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Increasing wildfires and changing sociodemographics in communities across California, USA

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A B S T R A C T

Research has documented how recent wildfires are characteristic of a new fire regime marked by larger, more severe, and damaging wildfires. However, there is less information on how these fire regimes are affecting communities with different sociodemographic characteristics across socio-ecologically diverse regions. Therefore, we spatiotemporally and statistically analyzed the sociodemographic characteristics of communities affected by wildfire in California, USA during 2010–2020. Second, we analyzed if specific sociodemographic groups and disadvantaged communities (DACs) were increasingly affected across socio-ecoregions (SE) during this analysis period. We used available US Census, California Environment Protection Agency, and wildfire perimeter data according to SEs and geospatial and trend analyses. Statewide findings show that higher income, Whites, and renters were indeed significantly and increasingly affected during the analysis period. However, Hispanics and Asian Americans were also increasingly affected statewide, particularly during 2016–2020, and noticeably in certain SEs. For example, Asian Americans were increasingly being affected in the Coastal Sage SE, while Hispanics were more affected in the Central Valley, Sierra Nevada, and Klamath SEs. Finally, we found that urban areas were statistically and increasingly being more affected statewide by wildfires. However, pollution-burdened DACs, as defined by the State of California, were increasingly, but not significantly, being affected by wildfires. The approach and findings can also be used to better define "communities", formulate environmental justice policies, and understand socio-ecological trajectories.

1. Introduction

Across the globe there is an accelerating trend towards longer fire seasons, increased fire severity, emerging fire effects, and total area burned [1,2]. These future increases in not only the size and severity of wildfires, but uncertainty as to where and when they will occur, are predicted to be exacerbated due to global change effects including prolonged droughts and increased temperatures [3]. These emerging wildfires have been documented as having important environmental, ecological, economic, and social impacts [4–6]. However, the focus of most media attention and academic literature is often on the size or area burned, the number of "structures" damaged and destroyed, and the number of people evacuated [7]. There is usually less information, however on "who" is being affected and evacuated and the types of demographic groups that are having their homes damaged and/or destroyed. Similarly, there is less attention to the socioeconomic, demographic, and ecological characteristics of the communities being affected by such wildfires across diverse socio-ecological regions [8,9]. Accordingly, we define community hereafter as not only the structures and buildings present in human settlements - as regularly used for wildfire planning and management – but also the socioeconomic, cultural, and

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language characteristics of people living in these human settlements.

Understanding these sociodemographic characteristics of wildfire-affected communities is becoming more important given future climatic and demographic changes in peri-urban areas [5]. In addition, real estate markets, COVID, and internal migration patterns are expanding populations and sociodemographic diversity in areas of high fire risk [10]. Most importantly, wildfires are now impacting different types of communities and human settlements in urban and wildland-urban interface (WUI) contexts [11], and are no longer confined to wildland and rural areas [11,12]. For example, in California, USA, most wildfire damage is not in forests but other fuel and vegetation types [13]. Many of these communities and populations are now more vulnerable, not only in terms of wildfire risk, but also in their ability to respond to and recover from a wildfire [14]. Therefore, there is a need to better understand how different and socio-demographically diverse groups are being exposed to and impacted by these larger, more frequent, and more severe wildfires across space, time, and socio-ecologically diverse regions.

In the United States (US), population and housing increases have largely been greater in ex-urban areas since the 1970s [15]. Indeed, urbanization of these areas often referred to as the WUI has been increasing in recent decades [16,17]. For example, between 1990 and 2010, the number of new houses in the WUI increased by 41 % and the amount of WUI area grew by 33 %, making it the fastest growing land-use category in the continental US [16]. This growth consisted of the construction of new houses near wildland vegetation and the regrowth of vegetation adjacent to existing housing areas. Relocation to the WUI has been driven by multiple factors including the desire for less traffic congestion, fewer social problems, more affordable housing, a lower cost of living, and proximity to more natural amenities [18,19]. Furthermore, increased human populations and densities in and near the WUI are related to increased human-caused ignitions and subsequent adverse impacts to life and property [16].

Historically, the dominant socio-demographics of these ex-urban and rural WUI areas in the United States were found by the US Census to be generally White and older [20–22]. However, beginning in the late twentieth century, internal migration and immigration have added to the racial/ethnic diversity in such peri-urban areas [23,24]. The 2020 census revealed that the suburbs have continued increasing their non-White populations: 63.1 % of Asian Americans (up from 53 % in 1990), 61.4 % of Hispanics (49.5 % in 1990), and 54.3 % Black (36.6 % in 1990) [25]. Meanwhile, between 2010 and 2020 the "median" rural county had a 3.5 % increase in its population of color [26]. Additionally, Cooke and Denton [27] noted "an increase in poverty in moderately dense residential areas". Davies et al. [20] also documented how the geography of poverty is changing as the population shifts from large metropolitan areas to suburbs and rural areas.

These urban communities are usually located in areas of lower wildfire risk [21], and many are designated as disadvantaged communities (DACs hereafter) as they are burdened by environmental problems and have limited resources to respond and adapt to wildfire and recovery services [28]. The most socioeconomically disadvantaged communities are often the most socially vulnerable, having the fewest internal resources and the lowest capacity to cope with natural disasters. Social vulnerability can be defined as "the adaptive capacity to absorb, recover and modify exposure to wildfires" [20]. Historically WUI census tracts have had lower social vulnerability relative to non-WUI tracts. Furthermore, census tracts that are predominantly Black, Hispanic, and Native American have high social vulnerability, while those with predominately White and Asian American populations tend to have lower social vulnerability [20].

The recent COVID-19 pandemic has accelerated recent internal migration away from large urban areas to smaller urban areas [29], with the increased availability in remote work one of the primary reasons for moves during the pandemic [30]. This movement to more suburban communities has meant that people are migrating to areas at higher risk of wildfire [30]. By late 2020 six of the areas at highest risk for wildfire were also among the top 10 fastest growing counties in the USA [31]. The increased diversity of these fire-prone areas could also be increasing their social vulnerability through a larger non-White population [32] which is often associated with higher levels of vulnerability [33]. However, little is known whether the increased sociodemographic diversity in these WUI communities is creating issues of equity and environmental justice in regards to wildfire risk and preparing and responding to wildfires [8]. Thus, measuring and mapping socio-demographics across space and time is key to understanding the diversity – and vulnerability - of different populations being affected by wildfires [33,34].

Despite the existing research on the WUI and its population growth and spatial increase [16] there is less information on its changing socio-demographics and the wildfire hazard burden to these areas and their populations from experiencing more frequent wildfires. Increased wildfire risk and demographic changes in communities are likely to influence the capacity of residents to adapt, recover from, and mitigate risk and exposure to wildfires [35]. For example, African Americans generally reside in areas with lower wildfire risk such as urban centers [36], but have high social vulnerability, so in the event of a wildfire they can have difficulties responding [20]. Yet, a predicted increase in wildfire risk in the Southern United States [37] and movement of this demographic into WUI areas suggests African Americans might be at higher risk in the future. Anderson et al. [38] found that government agencies were more receptive to post-wildfire demands for fuels management by higher income communities. Thus, a more equitable allocation of resources for post-wildfire efforts and programs is also crucial to meeting the environmental justice commitments currently being mandated by the US Government [8].

There has also been comparatively little research on which sociodemographic communities have previously been affected by wildfires [8]. Garrison and Huxman [36] used statewide US Census data to study the demographics in areas burned by wildfires relative to unburned areas in ten Southern California counties during 1980–2000. They found that areas affected by wildfires during the analysis period had lower proportions of residents that were non-White and living below the poverty line, as well as higher median house values. Masri et al. [22] also explored the demographics of communities affected by wildfires (i.e., located within one or more wildfire perimeters) from 2000 to 2020 across the state of California. In contrast to Garrison and Huxman [36], the authors found that wildfires had more frequently burned areas in census tracts that had higher proportions of elderly and low-income residents. They also found that racial/ethnic minorities, except for Native Americans, were more likely to be living in census tracts with lower fire frequencies. Finally, Wibbenmeyer and Robertson [39] recently analyzed the distributional incidence and demographic characteristics of populations and property values in high fire hazard areas in the western US. Their results showed that areas at high risk for wildfire have residents with higher per capita incomes, higher proportions of White residents; and that higher value properties were more likely to be in these high hazard areas. However, none of these aforementioned studies analyzed the influence of socio-ecological scale, temporal trends, and spatial heterogeneity on wildfire effects and sociodemographic groups.

Difference among these studies from California [22,36,39] point to the difficulties in identifying the specific characteristics of communities affected by wildfire given variations in definitions (i.e., what does 'affected' or 'community' mean), available data (i.e., the location of a structure within a fire perimeter does not necessarily mean it was damaged or destroyed), multiple options for sociodemographic variables to assess, and the socio-ecological nature of wildfire occurrence and impacts. In terms of socio-ecological context and scale, accounting for such complexity and differences in wildfire impacts to human populations across regional (i.e., meso) and local (i.e., micro) scale – as opposed to states, provinces, or other administrative departments – is important since there will be differences in terms of fire regimes, governance systems, economic sectors, and other socio-political contexts [9,40]. This is particularly important when developing wildfire risk mitigation and adaptation strategies, since not only are biophysical drivers important, but the socioeconomic and demographic differences must also be accounted for across regions and scales [40,41]. Indeed, the heterogeneity and complexity associated with wildfires and their effects varies from local to global scales, and temporally from days to years [9,42,43]. One way to account for such spatial and temporal heterogeneity is to account for their inherent socioeconomic, ecological, and fire regime characteristics [44,45]; for example stratifying regimes into integrated regions of interest called pyroregions, firesheds, or firescapes that are regularly used for fire management, research, and planning purposes [43,46,47]. However, these concepts often overlook the human component and instead focus on the vegetation, fuels, building, and structural components of these regions, units, or landscapes.

Accordingly, the use of "socio-ecoregions" could help improve our understanding of the socio-ecological effects of wildfire on the different sociodemographic characteristics of communities using available geospatial and census-based data [9]. These socio-ecoregions represented by vegetation-based ecoregions and available census-based demographic data can serve as an alternative to politically or administratively defined units that are used in many of the above studies and policies. Such an approach can also account for the spatial and temporal heterogeneity of wildfire impacts on sociodemographic groups across space and time [40].

Therefore, our study aim is to better understand how different sociodemographic groups have been exposed to wildfires across California's different communities and socio-ecoregions from 2010 to 2020; a period characterized by numerous large and destructive wildfires. Specifically, our study seeks to answer three questions. First, what were the sociodemographic characteristics of fire-affected communities across California during this 11-year analysis period? Second, did the sociodemographic characteristics of these fire-affected communities vary spatially across different regions in California? And third, have urban and disadvantaged communities (DACs) been increasingly affected by wildfires in different socio-ecoregions across California during the analysis period? We define affected as exposure to wildfires based on criteria presented in Sections 2.2 and 2.3 and when communities, human settlements, census tracts, or socio-demographic groups are located inside established wildfire perimeters.

2. Materials and methods

2.1. Study area

With an area of 403.78 km^2, California is the third largest US state by size and is home to over 39 million people, making it the most populous state in the country. From 2010 to 2020 the population increased by about 6 % [48]. The population is generally greater in the north-central and southeastern coastal areas (e.g., The San Francisco and Los Angeles-San Diego metropolitan areas). More sparsely populated areas are in northeastern, central, and southeastern California, most of the San Joaquin Valley in central California is agricultural land, while northeastern and southeastern California are characterized by extensive areas of wildlands with less populated sized cities, towns, and rural communities. In 2018, California's WUI covered an estimated 28,575 km^2 and included approximately 45 % of California's housing units [49]. The growth in the WUI is concentrated along coastal areas and to the west of the Sierra Nevada Mountains [49].

California is also the second most racially/ethnically diverse state in the US and is becoming more diverse, with the US census racial and diversity index increasing from 67.7 % to 69.7 % between 2010 and 2020 [48]. Hispanics comprise the largest racial/ethnic group, at 39.4 %, while Whites (not Hispanic) are second at 36.4 %, a decrease of 24 % since 2010 [48]. The Asian American population comprises 15.5 % of the state's population, and African Americans comprise 6.5 %, while Native American (1.6 %) and Native Hawaiian/Pacific Islander (0.5 %) populations are comparatively small. Notably, much of California's population growth is due to immigration, and 27 % of the population is foreign born.

The state is also ecologically diverse with offshore islands and coastal lowlands, large alluvial valleys, forested mountain ranges, deserts, and varied freshwater habitats [50]. California's climate and topography present a diversity of ecosystems, ranging from moist redwood forests that receive more than 200 cm of rain/year to desert shrublands with less than 5 cm in a year [51]. There are 12 ecoregions in California, most of which continue into ecologically similar parts of adjacent states and/or Mexico [50].

Fire is a natural part of most of California's landscape as its Mediterranean climate makes the vegetation highly susceptible to wildfires [52]. Most precipitation occurs during the winter when relatively mild temperatures allow for plant growth, adding to fuel loading. Then during the hot summer, the vegetation dries out increasing the landscape's flammability and susceptibility to wildfires. However, seasonal climatic effects are variable across vegetation types and geographic areas in the state. In the summer, wildfires tend to be concentrated in forest ecosystems in Northern and Central California with high fuel availability due to a history of fire suppression [3,53]. Historically these wildfires tended to be ignited by lightning and generally burned in areas with low populations. In contrast, during the fall months, the most destructive fires tend to occur in coastal shrubland areas and are driven by strong, offshore wind events [54,55]. These wildfires are more likely to be caused by humans and to burn in highly populated areas, commonly resulting in extensive damage to communities in and near the WUI [56].

