

The Social Vulnerability Index and Exposure to Heat in California Census Tracts

Elizabeth Ackert

ackert@ucsb.edu

University of California Santa Barbara <https://orcid.org/0000-0003-0023-3704>

Kathryn McMahon

University of California Santa Barbara

Gabrielle Husted

University of California San Francisco

Hannah Malak

University of California Santa Barbara

Frank Davenport

University of California Santa Barbara

Kathy Baylis

University of California Santa Barbara

Shraddhanand Shukla

University of California Santa Barbara

Research Article

Keywords: social vulnerability, heat exposure, heat stress, resilience, spatial scale

Posted Date: October 21st, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11066545/v1>

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16 Elizabeth Ackert*, Ph.D.
17 University of California, Santa Barbara
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19 Kathryn McMahon
20 University of California, Santa Barbara
21

22 Gabrielle Husted
23 University of California, San Francisco
24

25 Hannah Malak
26 University of California, Santa Barbara
27

28 Frank Davenport, Ph.D.
29 University of California, Santa Barbara
30

31 Kathy Baylis, Ph.D.
32 University of California, Santa Barbara
33

34 Shraddhanand Shukla, Ph.D.
35 University of California, Santa Barbara
36
37
38

39 ***Corresponding Author:** Please address all correspondence to Dr. Elizabeth Ackert,
40 ackert@ucsb.edu.
41
42

Abstract

California is getting hotter, which may disproportionately expose vulnerable populations within the state to excessive heat and heat shocks. A common measure of social vulnerability is the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry Social Vulnerability Index (CDC/ATSDR SVI). The SVI is meant to guide policy and allocate resources around climate hazards impacts, but it does not include any explicit climate indicators. Using the five-year American Community Survey (2018) and Parameter-elevation Regressions on Independent Slopes Model (PRISM) data (2014 to 2018), we examine whether census tracts in California (N=8,057) with high social vulnerability, based on the CDC/ATSDR SVI value and its component indicators, are at risk of excessive heat exposure, measured using the total number of hot days in the period from 2014 to 2018. We find that most SVI indicators are only weakly correlated with exposure to hot days in California census tracts. The association between the SVI and total hot days varies, however, in subregions of the state, such as by Core-Based Statistical Area (CBSA) and climatic region. Using latent class analysis (LCA), we combine the individual SVI indicators with measures of hot days. We identify three classes of tracts, including one class of tracts that has low social vulnerability and lower heat exposure, and intermediate and high social vulnerability classes where exposure to hot days is varied. Overall, in the California context, there is a weak spatial intersection between social vulnerability and exposure to hot days.

Key terms: social vulnerability, heat exposure, heat stress, resilience, spatial scale

1. Introduction

California is becoming hotter over time. Between 1895 and 2022, average summer month temperatures increased by approximately 0.2 degrees Fahrenheit (F) per year, with scientific predictions for future increases (Echeverria, 2022; Jung, 2022b; NOAA National Centers for Environmental Information, 2023). By 2100, the average annual maximum daily temperature in California is projected to increase by 5.6 – 8.8 degrees F compared to the 1960-2005 baseline (CA.gov; California’s Fourth Climate Change Assessment). Extreme heat events (i.e., heat waves), have increased in number and magnitude since 1950 (CA.Gov; Indicators of California Climate Change, 2022), and these events are projected to be even more intense, frequent, and longer lasting in the future (IPCC, 2021). These trends are worrisome because of the well-documented negative effects of exposure to excessive heat on morbidity and mortality (Ebi et al., 2021; Guirguis et al., 2014). California is a large state both on measures of area and population, however, prompting the question of which geographic areas in the state—and the socio-demographic groups within them—are the most at risk of experiencing exposure to high temperatures.

In this study, we use census and temperature data to investigate the linkage between social vulnerability and heat exposure in California census tracts. Social vulnerability is an important construct in research on climate hazard effects on human health, representing the capacity of a population, within a given geographic area affected by a hazard, to deal with negative effects of that hazard (Cutter, 2006; Cutter et al., 2009; Romanello et al., 2021). Yet, most prior research does not examine the association between social vulnerability and hazards exposure, such as heat exposure. Many social vulnerability indices, including the widely-used Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease

Registry (CDC/ATSDR) Social Vulnerability Index (SVI), do not include indicators of exposure to specific hazards. Prior research suggests, however, that spatial units with higher concentrations of socially and demographically vulnerable groups, such as groups in poverty and non-White groups, have the greatest exposure to heat (Benz and Burney, 2021; Hsu et al., 2021). Understanding who is likely to be affected by heat extremes is important for targeting investments to help those vulnerable communities protect themselves as temperatures increase over time. California's geographic characteristics, as well as the geographic distribution of socio-demographic groups within the state, also make the linkage between social vulnerability and heat exposure less clear for this context. California includes five climatic zones, and these zones do not neatly correspond with concentrations of socially vulnerable groups. Many large and diverse metros in California are located along the cooler coasts, while the more rural and sparsely populated regions which are home to many immigrant-origin farmworkers (such as the Central Valley and Mojave Desert) tend to be warmer than other parts of the state, and some warmer desert areas in the state are magnets for older, but wealthier populations, such as Palm Springs (Guirguis et al. 2014; Jung 2022a). Thus, it is uncertain if the strong correlation between socio-demographic vulnerability and heat exposure found in the prior literature is applicable to census tracts across California.

To contribute to literature on social vulnerability and climate hazards exposure, we investigate socio-demographic patterning in exposure to hot days in California census tracts for the period 2014 to 2018. For each California census tract, we integrate temperature data with CDC/ATSDR SVI values and indicators. We use the CDC/ATSDR SVI as a policy-relevant measure of vulnerability due to its frequent use to direct policy interventions, such as during COVID, and in FEMA's mapping of risk (Centers for Disease Control and Prevention, 2025;

(Dasgupta et al., 2020; Zuzak et al. 2022). We use quantitative methods to investigate associations between exposure to hot days within tracts, as measured using the total number of days 95F or higher within the 5-year interval, and both the SVI index and individual SVI indicators from census data. Using mixed effects models, we also assess variation in the association between the SVI and total hot days across Core-Based Statistical Areas (CBSAs) and climatic regions. We then perform a latent class analysis (LCA), integrating SVI indicators with the hot days measure for each tract, to attempt to identify California census tracts with higher proportions of socially vulnerable households that also have greater exposure to heat.

The CDC/ATSDR SVI is routinely used by U.S. state health departments to analyze public health trends, risks, and inform policy decisions both before and after hazard exposures occur. During the COVID-19 pandemic, the SVI was used to inform the placement of 240 COVID-19 testing sites across 33 states (Centers for Disease Control and Prevention, 2025) and was built into tools¹ and reports (Dasgupta et al., 2020) for use by government actors as they organized vaccine rollout. The SVI has also been integrated into government tools for proactive decision-making to protect public health, such as The Georgia Department of Public Health's Online Analytical Statistical Information System (OASIS)² platform and The Federal Emergency Management Agency's (FEMA) National Risk Index mapping tool³. The SVI is operationalized as one of three inputs to FEMA's Risk Index, which is designed to reflect vulnerability and shape preparedness and response strategies to natural hazards including extreme heat (Zuzak et al. 2022).

¹ <https://covid19vaccineallocation.org/>

² <https://oasis.state.ga.us/>

³ <https://hazards.fema.gov/nri/map>

Despite the frequent use of the SVI in policy, applications of the SVI to specific hazards have yet to be adequately supported by scientific research. When policymakers allocate public resources based on the SVI, without consideration of the underlying spatial patterns of the intersection of social vulnerability and hazards exposure, they may overlook important place-based and hazard-specific contexts. Here we use California as a test case for understanding the relationship between SVI and extreme heat. Our research highlights both potential concerns with using SVI on its own to direct resources to help communities respond to increasing heat exposure, as well as developing an alternative method to identify those locations particularly vulnerable to extreme heat, in order to inform harm-reducing interventions.

1. Background

1.1. The California Heat Context

California is getting warmer over time. Regardless of location, summer is the hottest period in the state, and exposure to summer heat is rising. Summer temperatures in the state have risen 3F on average since 1896, and half of this increase has occurred since the early 1970s (Bedsworth et al., 2018). This trend of increasing summer heat rise is most striking for daily minimum rather than maximum temperatures, which is also observed as a trend across the globe (Gershunov and Guirguis, 2012). Summer temperatures are dramatically shifting towards being hotter—falling into the “hot” and “extremely hot” categories—and they are expected to trend upward as anthropogenic climate change continues (Kasakove & Rojas, 2022).

These shifts are also reflected in several commonly used heat stress indices, which aim to capture the physiological risk of heat by taking four factors involved in heat stress into account: temperature, humidity, air movement, and radiated heat (US Department of Commerce et al., n.d.). These factors include the wet-bulb temperature (WBT), wet-bulb globe temperature

(WBGT), Heat Index, Humidex, and Universal Thermal Comfort Index (UTCI) among others. It is generally agreed that a wet-bulb temperature of 95F is the upper end of what the body can safely manage, but even temperatures starting at 86F and above can be dangerous and deadly (Raymond, 2020, Mellen & Neff, 2021, NIOSH, 2022). Within California, humidity has historically not been a concerning factor due to generally low humidity. However, due to the diversity of geography within California, and as California experiences more frequent and intense heat waves, regions of the state will increasingly experience more humidity over time, eventually making Southern California resemble the mugginess of Florida (Vega-Arroyo et al., 2019, Younger, 2023).

Although heat waves have a regional footprint, understanding how heat exposure varies within sub-regions is necessary to assess the impact of heat in California, due to the complex and clustered distribution of population and resources across the state (Gershunov and Guirguis, 2012). The coasts of California are being particularly impacted by rising temperatures, where it has been historically cool, and thus the population and infrastructure is unacclimated to temperature extremes. Along the coasts, historical analyses from 1950 to 2010 show rising nighttime temperatures and more frequent heat waves—defined as temperatures in the warmest 5% of summer conditions. Over time, desert heat waves are expected to become progressively and relatively less intense, while coastal heat waves are projected to intensify even relative to the background warming. Because the marine layer will offer protective effects in mid-season, California coastal areas are expected to be more vulnerable to early and late season heat extremes (Gershunov and Guirguis, 2012). These shifts in heat waves are leading to regional changes in exposure to hot days across California.

2.2. Social vulnerability and heat exposure

Social vulnerability is a term which has been defined in various ways in the literature, and can be defined as a tendency to be adversely affected by a hazard (IPCC, 2014). The literature also suggests that social vulnerability can be thought of as the inability of a person or population to respond to, adapt to, or recover from hazards or harm (Cutter and Finch, 2008). For heat stress, there is greater vulnerability for individuals with compromised thermoregulatory capacity (e.g., the old, the young, and the sick), those with limited socioeconomic capacity (e.g., the poor and the isolated), and those engaged in strenuous outdoor activities (Mora et al., 2017). Populations with comorbidities, such as chronic obstructive pulmonary disease (COPD) and high blood pressure, are at greater risk of heat illness, in addition to complications due to poor air quality, which can be exacerbated by heat and humidity (Kenny et al., 2010). While human bodies can adapt to a certain extent, at extreme temperature thresholds, the adaptation becomes dependent on mobility and resources, such as spending time indoors in air conditioning, which is inherently dependent on socioeconomic status and access to resources (Mellen & Neff, 2021).

The literature on climate exposures can help to inform expected associations between social vulnerability and exposure to heat. In the United States, people living in areas of high social vulnerability are more likely to experience hotter climate conditions than the overall population (Parsons et al., 2023). Additionally, even though this study does not seek to measure urban heat island (UHI) effects, the UHI literature is informative for this research, showing a strong association between social vulnerability and heat exposure. Specifically, disadvantaged and vulnerable communities, such as individuals in poverty and non-White groups, tend to have more exposure to heat than more advantaged and White populations (Benz and Burney, 2021; Hsu et al., 2021; Mitchell and Chakraborty, 2015). People of color are faced with higher summer

daytime surface UHI severity compared to the average person living below poverty (Hsu et al., 2021). Furthermore, UHI effects vary by geographic area of residence due to local climates, land use, and housing policies (Bolin et al., 2013; Mitchell and Chakraborty, 2018).

Linking emergency department records (ED) with heat measurements and social vulnerability indicators in California can also provide insight into the potential association between exposures and social vulnerability in the state. A recent study on ED visits for heat-related conditions within census tracts in California as a whole, and in Los Angeles County specifically, found a positive correlation between 6 SVI indicators and ED visits for heat-related illnesses, net of age composition and exposure to hot days (Derakhshan et al., 2024). Interestingly, this study found a stronger correlation between SVI indicators and heat-related ED visits at the LA County level of analysis than at the CA state level. Overall, this study suggests a positive correlation between SVI and heat exposure, but a weaker correlation at the broader spatial scale of the state.

