Racial/Ethnic Disparities in Cumulative Environmental Health Impacts in California: Evidence From a Statewide Environmental Justice Screening Tool (CalEnviroScreen 1.1)

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Objectives. We used an environmental justice screening tool (CalEnviroScreen 1.1) to compare the distribution of environmental hazards and vulnerable populations across California communities.

Methods. CalEnviroScreen 1.1 combines 17 indicators created from 2004 to 2013 publicly available data into a relative cumulative impact score. We compared cumulative impact scores across California zip codes on the basis of their location, urban or rural character, and racial/ethnic makeup. We used a concentration index to evaluate which indicators were most unequally distributed with respect to race/ethnicity and poverty.

Results. The unadjusted odds of living in one of the 10% most affected zip codes were 6.2, 5.8, 1.9, 1.8, and 1.6 times greater for Hispanics, African Americans, Native Americans, Asian/Pacific Islanders, and other or multiracial individuals, respectively, than for non-Hispanic Whites. Environmental hazards were more regressively distributed with respect to race/ethnicity than poverty, with pesticide use and toxic chemical releases being the most unequal.

Conclusions. Environmental health hazards disproportionately burden communities of color in California. Efforts to reduce disparities in pollution burden can use simple screening tools to prioritize areas for action. (*Am J Public Health.* 2015;105:2341–2348. doi:10.2105/AJPH.2015.302643)

Communities of color in the United States often reside in neighborhoods with worse air quality,[1] more environmental hazards,[2] and fewer health-promoting environmental amenities such as parks.[3] This unequal distribution of exposures may contribute to racial/ethnic health disparities in environmentally sensitive diseases such as cancer and asthma.[4] Research has shown that communities of color in California experience higher cancer risk from toxic air contaminants[5] and higher average levels of nitrate contamination in their drinking water[6] and that they live closer to hazardous waste sites[7] and traffic.[8] However, less is known about the extent to which communities of color are simultaneously exposed to multiple potential sources of pollution and the implications of such coexposures for health.

There is, thus, an increasing need for analytic frameworks and decision-making tools that account for exposures to multiple environmental hazards through a variety of routes. Such frameworks should also consider differential vulnerability to the health effects of those exposures, which can vary across the population because of both individual and community-level factors.[9–11] For example, age and health status, including suffering from preexisting cardiovascular disease or asthma, have been shown to increase susceptibility to the adverse health effects of air pollution.[12–14]

Several studies suggest that an individual's educational attainment modifies the health effects of air pollution: greater effects are observed among the less educated.[15,16] Poverty can hinder access to adequate nutrition and medical care to prevent and manage the health impacts of pollution. At the community level, the concentration of poverty in disadvantaged neighborhoods can lead to conditions that increase levels of chronic psychosocial stress that weaken the body's ability to defend against external challenges.[17] A cumulative impact approach that considers differential vulnerability and environmental stressors is particularly important for assessing racial/ethnic environmental health disparities because communities of color in the United States experience lower average levels of education[18] and wealth[19] and, for some groups, higher rates of chronic health conditions[20] that increase susceptibility to environmental health hazards.

Although the field is still in its infancy, several proposed methods are used to better reflect the cumulative impacts of environmental exposures and population vulnerabilities and provide assessments that can support the incorporation of equity and environmental justice goals into policymaking.[21–24] The California Environmental Protection Agency first released such a method—the California Communities Environmental Health Screening Tool, or CalEnviroScreen—in April 2013, and an updated version, CalEnviroScreen 1.1, was published in September 2013.[25] CalEnviroScreen is a screening tool that considers both pollution burden and population vulnerability in assessing the potential for cumulative impacts across California zip codes. It was developed following consultation with government, academic, business, and nongovernmental organizations and 12 public workshops in 7 regions of the state that resulted in more than 1000 oral and written comments on 2 preliminary drafts.[26] The tool employs a model that can be adapted to different applications and as new information becomes available. For example, subsequent iterations have been developed using a finer geographic resolution and the addition of new indicators.[27] It purposefully relies on publicly available data sets for transparency and relatively simple methods so that it can be understood by a general audience.