From 1972 to 2018, California experienced a fivefold increase in annual burned area [3,57], and the state is experiencing an accelerating trend towards larger and more destructive wildfires [14,56]. The last five wildfire seasons prior to 2022 have broken records and are often referred to as 'new' fire regimes driven by both climatic changes (drought, increased temperature) and the expansion of the WUI [3,57]. Eight of top 10 largest wildfires in the state's recorded history have occurred since 2017 [58]; as well as six of the 10 most destructive wildfires, including the 2018 Camp Fire which destroyed over 18,000 structures and resulted in over 80 civilian fatalities [59]. The 2020 wildfire season was record-breaking and resulted in over 4 million acres burned, more than double the previous record of 1.9 million acres. During this season, the August Complex was a series of fires that burned over 1 million acres, the state's largest wildfire since modern records began, while the Creek Fire set the size record (379,895 acres) for a single fire. However, this last record was broken the following season when in 2021 the Dixie Fire alone burned almost 1 million acres.

2.2. Datasets

To account for the sociodemographic context of our study area we used both state-level and community-level census tract data for California. Specifically, we used 2010 US Census Bureau statewide census tracts ($n = 8035$) representing decennial census data with a population size between 1200 and 8000 people, but with an optimum size of 4000 people per tract [60]. For this study, urban census tracts were defined as geographical areas, or communities, that encompass at least 2500 people according to the urban-rural classification of the US Census Bureau from 2010 to 2020. To better account for the different ecological and fire regime characteristics of these census tract across California, we used ecoregions or areas that account for spatial differences in the structure and function of ecosystems and their response to disturbances such as wildfires [61]. We specifically used Bailey's 12 Section Level 3 ecoregions for California that encompass similar ecosystem, vegetation, and fuel types. We then selected five of these as our representative socio-ecoregions based on their fire frequency and number of fire affected census tracts as explained in Section 2.3 [62]. Bailey's ecoregions are regularly used by the state of California for fire and resource assessment purposes and can therefore be used to better communicate study findings to policy and decision-makers.

We also analyzed the extent to which DACs in California were located within wildfire perimeters during the study period. Disadvantaged is defined per the California Environmental Protection Agency (CalEPA) as census tracts which most suffer from a combination of economic, health, and environmental burdens. These burdens include poverty, high unemployment, air and water pollution, the presence of hazardous waste, as well as high incidences of asthma and heart disease [63]. The statewide 2007 census tracts in California were classified by the CalEnviroScreen 3.0 tool into two broad groups of Pollution Burden and Population Characteristics as measured by 20 sociodemographic variables [64]. Averaged tract-level scores for these variables were multiplied to generate the final percentile score of 0–1, where higher values indicate a greater level of disadvantaged conditions in a census tract [57] (Fig. 1). Based on this approach, CalEnviroScreen has designated disadvantaged census tracts as those having the highest 25 %

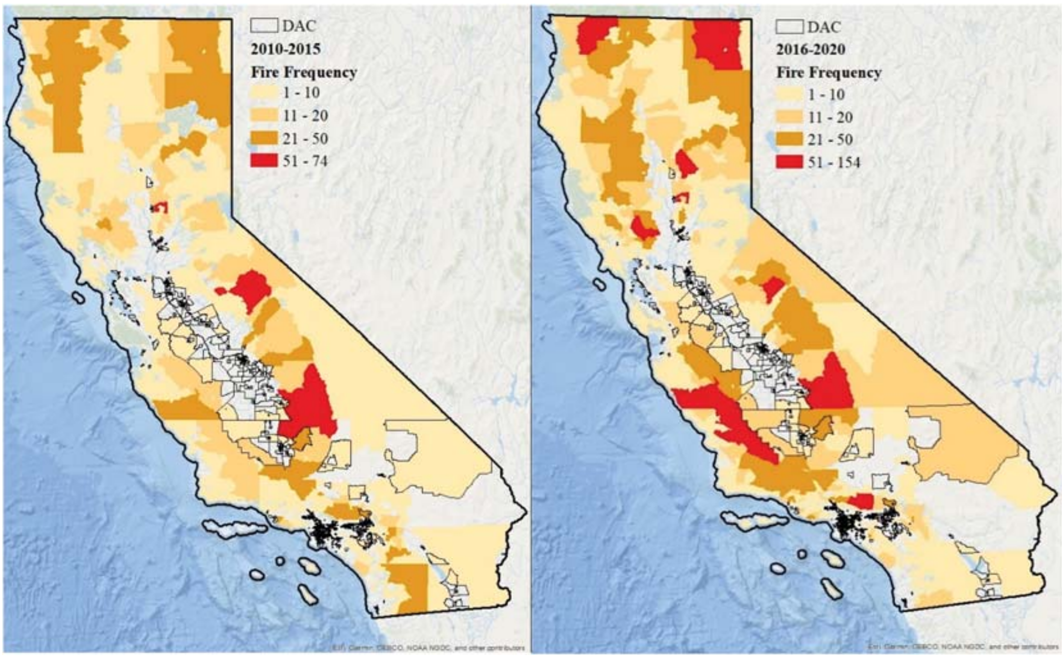

Fig. 1. Fire affected census tracts in California, USA symbolized by graduated colors based on fire frequency (i.e., number of fires occurred in each census tract during the analysis period), and disadvantaged communities (DACs) as defined by CalEnviroScreen [60]. Note: all the DACs are distributed over low fire frequency areas and not obscured under high fire frequency symbology colors.

Table 1
Five representative socio-ecoregions in California, USA showing dominant vegetation, sociodemographic, and fire occurrence (2010–2020) characteristics.

Socio-ecoregions	Ecological Characteristics (Bailey, 1983)	Sociodemographic characteristics (ACS 2020)	Fire Occurrence Characteristics** (FA=Fire affected)
Central California Valley	Flat, intensively farmed plains with long, hot, dry summers and mild winters. Extensive prairies, oak savannas, desert grasslands in the south, riparian woodlands. More than one-half of the region is now in cropland. Urban sprawl is one of the environmental concerns.	17 % population of the state $24,000 average annual per capita income 20 % population below poverty line (Poor) 38 % Hispanic 66 % White (non-Hispanic) 6 % African American 9 % Asian American 1 % Native American 60 % homeowners 22 % < high school graduate 10 % non-English speakers 2 % > 65 years of age	No. of FA Census Tracts: 30-45 Fire Frequency: 410
California Coastal Sage	Mediterranean climate of hot dry summers and cool moist winters. Vegetative cover comprising of primarily chaparral and oak woodlands; grasslands occur in some low elevations and patches of pine are found at high elevations.	79 % population of the state $35,000 average annual per capita income 5 % population below poverty line (Poor) 36 % Hispanic 60 % White (non-Hispanic) 6 % African American 14 % Asian American 1 % Native American 56 % homeowners 12 % < high school graduate 11 % non-English speakers 11 % > 65 years of age	No. of FA Census Tracts: >100 Fire Frequency: 4533
Klamath Mountains	Sierran Steppe mixed forest coniferous forest alpine meadow. Mixed conifer and montane hardwood forests. The mild, subhumid climate of is characterized by a lengthy summer drought.	1 % population of the state $23,000 average annual per capita income 21 % population below poverty line (Poor) 12 % Hispanic 84 % White (non-Hispanic) 1 % African American 2 % Asian American 6 % Native American 68 % homeowners 14 % < high school graduate 2 % non-English speakers 17 % > 65 years of age	No. of FA Census Tracts: 20-25 Fire Frequency: 634
Sierra Nevada	Sierran Steppe mixed forest coniferous forest alpine meadow. The vegetation grades from mostly ponderosa pine and Douglas fir at low elevations on the western side, to pines and Sierra juniper on the eastern side, and to fir and other conifers at higher elevations. Alpine conditions exist at the highest elevations.	2 % population of the state $30,000 average annual per capita income 13 % population below poverty line (Poor) 12 % Hispanic 89 % White (non-Hispanic) 1 % African American 1 % Asian American 2 % Native American 73 % homeowners 10 % < high school graduate 2 % non-English speakers 15 % > 65 years of age	No. of FA Census Tracts: 20-50 Fire Frequency: 1150
Southern and Baja California Pine-Oak Mountains	Chaparral forest and shrub coastal and alluvial plains, marine terraces, and some low hills, coastal sage scrub and chaparral vegetation communities.	2 % population of the state $35,500 average annual per capita income 11 % population below poverty line (Poor) 25 % Hispanic 75 % White (non-Hispanic) 5 % African American 6 % Asian American 1 % Native American	No. of FA Census Tracts: 20-40 Fire Frequency: 926

(*continued on next page*)

Table 1 (*continued*)

Socio-ecoregions	Ecological Characteristics (Bailey, 1983)	Sociodemographic characteristics (ACS 2020)	Fire Occurrence Characteristics** (FA=Fire affected)
		80 % homeowners 11 % < high school graduate 4 % non-English speakers 14 % > 65 years of age	

*Population count percentages are not weighted by the area of tract in a region; ** Intersect analysis performed on census tracts, socio-ecoregions, and Cal Fire data; Fire frequency is the number of fires that occurred during 2010–2020.

CalEnviroScreen scores. Of the 8035 census tracts in California, 2005 tracts were designated as DACs [63]. Additionally, 22 census tracts that scored in the highest 5 % of CalEnviroScreen's Pollution Burden, but without an overall score because of unreliable sociodemographic or health data, were also designated as disadvantaged [63].

2.3. Wildfire and sociodemographic data sources

The non-spatial data related to fire perimeters such as annual fire affected area (FAA) and fire frequency; defined as number of fires affecting a census tract over the analysis period; were available from the Fire and Resource Assessment Program (FRAP). The FRAP data compiled by multiple agencies (California Department of Forestry and Fire Protection (Cal Fire), the United States Forest Service Region 5, the Bureau of Land Management, and the National Park Service) provide fire perimeter occurrence and extent data for public and private lands throughout California [65]. This fire perimeter database contains the most complete spatial record of fire perimeters in California and provides the year, name of the fire, and estimated burned area.

Analyses were based on Bailey's 12 ecoregions that were characterized by their sociodemographic and fire regime including number of fires and census tracts affected during the 11-year analysis period (Table 1). Specifically, based on fire regime characteristics, five representative social-ecological regions (hereafter referred to as socio-ecoregions) were selected to better analyze the sociodemographic groups affected by wildfire in California (Fig. 2). Selected socio-ecoregions had a fire frequency of at least 400 and a minimum of 20 FA census tracts. Fire frequency, or the number of fire occurrences within an area of interest and time period, was the metric used to determine FA and subsequently what socio-demographic groups were exposed and affected by wildfire. Table 1 presents the ecological, sociodemographic, and fire occurrence characteristics for these five socio-ecoregions which include: dominant vegetation types, sociodemographic variables, fire frequency, and number of FA census tracts.

In addition to wildfire data, we selected 14 sociodemographic variables as identified by Thomas et al. [8] that accounted for economic, education, age, diversity, and housing factors to analyze FA and non-fire affected (NFA) census tracts at both statewide and socio-ecoregion scales [20,22,66] (Table 2). Specifically, using sociodemographic variables from the 5-year American Community Survey (ACS; 2010–2020) we characterized the per capita income, race/ethnicity, education, age, poverty, housing, and other demographic variables for all census tracts in the state of California.

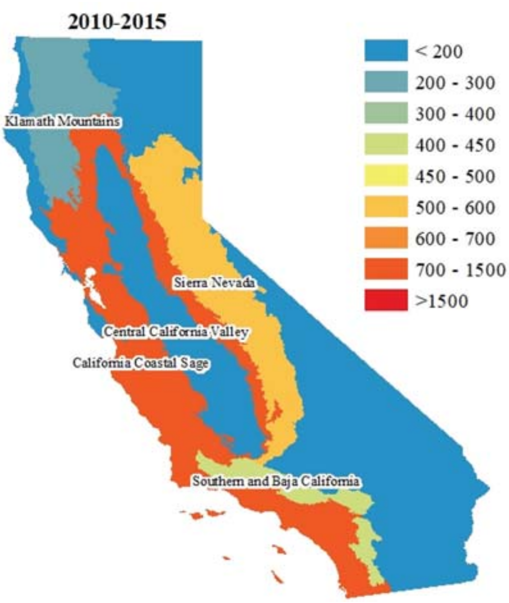

Fig. 2. Fire affected socio-ecoregions of California, USA based on Bailey [59] and symbolized by fire frequency (number of fires that occurred during 2010–2015 and 2016–2020). The selected socio-ecoregions have experienced a greater number of fires from the first period to the second period of five years in the last decade.

2.4. Spatial analysis

We spatially analyzed patterns and temporal trends in sociodemographic variables in both FA and NFA census tracts statewide, socio-ecoregions, urban census tracts, and DACs from 2010 to 2020 using an overlay analysis and spatial join approach. First, the fire perimeter spatial layers from 2010 to 2020 were intersected with 2010 census tracts using the Intersect tool in Arc Map version 10.8.2. Likewise, fire perimeters were also intersected with Bailey's ecoregions layer. The intersected layers were then assigned census tract and socio-ecoregion attributes (e.g., tract id, area, and name) and fire affected area (ha) estimates. Second, the census tracts, both statewide and in socio-ecoregions, that intersected with fire perimeters were then spatially joined to non-spatial sociodemographic variables based on the unique tract id of the census tract. The final spatially joined layer thus consisted of fire affected area (FAA), census tract area (A), and sociodemographic variables (V). The resulting variables were analyzed to better understand what specific sociodemographic groups were potentially affected by wildfires during the analysis period.

