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Research article

Do social vulnerability indices correlate with extreme heat health outcomes?

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ABSTRACT

Introduction. Several frameworks exist to measure vulnerability to extreme heat events using a health equity approach, but little evidence validates these measures and their applications. We investigated the degree to which social vulnerability measures and their constituent elements correlate with excess emergency room visits as an outcome measure. Methods. The relationship between six commonly used social vulnerability indicators and measured excess emergency room visit rates (processed by including heat-related illnesses and all-internal causes diagnosis, with considerations for age and heat days) was tested through geospatial analytics and statistical regressions, for both California and Los Angeles County. Results. The vulnerability indicators and the outcome measure were significantly positively associated at the census tract-level but weaker ($\sim$0.2 r_s) at the scale of California and stronger ($\sim$0.6 r_s) at the scale of Los Angeles County. Hazard-specific vulnerability indicators showed stronger relationships with outcome measures regardless of scale. A Poisson regression model showed a significant inter-county variation, indicating the importance of localized assessments for equitable environmental policies. Conclusion. The findings identify communities that are overburdened by heat and pollution and highlight the need for use of both social vulnerability and indicators of adverse outcomes from excessive heat. Patterns are found across all measures that suggest that populations facing accessibility barriers may be less likely to visit emergency rooms. This suggestion needs to be tested in other environmental settings to draw broader conclusions but has direct implications for environmental scientists and mitigation planners who use these methods.

1. Introduction

Heat causes more deaths than other weather-related hazards, although these could be reduced by up to 25% with effective mitigation [1]. In addition to heat waves, which are becoming more intense, more frequent, and of longer duration, average temperatures are expected to rise, particularly in urban areas because of the urban heat island effect, increasingly affecting residents of densely populated cities [2]. Impacts of heat events include hyperthermia, heat cramps, heat exhaustion, heat stroke, respiratory problems, worsened chronic conditions (e.g., cardiovascular disease), and increased mortality [3,4]. Even though most people can adapt to incremental increases in average temperatures, some susceptible groups may still suffer adverse effects [5], and adaptation can only occur to a certain degree.

Heat disproportionately harms some of the most vulnerable community members [6]. Several categories of people have been identified as being at a higher risk for heat-related health impacts [7,8]: children and infants [9]; age groups of 65 years and over [10]; socially isolated individuals, or from low-income populations [11]; residents of nursing homes, care facilities, or prisons without appropriate cooling measures [12,13]; persons living with chronic conditions such as disabilities, cardiovascular, pulmonary, or kidney and liver diseases, diabetes, or obesity [14–16]; pregnant women and their fetuses [17]; persons living with mental health issues [18]; persons of various races/ethnicities, which can be proxies for socioeconomic status, differential exposure and health treatment, and access to health care; those who have language barriers [19,20]; or persons that are homeless [21]. Individuals with occupational exposure, exemplified by the need to wear personal protective equipment [22], outdoor or agricultural workers [23,6], and workers in manufacturing locations without temperature control systems [24] are also susceptible to extreme heat.

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In a broader social-ecological system, socioeconomic factors such as income have shown stronger associations with heat exposure at home [25] due to the cost of air conditioning or other housing characteristics. Hence, a combination of socioeconomic and environmental factors together can represent heat exposure and vulnerability. Heat-related vulnerabilities have also been assessed in measurement schemes [26,27], and applied in a few cases like Atlanta, Georgia [28], Maricopa, Arizona [29], San Antonio, Texas [30], Georgia [31], and Massachusetts [32], although more studies are needed to show the effectiveness and use of these indicators. The “hazard of place” model identifies elements of hazard exposure in combination with underlying vulnerabilities to describe the risk level [33], which motivates this study to test the relationship between vulnerability indicators.

Interest in validating social vulnerability indicators (e.g., SoVI, SVI) and their ability to explain disaster event outcomes (e.g., losses) [34–36] has been growing. The challenges of measuring heat-event outcomes in terms of loss (financial and non-financial) adds to the complexities of validating vulnerability measures. Uejio et al. [37] applied mixed models to study heat mortality and distress calls by accounting for vegetation, temperatures, socioeconomic variables and neighborhood stability in Philadelphia, PA, and Phoenix, AZ. Similarly, Reid et al. [38] applied their Heat Vulnerability Index in metropolitan areas (in five U.S. states) and assessed the hospitalization and mortality counts in high-heat days using a Poisson regression, which showed strong associations, but predicted higher vulnerability than what was observed in some areas. Also, Chuang and Gober [39] used hospitalization records in Phoenix, AZ, to test the accuracy of their Heat Vulnerability Index.

California is the most populous state in the U.S. with a diverse population that is experiencing more frequent and intense heat waves with longer durations [40]. Model projections predict that more humid nighttime conditions and a lack of acclimatization in coastal populations will continue to exacerbate the impacts [41]. Individual variables of income and ethnicity have been tested in relation to heat exposure in California, which showed urban regions experience disparities in temperatures between the wealthiest and poorest neighborhoods [42]. The multi-dimensional construct of social vulnerability can identify influences of other socioeconomic factors in this context and several indices have been produced for vulnerability assessments in California. The state has developed several adaptation plans that use these indicators, to help target programs and funding in high-risk areas [43]. In this study, we evaluated whether vulnerability metrics for California can explain the reported heat-related excess emergency room visit pattern changes during heat events and whether the scale of the analysis influences the results. We also tested the associations across individual variables that contribute to the vulnerability indicators as well. Our goal was to help scientists and policymakers interested in mapping vulnerability indices and outcome measures prioritize neighborhoods for heat adaptation and response programs.

2. Material and methods

2.1. Vulnerability indicators

Social vulnerability as a concept is multi-dimensional and the spatial distribution of its place-based measurements can show the contributing factors to the abilities of communities to respond to hazard events. The “vulnerability of place” is tested through the indicators presented in previous studies and adopted plans as contributors to heat-related health impacts. The selected indicators from the commonly used sources in California (Appendix A) include several variables and methodologies:

1) *CalEnviroScreen* (CES) 4.0 is the California Communities Environmental Health Screening tool developed in 2021, released by the California Office of Environmental Health Hazard Assessment (OEHHA), which is a part of the California Environmental Protection Agency (CalEPA) [44]. CalEnviroScreen considers cumulative impacts, is place-based, and includes 36 indicators of public health, environmental, and socioeconomic conditions. The CalEnviroScreen Score is the result of average exposure and environmental effects that consider sensitive populations and socioeconomic factors [44]. The timeframe for each variable is different but covers 2009 to 2019 and data are updated as newer versions are released.
2) The *California Healthy Places Index* (HPI) is developed by the Public Health Alliance of Southern California in partnership with the UCLA Luskin Center for Innovation. The HPI applies a positive frame, includes indicators of socioeconomic conditions in addition to the environmental factors, and the HPI score combines 25 characteristics into a single score [45].
3) The *Climate Change & Health Vulnerability Indicators for California* (CCHVIs) is produced by the Climate Change and Health Equity Section of the California Building Resilience Against Climate Effects (CalBRACE) Project that is part of the California Department of Public Health. The CCHVIs is a database, which does not include a composite score [46], and each variable has a different timeframe from 2010 to 2019.
4) The development of *California Heat Assessment Tool* (CHAT) was funded by the California Natural Resources Agency as part of the California’s Fourth Climate Change Assessment and evaluations were conducted by a partnership of institutes [47]. The Heat Health Action Index is a statistically weighted result of indicators in three categories of social vulnerability, health, and environment, which range from 0 to 100. The data for each variable comes from different timeframes, from 1984 for historical records to 2050 for projected models.
5) The *Social Vulnerability Index* (SoVI®) using 5-year estimates for 2017 Census data. The SoVI measurement is a multi-dimensional construct [33] that follows a Principal Component Analysis (PCA) of normalized indicators (by z-scores) with varimax rotation. The raw data from the American Community Survey (ACS) 2017 5-year estimates at census tract-level were processed to run the SoVI model separately for California and for Los Angeles County. The SoVI model for California has seven factors explaining 68% of the variation in input variables (Appendix D), and the model for Los Angeles County has eight factors that explain 72% of the variation in input PCA variables [48].
6) *Social Vulnerability Index* (CDC’s SVI) by the Centers for Disease Control and Prevention (CDC), using data from the ACS, ranks census tracts on 16 social factors and groups them into four themes of socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation [49]. The SVI score is the sum of all 16 variables. The data used for this study is for year 2018.
7) The study area of Los Angeles County includes one additional measure of vulnerability, which is the *Social Sensitivity Scores* from the Los Angeles County Chief Sustainability Office published in 2021 with most recent data [50].