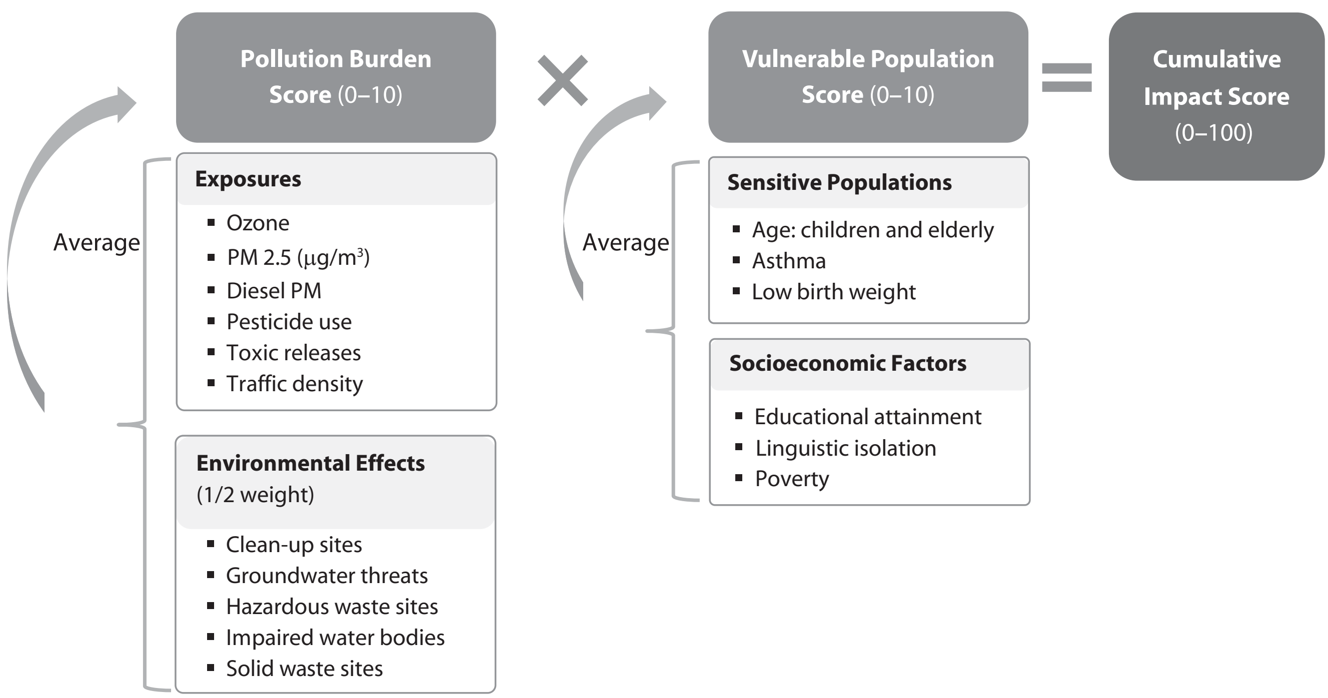
We used CalEnviroScreen 1.1 to assess the extent of geographic and racial/ethnic disparities in the potential for cumulative environmental health impacts from multiple environmental hazards in California. We employed a concentration index to examine which environmental hazards are most inequitably distributed, and we considered variations to CalEnviroScreen to evaluate the sensitivity of our findings to the structure of the model.

METHODS

CalEnviroScreen 1.1 consists of 17 indicators related to the pollution burden or population vulnerability of a community, which are aggregated into a final, relative cumulative impact score (Figure 1). We defined communities geographically on the basis of the 2010 Zip Code Tabulation Area of residence. Zip Code Tabulation Areas are generalized areal representations of US Postal Service zip code service areas created by the US Census Bureau and are delineated on the basis of the most common zip code within each census block. We chose Zip Code Tabulation Areas (hereafter "zip codes") for this analysis to mitigate the issue of changing zip code boundaries. A full description of data sources and the rationale for each indicator is available elsewhere.[25] Briefly, CalEnviroScreen includes 11 indicators of pollution burden and 6 of population vulnerability chosen because of (1) their environmental and public health relevance, (2) the availability of statewide data with adequate geographic resolution and variation to discern differences between zip codes, and (3) the accuracy, completeness, and currency of the data source and the likelihood that it will be maintained in the future (Table 1).

