Title: Classifying cumulatively disadvantaged communities in California: A quantitative comparison of environmental justice screening tools

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Abstract
Background: Government agencies at the state and federal levels have developed screening tools to classify disadvantaged communities, which are cumulatively burdened by social marginalization and environmental hazards. Status as a recognized disadvantaged community can determine access to public funding and protections associated with environmental justice policies. In California, multiple screening tools have been promulgated by state and federal agencies.
Objectives: To determine the extent to which screening tools differentially designated census block groups as disadvantaged. Also, to determine whether there were differences in the proportions of socially or racially marginalized individuals classified as living in disadvantaged communities between screening tools.
Methods: We quantitatively compared three screening tools used in California (CalEnviroScreen, Climate and Economic Justice Screening Tool [CEJST], and Environmental Justice Index [EJI]) and two proposed tools (a modified version of CalEnviroScreen and a trivariate metric). We developed a statistical method to determine the extent to which each screening tool differentially prioritizes socioeconomically or racially marginalized groups for designation as living in disadvantaged communities.
Results: While many census block groups were consistently classified as disadvantaged communities by all screening tools, there was substantial variation among the tools. For example, CEJST classified twice as many California residents as living in disadvantaged communities compared to EJI, a difference of approximately 7.5 million people. We observed small but statistically significant differences in disadvantaged community designations for racial/ethnic composition, proportion of households in poverty, and population density.
Conclusion: The screening tools we assessed, which are used for regulatory decision-making, advocacy, and research, yielded significant discordant classifications of disadvantaged communities, with potential implications for which sociodemographic groups have access to resources and other interventions through state and federal policy.

Key Words: environmental justice, disadvantaged communities, composite metrics

Introduction

Disadvantaged communities face cumulative burdens from multiple co-occurring environmental and social stressors, and residents in these communities have long advocated for interventions to mitigate associated health risks (Costa et al., 2002). Historically, policymakers and regulators have addressed environmental stressors in a piecemeal fashion, for example through establishing limits for pollutant emissions from specific industrial sites or motored vehicles (Haagen-Smit, 1964). Beginning in 2013, in response to community advocacy to consider cumulative exposures (Méndez, 2020), some state and federal agencies developed and promulgated screening tools (mathematical algorithms to combine data) that aim to quantify cumulatively disadvantaged communities (Balakrishnan, Su, Axelrod, & Fu, 2022). Disadvantaged communities identified by these screening tools may be eligible for certain grants, enhanced environmental protections, and sustainability projects.

CalEnviroScreen (CES), developed by academic researchers and government scientists in the California Office of Environmental Health and Hazard Assessment (OEHHA), was the first screening tool used in regulation and program implementation (Sadd, Pastor, Morello-Frosch, Scoggins, & Jesdale, 2011). The CES tool scores census tracts based on pollution burden, including exposures and environmental effects, and population characteristics, including socioeconomic factors and sensitive populations, and includes a composite score for all tracts across the state (August et al., 2021). The California Environmental Protection Agency (CalEPA) uses CES to allocate funds from the SB 535 cap-and-trade program to communities with the top 25% of the distribution of composite scores (California Office of Environmental Health Hazard Assessment, 2023; Greenhouse gases: investment plan: disadvantaged communities, 2016). Other California state agencies use CalEnviroScreen for to identify priority communities for urban forestry grants, enforcement of pollution controls, and allocation of solar electricity (California Office of Environmental Health Hazard Assessment, 2023). The CES tool is now in its fourth iteration, and it has served as a model for agencies in states including Maryland, Michigan, New York, and Washington, each of which have developed their own screening tools (Driver et al., 2019; Grier, Mayor, & Zeuner, 2019; Petroni, Howard, Howell, & Collins, 2021; Min et al., 2019).

In addition to CES, which is used for state-level regulatory and policy decision-making, there are screening tools developed by the federal government to implement federal policies across the U.S. These include the Environmental Justice Index (EJI) and the Climate and Economic Justice Screening Tool (CEJST). The EJI tool was developed the Centers for Disease Control and Prevention to aid in the identification of communities with cumulative health risks (McKenzie et al., 2022). The CEJST tool was developed by the White House Council on Environmental Quality to help allocate billions of dollars of investments from the Justice40 Initiative, which aims to direct 40% of climate, clean energy, and similar investments to disadvantaged communities (White House, 2022).

The use of screening tools to classify disadvantaged communities has become an integral part of environmental justice policy and implementation. Additionally, researchers use screening tools such as CES to quantify the associations between cumulative burdens and adverse birth outcomes (Huang et al., 2018; Padula et al., 2018), air quality (Mousavi, Yuan, Masri, Barta, & Wu, 2021; Tanzer, Malings, Hauryliuk, Subramanian, & Presto, 2019), and the siting of environmental hazards (Chan et al., 2023). As screening tools proliferate and, in some cases, overlap in the same geographies, it is necessary for stakeholders—including community residents, advocates, policymakers, regulators, and researchers—to decide which tools to use to achieve their aims. Prior work has qualitatively compared tool development, structure, and outcome type (Balakrishnan et al., 2022; Driver et al., 2019; Kuruppuarachchi, Kumar, & Franchetti, 2017). However, a quantitative analysis of the concordance or discordance of screening tools is necessary to understand similarities and differences among screening tools and whether certain tools implicitly prioritize certain subpopulations for designation as living in disadvantaged communities.

In the current study, we quantitatively compared the classification of disadvantaged communities from five screening tools that are currently used or that have been proposed for use in California (see Appendix A). California is an ideal setting to compare screening tools for several reasons. The first regulatory screening tool, CES, has been in use in California since 2013. The state has a large population with broad sociodemographic diversity, diverse geographies including major metropolitan areas and expansive agricultural communities, and numerous persistent environmental justice issues, including some of the most polluted cities in the country (American Lung Association, 2023). We had three overarching aims in this study. First, we examined to what extent different methods of classifying disadvantaged communities result in similar or dissimilar designations of communities as disadvantaged. Second, we examined how tools differ with regards to the characteristics of areas designated as disadvantaged communities. Specifically, we compared population density, poverty, and racial/ethnic composition. Finally, we developed a method to measure the extent to which tools prioritize different subpopulations, such as racial/ethnic minorities.

Methods

Study Design

We quantitatively compared the designations and characteristics of disadvantaged communities identified by five screening tools: CalEnviroScreen (CES), a modified version of CES (which we refer to as CES+) that incorporates recommendations from a recent report (Morello-Frosch et al., 2021), Environmental Justice Index (EJI), Climate and Economic Justice Screening Tool (CEJST), and a screening tool based on a policy implemented in New Jersey in 2020 that incorporates race/ethnicity, linguistic isolation, and poverty (which we refer to as trivariate). We evaluated summary statistics to understand the level of agreement between tools. We then statistically quantified sociodemographic differences among disadvantaged communities classified by each tool. Finally, we applied a novel statistical method to compare how tools prioritize the classification of different subpopulations as living in disadvantaged communities.

Community engagement

This project was a partnership between academic researchers and the Leadership Counsel for Justice and Accountability, a community-based environmental justice organization in California. Project goals were decided jointly by study authors and Leadership Counsel staff in a series of online meetings, and the drafts of research questions and methods were co-designed by researchers and community partners. In the initial phase of the project, we held a meeting with 20 representatives from Leadership Counsel to present initial project findings and solicit feedback. This feedback indicated that partners prioritized traffic, pesticides, and concentrated animal feeding operations (CAFOs) as environmental hazards, all of which are considered in CES and CES+; CEJST considers traffic proximity and volume, and EJI considers high-volume roads, but neither tool considers pesticide use or CAFOs. Linguistic isolation was also prioritized by partners, especially for members of immigrant communities and other Indigenous language speakers.

Data

We obtained data for the most recent versions at time of analysis for each of three current screening tools: CES version 4.0, EJI version 1.0, and CEJST version 0.1. The CES and CEJST tools both create explicit classifications of disadvantaged communities, while EJI creates a national EJI rank on a scale from 0 to 1. We considered census tracts with an EJI rank above 0.75 to be disadvantaged communities, in alignment with the suggested threshold in EJI's documentation (McKenzie et al., 2022). CES also uses the 75th percentile as the threshold score for classifying disadvantaged communities (August et al., 2021). The sociodemographic data used in CES, EJI, and CEJST were from the 2010 U.S. decennial census, including the census tract boundaries. Consequently, we used 2010 census tract and block group data to match these screening tools. According to the 2010 census, there were 39.3 million California residents in 23,212 census block groups and 8,057 census tracts. To assess differences between these five tools, we scaled the output of the screening tools from the census tract to the block group level. For each tract level tool, we classified a block group as a disadvantaged community if it was inside a census tract that was classified as a disadvantaged community.

To generate the CES+ tool, we incorporated recommendations from a 2021 report with the aim of informing the implementation of a policy by the California Department of Toxic Substances Control to limit the siting of hazardous facilities near disadvantaged communities (Morello-Frosch et al., 2021). The 2021 report suggested several modifications to CES, specifically the incorporation of census tract level data on racial/ethnic composition, voter participation, and proximity to oil and gas wells (Department of Toxic Substances Control, 2018; Department of Toxic Substances Control, 2022; Department of Toxic Substances Control & California Environmental Protection Agency, 2021; Morello-Frosch et al., 2021). We obtained data on active oil and gas well locations from the California Geologic Energy Management Division (CalGEM, 2023). We incorporated the percentile of oil well exposure into the Environmental Effects Indicators component of CES following CES 4.0 documentation for incorporation of hazardous waste generators and facilities (August et al., 2021). For voter turnout, we used data for the average proportion of eligible voters who voted in a census tract across the 2012 and 2016 presidential elections, which we incorporated into the Socioeconomic Factor Indicators component of CES 4.0. Voter turnout data are included as a proxy for political participation and power in census tracts because areas with less political participation may be exposed to more hazards or be more vulnerable to future hazards that are not already considered by CES (Mohai & Saha, 2015). Finally, we incorporated race and ethnicity data by census tract from the 2010 census as described in the documentation for CES version 1.0, which included these data from an earlier vintage of the census (Faust et al., 2013). We used the tidycensus (Walker & Herman, 2023) and tigris packages in R to access the block group and census tract level data used in this project.