While informative, much of the prior literature on social vulnerability indicators and heat exposure may not be applicable to the California state context. For instance, much of the prior literature on heat exposure among racial/ethnic or socioeconomic groups focuses on urban areas, rather than scaling up this concept to the state level and including both rural and urban areas. Focus on a statewide context is also meaningful because state governments are also key actors in setting and implementing climate adaptation and response policy. Additionally, region-specific urban heat management plans are informed by their local infrastructure, environment (topographical features, climatological features), vulnerabilities, and risks (Vargo et al., 2016, Shahmohamadi et al., 2011). For these reasons, within a state like California, it is important to

consider the intersections of social vulnerability and heat exposure at both the state and subregional levels.

California also presents a unique geographic and climatic context for considering linkages between social vulnerability and heat exposure. The state contains five climate types—desert, cool interior, highland, steppe, and Mediterranean (Atlas of the Biodiversity of California); the only place with a comparable variety of climates in such close geographic proximity is in central Chile (Kauffman, 2003). Most of California’s largest urban areas, which contain demographically diverse populations, are also located along the cooler coastal regions. An analysis of urban areas in California also shows substantial variability in heat effects across California, dependent on the size and density of the urban area, and/or whether the urban area experiences offshore or onshore warming effects (Taha, 2015). These factors may generate heterogeneity in exposure to heat among socially vulnerable groups across areas of the state.

Finally, prior research on heat effects on health outcomes by California region also suggests differential social variation in exposure to heat across the state. Research analyzing the July 2006 California heat wave in relation to 10 cause groups of ED visits and hospitalizations found that the Central Coast had a higher excess morbidity and rate ratio (than the average), whereas the Southeast Desert had a lower than average excess mortality and rate ratio (Knowlton et al., 2009; Gershunov and Guirguis, 2012). Therefore, understanding heat impacts in California must be paired with knowledge of both state and sub-regional patterns in heat exposures and indicators of social vulnerability.

2.3. Social Vulnerability Measurement

Even though social vulnerability is an important consideration in disaster risk management, it is difficult to capture with a single variable or statistical model. A large literature

has approached this problem by creating composite indices that incorporate multiple elements of vulnerability that can often be easily obtained using census data. The top three most common domains in these indices are the presence of at-risk populations (e.g., older adults, children or dependents), education levels, and indicators of socioeconomic status, while the least common domains are political instability and pollution (Mah et al., 2023). Notably, many of these indices do not include exposures to climate-related hazards as an indicator of vulnerability.

Social vulnerability indices have now become quite popular tools for environmental hazards research and policy, and have been used in the contexts of environmental and climatic change, disaster impacts and responses, and public health (Mah et al., 2023). These indices are chosen to provide a snapshot of social vulnerability that researchers can use in their own work and for decision makers. As such, they inherently depend on subjective choices made by the researcher. The most consequential of these choices involve the selection of indicators to include and the method for distributing weight among them. In general, researchers rely on some combination of expert input and statistical methods, like principal component analysis, to make these choices (Bucherie et al., 2022).

There are a variety of social vulnerability indices now available. Some popular examples include the Spatially Explicit Resilience-Vulnerability model (SERV), FEMA’s National Risk Index, the University of South Carolina’s Social Vulnerability Index (SoVI), and The Centers for Disease Control and Agency for Toxic Substances and Disease Registry (CDC/ATSDR) Social Vulnerability Index (SVI) (Wood et al., 2021). The CDC/ATSDR SVI is one of the most commonly cited social vulnerability indices, and is freely available to the public and easy to access. The SVI is constructed at the census tract level using data from the five-year American Community Survey (ACS). The census tract is a useful spatial unit of analysis for social

vulnerability, because the size of each tract is based on total population rather than area. Because of this, tracts are commonly used as proxies for neighborhoods among urban planning researchers. They are also frequently a spatial unit of interest in government and public health decision-making, making the tract-level SVI translatable to policy interventions and planning (Flanagan et al., 2011, Van Zandt et al., 2012).

The SVI ranks each tract based on 16 social factors, all categorized under four themes: socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation. It was originally created in 2011 to help government officials, policy makers, and health care providers to support communities in need before, during, or after disasters. It aims to assist in emergency planning and to guide community-based health promotion initiatives (CDC/ATSDR, 2023).

Composite indices like the SVI are attractive to stakeholders, practitioners, and decision makers, but there is a growing body of research, and a vocal set of researchers, warning that such indices are “blunt” instruments, lacking context specificity in their current form (Saisana et al., 2005b; Tate, 2012). Specifically, recent work highlights that a single social vulnerability score determined via an index can (1) diminish the significance of a lone variable, (2) overlook the relevancy of all interconnected variables, and (3) result in contradictory policy recommendations. For instance, Wood et al. (2021) demonstrate that a single variable for poverty may be equally appropriate for capturing social vulnerability to COVID-19 compared with a more complex composite measure. The SVI can also miss the nuance of interconnectivity between variables. Mah et al. (2023), for example, argue that addressing the bidirectional nature of social vulnerability within healthcare is essential, as vulnerability both increases likelihood of negative outcomes, and is a barrier to adequate response following an adverse health event.

227 Lastly, research suggests that vulnerability assessments are most popular in well-funded and
228 well-organized communities in the US, suggesting that these metrics are not being applied to
229 support the most vulnerable communities (Wood et al., 2021). This issue is amplified by the fact
230 that differently-constructed indices often yield conflicting results, allowing a given community to
231 be classified as vulnerable by some measures and not by others. Given the current proliferation
232 of indices used in the literature, a better system of cross-validation among measures is needed to
233 promote replicability and external validity (Spielman et al., 2020).

234 Finally, popular indices like the CDC/ATSDR SVI may not be equally appropriate for all
235 hazard contexts. While the scientific movement to develop measures of social vulnerability
236 initially centered around hazard-specific metrics, these have become increasingly generalized
237 across hazards (Bucherie et al., 2022). While such conglomeration may increase replicability and
238 interpretability across contexts, a growing number of studies show that the SVI and its fellows
239 may neglect important elements of vulnerability in hazard-specific settings. For example,
240 information on housing structure type may be very important in the context of extreme
241 precipitation events (Mazzorana et al., 2014), but contributes less to vulnerability in the context
242 of a disease outbreak. In the case of extreme heat, evidence suggests that regional adaptation and
243 access to air conditioning play a very large role in determining the health impact of extreme
244 events (Deschenes, 2014; Barreca et al., 2016), but this measure is not included in the SVI.
245 While other measures of socioeconomic status may serve as an adequate proxy for air
246 conditioning access in the SVI, this may not always be the case for urban populations along the
247 California coast. Furthermore, the SVI lacks any information on average levels of heat exposure,
248 which may be an important determinant of regional adaptation levels and heat preparedness.

2. Research Questions

We address the following research questions:

RQ1: Among California census tracts from 2014 to 2018, what is the association between social vulnerability measures from the CDC/ATSDR SVI and exposure to hot days, as defined by total days over 95F?

RQ2: How does the association between social vulnerability and exposure to hot days vary across California census tracts in different subregions of the state?

RQ3: Does our ability to identify tracts with high social vulnerability and high heat exposure improve when adding exposure to hot days to the SVI index measures via a latent class analysis (LCA)?

3. Data and Measures

The units of analysis are California census tracts (N=8,057), defined using 2010 census tract boundaries and associated TIGER/Line shapefiles. We extract data on daily maximum temperatures (Tmax) for each census tract using the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset from Oregon State University, which is available at a 4 kilometer X 4 kilometer spatial resolution. The strength of the PRISM dataset lies in application of high density stations (particularly in populated regions) and a topographically and physiographically sensitive PRISM interpolation process. In comparison to other spatial climate datasets, such as WorldClim and Daymet, it is more accurate in the western United States, which makes it particularly well suited for studying California (Daly et al., 2008). Comparison of PRISM relative to Daymet (available at 1km resolution) for estimating maximum daily heat index specifically for epidemiologic analyses has also shown that it outperforms the Daymet

dataset (Spangler et al., 2018). Additionally, PRISM has been commonly used in the literature to estimate heat exposure in the United States (Bernstein et al., 2022; Sarma et al., 2022). We employ PRISM data from the period 2014 to 2018 to match the temporal coverage of the 2018 CDC/ATSDR SVI and the 2014 to 2018 American Community Survey (ACS) data.

To define Tmax at the census tract level, we first construct a 25 kilometer buffer around the population-weighted centroid of each tract⁴. For each day between January 1st, 2014 and December 31st, 2018, we then calculate the mean Tmax value among all PRISM pixels that fall within the 25 kilometer (km.) buffer, and assign this mean value to the tract. After estimating a daily record of Tmax for each census tract and its buffer area, we estimate tract-level heat exposure by counting the total number of days from 2014-2018 that Tmax exceeded 95 degrees Fahrenheit.

We adopt this centroid approach with a 25 km. buffer—rather than using the tract boundaries—to measure Tmax because this method adjusts for the unequal spatial scale of (smaller) urban and (larger) rural tracts, and flexibly accounts for daily mobility and activity space patterns of populations, which usually extend beyond tract boundaries (Wong and Shaw., 2011; Jones and Pebley, 2014; Xu, 2022). We also considered the sensitivity of our heat estimations to our decision to use a 25 km. buffer around the census tract centroid. For each census tract, we estimated daily Tmax using a 10 km. buffer, a 25 km. buffer, a 50 km. buffer, a 75 km. buffer, a 100 km. buffer and a tract polygon approach (averaging over all of the grid cells within the tract polygon), and then recalculated the total count of hot days for tracts from 2014 to 2018. Appendix Table A1 lists the pairwise correlations between these estimates of total hot days. The correlations between the estimates of total hot days between the 25 km. buffer and 10

⁴ Population weighted census tract created by the GIS Lab at the Newman Library of Baruch College, CUNY (GIS Lab at the Newman Library of Baruch College, CUNY, 2021)

km. buffer approaches, as well as the 25 km. and tract polygon approaches, were strong ($p = 0.895$ and $p = 0.844$, respectively). For this reason, we chose the 25 km. buffer estimation approach for this analysis. To measure social vulnerability at the tract level, we first use the 2018 CDC/ATSDR SVI values for California census tracts. We then reconstruct 17 tract-level variables that are the same as or similar to the individual measures/components in the CDC/ATSDR SVI. We obtain aggregate socio-demographic measures for California census tracts from 2014-2018 using the five-year American Community Survey, accessed via the Tidycensus package in R (Walker and Herman, 2024). Our goal is to focus on indicators of socio-demographic vulnerability to climate hazards using the CDC/ATSDR SVI index, which capture differences in socio-economic status, household composition and disability, minority status and language, and housing type and transportation (Flanagan et al. 2018). We focus on the period 2014-2018 so as to match the ACS data as closely as possible to the 2018 CDC/ATSDR SVI, which is based on the same ACS data and time period⁵. After merging all ACS variables with our constructed heat variable and the 2018 SVI, the final integrated dataset includes, for each California census tract, the total number of hot days from 2014-2018, 17 socio-demographic indicators from the ACS, and the 2018 SVI value. All variables are listed in Table 1, along with summary statistics for all tracts.

4. Methods

We first conduct a correlational analysis of the SVI index, individual SVI measures, and total hot days among California census tracts from 2014 to 2018. We estimate both the Pearson's

⁵ Appendix Table A2 lists the ACS measures, how they were constructed using the original Tidycensus variables, and notes regarding variable creation (such as definitions and whether some measures were restricted to particular demographic groups).

correlation coefficient and Spearman’s rho correlation⁶. Because California is a large state, it is possible that the association between social vulnerability and total hot days in a pooled analysis (i.e., using all tracts in the state) masks variation within the state in associations between social vulnerability and heat exposure. To accommodate the potential for associations that vary across the state, we also estimate two sets of varying-intercept, varying-coefficient (i.e., varying-slope) mixed effects models. These models allow the intercept (mean of total hot days) and the slope (association between the SVI and total hot days) to vary between groups of tracts that are “nested” within a broader geographic area.

For the first set of mixed effects models, we “nest” census tracts within Core-Based Statistical Areas (CBSAs), which represent large urban areas and their associated surrounding functional regions and commuting zones (U.S. Census Bureau, 2023). We present results for the top 10 CBSAs in California, with results for all CBSAs in the appendix. We also estimate mixed effects models with varying intercepts and slopes for tracts “nested” within California Climatic Divisions, using the 7 climatic divisions from NOAA: 1. North Coast Drainage, 2. Sacramento Drainage, 3. Northeast Interior Basins, 4. Central Coast Drainage, 5. San Joaquin Drainage, 6. South Coast Drainage, 7. Southeast Desert Basin (NOAA Physical Sciences Laboratory, n.d.; NCEI, n.d.; Karl, T. R., & Koss, W. J., 1984; NCDC, 1994; Vose et al., 2024). These mixed effects models also incorporate the log-transformed total number of hot days as the dependent variable to deal with the skewed distribution of total hot days.

