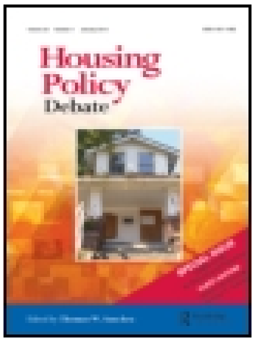

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Extreme Heat Vulnerability of Subsidized Housing Residents in California

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ABSTRACT

Extreme heat is the leading weather-related cause of mortality in the United States, but there is little evidence about how this climate hazard affects residents of different housing types. In this study, we examine whether Californians living in subsidized housing are more vulnerable to extreme heat than those living in unsubsidized housing. We create a tract-level data set combining housing characteristics, downscaled climate projections, and an index of adaptive capacity and sensitivity to heat. We analyze exposure and vulnerability to heat by housing type and location. We find that subsidized housing is disproportionately located in the hottest tracts that simultaneously also have the most sensitive populations and barriers to adaptation (high-high tracts). Whereas 8% of California's housing units are in high-high tracts, these tracts contain 16% of public housing units, 14% of Low-Income Housing Tax Credit units, and 10% of Section 8 Housing Choice Vouchers. Our findings indicate the need for targeted housing and land-use policy interventions to reduce heat vulnerability.

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affordable housing; subsidized housing; extreme heat; climate adaptation

Extreme heat is the largest cause of weather-related death in the United States, and climate change will worsen heat-related public health emergencies (National Weather Service, 2018; U.S. EPA, & CDC, 2016). People who are most sensitive to the effects of heat—including seniors, children, and those with preexisting health conditions—and those without access to air conditioning (AC) will face the greatest health challenges, making policy support for adaptation measures essential (Hajat & Kosatky, 2010; Kovats & Hajat, 2008).

This article assesses the vulnerability of Californians subsidized by major state and federal housing programs, comprising more than 12% of the state's rental households, to extreme heat. Vulnerability depends on a person's exposure, sensitivity, and adaptive capacity (IPCC, 2018). We employ a novel focus on subsidized housing because these dwellings both are home to more heat-sensitive populations and, for site-based subsidies, represent a durable indicator of where many of the state's most economically insecure people will live in the future. Additionally, policymakers have legal authority to retrofit certain subsidized units and shape future siting decisions.

In this study, we answer two questions. First, do neighborhoods in California with more subsidized housing demonstrate greater vulnerability to extreme heat than do neighborhoods with less unsubsidized housing, as measured by variation in residents' exposure, sensitivity, and adaptive capacity? Second, which counties are home to the greatest numbers of vulnerable subsidized households?

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We compile and create a census-tract level data set of housing characteristics, maximum daily temperature projections, and adaptive capacity and sensitivity factors. We focus on major federal housing subsidy programs, including Section 8 Housing Choice Vouchers, public housing, and Low-Income Housing Tax Credits (LIHTC). These programs have different models: Housing Choice Vouchers are portable subsidies that a recipient can apply on the private market; public housing is publicly developed and operated; and LIHTC housing is privately developed but publicly subsidized through tax credits. We also include a newer state subsidy program called the Affordable Housing and Sustainable Communities (AHSC) Program. We estimate the number of extreme heat days—those above the 98th percentile of historical averages—by census tract between 2040 and 2049 based on four climate models using the Representative Concentration Pathway (RCP) 8.5 scenario. We create an adaptive capacity and sensitivity index (ACSI) using key characteristics identified in the literature. We then describe our data; identify bivariate correlations; map the intersection of subsidized housing, extreme heat, adaptive capacity, and sensitivity; and present results using linear regression models.

Our findings suggest opportunities for targeted policy interventions at the building and neighborhood scales, including retrofitting the existing housing stock and building new subsidized housing that is more resilient to extreme heat. Neighborhood-scale interventions that increase urban greening and reduce impervious surfaces to moderate the urban heat island effect should also be considered both in California and throughout the U.S. Southwest.

Literature Review

A warming climate will lead to more extreme heat days and heat waves. By 2017, human-caused warming had increased temperatures by about 1°C above preindustrial levels globally, and temperatures have risen by an average of 0.2°C per decade (IPCC, 2018). The numbers of high-heat days and heat waves in the United States have generally increased since 1979, despite variation based on location and how these terms are defined (Smith, Zaitchik, & Gohlke, 2013). Looking to the end of the century, the IPCC concluded that, globally, "it is virtually certain that there will be more frequent hot and fewer cold temperature extremes.... It is very likely that heat waves will occur with a higher frequency and longer duration" (IPCC, 2014, p. 10).

Rising temperatures present a serious and growing public health crisis, leading to morbidity and premature mortality. In the United States between 1999 and 2009, an average of 658 heat-related deaths occurred per year; this likely represents an underestimate as heat-related deaths are often attributed to other causes (Fowler et al., 2013; Luber & McGeehin, 2008). Some extreme heat waves have led to thousands of deaths, including heat waves in 1995 in Chicago, Illinois; 2003 in Europe; and 2010 in Russia (Lopez et al., 2018). Moreover, about 65,000 people are hospitalized annually in the United States for acute heat-related illness including heat stroke and heat exhaustion (U.S. EPA, & CDC, 2016). Heat-related mortality and morbidity will likely increase as temperatures rise, the population ages, and more people are impacted by the urban heat island effect because of growing urbanization, although improved public health planning and response holds the potential to somewhat mitigate this impact (Luber & McGeehin, 2008).

The existing literature includes a variety of extreme heat exposure measures, which reflect the intersection of populations and heat. Scholars have analyzed high temperatures using both absolute and relative measures (Smith et al., 2013; Ye et al., 2012). Absolute measures include daily high temperatures, daily minimum temperatures, daily mean temperatures, and maximum daily heat index (Hajat & Kosatky, 2010; Robinson, 2001; Smith et al., 2013). Relative measures include, for example, days above the 90th, 95th, or 99th percentile of summertime averages (Robinson, 2001; Smith et al., 2013). There is no consensus on the definition of a heat wave, and thus heat waves are variously defined as periods of two, three, or more consecutive days of high temperatures (Robinson, 2001; Smith et al., 2013).

Several individual factors—including age, underlying chronic conditions, and living alone—increase sensitivity to extreme heat (Hajat, O'Connor, & Kosatsky, 2010; Klinenberg, 2002;

Knowlton et al., 2009; Kovats & Hajat, 2008; Semenza et al., 1996). Seniors' bodies have more difficulty regulating heat because of changes to their thermoregulatory systems (Kovats & Hajat, 2008). Young children, too, are generally more sensitive to heat (Kovats & Hajat, 2008). Additionally, other preexisting health conditions, such as cardiovascular disease and diabetes, lead to greater risk of hospitalization or premature death (Kovats & Hajat, 2008). At the same time, individuals may become more acclimated to high temperatures, meaning the same temperatures may be more dangerous in places that are typically cooler or before people have adjusted to higher summertime temperatures (Hatvani-Kovacs, Bush, Sharifi, & Boland, 2018).

