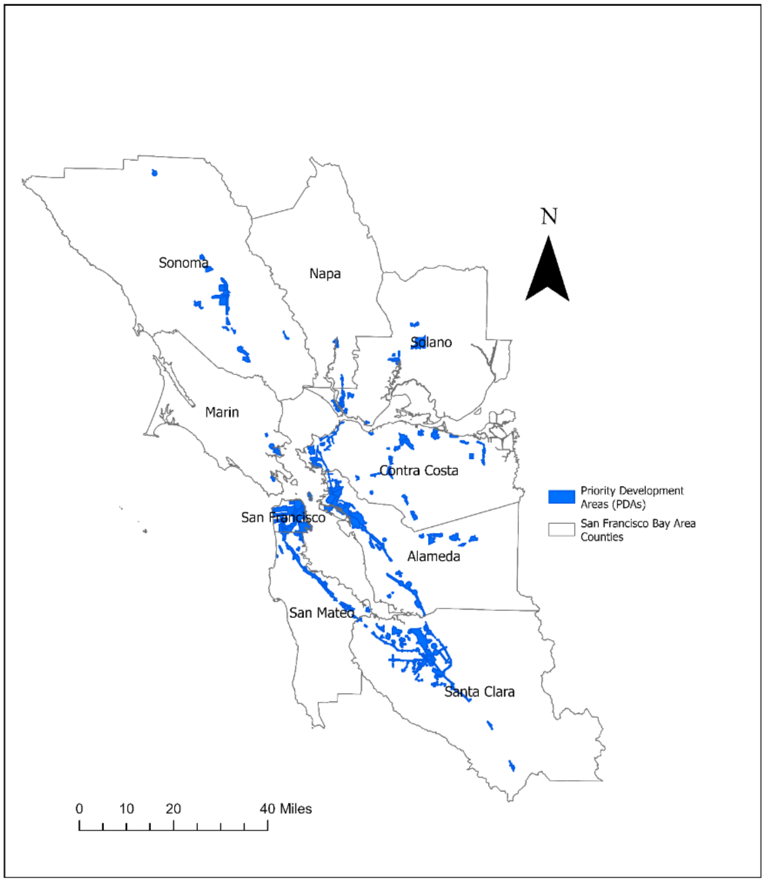
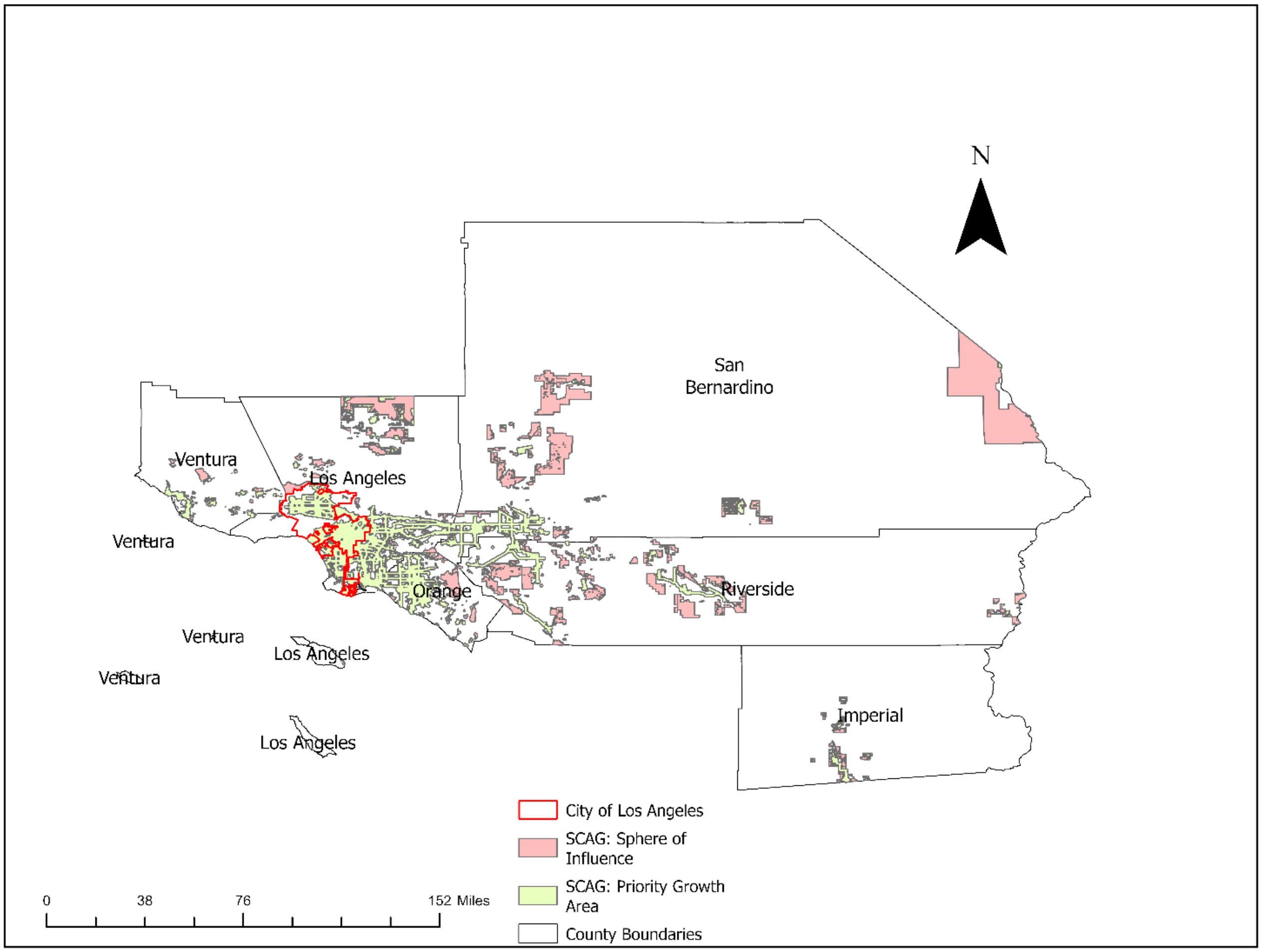


Figure 4. PGA and SOI Locations in the SoCal Region



As Figure 4 shows, a considerable proportion of the PGAs are in Los Angeles County, followed by Riverside, San Bernardino, and Ventura counties. A substantial proportion of the city of Los Angeles is earmarked as PGA. Large SOI areas are in San Bernardino County, followed by Riverside and Los Angeles counties. Notably, unlike the S.F. Bay Area region, many SOIs are in the unincorporated areas of the counties.

3.6 Step 6: Identify the Extent to Which New Growth is Planned in DACs and the Top Local Jurisdictions in Each Region Where this is Taking Place

The GIS files showing the PDAs were overlaid on the S.F. Bay Area region's GIS layer of the disadvantaged block groups. Similarly, the GIS files showing the PGAs, and SOIs outside of PGAs, were overlaid on the SoCal region's GIS layer of the disadvantaged block groups. These overlays helped to visually identify the location of DACs. See Figures 5 and 7 for such locations for the S.F. Bay Area and the SoCal regions, respectively. As Figure 5 shows, most of the large swathes of disadvantaged areas located in Marin, Napa, Sonoma, and Solano counties do not overlap with PDAs. Moreover, they are in the unincorporated areas of these counties. However, DACs around the bay that are in the vicinity of the shoreline (i.e., in the more urban and developed parts of the region), especially in Alameda and Contra Costa counties, tend to overlap with the PDAs. In contrast, several DACs in the unincorporated areas of SCAG counties overlap with SOIs (see Figure 7); additionally, large sections of disadvantaged areas of the city of Los Angeles overlap with PGAs (see Figure 8). As Figure 6 and Table 4 show, overall, close to a quarter (22%) of the area under PDAs and close to half (48%) of PGAs and SOIs are disadvantaged in the S.F. Bay Area and SoCal regions, respectively (see Table 4, Column 7). Meanwhile, the total area of these regions that are disadvantaged is only 14% and 26%, respectively (see Table 4, Column 6). In summary, the areas targeted for growth are more disadvantaged than the regions as a whole.