2.2. Excess emergency room visits

Excess emergency room visits rates are used as an outcome measure of heat-related adverse health effects to gage the relationship between vulnerability indicators and the resulting outcomes and test the level of predictability of these indices. Our study duration for data used is truncated to only capture the timeline before the COVID-19 pandemic (due to comorbidities). The data for emergency room visits were obtained from the California Department of Health Care Access and Information and analyzed to include diagnoses codes for emergency room visits due to heat-related illnesses and all-internal causes that are known to be exacerbated during heat events (up to 25

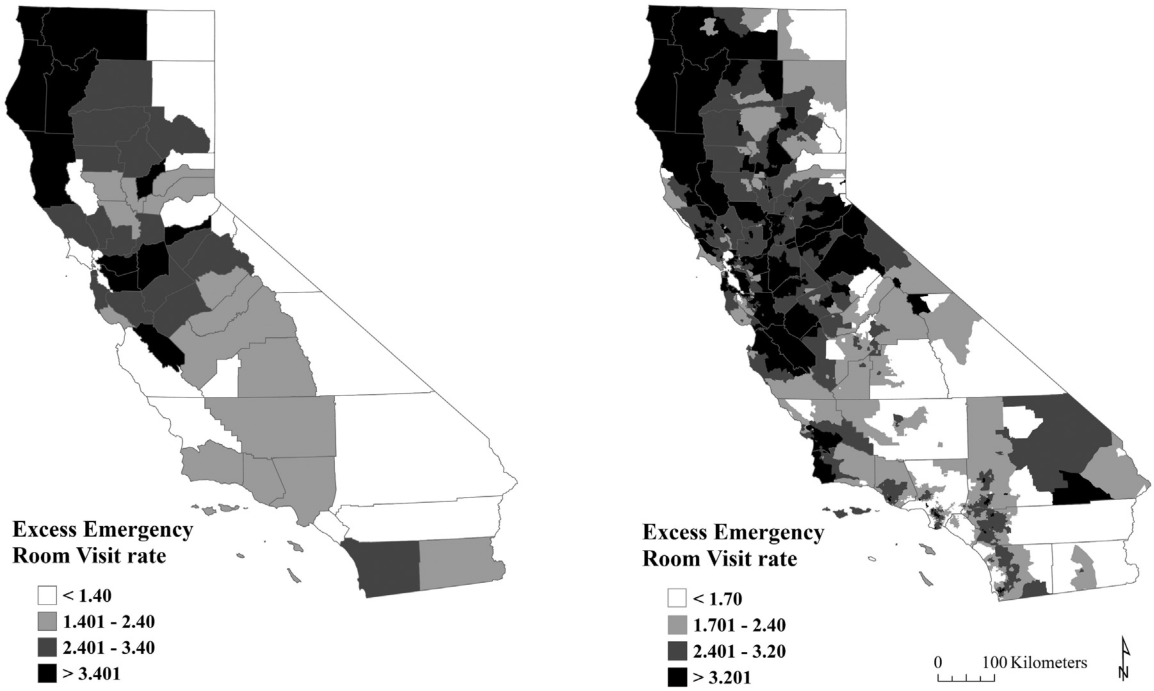

Fig. 1. Quantiles of excess emergency room visit rates across California at County scale (left) and Census tract scale (right).

diagnoses for each emergency room record) [51]. The analysis also considers age and heat event days during the meteorological summer and a lag of three days for each area (heat event days were defined using the Spatial Synoptic Classification (SSC) system version 3 that is adopted in climate and human health studies [23], and the SSC stations included were 67 in California and 13 in neighboring states of Oregon, Nevada, and Arizona) [51]. The produced data for excess emergency room visits are available at county and sub-county levels (Fig. 1) [51]. The excess daily emergency room visit rate corresponds to the number of excess emergency room visits per day per 10,000 persons in heat event days versus non-heat event days in that area (each rate was calculated separately for heat and non-heat event days then were age-adjusted, and finally subtracted to obtain the excess daily visit rates), which is computed for 2009 to 2018 (Using diagnoses ICD-9 codes of E900 or 992: "electrolyte imbalance (276); cardiovascular disease (390–398, 401–429, 430–438, 440–459); respiratory illness (460–519); acute kidney failure and chronic kidney disease (584–586); disease of urinary system (580–599); diabetes mellitus (250); dehydration (276.5) and disorders of fluid, electrolyte and acid-base balance (276)", for 2009–2016, and ICD-10 codes of X30 or T67: "cardiovascular (I00–I99); respiratory (J00–J99); acute kidney failure and chronic kidney disease (N17–N19); Disease of urinary system (N00–N39); diabetes (E08–E13); dehydration (E86); and disorders of fluid, electrolyte, and acid-base balance (E87)", for 2016–2018) [51].

2.3. Analysis

The scale of analysis, according to data constraints, are county and census tracts (counties are the primary spatial unit for operational levels of emergency management and public health in the US, and census tracts are their finer-spatial units for a stable presentation of data). The vulnerability indicators are available at the census tract level, and the zip code boundaries do not match with the tract boundaries, thus we obtained excess emergency room visits data at the tract level by extracting the average, minimum, maximum, and variance of the zip code level data that covers each tract in ArcGIS Pro-using Python. We calculated the Spearman's correlation between all vulnerability indicators and excess emergency room visit rates. For cross-comparisons, the variables are all standardized by converting them into percentiles, and for classifications of variables we have used the standard deviation from the mean (i.e., class 1< *mean - 0.5 Std.Dev.*; *mean - 0.5 Std.Dev.* < class 2 < *mean + 0.5 Std.*Dev.; and class 3> *mean + 0.5 Std.Dev.*).

To answer the question regarding variation of associations across California, we applied three methods of geospatial mapping through bivariate maps, a geographically weighted regression (GWR), and a Poisson log-linear regression model for vulnerability indicators and counties, in relation to the excess emergency room visit rates, which follow the model of:

$$\begin{aligned}\mathbf{L}og(\text{Excess emergency room visitrates}) &= \alpha + \beta_1(\text{Vulnerability indicator}) + \beta_2(\text{County})_1 \\ &\quad + \beta_3(\text{County})_2 \\ &\quad + \ldots + \beta_{i+1}(\text{County})_i\end{aligned}$$

Where α is the intercept, and β is the coefficient for vulnerability indicator, and each of the counties (i = 58).

For cross-comparison, the high and low classes of vulnerability indicators and the related classes of high and low excess emergency room visit rates are analyzed by concordant pairs (i.e., high-high, or low-low) or discordant pairs (i.e., high-low or low-high) to identify overlaps in classifications. Finally, to test the influence of individual indicators on the observed excess emergency room visit rates, the extremes of high and low rates are compared using an independent samples *t*-test. The highest and lowest rate groups were selected using two standard deviations from the mean (i.e., $\pm$*1.5 Std.Dev.*), which is approximately the same as the 1% top and 1% bottom (80 census tracts—high and low—for California). Analyses were performed in RStudio, SPSS, JMP, GeoDa, and ArcGIS Pro.

3. Results

3.1. Geographical patterns

The visual comparison of the spatial distribution of the excess emergency room visits rates and the vulnerability scores in bivariate maps indicate a similar pattern of association across the measurement