Some people are also better able to adapt to extreme heat than others because of characteristics of their built and socioeconomic environments (Reid et al., 2009; Rosenthal, Kinney, & Metzger, 2014; Uejio et al., 2011; Wilson & Chakraborty, 2018). The built environment affects adaptive capacity to extreme heat in a few ways. The most prominent example is through the availability of central AC, which is associated with better health outcomes (Hajat et al., 2010; Medina-Ramón & Schwartz, 2007; O'Neill, 2005; Reid et al., 2009; Semenza et al., 1996). However, central AC is expensive to operate, energy intensive, and often inaccessible, especially for people of color and low-income residents (O'Neill et al., 2003). Additionally, the urban heat island effect, which refers to the phenomenon of urban areas being hotter than their rural surroundings, hinders adaptation. Common mitigation measures include urban greening, parks, lighter colored paving and roofs, and turning off anthropogenic heat sources, such as air conditioners (Bornstein, 1968; Rizwan, Dennis, & Chunho, 2008). But communities of color and poorer neighborhoods disproportionately suffer from extensive pavement and a lack of greenery and shade, which has been called "thermal inequity" (Mitchell & Chakraborty, 2014, 2015). Lastly, there is limited evidence that urban air pollution acts as an exacerbating factor during extreme heat waves (Ye et al., 2012). Social and economic factors that affect an individual's ability to adapt to extreme heat include financial resources, access to health care, nutrition and food access, and neighborhood-level social capital (Anderson & Bell, 2009; Semenza et al., 1996).

Vulnerability to extreme heat is a function of a person's exposure, sensitivity, and adaptive capacity. The IPCC explains that vulnerability "encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt" (IPCC, 2018, p. 560). This conceptual framework underlies leading studies assessing vulnerability to extreme heat (Reid et al., 2009; Rosenthal et al., 2014; Uejio et al., 2011; Wilson & Chakraborty, 2018). That is, people are most vulnerable when they are exposed to high temperatures for sustained periods, are more sensitive to heat, and/or have less capacity to adapt to rising temperatures. Vulnerability encompasses both individual and community/place-level factors (Reid et al., 2009).

There is a growing scholarly and policy focus on variation in vulnerability to extreme heat, but there has been no analysis focused on residents of subsidized housing. Whereas the structural quality of U.S. subsidized housing stock itself is comparable with that of the general stock (Newman & Holupka, 2017), residents of these units have elevated sensitivity and adaptive capacity factors which potentially make them more vulnerable to high temperatures regardless of exposure. This is an important topic for both environmental justice scholars and policymakers because many subsidized households include vulnerable populations: seniors, people with preexisting health conditions, people of color, and people with lower and fixed incomes.

Data and Methods

Having outlined the need for additional research, we next describe our study data, including extreme heat, subsidized housing, and adaptive capacity and sensitivity measures, which are derived from different publicly available sources. We then describe our methods of overlaying and analyzing these data.

We first estimated extreme heat using downscaled climate projections. We focused on the four downscaled climate models chosen as the priority for California's fourth climate assessment, which were HadGEM2-ES (warm/dry), CNRM-CM5 (cool/wet), CanESM2 (average), and MIROC5 (range of outputs; State of California, 2019c). The state of California prepared data for two scenarios, RCP 4.5 and RCP 8.5,[1] for each of these four climate models (State of California, 2019c). These scenarios are the most commonly modeled and represent a range of possible futures, with RCP 4.5 as a moderate scenario and RCP 8.5 as a scenario with continued high emissions (State of California, 2015). In this article, we focus on the RCP 8.5 scenario. Although the RCP 8.5 reflects the high trend, the scenarios are relatively similar through the 2040s—the end period for our analysis—and diverge more considerably in the second half of the 21st century (IPCC, 2014).

We used these data to estimate *high-heat days* and identify *high-heat tracts*. High-heat days are days in which the high temperature exceeds the 98th percentile of historical averages for that specific location between April and October relative to the 1961–1990 period (State of California, 2019b). For example, a high-heat day in Sacramento would be 103.9°F, whereas the threshold in San Francisco would be 87°F. We compiled estimates of these days by model and census tract calculated by California's Cal-Adapt; the calculations are based on connecting census tract centroids with climate models downscaled to a grid of approximately 6 km x 6 km (Geospatial Innovation Facility, UC Berkeley, 2017; State of California, 2019b). These relative measures allow us to account for baseline adaptation and acclimatization in some of the hotter parts of the state. As a comparison between relative and absolute measures, we found a high correlation (corr = 0.83) between the 98th percentile extreme heat days in the 2040s and the number of days above 90 degrees in 2040. The number of high-heat days increases in practically every climate model and scenario, and although there is variation between models, the mean results under each scenario are comparable. We defined high-heat tracts as those in the top quartile of extreme heat days in the state.

We chose census tracts as our unit of analysis for several reasons. First, census tracts have been commonly used in the literature as a proxy for neighborhoods, particularly with respect to environmental hazards, although they do not always align with residents' perceptions of neighborhood boundaries (Coulton, 2012).[2] Census tracts have an average of 4,000 residents each but vary in geographic size, from less than 0.4 square miles in urban San Francisco and Los Angeles to more than 5 square miles in low-density and rural parts of the state (U.S. Census Bureau, 2013, 2019). The median census tract in California is about 0.7 square miles. Second, census tracts are the smallest geography for which most subsidized housing data are available. Third, local, state, and federal policymakers commonly use census tract data in their criteria for policies and programs. Examples include state allocations for LIHTC and the federal Opportunity Zone designations. However, one limitation with tract estimates from the American Community Survey is that the sampling approach produces high margins of error for many census tracts. Although most scholars and practitioners continue to use these estimates given the hollowing out of analyzable attributes from the decennial census, a potential conservative solution would be to exclude from the analysis tracts with a coefficient of variation above some threshold (Bazuin & Fraser, 2013; Folch, Arribas-Bel, Koschinsky, & Spielman, 2016).

We then collected and compiled data on major federal and state housing subsidy programs, along with unsubsidized housing. We first describe data on federal housing subsidies along with census data on unsubsidized housing. We incorporated 2017 U.S. Department of Housing and Urban Development (HUD) data for three main categories of federal subsidized housing programs: public housing, Section 8 Housing Choice Vouchers, and other project-based programs[3] (U.S. Department of Housing and Urban Development, 2017). We also included LIHTC units by selecting active LIHTC properties in 2018 using the National Housing Preservation Database, and aggregating the unit counts to the census tract using the included census identifier (PAHRC & NLIHC, 2018). Data on unsubsidized housing, which we report by tenure and dwelling type, are from the 2013–2017 American Community Survey (U.S. Census Bureau, 2017).