Similarly, the areas targeted for growth that are not disadvantaged as a percentage of total non-disadvantaged areas of the region are 2.5% and 6.1%, respectively (see Table 4, Column 8). In comparison, the areas targeted for growth that are disadvantaged as a percentage of total disadvantaged areas of the region are much higher, 4.3% and 16.1%, respectively (see Table 4, Column 9), showing that areas targeted for growth that are disadvantaged comprise a larger proportion of the DACs in these regions compared to similar non-disadvantaged areas.

Arguably, the use of gross area for the entire region could bias the percentages as it includes the non-habitable parts of the regions, such as hills, county parks, and lakes. Since such parts of the region are likely to be in unincorporated counties, the Table 4 numbers were re-run for just the cities, excluding unincorporated counties. It was found that while the area in square miles changed significantly, the percentages did not, or if they did, they further reinforced that disproportionately large population is being planned in DACs. For example, while the percentage of areas under cities that are disadvantaged reduced from 14% to 7% for the S.F. Bay Area region, the percentage of areas targeted for growth that are disadvantaged only went down from 22% to 21.4%. The targeted growth areas are three times more disadvantaged than the cities overall—21.4% compared to 7%. When the entire S.F. Bay Area region (including the unincorporated counites) is considered, the targeted growth areas are only 1.5 times more disadvantaged than the region overall—22% compared to 14%.

Table 4. Proportion of New Housing in the Region in DACs Versus Non-DACs

Col 1	**Col 2**	**Col 3**	**Col 4**	**Col 5**	**Col 6**	**Col 7**	**Col 8**	**Col 9**
Region A	Area of the region (sq. mi.) B	Area targeted for growth (PDAs for SF Bay Area and PGAs+SOIs for SoCal) C	Area of DACs D	Area targeted for growth (PDAs for SF Bay Area and PGAs+SOIs for SoCal) that is disadvantaged E	% of area that is disadvantaged (D divided by B) ×100%	% of area targeted for growth (PDAs for SF Bay Area and PGAs+SOIs for SoCal) that is disadvantaged (E divided by C) ×100%	Area targeted for growth (PDAs for SF Bay Area and PGAs+SOIs for SoCal) that is not disadvantaged as a % of total non-disadvantaged area of the region [(C-E) divided by (B-D)] ×100%	Area targeted for growth (PDAs for SF Bay Area and PGAs+SOIs for SoCal) that is disadvantaged as a % of total disadvantaged area of the region (E divided by D) ×100%
S.F. Bay Area	7,010	194	989	43	14%	22%	2.5%	4.3%
SoCal	38,637	3,342	9,975	1,610	26%	48%	6.1%	16.1%

Note: All areas are in sq. mi.

Figure 5. S.F. Bay Area Region: Overlay of PDAs on DACs

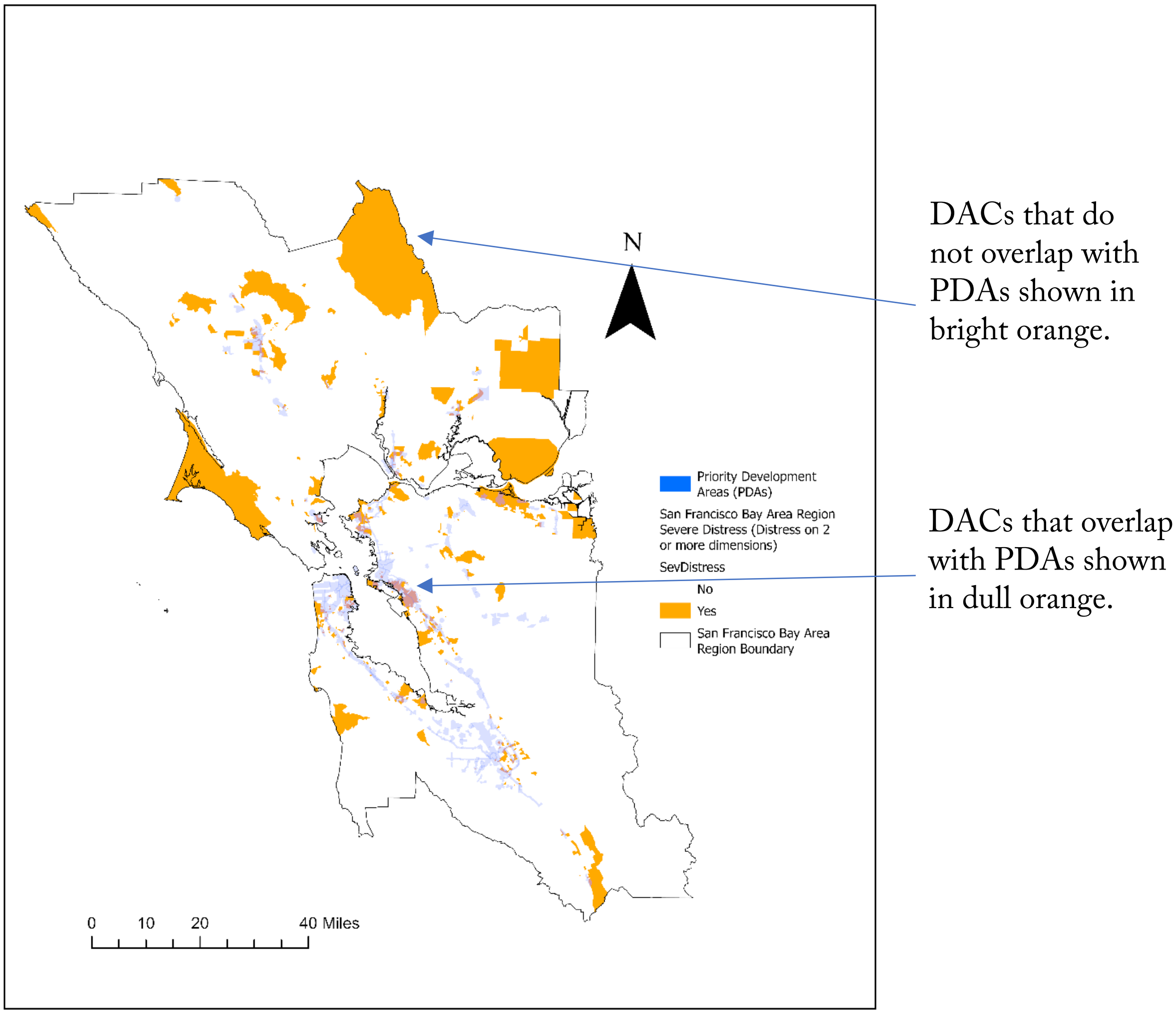


Figure 6. S.F. Bay Area Region and SoCal Region: Areas Targeted for Growth are More Disadvantaged than the Region as a Whole