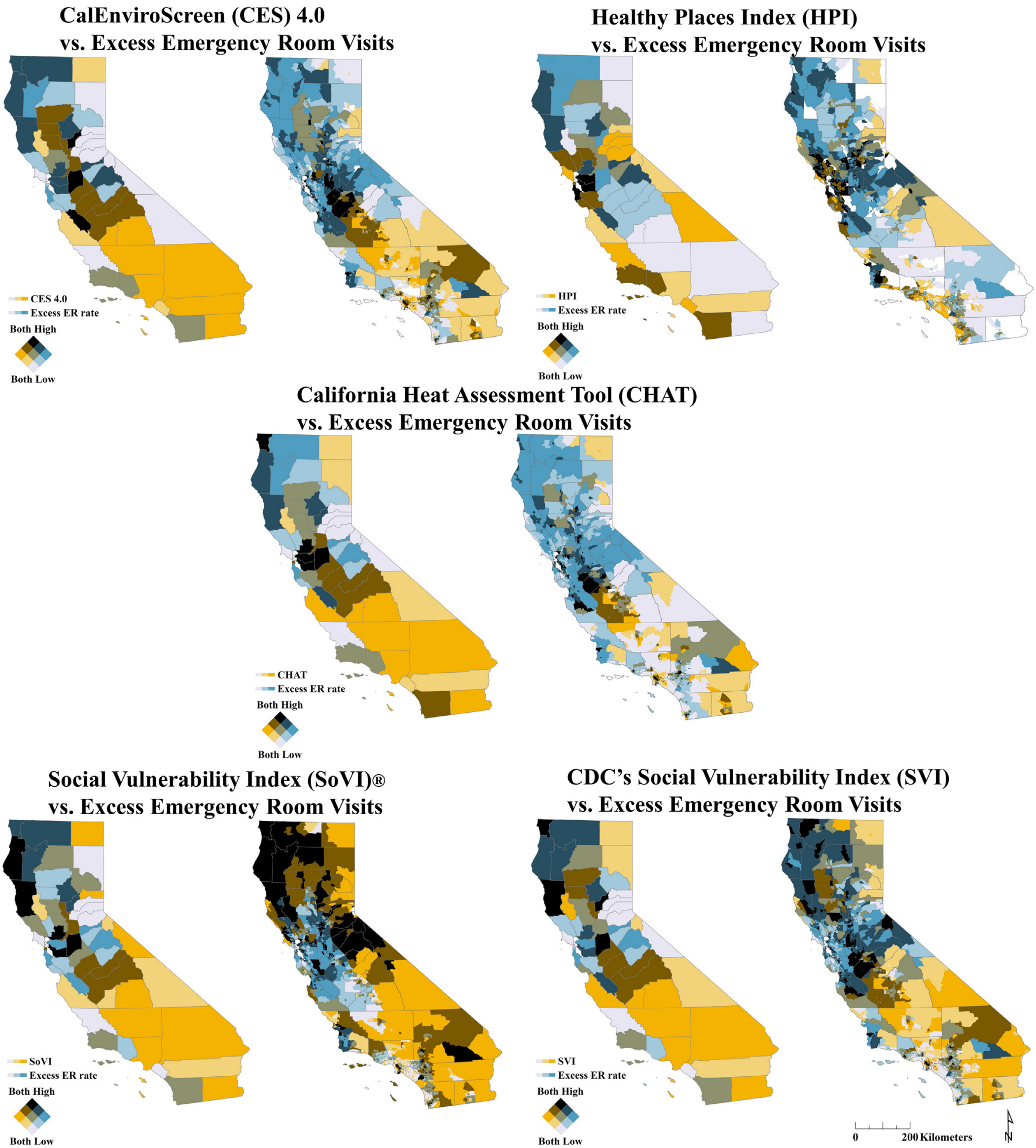

Fig. 2. Bivariate maps of quantiles of five different vulnerability indicators and excess emergency room visit rates at county and census tract scales.

schemes (Fig. 2). A concentration of high vulnerability and higher emergency room visit rates is seen in Del Norte, Yuba, Mendocino, San Benito, San Joaquin, Solano, and Alameda counties, while in Southern California a pattern of lower emergency room visits, and high vulnerability is observed. As expected, the patterns show higher variation by census tracts, where a concentration of higher emergency room visits and higher vulnerability follows an urban-rural pattern with concentration around Merced and Stanislaus counties, San Fernando Valley, and south-central Los Angeles County, western Riverside and San Bernardino counties, and central Monterey County.

3.2. County-Scale analysis

There are no strong correlations between the composite vulnerability scores and the rate of excess emergency room visits at the county scale for California (Table 1). The CCHVI method does not include a composite score and among their variables, the correlation is moderately significant and negative for the excess emergency room visit rate and tree canopy coverage ($r_s = -0.31$, $p < 0.05$), projected number of extreme heat days ($r_s = -0.3$, $p < 0.01$), and percent population without health insurance ($r_s = -0.28$, $p < 0.05$) as is also

Table 1
Correlation results for the county-scale measurements.

Indicator	County Daily excess rate of ER visit	
	Spearman's rho	Sig. (2-tailed)
CalEnviroScreen (CES) 4.0	0.124	0.353
Healthy Places Index (HPI)	0.012	0.928
CCHVIz		
Mean Tree Canopy	−0.308*	0.019
Projected Number Extreme heat 2040 −2060	−0.372**	0.004
Projected Number Extreme heat 2080 −2099	−0.337**	0.010
Percent Population without Health Insurance 2011−2015	−0.284*	0.030
Percent Population Age Below 5, 2011 −2015	0.076	0.571
Percent Pop Age 65 and more, 2011 −2015	0.014	0.918
Percent Without Car 2011−2015	0.252	0.056
Percent Not speaking English 2011−2015	−0.105	0.433
Percent Less than College Education 2011 −2015	−0.023	0.862
Particulate Matter (PM) 2.5, 2012−2014	−0.008	0.954
No Air Conditioning 2009	−0.153	0.251
CHAT Heat health index	0.058	0.665
Social Vulnerability Index (SoVI®)	−0.098	0.463
Factor 1 – Hispanic, education, linguistic isolation	−0.183	0.169
Factor 2 – Poverty, unemployment, mobile home	0.118	0.379
Factor 3 – Race (African American)	−0.072	0.594
Factor 4 – Nursing House Residents	−0.038	0.776
Factor 5 – No Health insurance, Race (Native American)	−0.382**	0.003
Factor 6 – Female	0.108	0.418
Factor 7 – No automobile access	0.277**	0.035
CDC's SVI Score	0.035	0.796
SVI Theme 1 – socioeconomic	0.008	0.952
SVI Theme 2 – Household composition/ disability	0.246	0.063
SVI Theme 3 – Minority status/language	−0.119	0.375
SVI Theme 4 – Housing type/ transportation	0.027	0.839

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

reflected in Factor 5 of SoVI® (r_s = −0.38, $p < 0.01$) (Table 1). The difference between the vulnerability scores for the counties with the highest and lowest excess emergency room visit rates is not significant.

3.3. Census tract-scale analysis

The average excess emergency room visit rates for California at the scale of census tracts have a significant but weak relationship with vulnerability scores (Table 2a, Fig. 3a), where the strongest association is with CHAT (r_s = 0.26, $p < 0.01$), followed by CDC's SVI (r_s = 0.23, $p < 0.01$) and SoVI (r_s = 0.2, $p < 0.01$). The highest vulnerability score class shows a higher average of excess emergency room visits for the CHAT and SoVI indicators (Fig. 3). The relationship for the CCHVI's indicators and the excess emergency room visit rates are also weak but significant. The top 10 census tracts with the highest rate of heat-related excess emergency room visits are from Los Angeles, Monterey, and El Dorado counties, while the lowest rates are from San Francisco, Nevada, Placer, San Diego, and Siskiyou Counties. The independent samples t-test for the highest and lowest rates, only indicates a significant difference for SVI's theme 4 (i.e., housing type and transportation) (t = 4.31, $p < 0.001$), CHAT (t = 3.6, $p < 0.005$), and CES (t = 3.79, $p < 0.001$).

Table 2
Correlation results (Spearman's rho) for the census tract-scale measurements for a) California and b) Los Angeles County study areas.

Indicator	Zipcode Daily excess ER visit rate				
	Avg	Min	Max	Var	Std.Dev.
a) CALIFORNIA					
CalEnviroScreen (CES) 4.0 score	.149**	.192**	.113**	−0.033**	−0.033**
Healthy Places Index (HPI)	−0.140**	−0.150**	−0.117**	.032**	.032**
Cal-heat.org (CHAT) Heat health action index	.265**	.337**	.194**	−0.075**	−0.075**
SoVI® score	.203**	.123**	.225**	.130**	.130**
Factor 1 – Poverty, Education, Hispanic	.239**	.283**	.192**	−0.049**	−0.049**
Factor 2 – Dependence and Age (elderly)	−0.006	−0.080**	.043**	.119**	.119**
Factor 3 – No automobile access, Renters	.043**	.030**	.037**	.009	.009
Factor 4 – Race (African American), Female	−0.098**	−0.098**	−0.084**	−0.031**	−0.031**
Factor 5 – Race (Native American)	.001	.097**	−0.055**	−0.109**	−0.109**
Factor 6 – Population density	.054**	.031**	.059**	.059**	.059**
Factor 7 – Nursing home residents, Race (Asian)	.064**	.012	.090**	.064**	.064**
CDC's SVI score	.234**	.266**	.192**	−0.028*	−0.028*
SVI Theme1 – socioeconomic	.201**	.224**	.165**	−0.032**	−0.032**
SVI Theme2 – Household composition/disability	.238**	.230**	.225**	.039**	.039**
SVI Theme3 – Minority status /language	.128**	.217**	.063**	−0.102**	−0.102**
SVI Theme4 – Housing type /transportation	.170**	.172**	.150**	.011	.011
b) LOS ANGELES COUNTY					
CalEnviroScreen (CES) 4.0	.637**	.641**	.566**	−0.012	−0.012
Healthy Places Index (HPI)	−0.587**	−0.606**	−0.504**	.070**	.070**
Cal-heat.org (CHAT) Heat health action index	.601**	.625**	.511**	−0.084**	−0.084**
SoVI® score	.449**	.392**	.441**	.109**	.109**
Factor 1 – Poverty, Hispanic, Education	.555**	.615**	.457**	−0.090**	−0.090**
Factor 2 – No automobile access, Renters	.045**	−0.006	.061**	0.018	0.018
Factor 3 – Dependence and Age (Elderly)	−0.048**	−0.075**	−0.010	.086**	.086**
Factor 4 – Female	0.015	−0.007	.035	.066**	.066**
Factor 5 – Race (African American, not-Asian)	.412**	.377**	.393**	0.027	0.027
Factor 6 – Mobile home residents	−0.046*	−0.051*	−0.040	.009	.009
Factor 7 – Race (Native American)	−0.008	−0.002	−0.013	−0.048*	−0.048*
Factor 8 – Population density	.086**	.029	.115**	.112**	.112**
CDC's SVI score	.556**	.583**	.475**	−0.061**	−0.061**

(continued)

Table 2 (*Continued*)

Indicator	Zipcode Daily excess ER visit rate				
	Avg	Min	Max	Var	Std.Dev.
Theme1 – socioeconomic	.576**	.596**	.492**	−0.059**	−0.059**
Theme2 – Household composition/ disability	.435**	.452**	.388**	−0.015	−0.015
Theme3 – Minority status / language	.444**	.498**	.360**	−0.092**	−0.092**
Theme4 – Housing type / transportation	.300**	.293**	.260**	−0.020	−0.020
LA County Sensitivity Score	.379**	.440**	.299**	−0.124**	−0.124**

3.4. Regression

The Poisson log-linear regression model for excess emergency room visit rates by each vulnerability score and county (using census tract data) shows variations across counties but a rather similar pattern across vulnerability scores (Appendix B). The results show the relationship is dependent on the location and local measures would be more predictive. The GWR results were not significant (R^2=0.001).