The area of the census tracts can vary widely depending on population and building densities but ideally, census tract boundaries remain stable over time to facilitate statistical comparisons across different census periods. However, overlay analysis resulted in splitting the census tracts/socio-ecoregions into fire affected areas during the analysis period, thus resulting in different spatial tract sizes. Combining or splitting the original census tracts will result in changes to population estimates [67]. In addition, census tract population estimates are assumed to be evenly and proportionally distributed across a census tract. However, there were many instances where residential housing was only clustered in a certain area of a tract or conversely, residential land cover was interspersed throughout the tract, but only a portion of that tract was inside a fire perimeter. Thus, all the sociodemographic variable proportions except average annual per capita income (measured in US Dollars) for the FA split census tracts were adjusted and weighted according to their respective fire affected area during the analysis period. This weighing was done via aerial interpolation to account for polygon incongruencies and scale mismatches and the process consisted of the following steps to better identify and quantify the types and proportion of different sociodemographic and disadvantaged groups in the wildfire affected areas [68]. We note that there was no fire affected area in NFA census tracts and therefore, the socio-demographic variables were not adjusted and weighted. Also, analyses of NFA census tracts were included in order to assess if trends in FA areas were different from communities not affected by fire at the state and socio-ecoregion level. Different trends between FA and NFA tracts would then indicate that fire is indeed a significant factor in socio-demographic trends in areas where fire has occurred.

The total fire affected area (*FAA*) of a FA census tract was initially estimated by summing the area of all the individual annual fire occurrences. The FAA can therefore also include overlapping areas affected by more than a single fire each year. The FAA and total area (*A*) of a FA census tract in-turn were used to calculate fire affected proportion (*FAP*) of a FA census tract using the following equation:

$$FAP = \frac{FAA}{A} \tag{1}$$

where *FAP* is fire affected proportion, *FAA* is fire affected area, and *A* is total area of a FA census tract.

The FAP and sociodemographic variable of interest (*V*) for a FA census tract were then calculated to derive an area weighted sociodemographic variable (V_w) to address the issues of human population density differences and various sized census tracts (e.g., very large but less populated versus small but highly populated census tracts). Accordingly, the sociodemographic variable (*V*) was multiplied by fire affected proportion (*FAP*) to derive a weighted sociodemographic variable (V_w) using the following equation:

$$Vw = V \times FAP \tag{2}$$

where 'V_w' is the weighted sociodemographic variable of a FA census tract. The fire area weighted sociodemographic variables (V_w) of FA census tracts were subsequently used to identify the relationship of wildfire effects on different sociodemographic groups over the analysis period. Average annual per capita income (US$ dollars) for each year was estimated by averaging non-weighted annual per

Table 2
Sociodemographic variables compiled from the American Community Survey 2010–2020, five-year estimates. Sources: [8,20,22,63].

Sociodemographic Group	Sociodemographic Variables	Relevance
Economic	Per capita income in US$ dollars (Average annual)	Ability to adapt and enhance resilience to natural hazards
	% Population below poverty level for whom poverty status is determined are Poor	
Education	% Population less than high school graduate >25 years of age	
Health	% Population with a disability	Capability to quickly react to and escape from an emergency
Population and People	% Non-English speaking population >5 years of age	
	% Population >65 years of age	
	% Children <5 years of age	
Race/Ethnicity	% Population White/Non-White	Adaptive capacity, which influences social vulnerability to natural hazards
	% Population Hispanic/Non-Hispanic	
	% Population African American	
	% Population Asian American	
	% Population Native American	
Housing	% Population with homeowners/renters	Housing status and affordability
	% Population with housing burden (paying more than 30 % income on housing)	

capital income (*V*) of FA and NFA census tracts to account for socioeconomic status of the census tracts and socio-ecoregions. However, the remaining weighted and non-weighted sociodemographic variables for both FA and NFA census tracts were summed for each year. These annual variables were then reported as percent of the total population count. This approach was repeated for spatial and temporal trend analyses in Section 2.5 that related the *Vw* of FA DACs.

2.5. Statistical analysis

The selected weighted and non-weighted sociodemographic variables from the housing, race, and economic groups for FA and NFA census tracts at both statewide and socio-ecoregion scale and urban census tracts - including FA DACs - were first analyzed using descriptive graphical analysis in the form of line and bar graphs to visually explore and identify possible patterns and trends over the analysis period. These sociodemographic variables were then statistically analyzed for non-linear, linear, or constant trends that depend on fire affected status over a period of 11 years.

Specifically, we used three models that were not based on year-to-year differences, but rather temporal trends. The three statistical models were: non-linear (i.e., Model 1), linear (i.e., Model 2), and a two-sample *t*-test (i.e., Model 3). The non-linear (model 1) and linear (model 2) regression were performed using Generalized Additive Mixed model "gam" function in the "gamm4" library and mean comparison was performed using two-sample T-Test function in R 4.2.0 computer programming language [69]. Model 1 was used to assess model parsimony, whereas Models 2 and 3 were used to determine significantly increasing or decreasing trends in variables during the analysis period. All three models were fitted to select sociodemographic variables with the goal of assessing their trend by comparing their Akaike Information Criteria (AIC). The AIC is a goodness of fit statistic for which smaller values indicate a better fit. The AIC also penalizes the fit by the number of parameters, akin to adjusted R-squared. Derivatives of the nonlinear models are reported to show instantaneous changes in trend over time. Confidence intervals for the nonlinear trends and derivatives are not reported, as they would be biased because we already performed model selection using AIC. Significant increasing and decreasing trends were analyzed based on p-values of nonlinear and linear regression models, derivatives of non-linear model, and mean comparisons (MC) of no interaction T-test model.

2.5.1. Model 1: non-linear generalized additive mixed (GAM) model

The weighted FA and non-weighted NFA sociodemographic variables (V_w) for each census tract were first analyzed using a non-linear generalized additive mixed (GAM) model (i.e., Model 1) [70] to test for model parsimony and non-linear temporal trends in socio-demographic variables during the analysis period. Non-linear relationships were estimated using low-rank thin-splines using the "s" function when specifying the regression model using the "gam" function. The most complex regression model assumes that the sociodemographic variable y_{ti} has a non-linear trend f_i that depends on fire affected status i = "FA","NFA" and overall average β_{0i} that also depends on fire affected status. The non-linear model is of the following form where t = 1, 2, …, 11 is time and ε_{ti} is error:

$$y_{ti} = \beta_{0i} + f_i(t) + \varepsilon_{ti} \quad \text{Eq 1}$$

2.5.2. Model 2: linear generalized additive mixed (GAM) model

Model 2 was based on a linear generalized additive mixed (GAM) model that was used to determine a statistically significant linear trend that depends on fire affected status during the analysis period from 2010 to 2020 specifically: 1) weighted and non-weighted sociodemographic variables of FA and NFA census tracts, respectively, at both statewide and socio-ecoregion scales, 2) count of statewide FA urban census tracts, and 3) count of FA DACs at the statewide and socio-ecoregion scale. The linear regression model is similar to Model 1, except that it assumes that the sociodemographic variable (y_{ti}) has a linear trend β_i that depends on fire affected status instead of non-linear trend f_i and has the following form:

$$y_{ti} = \beta_{0i} + \beta_i t + \varepsilon_{ti} \quad \text{Eq 2}$$

Both Model 1 and Model 2 trends for weighted sociodemographic variables in FA census tracts were tested for statistical significance using p-values. The linear model was performed on weighted sociodemographic variables in FA census tracts considering a null hypothesis that the trend is non-linear over time. The nonlinear and linear trends were statistically significant at $p < .05$. Both non-linear and linear tests were also examined for trends in socio-demographic variables that do not depend on fire affected status $i = \mathrm{FA}, \mathrm{NFA}$. The equations for these tests are not presented here. However, their AICs and p-values were compared with models that considered fire affected status in the regression model.

2.5.3. Model 3: two sample T-test

Finally, Model 3 or the two sample T-test, was performed for both FA and NFA tracts at the statewide and socio-ecoregion scale with the goal of assessing and comparing AICs and temporal trends for each sociodemographic variable that was constant. The final regression model used for the weighted sociodemographic variables (V_w) in FA and NFA census tracts, is the simplest approach to modelling the overall mean of fire affected status β_{0i}, as such it does not contain any trend component over time and has the following form:

$$y_{ti} = \beta_{0i} + \varepsilon_{ti} \quad \text{Eq 5}$$

Model 3 was used to determine if the unknown population means of weighted sociodemographic proportions of two groups, past and recent, were equal. This test was performed considering a null hypothesis that the mean and variance of sociodemographic variables of the two analysis periods, past and recent, were the same and of unequal variance. Accordingly, weighted socio-demographic variables for FA tracts, counts of FA urban census tracts statewide, and count of DACs (statewide and socio-ecoregions) were divided into two temporal groups – past and recent - of analysis period. We define past as being 2010–2015 and recent as being 2016–2020 to better facilitate the analysis of their means and variances for significant differences.

3. Results

3.1. Statewide trends in sociodemographic groups affected by wildfire

Results for our statewide analysis are presented below and are based on three broad sociodemographic groups: economic, race/ethnicity, and housing. Results for our economic group were explained by Model 1 and a lower AIC, indicating that high average annual per capita income populations were indeed increasingly affected in FA and NFA census tracts statewide during the analysis period (Fig. 3a). However, trends show that higher average annual per capita income census tracts were being statistically and significantly increasingly affected by wildfires during the analysis period ($p < .001$) according to Models 2 and 3 (Table 3). Conversely, the trends show that poor populations were statistically and significantly decreasingly (Fig. A1) being affected by wildfire during the analysis period ($p < .05$) according to model 2 (Table 3).

Using Model 1's low AIC and p-values ($p < .001$), we found that more recently, Whites were significantly and decreasingly being affected by wildfire during the analysis period. (Fig. 4a and A.1). Similarly, Native Americans were significantly and decreasingly affected by wildfire during the analysis period (Model 1, $p < .001$; Fig. 4b, Fig. A1, and Table 3). In contrast, Hispanic and Asian American populations were increasingly and significantly being affected by wildfire statewide (Model 1, $p < .001$; Fig. 4c and d, Fig. A1, and Table 3).

Findings show that statewide, renters were increasingly being affected by wildfires over the analysis period (Fig. 5), as indicated by an increasing statistically significant trend ($p < .001$) according to Model 1 (Table 3, Fig. A1) and Model 3 (24.87 in past versus 30.47 in recent years; Table 3).

3.2. Sociodemographic groups affected by wildfire in different socio-ecoregions

Results for our socio-ecoregion analysis are presented below and are based on three broad sociodemographic groups: economic, race/ethnicity, and housing (Table 4). The average annual per capita income across all the socio-ecoregions was best explained by linear Model 2, as indicated by the lowest p-values, shows an increasing trend over time in the census tracts (FA and NFA) (Fig. 6). However, models 2 and 3 show that indeed higher average annual per capita income census tracts were statistically and significantly increasingly being more recently affected by wildfire (indicated by $p < .001$ and (+) mean comparison) in the Klamath, Coastal Sage, and Sierra Nevada socio-ecoregions (Table 4 and Fig. 6).

However, we also found that Hispanics were increasingly being affected by recent wildfires in the Sierra Nevada, Klamath, and Central Valley socio-ecoregions but decreasingly being affected in the Coastal Sage and South Baja during the analysis period, as indicated by the statistically significant trends in Model 1 and Model 2 ($p < .05$) and Model 3 (decreasing mean comparison of 30.42 in past versus and 26.91 in recent years; Fig. 7). Conversely, African Americans, according to Models 1, 2, and 3, were statistically and significantly increasingly being affected by wildfire in all the socio-ecoregions except the Sierra Nevada and Coastal Sage ($p < .05$, Table 4), while Asian Americans were statistically and significantly increasingly being affected by wildfire in the Coastal Sage socio-

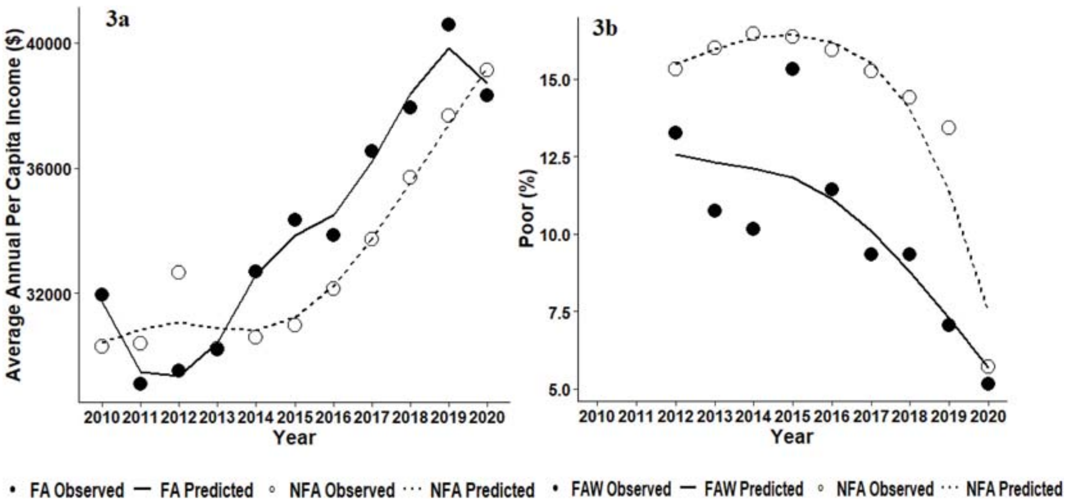

Fig. 3. Average annual per capita income (3a; left figure) and percent poor population (3b; right figure) in fire-affected (FA), and non-fire affected (NFA) census tracts using observed trends and non-linear model (i.e., model 1) predicted trends in California, USA from 2010 to 2020. The observed fire-affected (FA) average annual per capita income (3a), weighted fire-affected (FAW) poor population (3b), and non-fire affected (NFA) average annual per capita income in US$ and poor population in percent (3a and3b, respectively) trends are represented by points whereas predicted trends are represented by a line. Note, both observed and predicted trends are shown to clearly demonstrate overall trends in the variables during the analysis period.