We conclude by investigating if including heat exposure measures (hot days) alongside the SVI measures can better identify tracts in California that are both socially vulnerable and

⁶ We log-transformed the total number of hot days to deal with skewed, left-truncated distribution of total hot days. We refer to “log-transformed total hot days” using the abbreviation LTHD.

have higher heat exposure using latent class analysis (LCA). For the LCA, we first select only the census variables used in the construction of the SVI (see Table 1) and the total number of hot days ($T_{max} > 95$) from 2014-2018. Given that local heat levels are not factored into the SVI, we include this measure in the LCA to identify “hotspots” of high heat exposure and high social vulnerability. Next, as the LCA method requires that input variables be categorical, and to make measures comparable across variables, we discretize all variables into quartiles, defined using cutoff points at the 0.25, 0.5, and 0.75 quantiles of their respective distributions. Next, we run the three-class LCA using the poLCA package in R (Linzer and Lewis, 2011).

For each variable, the model provides a probability that a tract belonging to a given class will fall in the first, second, third, or fourth quartile of the variable’s distribution. Finally, we use the model to predict class membership for each tract in our sample, which allows us to directly compare classifications between using only the SVI values versus our LCA. We identified a three-class model as the most appropriate model for this analysis. Beyond three classes, model fit statistics (including Akaike Information Criterion, Bayesian Information Criterion, and maximum log-likelihood) saw little improvement, while interpretability was increasingly lost. See Appendix Figures A1-A2 for a set of alternative results using a two-class model⁷.

5. Results

5.1. Summary statistics

Table 1 shows descriptive statistics for all variables used to construct the SVI for California census tracts. On average, census tracts over the period from 2014-2018 (1,825 total days) experienced 89.8 hot days over 95F (5% of all days), with a range of 0 (0%) to 701 (38%). The descriptive statistics in Table 1 show wide variation in socio-demographic characteristics

⁷ All analyses are done with the R programming language. Code is available upon request from the authors.

used to comprise the SVI across California census tracts. For instance, the average percentage of the population living below the poverty line (the monetary threshold for poverty established by the U.S. Census Bureau that differs by family size and composition) is 14.6%, but this value ranges from 0-100%. Similarly, there is a wide range of household age compositions across different census tracts, although on average there is a higher proportion of children (ages 18 and younger) in state tracts (22.4%) than older adults ages 65 and older (14.4%).

The descriptive statistics in Table 1 also show that California's population is racially and ethnically diverse, with census tracts being, on average, 61.0% non-white and 37.9% Latinx, but these values again range substantially from low to high values across tracts. A noticeable percentage of tracts have significant shares of their population living in multi-family and "crowded" housing. On average, the percentage of multi-family housing (structures with 10 units or more) within a tract is 16.0%. Almost 10% of residents within tracts have more residents than rooms, which is one indicator of crowding. Housing types also vary significantly across the state. In some tracts, up to 100% of residents live in multifamily housing, 95% of residents live in mobile homes, 69% live in crowded housing, and 100% live in group quarters. Overall, these descriptive statistics highlight substantial diversity across California census tracts and indicators of social vulnerability.

Figure 1 depicts the geographic variation in total hot days in California census tracts for years 2014-2018 (1,825 total days). In some areas of the state, over one third of all days were hot days during this period, including the Central Valley and desert regions. For census tracts in Imperial County, for example, average annual hot days ranged from 118 to 140 days per year during the study period. By contrast, all census tracts but one in San Diego County—a coastal county directly west of Imperial County—had 17 or fewer hot days per year. In San Francisco

County, no tract experienced more than two days with $T_{max} > 95^{\circ}\text{F}$ during the entire five-year period. This geographic pattern illustrates that residents in tracts of large urban areas along the coasts have lower exposure to hot days than those in the Central Valley and desert areas. This figure also shows this variation for four major Core-Based Statistical Areas (CBSAs): San Francisco-Oakland-Hayward, Sacramento-Roseville-Arden-Arcade, Los Angeles-Long Beach-Anaheim, and San-Diego-Carlsbad. This subregional view shows a lack of a granular heat-island effect—there is little variation in the total number of hot days within these major metro areas.

Figure 2 presents the SVI scores for each census tract in California, with values ranging from 0 (least vulnerable) to 1 (most vulnerable). Whereas the tract total hot days map (Figure 1), showed a clear geographic pattern of more/less exposure to hot days in California, the SVI map shows much greater heterogeneity in social vulnerability across tracts. Many of the tracts within the high heat exposure regions (Central Valley and desert areas) have high social vulnerability, but there are also areas in these regions with medium and low social vulnerability. Additionally, there are socially vulnerable tracts within the coastal areas, and within the major CBSAs, which tend to have lower exposure to hot days than the Central Valley and desert areas. This descriptive analysis suggests that exposure to hot days does not map neatly onto social vulnerability in California census tracts.

5.2. Correlations Between Tract Hot Days and Social Vulnerability

Table 2 presents Pearson’s correlation coefficients and Spearman’s rho between SVI measures and the logged total number of days over 95 degrees F in California census tracts from 2014-2018, along with p-values. Note that the Pearson’s and Spearman’s correlation estimates are very similar, so we only discuss the Pearson’s correlation results below. We also refer to values as “significant” if the p-value is 0.001 or less. The correlation between the SVI index and

the logged total number of hot days (LTHD) is positive and significant, but weak ($r = 0.229$). The other correlations between SVI indicators and LTHD displayed in Table 2 are all weak and/or in the opposite direction of the expected association.

However, of the weak and statistically significant correlations, the strongest are socioeconomic status indicators, such as percent poverty ($r = 0.222$), percent unemployed ($r = 0.250$), and per capita income ($r = -0.377$) variables. The percent of the population with no high school diploma was another socioeconomic indicator positively and significantly correlated with hot days, but with a weak overall correlation ($r = 0.176$).

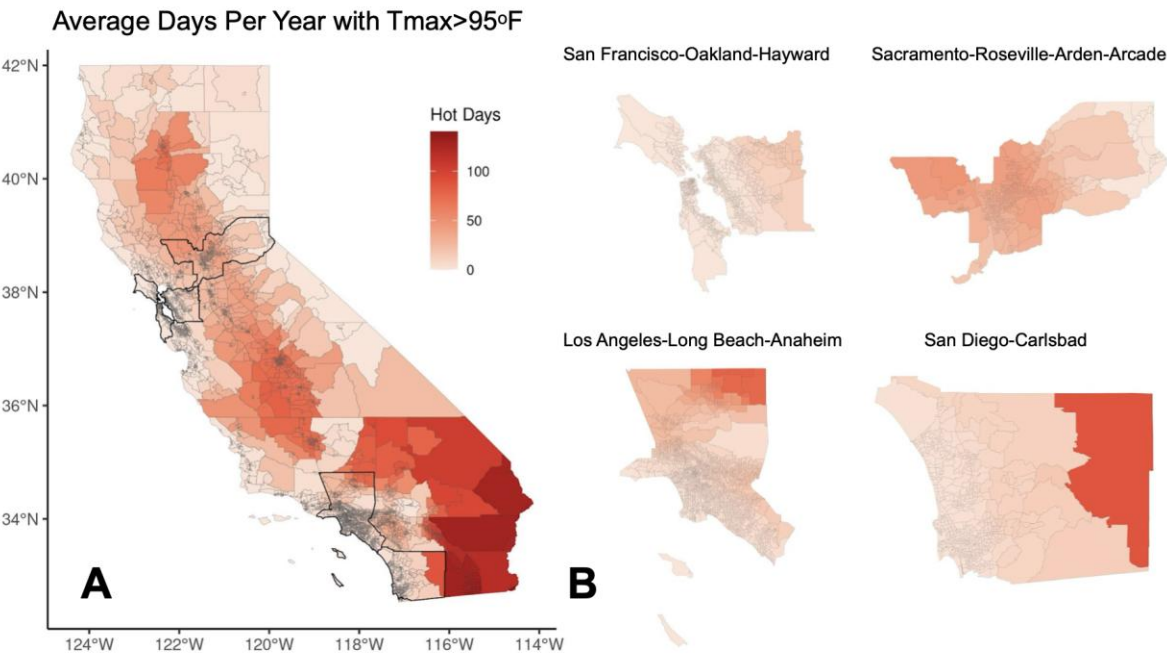
The minority status and language indicators showed mixed results, with percent non-White having a very weak positive significant correlation ($r = 0.052$) with LTHD, and percent with limited English proficiency a very weak positive and non-significant correlation ($r = 0.019$). Percent Latinx exhibited a stronger and significant correlation with LTHD ($r = 0.237$). For household composition and disability, several compositional variables were in the expected (positive) direction, but with weak correlations with hot days overall, including percent under 18 ($r = 0.297$), percent with a disability ($r = 0.213$), and single-parent households ($r = 0.215$). For housing types, living in a mobile home was also positively, but weakly, correlated with hot days ($r = 0.182$).

Several of the other SVI indicators had correlations with LTHD that were near zero ($< |0.1|$), including percentage without health insurance and percent age 65 or older (which were both non-significant), percent housing units with more residents than rooms (i.e., “crowding”), percent without a vehicle (non-significant), and percent living in group quarters (also non-significant). Some of the SVI indicators were also correlated with exposure to LTHD in unexpected ways.

425 **Table 1. Descriptive statistics for the SVI, total hot days, and variables used to construct**
426 **the California tract-level SVI (2014-2018).**

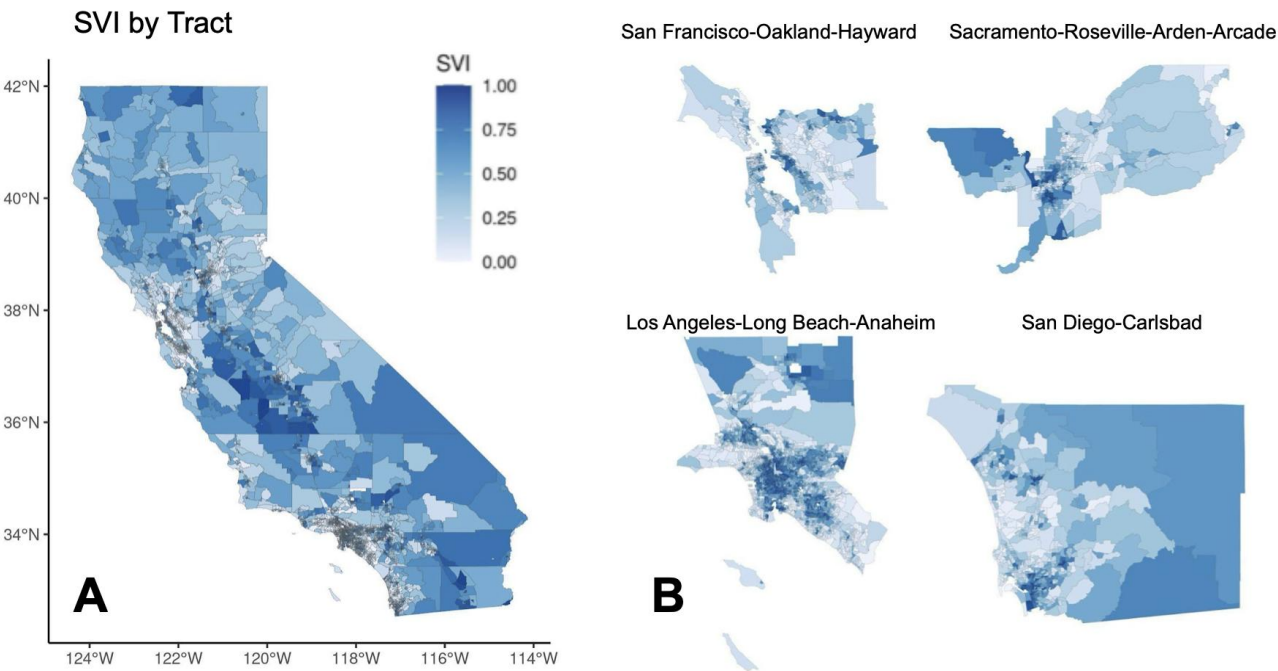
	Mean	SD	Min	Median	Max
SVI (Overall)	0.5	0.3	0	0.5	1
Total days with Tmax>95°F	90	115	0	37	701
<i>Socioeconomic Status:</i>					
Below the poverty line (%)	15	11	0	12	100
Unemployed (%)	4.3	2.4	0	3.8	20
Income (per capita)	35,904	21,380	729	30,656	171,298
No high school diploma (%)	18	15	0	13	77
No health insurance (%)	8.6	6	0	7.2	54
<i>Household Composition and Disability</i>					
Aged 65 or older (%)	14	8.1	0	13	100
Aged 18 or younger (%)	22	7.1	0	23	57
Person with a disability (%)	11	4.8	0	10	100
Single-parent households (%)	9.3	6.6	0	7.9	100
<i>Minority Status and Language:</i>					
Non-White (%)	61	26	0	62	100
Latinx (%)	38	26	0	31	100
Limited English Proficiency (%)	9.8	9.4	0	6.6	64
<i>Housing Type and Transportation</i>					
Housing structures within 10+ units (%)	16	20	0	8.4	100
Living in mobile homes (%)	3.6	8.3	0	0	95
Housing units with more residents than rooms (%)	9.1	9.3	0	5.9	69
No vehicle (%)	7.4	8.5	0	4.8	89
Living in Group Quarters (%)	2.0	9.5	0	0.3	100

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429 **Figure 1. Geographic Variation in Annual Average Total Hot Days in California Census**
430 **Tracts (2014-2018).**



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432 **Figure 2. Social Vulnerability Index Score Across California Census Tracts (2018).**

For example, the concentration of multifamily housing, as measured by the percent of housing structures with 10 or more units, was negatively and significantly correlated with hot days ($r = -0.208$).