We sought to minimize the number of indicators and the potential overlap between them for parsimony and to minimize the potential for double counting. We characterized pollution burden using 6 indicators of exposure and 4 of environmental effects. Exposure indicators include measures of pollutant sources, releases, and environmental concentrations. Environmental effects indicators are measures of threats to the environment and degraded ecosystems. We gave the environmental effects indicators half the weight of the exposure indicators in our calculation of the cumulative impact score because the route of human exposure to these hazards is less immediate. The 6 indicators of population vulnerability include biological traits (e.g., age and disease status) and factors related to socioeconomic status (e.g., poverty and education level) that can increase susceptibility to the adverse health impacts of pollutants.[10]

To arrive at the cumulative impact score, we assigned zip codes across California a percentile ranging from 0 to 100 on the basis of their value for each indicator. We then averaged the percentiles and divided them by 10 to derive separate scores for pollution burden (0–10) and population vulnerability (0–10). We then



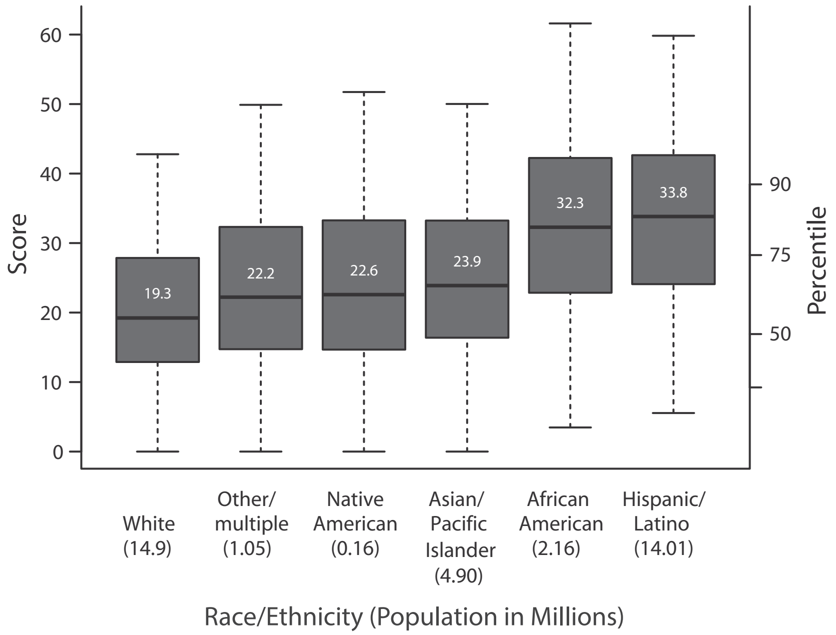
Note. PM = particulate matter. The model combines 11 indicators of pollution burden and 6 indicators of population vulnerability into a relative cumulative impact score that can be used to identify communities with higher potential for cumulative environmental health impacts.

FIGURE 1—The CalEnviroScreen 1.1 model: California, 2013.

TABLE 1—The 17 Indicators of Cumulative Environmental Health Impact Included in CalEnviroScreen 1.1: California