We included data on California's AHSC Program. This state program supports subsidized housing developments that reduce greenhouse gas emissions; we included data from the program's first three rounds, between 2014 and 2017 (State of California, 2019a). We geocoded the AHSC locations using the *ggmap* package in R and the Data Science Toolkit (Kahle, Wickham, Jackson, & Korpela, 2019). We then used the *sf* package in R to spatially join each AHSC location point with its underlying census tract (Pebesma, 2018).

All of these are site-based subsidy programs, with the exception of Housing Choice Vouchers. Housing Choice Vouchers, often referred to as Section 8 or simply vouchers, are portable subsidies that qualifying households can use on the private market to rent units that meet certain price and quality standards (Schwartz, 2010). The nature of affordable housing finance means that there are some overlaps between housing unit counts by subsidy, as subsidized housing units may receive several subsidies (U.S. Department of Housing and Urban Development, 2018).

We created a neighborhood-level Adaptive Capacity and Sensitivity Index based on models proposed by Reid et al. (2009) and Wilson and Chakraborty (2018). We chose 19 variables for the ACSI; these authors' articles and data, available statewide, informed our variable selection. Most of these data were drawn from the 2013–2017 American Community Survey, by census tract (U.S. Census Bureau, 2017). Shares of land area with an impervious surface and without tree canopy were derived from the state's CalBRACE public health and climate change initiative (State of California, 2019d). We assigned each tract the share of its associated county's households with central AC in 2009—collected by the California Energy Commission and available through CalBRACE. The variables are summarized in Table 1.

We created a tract-level index using three steps: (a) a principal component analysis (PCA), (b) standardizing values for the major components, and (c) summing the scores. PCA is an increasingly common technique for creating indices related to socioeconomic status and vulnerability to climate hazards, including extreme heat (Bao, Li, & Yu, 2015; Reid et al., 2009; Vyas & Kumaranayake, 2006; Wolf & McGregor, 2013). The PCA reduced the number of variables in our analysis without losing most of the census tract-level information from the full data set (Jolliffe, 2011). We selected five components to use in our index based on three common criteria: how much variance they explained, the Kaiser–Guttman rule for eigenvalues above 1, and the scree plot test (Jolliffe, 2011). The five selected components explain almost 64% of the variance across the state's tract-level data. Table 2 summarizes the five components. We assigned each census tract an unstandardized value for each of the five components. We then standardized the tract values by converting to a *z* score, with a mean of 0 and a standard deviation (*SD*) of 1. We scored each tract based on the number of *SD*s from the mean value; tracts were scored as 1 (> 2 *SD* below the mean), 2 (1–2 *SD* below mean), 3 (0–1 *SD* below mean), 4 (0–1 *SD* above mean), 5 (1–2 *SD* above mean), or 6 (> 2 *SD* above mean). We added the scores across the five categories; the lowest possible score was 5 (if a tract scored 1 on all five principal components) and the highest possible score was 30 (if a tract scored 6 on all five principal components). We define high-ACSI tracts—those most challenged in terms of adaptive capacity and sensitivity—as ones in the top quartile of the index (see Table 3).

The overlap between the hottest tracts and those with the highest ACSI scores reflects particularly vulnerable tracts (see Table 3). We call these high-high tracts, representing tracts in the top quartile

Table 1. Variables in the adaptive capacity and sensitivity index (ACSI).

Adaptive capacity (%)	Sensitivity (%)	Both adaptive capacity and sensitivity (%)
Median household income	Population under 18	Black
In group quarters	Population over 65	Asian
With no high school diploma		Other race
Female-headed households		Hispanic
Poverty rate		
With no plumbing		
With no kitchen		
No car		
Renters		
Manufactured housing		
Impervious surface		
Without tree canopy		
Central air conditioning (county)		

Table 2. Variables with largest contributions to each component of the Adaptive Capacity and Sensitivity Index.

Component	Variance explained (%)	Variables with largest contribution to the component (%)
1	28.0	With no high school
		Hispanic
		Poverty rate
		Median household income
		Other race
2	13.4	No car
		With no kitchen
		Population under 18
		With no plumbing
		Impervious surface
3	9.3	Manufactured housing
		Impervious surface
		Asian
		Without tree canopy
		Population over 65
4	7.1	Black
		In group quarters
		With no plumbing
		With no kitchen
		Female-headed households
5	5.7	In group quarters
		Female-headed households
		population under 18
		Black
		Manufactured housing

Table 3. Summary of tract-level heat, adaptive capacity, and sensitivity terms.

Term	Explanation
High-heat tracts	Top quartile of tracts in terms of projected days in the 2040s above the 98th percentile of historical averages.
High-ACSI tracts	Top quartile of tracts based on adaptive capacity and sensitivity index (ACSI); higher scores denote tracts with more challenges for adaptive capacity and sensitivity.
High-high tracts	Tracts that are both high-heat and high-ACSI.

of both our extreme heat and our ACSI measures. About 7.7% of California's tracts (620 of 8,051) are in the high-high category.

We used bivariate correlations to measures associations between housing, heat, adaptive capacity, and sensitivity. We estimated two sets of bivariate (Pearson) correlations using the *psycho* package in R (Makowski, 2018). The first set correlated tract-level housing counts by type with the tract's modeled high-heat days in the 2040s. The second set correlated tract-level housing counts with three key built-environment factors that may improve or worsen residents' abilities to adapt to extreme heat. These three built-environment factors were county-level percentage of households with AC, tract-level tree canopy coverage, and tract-level impervious surface.

For each bivariate association, we calculated the bivariate Moran's I, a measure of global spatial autocorrelation (Anselin, 2019a). The bivariate Moran's I measures the correlation of one variable with the spatial lag of a second variable (Anselin, 2019a). We used GeoDa software to first create a queen contiguity matrix, which relates each census tract to its neighbors that share common edges or vertices (Anselin, 2019b). We then applied GeoDa's Bivariate Moran's I function and report the spatial autocorrelation coefficient (Anselin, 2019a, 2019b).

We explored several data sets to explain the prevalence and type of available AC. This is important because our tract-level analysis does not measure the heat-protective quality or thermal properties of individual housing units, which mediate structure-based adaptive capacity to extreme heat. Along with the county-level Residential Appliance Saturation Study (RASS) maintained by the California

Energy Commission, mentioned above, we explored two additional data sets to assess the heat-protective quality of different housing types: the Residential Energy Consumption Survey (RECS) maintained by the U.S. Energy Information Administration and the American Housing Survey maintained by the U.S. Census Bureau. Even these sources have their limitations; the latest (2015) RECS does not include any distinction in housing type which would be meaningful for a California-specific sample. Meanwhile, the RASS has not been updated since 2009 (a new version will be released in 2020) and only contains AC data at the county level. The representative California sample of the 2017 American Housing Survey is thus our best source, despite its limitation in terms of the lack of substate geographic identifiers.