To check the sensitivity of our results to the choice of total hot days as our heat exposure measure of interest, we re-estimated the correlations in Table 2, but used the average tract maximum daily temperatures (Tmax) for the summer months (June, July, and August; JJA) during this same time period (2014-2018). The results for these correlations are displayed in Appendix Table A3. The differences between the correlation values (Pearson's R or Spearman's rho) for the SVI measures and the JJA Tmax averages (in Appendix Table A3) and those in Table 2 (using LTHD) are $|\leq .03|$ or less. Additionally, there is no clear pattern of over- or under-estimation of the correlation coefficients between the two types of estimates, with some correlations being weaker when using the JJA Tmax measure versus logged hot days measure (e.g., per capita income, percent aged 65 and over, living in mobile homes), but other correlations being stronger using this measure (e.g., housing structures with 10+ units, housing units with more residents than rooms). The overarching pattern found in Table 2 persists in these sensitivity analyses (Appendix Table A3), with weak correlations between SVI measures and tract JJA Tmax values overall (absolute value of 0.4 or lower), but with some of the stronger correlations between measures related to residential mobility and neighborhood choice (e.g., percent below the poverty line, per capita income) and exposure to hotter average summer temperatures.

5.3. Mixed Effects Model Results

We next turn to an analysis of variation in the association between the SVI and total hot days in California census tracts by sub-regions within the state using varying-intercept, varying-

slope mixed effects models. The first subregion of focus are CBSAs, which are combinations of metropolitan and micropolitan statistical areas that are grouped based on population size and economic integration.

The dependent variable in the model is logged total hot days (LTHD) in the tract, and the main independent variable is the SVI for the tract. Each tract is nested within a CBSA. For the sake of brevity, we focus on results only for the top 10 CBSAs in California based on population size (Figure 3). The coefficients in the upper-right corner for each CBSA represent how the log-transformed total number of hot days changes with a one-point increase in the SVI for tracts within that CBSA.

As the results in Figure 3 demonstrate, the association between the SVI and LTHD for census tracts varies across CBSAs. For a number of CBSAs, the association between the SVI and LTHD is positive, including for San Diego-Carlsbad, Bakersfield, Riverside-San Bernardino-Ontario, San Jose-Sunnyvale-Santa Clara, and Los Angeles-Long Beach-Anaheim. In these areas, more socially vulnerable census tracts have increased heat exposure. For others, the association is close to zero, such as for Fresno and Stockton-Lodi. And yet for others, this association is negative, indicating that socially vulnerable tracts have fewer total hot days, such as for Oxnard-Thousand Oaks-Ventura, San Francisco-Oakland- Hayward, and Sacramento-Roseville-Arden-Arcade. The results displayed in Appendix Figure A3, for all California CBSAs, confirm significant variation in the association between the SVI and LTHD for all CBSAs across the state.

Table 2. Correlations between SVI measures and the log-transformed number of days over 95 degrees F, California, 2014-2018 (N=7,974 tracts).

SVI Measure (CA Tracts, 2014-2018 ACS)	25km buffer			
	Pearson's R	p-value	Spearman's rho	p-value
<i>SVI (Overall)</i>	0.229	< 0.001	0.231	< 0.001
<i>Socioeconomic Status:</i>				
Below the poverty line (%)	0.222	< 0.001	0.241	< 0.001
Unemployed (%)	0.250	< 0.001	0.241	< 0.001
Income (per capita)	-0.377	< 0.001	-0.355	< 0.001
No high school diploma (%)	0.176	< 0.001	0.219	< 0.001
No health insurance (%)	0.115	< 0.001	0.156	< 0.001
<i>Household Composition and Disability:</i>				
Aged 65 or older (%)	-0.059	< 0.001	-0.090	< 0.001
Aged 18 or younger (%)	0.297	< 0.001	0.306	< 0.001
Persons with a disability (%)	0.213	< 0.001	0.258	< 0.001
Single-parent households (%)	0.215	< 0.001	0.242	< 0.001
<i>Minority Status and Language:</i>				
Non-White (%)	0.052	< 0.001	0.028	0.014
Latinx (%)	0.237	< 0.001	0.256	< 0.001
Limited English Proficiency (%)	0.019	0.092	0.039	< 0.001
<i>Housing Type and Transportation:</i>				
Housing Structures with 10 + Units (%)	-0.208	< 0.001	-0.237	< 0.001
Living in Mobile Homes (%)	0.182	< 0.001	0.229	< 0.001
Housing Units with More Residents than Rooms (%)	-0.008	0.498	0.023	0.045
No Vehicle (%)	-0.163	< 0.001	-0.070	< 0.001
Living in Group Quarters (%)	-0.007	0.511	-0.035	0.002

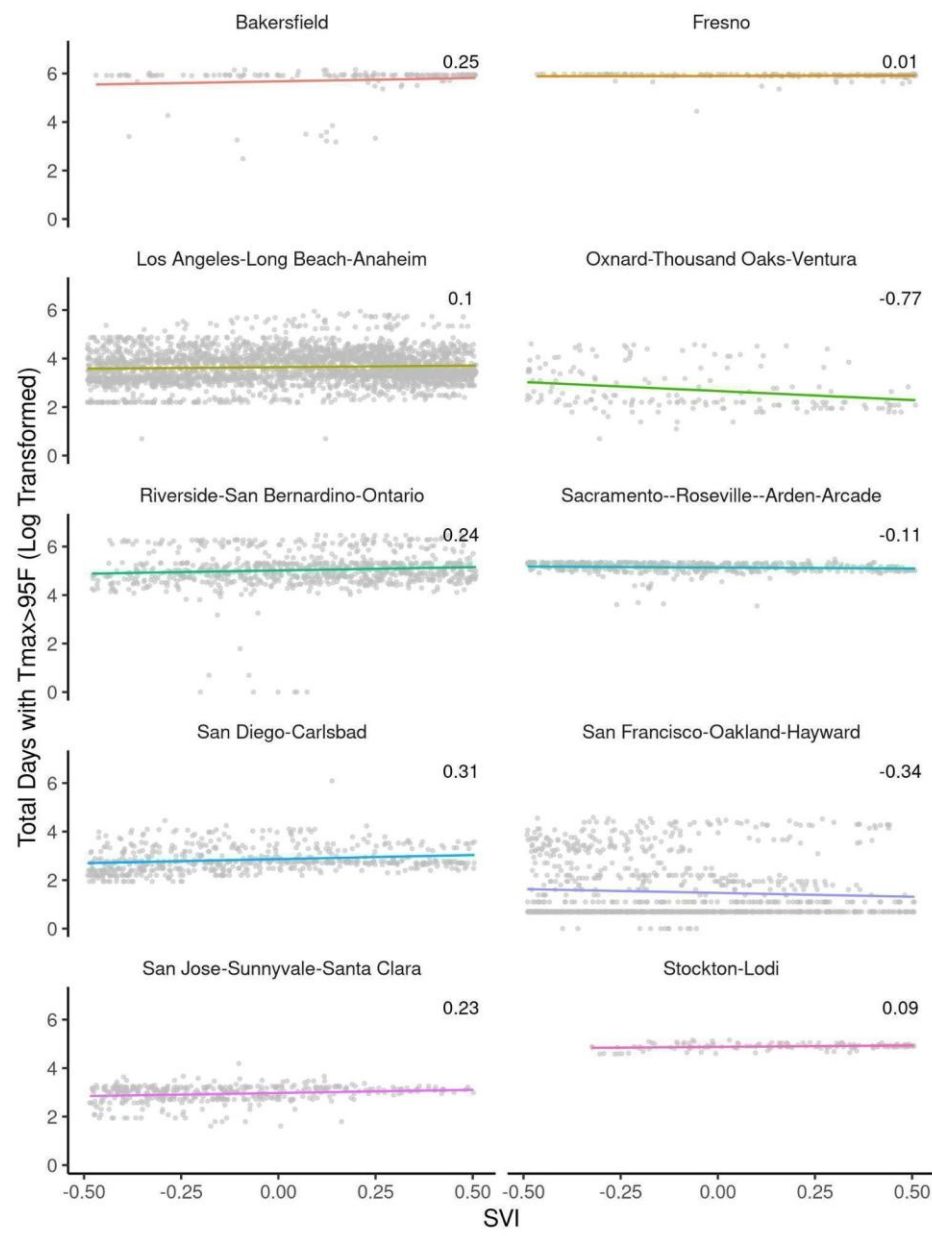
Note: P-values reported from a two-sided t-test.

To check the sensitivity of the CBSA mixed effects results to the choice of heat exposure measure (i.e., LTHD), we re-estimated the mixed effects models using tract average maximum temperatures in June, July, and August (i.e., JJA Tmax) from 2014 to 2018 as the dependent variable. These results are displayed in Appendix Figure A4. For brevity, we only discuss similarities and differences in the results for the top 10 CBSAs.

For 8 of the top 10 CBSAs, the direction of the association remained the same (i.e., positive or negative) when estimating average JJA Tmax rather than LTHD. (Coefficients should not be directly compared across these models because the dependent variables are on different scales.) Two exceptions were for the Fresno CBSA, where this association was positive but near zero ($b = 0.01$) in the model estimating LTHD, but negative and also close to zero ($b = -0.04$) in the model estimating JJA Tmax, and for Sacramento-Roseville-Arden-Arcade, which had a negative association for the LTHD models ($b = -0.11$) but a positive association for the JJA Tmax models ($b = 0.22$). Overall, this sensitivity check shows that most of the results for the mixed effects models are consistent when looking at associations between the SVI and heat exposure, regardless of whether heat exposure is measured using tract (logged) total hot days or average JJA Tmax. Where results do differ, they are for CBSAs where the association between the SVI and heat exposure is fairly weak overall.

Next, we consider the associations between the SVI and LTHD for census tracts within California climatic divisions (Figure 4). Similar to the results for CBSAs, the association between the SVI and LTHD for census tracts varies by climatic division.

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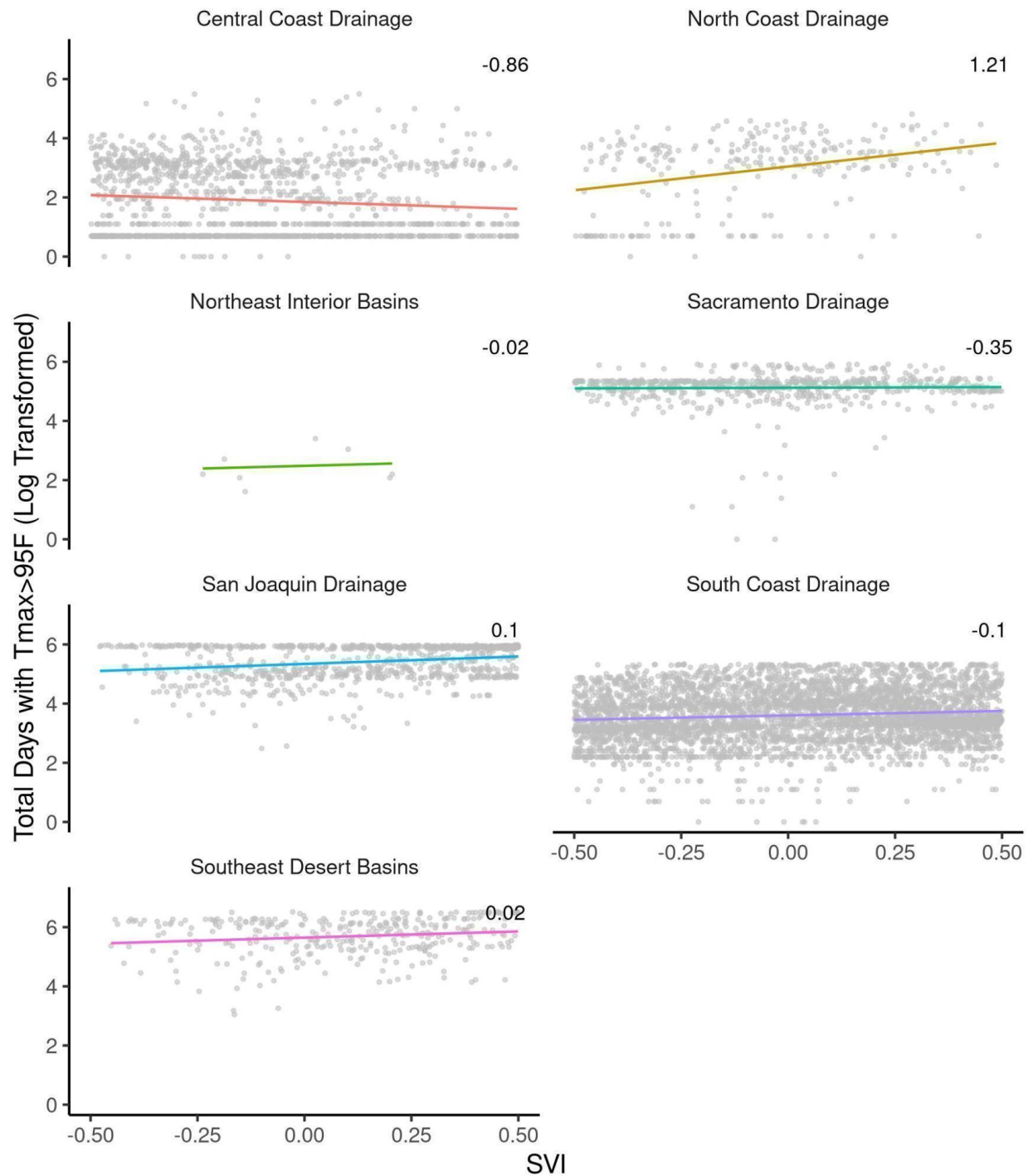
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Figure 3. Association between total number of hot days (log transformed) and the SVI for the top 10 CBSAs in California. (Note: Mixed effects model results. Coefficients for the SVI variable are displayed in the upper- right corner.)