Table 3
Trend analysis of sociodemographic variables in the state of California, USA during 2010–2020 using the Non-Linear (Model 1), Linear (Model 2), and Two Sample T-test (Model 3). The significance of the nonlinear and linear model in Fire Affected census tracts were represented by p-values. Model 1 and 2 were significant at $p < .001$ (*) and $p < .05$ (**). The increasing or decreasing trends in sociodemographic variables were determined by comparing the means of past and recent periods (MC) using Model 3. Note, (+) in Model 3 shows increasing trends while (−) shows decreasing trends in variables during the analysis period.

Sociodemographic Group	Sociodemographic Response Variables	Statewide					
		Mode l (Nonlinear)		Model 2 (Linear)		Model 3 T-Test	
		AIC	p-value	AIC	p-value	Means of past and recent MC (±)	AIC
Economic	Per Capita Income (in dollars)	361.42	.01**	393.93	<.001*	30686.80 and 36920.33 (+)	425.68
	Poor (%)	74.88	<.001*	87.45	<.05**	12.36 and 8.46 (−)	97.01
Race/Ethnicity	White (%)	104.04	<.001*	147.87	.04**	75.0 and 72.1 (−)	144.33
	Non-White (%)	95.13	<.001*	146.57	.01**	26.2 and 26.5 (+)	143.85
	Hispanic (%)	55.39	<.001*	142.36	.01**	25.2 and 26.6 (+)	138.95
	African American (%)	72.95	.001*	87.82	.01**	4.7 and 3.6 (−)	85.28
	Asian American (%)	−22.07	<.001*	102.09	.01**	6.32 and 8.38 (+)	106.17
	Native American (%)	−140.62	<.001*	35.67	.01**	1.6 and 1.13 (−)	36.40
Housing	Homeowners (%)	96.45	<.001*	129.08	.04**	75.13 and 69.53 (−)	137.37
	Renters (%)	96.45	<.001*	129.08	.01**	24.87 and 30.47 (+)	137.37

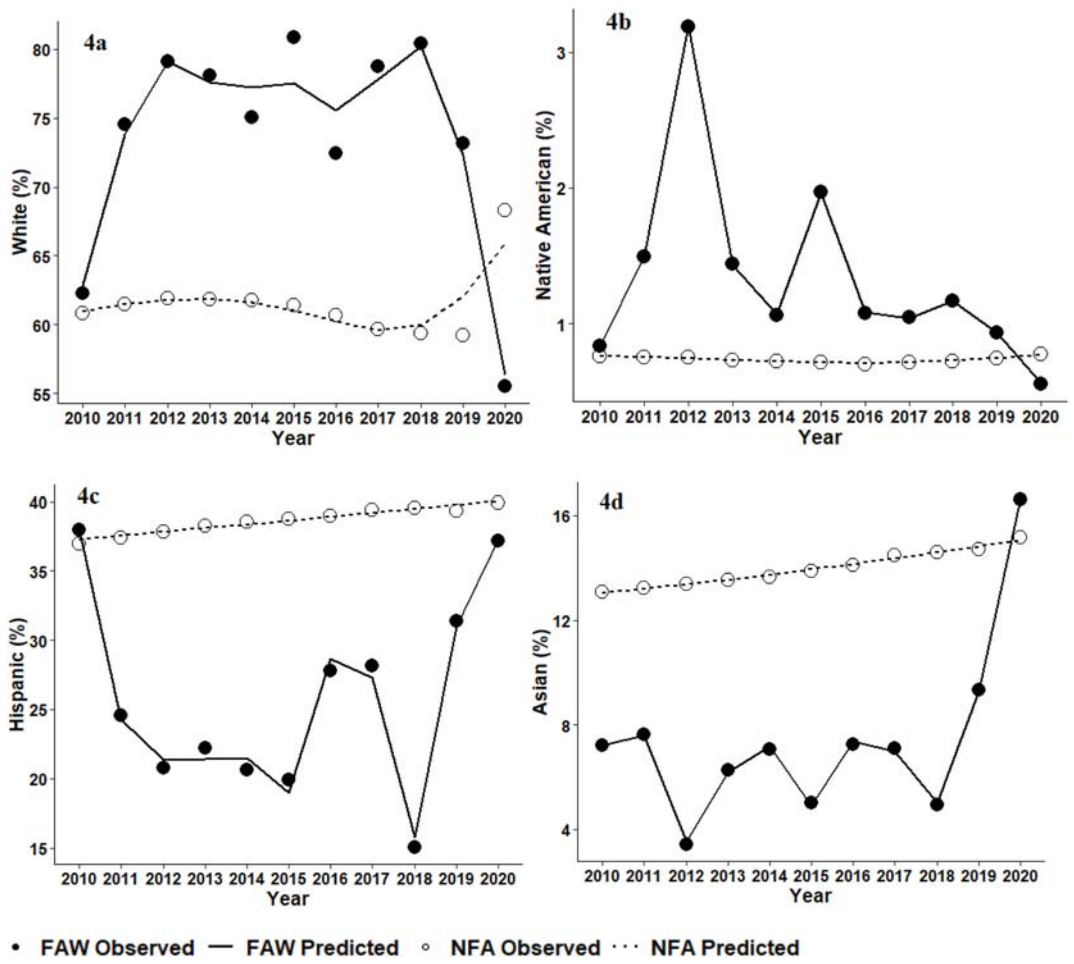

Fig. 4. Whites (4a), Native Americans (4b), Hispanics (4c), and Asian Americans (4d) in fire affected (FA), and non-fire affected (NFA) census tracts using observed trends and non-linear Model 1 predicted trends in California, USA from 2010 to 2020. The observed fire-affected (FA), weighted fire-affected (FAW), and non-fire affected (NFA) trends are represented by points whereas predicted trends are represented by a line. Note, both observed and predicted trends are shown to clearly demonstrate overall trends in the variables during the analysis period.

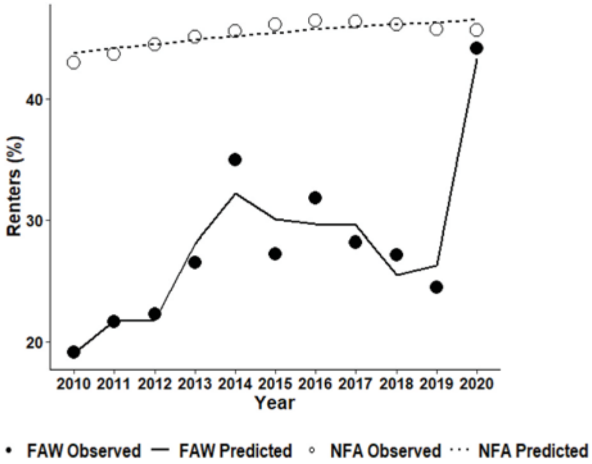

Fig. 5. Renters in fire affected (FA), and non-fire affected (NFA) census tracts using observed trends and non-linear model (i.e., model 1) predicted trends in California, USA from 2010 to 2020. The observed weighted fire affected (FAW) and non-fire affected (NFA) trends are represented by points whereas predicted trends are represented by a line. Note, both observed and predicted trends are shown to clearly demonstrate overall trends in the variables during the analysis period.

Table 4
Trend analysis of sociodemographic variables in fire affected (FA) and non-fire affected (NFA) census tracts in five socio-ecoregions (SE) of California, USA during 2010–2020 using nonlinear (Model 1), linear (Model 2), and mean comparison (MC; Model 3). The Akaike Information Criteria (AIC) and p-values are reported for each variable that explained the trend with lowest AIC and *p*-values in FA census tracts in socio-ecoregions. Note: Model 1 and Model 2 are significant at *p* < .001 (*) and *p* < .05 (**). In Model 3, '+' shows an increasing trend, while '-'shows a decreasing trend in variables during the analysis period.

Sociodemographic Group	Sociodemographic Variable	Central Valley SE (Model 1; Model 2 p-value) MC (±)	Coastal Sage SE (Model 1; Model 2 p-value) MC (±)	South Baja SE (Model 1; Model 2 p-value) MC (±)	Sierra Nevada SE (Model 1; Model 2 p-value) MC (±)	Klamath SE (Model 1; Model 2 p-value) MC (±)
Economic	Per Capita Income (in US dollars)	(.21; .12) 27077.80 and 28641.83 (+)	(.54; <.001*) 34152.80 and 39840.67 (+)	(.45; 0.82) 32435.8 and 36948.5 (+)	(.29; <.001*) 27443.60 and 33301.17 (+)	(.28; <.001*) 22146.60 and 27238.17 (+)
	Poor %	(.86; 0.38) 11.16 and 16.98 (+)	(.01**; .16) 10.25 and 8.99 (−)	(.77; .72) 10.21 and 8.27 (−)	(.11; .77) 14.39 and 12.14 (−)	(.80; .31) 21.24 and 14.01 (−)
Race and Ethnicity	White %	(<.001*; 0.58) 78.84 and 74.74 (−)	(<.001*; .06) 70.74 and 72.62 (+)	(.01**; .23) 73.46 and 74.47 (+)	(.31; .18) 89.57 and 84.23 (−)	(.82; .02**) 80.22 and 82.33 (+)
	Non-White %	(<.001*: 0.19) 21.16 and 25.26 (+)	(<.001*; .01**) 29.26 and 27.38 (−)	(.01**; .12) 26.54 and 25.53 (−)	(.31; .09) 10.43 and 15.77 (+)	(.82; .04**) 19.78 and 17.67 (−)
	Hispanic %	(<.001*; 0.18) 20.17 and 25.20 (+)	(.001*; .03**) 30.42 and 26.91 (−)	(.03**; .13) 27.93 and 25.50 (−)	(.02**; .12) 11.54 and 12.44 (+)	(.01**; .05**) 7.42 and 20.10 (+)
	African American %	(<.001*; 0.34) 1.58 and 2.71 (+)	(.70; <.001*) 5.35 and 4.19 (-)	(.001*; .17) 4.53 and 4.56 (+)	(.24; .12) 1.01 and 1.24 (+)	(.12; .05**) 0.56 and 1.05 (+)
	Asian American %	(0.16; 0.10) 6.91 and 8.65 (+)	(.03*; <.001*) 7.73 and 9.26 (+)	(.07; .09) 5.94 and 8.21 (+)	(.36; .11) 1.23 and 2.99 (+)	(.49; .08) 1.79 and 2.45 (+)
	Native American %	(<.001*; 0.49) 1.16 and 0.81 (−)	(.01**; .01**) 1.06 and 0.94 (−)	(.01**; .14) 1.42 and 0.71 (−)	(<.001*; .76) 2.58 and 2.67 (+)	(.01**; .19) 8.89 and 4.51 (−)
Housing	Homeowners %	(.001*; 0.84) 72.74 and 68.95 (−)	(.64; .05**) 77.00 and 69.51 (−)	(.05**; .29) 81.41 and 67.64 (−)	(.002**; .17) 76.97 and 76.26 (−)	(.33; .04*) 72.51 and 71.22 (−)
	Renters %	(.001*; 0.22) 27.26 and 31.05 (+)	(.64; .02**) 23.0 and 30.5(+)	(.05**; .07) 18.60 and 32.36 (+)	(.002**; .11) 23.03 and 23.74 (+)	(.33; .03**) 27.49 and 28.80 (+)

ecoregion over the analysis period, according to Models 1 and 2 ($p < .05$; Table 4). In contrast, Native Americans were found to be significantly and decreasingly being affected by wildfire in all the socio-ecoregions except the Sierra Nevada, in which they were significantly increasingly affected by wildfire according to Models 1, 2, and 3 ($p < .01$; Table 4 and Fig. 7). Statewide analyses show that renters were significantly and increasingly being affected by wildfire in all five socio-ecoregions during the analysis period (Fig. 8; Table 4) according to Models 1 and 2 ($p < .05$).