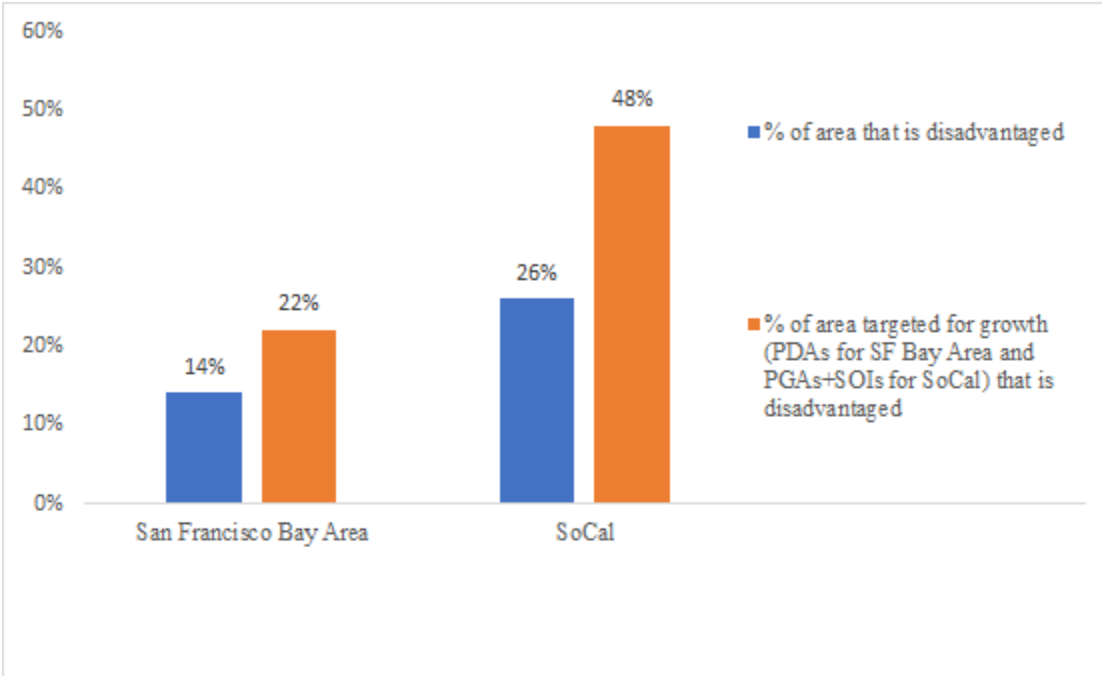


Figure 7. SoCal Region: Overlay of PGAs and SOIs on DACs

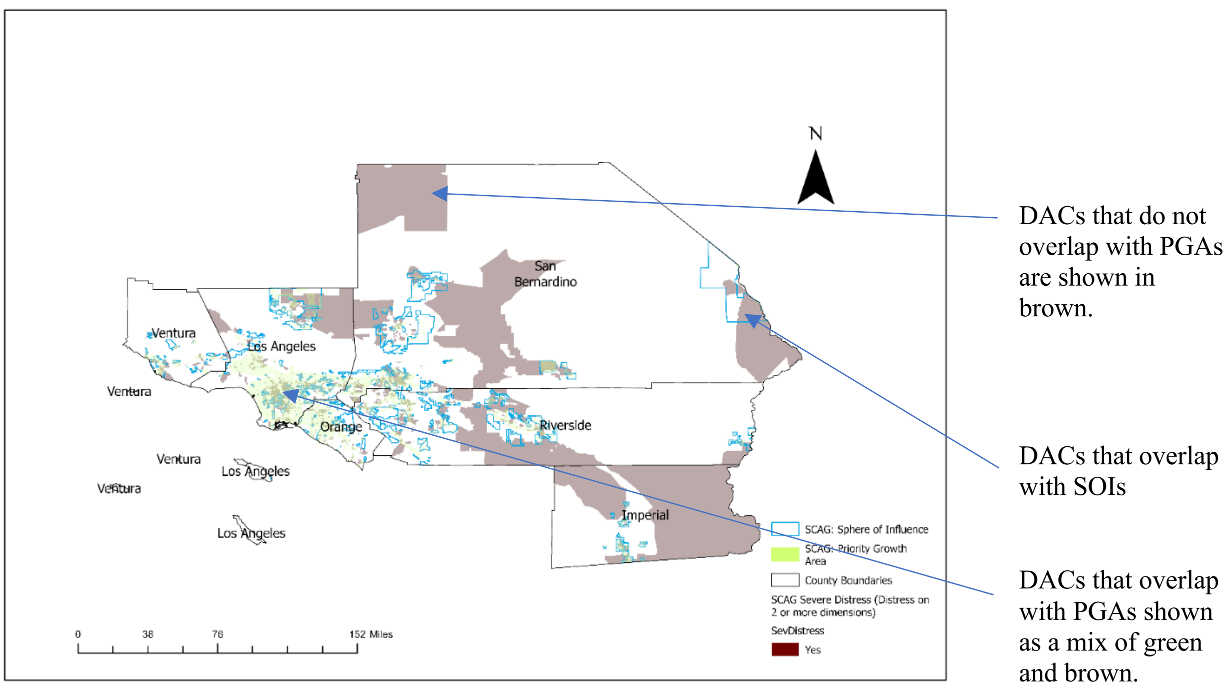
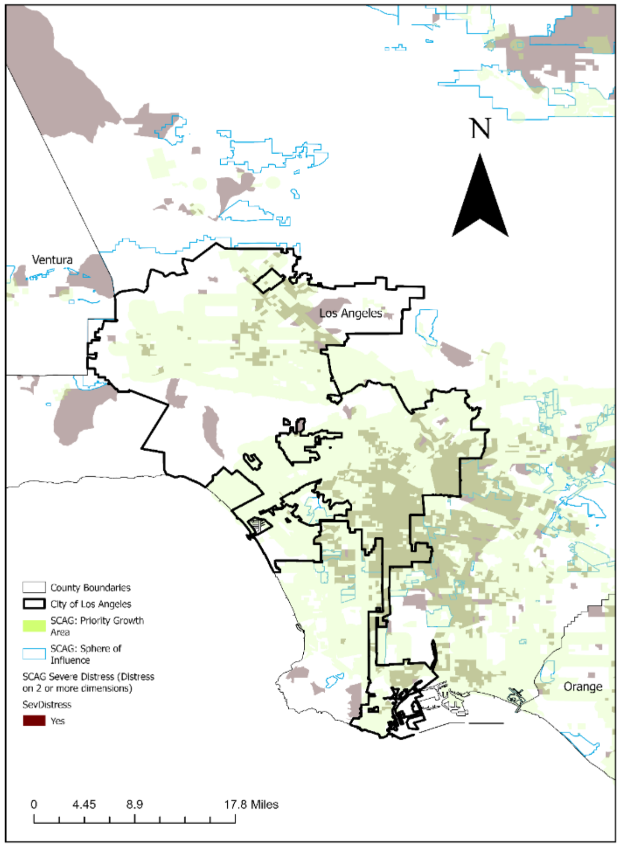


Figure 8. Overlay of PGAs and SOIs on the DACs of the City of Los Angeles



Next, the following methodology was adopted to identify the top four jurisdictions in each region where a large proportion of the new development is being planned in DACs. The methodology varies slightly between the two regions for reasons that will be explained.

Methodology for identifying the top impacted jurisdictions in the San Francisco Bay Area Region

To begin, the total area of disadvantaged PDAs for all the 100-plus jurisdictions in the S.F. Bay Area region was calculated. From that list, jurisdictions with a minimum of one square mile of disadvantaged PDAs were selected, producing a list of twelve jurisdictions. See Columns 1 and 3 of Table 5 for the name and rank of each jurisdiction.

The percentage of the PDA area disadvantaged for all the S.F. Bay Area region jurisdictions was then calculated to identify the top twelve jurisdictions. See Columns 4 and 6 of Table 5 for the name and rank of the jurisdictions, respectively.

Jurisdictions among the top twelve that were in both of the lists were identified, which included six jurisdictions (see the bolded names in Columns 1 and 4 of Table 5). Finally, their ranks on both criteria were summed to identify the top four jurisdictions (see Table 6). These include (in decreasing order of disadvantage) Pittsburg, Oakland, unincorporated Contra Costa County, and

Fairfield. For example, Pittsburg ranked 5th among the jurisdictions with the largest area of disadvantaged PDAs and second on the percentage of disadvantaged PDA areas in each jurisdiction for a total score of 7 (5+2). See Table 6, Column 2 for the cumulative rank. Figure 9 shows the location of these jurisdictions.