The association is positive, with more socially vulnerable tracts experiencing more hot days, in the Southeast Desert Basins (encompassing desert areas, such as Inyo County, Imperial County, and the eastern portions of Riverside and San Bernardino Counties), the North Coast Drainage (the northern, coastal portion of the state, including counties such as Sonoma, Mendocino and Humboldt), and the San Joaquin Drainage (including much of what is called the “Central Valley,” including Stanislaus, Merced, Madera, and Fresno Counties as well as other counties). The strongest positive association between the SVI and LTHD is for the North Coast Drainage ($b = 1.21$).

In contrast, the association between the SVI and the logged total number of hot days is negative, with lower heat exposure among more socially vulnerable tracts, in the Central Coast Drainage (the coastal counties stretching from San Luis Obispo to San Francisco County), the Sacramento Drainage (including the Sacramento Valley and most of the Shasta Cascades), the Northeast Interior Basins (the narrow northern portion of the state bordering Nevada, including most of Lassen County and other counties), and in the South Coast Drainage (the mostly coastal areas of the counties stretching from San Diego to Santa Barbara County). The strongest negative association for the SVI and (logged) total hot days is for the Central Coast Drainage ($b = -0.86$). To check the sensitivity of the results for the association between the SVI and heat exposure to the choice of (logged) total hot days as the focal measure of heat exposure in this model, we re-estimated the California climatic divisions mixed effects model, but used tract average JJA Tmax as the dependent variable. These results are displayed in Appendix Figure A5.



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Figure 4. Association between total number of hot days (log transformed) and the SVI for

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California climatic divisions. (Note: Mixed effects model results. Coefficients for the SVI

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variable are displayed in the upper- right corner.)

The direction of the coefficients (positive versus negative) is the same for 6 of the 7 climatic divisions. For the Northeast Interior Basins (the narrow northern portion of the state bordering Nevada), the coefficient on the SVI is negative (and near zero) when estimating LTHD ($b = -0.02$), but positive when estimating average JJA Tmax ($b = 0.48$). Thus, the mixed effects results are largely consistent for climatic divisions across the two types of heat exposure measures (LTHD and average JJA Tmax).

5.4. Latent Class Analysis

Figure 5 presents results from the latent class analysis with three classes. Full model results are included in Appendix Table A4. As evidenced by Figure 5, the classes identified by the model tend to separate tracts that fall in the left tail, the middle, and the right tail of the distribution for each variable in the model (the individual SVI variable and total hot days quartiles). For example, those tracts that have the lowest per capita income also tend to have a high percentage of residents without health insurance and without a high school degree. We therefore label this class as the “Most Vulnerable” class. The opposite trends are true for the “Least Vulnerable” class, and tracts in the “Intermediate” class tend to fall in the second and third quartiles for each variable. The values in Figure 5 report the probabilities of variable outcomes (in quartiles) for each class (Least Vulnerable, Intermediate, and Most Vulnerable). Estimated class population shares are 0.387 (Least Vulnerable), 0.355 (Intermediate), and 0.258 (Most Vulnerable) across the sample of tracts.

Figure 5 reveals that the classes are highly divided for variables that capture race (percent non-White) and socioeconomic status (per capita income, percent without health insurance, and percent without a high school degree). By contrast, classes look more similar – though still

distinct – across variables that describe age structure and tract characteristics that are more transitory in nature (such as percent unemployed).

Finally, our variable for the number of days with temperatures exceeding 95F exhibits the least variability in trends across classes. Tracts classified as Least Vulnerable are the most likely to fall in the lowest quartile of heat exposure, while the Intermediate and Most Vulnerable tracts are similarly likely to fall in the second, third, or fourth quartile for heat exposure. \

Using the same model, we next predict class membership at the tract level based on each tract's characteristics. Figure 6 shows the resulting spatial distribution of Least Vulnerable, Intermediate, and Most Vulnerable tracts across California (Panel A) and within each of the four major metropolitan areas (Panel B). Panel A reveals that there is considerable spatial contiguity within each class at the state level, such that tracts of the same class tend to be clustered together in space.

For example, tracts predicted to be Most Vulnerable by the model are largely concentrated in low-income areas dominated by agriculture, including California's Central Valley, Salinas Valley, and Imperial Valley. Meanwhile, tracts classified as Least Vulnerable tend to fall near the state's wealthier coastal metropolitan areas (including San Diego, Los Angeles, and the San Francisco Bay area) as well as in the Northern and Eastern parts of the state, which are cooler on average than tracts in Southern California (see Figure 1). Panel B reveals that there is notable heterogeneity in predicted class within urban areas, though considerable spatial clustering persists at the sub-metropolitan scale. The variation in vulnerability is particularly evident in the Los Angeles metropolitan area, where pockets of Most Vulnerable tracts are clustered in neighborhoods at the center of the city (e.g., Compton) but are surrounded by Least Vulnerable tracts on all sides.

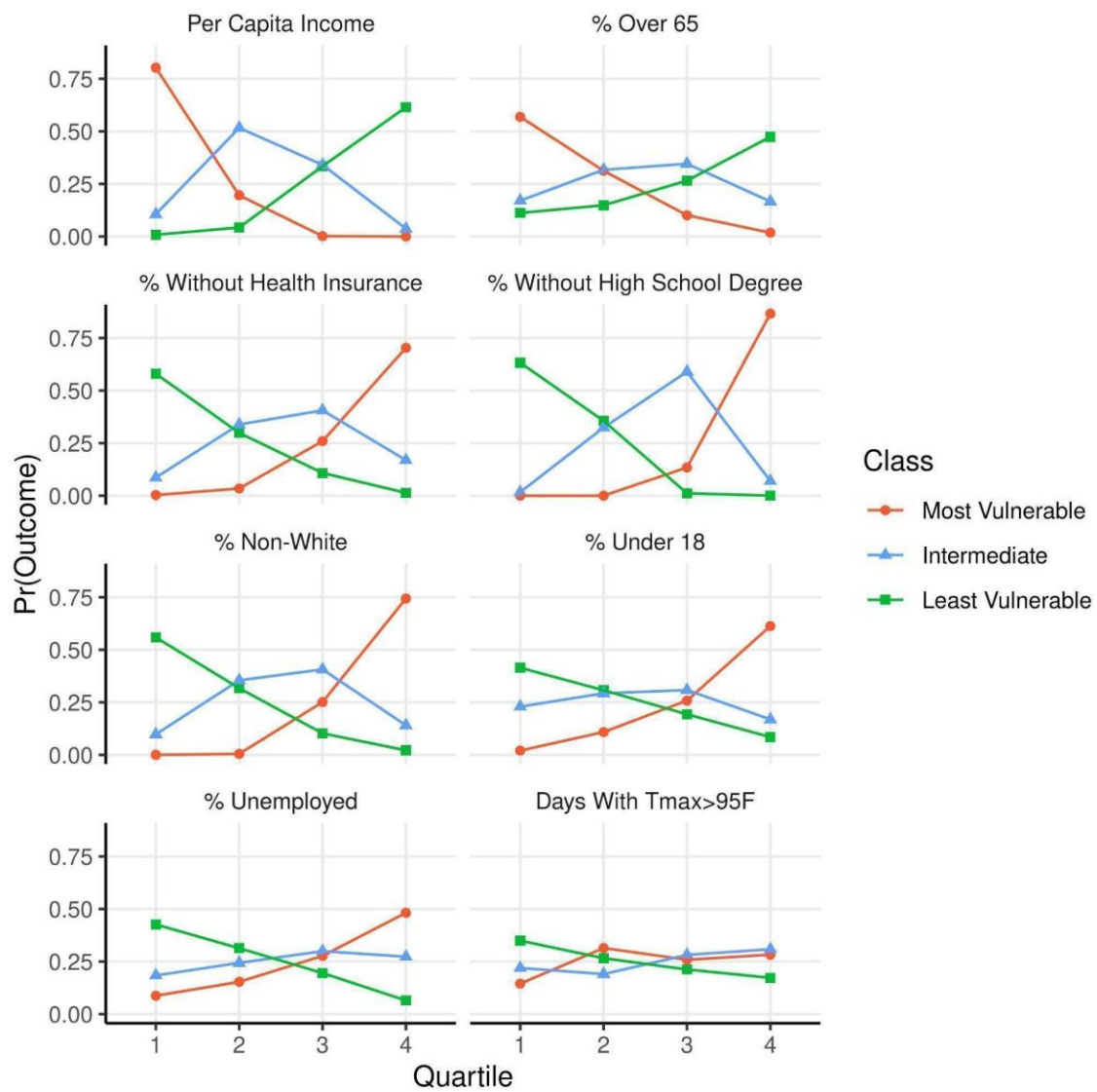
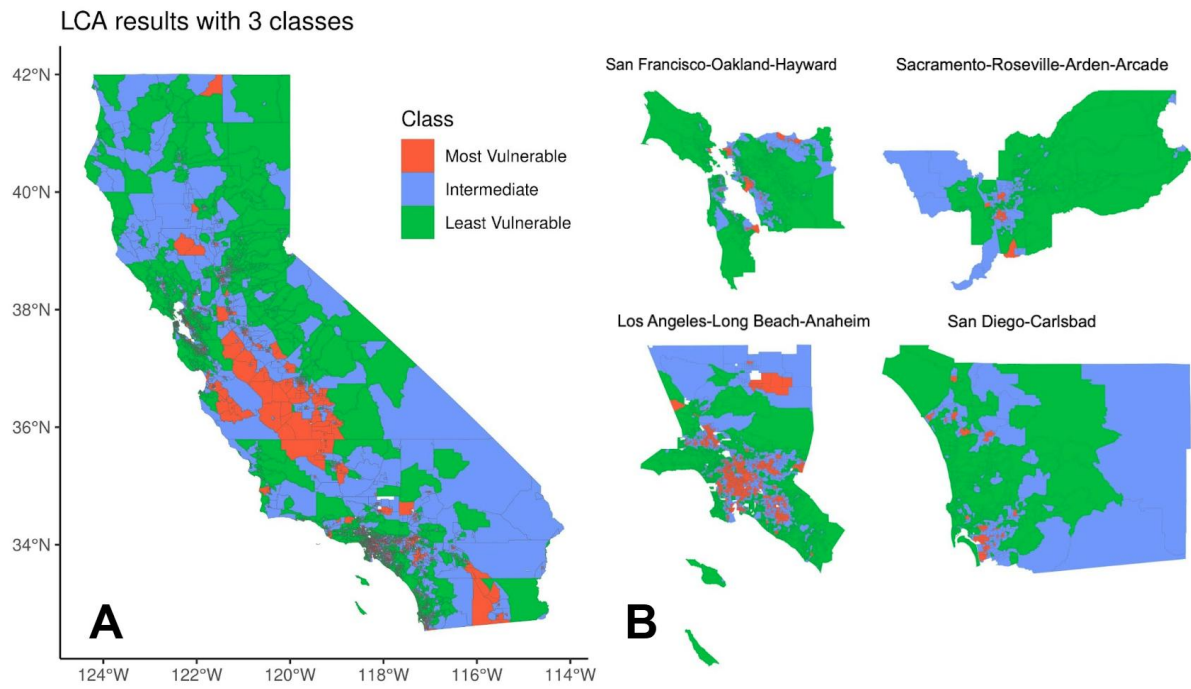


Figure 5. Latent Class Results for a Subset of SVI Variables for 3 Classes

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592 **Figure 6. Map of predicted class membership for each California census tract from main**
593 **latent class analysis with three classes.**

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6. Discussion

Focusing on census tracts within the state of California from 2014-2018, this study investigates the association between exposure to heat, measured by the total number of hot days within this 5-year period, and social vulnerability, operationalized using the CDC/ATSDR SVI values and individual indicators from the ACS. A correlational analysis showed that the SVI index itself, as well as several individual SVI indicators, were only weakly correlated with exposure to total (log-transformed) hot days (LTHD; $r < |0.3|$). Many of the stronger (but still weak) correlations were between heat and measures associated with residential mobility, neighborhood choice and attainment, and residential segregation (Alba & Logan, 1993; Charles, 2003; Krysan & Crowder, 2017), including the percent of population below the poverty line (positive correlation with hot days) and per capita income (negative correlation). Other indicators of social vulnerability that were weakly but positively correlated with the LTHD (r between + 0.2 and + 0.3), were percent unemployed, the percentage of children (18 and younger), percent of persons with a disability, percent single-parent households, and percent Latinx.