Lastly, we conducted an exploratory analysis, using linear regression models, to further understand relationships between extreme heat and subsidized housing. The literature described above suggests that other factors may mediate the vulnerability of subsidized residents to extreme heat. These factors include age, socioeconomic status, race and ethnicity, and neighborhood physical characteristics. The unit of analysis is the census tract and the dependent variable in our models is the average annual number of extreme heat days in 2040, which we log transform. The primary independent variable of interest in each model is the number of subsidized housing units by type. Other independent variables include percentage of residents under 18 years of age, percentage above 65 years of age, percentage black, percentage Hispanic, percentage below the poverty line, percentage tree canopy, and percentage impervious surface. We specify ordinary least squares (OLS) models using county fixed effects to control for unobservable factors, in the form of Equation (1). We tested for multicollinearity by estimating the variance inflation factor for each independent variable in the model. All variables had variance inflation factor scores between 1.2 and 2.2—with a mean of 1.7—indicating limited cause for concern about multicollinearity.

$$\text{ExtremeHeatDays}_i = \alpha + \beta_1\text{SubsidizedUnits}_i + \beta_2\text{PopulationCharacteristics}_i + \beta_3\text{NeighborhoodCharacteristics}_i + \varepsilon_i \quad (1)$$

Given the possibility of spatial autocorrelation, we use Moran's I to test for spatial autocorrelation in the residuals of our model. The Moran's I values are above 0.8, indicating strong spatial autocorrelation. As such, we specify maximum likelihood spatial lag models to account for spatial dependence. A spatial lag model is appropriate if the values of the dependent variable for nearby observations are related to each other (Anselin, 2005). In this case, the projected numbers of extreme heat days for neighboring census tracts are generally highly correlated. We use the R package *spdep* to calculate a queen contiguity matrix and estimate the spatial lag models (Bivand & Wong, 2018).

Results

California has a diverse housing stock, with about 6% of units subsidized through major federal and/or state programs. Table 4 summarizes California's occupied housing stock and major housing subsidy programs. The largest form of subsidized housing is Housing Choice Vouchers, which can be applied on the private market and are not associated with specific site-based housing units. The most sizable supply-side type of subsidized housing is LIHTC.

Tracts with the most extreme heat days in the 2040s—defined as the state's top quartile of tracts—tend to be inland and farther south. These tracts average 25.7 annual extreme heat days, compared with 14.5 for the entire state.[4] These include many lower density urban, suburban, and rural parts of California, including the Central Valley and the Inland Empire east of Los Angeles. These tracts disproportionately include detached and manufactured housing. In contrast, most or all of the major coastal cities, including Los Angeles, San Diego, San Jose, and San Francisco, fall outside of the top quartile zone. Because the bulk of subsidized housing is in these coastal population centers, the hottest tracts in California include somewhat smaller shares of most subsidized types: 22% of public housing units, 20% of vouchers, 17% of other HUD program units, and 22% of AHSC. At the same time, these tracts include a slightly higher share (26%) of LIHTC units.

Table 4. Housing units, by type, in the top quartile of heat, adaptive capacity and sensitivity index, and combined measure.

	Housing type	Total units	% of units in high-heat tracts (25% of CA tracts)	% of units in high-ACSI tracts (25% of CA tracts)	% of units in high-high tracts (7.7% of CA tracts)
All occupied housing	Occupied housing units	12,888,128	25	24	8
	Owner occupied	7,024,315	28	18	7
	Renter occupied	5,863,813	22	31	8
	Detached	7,543,682	31	20	8
	Attached	4,886,034	14	31	6
	Manufactured housing	443,564	43	34	17
	Other housing	14,848	38	36	15
Subsidized housing[a]	Public housing	28,786	22	69	16
	Housing Choice Voucher	330,938	20	42	10
	Other HUD housing	119,126	17	53	10
	Low-Income Housing Tax Credit	267,358	26	47	14
	California Affordable Housing and Sustainable Communities	6,186	22	58	14

[a]There may be some double counting if Housing Choice Voucher households use their voucher in a unit that received another subsidy, or if AHSC projects also receive another type of subsidy.

Individuals have a harder time responding to extreme heat if they have poor adaptive capacity and/or are more heat sensitive. Our ACSI measures tract adaptation barriers and sensitivity. The tract index scores ranged from 12 to 27. Unsurprisingly, we see a disproportionate number of rental units in tracts with the highest ACSI scores. Among unsubsidized types, detached single-family housing is least likely (20%) to be in the top ACSI quartile, whereas manufactured housing (34%) and other housing types including recreational vehicles and boats (36%) intersect most with this quartile. All subsidized housing types are disproportionately located in high-ACSI tracts, most commonly public housing and AHSC housing. Still, 42% of vouchers and 47% of LIHTC units are in the most challenged tracts in terms of ACSI.

We then identified high-high tracts: those that are in the top quartile of both extreme heat and ACSI. These 620 tracts reflect the intersection of neighborhood-scale extreme heat, low adaptive capacity, and high heat sensitivity. Although 8% of California's housing units fall into these tracts, these tracts are home to 17% of the state's manufactured housing, 16% of its public housing, and 14% of its LIHTC units. The other housing subsidy programs are also above the state average of 8%. These subsidized units are an important focus because they include tens of thousands of California households that will be most vulnerable to rising temperatures.

Tract-level counts of most types of subsidized housing are not correlated or are negatively correlated with extreme heat (see Table 5). Owner-occupied housing, detached housing, manufactured housing, and other precarious housing types (e.g., boats, vans) are positively correlated with high-heat days. Renter-occupied and attached housing counts are negatively correlated with the propensity of high-heat days. Subsidized housing types either are negatively correlated with high-heat days or display no significant associations. Vouchers and other HUD housing types are negatively correlated with high-heat days, whereas there are no significant associations between public housing, LIHTC, and California's AHSC units and high-heat days. The coefficients are nearly the same for the bivariate correlations and the Moran's I, indicating that spatial autocorrelation is a limited factor in these relationships.

Table 5. Bivariate correlations and bivariate Moran's I between housing type and extreme heat days, and between housing type and the adaptive capacity and sensitivity index (ACSI).