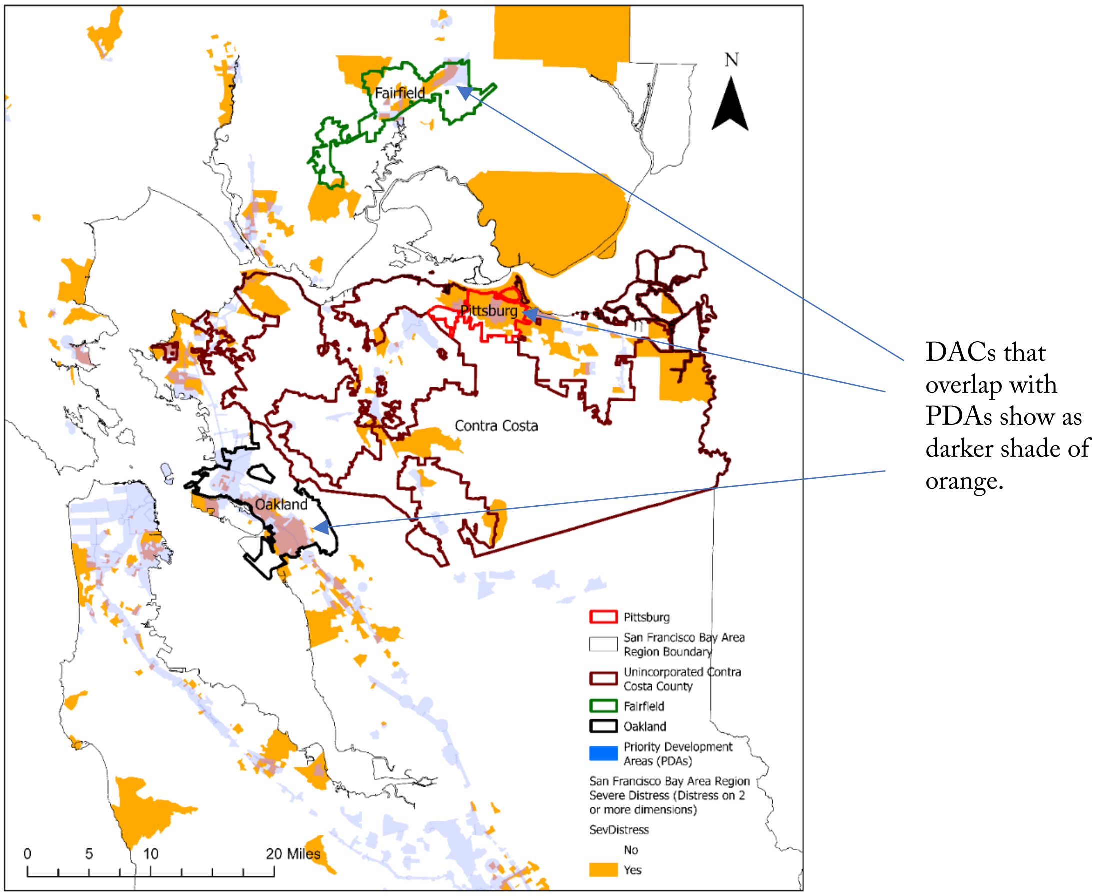
Table 5. Top Disadvantaged Jurisdictions in the S.F. Bay Area Region

Area of disadvantaged PDAs in each jurisdiction (sq. mi.)			**% of PDA area disadvantaged in each jurisdiction**		
Jurisdiction	Area (sq. mi.)	Rank	Jurisdiction	% Area	Rank
Oakland	11.59	1	East Palo Alto	100.0	1
San Francisco	3.12	2	**Pittsburg**	95.3	2
San José	2.72	3	San Pablo	76.5	3
Fairfield	2.55	4	Gilroy	68.8	4
Pittsburg	2.30	5	**Unincorporated Contra Costa County**	62.0	5
Santa Rosa	2.25	6	Morgan Hill	58.3	6
Vallejo	1.97	7	**San Rafael**	56.8	7
Unincorporated Contra Costa County	1.86	8	Antioch	55.1	8
Richmond	1.74	9	**Oakland**	54.2	9
San Rafael	1.48	10	Unincorporated San Mateo County	52.8	10
Unincorporated Alameda	1.23	11	**Alameda**	50.4	11
Alameda	1.08	12	**Fairfield**	47.0	12

Table 6. Top Four Disadvantaged Jurisdictions in the S.F. Bay Area Region

Jurisdiction	**Cumulative Rank**	**Final Rank**
Oakland	10	2
Fairfield	16	4
Pittsburg	7	1
Unincorporated Contra Costa County	13	3

Figure 9. Overlay of PDAs on DACs of the Top Four Impacted Jurisdictions of S.F. Bay Area Region



This two-criteria approach of combining the non-normalized and normalized data is an improvement over a single-criterion approach that only considers the non-normalized data—the total area of disadvantaged PDAs. Had the latter approach been utilized, San Francisco and San José would have been in the top four (see Table 5, columns 1 through 3) even though a very small proportion of the total area under PDAs is disadvantaged in these cities—11% for San Francisco and 9% for San José—compared to 54% for Oakland on the lower side and 95% for Pittsburg on the upper side among the top-four disadvantaged jurisdictions.

Alternatively, if only the normalized data had been used—percentage of PDA area disadvantaged in each jurisdiction—it would have overemphasized small jurisdictions that have a substantial proportion of disadvantaged PDAs, such as East Palo Alto, where 100% of the area under the PDAs is disadvantaged, but PDAs only account for 0.5 square miles.

Methodology for identifying the top impacted jurisdictions in the SoCal Region

First, the total area of disadvantaged PGAs, and SOIs outside PGAs was calculated, for all the approximately 200 jurisdictions in SoCal. Jurisdictions with a minimum of one square mile of disadvantaged PGAs and SOIs were selected from that list, producing a list of 66 jurisdictions. Then, the percentage of the PGAs and SOIs area that is disadvantaged in each jurisdiction was calculated.

Next, it would have been preferred to employ the same methodology as used for the S.F. Bay Area region—that is, to calculate the cumulative ranking on both these criteria. However, in the SoCal region, the jurisdictions with large areas of disadvantaged PGAs and SOIs also have vast areas under PGAs and SOIs. Therefore, their ranking on the second criterion—percentage of PGAs and SOIs area under disadvantage in each jurisdiction—is very low (see Table 7). For example, while 321 square miles of PGAs and SOIs are disadvantaged in unincorporated San Bernardino County, given the large size of the area under PGAs and SOIs in the unincorporated area of the county (1,029 square miles), only 31% of its PGAs and SOIs are disadvantaged. Therefore, its cumulative ranking of these two criteria is extremely low (see Table 7, Column 5).

The methodology adopted for identifying the top impacted jurisdictions in the S.F. Bay Area region would have yielded Lancaster, San Bernardino, Moreno Valley, and Calexico as the top four impacted jurisdictions (see Table 8)—all jurisdictions with much smaller areas of disadvantaged PGAs and SOIs than those for jurisdictions in Table 7. For example, ranked by the area of disadvantaged PGAs and SOIs, the fourth-placed Los Angeles (71.36 square miles of disadvantaged PGAs and SOIs) is more than four times the top-placed San Bernardino (17.71 square miles of disadvantaged PGAs and SOIs). Therefore, only the first criterion—the area of disadvantaged PGAs and SOIs in each jurisdiction—was employed to identify the top impacted jurisdictions in the SoCal region. These jurisdictions (in decreasing order of disadvantage) are unincorporated San Bernardino County, unincorporated Los Angeles County, unincorporated Riverside County, and the city of Los Angeles (see Table 7).

In summary, it is recommended to adopt the first methodology when the sizes of the disadvantaged targeted areas for growth per jurisdiction are very similar, but the percentages of such areas are very different (as is the case in the S.F. Bay Area region) and use the latter methodology when the sizes are drastically different (as is the case in the SoCal region).