Several SVI variables had correlations with LTHD that were near zero, including percent age 65 or older, percent non-White, percent limited English proficiency, percent housing units with more residents than rooms, and percent living in group quarters. The percentage of multifamily housing in a tract was negatively correlated with LTHD, likely reflecting concentrations of these housing types in cooler coastal metropolitan areas. These results were qualitatively unchanged when using the average daily maximum temperatures in summer months as the measure of heat exposure.

Overall, these results indicate that social vulnerability does not strongly map to exposure to hot days in California census tracts—a finding that contrasts with prior studies reporting strong

links between vulnerability indicators and heat or heat stress (Benz and Burney 2021; Hsu et al. 2021; Mitchell and Chakraborty 2015, 2018). The lack of a correlation between percent non-White in the tract and exposure to hot days was particularly surprising in light of previous findings regarding increased heat in neighborhoods with higher concentrations of non-White residents in major U.S. cities (Benz and Burney 2021; Hsu et al. 2021; Mitchell and Chakraborty 2018). These differences may stem from both our statewide geographic scope and our spatial scale of analysis. While Hsu et al. (2021) also analyzed census tracts, their focus on individual urban areas differs from our statewide approach. Other studies examined coarser spatial aggregations—counties (Benz and Burney 2021) or metropolitan statistical areas (Mitchell and Chakraborty 2018)—which may obscure within-region variation. Our focus on the entire state of California, with its distinctive inland-coastal gradients in temperature, wealth, and racial composition, may explain this difference.

Importantly, this study does not analyze urban heat island (UHI) effects. Our measurement of ambient air temperature across all geographic contexts differs from UHI studies that examine localized temperature variations within urban areas created by built environment features. While UHI research captures intra-urban disparities in land surface temperature, our analysis examines regional climate patterns that span urban, peri-urban, and rural census tracts statewide. This broader climactic lens is advantageous for understanding population-level exposure across diverse regions, though UHI-based approaches may reveal localized inequities our data cannot detect.

Our findings showed that tract percent Latinx was positively but weakly correlated with exposure to hot days, which could potentially be due to the high concentrations of Latinx residents living in the hottest areas of the state, including the Central Valley and desert areas.

648 Additionally, as mentioned, correlations between other variables related to residential mobility,
649 neighborhood attainment, and housing (e.g., percent poverty, per capita income) were related to
650 exposure to hot days in expected ways. These results are consistent with the notion that
651 residential housing markets and factors that shape residential segregation may explain
652 differential exposure to heat among socially vulnerable groups (Hsu et al. 2021).

653 There are several potential reasons why this study did not find stronger associations
654 between social vulnerability and total hot days in California census tracts. Scale is likely
655 important. Our method compared all census tracts across the entire state of California, whereas
656 most studies of indicators of social vulnerability and heat exposure analyze one or several
657 metropolitan areas (see Benz and Burney 2021; Hsu et al. 2021; Mitchell and Chakraborty 2015,
658 2018). Additionally, many UHI studies focus on fine-scale intra-urban temperature variations
659 that may not be relevant at the statewide scale where heat exposure patterns are shaped by
660 broader climatic gradients rather than localized urban heat island effects. The scale of analysis
661 may affect the strength of correlations, for instance a recent study found that the correlation
662 between 6 social vulnerability indicators and ED visits for heat-related illnesses was much
663 stronger at the Los Angeles scale than statewide (Derakhshan et al., 2024). Similarly, another
664 study also found that socio-demographic patterning of exposure to heat wave intensity was more
665 apparent when aggregating neighborhoods at a more granular local scale than at the broader state
666 or regional scale (Rastogi et al., 2023). While the 25 km buffer may dilute localized heat island
667 effects, strong correlations ($r > 0.84$) with smaller-scale and tract-level estimates suggest our
668 statewide temperature measure remains robust across spatial scales.

669 To investigate potential heterogeneity in the association between the SVI and exposure to
670 hot days around the state, we estimated two sets of mixed effects models: One set of models

nesting tracts within core-based statistical areas (CBSAs) and the other nesting tracts within California climatic divisions. The results from this analysis confirmed that the association between the SVI and total hot days in the tract varies noticeably both within CBSAs and climatic divisions. However, the results did not indicate a clear geographic or climatic pattern in the association between the SVI and exposure to hot days.

For example, in some CBSAs located along the California coast, including Los Angeles-Long Beach-Anaheim and San Diego-Carlsbad CBSAs, the association between the SVI and LTHD was positive, but in other coastal CBSAs such as Oxnard-Thousand Oaks-Ventura, and San Francisco-Oakland-Hayward, the association between the SVI and logged hot days was negative. Similarly, some inland CBSAs had positive correlations for the SVI and logged hot days (Bakersfield, Riverside-San Bernardino-Ontario, San Jose-Sunnyvale-Santa Clara), while others had correlations that near zero (Fresno, Stockton-Lodi), and others had a negative correlation (Sacramento-Roseville-Arden-Arcade). It may be the case that these patterns have little to do with geographic location, but rather to other features within the CBSA that relate to the distribution of population within the CBSA, such as population density, zoning, and housing policies.

Similarly, there is no clear pattern in the association between the SVI and exposure to hot days across California climatic divisions. For example, this association varied across the 3 coastal climatic divisions; it was positive for the North Coast Drainage, negative for the Central Coast Drainage, and near zero for the South Coast Drainage. For the desert and central valley areas (Southeast Desert Basins, San Joaquin Drainage), the association was close to zero, but in the adjacent Sacramento Drainage area (which also includes some very dry areas) the association was negative. Some of the results for the climatic divisions are also perplexing in light of the

results for CBSAs. For example, the association between the SVI and (logged) total hot days was negative (and near zero) for the South Coast Drainage, but this area includes the bulk of the San Diego-Carlsbad CBSA and the Los-Angeles-Long Beach-Anaheim CBSA, where the associations between the SVI and total hot days were positive. For these reasons, we argue that the climatic divisions are not necessarily useful when trying to understand variation in the association between social vulnerability and exposure to hot days, and that the features of other administrative, political, and functional areas may be more important in explaining variability in the SVI and hot days association around the state. Previous research indicates, for example, that built-up environments, low vegetation, and high population density help to explain racial/ethnic and socioeconomic disparities in exposure to extreme summer surface temperature events among tracts within U.S. counties (Benz and Burney, 2021). As mentioned, factors that affect residential sorting, such as zoning, housing markets, and historical segregation patterns may also be playing a role in explaining variation in the association between social vulnerability and exposure to heat (Hsu et al. 2021).

The LCA results further illustrate the point that social vulnerability does not uniformly predict exposure to hot days in California, even among subunits within the state. We had expected that adding hot days to the SVI via the LCA would provide a clearer picture of tracts that were both socially vulnerable and had increased exposure to hot days. Instead, the LCA results revealed one class of tracts that were less socially vulnerable and cooler, but two socially vulnerable classes with varying temperature (hot day) profiles. Therefore, social vulnerability indicators are not strongly correlated with heat exposure in California census tracts in part because socially vulnerable tracts in the state as a whole experience a variety of heat exposures.

These results have several implications for understanding the intersection of social vulnerability and climate hazards exposure. First, because social vulnerability does not correlate strongly with exposure to hot days at the California state scale, and because the association between social vulnerability and exposure to hot days varies across subregions of the state, it is essential to acknowledge that social vulnerability does not automatically predict higher heat exposure in this state context, and to recognize that socially vulnerable groups in this state have a range of exposures to hot days. Relatedly, it is important to incorporate temperature metrics when trying to identify the intersection of social vulnerability and heat exposure in California census tracts. We attempted to do so using an LCA approach, but even this approach had difficulties identifying tracts that were both socially vulnerable and that had higher exposure to hot days. Therefore, future work should continue to scrutinize the best methods for identifying socially vulnerable tracts with high heat exposures. While SVI can be useful to identify vulnerable populations in California, it cannot by itself identify the vulnerable populations that are most at risk of experiencing heat hazards in the state.

Second, these results indicate a need to investigate associations between social vulnerability and heat exposure across multiple contexts and at different spatial scales. Much of the prior literature suggests, and confirms empirically, that socially vulnerable populations have increased heat exposure (Benz and Burney 2021; Hsu et al. 2021; Mitchell and Chakraborty 2015, 2018), but often at urban or metro scales; our results emphasize the value of extending this inquiry to broader geographic and policy contexts. While UHI studies examine fine-scale temperature variation within urban neighborhoods, our work addresses the statewide scale at which climate adaptation policies and resources are typically allocated. Decision-making around the intersection of social vulnerability and heat hazards often takes place at the local, regional,

and state levels. Therefore, future work should continue to investigate linkages between social vulnerability and heat exposures between different climatic and policy contexts and at varying spatial scales.

Lastly, given that some of our results point to variables related to residential mobility and neighborhood choice (e.g., poverty and income) as having the “strongest weakest” correlations with exposure to hot days, and given results about variation in the association between the SVI and hot days across CBSAs, our study points to a need to further scrutinize how processes of neighborhood mobility, residential choice, and residential segregation, as well as zoning and housing markets and policies, shape the intersections of social vulnerability and exposure to heat, in the California context and beyond. One recent study, for example, shows that people are moving away from places with heat waves, but towards places with hotter summers (Clark et al., 2022). Another study shows that vulnerable groups in the South, such as older residents, are moving towards heat and other hazards (Gao, & Wang, 2024). Future research should identify how individual, group, and contextual factors related to residential mobility and neighborhood choices, socioeconomic and racial/ethnic segregation, zoning and housing policies, and population density shape differential exposure to excessive heat among socially vulnerable groups within California.

This study has several limitations that could be addressed by future research. First, we focused on hot days (over 95F) in census tracts as our heat metric of interest, and added sensitivity analyses for estimates of average summer maximum temperatures, but there may be other heat measures that have a tighter connection to SVI indicators than total hot days and average maximum summer temperatures, such as exposure to heat waves or shocks. Second, we use modeled, station-based temperature data (PRISM) and assign this to census tract centroids

and their surrounding 25K buffer zones. These results may differ if using other datasets, other heat measurement techniques (such as satellite-based land surface temperature measures), or other ways of assigning heat to census tract spatial areas. Third, as discussed, our conclusions are based on a comparison of census tracts within the entire state of California, and the results are likely context dependent and sensitive to issues of scale. Future work should conduct similar analyses in other states, and future studies, such as meta-analyses, could also compare and summarize results on linkages between social vulnerability and hazards exposures at different scales. Last, this analysis has focused on the association between social vulnerability and heat exposure, and not social vulnerability and heat effects. The social vulnerability index is meant to help capture resources for resilience or vulnerability in the face of climate and anthropogenic hazards. Therefore, future research should not only continue to examine relationships between social vulnerability and heat exposures, but also climate effects for communities with similar heat exposures but varying levels of social vulnerability.

7. Conclusion

As heat and heat shocks continue to increase in California, it will be crucial for research to delineate the socio-demographic groups within the state that are the most at risk of experiencing exposure to rising heat and heat shocks. This study has addressed this issue by looking at the associations between social vulnerability and exposure to hot days in California census tracts. We found surprisingly weak linkages between social vulnerability indicators and exposure to hot days in California census tracts, but variation in these linkages around the state. Socially vulnerable groups in tracts in the state do not all have higher exposure to hot days than less vulnerable groups in tracts. Therefore, social vulnerability does not proxy for increased heat exposure in this state.

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Statements and Declarations

Funding

This work was supported by a germination seed grant to Drs. Ackert, Baylis, Davenport, and Shukla, from the UCSB Office of Research (\$9,976; 2022-2023).