3.5. Individual indicators

Testing the individual indicators that are used to construct the vulnerability scores, shows variations in their associations with the outcome measure of excess emergency room visit rates. The individual indicators are tested for the two groups at the top and the bottom 1 % of census tracts, ranked by the average excess emergency room visit rates, in an independent sample *t*-test comparison of means (Appendix C). Individual indicators like lead pollution, asthma, cardiovascular disease, poverty,% households without a car, and % households without air conditioning have a significant difference between the two groups with a large effect (i.e., Cohen's *d*> 0.8) and a positive t-value referring to their impact in higher emergency room visit rates. A number of other indicators have a significant difference and large effect size (i.e., Cohen's *d*> 0.8) with a negative t-value, suggesting an inverse relationship with the higher emergency room visit rates, which include average ozone concentration (ppm),% elderly,% White, homeownership, per capita income, and no transit access. Some other indicators, with smaller effect sizes (Cohen's *d*< 0.6), do show a significant difference, like housing burden, unemployment, linguistic isolation, less college education, %Hispanic, %African American, %Asian, and pollution burden.

3.6. Los Angeles county

Vulnerability indicators associated with the excess emergency room visits in Los Angeles County show a stronger relationship than across all tracts in California (Table 2b, Fig. 3b). This is even more pronounced in South-Central Los Angeles and San Fernando Valley (Fig. 4). There are more concordant pairs than discordant pairs of vulnerability indicators and excess emergency room visit rates (i.e., high-high, or low-low, than high-low) at both study areas, but the pairs are more synchronous at the Los Angeles County study area (with more than 70% overlap) than in California and (with more than 30%overlap) across all indicators (Table 3). For example, there are low visit rates and low vulnerability ranges from 41.5% to 46.7% among the five indicators for the state, while for the high rates and

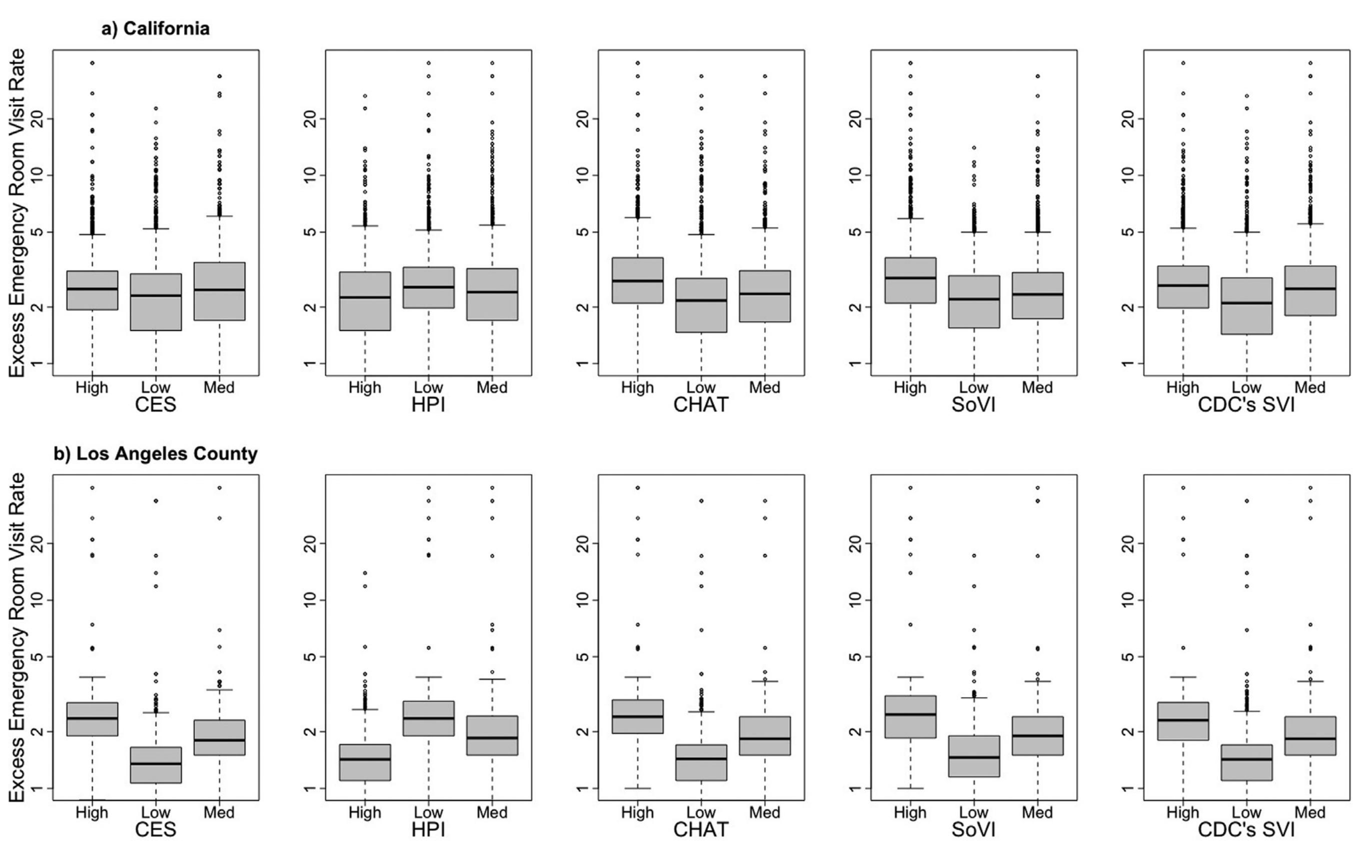

Fig. 3. Boxplots of the average excess emergency room visit rates (by Log-scale) and vulnerability indicator classes (classified in three classes by standard deviation from the mean: low< *mean − 0.5 Std.Dev.*; *mean − 0.5 Std.Dev.* < medium < *mean + 0.5 Std.Dev.*; and high> *mean + 0.5 Std.Dev.*) for a) California, and b) Los Angeles County.