Indicator	Description	Source	Range	Mean ±SD	Median
Pollution burden					
Ozone (ppm)	Portion of the daily maximum 8-h ambient concentration over the federal standard (2007–2009)	CARB	0.0–1.3	0.1 ±0.2	0.1
PM 2.5 ($\mu g/m^3$)	Annual mean ambient concentration (2007–2009)	CARB	3.6–21.2	10.5 ±3.1	10.2
Diesel PM (kg/d)	Emissions from on-road and nonroad sources for a 2010 summer day in July	CARB	0.1–125.3	10.3 ±14.3	4.6
Pesticide use (lb/square mile)	Selective active ingredients used in production agriculture (2009–2010)	California Department of Pesticide Regulation	0.0–32 671.0	344.0 ±1975.0	0.1
Toxic releases (toxicity-weighted lb/y)	Releases to air or water (2008–2010)	Toxics Release Inventory, US Environmental Protection Agency	0.0–5.1×10^8	$1.73 \times 10^6 \pm 1.74 \times 10^7$	0.0
Traffic density (vehicle-km per h/km)	Traffic volume by road length within 150 meters of zip code boundary (2004)	CEHTP, CDPH	0.0–8 417.0	916.0 ±892.0	665.2
Cleanup sites (weighted sum)	Cleanup sites weighted by site type and status (2013)	DTSC EnviroStor database	0.0–511.0	24.5 ±46.6	8.0
Groundwater threats (weighted sum)	Potential contamination sources and monitoring wells, weighted by site type and status (2013)	SWRCB GeoTracker database	0.0–4 530.0	87.7 ±231.0	32.0
Hazardous waste (weighted sum)	Permitted hazardous waste facilities and generators, weighted by waste type and volume (2013)	DTSC EnviroStor database	0.0–58.8	2.2 ±4.0	0.8
Impaired water bodies (sum of pollutants)	Number of pollutants across water bodies designated as impaired (2010)	SWRCB 303(d) List of Impaired Water Bodies	0.0–32.0	4.0 ±4.9	2.0
Solid waste (weighted sum)	Solid waste facilities, operations, and disposal sites, weighted by site type and status (2013)	SWIS and CIA Disposal Sites Program, Department of Resources, Recycling and Recovery	0.0–57.0	4.7 ±6.4	2.0
Vulnerable populations					
Children and elderly (%)	% population aged < 10 y or > 65 y (2010)	US Census Bureau	0.0–100.0	25.9 ±6.5	25.6
Asthma (visits per 10 000/y)	Spatially modeled, age-adjusted rate of emergency department visits (2007–2009)	CEHTP, Office of Statewide Health Planning and Development	6.9–312.2	42.5 ±27.0	36.1
Low birth weight (%)	% births weighing < 2500 g (2007–2011)	CDPH Vital Statistics	1.0–14.8	6.7 ±1.4	6.6
Educational attainment (%)	% population aged > 25 y with < high school education (2007–2011)	ACS 5-y estimates, US Census Bureau	0.0–82.7	17.3 ±14.8	13.0
Linguistic isolation (%)	% households in which no one aged ≥ 14 y speaks English “very well” (2007–2011)	ACS 5-y estimates	0.0–100.0	10.4 ±10.3	7.4
Poverty (%)	% population living below twice the federal poverty level (2007–2011)	ACS 5-y estimates	0.0–96.6	33.8 ±17.8	31.6

Note. ACS = American Community Survey; CARB = California Air Resources Board; CDPH = California Department of Public Health; CEHTP = California Environmental Health Tracking Program; CIA = Closed, Illegal, and Abandoned; DTSC = Department of Toxic Substances Control; PM = particulate matter; SWIS = Solid Waste Information System; SWRCB = State Water Resources Control Board.



Note. The scores indicate that non-Hispanic White Californians are likely to experience lower cumulative environmental health impacts than are other groups (total sample population = 37 269 815). The bar indicates the median cumulative impact score for each group. The box delineates the interquartile range (IQR; 25th–75th percentile). The whiskers extend to the most extreme values within 1.5 × IQR of the median. Data are from zip codes throughout California.

FIGURE 2—Distribution of cumulative impact scores for racial/ethnic groups: CalEnviroScreen 1.1, California, 2013.

multiplied these scores to arrive at a final relative cumulative impact score that ranged from 0 to 100 (Figure 1). We chose a multiplicative model in keeping with other risk assessment practices and epidemiological evidence of effect modification of the health impacts of air pollution by socioeconomic and disease status on a multiplicative scale.[28,29] We also compared the sensitivity of our findings to that of an additive model in which we summed the pollution burden and population vulnerability scores.

We conducted all statistical analyses using R version 3.0.1.[30] We compared the distribution of cumulative impact scores across geographic regions of California and the urban versus rural characteristics of communities. We defined geographic regions of the state in county groupings roughly corresponding to the extent of regional governmental bodies. We used Spearman correlation coefficients to compare individual indicators to 2 measures we derived from the 2010 US Census: population density and the percentage of the zip code's population that lived in an unincorporated community (i.e., census-designated places, which we considered an indicator of rural communities).

We visually compared the distribution of cumulative impact scores across categories of self-identified race/ethnicity from the 2010 US Census using box plots (Figure 2). We calculated the unadjusted odds of living in one of the 10% of zip codes with the highest cumulative impact score for each racial/ethnic group and used logistic regression to calculate the odds adjusted for population density.