3.3. Urban census tracts and disadvantaged communities affected by wildfires

The sociodemographic analysis of statewide FA urban census tracts (population >2500 residents) indicated that they were

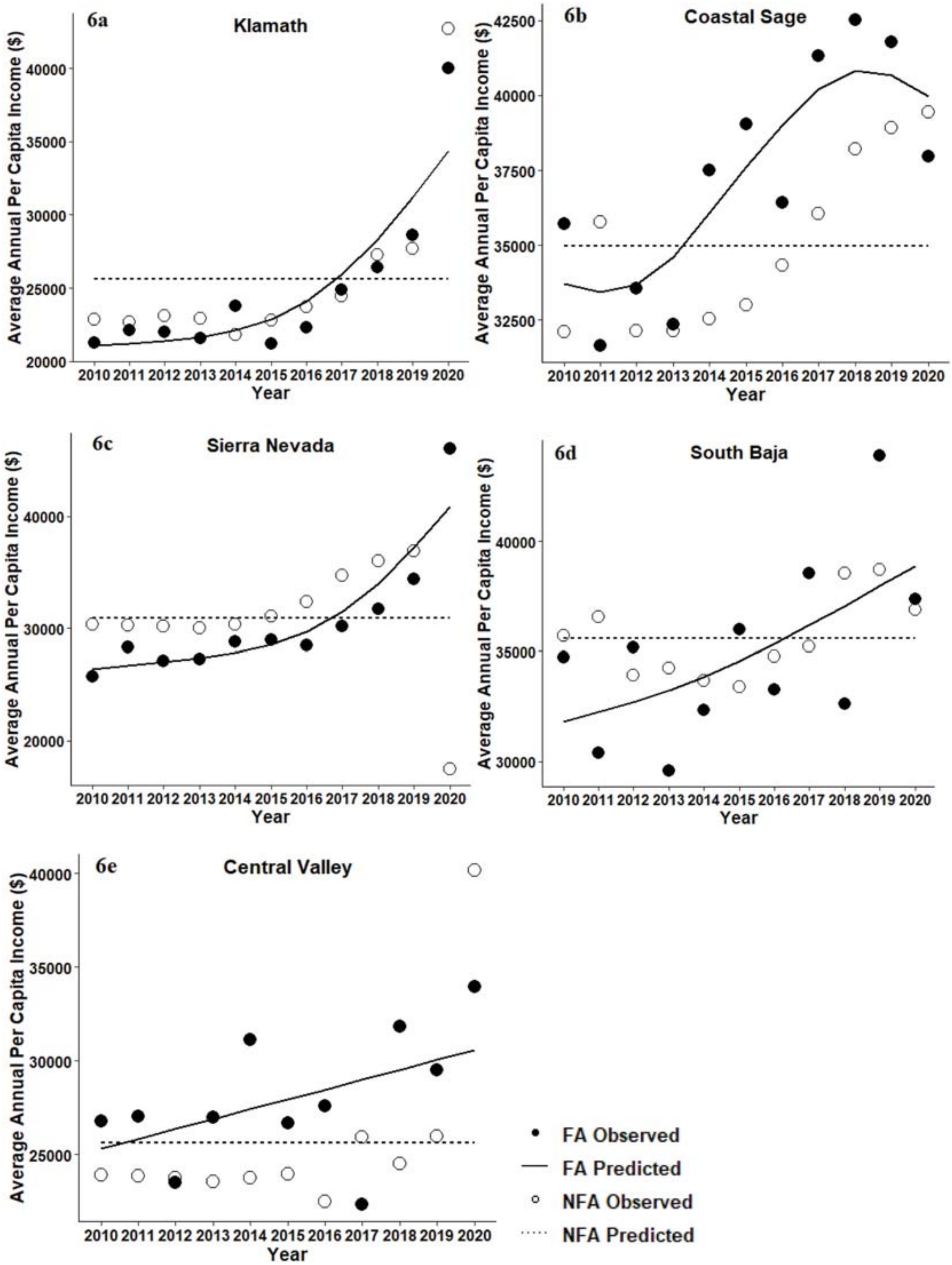

Fig. 6. Average annual per capita income in fire affected (FA), and non-fire affected (NFA) census tracts using observed trends and predicted by non-linear model (i.e., model 1) trends in the Klamath (6a), Coastal Sage (6b), and Sierra Nevada (6c), South Baja (6d), and Central Valley (6e) socio-ecoregions of California, USA from 2010 to 2020. The observed fire-affected (FA), weighted fire-affected (FAW), and non-fire affected (NFA) trends are represented by points and whereas predicted trends are represented by a line. Note, both Observed and predicted trends are shown to clearly demonstrate overall trends in the variables during the analysis period.

significantly ($p < .05$) and increasingly affected by more recent wildfires over the analysis period (Fig. 9) according to Models 1, 2, and 3. Statewide, DACs were increasingly affected by wildfire after 2014. Similarly, at a regional level, DACs were increasingly affected in the California Valley and Coastal Sage socio-ecoregions from 2010 to 2020 and DACs in the Coastal Sage socio-ecoregion were increasingly affected by wildfire from 2014 to 2018 in the California Valley. However, none of these trends in DACs were statistically significant according to Models 2 and 3. We also found that only two DACs were affected by wildfire in the South Baja and Sierra

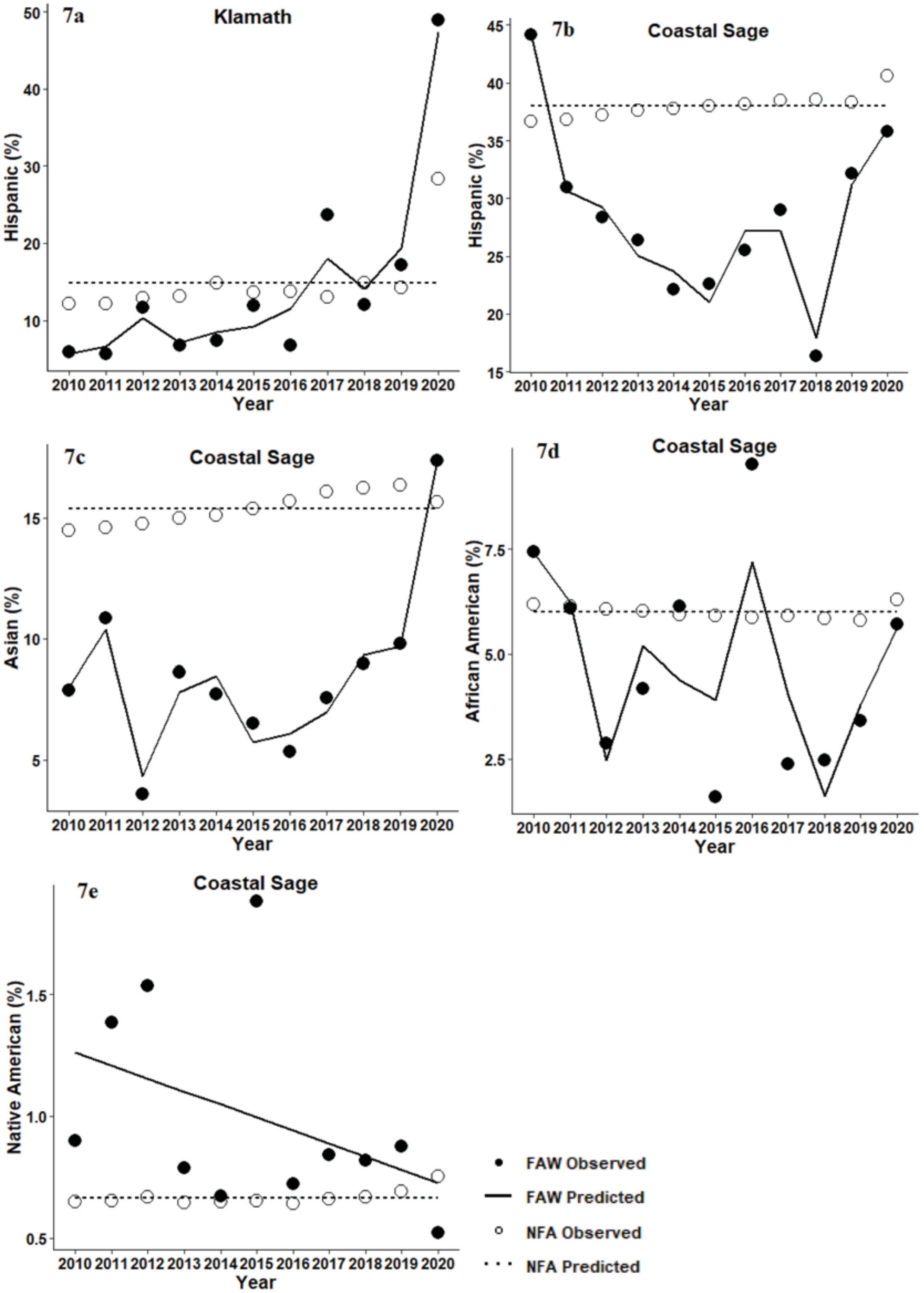

Fig. 7. Hispanic (7a and 7b), Asian American (7c), African American (7d), and Native American (7e) in fire affected (FA), and non-fire affected (NFA) census tracts using observed trends and predicted by non-linear model (i.e., model 1) in Klamath and Coastal Sage socio-ecoregions of California, USA from 2010 to 2020. The observed fire-affected (FA), weighted fire-affected (FAW), and non-fire affected (NFA) trends are represented by points whereas predicted trends are represented by a line. Note, both Observed and predicted trends are shown to clearly demonstrate overall trends in the variables during the analysis period.

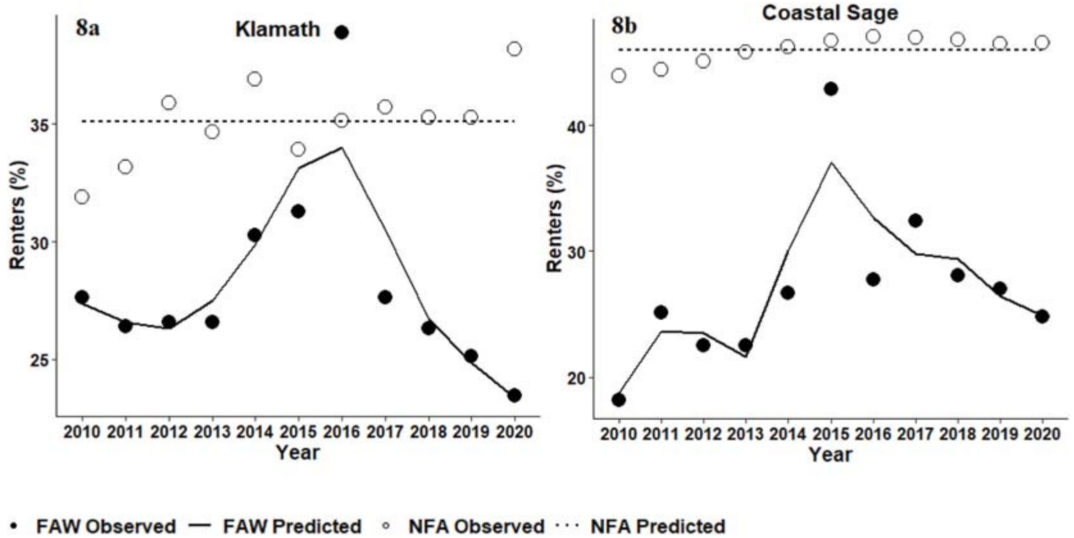

Fig. 8. Renters in fire affected (FA), and non-fire affected (NFA) census tracts using observed trends and predicted by the non-linear model (i.e., model 1) in the Klamath (8a) and Coastal Sage (8b) socio-ecoregions of California, USA from 2010 to 2020. The observed fire-affected (FA), weighted fire-affected (FAW), and non-fire affected (NFA) trends are represented by points and whereas predicted trends are represented by a line. Note, both Observed and predicted trends are shown to clearly demonstrate overall trends in the variables during the analysis period.

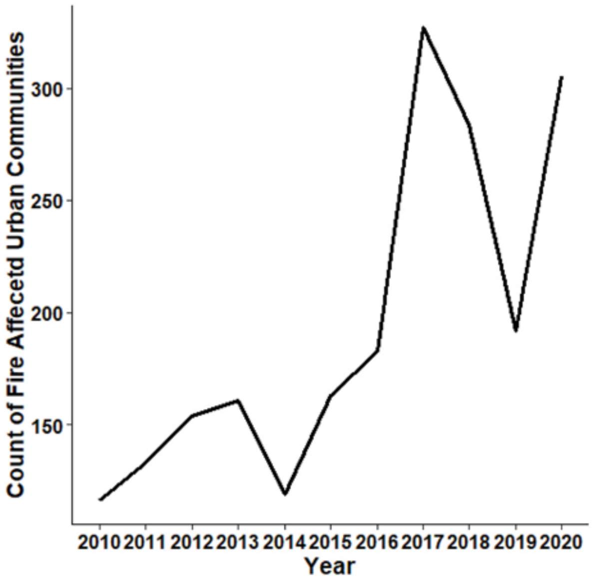

Fig. 9. Linear trend in fire affected urban census tracts in California, USA from 2010 to 2020.

Nevada socio-ecoregions during the entire analysis period.

4. Discussion

Across the world, climate change, vegetation and fuel dynamics, and urbanization are factors altering socio-ecological landscapes and fire regimes [71]. Similarly, many national-level wildfire mitigation and response polices (e.g., USDA Forest Service's 2022 Wildfire Crisis Strategy [7]) are defining "communities" primarily based on the number of structures or building footprint density. But, for communities to successfully adapt to future wildfires, it is important to understand how such changes in these socio-ecological systems will interact to alter risk, hazard, exposure, and the occurrence of wildfire in diverse communities. Although previous studies have looked at how wildfires affect socio-demographic groups across space and time, they generally focus on specific wildfires occurring at the scale of local and regional administrative units such as the county or state level [22,36,39]. Here, in this study we explored how different sociodemographic groups have been exposed to wildfires across California's different communities and socio-ecoregions over a decade that was characterized by a changing fire regime. Most importantly as shown in our study, wildfires do not affect communities – and their sociodemographics- equally, but instead present different and varying degrees of challenges as evidenced by a community's socio-ecological and spatio-temporal context [2,35,72].