		High-heat days		ACSI	
	Housing type	Bivariate correlation	Bivariate Moran's I	Bivariate correlation	Bivariate Moran's I
All housing	Occupied housing units	0.00	− 0.007	− 0.03	− 0.082
	Owner occupied	0.16***	0.167	− 0.29***	− 0.214
	Renter occupied	− 0.18***	− 0.191	0.28***	0.118
	Detached	0.28***	0.282	− 0.24***	− 0.146
	Attached	− 0.33***	− 0.34	0.18***	0.042
	Manufactured housing	0.19***	0.215	0.1***	0.037
	Other housing	0.08***	0.084	0.06***	0.032
Subsidized housing	Public housing	− 0.01	− 0.017	0.14***	0.052
	Housing Choice Voucher	− 0.15***	− 0.162	0.31***	0.178
	Other HUD housing	− 0.08***	− 0.085	0.24***	0.126
	Low-Income Housing Tax Credit	− 0.01	− 0.016	0.27***	0.123
	California Affordable Housing and Sustainable Communities	− 0.03	− 0.024	0.11***	0.078

*$p < .05$. **$p < .01$. ***$p < .001$.

Meanwhile, tract-level counts of lower cost housing types are associated with lower neighborhood adaptive capacity and increased sensitivity (see Table 5). Higher ACSI scores mean that a neighborhood is more vulnerable to extreme heat. Owner-occupied and detached single-family housing are negatively associated with the ACSI scores. Rental housing, multifamily housing, manufactured housing, and subsidized housing are positively associated with higher ACSI scores; LIHTC, all rental housing, and vouchers have the largest coefficients. The bivariate Moran's I coefficients show some spatial autocorrelation between most housing types and ACSI variables.

A county-level analysis allows us to better identify places most suitable for municipal and/or county policy interventions. Counties with neighborhoods where subsidized housing and extreme heat overlap the most are located in the Central Valley and the Inland Empire (see Table 6 and Figure 1). In these counties—particularly Fresno, Riverside, and San Bernardino—most (or all) of the subsidized housing is in high-heat tracts.

The same general trends hold when looking at each type of subsidized housing. Fresno, Kern, Imperial, Tulare, and San Bernardino counties each contain over 600 public housing units in high-heat tracts. Nearly 20% of California's high-heat tract voucher holders live in Fresno County, followed

Table 6. Counties with the most subsidized housing units in high-heat tracts.

County	Public housing	Housing Choice Voucher	Other HUD housing	Low-Income Housing Tax Credit	California Affordable Housing and Sustainable Communities	Total subsidized units[a]	% of county's subsidized units
Fresno	1,026	12,656	3,194	8,840	271	25,987	100
Riverside	—	7,883	2,509	10,777	138	21,307	81
San Bernardino	656	7,650	2,937	5,235	148	16,626	73
Los Angeles	139	7,782	2,797	4,911	—	15,629	8
Kern	738	3,401	1,058	6,449	222	11,868	89
Sacramento	352	3,680	816	6,877	—	11,725	31
Tulare	676	2,855	608	3,117	157	7,413	100
Imperial	732	1,942	409	2,708	—	5,791	100
San Joaquin	356	3,418	673	1,132	72	5,651	55
Merced	420	2,750	330	1,761	—	5,261	100
All other counties	1,271	11,195	4,626	17,478	333	34,903	9
Total	6,366	65,212	19,957	69,285	1,341	162,161	22

[a]There may be some double counting if Housing Choice Voucher households use their voucher in a unit that received another subsidy.

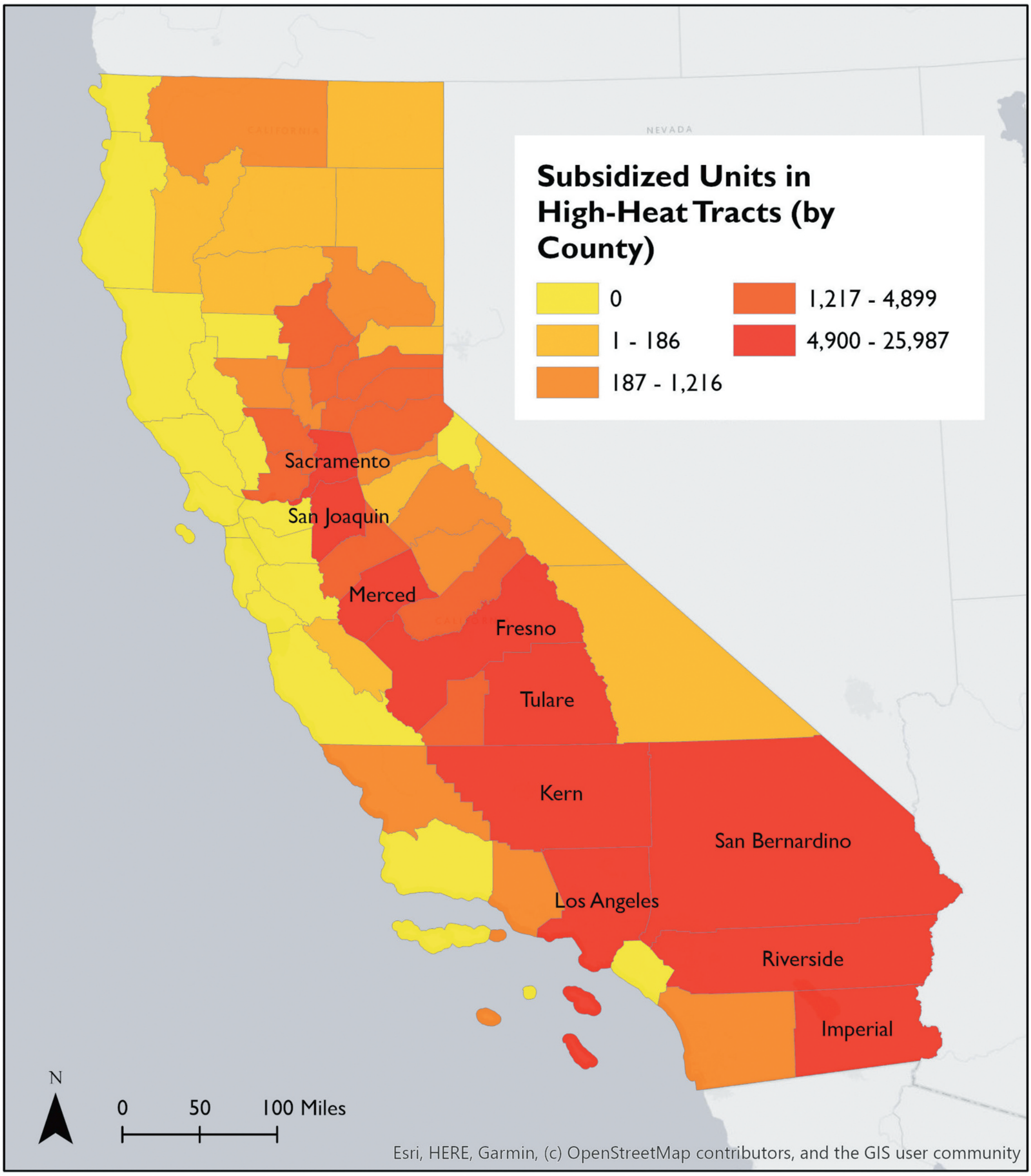

Figure 1. Number of subsidized housing units in high-heat tracts, by county.

by Riverside, Los Angeles, and San Bernardino counties. Over 15% of the state's hottest LIHTC units are in Riverside County, followed by 13% in Fresno, 10% in Sacramento, and 9% in Kern counties. The most AHSC units are in the urban San Joaquin Valley counties (Fresno, Kern, Tulare, and San Joaquin) or the Inland Empire counties (San Bernardino and Riverside).