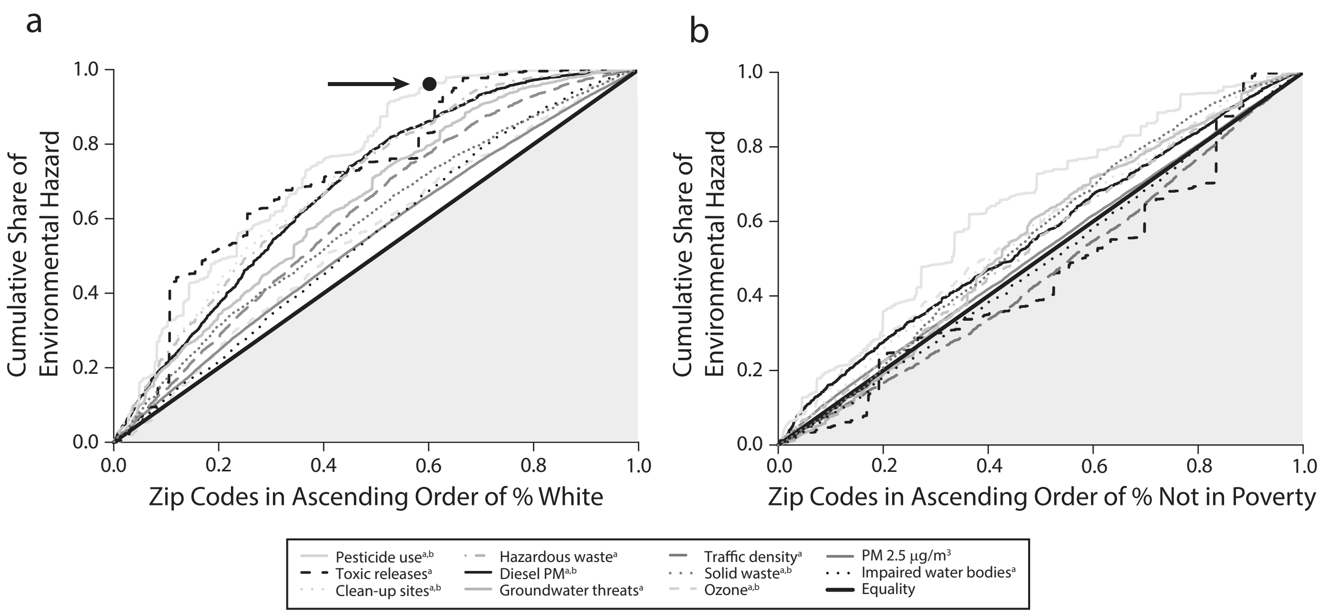
To assess which aspects of pollution burden were most regressively distributed, we plotted concentration curves and calculated a concentration index for each indicator with respect to zip code–level racial/ethnic makeup and the percentage of the population living in poverty, similar to the method of Su et al.[31] (Figure 3). We constructed the concentration curve by ordering all zip codes across the x-axis from lowest to highest in terms of the percentage of the population that is either non-Hispanic White or living above twice the federal poverty line according to the US Census Bureau's American Community Survey 2007–2011 5-year estimates. We classified multiracial individuals and Hispanic individuals of any race as non-White. The cumulative proportion of the pollution indicator is graphed on the y-axis. If an indicator is perfectly evenly distributed, the line will equal a diagonal that crosses the origin. Curves above the equality line indicate a regressive distribution (zip codes with a higher percentage of residents of color or poor residents shoulder a disproportionate burden of the environmental hazard), whereas curves below the line indicate an unequal distribution in which more advantaged (higher percentage White or wealthy) zip codes are more burdened.

We calculated a standard concentration index proportional to the area between the concentration curve and the diagonal line of equality as follows:

$$(1)\quad C = \frac{2}{n \times \mu} \sum_{i=1}^{n} x_i R_i - 1,$$

where n is the sample size, x_i is the indicator of pollution burden for each zip code i, μ is the mean of the pollution burden indicator, and R_i is the fractional rank in percentage White or percentage not poor of the ith zip code from least ($i = 1$) to most ($i = n$) disadvantaged.[32] The index ranges from −1 to 1, with zero indicating equality; negative (positive) values indicate that the environmental hazard disproportionately affects less (more) advantaged communities. The magnitude of C reflects both the strength of the relationship between socioeconomic status and pollution burden and the degree of variability in the pollution variable. We used the SE of C, also given by Kakwani et al.,[32] to test the null hypothesis that $C = 0$.