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Drs. Ackert, Baylis, Davenport, and Shukla contributed to the conception and design of the study. Authors Husted, McMahon, and Malak conducted a comprehensive literature review. Authors McMahon and Malak obtained, cleaned, coded, and analyzed data. All authors participated in the writing and drafting of the manuscript.

Appendix

Appendix Table A1. Pairwise correlations between the total number of days (with Tmax over 95 degrees F) identified using different buffer sizes and a tract polygon approach.

Method	10km buffer	25km buffer	50km buffer	75km buffer	100km buffer
25km buffer	0.895				
50km buffer	0.776	0.852			
75km buffer	0.698	0.754	0.857		
100km buffer	0.615	0.654	0.729	0.848	
Tract polygon	0.923	0.844	0.750	0.672	0.594

1070 **Appendix Table A2.** Description of Construction of California Tract-Level SVI Indicators in the
1071 2014-2018 ACS.
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SVI Measure (CA Tracts, 2014-2018 ACS)	Tidycensus Variable Name	Notes
Below the poverty line (%)	S0601_C01_049	
Unemployed	DP03_0005P	Applies to those age 16 and older
Income (per capita)	B19301_001	
No high school diploma (%)	S0601_C01_033	Applies to those age 25 and older
No health insurance (%)	DP03_0099P	Equivalent to S2701_C05_001
Aged 65 or older (%)	S0101_C02_030	
Aged 18 or younger (%)	(B09001_001/S0601_C01_001)*100	Estimate converted to a percent using the total population estimate
Persons with a disability (%)	DP02_0071P	
Single-parent households (%)	((DP02_0009 + DP02_0007)/DP02_0001)*100	Combines single mother and single father households; converted to a percent using the total household estimate
Non-White (%)	((S0601_C01_001 - B01001H_001)/S0601_C01_001)*100	Total population - non-Hispanic White population; converted to a percent using the total population estimate
Latinx (%)	DP05_0071P	
Limited English Proficiency (%)	((B16005_007 + B16005_008 + B16005_012 + B16005_013 + B16005_017 + B16005_018 + B16005_022 + B16005_023 + B16005_029 + B16005_030 + B16005_034 + B16005_035 + B16005_039 + B16005_040 + B16005_044 + B16005_045)/B16005_001)*100	Combines all cases where English is spoken "not well" or "not at all"; converted to a percent using the estimated population age 5 and over

Housing Structures with 10+ Units (%)	$((DP04_0012 + DP04_0013)/DP04_0001)*100$	Combines housing structures with 10-19 units and those with 20 or more units; converted to a percent using the total housing units estimate
Living in Mobile Homes (%)	DP04_0014P	
Housing Units with More Residents than Rooms (%)	$((DP04_0078 + DP04_0079)/DP04_0002)*100$	Combines housing units with 1.01-1.5 residents per room and those with 1.51 or more residents per room; converted to a percent using the total estimate of occupied housing units
No Vehicle (%)	DP04_0058P	
Living in Group Quarters (%)	$(B26001_001/S0601_C01_001)*100$	Estimate converted to a percent using the total population estimate

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Appendix Table A3. Correlations between SVI measures and mean average maximum temperatures for June, July, and August, California census tracts, 2014-2018. P-values reported from a two-sided t-test.

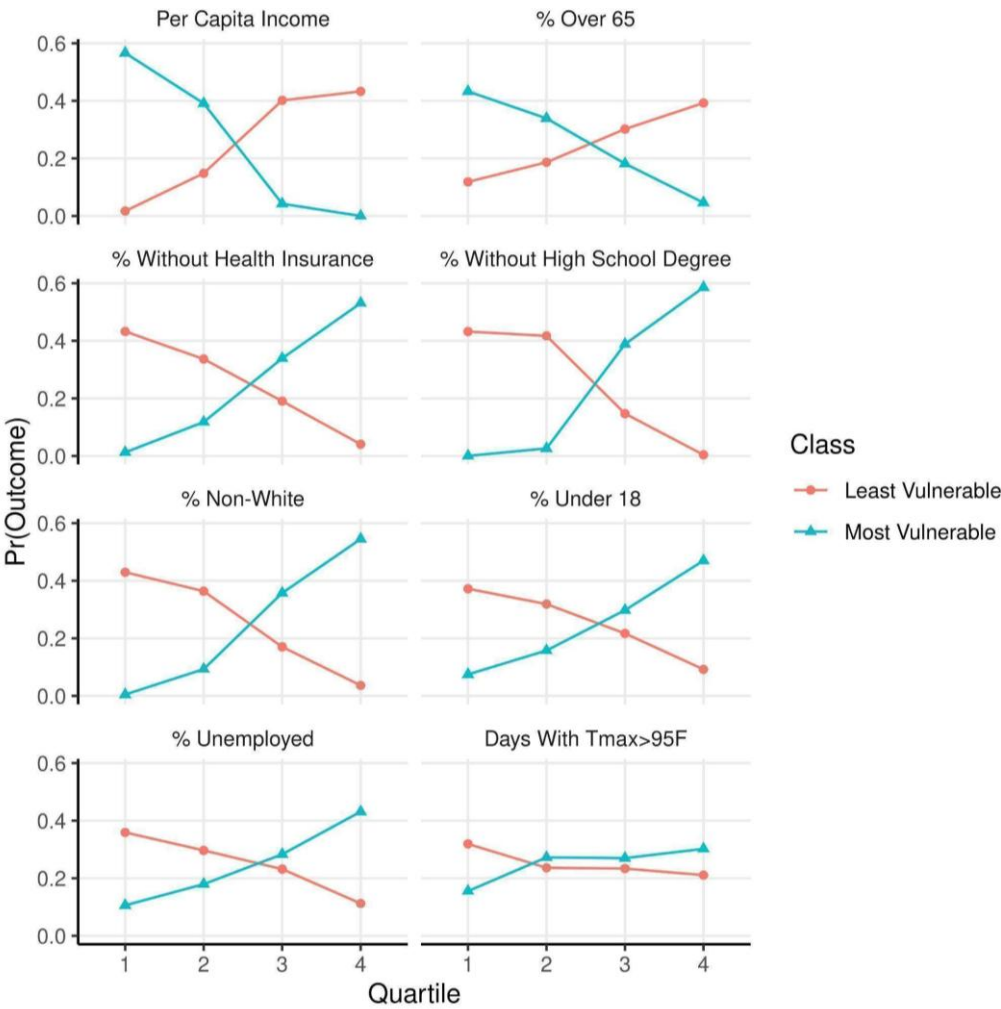
SVI Measure (CA Tracts, 2014-2018 ACS)	25km buffer			
	Pearson's R	p-value	Spearman's rho	p-value
<i>SVI (Overall)</i>	0.222	< 0.001	0.217	< 0.001
<i>Socioeconomic Status:</i>				
Below the poverty line (%)	0.227	< 0.001	0.230	< 0.001
Unemployed (%)	0.251	< 0.001	0.233	< 0.001
Income (per capita)	-0.359	< 0.001	-0.337	< 0.001
No high school diploma (%)	0.161	< 0.001	0.203	< 0.001
No health insurance (%)	0.087	< 0.001	0.138	< 0.001
<i>Household Composition and Disability:</i>				
Aged 65 or older (%)	-0.030	0.008	-0.073	< 0.001
Aged 18 or younger (%)	0.292	< 0.001	0.298	< 0.001
Persons with a disability (%)	0.229	< 0.001	0.261	< 0.001
Single-parent households (%)	0.205	< 0.001	0.226	< 0.001
<i>Minority Status and Language:</i>				
Non-White (%)	0.020	0.080	0.006	0.591
Latinx (%)	0.219	< 0.001	0.240	< 0.001
Limited English Proficiency (%)	-0.003	0.771	0.025	0.024
<i>Housing Type and Transportation:</i>				
Housing Structures with 10 + Units (%)	-0.229	< 0.001	-0.240	< 0.001
Living in Mobile Homes (%)	0.200	< 0.001	0.231	< 0.001
Housing Units with More Residents than Rooms (%)	-0.036	0.001	0.010	0.381
No Vehicle (%)	-0.169	< 0.001	-0.078	< 0.001
Living in Group Quarters (%)	-0.004	0.727	-0.030	0.007

1111 **Appendix Table A4.** Latent class analysis results with three classes. Probabilities of variable
1112 outcomes (in quartiles) for each class (Least, Intermediate, and Most Vulnerable). Estimated
1113 class population shares are 0.387 (Least Vulnerable), 0.355 (Intermediate), and 0.258 (Most
1114 Vulnerable).
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		Quartile			
		Lowest	Low	High	Highest
Days with Tmax>95C					
	Least Vulnerable	0.3493	0.2658	0.2123	0.1725
	Intermediate	0.2193	0.1904	0.2817	0.3086
	Most Vulnerable	0.1447	0.3141	0.2585	0.2826
Below the poverty line (%)					
	Least Vulnerable	0.5383	0.3148	0.1178	0.0291
	Intermediate	0.1118	0.318	0.3586	0.2116
	Most Vulnerable	0.0078	0.0757	0.2895	0.6269
Unemployed (%)					
	Least Vulnerable	0.4263	0.3135	0.1953	0.0649
	Intermediate	0.1838	0.2439	0.2995	0.2728
	Most Vulnerable	0.0873	0.1535	0.2771	0.4821
Income (per capita)					
	Least Vulnerable	0.0083	0.0425	0.3343	0.6148
	Intermediate	0.1059	0.5166	0.3406	0.0369
	Most Vulnerable	0.8028	0.1956	0.0016	>0.0001
No high school diploma (%)					
	Least Vulnerable	0.6324	0.3559	0.0114	0.0003
	Intermediate	0.0166	0.324	0.5896	0.0697
	Most Vulnerable	>0.000 1	>0.000 1	0.134	0.866
No health insurance (%)					
	Least Vulnerable	0.58	0.2985	0.1081	0.0134
	Intermediate	0.0864	0.3387	0.4059	0.1689
	Most Vulnerable	0.003	0.0341	0.2594	0.7035
Aged 65 or older (%)					
	Least Vulnerable	0.112	0.1486	0.2655	0.4739
	Intermediate	0.1705	0.3173	0.3458	0.1664
	Most Vulnerable	0.5689	0.3125	0.1007	0.018
Aged 18 or younger (%)					
	Least Vulnerable	0.4144	0.3076	0.1932	0.0848
	Intermediate	0.2296	0.293	0.3084	0.169
	Most Vulnerable	0.0203	0.1087	0.2583	0.6127
Persons with a disability (%)					

	Least Vulnerable	0.3573	0.2627	0.1905	0.1895
	Intermediate	0.1495	0.2271	0.2875	0.3359
	Most Vulnerable	0.2585	0.2702	0.2789	0.1924
Single-parent households (%)					
	Least Vulnerable	0.5006	0.35	0.131	0.0185
	Intermediate	0.147	0.2723	0.3764	0.2042
	Most Vulnerable	0.0144	0.0698	0.2551	0.6608
Non-White (%)					
	Least Vulnerable	0.5588	0.3172	0.1024	0.0216
	Intermediate	0.098	0.3548	0.4067	0.1405
	Most Vulnerable	>0.000 1	0.0048	0.2514	0.7438
Latinx (%)					
	Least Vulnerable	0.5892	0.3702	0.0402	0.0004
	Intermediate	0.0678	0.2915	0.5434	0.0973
	Most Vulnerable	0.0008	0.0067	0.1587	0.8338
Limited English Proficiency (%)					
	Least Vulnerable	0.5563	0.3338	0.102	0.008
	Intermediate	0.0941	0.3336	0.4331	0.1392
	Most Vulnerable	0.0008	0.0088	0.2219	0.7686
Housing Structures with 10 + Units (%)					
	Least Vulnerable	0.3269	0.2507	0.216	0.2064
	Intermediate	0.2316	0.2484	0.2663	0.2538
	Most Vulnerable	0.1586	0.2522	0.279	0.3102
Living in Mobile Homes (%)					
	Least Vulnerable	0.6345	0.1953	0.1702	
	Intermediate	0.4849	0.2085	0.3066	
	Most Vulnerable	0.4659	0.2428	0.2913	
Housing Units with More Residents than Rooms (%)					
	Least Vulnerable	0.5702	0.3333	0.0876	0.0088
	Intermediate	0.0811	0.3345	0.4653	0.1191
	Most Vulnerable	0.0007	0.0091	0.1977	0.7925
No Vehicle (%)					
	Least Vulnerable	0.4081	0.2806	0.1935	0.1178
	Intermediate	0.2118	0.259	0.2813	0.2479
	Most Vulnerable	0.0901	0.1747	0.298	0.4371
Living in Group Quarters (%)					
	Least Vulnerable	0.3539	0.186	0.237	0.2232
	Intermediate	0.2267	0.2006	0.2692	0.3035
	Most Vulnerable	0.3416	0.2056	0.2469	0.2059