In order to create the trivariate tool, we used block group-level data from the 2019 American Community Survey 5-year summary on the proportion of residents who were Hispanic or non-white, the proportion of households living below 200% of the federal poverty level, and the proportion of households in which no resident over 14 speaks English "very well." These variables match the method used in the development of the New Jersey trivariate tool (New Jersey Department of Environmental Protection, 2023). In collaboration with Leadership Counsel staff, we defined thresholds for these three measures adapted to the California context. For purposes of the current study, we defined block groups as disadvantaged communities if at least one of the following conditions was met: > 75% of residents were Hispanic or non-white; > 35% of households had income below 200% of the federal poverty level; or > 40% of households were linguistically isolated.

We obtained data on tribal lands from the Bureau of Indian Affairs Land Area Representation (LAR) Dataset, accessed through the U.S. Department of Justice Data Catalog (U.S. Department of Justice, 2023). Notably, CEJST marks all federally recognized tribal lands as disadvantaged communities. We used the LAR dataset to assess the extent to which each screening tool incorporated state or federally recognized tribal lands within disadvantaged communities in a supplemental analysis.

Given the broad range in size of census tracts and block groups, some areas defined by screening tools as disadvantaged communities are far from residential areas. We were interested in comparing the extent of uninhabited areas defined as disadvantaged communities among the five screening tools. To do this, for each block group defined as disadvantaged communities in any screening tool, we determined the proportion of the block group that was within 1 km of populated areas using a dasymetric dataset previously developed for California (Depsky, Cushing, & Morello-Frosch, 2022).

Statistical analyses

To compare census tract geometries classified as disadvantaged communities, we used the Kappa statistic, which has previously been used to compare maps of vegetation types (Monserud & Leemans, 1992). The Kappa statistic for comparing screening tool A to tool B was calculated following Monserud & Leemans (1992) (Equation 1). We calculated pairwise Kappa statistics for all tools. A Kappa value under 0.4 indicates poor agreement, a value from 0.4 to 0.55 indicates fair agreement, and values above 0.55 indicate good agreement between two sets of spatial data (Monserud & Leemans, 1992).

$$K = \frac{p_{ii} - p_{i.}p_{.i}}{(p_{i.} + p_{.i})/2 - p_{i.}p_{.i}} \qquad \text{(Equation 1)}$$

p_{ii} = proportion of land area classified as disadvantaged communities by tool A and tool B
$p_{i.}$ = proportion of land area classified as disadvantaged communities by tool A
$p_{.i}$ = proportion of land area classified as disadvantaged communities by tool B

Next, we calculated the proportion of Black residents, Hispanic/Latino residents, residents living under 200% of the federal poverty level, and population density for each block group and aggregated these values for all block groups classified as disadvantaged communities by each screening tool. We compared these sets of population densities or proportions using ANOVA tests. In order to determine which subgroups were significantly different, we performed standard post-hoc Tukey tests. We also performed a chi-square test of independence to determine whether the racial/ethnic compositions of residents of disadvantaged communities were different across the five tools.

We developed a novel measure of the extent to which screening tools prioritize different subpopulations for designation as living in disadvantaged communities. To measure this, we modeled the process of a screening tool classifying disadvantaged communities as Wallenius' noncentral hypergeometric distribution (a weighted hypergeometric distribution with known sample size) (Fog, 2008). Wallenius' noncentral hypergeometric distribution can be described in the usual setting of a hypergeometric distribution, which involves drawing red and white balls from an urn without replacement and counting the number of red balls drawn. Wallenius' noncentral hypergeometric distribution weights the red and white balls differently, and the ratio of these weights is called the odds ratio (OR) (Fog, 2008). This distribution has been used in the past to model the number of animals of two species expected to die when competing over a food source (Manly, 1985). In our application of Wallenius' noncentral hypergeometric distribution, we think of the balls as block groups in California. Red balls correspond to block groups with proportions of a subpopulation above the statewide block group median proportion. White balls correspond to block groups with proportions of the subpopulation below the statewide block group median proportion. The block groups are weighted according to the OR. Taking the weights into account, a screening tool picks disadvantaged community block groups without replacement. The total number of block groups picked is the number of disadvantaged communities identified by the screening tool. We can then record the number of block groups classified as disadvantaged communities that are above the statewide block group median proportion of our subpopulation of interest.

The key characteristic of Wallenius' noncentral hypergeometric distribution is that it does not depend on the proportion of the state that a screening tool classifies as disadvantaged communities. This lack of dependence is necessary because a screening tool that classifies more communities as disadvantaged will generally have compositions of people living in disadvantaged communities that are closer to statewide compositions than a tool that does not classify as many communities as disadvantaged. For example, if two screening tools classify communities as disadvantaged solely based on their poverty rates, but tool A classifies half of California as disadvantaged communities, while tool B classifies only 25% of California as disadvantaged communities, the people living in disadvantaged communities under tool A will have lower average poverty rates than the people living in disadvantaged communities under tool B, though both tools give the same priority to poverty.

Using this distribution as our model, we can determine the ratio of weights that a screening tool would have to place on the groups for us to expect it to classify the observed number of communities in each group as disadvantaged, the OR. For a given screening tool, we can determine the OR since we know the outcome of the distribution (the number of communities over the statewide median that the screening tool chose as disadvantaged communities) and how many communities the screening tool classifies as disadvantaged overall. We also know the number of communities above and below the statewide block group median for each characteristic of interest. Using these values, we can solve for the OR, ω, in the formula for the expected value of Wallenius' noncentral hypergeometric distribution (Equation 2; Fog, 2008). We can produce this estimate for the OR whether or not a screening tool specifically considers the subpopulation of interest.

$$(1 - \frac{n-\mu}{N-m})^{\omega} - 1 + \frac{\mu}{m} = 0 \qquad \text{(Equation 2)}$$

n = number of communities classified as disadvantaged
μ = number of communities classified as disadvantaged over statewide median for characteristic
N = number of communities
m = number of communities over statewide median for characteristic
ω = odds ratio (OR)

After estimating an OR, we bootstrapped confidence intervals by sampling with replacement 250 times from block groups, then recalculating m, n, and μ, and using these new values to calculate a bootstrapped ω.

All analyses were completed in R version 2021.09.0.

Results

Disadvantaged community designations

We found that there were areas of both concordance and discordance across screening tools with respect to disadvantaged community designation (Figure 1). In some areas of California, such as the Central Valley, block groups were consistently classified as disadvantaged communities across all five screening tools. In other areas, block groups were classified as disadvantaged by a few of the screening tools or just one screening tool. The most concordant screening tools were CES and CES+ (Kappa value above 0.55), and the dyads of CEJST and the trivariate tool, as well as CEJST and EJI, both had good agreement (Kappa values between 0.4 and 0.55) (Table 2). The agreement between almost all the other screening tools was poor (Kappa values below 0.4). These results generally match the results of Pearson correlation coefficients between the screening tools (Table 3), in which the strongest relationships were between CES and CES+. The screening tools also differed in how much land area they classify as disadvantaged communities: CEJST, EJI, and the trivariate tool all classify much larger proportions of land in California as being disadvantaged communities compared to CES and CES+ (Table 1).

Among block groups designated as disadvantaged communities by any of the five screening tools, 4,392 (33.9%) were designated as disadvantaged communities by 2–3 of the 5 tools. These block groups were the areas with the greatest discordance among screening tools; either 2 tools classify them as disadvantaged communities and 3 did not, or 3 tools classify them as disadvantaged and 2 did not. To understand which tools most often disagreed on disadvantaged community designations, we calculated the proportion of each tool's disadvantaged communities that were classified as disadvantaged communities by only 2 or 3 tools (Table 4). The CEJST and trivariate tools had the highest proportions, indicating that many communities they classified as disadvantaged were unstable or uncertain in their designations by other screening tools. Similarly, we observed that the trivariate tool and CEJST often classify people as living in disadvantaged communities that other tools do not (Figure 2). When we restricted the comparisons to CES, EJI, and CEJST (the screening tools currently in use or expected to be in use), we observed that CEJST again had the greatest discordance (Table S1).

Characteristics of populations in disadvantaged communities

We also investigated the extent to which each screening tool prioritized communities with respect to several sociodemographic characteristics: population density, a metric that was not included in any of the tools; proportion of households under 200% of the federal poverty level, which was explicitly considered by all tools; and racial/ethnic composition, which was explicitly considered by EJI, CES+, and the trivariate tool. Even though population density was not used by any of the screening tools, measuring the extent to which the screening tools prioritized communities with high population densities measures how tools balance rural and urban environmental justice concerns.

For population density, ANOVA followed by post-hoc Tukey tests indicated that disadvantaged communities classified by CEJST, CES, and CES+ generally had slightly higher population densities than disadvantaged communities under EJI and the trivariate tool (Figure S1a). For every tool, over 80% of communities classified as disadvantaged have population densities over 1,000 people/square mile, indicating that most communities classified as disadvantaged by the tools are urban (U.S. Census Bureau, 1992) (Table S2). We found that CEJST, EJI, the trivariate tool designated the highest proportions of land near unpopulated areas as disadvantaged communities (Table S3).

We found that EJI was more likely to designate communities with higher proportions of households in poverty as disadvantaged, followed by CES and CES+, and CEJST (Figure S1b). The trivariate tool designates communities with lower proportions of households in poverty as disadvantaged than the other tools, since the threshold for the tool can also be met based on racial/ethnic composition or linguistic isolation. We found that 27% of disadvantaged block groups under the trivariate tool did not meet the poverty threshold.

Block groups with higher population densities were generally more likely to be classified as disadvantaged communities by CES, CES+, and CEJST. Block groups with high proportions of households in poverty were also more likely to be considered disadvantaged. Though CES and CEJST do not explicitly consider race/ethnicity, we similarly observed that block groups with high proportions of Hispanic/Latino people and high proportions of Black people were more likely to be considered disadvantaged by all tools (Figure 3). For distributions of these characteristics by tool, see Figure S2.