Table 7. Top Four Disadvantaged Jurisdictions in the SoCal Region

Area of disadvantaged PGAs + SOIs in each jurisdiction (sq. mi.)			**% of PGA+SOI area disadvantaged in each jurisdiction**	
Jurisdiction	Area (sq. mi.)	Rank	% Area	Rank
Unincorporated San Bernardino County	320.67	1	31.15	47
Unincorporated Los Angeles County	149.46	2	38.00	37
Unincorporated Riverside County	97.38	3	20.14	60
City of Los Angeles	71.36	4	24.46	53

Table 8. Top Four Disadvantaged Jurisdictions in the SoCal Region Based on the Methodology Employed for the S.F. Bay Area Region

Area of disadvantaged PDAs in each jurisdiction (sq. mi.)			**% of PGA+SOI area disadvantaged in each jurisdiction**		**Cumulative rank**
Jurisdiction	Area (sq. mi.)	Rank	% Area	Rank	
Lancaster	5.24	13	76.77	7	20
San Bernardino	17.71	6	63.41	14	20
Moreno Valley	10.01	8	53.85	20	28
Calexico	4.14	23	76.52	8	31

4. Discussion and Policy Implications

In this research, (a) the location and extent to which new housing is being planned in the DACs of the S.F. Bay Area and the SoCal regions was examined and (b) the major jurisdictions in each region where this housing is being planned in the DACs were identified. Specifically, the following research questions were asked:

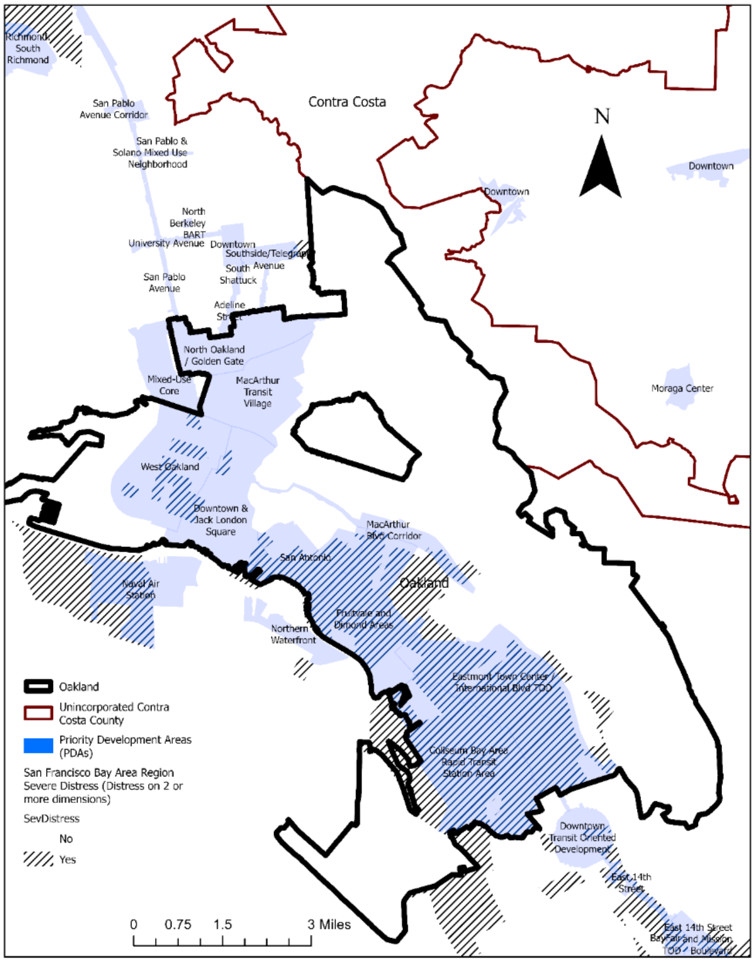
- RQ1: At which locations is new housing being planned in the DACs of the S.F. Bay Area and the SoCal regions?
- RQ2: Is new housing being disproportionately planned in DACs?
- RQ3: What are the top four jurisdictions in each region where DACs are planned to take new housing?

To answer these questions, the dimensions and sub-dimensions of disadvantage and the variables that operationalize them were identified. Next, through GIS, the spatial locations where new housing is being planned in the DACs were displayed. It was found that the new housing is disproportionately planned in DACs in both the case study regions. Finally, the top four jurisdictions in each region planning to accommodate new housing in DACs were identified. Four of eight jurisdictions were unincorporated counties—one in the S.F. Bay Area region and three in the SoCal region. To the extent county governments might not be well-equipped to mitigate some of the ill effects of concentrating new housing in DACs (such as the burden on already poor transportation accessibility, low-quality schools, and environmental pollution), this is a concerning finding. Furthermore, to the extent that the top four jurisdictions in each region might not be the wealthiest (for example, Oakland, Pittsburg, and Fairfield in the S.F. Bay Area region and the city of Los Angeles in SoCal), these jurisdictions might need significant financial assistance to mitigate the negative impacts of this housing.

More research is needed to assess the impacts of this concentration of new housing on the DACs of these top-impacted jurisdictions. The first step in this direction would be to do a more fine-grained, jurisdiction-level examination to document the negative impacts of housing concentration and whether plans, policies, and funding programs are being developed or are in place to mitigate these impacts. If yes, how effective they are or likely to be? For example, Figure 10 shows that many of the disadvantaged areas of Oakland are in PDAs for which the city has likely developed plans and programs—such as the West Oakland Specific Plan (City of Oakland, n.d.). However, the efficacy of this plan needs to be examined. Similarly, some efforts are underway to support disadvantaged communities, but research is needed to evaluate their effectiveness. For example, in the S.F. Bay Area region, MTC-ABAG invests in and supports local jurisdictions' applications for state-level transportation and affordable housing funds if these funds target underserved areas of applicant jurisdictions. MTC-ABAG calls these areas equity priority communities, or EPCs

(MTC-ABAG, n.d.). Similarly, the city of Richmond in Contra Costa County prioritizes capital improvement projects in “economically depressed neighborhoods with the highest need” (City of Richmond, n.d., pg. 11).

Figure 10. Overlay of PDAs on DACs of Oakland



On a methodological level, some of the DAC metrics are unidimensional (e.g., HUD’s School Proficiency Index) or focus on socioeconomic characteristics, leaving out major dimensions of disadvantage such as education quality, environment, and transportation. Even when these often omitted dimensions are measured, the measurements have little content validity. For example, MTC-ABAG’s metrics to identify EPCs do not include education and environment dimensions. Additionally, the metrics measure transportation access through only one variable—percentage of zero-vehicle households in a census tract (MTC-ABAG, n.d.)—leaving out variables that assess transportation access more comprehensively. In this research, we use five variables to operationalize transportation disadvantages that cover auto and transit access at the local and regional levels. Furthermore, we measure these variables at the block group level, not at the coarser census tract level used by MTC-ABAG (see Table 3).

From a policy perspective, it is not enough to consolidate all the dimensions of disadvantage and display areas that are overall disadvantaged. It is equally essential to transparently show on which dimensions these areas are disadvantaged, so that policies can be targeted to mitigate that disadvantage. For example, policies to address environmental disadvantage might differ from those for education disadvantage, hence the utility of the maps provided in the Appendix. Furthermore, it might be important to examine disadvantage at the sub-dimension level. For example, the S.F. Bay Area region has no environmental disadvantage overall, but it fares very poorly on one of the important sub-dimensions—children's lead risk from housing—and begs policymakers' and planners' immediate attention.

The DAC Index's ease of use and replicability is critical from a policy perspective. Indices that employ complex statistical methods (such as factor analysis) or need primary data collection (such as local transportation surveys) are less likely to be widely used. The DAC metrics must balance data availability with methodological sophistication, which was also our aim. Therefore, we used either the US Census data or data from other off-the-shelf public sources. The use of such sources comes at the cost of recency, though. For example, the EPA Smart Location database and HUD's School Proficiency Index use 2013-2014 data. For this reason, policymakers at the state and national levels should advocate regular updates of such public databases.

5. Future Research Opportunities

Future research should include TRAs and HRAs in the analysis for the S.F. Bay Area region to examine whether they are disproportionately located in DACs.

There is a need to explore whether there are state, regional, and local level efforts to mitigate current challenges faced by DACs and address the additional challenges new growth might bring to these communities. Once such efforts are documented, an evaluation framework can be established to assess and evaluate the effectiveness of these efforts.

Through the research completed in this study, a generalizable methodology across geographies has been developed. Future research could test the DAC Index's validity by testing it on other regions. Finally, this study uses the area of the DACs as a measure of the magnitude of disadvantage; future research could test the validity of this measure and assess whether the intensity of use should also be considered. For example, one square mile of a high-density inner-city location likely equals several miles of sprawled unincorporated county area in terms of the magnitude of development.