Finally, we considered the sensitivity of our results to the removal of any 1 indicator from the CalEnviroScreen model and an additive model in which we summed rather than multiplied the pollution burden and population vulnerability scores. We focused on changes within the decile of zip codes with the highest cumulative impact score (hereafter "most affected 10%") because we are primarily concerned with consistently identifying the



Note. PM = particulate matter. The concentration curves show the degree of inequality in the distribution of indicators of pollution burden across California zip codes with respect to their racial/ethnic makeup (% non-Hispanic White) and wealth (% above twice the federal poverty line). Curves in the white area above the equality line indicate that communities of color or poor communities host a disproportionate amount of the environmental hazards. Curves in the gray area below the equality line indicate that more privileged (more White or wealthy) communities are disproportionately burdened. The point indicated by the arrow illustrates that the 60% of zip codes with the highest proportion of residents of color host > 95% of agricultural pesticide use in the state. We used a concentration index proportional to the area between the concentration curve and the diagonal line of equality to assess the statistical significance of departures from equality. No hazard disproportionately burdens zip codes with a higher proportion of White or wealthy residents at $P < .05$.

[a]Zip codes with a higher proportion of residents of color are disproportionately burdened ($P < .05$).

[b]Zip codes with a higher proportion of residents living in poverty are disproportionately burdened ($P < .05$).

FIGURE 3—Concentration curves illustrating the distribution of pollution indicators with regard to community (a) racial/ethnic makeup and (b) poverty: CalEnviroScreen 1.1, California, 2013.

most affected communities. We used the inverse-rank measure to compare the rankings generated by the alternate models. The inverse-rank measure provides a quantitative measure of the degree of similarity between ordered sets that do not necessarily share all elements.[33] It has been used to compare the results of Internet search engines, and this is, to our knowledge, a novel application of this measure.

The inverse-rank measure considers both the elements that comprise the set and how they are ordered and ranges from zero (no zip codes in set A are contained in set B) to 1 (the same zip codes are in both sets, and they are ordered identically). Changes in rank that occur near the top of the set (e.g., the 2% highest scoring communities) are given more weight than are changes in rank near the bottom of the set (e.g., the highest 8%–10% of communities) to, again, pay particular attention to our ability to consistently identify the most affected communities. We also compared the robustness of our findings regarding the distribution of cumulative impact score by race/ethnicity with the model structure (multiplicative vs additive).

RESULTS

Ten of California's 1769 zip codes did not have a resident population in the 2010 Census and we excluded them from the analysis, leaving a sample size of 1759. Zip codes varied greatly in area (0.01–1394.98 square miles) and population (1–105 549). Data sources and descriptive statistics for the 17 indicators constituting the CalEnviroScreen model are given in Table 1. Several indicators had a highly right-skewed distribution, many zeroes, or both. The percentage of the population living below twice the federal poverty level exhibits a bimodal distribution (peaks near 20% and 40%; data not shown), possibly indicating residential income segregation at the zip code level. The raw indicator values, percentiles, and cumulative impact scores generated by CalEnviroScreen are publicly available in both spreadsheet and geospatial file formats.[34]

We found an uneven geographic distribution of the highest cumulative impact scores across the state. The San Joaquin Valley and Southern California (particularly the Greater Los Angeles area) had the greatest proportion of communities ranking among the most affected 10% statewide (data available as a supplement to the online version of this article at http://www.ajph.org). Northern California, Sacramento, the San Francisco Bay Area, and San Diego were home to a smaller proportion of these most affected communities, whereas no such communities were found in the Eastern Sierra and Central Coast regions.

The cumulative impact score was positively correlated with population density (Spearman correlation coefficient = 0.48; $P < .001$) and negatively correlated with the percentage of residents living in unincorporated communities (Spearman correlation coefficient = –0.21; $P < .001$), suggesting that urban areas tend to be more highly affected.

The median cumulative impact score was 75% higher for Hispanics and 67% higher for African Americans than it was for non-Hispanic Whites, for whom the average score was lowest (Figure 2). This pattern was driven jointly by the pollution burden and the population vulnerability scores, which were both higher for Hispanics and African Americans than for other groups. Native Americans had the third highest median population vulnerability score but a lower median pollution burden score than did other groups (data not shown). Asian/Pacific Islanders had the third highest median pollution burden score but lower median population vulnerability scores than did Hispanics, African Americans, and Native Americans (data not shown). Using an additive rather than a multiplicative model attenuated the percentage differences in the median cumulative impact score relative to Whites by about half but did not change the ordering of racial/ethnic groups with respect to average cumulative impact score (data not shown).