Disadvantaged communities classified by the trivariate tool had the lowest mean proportions of Hispanic/Latino residents (0.53 (s.d. 0.28)), followed by CEJST (0.57 (s.d. 0.28)). CEJST had the lowest mean proportions of Black residents (0.07 (s.d. 0.11)), followed by the trivariate tool (0.08 (s.d. 0.13)). The CES, CES+, and EJI tools had proportions between 0.63 and 0.65 for Hispanic/Latino residents and 0.09 and 0.1 for Black residents in disadvantaged communities, and we did not observe significant differences in these proportions (Figure S1c, d). The trivariate tool had the lowest mean proportion of Hispanic/Latino residents and Black residents in disadvantaged communities. This may be because many communities classified as disadvantaged by the trivariate tool met only the poverty threshold (3,209 block groups, 4,956,748 people), and thus can be designated as disadvantaged communities despite low proportions of people of color and linguistically isolated people. Additionally, CES had one of the highest mean proportions of Hispanic/Latino people in disadvantaged communities, although it does not explicitly consider ethnicity (Table 5).

The various tools incur tradeoffs with respect to the racial/ethnic compositions of people living in communities they designate as disadvantaged (Figure 4, Figure S3). A chi-square test of independence indicated that the tools classify significantly different compositions of racial/ethnic groups as living in disadvantaged communities (X^2 (24) = 960,538, $p < .000001$). The CEJST and trivariate tools designated the highest proportions of non-Hispanic white people and Asian people as living in disadvantaged communities, and they designated the lowest proportions of Black people and Hispanic/Latino people as living in disadvantaged communities. American Indian/Alaska Native people were more likely to reside in disadvantaged communities under all screening tools.

Tribal Lands

While all five tools examined in this study designated disadvantaged communities at the census tract or block group level, the CEJST tool also designated all tribal lands as disadvantaged communities. In a secondary analysis, we found that CEJST, EJI, and the trivariate tool all designated a larger proportion of tribal lands as disadvantaged communities compared to the proportion of land area they designate as disadvantaged communities statewide (Table S4). The CES and CES+ tools designated lower proportions of tribal lands as disadvantaged communities compared to the proportion of land area they designated as disadvantaged communities statewide. They also classified smaller proportions of tribal lands (6% for both tools) as being within disadvantaged communities across the state than all other tools. Notably, in addition to disadvantaged communities identified as in the top 25% of CES scores, CalEPA also designates all land controlled by federally recognized tribes as disadvantaged communities (CalEPA, 2022).

Quantifying tool priorities

We estimated ORs for block groups with proportions of Black and Hispanic/Latino residents above the statewide block group median proportions using Wallenius' noncentral hypergeometric distribution. All screening tools we examined had ORs greater than 1 for both racial/ethnic groups, indicating that the screening tools prioritized block groups with proportions of these groups above the statewide median for designation as disadvantaged communities (Figure 5). The CES and CES+ tools had the highest ORs for block groups with proportions of Black and Hispanic/Latino residents above the statewide median. Notably, CES did not explicitly consider racial/ethnic composition, indicating that the weights given to sociodemographic factors correlated with race/ethnicity accounted for the racial/ethnic composition of block groups. The CEJST tool had the lowest OR for proportion Black residents, and the trivariate tool had the lowest OR for proportion Hispanic/Latino residents.

Discussion

We conducted a comparative analysis of environmental justice screening tools developed by state and federal agencies, with the aim of determining the concordance or discordance of classifications of disadvantaged communities in California. We found that, though these screening tools consistently classified some areas of California as disadvantaged communities, there were substantial differences in terms of which populations fit each screening tool's criteria for disadvantaged communities. For example, much of the San Joaquin Valley was consistently classified as disadvantaged by all screening tools, while there was disagreement among screening tools for certain communities in the Sacramento Valley. We observed small but statistically significant differences in some characteristics of populations classified as living in disadvantaged communities across screening tools, though this may be spuriously attributable to the large sample size. Areas classified as disadvantaged across screening tools clearly face cumulative burdens, indicating that these regions may be of particular importance in environmental justice research and policymaking. The aggregate population characteristics in disadvantaged communities were similar (with large standard deviations) across screening tools, but there was substantial variation in the actual communities classified as disadvantaged.

The structure of screening tools can lead to unexpected mean characteristics of populations classified as disadvantaged communities and provide insights about the extent to which screening tools capture intersectional measurements of disadvantage. We observed small but statistically significant differences among screening tools for factors not considered by any screening tool (e.g., population density), factors considered by all screening tools (e.g., poverty), and factors considered only by some screening tools (e.g., race/ethnicity). Screening tools that were not significantly different from one another across one factor could be statistically significantly different for another factor. Additionally, the structure of formulas that tools use to classify disadvantaged communities can lead to unexpected results when examining the characteristics of disadvantaged communities. For example, the trivariate tool considers only three factors, one of which is race/ethnicity, but we found that this tool generally classified block groups as disadvantaged with lower average proportions of Hispanic/Latino residents and Black residents compared to the other tools. This is likely because the trivariate tool classifies a larger proportion of block groups in California as disadvantaged communities than the other tools, many of which met the criteria for disadvantaged community classification based on the poverty threshold alone. These communities with high poverty rates may not also face the types of burdens considered by other tools, so they may not be prioritized by these tools.

We developed a quantitative approach to arrive at implicit levels of prioritization that tools give to various characteristics that is unaffected by the fact that different tools classify different proportions of land in California as disadvantaged communities. This method, which models the process of selecting disadvantaged communities using Wallenius' noncentral hypergeometric distribution, showed that the CES and CES+ had the highest implicit weights on block groups with proportions of Hispanic/Latino residents and Black residents above the statewide block group median. These findings are similar to analyses from CalEPA, which indicate that CES implicitly prioritizes areas with high proportions of racially marginalized people despite not explicitly considering race or ethnicity (California Office of Environmental Health Hazard Assessment, 2021). This method of quantitatively evaluating tools based on inferring weights given to various characteristics is a new way to understand the level of priority that different screening tools give to different groups of people, and it provides a framework for analysis of future screening tools and decision-making in tool design.

By comparing outcomes of tools in a way that is not influenced by the proportion of communities classified as disadvantaged, we can arrive at a more complete understanding of tool priorities than through methods like comparing general characteristics of populations classified as disadvantaged communities. We were able to detect instances when screening tools that classified large proportions of California as disadvantaged placed higher implicit weights on Black and Hispanic populations than tools that classified smaller proportions of California as disadvantaged communities. For example, communities classified as disadvantaged by EJI had comparatively high average proportions of Hispanic/Latino and Black residents. This was not unexpected, given that EJI classified the lowest number of block groups as disadvantaged communities among all five screening tools. When we compared ORs, however, we observed that EJI gave lower estimated weights to block groups with proportions of Hispanic/Latino and Black residents above the statewide median than both CES (which did not explicitly consider race/ethnicity) and CES+. The estimated ORs for EJI indicated that our approach has merit in quantitatively comparing the implicit prioritization of screening tools that that classify discrepant geographies as disadvantaged.

The inconsistencies in the classification of disadvantaged communities among screening tools, attributable to both explicit and implicit differences, can have real-world impacts that, in some cases, may hinder environmental justice policy goals. We observed that the tools contributing most to the instability of disadvantaged community designation were the trivariate tool and CEJST. Indeed, CEJST often disagreed with CES and EJI, the two tools that are currently in use in California. The CEJST tool was designed to help in the implementation of the Biden Administration's Justice40 Initiative, which aims to direct at least 40% of benefits from specific federal investments to disadvantaged communities. However, as we observed in the current study, CEJST appeared to implicitly under-weight the proportion Black and Hispanic/Latino residents in comparison to the other screening tools. Indeed, prior work has found that the use CEJST to allocate federal resources would not alleviate racial/ethnic disparities in exposure to fine particulate matter and may in fact exacerbate these disparities (Wang et al., 2023).

As screening tools proliferate (Driver et al., 2019; Grier, Mayor, & Zeuner, 2019; Petroni, Howard, Howell, & Collins, 2021; Min et al., 2019), there are ongoing opportunities for community members, policymakers, agency staff, and researchers to discuss the development and application of specific tools to support environmental justice priorities. Criticisms have been raised regarding the use of screening tools to identify cumulatively burdened communities, including that broad-scale aggregated data do not adequately capture community concerns, that certain cumulatively-burdened communities are not classified as disadvantaged because they are subsumed in larger census tracts or compared to statewide baselines, and that quantitative and spatially discrete analyses oversimplify complex environmental justice issues (Zrzavy et al., 2022). There are also constraints in data accessibility, such as state- and national-scale tools that incorporate protected health information in aggregate scores, but which are not otherwise publicly available, constraining the ability to downscale these screening tools to specific neighborhoods (McKenzie et al., 2022). In community-engaged research, there are opportunities to collectively define what cumulative disadvantage means for residents of the affected communities, allowing for greater responsiveness to local concerns. Examples of this include the West Oakland Environmental Indicators Project (Costa et al., 2002).

This study has several limitations. The agencies that developed the screening tools we assessed have different definitions of cumulative disadvantage, and the screening tools themselves do not necessarily reflect all areas designated as disadvantaged communities. For example, CalEPA defines disadvantaged communities based on the results of CES 4.0, as well as communities designated as disadvantaged in 2017 and land controlled by federally-recognized tribes (CalEPA, 2022). Since tribal lands do not follow boundaries of Census Block Groups, we excluded them from analysis, potentially resulting in underestimation of American Indian and Alaska Native individuals residing in disadvantaged communities. In our analyses, we down-scaled census tract level disadvantaged community designations to the block group level. Our measurements of the variation in block group characteristics of areas classified as disadvantaged communities may overstate the variation in classified regions, since many of the tools classify disadvantaged communities based on tract level characteristics. Since scaling down the disadvantaged community designations to the block group level would have increased the variability in characteristics of disadvantaged communities, our findings about the significance and magnitude of differences between the tools are likely to be underestimates rather than overestimates. When evaluating the federal tools (EJI and CEJST), we used the classifications of disadvantaged communities based on the national baseline rather than rescaling these tools to California, as these are the thresholds that would be used in policy and regulatory decision-making. Our assessments were cross sectional using the most recent versions of each tool at the time of analysis. Given the dynamic nature of data inputs (social factors and environmental exposures) and screening tool methodologies, ongoing comparative assessments may be necessary to identify which tools are most effective in capturing these dynamic processes. Additionally, uncertainty quantification will become more important as tools continue to take more data into account.