Appendix

Section A: Maps for the San Francisco Bay Area Region

Figure A1. S.F. Bay Area Region: Economic Disadvantage

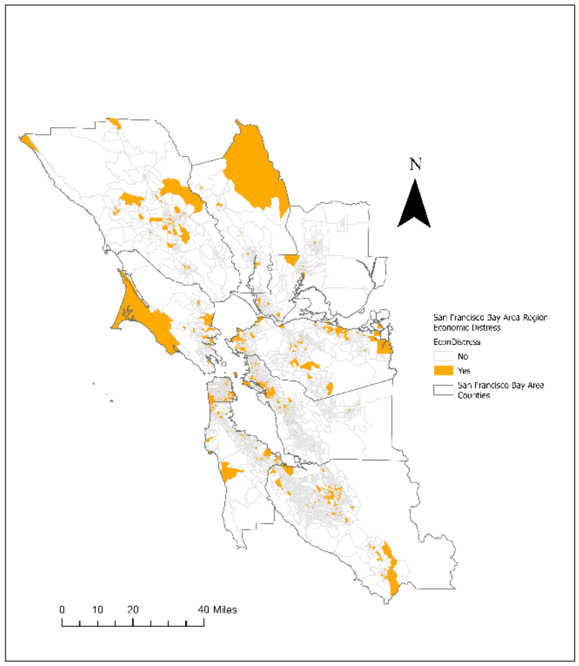


Figure A2. S.F. Bay Area Region: Demographic Disadvantage

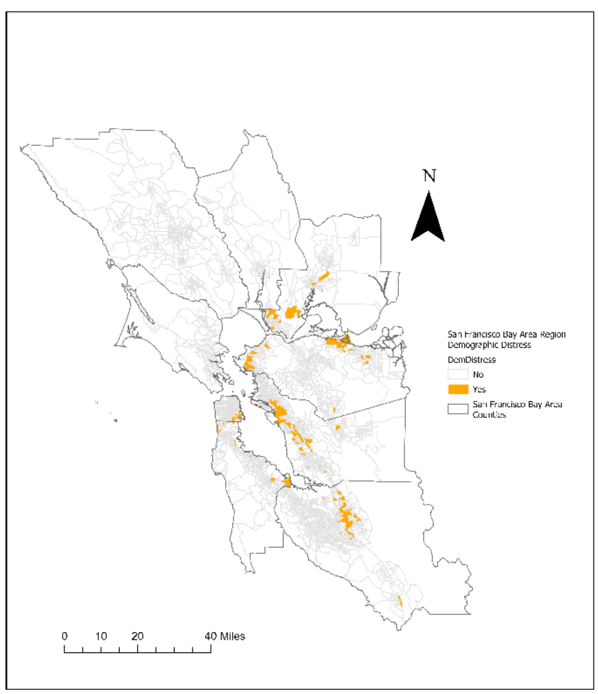


Figure A3. S.F. Bay Area Region: Transportation Disadvantage

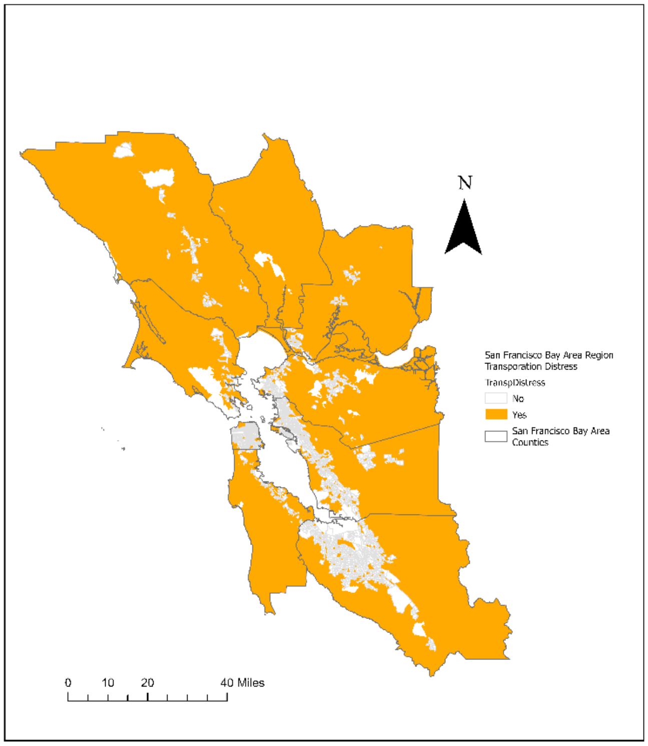


Figure A4. S.F. Bay Area Region: PDAs Overlaid on Transportation Disadvantage

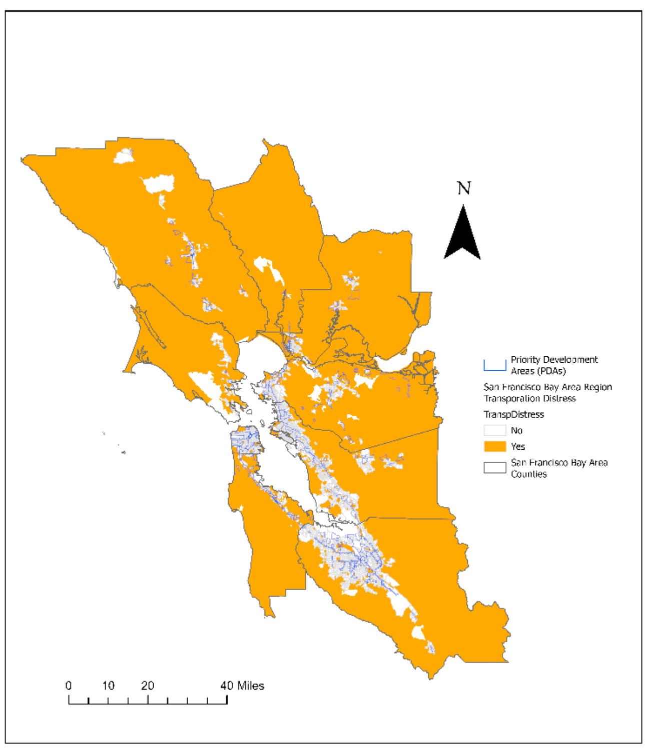


Figure A5. S.F. Bay Area Region: Education Disadvantage

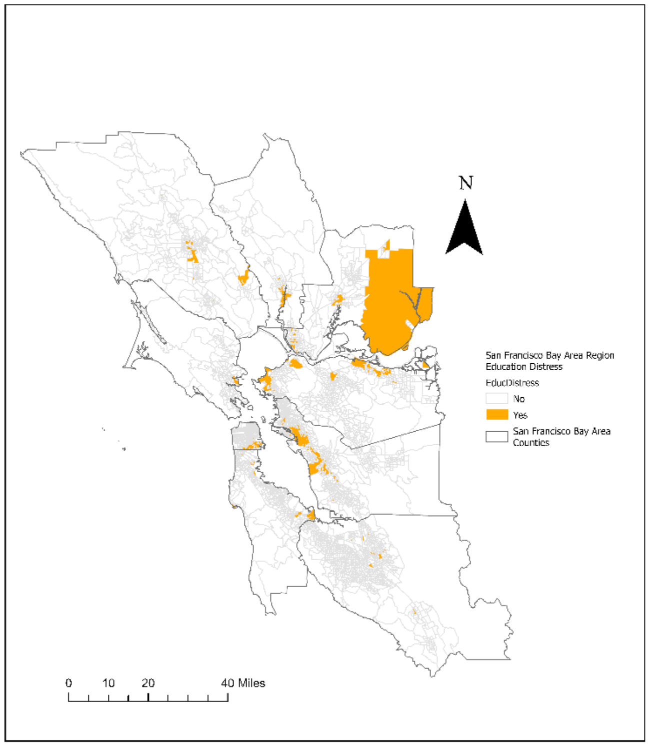


Figure A6. S.F. Bay Area Region: Environment Disadvantage

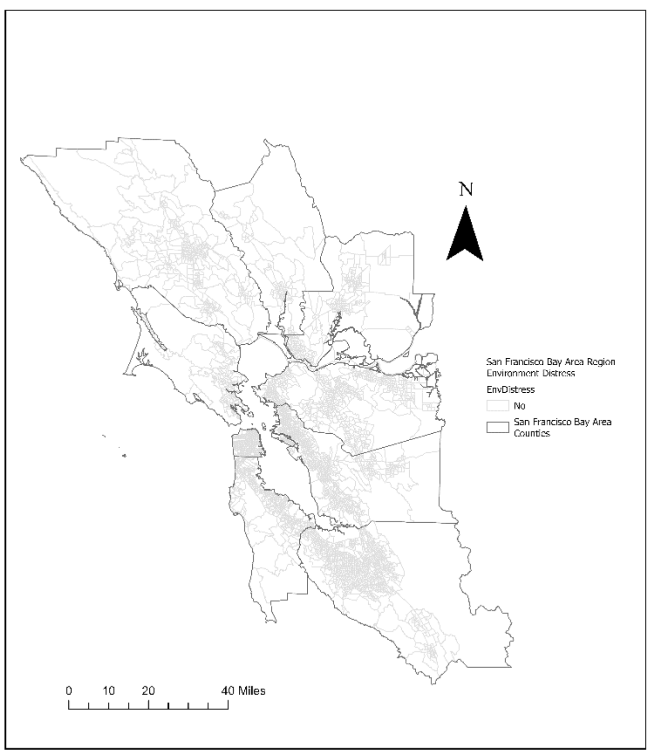
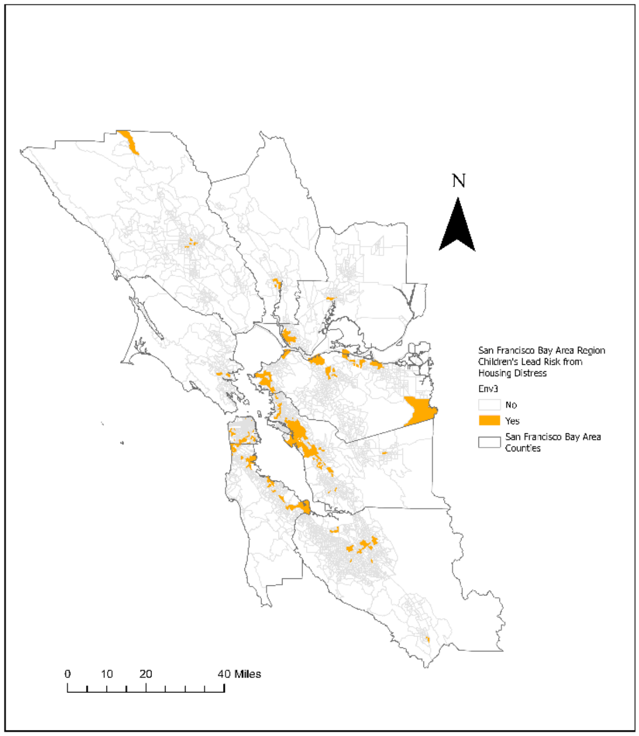


Figure A7. S.F. Bay Area Region: Env 3 Disadvantage—
Distress Due to Children's Lead Risk from Housing