The results for high-high tracts are similar to those for high-heat tracts (see Table 7 and Figure 2). Neighborhoods' subsidized housing, high-heat, sensitive populations, and barriers to adaptation overlap in the Central Valley and Inland Empire. The most high-high subsidized housing units are in the Central Valley counties of Fresno, Kern, Tulare, and Sacramento, and the Inland Empire counties of San Bernardino and Riverside. More than 20% of the state's high-high subsidized housing is in

Table 7. Counties with the most subsidized housing units in high-high tracts.

County	Public housing	Housing Choice Voucher	Other HUD housing	Low-Income Housing Tax Credit	California Affordable Housing and Sustainable Communities	Total subsidized units[a]	% of county's subsidized units
Fresno	798	8,399	2,569	6,366	271	18,403	71
San Bernardino	615	4,407	1,925	4,051	148	11,146	49
Riverside	—	2,684	1,005	3,946	138	7,773	29
Kern	404	2,401	797	3,672	63	7,337	55
Tulare	475	1,897	361	2,225	92	5,050	68
Sacramento	180	1,468	457	2,939	—	5,044	13
San Joaquin	356	2,153	744	1,465	123	4,841	47
Los Angeles	—	1,683	1,095	1,732	—	4,510	2
Merced	302	1,777	327	1,166	—	3,572	68
Butte	266	1,366	450	1,224	—	3,306	68
All other counties	1,340	5,270	2,695	7,685	61	17,051	4
Total	4,736	33,505	12,425	36,471	896	88,033	12

[a]There may be some double counting if Housing Choice Voucher households use their voucher in a unit that received another subsidy.

Fresno County, and these units comprise 71% of the county's subsidized stock. High-high housing also makes up the majority of the subsidized housing stock in Kern, Tulare, Merced, and Butte counties. The breakdown for individual subsidized housing types largely aligns with these broader trends.

We also explored relationships between housing types and built-environment factors that affect adaptive capacity, and influence local, state, and/or federal governments (see Table 8). The subsidized housing types all tend to be negatively associated with county AC adoption, indicating that these housing units are more likely to be located in parts of the state with less AC.

Household-level data from the 2017 American Housing Survey point to several housing types with lower AC prevalence in California. Site-based public housing, and to a lesser extent multifamily subsidized housing, has much lower prevalence of any type of AC and of central AC than the general housing stock and compared with all households with similarly low income levels in units not subsidized through supply-side programs. Site-based public housing also has a much higher prevalence of inadequate insulation than the general housing stock does. On the other hand, mobile homes and voucher recipients have similar, albeit slightly lower, levels of AC and insulation compared with the general housing stock.[5] We lack data to assess building characteristics such as glazing, ventilation, and thermal mass, which are also important factors that affect indoor temperatures.

Three subsidized housing types—Housing Choice Vouchers, LIHTC, and other HUD housing—are also negatively associated with tree canopy, as are rental and attached housing in general. Owner-occupied, detached single-family, and manufactured housing are all associated with more tree canopy. The associations with tree canopy are largely consistent with those for impervious surface. In the next section, we describe opportunities for cities and counties to reverse these disparities.

The regression results show little specific correlation between subsidized housing and extreme heat after controlling for other correlates of extreme heat (see Table 9). We show only the three largest housing categories in Table 9, but the results are consistent across housing categories. In the OLS models, the only significant associations between housing types and extreme heat are small negative associations for public housing (not shown) and Housing Choice Vouchers (see Table 9, Model 3). Once we account for spatial autocorrelation using the spatial lag models, we no longer observe any significant associations between housing and extreme heat. Several neighborhood characteristics are associated with hotter days in the OLS models, but most of these associations disappear in the spatial lag models. The exceptions are tree canopy and impervious surface, which are both negatively associated with extreme heat across models.

The negative relationship between impervious surface and extreme heat may seem counterintuitive but is explained by the scale of the analysis. Within a city, impervious surface is associated