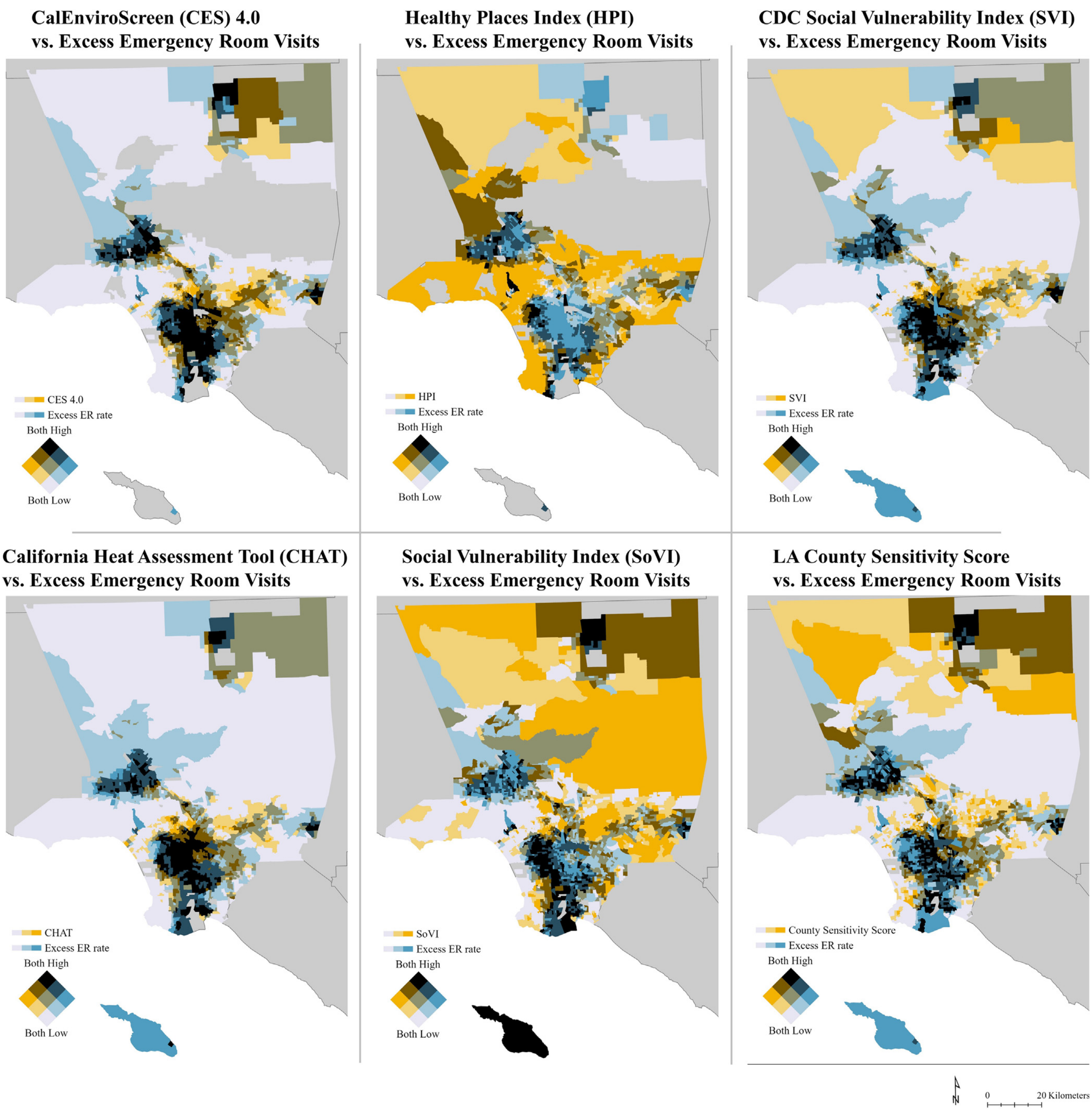

Fig. 4. Bivariate maps of quantiles of vulnerability indicators and excess emergency room visit rates for Los Angeles County by census tract.

high vulnerability the indicators range from 29.5% to 46.7%. At the Los Angeles County scale, the low rates and low vulnerability range from 63.7% to 86.1% among the six indicators, while for the high rate and high vulnerability pairs, they also exceed 70% in each indicator (only exception is the County Sensitivity Score with a lower coverage, with 46%).

The CDC's SVI score has a higher significant association with the rate of excess emergency room visits ($r_s = 0.556$, $p < 0.001$), which is close to SoVI score ($r_s = 0.449$, $p < 0.001$); and the Factor 1 of SoVI has the strongest association among the factors ($r_s = 0.55$, $p < 0.001$) representing poverty, linguistic isolation, and Hispanic population. The county sensitivity score has a moderate association with the excess emergency room visit rates ($r_s = 0.379$, $p < 0.001$). The HPI has a moderate-strong negative association ($r_s = -0.587$, $p < 0.001$), and the CHAT score has a stronger positive correlation ($r_s = 0.601$, $p < 0.001$). Comparing the top and the bottom 1% census tracts with the highest excess emergency room visits for Los Angeles County, shows a significant difference between the means for all the vulnerability scores tested, but not for all the individual variables (e.g., transit access, ozone exceedance, %Native American, %Asian American, park access, %with disabilities, %female, and %mobile home residents).

4. Discussion and conclusion

In response to climate change and the increase in number, extent, and duration of heat events, several vulnerability indicators have been proposed but it is uncertain how much they reflect observed disparities in the heat-impact across communities. In this study, we

Table 3
High and low classes of vulnerability indicators and the related classes of high and low excess emergency room visit rates (all classes classified by standard deviation from the mean) for a) California, and b) Los Angeles County.

Excess emergency room visit rate	CES	HPI	CHAT	SoVI®	CDC's SVI	LA County Sensitivity Score
CALIFORNIA (n = 8041)						
Low Vulnerability Score						
Low (n = 2175)	46.1% (n = 1003)	43.8% (n = 953)	45.5% (n = 989)	41.5% (n = 903)	49.6% (n = 1080)	–
High (n = 1365)	28% (n = 382)	29.2% (n = 399)	18.5% (n = 252)	15.9% (n = 347)	23% (n = 315)	–
High Vulnerability Score						
Low (n = 2175)	20.4% (n = 443)	19.8% (n = 430)	14.4% (n = 314)	22.6% (n = 309)	21.3% (n = 464)	–
High (n = 1365)	29.5% (n = 403)	32.4% (n = 442)	46.7% (n = 637)	36.3% (n = 496)	40.4% (n = 552)	–
LOS ANGELES COUNTY (n = 2320)						
Low Vulnerability Score						
Low (n = 201)	86.1% (n = 173)	78.1% (n = 157)	79.1% (n = 159)	64.2% (n = 129)	77.1% (n = 155)	63.7% (n = 128)
High (n = 177)	5.6% (n = 10)	6.2% (n = 11)	6.2% (n = 11)	7.3% (n = 13)	9.6% (n = 17)	22.6% (n = 40)
High Vulnerability Score						
Low (n = 201)	2.5% (n = 5)	4.5% (n = 9)	4.5% (n = 9)	2.5% (n = 5)	6% (n = 12)	9.9% (n = 20)
High (n = 177)	77.4% (n = 137)	74% (n = 131)	80.8% (n = 143)	64.4% (n = 114)	72.9% (n = 129)	46.3% (n = 82)

used the rate of excess emergency room visits as an outcome measure to test the explanatory power of existing indicators for California. Our findings have four main implications.

First, while comparisons showed a similar statistical relationship with available vulnerability indicators, we observed a stronger relationship with CHAT and CES. The relevance of heat-specific vulnerability indicators confirms the appropriateness of hazard-specific vulnerability measures that has been seen in context of the COVID-19 pandemic and floods as well [52]. Therefore, custom indicators that incorporate vulnerability attributes related to the hazard type might be more defining than an all-hazards approach, at least in case of extreme heat. Single-hazard vulnerability assessments may be necessary for effective hazard preparedness and mitigation.

Second, the observed strong patterns of differential impact between urban and rural areas with clusters for disproportionately high impacts in rural, northern California signifies the necessity to identify regionally relevant policy solutions or infrastructural needs. Lack of acclimatization to heat, decreased availability of air conditioning and lack of community experience forcing inadequate response might all be contributing factors.

Third, the strength of association between vulnerability indicators and excess emergency room visit rates is higher at finer scales. The two levels of analysis (i.e., county and census tracts) and the focused study area of Los Angeles County, highlight the importance of scale and unit of analysis, where associations vary across counties and within county (Figs. 2 and 4). There are more pairs that identify the similar level of susceptibility to suffer harm in the Los Angeles County study area (> 70 % overlap) than in California (> 30 % overlap) across all vulnerability indicators, demonstrating that these indicators may be closer in identifying the vulnerable tracts in a more focused study area. Therefore, this finding suggests that localized studies are more appropriate for mitigation planning and policy implementations.

Fourth, individual variables tested against the rate of excess emergency room visits, indicated a significant association with lead pollution, asthma and cardiovascular disease, poverty, access to a car, and access to air conditioning. Based upon this finding one could consider the possibility of merging policies and mitigation plans with efforts on urban greening and public health to bring co-benefits for overburdened communities (e.g. parts of Merced County, Stanislaus County near Turlock, and parts of Los Angeles County like south-central Los Angeles). In contrast, the inverse association between emergency room visits and some indicators (e.g., transit access), demonstrates that the outcome measure of emergency room visits might not represent all vulnerable groups. The under-representations of some groups in emergency room visits could stem from not having the access to reach emergency rooms and seeking care in local clinics or not at all. However, the indicators for socioeconomic status or health seem to have a strong positive relationship with visit rates (e.g., poverty, asthma). Thus, some vulnerable populations (e.g., those with accessibility issues) might not be counted if we only use the outcome measures such as emergency room visit rates for locating the populations in need of support, as they might be under-reported or under-represented in those outcome data.

There are a number of limitations in our study including those associated with data availability and timeframes for the selected indicators, and potential confounding bias or inaccuracy in accounting for heat exposure effects in the excess emergency room visit rate calculations. Nevertheless, the stronger association with sub-county data validates the use of the vulnerability indicators for environmental policy implementation and highlights the need for both outcome measures and socio-environmental vulnerability indices. Consequently, we encourage further emphasis on local knowledge and assessments to identify — at the operational level —the priority groups for implementing mitigation measures or for response to heat events.