Our assessment of screening tools demonstrates several ways in which these tools can be quantitatively compared for research and policy decisions. The task of categorizing communities based on cumulative disadvantage is influenced by specific decisions made in the structure of tools and the factors included in tool designs. Care should be taken in determining which datasets, analytical frameworks, and tools to use for specific research, policy, and advocacy purposes. This is particularly important as new vintages of data are released, existing screening tools are restructured or updated, and new screening tools emerge. Comparisons of these tools are necessary, given the counterintuitive differences we observed for some screening tools and the impacts that small methodological distinctions have on outcomes. In addition, the perspectives of residents of cumulatively disadvantaged communities have and will continue to be a critical part of designing effective screening tools. Importantly, these screening tools are currently used, or are designed to be used, in ways that influence communities' access to resources and exposure to environmental hazards. Researchers incorporating measures of cumulative disadvantage into their work should consider how the choice of screening tool influences study populations and, consequently, study findings and conclusions. Understanding the differences between tools will help researchers, policymakers, advocates, and residents make better-informed decisions regarding the design and implementation of environmental justice policies.

Code Availability

All code supporting this paper is publicly available at https://github.com/MortonC78483/DAC-metrics.

References

Ahn, E., Wan, S., Yeung, M., Moss, S., Shaw, R., Falk, D., … Woo, K. (2021). *Re: Draft CalEnviroScreen 4.0* [PDF File]. https://oehha.ca.gov/media/dockets/20006/20384-nonprofit_coalition_for_environmental_justice/cbocoalitionletter-draftces4-5.14.21.pdf.

American Lung Association. (2023). *State of the Air Report.* https://www.lung.org/research/sota.

August, L., Bangia, K., Plummer, L., Prasad, S., Ranjbar, K., Slocombe, A., …, Zeise, L. (2021). *CalEnviroScreen 4.0* [PDF File]. https://oehha.ca.gov/media/downloads/calenviroscreen/report/calenviroscreen40reportf2021.pdf.

Balakrishnan, C., Su, Y., Axelrod, J., & Fu, S. (2022). Screening for Environmental Justice: A Framework for Comparing National, State, and Local Data Tools [PDF File]. *Urban Institute*. https://www.urban.org/sites/default/files/2022-11/Screening%20for%20Environmental%20Justice-%20A%20Framework%20for%20Comparing%20National%2C%20State%2C%20and%20Local%20Data%20Tools.pdf.

CalGEM. (2023). Oil and Gas Wells GIS, California. https://gis.conservation.ca.gov/portal/home/item.html?id=335e036c6a4f4cc39148ca2a9e0389c7.

California Department of Tax and Fee Administration. (2023). *Hazardous Waste Fee* (Division 20, Chapter 6.5, Article 9, Section 25200.21). https://www.cdtfa.ca.gov/lawguides/vol4/hwf/hwf-25200-21.html.

California Environmental Protection Agency. (2022). *Final Designation of Disadvantaged Communities Pursuant to Senate Bill 535* [PDF File]. California Environmental Protection Agency. https://calepa.ca.gov/wp-content/uploads/sites/6/2022/05/Updated-Disadvantaged-Communities-Designation-DAC-May-2022-Eng.a.hp_-1.pdf.

California Office of Environmental Health Hazard Assessment. (2021). *Preliminary Analysis of Race/Ethnicity and Draft CalEnviroScreen 4.0 Scores* [PDF File]. California Environmental Protection Agency. https://oehha.ca.gov/media/downloads/calenviroscreen/document/calenviroscreen40preliminaryraceanalysisd12021.pdf.

California Office of Environmental Health Hazard Assessment. (2023). *Uses of CalEnviroScreen.* https://oehha.ca.gov/calenviroscreen/how-use.

Casey, J. A., Kioumourtzoglou, M. A., Padula, A., González, D. J. X., Elser, H., Aguilera, R., ... & Benmarhnia, T. (2023). Measuring Long-Term Exposure to Wildfire PM2. 5 in California: Time-Varying Inequities in Environmental Burden.

Centers for Disease Control and Prevention. (2023). *Environmental Justice Index (EJI) Explorer*. https://onemap.cdc.gov/portal/apps/sites/#/eji-explorer.

Chan, M., Shamasunder, B., & Johnston, J. E. (2023). Social and Environmental Stressors of Urban Oil and Gas Facilities in Los Angeles County, California, 2020. *American Journal of Public Health*, *113*(11), 1182-1190.

Costa, S., Palaniappan, M., Wong, A. K., Hays, J., Landiero, C., & Rongerude, J. (2002). Neighborhood Knowledge for Change: The West Oakland Environmental Indicators Project [PDF File]. https://woeip.org/wp-content/uploads/2020/11/WOEIP-research-neighborhood_knowledge_for_change3.pdf

Department of Toxic Substances Control. (2018). Hazardous Waste Facility Permitting Criteria Regulations [PDF File]. https://dtsc.ca.gov/wp-content/uploads/sites/31/2019/04/SB-673-Regulations-Overview-Fact-Sheet-12-13-2018.pdf.

Department of Toxic Substances Control (2022). Track 2 - Vulnerable Communities and Cumulative Impacts Permitting Criteria. https://dtsc.ca.gov/sb-673-permit-criteria-implementation/#track2

Department of Toxic Substances Control & California Environmental Protection Agency. (2021). SB673 Cumulative Impacts and Community Vulnerability Draft Regulatory Framework [PDF File]. https://dtsc.ca.gov/wp-content/uploads/sites/31/2021/07/2021MAY-DRAFT-CI-Regulatory-Framework_Accessible.pdf.

Depsky, N. J., Cushing, L., & Morello-Frosch, R. (2022). High-resolution gridded estimates of population sociodemographics from the 2020 census in California. *PLoS One*, *17*(7), e0270746.

Driver, A., Mehdizadeh, C., Bara-Garcia, S., Bodenreider, C., Lewis, J., & Wilson, S. (2019). Utilization of the Maryland environmental justice screening tool: A Bladensburg, Maryland case study. *International journal of environmental research and public health*, *16*(3), 348.

Exec. Order No. 14008, 86 Fed. Reg. 19 (January 27, 2021).

Faust, J., August, L. M., Alexeeff, G., Cendak, R., Cushing, L., Kadir, T., …, Prasad, S. (2013). *California Communities Environmental Health Screening Tool, Version 1 (CalEnviroScreen 1.0): Guidance and Screening Tool* [PDF File]. https://oehha.ca.gov/media/downloads/calenviroscreen/report/042313calenviroscreen1.pdf.

Fog, A. (2008). Calculation methods for Wallenius' noncentral hypergeometric distribution. *Communications in Statistics—Simulation and Computation®*, *37*(2), 258-273.

Greenhouse gases: investment plan: disadvantaged communities, Cal. Assemb. B. 1550 (2015-2016), Chapter 369 (Cal. Stat. 2016).

Grier, L., Mayor, D., & Zeuner, B. (2019). Assessing the State of Environmental Justice in Michigan.

Haagen-Smit, A. J. (1964). The control of air pollution. *Scientific American*, *210*(1), 24-31.

Huang, H., Woodruff, T. J., Baer, R. J., Bangia, K., August, L. M., Jellife-Palowski, L. L., ... & Sirota, M. (2018). Investigation of association between environmental and socioeconomic factors and preterm birth in California. *Environment international*, *121*, 1066-1078.

Kuruppuarachchi, L. N., Kumar, A., & Franchetti, M. (2017). A comparison of major environmental justice screening and mapping tools. *Environ. Manag. Sustain. Dev*, *6*, 59-71.

Manly, B. F. (2013). *The statistics of natural selection on animal populations*. Springer Science & Business Media.

McKenzie, B., Berens, A., Bogović, S., Conn, M., Dent, A., Flanagan, B., …, Werner, A. (2022). *Technical Documentation for the Environmental Justice Index 2022* [PDF File].https://www.atsdr.cdc.gov/placeandhealth/eji/docs/EJI-2022-Documentation.pdf.

Méndez, M. (2020). *Climate change from the streets: How conflict and collaboration strengthen the environmental justice movement*. Yale University Press.

Min, E., Gruen, D., Banerjee, D., Echeverria, T., Freelander, L., Schmeltz, M., ... & Seto, E. Y. (2019). The Washington State Environmental Health Disparities Map: Development of a community-responsive cumulative impacts assessment tool. *International journal of environmental research and public health*, *16*(22), 4470.

Mohai, P., & Saha, R. (2015). Which came first, people or pollution? A review of theory and evidence from longitudinal environmental justice studies. *Environmental Research Letters*, *10*(12), 125011.

Monserud, R. A., & Leemans, R. (1992). Comparing global vegetation maps with the Kappa statistic. *Ecological modelling*, *62*(4), 275-293.

Morello-Frosch, R., Cushing, L., London, J., English, P., Sadd, J., & Pastor, M. (2021). Integrating a Community Cumulative Impacts Framework in the Implementation of AB617 and SB 673 [PDF File]. https://ww2.arb.ca.gov/sites/default/files/2021-

06/FINAL%20REPORT%20CONTRACT%20CARB%20%2317RD035%20%26%20DTSC%20%2317-T4471.pdf.

Mousavi, A., Yuan, Y., Masri, S., Barta, G., & Wu, J. (2021). Impact of 4th of July fireworks on spatiotemporal PM2. 5 concentrations in California based on the PurpleAir Sensor Network: Implications for policy and environmental justice. *International journal of environmental research and public health*, *18*(11), 5735.