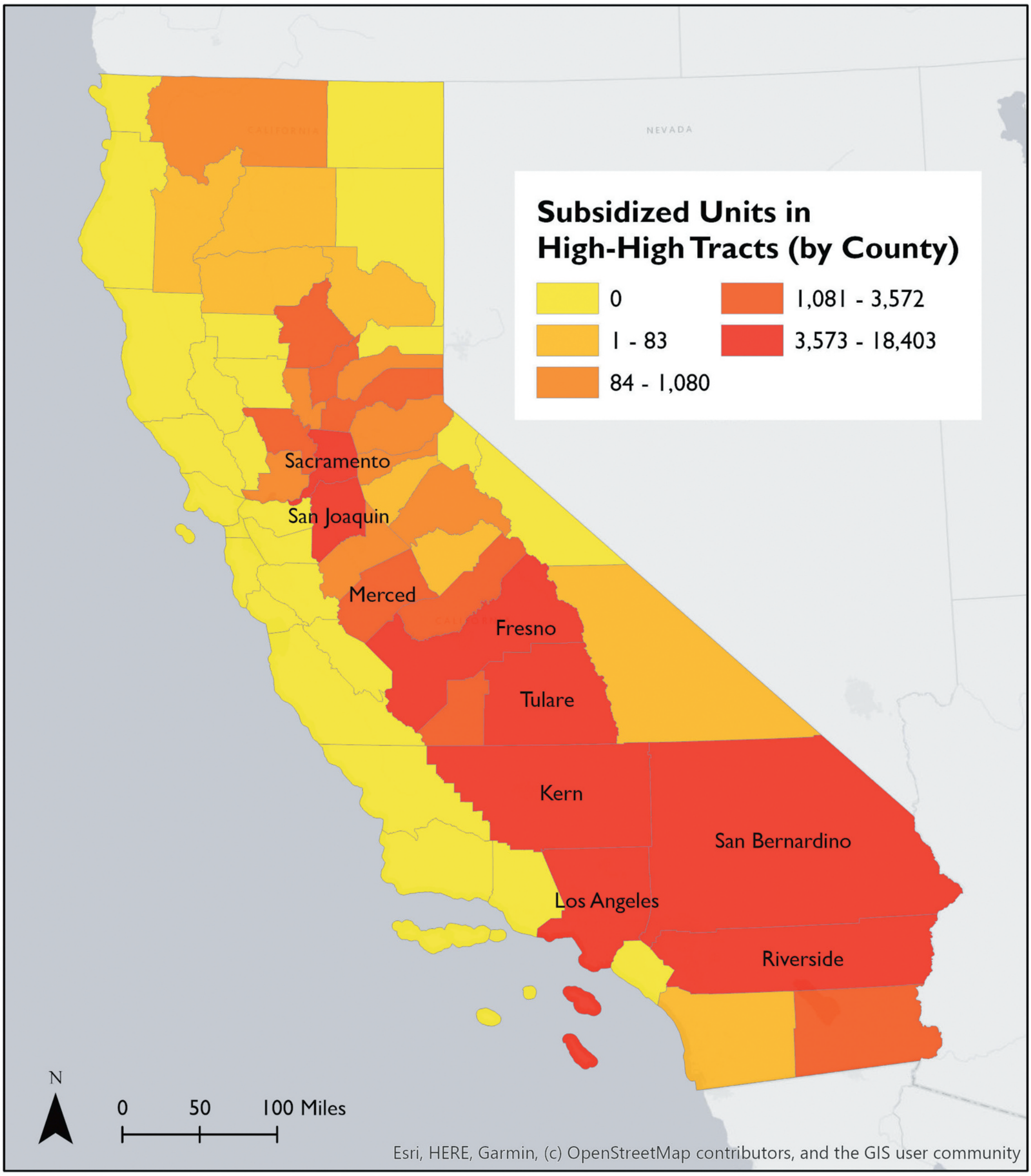

Figure 2. Number of subsidized housing units in high-high tracts, by county.

with urban heat islands. On a statewide basis, however, impervious surface is a proxy for urbanization, and much of California's urbanization is in the state's relatively cooler coastal metropolitan areas. This may change over time, however, as high housing prices in coastal counties push households to less expensive inland areas.

Discussion

We have two main findings. First, a disproportionate share of low-income, subsidized Californians live in neighborhoods with simultaneously more heat, more sensitive populations, and higher

Table 8. Bivariate correlations between housing types, and built-environment factors that support or inhibit adaptation to extreme heat.

	Housing type	County AC (%)	Tree canopy (%)	Impervious surface (%)
All housing	Occupied housing units	− 0.02	0.04	− 0.05**
	Owner occupied	0.06***	0.19***	− 0.42***
	Renter occupied	− 0.09***	− 0.16***	0.38***
	Detached	0.16***	0.17***	− 0.44***
	Attached	− 0.21***	− 0.15***	0.44***
	Manufactured housing	0.10***	0.06***	− 0.24***
	Other housing	0.03	0.06***	− 0.10***
Subsidized housing	Public housing	0	− 0.02	0.04
	Housing Choice Voucher	− 0.11***	− 0.15***	0.30***
	Other HUD housing	− 0.07***	− 0.05*	0.17***
	Low-Income Housing Tax Credit	0.00	− 0.08***	0.12***
	California Affordable Housing and Sustainable Communities	− 0.03	− 0.03	0.07***

*$p < .05$. **$p < .01$. ***$p < .001$.

barriers to adaptation. These units are predominantly located in the Central Valley and Inland Empire in California. Second, subsidized housing is located in neighborhoods with fewer trees and more impervious surfaces relative to the overall housing stock, motivating our focus on these interventions.

Although subsidized housing is somewhat less prevalent in hotter areas, many California households live in the hottest areas, and subsidized households disproportionately live in high-high tracts. The top quartile of high-heat census tracts contains more than 160,000 subsidized housing units. As temperatures rise, the hundreds of thousands of residents in these housing units, predominantly in the Central Valley and Inland Empire, will experience historically extreme temperatures. Many or most, depending on the program, subsidized housing units are located in neighborhoods with sensitive populations and limited adaptive capacity. These neighborhoods include people with lower incomes, people of color, children, and seniors, as well as fewer trees and more pavement. There may be unique opportunities to make LIHTC units more resilient to high temperatures given that LIHTC is the largest supply-side subsidized housing program, and about 14% of California's LIHTC units are in high-high tracts.

Manufactured housing faces a nexus of heat exposure, high sensitivity, and low adaptive capacity. Manufactured housing is the most prevalent type of unsubsidized low-cost housing, with 43% of manufactured housing units in high-heat tracts and 17% in high-high tracts. This is troubling given research regarding residents' economic status and mobility patterns, and manufactured housing quality characteristics. Whereas residents of manufactured housing tend to be poorer than the typical renter, they are also less likely to move and have better perceptions of the quality of their housing units and neighborhoods (Boehm & Schlottmann, 2006, 2008). Manufactured housing has also historically been more prone to utility shutoffs (Pierce & Jimenez, 2015) and has been much less energy efficient than conventional housing, although this gap has narrowed over time (Wilson, 2012). We need to better understand the thermal performance of manufactured housing in the U.S. Southwest, along with residents' exposure and sensitivity to heat and other climate hazards; these topics merit detailed, focused research.

High-high census tracts contain a diversity of subsidized housing developments and mobile home parks (MHPs), as illustrated by Fresno County, which has the most subsidized housing units in high-high tracts of anywhere in the state. In particular, there are nearly 6,400 LIHTC units and over 4,100 manufactured housing units in the county's high-high tracts—of which about 2,300 are in MHPs. The LIHTC developments vary in size, age, and resident profile. Developments contain from

Table 9. Ordinary least squares (OLS) and spatial lag regression results for log of extreme heat days in the 2040s (selected housing types).

	Model					
	(1)	(2)	(3)	(4)	(5)	(6)
Housing type	OLS	Spatial lag	OLS	Spatial lag	OLS	Spatial lag
Renter occupied	0.00000	0.00000				
	− 0.00001	0.00000				
Housing Choice Voucher			− 0.001***	− 0.00001		
			− 0.0001	− 0.00001		
Low-Income Housing Tax Credit					0.0001	0.00000
					− 0.0001	− 0.00001
Population per sq. mi.	− 0.00001***	0.00000	− 0.00001***	0.00000	− 0.00001***	0.00000
	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
% population under 18	1.113***	0.015	1.182***	0.02	1.106***	0.019
	− 0.099	− 0.014	− 0.098	− 0.014	− 0.098	− 0.014
% population over 65	0.143	− 0.013	0.165*	− 0.007	0.144	− 0.007
	− 0.083	− 0.012	− 0.081	− 0.012	− 0.081	− 0.012
% black	− 0.879***	− 0.001	− 0.757***	0.002	− 0.884***	− 0.001
	− 0.06	− 0.009	− 0.063	− 0.009	− 0.06	− 0.009
% Hispanic	− 0.003	0.001	− 0.011	0.003	0.002	0.003
	− 0.028	− 0.004	− 0.028	− 0.004	− 0.028	− 0.004
Poverty rate	0.959***	0.004	1.049***	0.002	0.933***	0.0003
	− 0.056	− 0.008	− 0.056	− 0.008	− 0.055	− 0.008
% tree canopy	− 1.024***	− 0.023**	− 1.010***	− 0.023**	− 1.020***	− 0.023**
	− 0.058	− 0.008	− 0.057	− 0.008	− 0.057	− 0.008
% impervious surface	− 1.168***	− 0.029***	− 1.134***	− 0.029***	− 1.171***	− 0.030***
	− 0.032	− 0.005	− 0.032	− 0.005	− 0.032	− 0.005
No. observations	7,991	7,991	7,991	7,991	7,991	7,991
Adjusted R^2	0.376		0.38		0.376	
Log likelihood		9,171.40		9,170.06		9,169.55
Akaike information criterion		− 18,318.79		− 18,316.12		− 18,315.10