Author agreement

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All authors have reviewed the order of the authors and agree to it.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Data sources for selected variables and indicators for California

	Variable	Source
Socio-Economic and pre-existing conditions		
Independent variables	CalEnviroScreen (CES) 4.0	California Office of Environmental Health Hazard Assessment (OEHHA)
	Healthy Places Index (HPI)	Public Health Alliance of Southern California
	Climate Change & Health Vulnerability Indicators for California (CCHVIs)	California Building resilience Against Climate Effects (CalBRACE)
	California Heat Assessment Tool (CHAT)	California's Fourth Climate Change Assessment
	Social Vulnerability Index (SoVI)® for California	Authors; raw variables from ACS
	Social Vulnerability Index (SVI)	Centers for Disease Control and Prevention (CDC)
	Only for Los Angeles County Subset	
	Social Sensitivity scores	Los Angeles County Chief Sustainability Office
	Social Vulnerability Index (SoVI)® for Los Angeles County	Authors; raw variables from ACS
Outcome measure		
Dependent variables	Excess emergency room visits	California Department of Health Care Access and Information (2009–2018)

Appendix B. Poisson log-linear regression model for excess emergency room visit rates by vulnerability indicators and county (census tract -scale data), *standard error in parenthesis*

	CES	HPI	CHAT	SoVI®	CDC's SVI
Intercept	0.845 (0.02)**	1.066 (0.02)**	0.753 (0.02)**	1.074 (0.02)**	0.612 (0.03)**
Vulnerability indicator	0.011 (0.00)**	−0.34 (0.01)**	0.011 (0.00)**	0.035 (0.00)**	0.069 (0.00)**
Alameda	0.400 (0.03)**	0.601 (0.03)**	0.269 (0.03)**	0.465 (0.03)**	0.452 (0.03)**
Alpine	1.678 (0.25)**	0.00 (0)	1.750 (0.25)**	1.237 (0.26)**	1.464 (0.25)**
Amador	0.509 (0.14)**	0.510 (0.15)**	0.557 (0.14)**	0.377 (0.15)*	0.530 (0.14)**
Butte	−0.01 (0.08)	−0.05 (0.08)	−0.01 (0.08)	−0.055 (0.08)	−0.03 (0.08)
Calaveras	0.204 (0.17)	0.133 (0.18)	0.253 (0.17)	−0.056 (0.17)	0.174 (0.17)
Colusa	−0.26 (0.28)	−0.25 (0.28)	−0.26 (0.28)	−0.110 (0.28)	−0.31 (0.28)
Contra Costa	0.260 (0.04)**	0.436 (0.04)**	0.182 (0.04)**	0.311 (0.04)**	0.318 (0.04)**
Del Norte	1.082 (0.12)**	0.922 (0.13)**	1.015 (0.12)**	0.917 (0.13)**	0.948 (0.12)**
El Dorado	0.277 (0.08)**	0.111 (0.09)	0.341 (0.08)**	0.107 (0.08)	0.220 (0.08)*
Fresno	−0.58 (0.05)**	−0.48 (0.05)**	−0.54 (0.05)**	−0.321 (0.05)**	−0.46 (0.05)**
Glenn	0.137 (0.20)	0.104 (0.20)	0.176 (0.20)	0.257 (0.21)	0.118 (0.20)
Humboldt	1.081 (0.06)**	1.046 (0.06)**	1.014 (0.06)**	0.975 (0.06)**	1.026 (0.06)**
Imperial	−0.62 (0.12)**	−0.56 (0.13)**	−0.63 (0.12)**	−0.465 (0.12)**	−0.60 (0.12)**
Inyo	−0.40 (0.29)	−0.38 (0.29)	−0.50 (0.29)	−0.541 (0.29)	−0.45 (0.29)
Kern	−0.71 (0.06)**	−0.68 (0.06)**	−0.67 (0.06)**	−0.496 (0.06)**	−0.62 (0.06)**
Kings	−0.54 (0.13)**	−0.45 (0.13)**	−0.51 (0.12)**	−0.251 (0.13)	−0.43 (0.12)**
Lake	0.716 (0.10)**	0.585 (0.10)**	0.660 (0.10)**	0.559 (0.11)**	0.619 (0.10)**
Lassen	−0.50 (0.26)	−0.68 (0.28)*	−0.59 (0.25)*	−0.718 (0.25)**	−0.57 (0.25)*
Los Angeles	−0.58 (0.02)**	−0.41 (0.02)**	−0.52 (0.02)**	−0.344 (0.03)**	−0.42 (0.02)**
Madera	−0.46 (0.13)**	−0.36 (0.14)*	−0.35 (0.13)*	−0.217 (0.13)	−0.35 (0.13)*
Marin	−0.04 (0.08)	0.134 (0.08)	−0.05 (0.08)	−0.121 (0.09)	−0.05 (0.08)
Mariposa	−0.21 (0.26)	−0.25 (0.27)	−0.09 (0.26)	−0.395 (0.26)	−0.24 (0.26)
Mendocino	0.259 (0.11)*	0.200 (0.11)	0.234 (0.11)*	0.189 (0.11)	0.155 (0.11)
Merced	−0.12 (0.07)	0.014 (0.07)	−0.04 (0.07)	0.193 (0.08)*	0.000 (0.07)
Modoc	−1.03 (0.48)*	−1.04 (0.51)*	−1.11 (0.48)*	−1.155 (0.48)*	−1.09 (0.48)*
Mono	0.321 (0.29)	0.274 (0.29)	0.337 (0.29)	0.144 (0.29)	0.288 (0.29)
Monterey	0.448 (0.05)**	0.429 (0.05)**	0.347 (0.05)**	0.505 (0.05)**	0.398 (0.05)**
Napa	−0.07 (0.09)	0.045 (0.10)	−0.09 (0.09)	−0.077 (0.09)	−0.07 (0.09)
Nevada	−0.21 (0.15)	−0.23 (0.15)	−0.13 (0.15)	−0.383 (0.15)*	−0.21 (0.15)
Orange	−0.70 (0.04)**	−0.55 (0.04)**	−0.70 (0.04)**	−0.594 (0.04)**	−0.63 (0.04)**
Placer	0.209 (0.06)*	0.188 (0.06)*	0.199 (0.06)*	0.072 (0.06)	0.191 (0.06)*
Plumas	−0.12 (0.23)	−0.14 (0.27)	−0.11 (0.23)	−0.353 (0.24)	−0.12 (0.23)
Riverside	−0.42 (0.04)**	−0.41 (0.04)**	−0.37 (0.03)**	−0.366 (0.04)**	−0.39 (0.03)**
Sacramento	0.177 (0.03)**	0.269 (0.03)**	0.132 (0.03)**	0.215 (0.04)**	0.213 (0.03)**
San Benito	0.388 (0.13)*	0.490 (0.13)**	0.394 (0.13)*	0.529 (0.14)**	0.435 (0.13)*
San Bernardino	−0.36 (0.04)**	−0.30 (0.04)**	−0.31 (0.04)**	−0.218 (0.04)**	−0.27 (0.04)**
San Diego	−0.29 (0.03)**	−0.23 (0.03)**	−0.36 (0.03)**	−0.272 (0.04)**	−0.28 (0.03)**
San Francisco	0.146 (0.04)**	0.363 (0.04)**	−0.06 (0.04)	0.159 (0.04)**	0.156 (0.04)**
San Joaquin	0.104 (0.04)*	0.225 (0.04)**	0.145 (0.04)*	0.329 (0.05)**	0.206 (0.04)**
San Luis Obispo	−0.05 (0.08)	−0.05 (0.09)	−0.08 (0.08)	−0.199 (0.09)*	−0.09 (0.08)
San Mateo	0.295 (0.04)**	0.521 (0.04)**	0.245 (0.04)**	0.359 (0.05)**	0.353 (0.04)**
Santa Barbara	−0.02 (0.06)	0.032 (0.06)	−0.05 (0.06)	0.023 (0.07)	−0.05 (0.06)
Santa Clara	0.055 (0.03)	0.215 (0.03)**	−0.00 (0.03)	0.118 (0.04)*	0.064 (0.03)
Santa Cruz	−0.02 (0.08)	0.046 (0.08)	−0.02 (0.08)	−0.038 (0.08)	−0.06 (0.08)
Shasta	−0.04 (0.08)	−0.12 (0.09)	−0.05 (0.08)	−0.169 (0.09)	−0.10 (0.08)
Sierra	−0.75 (0.84)	−0.84 (0.84)	−0.72 (0.84)	−0.975 (0.84)	−0.72 (0.84)
Siskiyou	0.333 (0.13)*	0.308 (0.14)*	0.337 (0.13)*	0.203 (0.13)	0.227 (0.13)
Solano	0.081 (0.05)	0.179 (0.06)*	−0.04 (0.05)	0.110 (0.06)	0.134 (0.05)*
Sonoma	0.139 (0.06)*	0.206 (0.06)**	0.105 (0.06)	0.093 (0.06)	0.102 (0.06)

(*continued*)

(*Continued*)