New Jersey Department of Environmental Protection. (2023). *Overburdened Communities (OBC).* https://dep.nj.gov/ej/communities/.

Padula, A. M., Huang, H., Baer, R. J., August, L. M., Jankowska, M. M., Jellife-Pawlowski, L. L., ... & Woodruff, T. J. (2018). Environmental pollution and social factors as contributors to preterm birth in Fresno County. *Environmental Health*, *17*, 1-21.

Padula, A. M., Ma, C., Huang, H., Morello-Frosch, R., Woodruff, T. J., & Carmichael, S. L. (2021). Drinking water contaminants in California and hypertensive disorders in pregnancy. *Environmental Epidemiology*, *5*(2).

Petroni, M., Howard, S., Howell, I. B., & Collins, M. B. (2021). NYenviroScreen: An open-source data driven method for identifying potential environmental justice communities in New York State. *Environmental Science & Policy*, *124*, 348-358.

Sadd, J. L., Pastor, M., Morello-Frosch, R., Scoggins, J., & Jesdale, B. (2011). Playing it safe: assessing cumulative impact and social vulnerability through an environmental justice screening method in the South Coast Air Basin, California. *International journal of environmental research and public health*, *8*(5), 1441-1459.

S232, N.J. Senate B. 232 (2020-2021), 219th Legislature (N.J. Stat. 2020).

Tanzer, R., Malings, C., Hauryliuk, A., Subramanian, R., & Presto, A. A. (2019). Demonstration of a low-cost multi-pollutant network to quantify intra-urban spatial variations in air pollutant source impacts and to evaluate environmental justice. *International journal of environmental research and public health*, *16*(14), 2523.

U.S. Census Bureau (1992). The Urban and Rural Classifications [PDF File]. https://www2.census.gov/geo/pdfs/reference/GARM/Ch12GARM.pdf.

U.S. Department of Justice. (2023). *BIA National LAR*. https://catalog.data.gov/dataset/bia-national-lar.

U.S. Environmental Protection Agency (2023). *EJScreen: Environmental Justice Screening and Mapping Tool*. https://www.epa.gov/ejscreen.

Walker K, Herman M (2023). *tidycensus: Load US Census Boundary and Attribute Data as 'tidyverse' and 'sf'-Ready Data Frames*. R package version 1.4.3, https://walker-data.com/tidycensus/.

Wallenius, K. T. (1963). Biased Sampling: The Non-Central Hypergeometric Probability Distribution. Ph.D. thesis, Stanford University (Also published with the same title as Technical report No. 70), Department of Statistics, Stanford University.

Wang, Y., Apte, J. S., Hill, J. D., Ivey, C. E., Johnson, D., Min, E., ... & Marshall, J. D. (2023). Air quality policy should quantify effects on disparities. *Science*, *381*(6655), 272-274.

White House. (2022). *FACT SHEET: Biden-Harris Administration Holds Justice40 Week of ACtion to Highlight Historic Investments in Overburdened and Underserved Communities.* https://www.whitehouse.gov/briefing-room/statements-releases/2022/05/23/fact-sheet-biden-harris-administration-holds-justice40-week-of-action-to-highlight-historic-investments-in-overburdened-and-underserved-communities/.

White House Council on Environmental Quality. (2022). Climate and Economic Justice Screening Tool: Technical Support Document Public Beta, Version 0.1 [PDF File]. https://static-data-screeningtool.geoplatform.gov/data-pipeline/data/score/downloadable/cejst_technical_support_document.pdf.

Zrzavy, A., Blondell, M., Kobayashi, W., Redden, B., & Mohai, P. (2022). Addressing Cumulative Impacts: Lessons from Environmental Justice Screening Tool Development and Resistance. *Env't L. Rep.*, *52*, 10111.

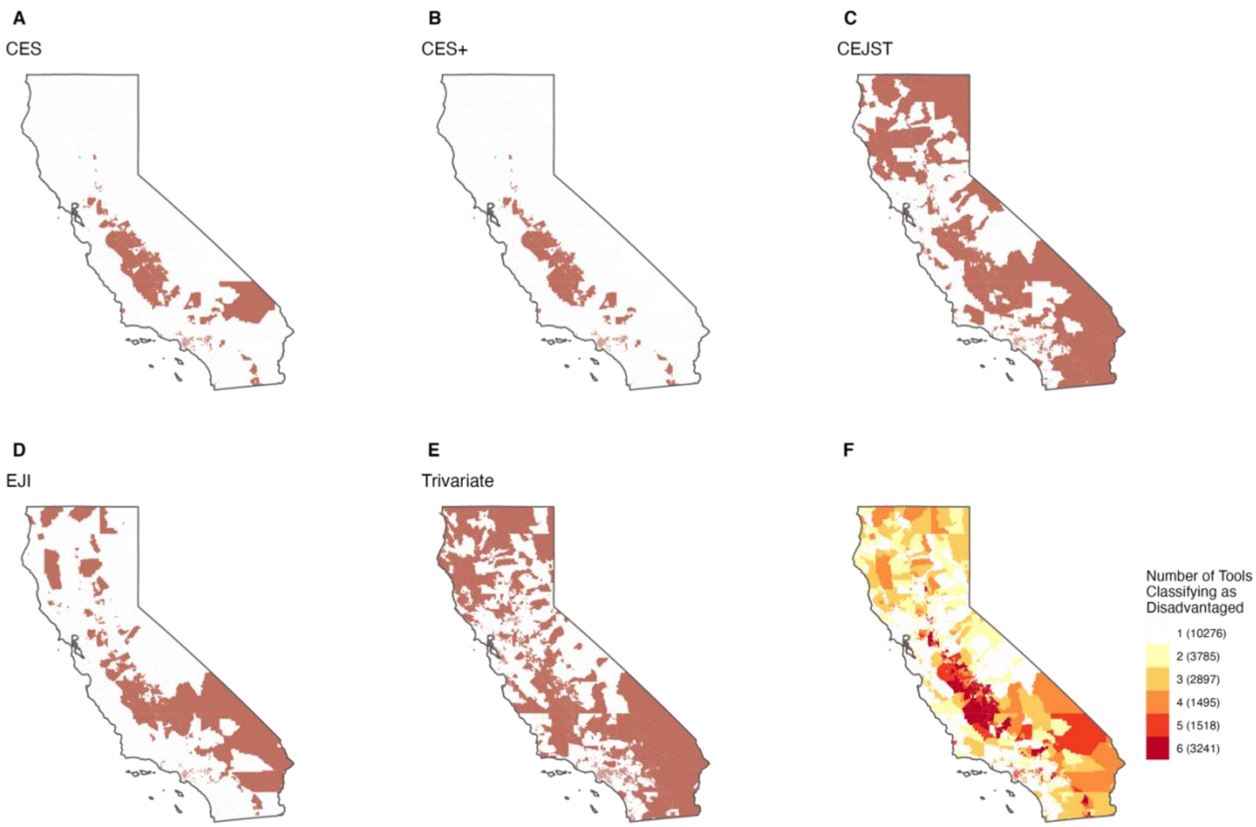

Figure 1. Comparison of disadvantaged communities classified by each tool. A-E map disadvantaged communities in red, F maps block groups colored by number of tools classifying as disadvantaged communities.

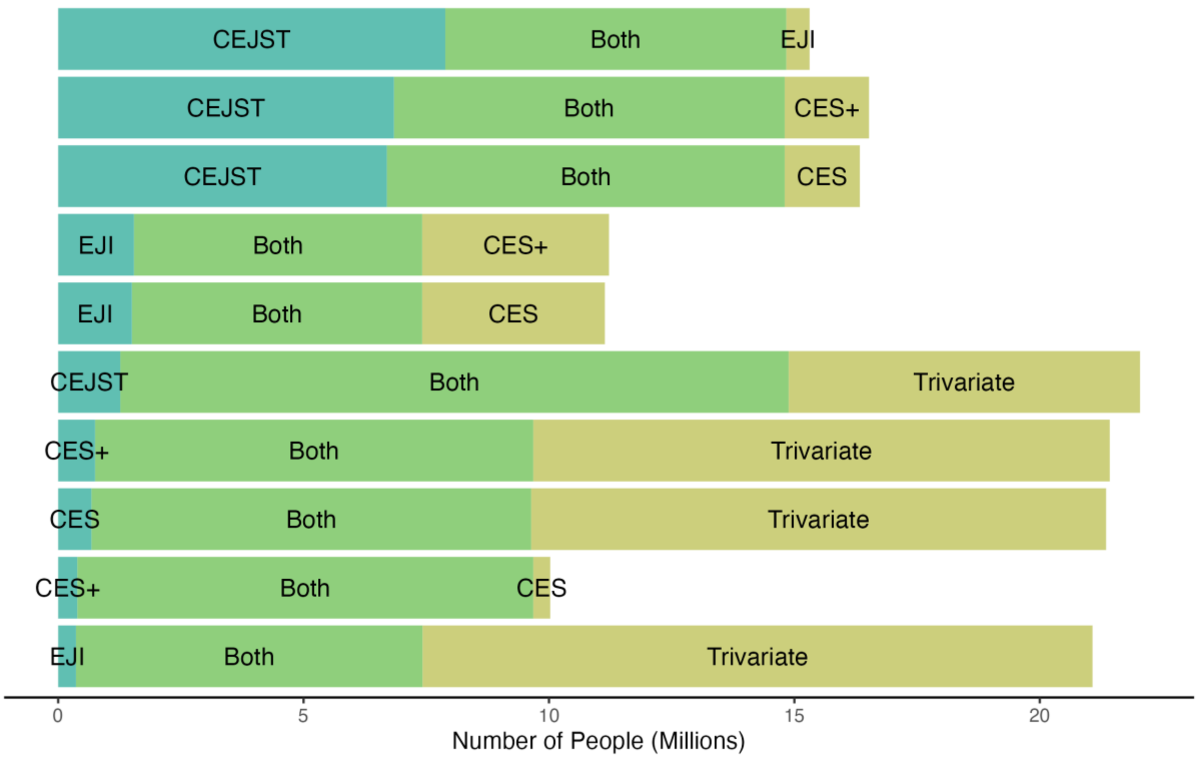

Figure 2. Number of people classified as living in disadvantaged communities for all pairs of tools. "Both" indicates the number of people classified as living in disadvantaged communities by both tools in a given row, while the lengths of the red and blue boxes represent the number of people classified as living in disadvantaged communities by one of the two tools, but not both.