Results of our statewide analysis showed that during 2010–2020, higher per capita income individuals were more likely to be affected by wildfires (Fig. 3; Table 3). This is consistent with Wibbenmeyer and Robertson's [39] finding that between 2011 and 2018 higher valued properties in eleven western US states were more likely to be located within fire perimeters, despite other findings that fires are more likely to be suppressed near high value homes [73]. Similarly, Garrison and Huxman [36] found that higher income census tracts across California/Southern California were also more affected by wildfire during a similar analysis period, as compared with non-wildfire affected areas. These studies, in addition to ours, show that higher income populations have been increasingly affected by wildfires since 2010 (Fig. 3; Table 3). This corroborates the notion that WUI areas are still predominantly more affluent [3,57] despite intercity migration and urbanization factors occurring in California's WUI and cities [23,24,27]. However, as indicated by regional and socio-ecoregion results; statewide and national-level analyses need to account for socio-ecological scales and contexts, and their inherent socioeconomic and ecological heterogeneity.

We also found that statewide census tracts with a greater proportion of homeowners were increasingly being affected by wildfires during the analysis period (Fig. 5; Table 3). This finding corroborates previous literature that, in general, more affluent and resource rich individuals are living in WUI areas of the western US [20,74]. This statewide and region-scale result and the previous findings on greater per capita incomes being increasingly affected by wildfire, has implications for these communities and individuals to be able to respond and adapt to past and future wildfires. For example, the sociodemographic characteristics of a community influence the capacity of people in those areas to adapt, recover from, and mitigate risk and exposure to wildfires [35,75–77]. Sánchez et al. [78] found that economic costs and access to financial incentives are significant barriers to implementing recommended home mitigation actions since higher-income households, as opposed to low income, were more likely to be able to afford the high mitigation costs required of reducing fire risk on their properties. Additionally, these higher income communities are more likely to be able to afford the required levels of home fire insurance [79]. That said, as we will later discuss, the proportion of renters affected by wildfires in California is also significantly increasing (Fig. 5; Tables 3 and 4).

However, our study also found that Hispanics and Asian Americans were increasingly being affected by wildfires statewide over the analysis period (Fig. 4; Table 3), possibly reflecting a "diversification of the suburbs", or an increasing migration of groups who typically lived in more urban neighborhoods to peri-urban areas [20]. Similarly, the increasing frequency of fires in urban areas beyond established WUI boundaries might also be a factor [30]. These findings can have important implications for how communities prepare and respond to wildfires, assuming that many Hispanic and Asian American communities have a higher proportion of non-English speakers, or those that do not speak the language proficiently, who might encounter barriers in understanding and responding to evacuation warnings which are often issued only in English [80]. Similarly, informational material and social media on wildfire preparation might not be in the preferred language [81]. Furthermore, Hispanic immigrant communities can have undocumented residents and other Indigenous groups that are often historically marginalized and underserved regardless of wildfire impacts [80,82]. However, despite its importance, the influence of language in preparation for and response to wildfires is an understudied topic [8].

In terms of our subregional level analysis, the Coastal Sage socio-ecoregion exhibited increasing occurrences of wildfire on census tracts with higher per capita incomes, as well as on those with Asian Americans; conversely African Americans in this socio-ecoregion were decreasingly affected by wildfires during the analysis period (Table 4). More specifically in terms of race/ethnicity, results show that Hispanics are increasingly affected by wildfires in inland and northern SEs such as the Klamath (Fig. 7a and b, and Table 4), while being less affected over time in the Coastal Sage socio-ecoregion (Table 4) where they comprise 36% of the population (Table 1). This is likely a result of demographic changes in the state and that larger wildfires, which historically tended to occur in southern California, are now occurring in northern areas of the state where other racial/ethnic groups live or are migrating to.

In terms of renters, both at the statewide and SE scale, they were increasingly affected by wildfire during the analysis period (Table 4; Fig. 8). Renters generally do not have control over implementing many of the defensible space recommendations (e.g., where trees are planted, non-combustible alternatives to decks, fencing, and roofs). Therefore, mitigation programs and efforts to prepare homes for wildfire, including smoke-mitigation and ventilation, should be targeted accordingly and focus on not only homeowners but renters as well [83]. Furthermore, renters are likely to be disproportionately impacted if their housing is damaged or destroyed. For example, renters often experience price gouging post-fire as landlords can raise their rates in response to housing shortages [20,80,84]. Similarly, they are less likely to be able to compete for available housing and a decision over whether to return to their former home is entirely dependent on the owner; making renters more likely to experience long-term permanent displacement [85]. Despite this, multiple studies [80,84] have noted how much of the wildfire research is focused on homeowners.

Overall, our findings show that these new fire regimes are increasingly affecting more urban census tracts state-wide, meaning greater numbers and more diverse groups of people are being and possibly will be affected by wildfires. As evidenced in this study from California and in other regions internationally such as southern Europe, Australia, and Chile; wildfires are no longer confined to wildland, rural areas [11,12,34]. Indeed, in California recent years have seen more wildfires in large metropolitan urban neighborhoods such as the 2017 Tubbs and Thomas Fires which burned urban neighborhoods in Santa Rosa (population ~178,000) and Ventura (population ~109,000), respectively, as well as other smaller, just as damaging wildfires that occurred in the Coastal Sage socio-ecoregion [37]. However, despite this urban phenomenon, we found no evidence that DACs - as defined in California State policies for pollution burdened populations – are being increasingly affected by wildfires. We note that CALEPA's definition of DACs is heavily weighted towards pollution burden and thus other indicators of – or metaphors for-wildfire risk, vulnerability, and susceptibility might need to be considered to better account for environmental justice issues. In addition, the terms disadvantaged, underserved, underrepresented, marginalized (among others) will have different meanings and environmental justice implications [8, 34].

That said, several key findings from this study are relevant to preparing communities for future wildfires. For example, the increasing occurrence of wildfires in urban areas suggests a need for increased outreach to residents of more urbanized neighborhoods and communities that have never experienced wildfires. Even in those that have historically been sporadically affected by wildfire, their residents are likely to have lower perceptions of risk, believing that wildfires will not occur in their neighborhoods. Similarly, they are likely to be less prepared for wildfires, such as having a “go bag” or completing home mitigation measures [86]. As previously discussed, knowing which specific sociodemographic groups are being increasingly affected can also encourage and assist organizations and institutions with creating more targeted outreach and policies to better reach key groups and help reduce social vulnerability to wildfire.

The trend variations between socio-ecoregions also confirms the need to account for complexity in communities by using more socio-ecological approaches to better understand the multi-scale interactions among social and ecological factors [40,87]. Accordingly, available municipal level social and biophysical data can be used to analyze not only the factors behind wildfire frequency but also impacts to communities, and how those communities are defined. Climate change will also alter future fire regimes, although the specific changes will vary between different ecoregions. For example, parts of the Sierra Nevada socio-ecoregion could experience a 2-4-fold increase in burned area under some of the more extreme projections [88]. This socio-ecoregion is currently home to a majority White population, with a high rate of home ownership, suggesting mainly a population of lower social vulnerability, although future sociodemographic changes could bring in different groups and urbanization could affect the fire regime (i.e., Hispanics in the Klamath socio-ecoregion; Table 4). Conversely in the Southern and Baja socio-ecoregions, conversion from shrubland to grassland has strengthened the relationship between burned area and prior year rainfall [53] and these socio-ecoregions are much more ethnically/racially diverse than the Sierra Nevada socio-ecoregion. Studies in addition to ours are also now using a more socio-ecological approach for empirical analyses of the effects of wildfire on ecosystems and communities [38,39,80].

Despite the above findings, we do note some study limitations. First, our sociodemographic analyses are based on the American Community Survey which is the best available data and has been used in similar studies such as Davies et al. [20] and Masri et al. [22]. However, there are some limitations in using ACS data because of tradeoffs between the spatial and temporal resolutions of the data [89]. In particular, there are uncertainties in smaller sized census tracts, especially in rural areas, due to survey design and small sample sizes that result in higher margin and standard errors [89], despite our use of 5-year data that is pooled over multiple years to overcome small sample size problems. Also, Greiman [90] reports that there are some data gaps in disability and poverty estimates due to inadequate sample sizes for 2010 and 2011, and there are likely some data quality issues in 2020 estimates due to the COVID-19 pandemic, and groups such as African-Americans, Hispanics, and seasonal migrant workers had lower coverage rates and were less represented. Second, we also note that our spatial and temporal analysis results are based on sociodemographic variables weighted by the fire affected area of census tracts since it is not possible to precisely account for the spatial distribution of different demographic groups in the census tracts. Similarly, we also assumed that US Census tract boundaries remained stable over time. Thus, the results might not be representative of trends on communities outside of the wildfire perimeters within a census tract. Finally, this analysis only accounts for a community’s fire exposure or direct and indirect effects within the fire perimeter, whereas smoke and flood impacts, as well as post-fire restoration and building damage impacts, were not included.

5. Conclusions

Results from the statewide analysis were largely consistent with previous research on the socio-demographics of fire affected communities, although in several socio-ecoregions more socially diverse populations were being increasingly affected by wildfire. However, given that our analysis also found that wildfires are increasingly occurring in urban areas, there is now the potential for these observed trends to become more prominent in the future. This changing nature of wildfire means that both more and a greater diversity of sociodemographic groups are being affected, both directly as analyzed in this study and indirectly through smoke exposure. Accordingly, there is likely a future need to account for this increased diversity and populations when referring to wildfires and communities. Indeed, as shown in this and other studies we cite, the common definition of “communities” as being clusters of building footprints that are regularly used for wildfire planning and management, could include more socioeconomic, cultural, and language aspects and variables like those described and presented in our study.

Additionally, our methods and approach could also be used for future studies. For example, although “disadvantaged” communities, per CALEPA, were not increasingly directly affected by wildfire, other vulnerable sociodemographic groups in certain socio-ecoregions, administrative areas, or communities are, or might be, as is the case for non-English speaking immigrants, elderly, and low-income households. Similarly, the approach and data used in this study could be used to forecast future wildfire effects on communities and sociodemographic groups as human populations change and migrate, urbanization increases, and climate change alters fire regimes.

Understanding the sociodemographic characteristics of communities being exposed to wildfires can help assist governmental and non-governmental organizations better prepare for and respond to post-wildfire recovery (e.g., policies, relief efforts). Similarly, this type of information can help those communities rebuild and prepare for future fires through pre-wildfire outreach and mitigation efforts. On the other hand, omitting the sociodemographic characteristics of different communities’ leaves gaps in fire response and recovery and can further exacerbate inequalities. Communities have different levels of adaptive capacity and subsequently different needs; yet recovery policies are historically aimed at people who can afford to reduce fire risk on their properties. Additionally, it is important to note that even though wildfire will affect socio-demographic communities that are not vulnerable and having high adaptive capacity, there is often a subset of the population in these communities that is more vulnerable.

Although our study corroborates that while higher income White homeowners are still the most affected, other groups historically at lower risk from wildfire are increasingly now, and in the future possibly, living in areas of higher risk that will eventually expose their communities to wildfire. Indeed, climate change projections for California [88] show that under various general circulation model scenarios, there will be increases in both the amount of fire affected area and frequency of extreme wildfires. Accounting for these changing and local-scale demographics, socio-ecological scale, and spatiotemporal heterogeneity will have profound implications on the ability of different societal groups to recover from and adapt to future extreme events. This study possibly indicates that in California and other regions across the globe, the societal costs from extreme-event related disasters are likely to be unevenly distributed and affect those that are already more vulnerable. Thus, higher level analysis (i.e., national or statewide) might average out such local and regional level complexity that is necessary to better understand and respond to a community's adaptive resilience or vulnerability to extreme events.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A