	CES	HPI	CHAT	SoVI®	CDC's SVI
Stanislaus	−0.07 (0.06)	0.050 (0.05)	0.012 (0.05)	0.172 (0.06)	0.032 (0.05)
Sutter	−0.08 (0.12)	−0.00 (0.12)	0.021 (0.12)	0.082 (0.12)	−0.06 (0.12)
Tehama	0.000 (0.16)	−0.04 (0.16)	0.015 (0.16)	−0.007 (0.17)	−0.04 (0.16)
Trinity	0.305 (0.22)	0.014 (0.26)	0.354 (0.22)	0.016 (0.23)	0.174 (0.22)
Tulare	−0.70 (0.08)**	−0.63 (0.08)**	−0.60 (0.08)**	−0.398 (0.08)**	−0.61 (0.08)**
Tuolumne	0.399 (0.15)*	0.387 (0.15)*	0.434 (0.14)*	0.254 (0.15)	0.362 (0.14)*
Ventura	−0.21 (0.05)**	−0.13 (0.05)*	−0.23 (0.05)**	−0.144 (0.05)*	−0.20 (0.05)**
Yolo	0.087 (0.08)	0.199 (0.08)*	0.084 (0.08)	0.035 (0.00)**	0.119 (0.08)
Goodness of Fit					
Pearson Chi-Square	6441.5	4426.9	6138.2	6108.7	6420.5
Log Likelihood	1491.3**	1468.1**	1509.1**	1303.4**	1446.1**

** Significant at the 0.001 level; *. Significant at the 0.01 level.

Appendix C. Independent samples *t*-test results for comparison of top 1 % and bottom 1 % of census tracts' average emergency room visit rates (1 % = 80 census tracts), for all independent indicators by each measurement scheme (equal variance not assumed)

Indicator	Levene's Test		t	df	Significance		Mean Difference	Std. Error Difference	Cohen's d
	F	Sig.			One-Sided p	Two-Sided p			
ER rate	71.34	0.00	15.95	79.05	0.00	0.00	13.00	0.81	2.52
CES 4.0									
CES 4.0 score	39.16	0.00	8.04	100.76	0.00	0.00	14.93	1.86	1.28
Average ozone concentration (ppm)	0.64	0.42	−13.44	154.19	0.00	0.00	−0.02	0.00	−2.14
Particulate Matter (PM) 2.5	0.55	0.46	0.62	154.99	0.27	0.54	0.23	0.38	0.10
Diesel Particulate Matter	45.92	0.00	4.29	97.73	0.00	0.00	0.16	0.04	0.67
Drinking Water	23.62	0.00	−1.03	119.75	0.15	0.30	−27.05	26.22	−0.16
Lead risk from housing	3.53	0.06	7.66	146.34	0.00	0.00	25.78	3.37	1.24
Pesticides use (lbs/sq.mi.)	8.67	0.00	1.54	81.02	0.06	0.13	55.65	36.17	0.24
Toxic releases from facilities	3.61	0.06	1.72	141.30	0.04	0.09	173.91	101.34	0.27
Traffic impacts	7.99	0.01	−0.50	149.04	0.31	0.62	−59.74	118.58	−0.08
Cleanup sites	23.10	0.00	3.48	106.49	0.00	0.00	6.09	1.75	0.55
Groundwater threats	2.63	0.11	2.21	144.41	0.01	0.03	21.22	9.62	0.35
Hazardous waste generators and facilities	2.56	0.11	1.50	124.16	0.07	0.14	0.42	0.28	0.24
Solid waste sites and facilities	7.92	0.01	2.68	150.08	0.00	0.01	2.07	0.77	0.43
Pollution burden	7.06	0.01	4.00	146.20	0.00	0.00	7.12	1.78	0.63
Asthma	65.18	0.00	7.74	85.87	0.00	0.00	51.60	6.67	1.22
Cardiovascular disease	43.24	0.00	8.01	114.82	0.00	0.00	6.44	0.80	1.27
Linguistic isolation	12.97	0.00	2.93	112.94	0.00	0.00	3.34	1.14	0.49
Educational attainment	27.80	0.00	5.73	116.42	0.00	0.00	10.06	1.76	0.93
Poverty	4.68	0.03	5.35	144.42	0.00	0.00	15.15	2.83	0.86
Unemployment	4.68	0.03	3.06	122.60	0.00	0.00	2.37	0.77	0.51
Housing burden	7.58	0.01	3.68	137.17	0.00	0.00	6.21	1.69	0.60
Population characteristics	14.37	0.00	8.56	136.97	0.00	0.00	25.00	2.92	1.38
Total population	1.20	0.27	3.22	151.92	0.00	0.00	985.72	305.67	0.51
Children, less than 10 years (%)	0.04	0.84	2.26	153.57	0.01	0.03	1.77	0.78	0.36
Population between 10 and 64 years (%)	5.34	0.02	5.73	134.41	0.00	0.00	11.09	1.94	0.92
Elderly, more than 64 years (%)	15.60	0.00	−6.05	118.11	0.00	0.00	−12.86	2.13	−0.97
Hispanic (%)	9.11	0.00	2.84	144.70	0.00	0.01	8.45	2.98	0.45
White (%)	47.85	0.00	−6.23	122.03	0.00	0.00	−24.29	3.90	−0.99
African American (%)	75.79	0.00	4.81	84.00	0.00	0.00	7.14	1.49	0.76
Native American (%)	16.92	0.00	2.68	87.15	0.00	0.01	1.60	0.60	0.42
Asian American (%)	39.43	0.00	3.56	114.61	0.00	0.00	5.26	1.48	0.57
Other/Multiple (%)	1.30	0.26	4.71	151.20	0.00	0.00	1.84	0.39	0.75
HPI									
HPI score	0.86	0.35	−3.74	131.03	0.00	0.00	−0.36	0.10	−0.64
Economic	0.16	0.69	−4.41	132.00	0.00	0.00	−0.75	0.17	−0.76
Education	0.76	0.39	−1.81	128.00	0.04	0.07	−0.29	0.16	−0.31
Insurance	0.08	0.77	−2.33	131.55	0.01	0.02	−0.35	0.15	−0.40
Clean environment	21.29	0.00	4.36	107.00	0.00	0.00	0.41	0.09	0.74
Housing	8.83	0.00	−5.01	124.73	0.00	0.00	−0.54	0.11	−0.86
Neighborhood	2.43	0.12	3.28	126.90	0.00	0.00	0.38	0.12	0.57
Social	1.92	0.17	−1.58	128.41	0.06	0.12	−0.25	0.16	−0.27
Transportation	2.23	0.14	−1.50	129.50	0.07	0.14	−0.11	0.08	−0.26
Above poverty	3.75	0.05	−5.21	128.05	0.00	0.00	−0.15	0.03	−0.89
Automobile access	56.95	0.00	−6.09	89.57	0.00	0.00	−0.08	0.01	−1.03
Bachelors' education	0.01	0.94	−4.43	131.36	0.00	0.00	−0.16	0.04	−0.77
Census response	0.44	0.51	2.77	129.95	0.00	0.01	0.06	0.02	0.48
Active commuting	7.35	0.01	3.90	122.55	0.00	0.00	0.09	0.02	0.67
Diesel Particulate Matter	39.02	0.00	3.90	90.83	0.00	0.00	0.13	0.03	0.66

(*continued*)

(*Continued*)