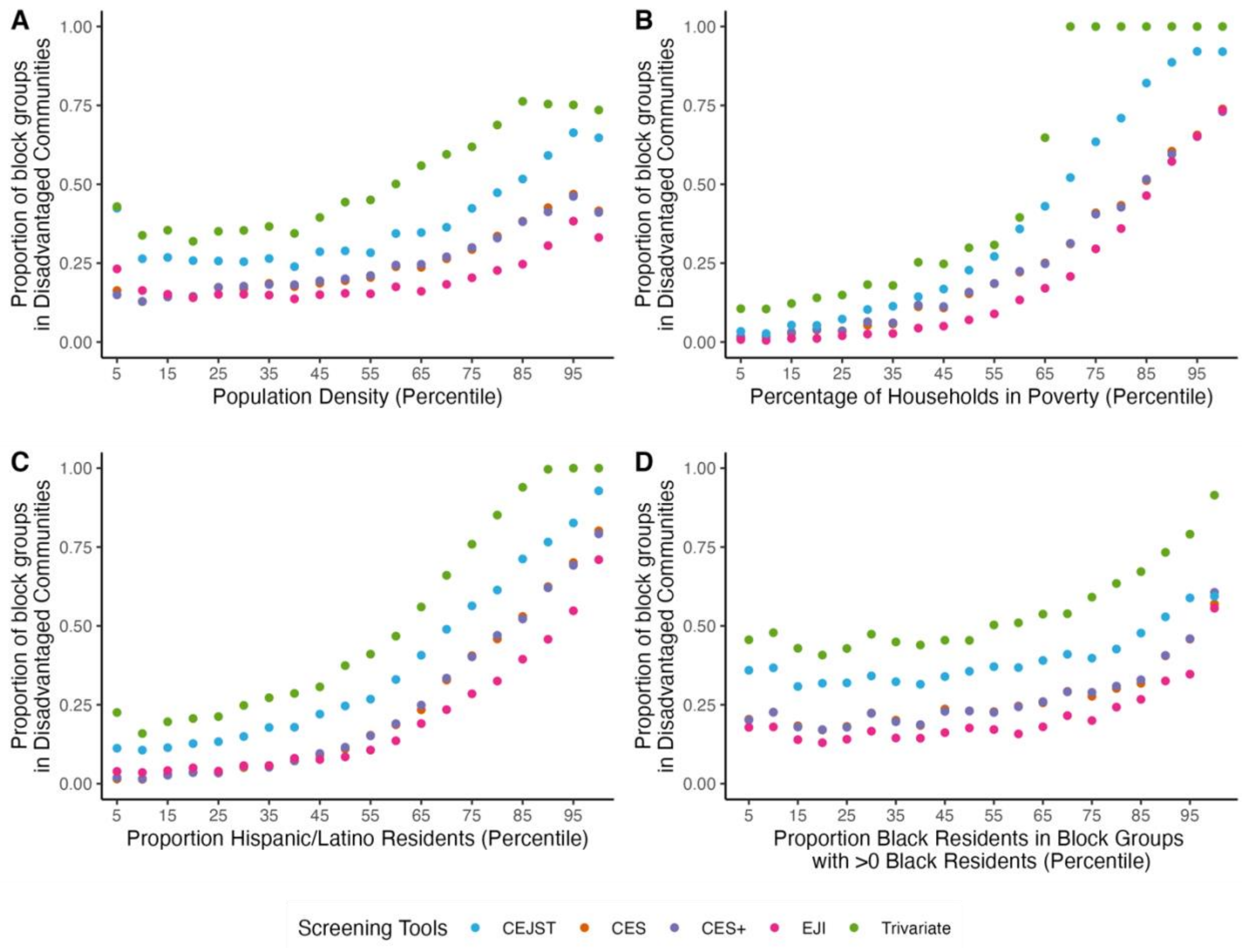

Figure 3. Proportion of block groups in disadvantaged communities by percentile of (a) population density, (b) proportion of households under 200% of the federal poverty level, (c) proportion of Hispanic/Latino residents, and (d) proportion of Black residents among block groups with > 0 Black residents. Colors correspond to different tools. Leftmost point represents 0-5th percentile.

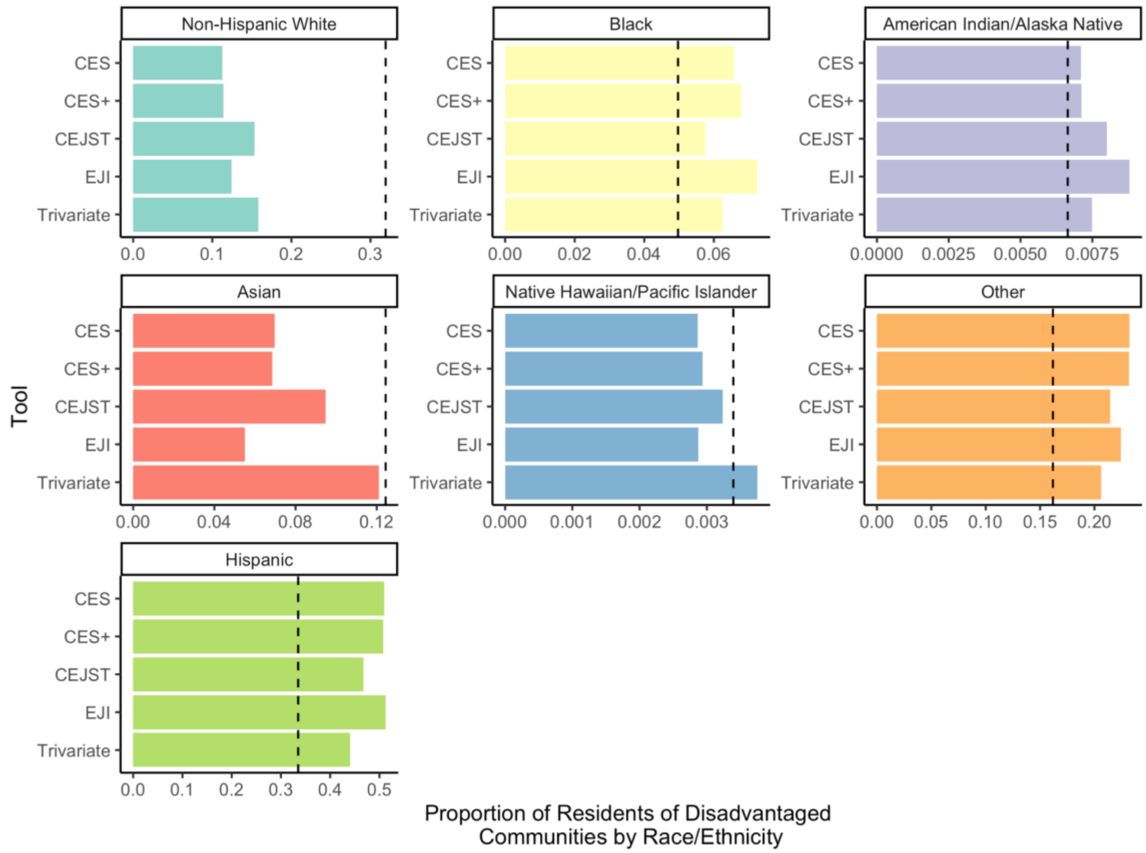

Figure 4. Proportion of the population designated as living in disadvantaged communities and the proportion of the statewide population (dotted lines) that belong to various racial/ethnic groups, by tool.

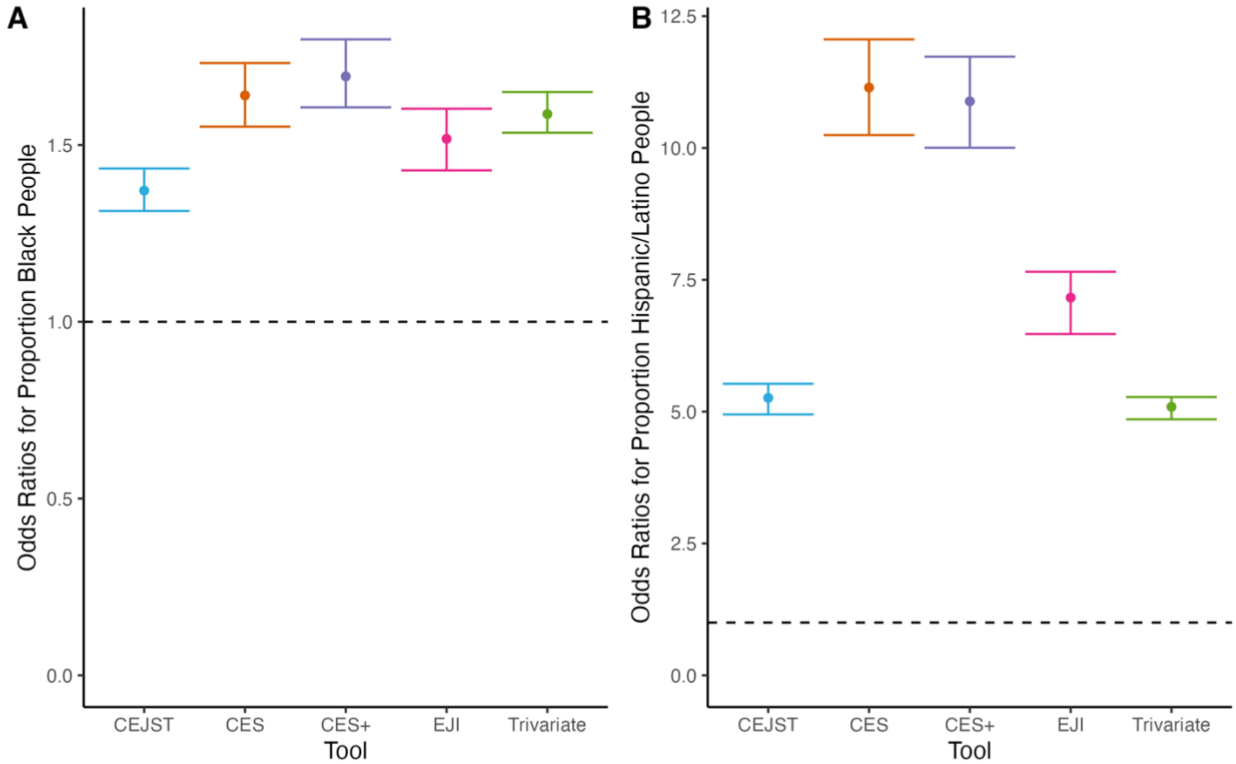

Figure 5. Estimated weights given to block groups with proportions of Black people (a) and Hispanic/Latino people (b) above the statewide median by tools. Intervals are bootstrap 95% confidence intervals. Note that the y-axes differ between the two panels.