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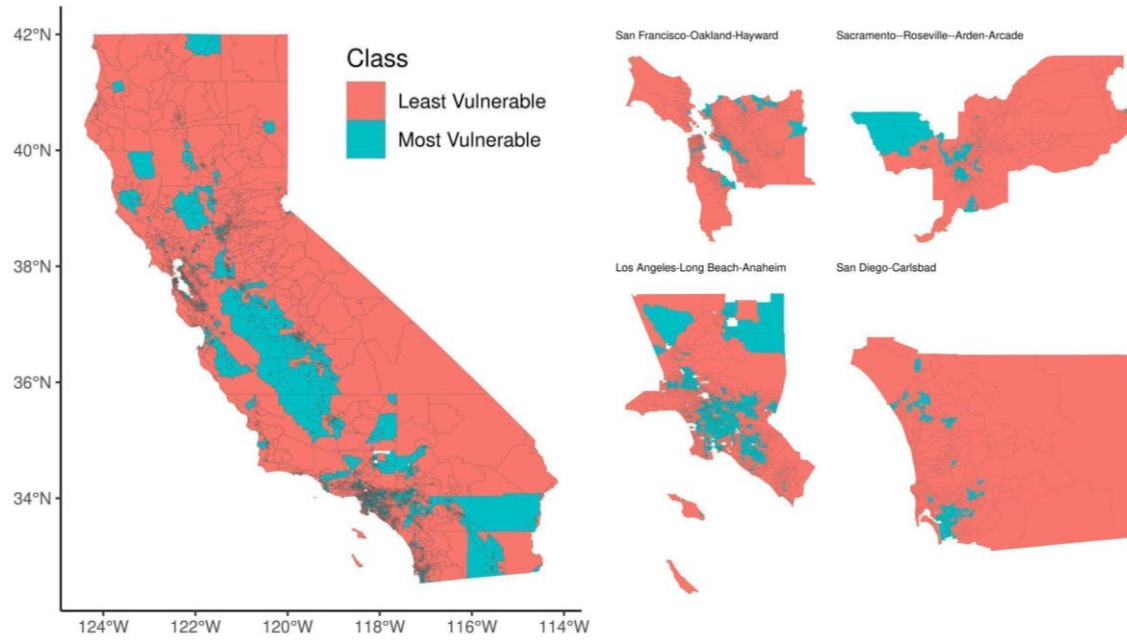
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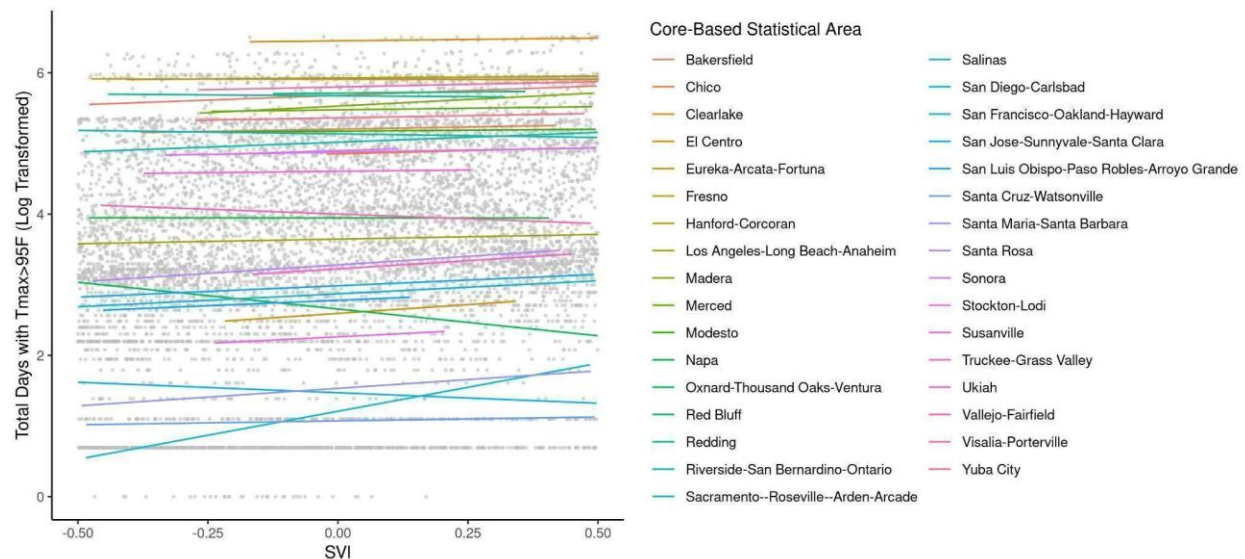
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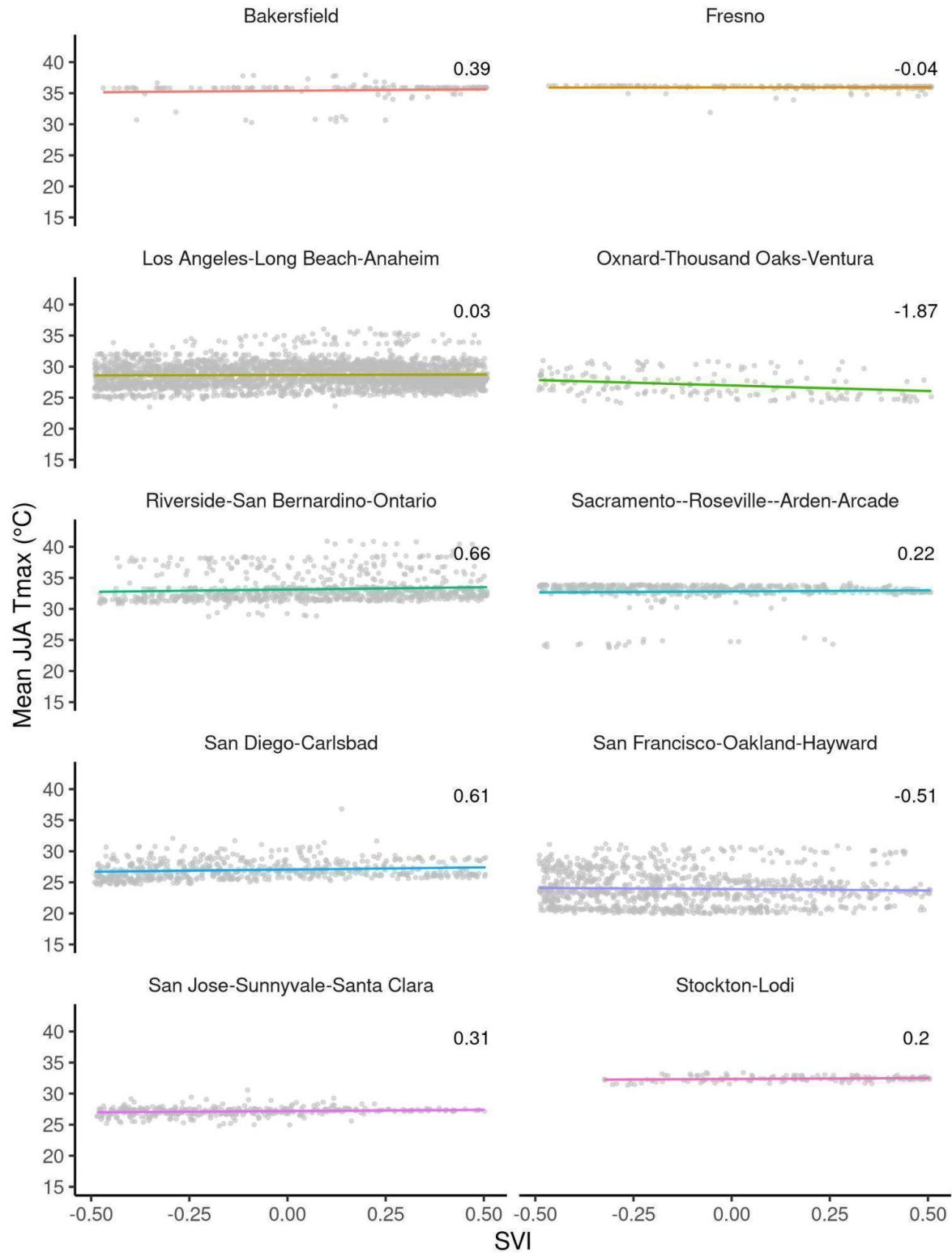
Appendix Figure A1. Selected results from a supplementary latent class analysis with two classes. Values report the probabilities of variable outcomes (in quartiles) for each class (Least Vulnerable and Most Vulnerable). Estimated class population shares are 0.580 (Least Vulnerable) and 0.420 (Most Vulnerable).



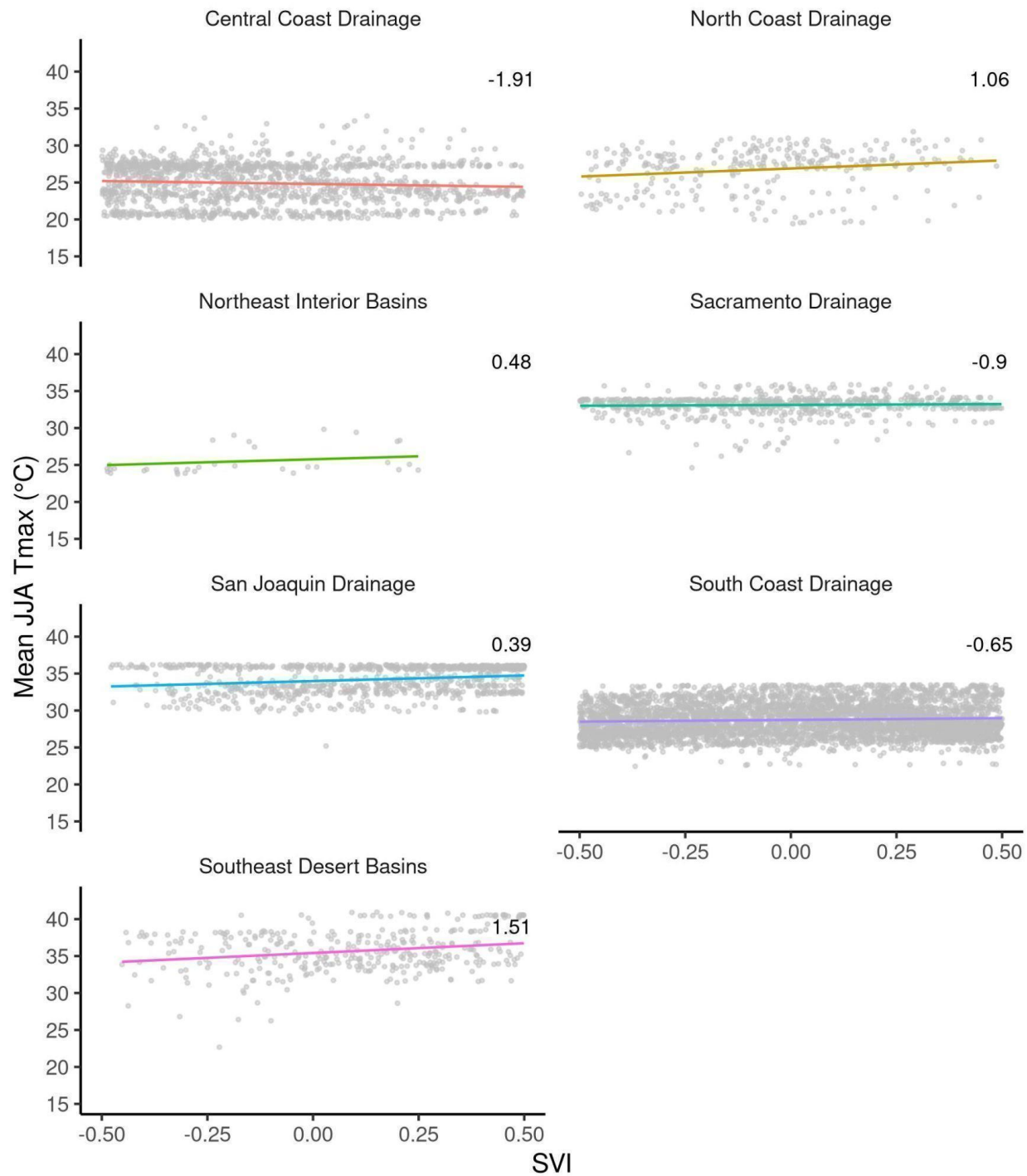
Appendix Figure A2. Map of predicted class membership for each California census tract from a supplementary latent class analysis with two classes. Panel A presents the state-wide results, while Panel B provides a closer view of the four largest metropolitan areas.



Appendix Figure A3. Mixed effects model results for association between the SVI and total hot days (logged) in census tracts, California CBSAs.



Appendix Figure A4. Mixed effects model results for association between the SVI and mean maximum temperatures in June, July, and August (2014-2018) in census tracts, top 10 California CBSAs.



Appendix Figure A5. Mixed effects model results for association between the SVI and mean maximum temperatures in June, July, and August (2014-2018) in census tracts, California Climatic Divisions.