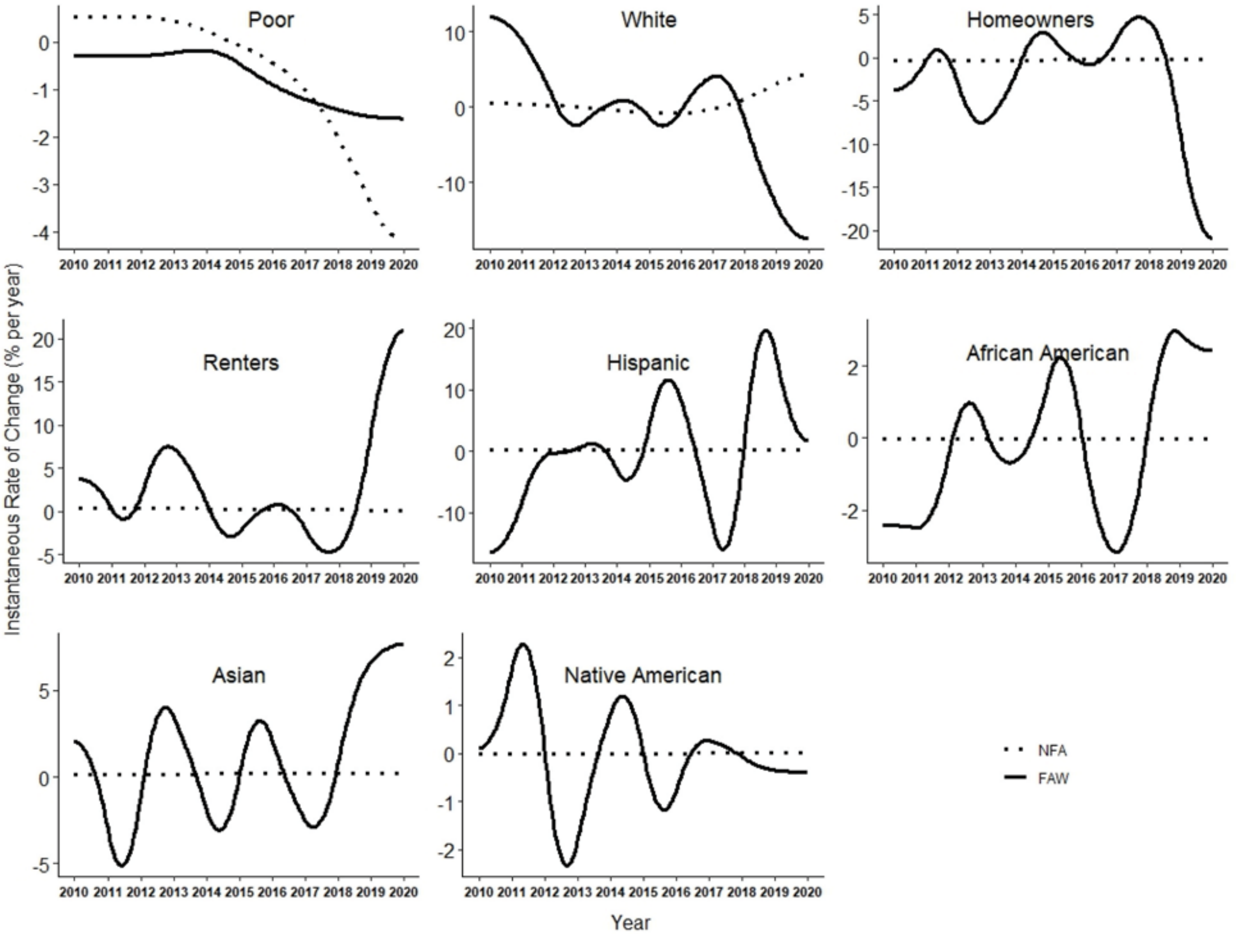

Fig. A.1. Plot of the derivatives for Poor, White, Homeowners, Renters, Hispanic, African American, Asian American, and Native American socio demographic variables from 2010 to 2020 derived from the non-linear model (i.e., Model 1). The weighted fire affected (FAW) and non-fire affected (NFA) derivatives are represented by a solid and dotted line, respectively.

References

[1] W.M. Jolly, M.A. Cochrane, P.H. Freeborn, Z.A. Holden, T.J. Brown, G.J. Williamson, D.M.J.S. Bowman, Climate-induced variations in global wildfire danger from 1979 to 2013, Nat. Commun. 6 (2015) 7537, https://doi.org/10.1038/ncomms8537.

[2] T. Schoennagel, J.K. Balch, H. Brenkert-Smith, P.E. Dennison, B.J. Harvey, M.A. Krawchuk, N. Mietkiewicz, P. Morgan, M.A. Moritz, R. Rasker, M.G. Turner, C. Whitlock, Adapt to more wildfire in western North American forests as climate changes, Proc. Natl. Acad. Sci. USA 114 (2017) 4582–4590, https://doi.org/10.1073/pnas.1617464114.

[3] A.P. Williams, J.T. Abatzoglou, A. Gershunov, J. Guzman-Morales, D.A. Bishop, J.K. Balch, D.P. Lettenmaier, Observed impacts of anthropogenic climate change on wildfire in California, Earth's Future 7 (2018) 892–910, https://doi.org/10.1029/2019EF001210.

[4] C. Stephenson, J. Handmer, R. Betts, Estimating the economic, social and environmental impacts of wildfires in Australia, Environ. Hazards 12 (2013) 93–111, https://doi.org/10.1080/17477891.2012.703490.

[5] M.A. Moritz, E. Batllori, R.A. Bradstock, A.M. Gill, J. Handmer, P.F. Hessburg, J. Leonard, S. McCaffrey, D.C. Odion, T. Schoennagel, A.D. Syphard, Learning to coexist with wildfire, Nature 515 (2014) 58–66, https://doi.org/10.1038/nature13946.

[6] D.B. McWethy, T. Schoennagel, P.E. Higuera, M. Krawchuk, B.J. Harvey, E.C. Metcalf, C. Schultz, C. Miller, A.L. Metcalf, B. Buma, A. Virapongse, J.C. Kulig, R. C. Stedman, Z. Ratajczak, C.R. Nelson, C. Kolden, Rethinking resilience to wildfire, Nat. Sustain. 2 (2019) 797–804, https://doi.org/10.1038/s41893-019-0353-8.

[7] USDA Forest Service, Confronting the Wildfire Crisis, USDA Forest Service, Washington, D.C., 2022.

[8] A.S. Thomas, F.J. Escobedo, M.R. Sloggy, J.J. Sánchez, A burning issue: reviewing the socio-demographic and environmental justice aspects of the wildfire literature, PLoS One 17 (2022), e0271019, https://doi.org/10.1371/journal.pone.0271019.

[9] I. Vigna, A. Besana, E. Comino, A. Pezzoli, Application of the socio-ecological system framework to forest fire risk management: a systematic literature review, Sustainability 13 (2021) 2121, https://doi.org/10.3390/su13042121.

[10] M.R. Auer, Considering equity in wildfire protection, Sustain. Sci. 16 (2021) 2163–2169, https://doi.org/10.1007/s11625-021-01024-8.

[11] M.-L. Chas-Amil, E. García-Martínez, J. Touza, Iberian peninsula october 2017 wildfires: burned area and population exposure in galicia (NW of Spain), Int. J. Disaster Risk Reduc. 48 (2020), 101623, https://doi.org/10.1016/j.ijdrr.2020.101623.

[12] N.J. Abram, B.J. Henley, A. Sen Gupta, T.J.R. Lippmann, H. Clarke, A.J. Dowdy, J.J. Sharples, R.H. Nolan, T. Zhang, M.J. Wooster, J.B. Wurtzel, K.J. Meissner, A.J. Pitman, A.M. Ukkola, B.P. Murphy, N.J. Tapper, M.M. Boer, Connections of climate change and variability to large and extreme forest fires in southeast Australia, Commun, Earth Environ. 2 (2021) 8, https://doi.org/10.1038/s43247-020-00065-8.

[13] M.W. Schwartz, A.D. Syphard, Fitting the solutions to the problems in managing extreme wildfire in California, Environ. Res. Commun 3 (2021), 081005, https://doi.org/10.1088/2515-7620/ac15e1.

[14] C.A. Kolden, C. Henson, A socio-ecological approach to mitigating wildfire vulnerability in the wildland urban interface: a case study from the 2017 Thomas fire, Fire 2 (2019) 9, https://doi.org/10.3390/fire2010009.

[15] K. Johnson, A. Nucci, L. Long, Population trends in metropolitan and nonmetropolitan America: selective deconcentration and the rural rebound, Popul. Res. Pol. Rev. 24 (2005) 527–542, https://doi.org/10.1007/s11113-005-4479-1.

[16] V.C. Radeloff, D.P. Helmers, H.A. Kramer, M.H. Mockrin, P.M. Alexandre, A. Bar-Massada, V. Butsic, T.J. Hawbaker, S. Martinuzzi, A.D. Syphard, S.I. Stewart, Rapid growth of the US wildland-urban interface raises wildfire risk, Proc. Natl. Acad. Sci. USA 115 (2018) 3314–3319, https://doi.org/10.1073/pnas.1718850115.

[17] M.M. Godoy, S. Martinuzzi, H.A. Kramer, G.E. Defossé, J. Argañaraz, V.C. Radeloff, Rapid WUI growth in a natural amenity-rich region in central-western Patagonia, Argentina, Int. J. Wildland Fire 28 (2019) 473–484, https://doi.org/10.1071/WF18097.

[18] S.-H. Cho, S.G. Kim, R.K. Roberts, Values of environmental landscape amenities during the 2000–2006 real estate boom and subsequent 2008 recession, J. Environ. Plann. Manag. 54 (2011) 71–91, https://doi.org/10.1080/09640568.2010.502760.

[19] H. Gosnell, J. Abrams, Amenity migration: diverse conceptualizations of drivers, socioeconomic dimensions, and emerging challenges, Geojournal 76 (2011) 303–322, https://doi.org/10.1007/s10708-009-9295-4.

[20] I.P. Davies, R.D. Haugo, J.C. Robertson, P.S. Levin, The unequal vulnerability of communities of color to wildfire, PLoS One 13 (2018), e0205825, https://doi.org/10.1371/journal.pone.0205825.

[21] G. Wigtil, R.B. Hammer, J.D. Kline, M.H. Mockrin, S.I. Stewart, D. Roper, V.C. Radeloff, Places where wildfire potential and social vulnerability coincide in the coterminous United States, Int. J. Wildland Fire 25 (2016) 896, https://doi.org/10.1071/WF15109.

[22] S. Masri, E. Scaduto, Y. Jin, J. Wu, Disproportionate impacts of wildfires among elderly and low-income communities in California from 2000–2020, Int. J. Environ. Res. Publ. Health 18 (2021) 3921, https://doi.org/10.3390/ijerph18083921.

[23] R.L. Winkler, K.M. Johnson, Moving toward integration? Effects of migration on ethnoracial segregation across the rural-urban continuum, Demography 53 (2016) 1027–1049, https://doi.org/10.1007/s13524-016-0479-5.

[24] B.A. Lee, G. Sharp, Ethnoracial diversity across the rural-urban continuum, Ann. Am. Acad. Polit. Soc. Sci. 672 (2017) 26–45, https://doi.org/10.1177/0002716217708560.

[25] W.H. Frey, Today's Suburbs Are Symbolic of America's Rising Diversity: A 2020 Census Portrait, 2022. https://www.brookings.edu/articles/todays-suburbs-are-symbolic-of-americas-rising-diversity-a-2020-census-portrait/. (Accessed 10 July 2023).

[26] D. Rowlands, H. Love, Mapping Rural America's Diversity and Demographic Change, Brook. Inst., 2021. https://www.brookings.edu/articles/mapping-rural-americas-diversity-and-demographic-change/. (Accessed 21 July 2023).

[27] T.J. Cooke, C. Denton, The suburbanization of poverty? An alternative perspective, Urban Geogr. 36 (2015) 300–313, https://doi.org/10.1080/02723638.2014.973224.

[28] C. Dimke, M.C. Lee, J. Bayham, COVID-19 and the renewed migration to the rural west, west, Econ. Forum. 19 (2021) 15, https://doi.org/10.22004/ag.econ.311309.

[29] J.P. Brown, C. Tousey, How the Pandemic Influenced Trends in Domestic Migration across U.S. Urban Areas, Federal Reserve Bank of Kansas City, 2021. https://www.kansascityfed.org/Economic%20Review/documents/8524/EconomicReviewV106N4BrownTousey.pdf. (Accessed 8 September 2023).

[30] M.B. Clark, E. Nkonya, G.L. Galford, Flocking to fire: how climate and natural hazards shape human migration across the United States, Front. Hum. Dyn. 4 (2022). https://www.frontiersin.org/articles/10.3389/fhumd.2022.886545.

[31] L. Dickerson, People Keep Moving to Areas Most at Risk of Wildfire, 2020. https://www.inman.com/2020/11/17/people-keep-moving-to-areas-most-at-risk-of-wildfire-climatecheck/. (Accessed 8 September 2023).

[32] C.H.A. Kuran, C. Morsut, B.I. Kruke, M. Krüger, L. Segnestam, K. Orru, T.O. Nævestad, M. Airola, J. Keränen, F. Gabel, S. Hansson, S. Torpan, Vulnerability and vulnerable groups from an intersectionality perspective, Int. J. Disaster Risk Reduc. 50 (2020), 101826, https://doi.org/10.1016/j.ijdrr.2020.101826.

[33] S.L. Cutter, B.J. Boruff, W.L. Shirley, Social vulnerability to environmental hazards, Soc. Sci. Q. 84 (2003) 242–261, https://doi.org/10.1111/1540-6237.8402002.

[34] S. Akter, R.Q. Grafton, Do fires discriminate? Socio-economic disadvantage, wildfire hazard exposure and the Australian 2019–20 'Black Summer' fires, Clim. Change 165 (2021) 53, https://doi.org/10.1007/s10584-021-03064-6.

[35] M. Carroll, T. Paveglio, Using community archetypes to better understand differential community adaptation to wildfire risk, Philos. Trans. R. Soc. B Biol. Sci. 371 (2016), 20150344, https://doi.org/10.1098/rstb.2015.0344.

[36] J.D. Garrison, T.E. Huxman, A tale of two suburbias: turning up the heat in Southern California's flammable wildland-urban interface, Cities 104 (2020), 102725, https://doi.org/10.1016/j.cities.2020.102725.

[37] C. Dong, A.P. Williams, J.T. Abatzoglou, K. Lin, G.S. Okin, T.W. Gillespie, D. Long, Y.-H. Lin, A. Hall, G.M. MacDonald, The season for large fires in Southern California is projected to lengthen in a changing climate, Commun. Earth Environ. 3 (2022) 22, https://doi.org/10.1038/s43247-022-00344-6.