Tool	Land area (proportion)	Number of block groups (proportion)	Number of people (proportion)
CEJST	86700 (0.56)	8648 (0.37)	14882600 (0.38)
CES	22200 (0.14)	5695 (0.25)	9636500 (0.25)
CES+	14200 (0.091)	5710 (0.25)	9679400 (0.25)
EJI	49500 (0.32)	4565 (0.20)	7423500 (0.19)
Trivariate	89600 (0.58)	11723 (0.51)	20777400 (0.53)

Table 1. Proportion of land area, proportion of block groups, and proportion of people in disadvantaged communities as classified by the 5 tools.

Tool	CEJST	CES	CES+	EJI	Trivariate
CEJST		0.18	0.11	0.46	0.48
CES			0.74	0.37	0.15
CES+				0.2	0.08
EJI					0.31
Trivariate					

Table 2. Kappa statistics for similarity between tools.

Tool	CEJST	CES	CES+	EJI	Trivariate
CEJST		0.55	0.53	0.57	0.60
CES			0.95	0.62	0.48
CES+				0.62	0.47
EJI					0.43
Trivariate					

Table 3. Pearson correlation coefficients between all tools.

Trivariate	CES	CES+	EJI	CEJST
0.337	0.169	0.171	0.198	0.403

Table 4. Proportion of block groups classified as disadvantaged communities by each tool that were classified as disadvantaged communities by 2 or 3 tools in total.

Characteristic	**Main Findings**
Population density	CEJST, CES, and CES+ had higher mean population densities in disadvantaged communities than EJI and the trivariate tool, potentially attributable to the fact that CEJST, CES, and CES+ all consider both traffic impacts and diesel particulate matter.
Poverty	EJI generally designates communities with the highest poverty rates as disadvantaged, and the trivariate tool designates communities with the lowest poverty rates, due both to the trivariate tool's low poverty threshold and the fact that the tool designates the majority of California's block groups as disadvantaged communities.
Hispanic/Latino Residents	Disadvantaged communities classified by the trivariate tool and CEJST had the lowest mean proportion of Hispanic/Latino residents, followed by CES, CES+, and EJI. CES+ and EJI explicitly consider race/ethnicity, but the trivariate tool does not.
Black Residents	Disadvantaged communities classified by the trivariate tool and CEJST had the lowest mean proportion of Black residents, followed by CES, CES+, and EJI. CES+ and EJI explicitly consider race/ethnicity, but the trivariate tool does not.

Table 5. Main findings from ANOVA and post-hoc Tukey tests.

Supplemental Figures and Tables

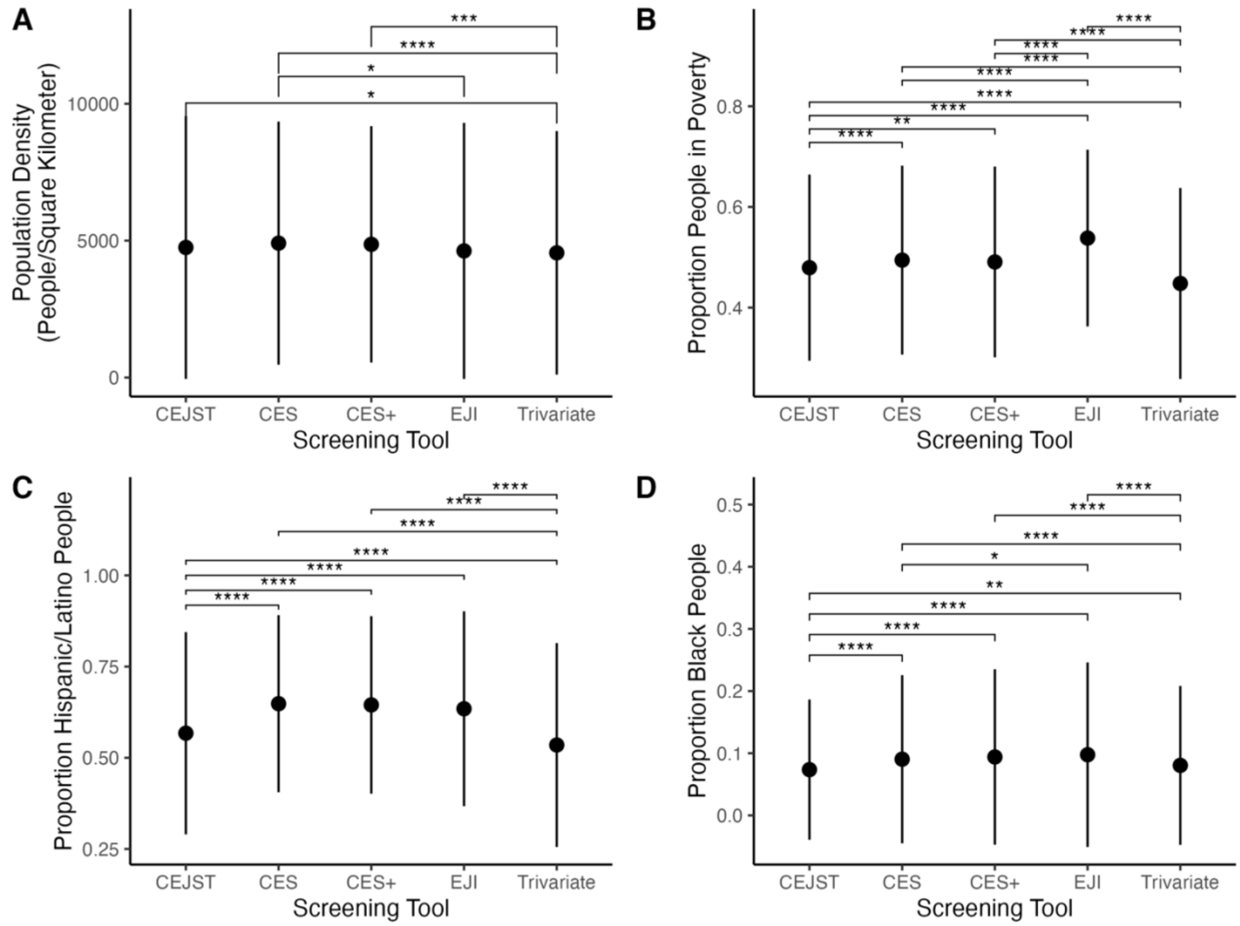

Figure S1. Distribution of characteristics for disadvantaged communities identified by each screening tool. Figures show mean (points) plus or minus one standard deviation (bars). The largest differences in mean population density, proportion of households in poverty, proportion of Hispanic/Latino people, and proportion of Black people were 353.5 people/square kilometer, 0.09, 0.11, and 0.02 respectively.
* p < 0.05; ** p < 0.01; *** p < .001; **** p < 1e-04