The unadjusted odds of living in one of the 10% most affected communities was higher for all non-White groups than Whites (Hispanics: unadjusted odds ratio [OR] = 6.15; 95% confidence interval [CI] = 6.14, 6.17; African Americans: OR = 5.75; CI = 5.73, 5.77; Native Americans: OR = 1.94; CI = 1.92, 1.94; Asian/Pacific Islanders: OR = 1.83; CI = 1.83, 1.84; other or multiracial: OR = 1.63; CI = 1.62, 1.64). ORs decreased slightly when we adjusted for population density (Hispanics: OR = 5.8; CI = 5.5, 6.1; African Americans: OR = 5.2; CI = 4.7, 5.7; Native Americans: OR = 1.8; CI = 1.2, 2.6; Asian/Pacific Islanders: OR = 1.7; CI = 1.6, 1.9; other or multiracial: OR = 1.6; CI = 1.4, 1.9).

Concentration curves illustrating the distribution of pollution indicators with regard to community racial/ethnic makeup and poverty are presented in Figure 3. Concentration indices and their 95% CIs suggested that all indicators except particulate matter (PM) 2.5 exhibit a statistically significant regressive distribution with respect to race/ethnicity ($P < .05$; data available as a supplement to the online version of this article at http://www.ajph.org). Pesticide use and toxic chemical releases were the most regressively distributed with respect to race/ethnicity, closely followed by cleanup sites, hazardous waste, and diesel PM. Pesticide use, ozone, cleanup sites, solid waste, and diesel PM were also regressively distributed with respect to poverty at $P < .05$. No pollution indicators disproportionately burdened White or wealthy zip codes at $P < .05$.

The results of the sensitivity analysis suggest that the rankings generated by CalEnviroScreen are most sensitive to the pesticide use, ozone, toxic releases, and low birth weight indicators (data available as a supplement to the online version of this article at http://www.ajph.org). Among the 176 zip codes originally identified as the most affected 10%, 7 to 27 fell below this benchmark when we removed 1 indicator from the model. Using an additive rather than a multiplicative model resulted in 11 changes within this group of zip codes. All the communities that we no longer identified as among the most affected 10% using the additive model were still among the most affected 15%.

DISCUSSION

We have presented a screening tool that produces a relative cumulative impact score that can be used to rank communities in California with regard to their potential for cumulative environmental health impacts. The tool does not quantify the probability of harm or health risk. Instead, it identifies communities that warrant further attention and can help policymakers and decision makers prioritize their activities to the benefit of communities disproportionately burdened by multiple environmental health hazards. It can and should be tailored to specific uses by modifying the geographic units of analysis; adding, removing, or improving specific indicators; or updating the indicators with subsequent years of data to track progress toward environmental justice goals.

We found that the potential for cumulative environmental health impacts varies across regions of California, with the Greater Los Angeles area and San Joaquin Valley being most heavily affected. We also observed significant inequality in the distribution of pollution and population vulnerability indicators within regions. Although useful for state-level agencies and decision making, the statewide relative ranking produced by CalEnviroScreen may not be as informative about inequalities within regions, in part because some indicators included in the model are less relevant in some regions than in others. Performing regional rankings may be another way to inform regional authorities about disproportionately affected areas within their jurisdiction.

The correlation we found between cumulative impact score and population density is consistent with the presence of many pollution sources, such as vehicles, in urban areas. It may also indicate that CalEnviroScreen 1.1 does not adequately capture unique exposure pathways and vulnerabilities associated with rural living. The choice of indicators is limited by the availability of comprehensive, statewide monitoring and data gaps that are particularly a problem in rural areas. Disparities in water quality by ethnicity have been observed in small drinking water systems, particularly in rural California,[6] and a drinking water quality indicator has been incorporated into a more recent iteration of CalEnviroScreen.[27]

We found a strong disparity in the cumulative impact score with regard to community racial/ethnic makeup, with all non-White groups (and Hispanics and African Americans in particular) being disproportionately affected. The fact that people of color are more likely to live in more densely populated communities did not explain the disparity: controlling for population density only slightly decreased the odds of living in one of the most affected 10% of communities relative to Whites. The results were also qualitatively robust to the choice of model structure. Using an additive rather than a multiplicative model changed the unadjusted ORs by less than 5% for all groups. Although the percentage differences in median cumulative impact scores were significantly smaller (about half) using an additive model, substantial differences between racial/ethnic groups remained and their order relative to Whites did not change.