Indicator	Levene's Test		t	df	Significance		Mean Difference	Std. Error Difference	Cohen's d
	F	Sig.			One-Sided p	Two-Sided p			
Employed	1.48	0.23	−0.66	131.98	0.25	0.51	−0.01	0.02	−0.11
Drinking water contamination	21.08	0.00	−2.34	101.86	0.01	0.02	−61.41	26.24	−0.40
Homeownership	11.27	0.00	−4.66	126.03	0.00	0.00	−0.18	0.04	−0.80
House repair	6.98	0.01	−2.49	100.10	0.01	0.01	−0.01	0.00	−0.42
In high school	0.93	0.34	0.52	130.23	0.30	0.60	0.01	0.02	0.09
In pre-school	3.40	0.07	−1.71	124.73	0.04	0.09	−0.09	0.05	−0.30
Insured adults	0.08	0.77	−2.33	131.55	0.01	0.02	−0.03	0.01	−0.40
Homeowner severe housing cost burden	8.47	0.00	1.00	101.63	0.16	0.32	0.02	0.02	0.17
Ozone	0.05	0.82	−14.89	131.74	0.00	0.00	−0.02	0.00	−2.57
Park access	0.07	0.80	1.38	131.56	0.09	0.17	0.08	0.06	0.24
Per capita income	13.98	0.00	−4.76	112.28	0.00	0.00	−27,477.37	5777.97	−0.83
Particulate Matter (PM) 2.5	0.02	0.89	0.57	131.19	0.29	0.57	0.22	0.39	0.10
Renter severe housing cost burden	1.82	0.18	3.18	131.80	0.00	0.00	0.07	0.02	0.55
Retail density	12.19	0.00	2.22	73.54	0.01	0.03	5.83	2.63	0.37
Tree canopy	1.87	0.17	2.19	128.81	0.02	0.03	0.05	0.03	0.38
Un-crowded housing	27.15	0.00	−5.02	112.58	0.00	0.00	−0.06	0.01	−0.85
Voting	25.51	0.00	−6.61	106.60	0.00	0.00	−0.10	0.02	−1.12
Latino (%)	9.12	0.00	2.84	144.69	0.00	0.01	0.08	0.03	0.45
White (%)	47.80	0.00	−6.23	122.05	0.00	0.00	−0.24	0.04	−0.99
Black (%)	75.71	0.00	4.81	84.02	0.00	0.00	0.07	0.01	0.76
Asian (%)	37.52	0.00	3.39	115.29	0.00	0.00	0.05	0.01	0.54
Multiple (%)	2.30	0.13	4.43	150.10	0.00	0.00	0.02	0.00	0.71
Native American (%)	16.98	0.00	2.69	87.10	0.00	0.01	0.02	0.01	0.43
Pacific Islander (%)	11.85	0.00	2.27	93.50	0.01	0.03	0.00	0.00	0.36
Other races (%)	6.11	0.01	1.77	114.79	0.04	0.08	0.00	0.00	0.28
CCHVI									
No tree Canopy_ Area Weight 2011 (%)	9.60	0.00	−2.91	141.52	0.00	0.00	−8.61	2.96	−0.46
No tree Canopy _Pop Weight 2011 (%)	0.21	0.65	−1.80	155.67	0.04	0.07	−5.24	2.91	−0.29
Households No AC _2009 (%)	29.31	0.00	10.47	125.77	0.00	0.00	36.03	3.44	1.73
Projected N extreme Heat Days 2040−2060	0.92	0.34	−8.14	154.98	0.00	0.00	−10.49	1.29	−1.30
Ave Daily Max Ozone 2012−2014	1.31	0.25	−11.08	152.20	0.00	0.00	−0.02	0.00	−1.77
Annual Mean (Particulate Matter 2.5) 2012−2014	4.10	0.04	0.37	154.32	0.35	0.71	0.17	0.45	0.06
Pop Age 65 plus_2010−2015 (%)	19.29	0.00	−5.23	115.00	0.00	0.00	−11.23	2.15	−0.84
Pop Age Less 5 years_2011−2015 (%)	0.13	0.72	2.44	155.98	0.01	0.02	1.14	0.47	0.39
Violent Crime Per 1000 Pop Ave 2000−13	25.65	0.00	2.06	149.01	0.02	0.04	0.53	0.26	0.33
Population Disability_2011−2015 (%)	0.65	0.42	0.58	155.92	0.28	0.56	0.62	1.07	0.09
Less College Education_2011−2015 (%)	0.02	0.90	3.89	155.97	0.00	0.00	13.77	3.54	0.62
Without Health Insurance_2011−2015 (%)	2.44	0.12	2.21	145.41	0.01	0.03	2.99	1.35	0.36
Households No English_2011−2015 (%)	26.60	0.00	3.91	110.41	0.00	0.00	4.45	1.14	0.63
Population Working Outdoor_2011−2015 (%)	0.07	0.79	1.99	153.66	0.02	0.05	1.71	0.86	0.32
Households No Car_2011−2015 (%)	44.78	0.00	5.94	108.49	0.00	0.00	7.24	1.22	0.95
CHAT									
CHAT Heat health action index	47.03	0.00	7.39	107.01	0.00	0.00	18.28	2.47	1.17
Children (%)	0.00	0.96	2.51	153.97	0.01	0.01	1.15	0.46	0.40
No high school diploma (%)	19.20	0.00	4.87	127.89	0.00	0.00	8.72	1.79	0.77
Elderly (%)	20.36	0.00	−5.24	112.71	0.00	0.00	−11.22	2.14	−0.85
Outdoor workers (%)	0.02	0.89	1.80	153.97	0.04	0.07	1.52	0.85	0.29
Population	0.17	0.68	3.40	155.05	0.00	0.00	995.66	292.97	0.54
Poverty (%)	15.26	0.00	4.92	123.16	0.00	0.00	11.29	2.29	0.79
Two races (%)	15.18	0.00	5.67	127.11	0.00	0.00	2.25	0.40	0.90
Non-white (%)	37.01	0.00	5.79	129.56	0.00	0.00	23.25	4.01	0.92
No vehicle access (%)	32.43	0.00	5.73	107.95	0.00	0.00	6.13	1.07	0.93
Linguistic isolation (%)	26.06	0.00	3.85	111.18	0.00	0.00	4.34	1.13	0.62
No transit access (%)	0.99	0.32	−8.46	95.88	0.00	0.00	−60.49	7.15	−1.65
Asthma prevalence	68.97	0.00	8.60	90.18	0.00	0.00	47.52	5.53	1.36
Low birth weight (%)	1.98	0.16	1.36	121.71	0.09	0.18	0.49	0.36	0.24
Cardio disease prevalence	18.23	0.00	6.59	123.24	0.00	0.00	3.03	0.46	1.05
Ambulatory disability (%)	0.10	0.75	1.24	153.07	0.11	0.22	0.82	0.66	0.20
Cognitive disability (%)	6.15	0.01	4.20	136.17	0.00	0.00	2.12	0.50	0.67
Particulate Matter (PM) 2.5 concentration	0.04	0.83	1.26	146.22	0.10	0.21	0.60	0.48	0.21
Impervious surfaces (%)	14.52	0.00	1.03	142.94	0.15	0.30	3.66	3.54	0.16
Change in development	35.69	0.00	−5.99	111.28	0.00	0.00	−12.27	2.05	−0.95
No tree canopy (%)	0.75	0.39	−1.06	151.03	0.15	0.29	−3.10	2.93	−0.17
Urban heat island (UHII) average Delta T	0.04	0.83	3.51	32.30	0.00	0.00	0.56	0.16	0.97
Ozone exceedance	352.11	0.00	−7.49	72.76	0.00	0.00	−0.12	0.02	−1.23
SoVI®									
SoVI score	2.74	0.10	−0.77	146.3	0.22	0.44	−0.41	0.53	−0.12
Factor 1 − Poverty, Education, Hispanic	2.27	0.13	5.27	149.5	0.00	0.00	0.89	0.17	0.85
Factor 2 − Dependence and Age (elderly)	14.24	0.00	−4.74	121.6	0.00	0.00	−1.22	0.26	−0.76
Factor 3 − No automobile access, Renters	24.80	0.00	1.75	122.5	0.04	0.08	0.26	0.15	0.93
Factor 4 − Race (African American), Female	0.00	0.99	−3.38	151.9	0.00	0.00	−0.50	0.15	−0.54
Factor 5 − Race (Native American)	0.06	0.80	2.42	152.8	0.00	0.02	0.70	0.29	0.39
Factor 6 − Population density	0.83	0.36	0.96	142.4	0.17	0.34	0.14	0.15	0.15

(*continued*)

(*Continued*)

Indicator	Levene's Test		t	df	Significance		Mean Difference	Std. Error Difference	Cohen's d
	F	Sig.			One-Sided p	Two-Sided p			
Factor 7 – Nursing home residents, Race (Asian)	0.24	0.62	−2.67	152.0	0.00	0.00	−0.29	0.11	−0.42
CDC's SVI									
CDC'SVI Score	0.93	0.34	6.65	156.26	0.00	0.00	2.15	0.32	1.05
Theme1_ socioeconomic	0.58	0.45	6.56	156.39	0.00	0.00	0.88	0.13	1.04
Theme2_ Household composition/disability	14.71	0.00	0.72	133.97	0.23	0.47	0.07	0.10	0.11
Theme3_ Minority status /language	27.70	0.00	5.14	129.44	0.00	0.00	0.40	0.08	0.81
Theme4_ Housing type /transportation	0.70	0.40	5.84	157.00	0.00	0.00	0.79	0.14	0.92

Appendix D. Social Vulnerability Index (SoVI)® components for California (2017)

Component	Name	% Variance Explained	Dominant Variables
1	Poverty, Education, Ethnicity (Hispanic)	26.10 %	Percent with Less than 12th Grade Education Percent Female Headed Households Percent Hispanic Percent Employment in Service Industry Percent Speaking English as a Second Language with Limited English Proficiency Percent Poverty Percent Civilian Unemployment Percent Children Living in Married Couple Families Median Gross Rent Median Housing Value Percent Households Earning over $200,000 annually Per Capita Income
2	Dependence and Age (Elderly)	10.70 %	Percent Households Receiving Social Security Benefits Percent Population under 5 years or 65 and over Median Age
3	No automobile access, Renters	8.70 %	Percent of Housing Units with No Car Percent Renters
4	Race (African American), Female in labor force	7.70 %	Percent Employment in Extractive Industries Percent Black Percent Female Participation in Labor Force
5	Race (Native American)	5.90 %	Percent Mobile Homes Percent Native American Percent Unoccupied Housing Units
6	Population density	4.60 %	People per Unit Percent Female
7	Nursing home residents, Race (not Asian)	4.30 %	Nursing Home Residents Per Capita Percent Asian

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