Section B. Maps for the SoCal Region

Figure B1. SoCal Region: Economic Disadvantage

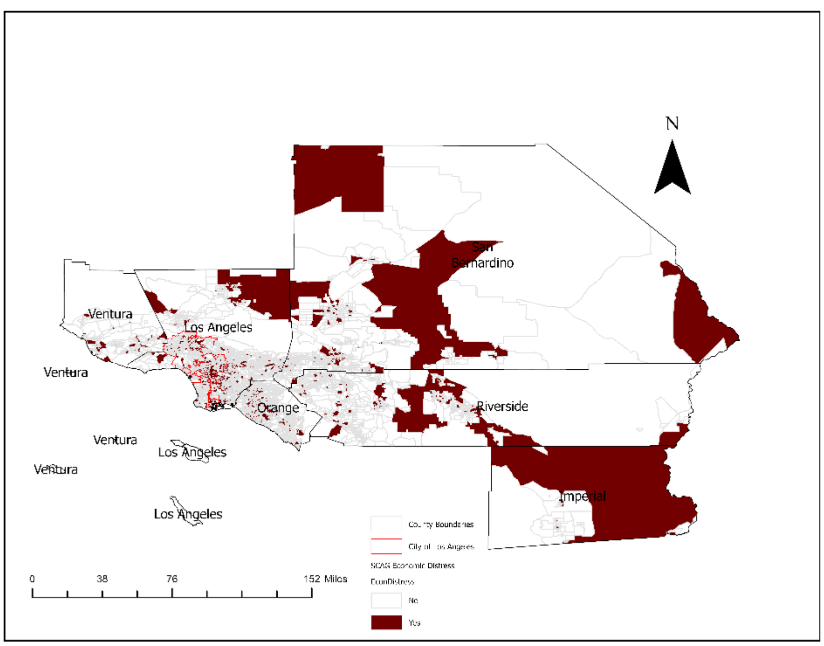


Figure B2. SoCal Region: Demographic Disadvantage

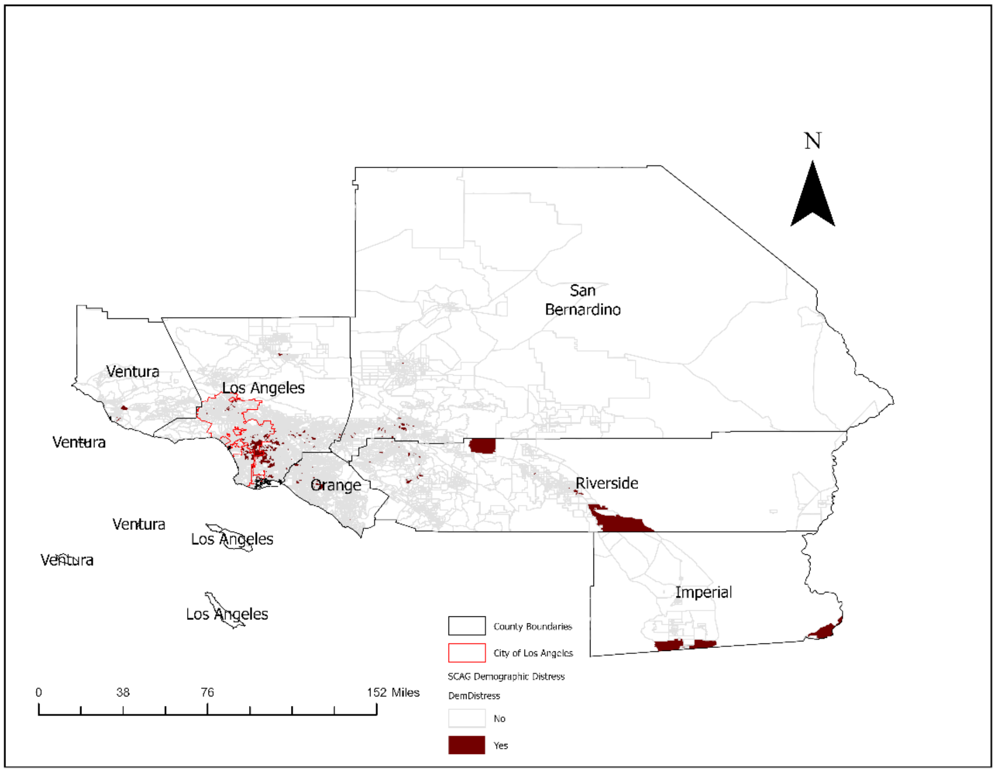


Figure B3. SoCal Region: Transportation Disadvantage

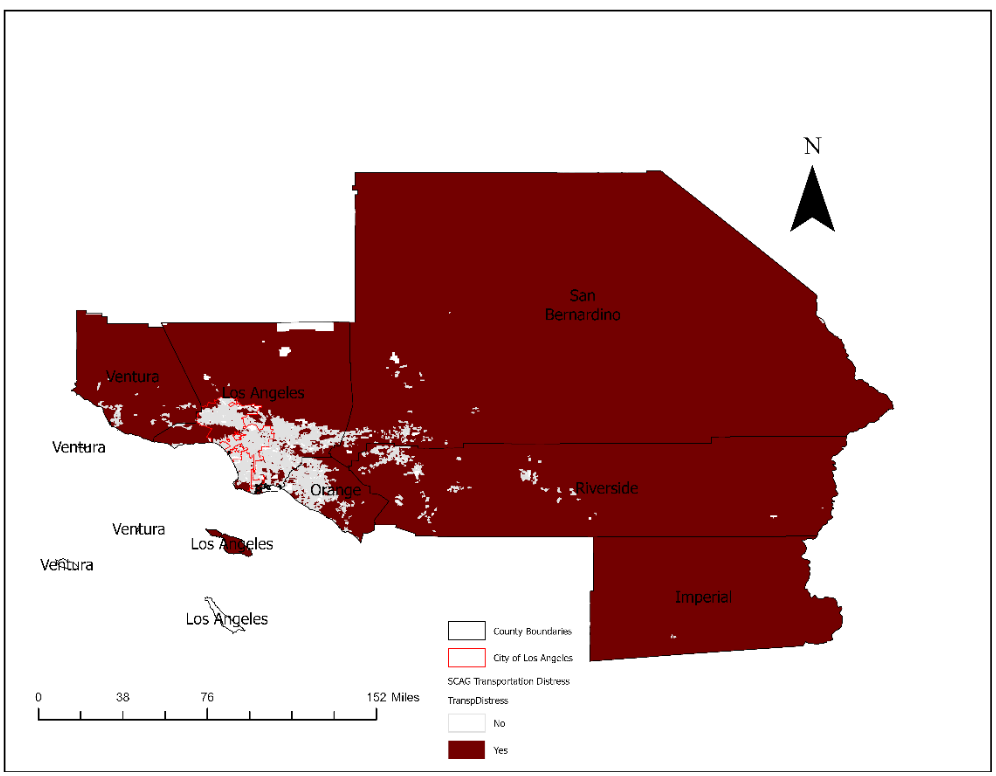


Figure B4. SoCal Region: Education Disadvantage

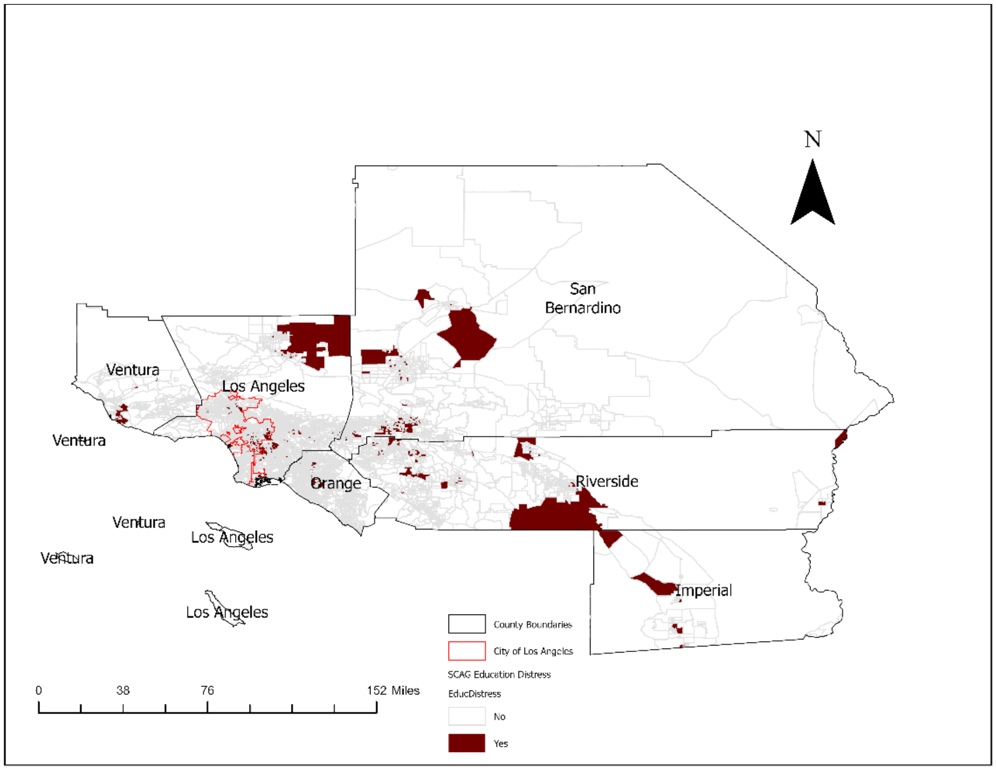
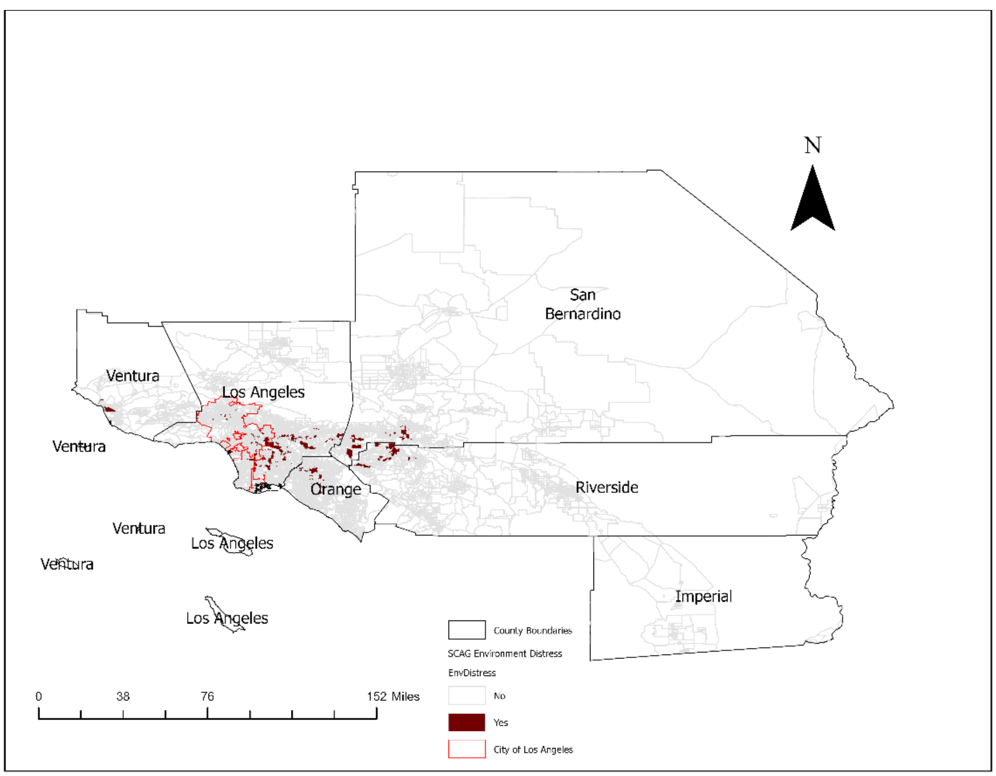


Figure B5. SoCal Region: Environment Disadvantage



Acronyms and Abbreviations

ABAG	Association of Bay Area Governments
ACS	American Community Survey
CTCAC	California Tax Credit Allocation Committee
CTOD	Center for Transit Oriented Development
CARB	California Air Resource Board
DACs	disadvantaged communities
EPA	United States Environmental Protection Agency
GHG	greenhouse gas
GIS	geographic information system
GTFS	General Transit Feed Specification
HCD	California Housing and Community Development Department
HUD	US Department of Housing and Urban Development
LEHD	Longitudinal Employer-Household Dynamics
LIHTC	low-income housing tax credit
PDAs	priority development areas
PGAs	priority growth areas
MPOs	metropolitan planning organizations
MTC	Metropolitan Transportation Commission
NMAs	Neighborhood Mobility Areas
NSES	neighborhood socioeconomic status
SANDAG	San Diego Association of Governments

SCAG	Southern California Association of Government
SCSs	sustainable community strategies
SES	socioeconomic status
SoCal	Southern California
SOIs	spheres of influence
SLD	Smart Location Database
TAZ	transportation analysis zone
TODs	transit-oriented developments
VMT	vehicle miles travelled
US	United States
ZCTA	ZIP Code Tabulation Area

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