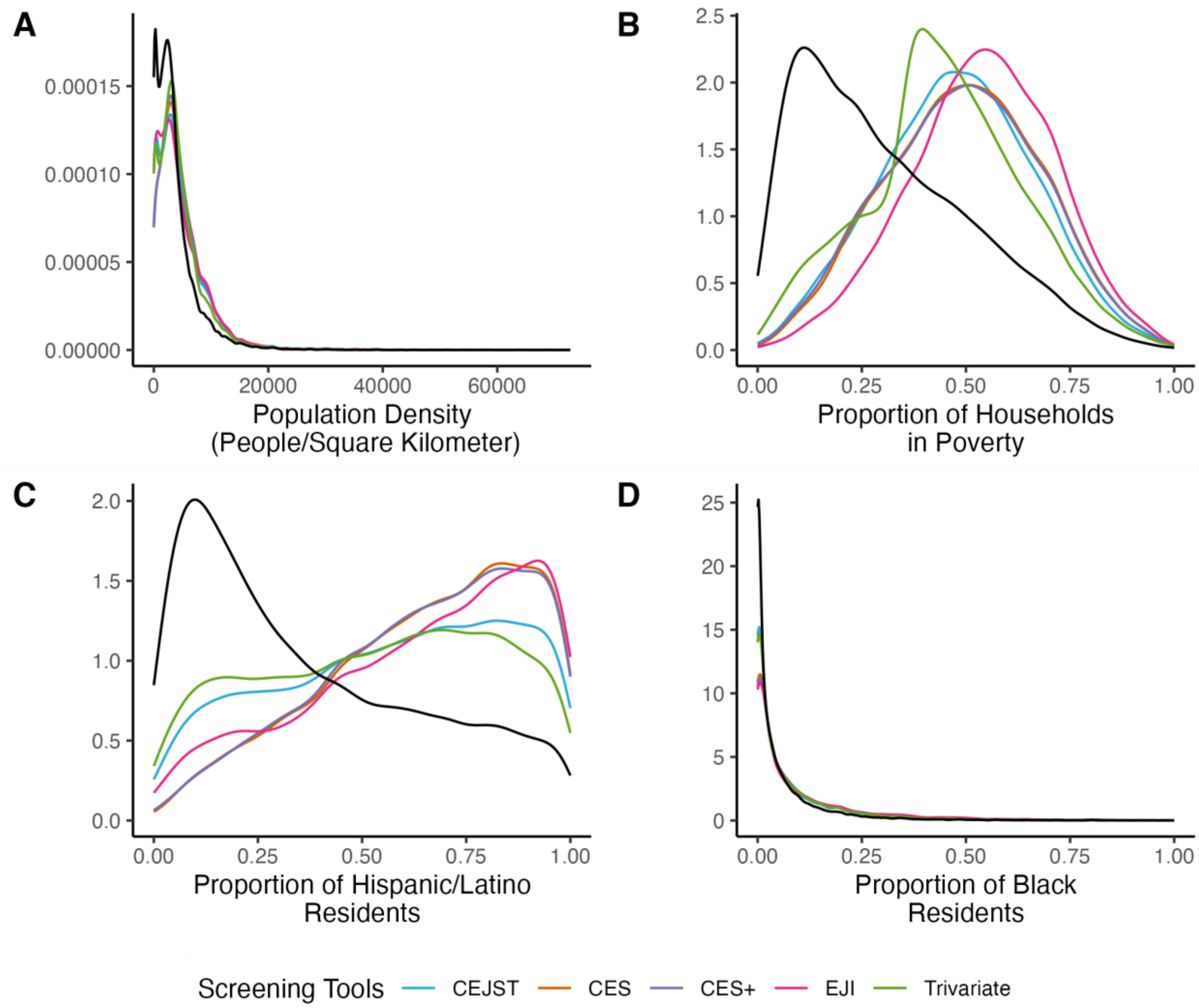

Figure S2. Distributions of population characteristics in disadvantaged communities classified by all tools and in statewide population (black line represents statewide population).

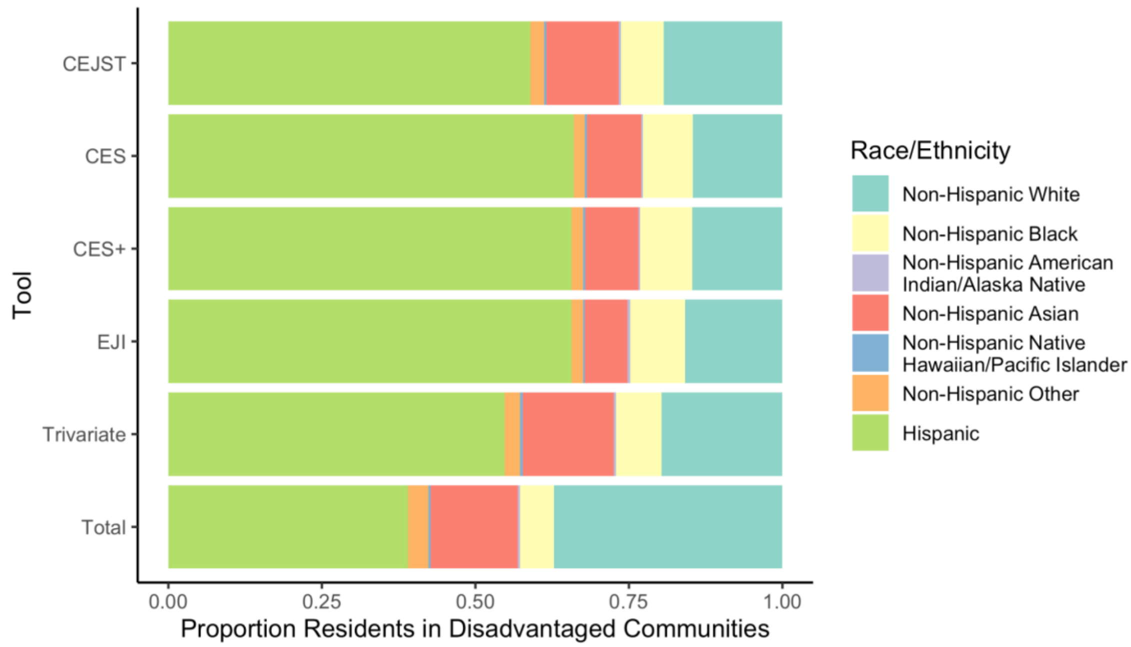

Figure S3. Aggregate proportion of people in disadvantaged communities by race/ethnicity and tool (Total represents statewide population proportions).

CEJST	CES	EJI
.602	.401	.252

Table S1. Proportion of block groups classified as disadvantaged communities by tools currently in use in California (CES, EJI, and CEJST) that were classified as disadvantaged communities by 1 or 2 of these tools.

CEJST	CES	CES+	EJI	Trivariate
0.889	0.929	0.931	0.883	0.907

Table S2. Proportion of block groups classified as disadvantaged communities with population densities over 1,000 people/square mile by tool.

CEJST	CES	CES+	EJI	Trivariate
0.25	0.37	0.53	0.23	0.25

Table S3. Proportion of land area classified as disadvantaged communities within 1km (.62 mi) of a populated area by tool.

Tool	Proportion Tribal Lands in Disadvantaged Communities (Standardized)
CEJST	1 (1.8)
CES	0.06 (0.43)
CES+	0.06 (0.67)
EJI	0.51 (1.61)
Trivariate	0.73 (1.27)

Table S4. Proportion of tribal lands in disadvantaged communities by tool. “Standardized” indicates the proportion of tribal lands in disadvantaged communities for a tool divided by the proportion of land area in California classified as disadvantaged communities by the tool.

Appendix A: Overview of Tools

This project compares 5 different tools meant to assess cumulative burdens on communities in California. Three of the tools were chosen based on their prominence in California and national legislation (CES, CEJST, EJI), and the other two tools were created based on recommendations in literature and policies implemented in other states (trivariate, CES+). We created the trivariate tool through extending a tool in use in New Jersey to California, and we created the CES+ tool through adding three variables to CES that had been recommended by a past study (Morello-Frosch et al., 2021). We note that we use the word "disadvantaged" to refer to cumulatively burdened communities because of its prevalence in the literature and the documentation of the tools we analyze. However, we recognize that disadvantaged is not always the most appropriate word – while proximity to environmental hazards inherently has a negative impact on communities, disadvantage mediated by, for example, the social construct of race is attributable to structural and interpersonal racism.

CalEnviroScreen

CalEnviroScreen (CES) is used by the California Office of Environmental Health Hazard Assessment and the California Environmental Protection Agency to classify disadvantaged census tracts. Information on which census tracts are classified as disadvantaged by CES informs the allocation of 25% of funds from California's cap-and-trade program (Greenhouse gases: investment plan: disadvantaged communities, 2016). CES considers 21 factors that are separated into pollution burden and population characteristics scores. These scores are multiplied to produce the final CES score. The tracts with CES scores in the top 25% are considered disadvantaged communities (August et al., 2021).

CalEnviroScreen+

This tool was calculated for the purposes of this study. It is similar to CES, but it contains several additional components: race/ethnicity and voter turnout are added to the socioeconomic factors component of the score, and count of active oil wells are added as an environmental hazard in the environmental effects component of the score. Race/ethnicity data were added following the procedure in version 1.0 of CES (Faust et al., 2013). Voter turnout was the average of the proportion of eligible voters who voted in the 2012 and 2016 elections. Subsequent versions of CES have not incorporated information on race or ethnicity because of the role of CES in statewide funding allocation. These suggestions were incorporated based on recommendations from academic researchers (Morello-Frosch et al., 2021). The tracts with scores in the top 25% are considered disadvantaged communities. Adding race/ethnicity, voter turnout, and oil wells to CES to produce the CES+ tool resulted in 71 new census tracts (with 388,592 people) being designated as disadvantaged communities, with 35 of these tracts located in Los Angeles County. A paired Wilcoxon Signed-Rank test indicated that the shift between scores of tracts in CES to the scores of tracts in CES+ was significantly different from zero ($V = 9{,}725{,}262$, $p < 0.000001$), and a test of Kendall's rank correlation tau similarly indicated that the paired ranks of tracts in CES and CES+ were significantly different ($Z = 127.7$, $p < 0.000001$).

Climate and Economic Justice Screening Tool

The Climate and Economic Justice Screening Tool (CEJST) was created by the Council on Environmental Quality in response to President Biden's Executive Order 14008, which mandated the creation of a tool to identify disadvantaged communities nationally (Exec. Order No. 14008, 2021). The disadvantaged communities identified by CEJST will receive 40% of benefits from federal grant allocations related to environmental projects through the Justice40 Initiative. To designate disadvantaged communities, CEJST evaluates environmental and socioeconomic indicators for 8 different categories. A community is designated as disadvantaged if it exceeds thresholds for at least one climate indicator and at least one socioeconomic indicator within at least one category (White House Council on Environmental Quality, 2022).

Environmental Justice Index

The Environmental Justice Index (EJI) is a national index meant to identify communities facing cumulative health risks. It was produced by the Centers for Disease Control and Prevention. The EJI evaluates 36 component factors and groups them into three modules: environmental burden, social vulnerability, and health vulnerability. The scores from these modules are summed to create the EJI Score, which can also be percentile ranked (McKenzie et al., 2022). While EJI does not officially classify disadvantaged communities, this study classifies a tract as disadvantaged in the EJI if the tract is in the top 25% of scoring tracts in the US.

Trivariate

The state of New Jersey imposes strict permitting regulations on hazardous facilities sited in census block groups exceeding thresholds for linguistic isolation, poverty, and race/ethnicity (S232, 2020). Based on recommendations from our community partners (see Community Engagement), we considered a similar tool for block groups in California. Under the trivariate tool, a block group is classified as disadvantaged if it exceeds any one of the following thresholds: over 75% Hispanic/Latino or non-white residents, over 35% of households have income below 200% of the federal poverty level, or over 40% of households have limited English proficiency (linguistically isolated).