The concentration indices further revealed that disparities in pollution burden were generally greater with respect to race/ethnicity than they were with respect to poverty (data available as a supplement to the online version of this article at http://www.ajph.org). This finding is consistent with the results of a meta-analysis of 49 environmental equity studies from the United States that concluded that the evidence of class-based inequalities was less consistent than was the evidence of race-based inequalities.[35] Nevertheless, we still found statistically significant evidence that pesticide use, concentrations of ozone and diesel PM, and cleanup and solid waste sites in California are disproportionately located in communities with higher levels of poverty.

The concentration indices also suggest that some pollution sources are more unequally distributed with regard to race/ethnicity than are others, namely pesticide use, toxic releases from industry, cleanup sites, hazardous waste, and diesel PM. We caution that these indices are metrics of relative difference and do not give an indication of the health risk posed by any single hazard in absolute terms. Although useful as a starting point, more research on the degree of risk posed by each hazard is needed to prioritize action to reduce environmental health disparities. The percentage of the environmental indicator that would need to be linearly redistributed from the less advantaged to the more advantaged half of the zip codes to arrive at an equal distribution (index of zero) can be calculated by multiplying the concentration index by 75.[36] Using this property to provide another perspective on the degree of inequality, approximately a third of the most regressively distributed pollution variables would need to be transferred from the communities with higher than average proportions of people of color to those with less to achieve a perfectly even distribution.

The sensitivity analysis suggested that the CalEnviroScreen model is relatively robust to changes associated with the removal of any single indicator. Nonetheless, changes to which zip codes we identified as the 10% most affected communities were substantial enough to suggest that each indicator makes a unique contribution to our measure of cumulative impact. The inverse-rank measure we used may be useful for comparing the results of our findings with those of other environmental justice screening tools.

As with any geographic analysis using discrete areas, our results are sensitive to the choice of geographic boundaries (the "modifiable areal unit problem"[37]). Others have found that the strength and even the direction of the association between race, income, and the location of environmental hazards can change with the geographic scale of the analysis.[38] Zip codes vary widely in terms of area and population size, and visual examination shows that some zip codes encompass distinct communities that differ greatly in terms of socioeconomic status. However, preliminary analysis of a newer version of CalEnviroScreen using census tract geography[27] suggests that the strength of the associations between race/ethnicity and cumulative impact persists with the move to a smaller geographic unit of analysis.

Together, our results provide evidence of significant racial/ethnic inequalities in residential proximity to multiple environmental health hazards in California. CalEnviroScreen is a screening tool that can be used to help guide regulatory, enforcement, and other efforts to reduce cumulative environmental health burdens in disproportionately affected communities. Specific indicators included in CalEnviroScreen may have various levels of relevance depending on the policy and jurisdictional context in which it is applied, and the underlying data were made publicly available to allow users to tailor the tool for different applications. Future research is needed to improve methods for addressing the sensitivity of environmental justice screening tools to the geographic unit of analysis; inform the approach to relative scoring, including the way variables are standardized, weighted, and combined; and, most importantly, identify specific ways that cumulative impact assessment can be most effectively used to reduce environmental inequalities. ■

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Contributors

L. Cushing conducted statistical analyses, wrote the article, and prepared the figures. L. Cushing, L. M. August, R. Cendak, and W. Wieland conducted the analysis that created the indicators. J. Faust and G. Alexeeff planned and supervised the development of CalEnviroScreen. R. Cendak conducted the sensitivity analysis using the inverse-rank measure. All authors interpreted the results and reviewed drafts of the article.

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Note. This publication has not been formally reviewed by the EPA, and the views expressed in it are solely those of the authors. The EPA does not endorse any products or commercial services mentioned in this publication.

Human Participant Protection

This study did not require protocol approval because we used only de-identified and aggregate data, which we obtained from secondary sources.

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