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

less than a dozen to more than 400 housing units, and some date from the beginning of the program in the 1980s whereas others were completed after 2010. The MHPs in Fresno County also range dramatically in size from 3 to more than 300 lots, with a median of 51 lots. Contrasting with LIHTC housing in high-high tracts, the county's MHPs are long established, with many predating 1960. This diversity illustrates the necessity for subsequent project-level analyses and tailored policy approaches.

Opportunities exist for city- and county-level interventions that expand the tree canopy and reduce impervious surfaces. Local governments can prioritize urban forestry initiatives in places with sizable low-income populations. Cities can limit the amount of space devoted to parking, and encourage reflective roofs and paving, green roofs, and permeable paving. A natural place to expand these interventions is in cities with the most subsidized housing in high-high neighborhoods, including the cities of Fresno, San Bernardino, Riverside and Bakersfield.

State and federal programs could retrofit existing housing and mitigate extreme heat in new subsidized developments. California's AHSC program could be a model for incorporating climate considerations into subsidized housing. The AHSC program is funded through revenue from the state's cap-and-trade program and funds housing developments and other projects that reduce greenhouse gas emissions (State of California, 2019a). The program provides incentives for mitigation and adaptation to climate change, including extreme heat. Scoring criteria include GHG efficiency, green buildings and renewable energy, urban greening, community climate resiliency,[6] and community air pollution exposure mitigation (California Strategic Growth Council, 2019).

Our article has several limitations that point to opportunities for future research. First, we lack data on the demographics of subsidized households or the characteristics of subsidized units. Household-level characteristics would allow us to identify individuals in subsidized housing at particular risk because of age, health, and/or socioeconomic status. Second, the Housing Choice Voucher Program is the largest portable subsidy, but it is unknown how voucher households account for temperature in making their housing decisions, such as moving to cooler parts of a metro area, or choosing a unit with AC or on a shady lot.[7] Third, we lack data to assess structure-based adaptive capacity including AC availability or whether utility shutoff prevalence is higher in certain housing types (see Pierce & Jimenez, 2015), which may affect vulnerability to extreme heat events. Fourth, our 98th percentile heat measure does not capture likely variation in the relationship between temperature and mortality (see Anderson & Bell, 2009; Armstrong et al., 2011), which should be incorporated into future studies. Lastly, whereas subsidized housing itself was not statistically associated with extreme heat in the regression models, subsidized housing remains important because policymakers have the most influence over subsidized housing locations and attributes. Beyond subsidized housing, there is a broad need to address low-income households' energy insecurity and locations in neighborhoods with fewer trees and more impervious surfaces.

Conclusions

This study compared the vulnerability of different subsidized and unsubsidized housing groups in California to extreme heat. We found that neighborhoods with more subsidized housing have greater vulnerability—referring to the intersection of exposure, sensitivity, and reduced adaptive capacity—to extreme heat than other kinds of neighborhoods do. Public housing and LIHTC units are particularly likely to be in high-heat neighborhoods and/or neighborhoods with limited adaptive capacity and higher sensitivity. Extreme heat risk is not evenly distributed across housing types and locations in California. Vulnerable subsidized households are clustered in certain cities and counties, particularly in the Central Valley and the eastern parts of Southern California's Inland Empire.

These findings point to opportunities for further research and policy intervention. Scholars need to continue building an evidence base around evolving climate justice issues, which includes identifying disparities in vulnerability and high-risk populations. This scholarship must be interdisciplinary, bringing together scholars from climate science to urban planning, and public health to economics. Meanwhile, climate adaptation must be incorporated into policies and programs that serve seniors, children, people with lower incomes, people of color, and people living with chronic illness. California's AHSC program—which encourages subsidized housing developers to incorporate green features, reduce impervious surface, improve energy efficiency and reduce energy costs, and incorporate cooling centers—could serve as a model for larger state and federal subsidy programs. It will be crucial to design housing that accounts for extreme heat as temperatures rise, populations age, and cities grow.

Notes

1. RCP refers to Representative Concentration Pathways, which are scenarios about the future emissions, concentrations, and land-use change, that serve as inputs to climate models (Van Vuuren et al., 2011). The four RCPs are based on radiative forcing in 2100, referring to 2.6, 4.5, 6, and 8.5 W/m^2 (Van Vuuren et al., 2011). We can broadly think of RCP 2.6 as a low emissions scenario, RCPs 4.5 and 6 as intermediate emissions scenarios, and RCP 8.5 as a high or business-as-usual scenario (IPCC, 2014; Van Vuuren et al., 2011).
2. Additionally, the neighborhood characteristics of two adjacent census tract edges may be more similar than are distant locations within the same tract.

3. Other project-based programs are Section 8 moderate rehabilitation, Section 8 project-based rental assistance, rent supplement, rental assistance payment, Section 236, Section 202 for the elderly, and Section 811 for persons with disabilities.
4. Although these extreme heat days are calculated based on 98th percentile temperatures for the specific location, they are highly correlated with extreme heat days calculated based on a temperature threshold (e.g., 90°F).
5. More broadly, across the United States, differences across housing types are noticeable in terms of central AC and insulation, but not for general prevalence of AC. The national RECS estimates on AC are similar to those from the national American Housing Survey, which give us confidence about using the American Housing Survey estimates for more detailed housing types in California.
6. The community climate resiliency points include a climate adaptation assessment matrix with risks including heat waves, wildfires, and sea level rise. The matrix for extreme heat asks the proposers to characterize the degree to which they are planting trees, providing shade, enhancing insultation, installing cool roofs, reducing electricity demand and cooling costs, and adding permeable land cover. Proposers must also assess the degree to which they replace natural land cover with impervious surfaces (California Strategic Growth Council, 2019).
7. Given Goetz and Chapple's (2010) observation that mobility decisions are often less a result of preferences than of problem-solving in an environment with time constraints and limited housing availability, it seems likely that extreme heat may be a minor consideration for voucher households.

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Notes on Contributors

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