[38] S. Anderson, A. Plantinga, M. Wibbenmeyer, Inequality in agency responsiveness: evidence from salient wildfire events, Resour Future: Washington, DC, USA (2020) 36. https://media.rff.org/documents/WP_20-22.pdf.

[39] M. Wibbenmeyer, M. Robertson, The distributional incidence of wildfire hazard in the western United States, Environ. Res. Lett. 17 (2022), 064031, https://doi.org/10.1088/1748-9326/ac60d7.

[40] M. Hamilton, A.P. Fischer, A. Ager, A social-ecological network approach for understanding wildfire risk governance, Global Environ. Change 54 (2019) 113–123, https://doi.org/10.1016/j.gloenvcha.2018.11.007.

[41] M. Elia, V. Giannico, D. Ascoli, J.P. Argañaraz, M. D'Este, G. Spano, R. Lafortezza, G. Sanesi, Uncovering current pyroregions in Italy using wildfire metrics, Ecol. Process. 11 (2022) 15, https://doi.org/10.1186/s13717-022-00360-6.

[42] D.M.J.S. Bowman, J. Balch, P. Artaxo, W.J. Bond, M.A. Cochrane, C.M. D'Antonio, R. DeFries, F.H. Johnston, J.E. Keeley, M.A. Krawchuk, C.A. Kull, M. Mack, M.A. Moritz, S. Pyne, C.I. Roos, A.C. Scott, N.S. Sodhi, T.W. Swetnam, The human dimension of fire regimes on Earth, J. Biogeogr. 38 (2011) 2223–2236, https://doi.org/10.1111/j.1365-2699.2011.02595.x.

[43] C.I. Roos, D.M.J.S. Bowman, J.K. Balch, P. Artaxo, W.J. Bond, M. Cochrane, C.M. D'Antonio, R. DeFries, M. Mack, F.H. Johnston, M.A. Krawchuk, C.A. Kull, M. A. Moritz, S. Pyne, A.C. Scott, T.W. Swetnam, Pyrogeography, historical ecology, and the human dimensions of fire regimes, J. Biogeogr. 41 (2014) 833–836, https://doi.org/10.1111/jbi.12285.

[44] T. Fréjaville, T. Curt, Spatiotemporal patterns of changes in fire regime and climate: defining the pyroclimates of south-eastern France (Mediterranean Basin), Clim. Change 129 (2015) 239–251, https://doi.org/10.1007/s10584-015-1332-3.

[45] P. Krebs, G.B. Pezzatti, S. Mazzoleni, L.M. Talbot, M. Conedera, Fire regime: history and definition of a key concept in disturbance ecology, Theor. Biosci. 129 (2010) 53–69, https://doi.org/10.1007/s12064-010-0082-z.

[46] M.A. Krawchuk, M.A. Moritz, M.-A. Parisien, J. Van Dorn, K. Hayhoe, Global pyrogeography: the current and future distribution of wildfire, PLoS One 4 (2009), e5102, https://doi.org/10.1371/journal.pone.0005102.

[47] P. Morgan, C.C. Hardy, T.W. Swetnam, M.G. Rollins, D.G. Long, Mapping fire regimes across time and space: understanding coarse and fine-scale fire patterns, Int. J. Wildland Fire 10 (2001) 329, https://doi.org/10.1071/WF01032.

[48] US Census Bureau, Racial and Ethnic Diversity in the United States: 2010 Census and 2020 Census, 2021. https://www.census.gov/library/visualizations/interactive/racial-and-ethnic-diversity-in-the-united-states-2010-and-2020-census.html. (Accessed 3 September 2022).

[49] S. Li, V. Dao, M. Kumar, P. Nguyen, T. Banerjee, Mapping the wildland-urban interface in California using remote sensing data, Sci. Rep. 12 (2022) 5789, https://doi.org/10.1038/s41598-022-09707-7.
[50] G.E. Griffith, J.M. Omernik, D.W. Smith, T.D. Cook, E. Tallyn, K. Moseley, C.B. Johnson, Ecoregions of California, Reston, VA, 2016. http://pubs.er.usgs.gov/publication/ofr20161021.
[51] H. Mooney, E. Zavaleta, Ecosystems of California: Threats and Responses. Supplement for Decision-Making, Berkley, University of California Press, 2016.
[52] J.E. Keeley, H.D. Safford, Fire as an ecosystem process, in: Ecosyst. Calif. Threats Responses Suppl. Decis.-Mak., The Regents of the University of California, 2016.
[53] J.E. Keeley, A.D. Syphard, Different historical fire–climate patterns in California, Int. J. Wildland Fire 26 (2017) 253, https://doi.org/10.1071/WF16102.
[54] J. Guzman-Morales, A. Gershunov, J. Theiss, H. Li, D. Cayan, Santa Ana Winds of Southern California: their climatology, extremes, and behavior spanning six and a half decades, Geophys. Res. Lett. 43 (2016) 2827–2834, https://doi.org/10.1002/2016GL067887.
[55] N.J. Nauslar, J.T. Abatzoglou, P.T. Marsh, The 2017 north bay and southern California fires: a case study, Fire 1 (2018) 17, https://doi.org/10.3390/fire1010018.
[56] H. Buechi, P. Weber, S. Heard, D. Cameron, A.J. Plantinga, Long-term trends in wildfire damages in California, Int. J. Wildland Fire 30 (2021) 757, https://doi.org/10.1071/WF21024.
[57] H.A. Kramer, M.H. Mockrin, P.M. Alexandre, S.I. Stewart, V.C. Radeloff, Where wildfires destroy buildings in the US relative to the wildland–urban interface and national fire outreach programs, Int. J. Wildland Fire 27 (2018) 329, https://doi.org/10.1071/WF17135.
[58] Cal Fire, Top 20 largest California wildfires. https://www.fire.ca.gov/media/4jandlhh/top20_acres.pdf (accessed September 3, 2022).
[59] Cal Fire, Top 20 most destructive California wildfires. https://www.fire.ca.gov/media/t1rdhizr/top20_destruction.pdf (accessed September 3, 2022)..
[60] US Census Bureau, TIGER/Line Shapefiles, 2010. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html. April 10, 2022.
[61] S.A. Bryce, A.J. Woods, J.D. Morefield, J.M. Omernik, T.R. McKay, G.K. Brackley, R.K. Hall, D.K. Higgins, D.C. McMorran, K.E. Vargas, E.B. Petersen, D. C. Zamudio, J.A. Comstock, Ecoregions of Nevada (Color Poster with Map, Descriptive Text, Summary Tables, and Photographs), 2003.
[62] R.G. Bailey, Delineation of ecosystem regions, Environ. Man 7 (1983) 365–373, https://doi.org/10.1007/BF01866919.
[63] M. Rodriquez, E.G. Brown, Designation of Disadvantaged Communities, California Environmental Protection Agency, 2017. https://calepa.ca.gov/wp-content/uploads/sites/6/2017/04/SB-535-Designation-Final.pdf.
[64] CalEnviroScreen, Disadvantaged communities, (2022). https://oehha.ca.gov/calenviroscreen/sb535 (accessed April 24, 2022)..
[65] Cal Fire, Cal Fire GIS Data,. https://frap.fire.ca.gov/mapping/gis-data/.
[66] P. Palaiologou, A.A. Ager, M. Nielsen-Pincus, C.R. Evers, M.A. Day, Social vulnerability to large wildfires in the western USA, Landsc. Urban Plann. 189 (2019) 99–116, https://doi.org/10.1016/j.landurbplan.2019.04.006.
[67] J.R. Logan, Z. Xu, B.J. Stults, Interpolating U.S. Decennial census tract data from as early as 1970 to 2010: a longitudinal tract database, Prof. Geogr. 66 (2014) 412–420, https://doi.org/10.1080/00330124.2014.905156.
[68] C. Prener, Area Weighted Interpolation, 2022. https://cran.r-project.org/web/packages/areal/vignettes/areal-weighted-interpolation.html. (Accessed 20 August 2022).
[69] R Core Team, R, A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, 2022. MSOR Connect. 1, https://www.R-project.org/.
[70] S. Wood, F. Scheipl, Package 'gamm4,'. https://cran.r-project.org/web/packages/gamm4/gamm4.pdf, 2022.
[71] J.G. Pausas, J.E. Keeley, Wildfires and global change, Front. Ecol. Environ. 19 (2021) 387–395, https://doi.org/10.1002/fee.2359.
[72] S. Oliveira, J.L. Zêzere, M. Queirós, J.M. Pereira, Assessing the social context of wildfire-affected areas. The case of mainland Portugal, Appl. Geogr. 88 (2017) 104–117, https://doi.org/10.1016/j.apgeog.2017.09.004.
[73] A.J. Plantinga, R. Walsh, M. Wibbenmeyer, Priorities and effectiveness in wildfire management: evidence from fire spread in the western United States, J. Assoc. Environ. Resour. Econ. 9 (2022) 603–639, https://doi.org/10.1086/719426.
[74] C.J. Gabbe, G. Pierce, E. Oxlaj, Subsidized households and wildfire hazards in California, Environ. Man 66 (2020) 873–883, https://doi.org/10.1007/s00267-020-01340-2.
[75] K. Lynn, W. Gerlitz, Mapping the relationship between wildfire and poverty, in: Fuels Manag.- Meas. Success Conf. Proc., Fort Collins, CO, U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Portland, Oregon, 2006, pp. 401–415.
[76] A. Evans, M. DeBonis, E. Krasilovsky, M. Melton, Measuring Community Capacity for Protection from Wildfire, For. Guild Res. Pap, 2007. https://www.foreststewardsguild.org/wp-content/uploads/2019/06/community_capacity_wildfire.pdf.
[77] S.L. Cutter, C.T. Emrich, Social Vulnerability Index (SoVI®): Methodology and Limitations, 2017. https://data.femadata.com/FIMA/NHRAP/NationalRiskIndex/FinalDocumentation/Social%20Vulnerability%20-%20SoVI/Social%20Vulnerability%20Index%20Primer.pdf. (Accessed 15 December 2022).
[78] J.J. Sánchez, T.P. Holmes, J. Loomis, A. González-Cabán, Homeowners willingness to pay to reduce wildfire risk in wildland urban interface areas: implications for targeting financial incentives, Int. J. Disaster Risk Reduc. 68 (2022), 102696, https://doi.org/10.1016/j.ijdrr.2021.102696.
[79] T. Collins, The political ecology of hazard vulnerability: marginalization, facilitation and the production of differential risk to urban wildfires in Arizona's White Mountains, J. Polit. Ecol. 15 (2008) 21–43, https://doi.org/10.2458/v15i1.21686.
[80] M. Méndez, G. Flores-Haro, L. Zucker, The (in)visible victims of disaster: understanding the vulnerability of undocumented Latino/a and indigenous immigrants, Geoforum 116 (2020) 50–62, https://doi.org/10.1016/j.geoforum.2020.07.007.
[81] J.W. Bethel, S.C. Burke, A.F. Britt, Disparity in disaster preparedness between racial/ethnic groups, Disaster Health 1 (2013) 110–116, https://doi.org/10.4161/dish.27085.
[82] D. Domínguez, C. Yeh, Social justice disaster relief, counseling, and advocacy: the case of the Northern California wildfires, Counsell. Psychol. Q. 33 (2020) 287–311, https://doi.org/10.1080/09515070.2018.1542593.
[83] A.D. Syphard, T.J. Brennan, J.E. Keeley, The importance of building construction materials relative to other factors affecting structure survival during wildfire, Int. J. Disaster Risk Reduc. 21 (2017) 140–147, https://doi.org/10.1016/j.ijdrr.2016.11.011.
[84] J. Chase, P. Hansen, Displacement after the Camp fire: where are the most vulnerable? Soc. Nat. Resour. 34 (2021) 1566–1583, https://doi.org/10.1080/08941920.2021.1977879.
[85] E.J. Mueller, H. Bell, B.B. Chang, J. Henneberger, Looking for home after katrina: postdisaster housing policy and low-income survivors, J. Plann. Educ. Res. 31 (2011) 291–307, https://doi.org/10.1177/0739456X11413602.
[86] S. Cowan, E.B. Kennedy, Determinants of residential wildfire mitigation uptake: a scoping review, 2013–2022, Fire Saf. J. 140 (2023), 103851, https://doi.org/10.1016/j.firesaf.2023.103851.
[87] A.P. Fischer, T.A. Spies, T.A. Steelman, C. Moseley, B.R. Johnson, J.D. Bailey, A.A. Ager, P. Bourgeron, S. Charnley, B.M. Collins, J.D. Kline, J.E. Leahy, J. S. Littell, J.D. Millington, M. Nielsen-Pincus, C.S. Olsen, T.B. Paveglio, C.I. Roos, M.M. Steen-Adams, F.R. Stevens, J. Vukomanovic, E.M. White, D.M. Bowman, Wildfire risk as a socioecological pathology, Front. Ecol. Environ. 14 (2016) 276–284, https://doi.org/10.1002/fee.1283.
[88] A.L.R. Westerling, Wildfire Simulations for California's Fourth Climate Change Assessment: Projecting Changes in Extreme Wildfire Events with a Warming Climate: A Report for California's Fourth Climate Change Assessment, California Energy Commission, Sacramento, California, 2018. https://www.energy.ca.gov/sites/default/files/2019-11/Projections_CCCA4-CEC-2018-014_ADA.pdf.
[89] S.E. Spielman, D. Folch, N. Nagle, Patterns and causes of uncertainty in the American community survey, Appl. Geogr. 46 (2014) 147–157, https://doi.org/10.1016/j.apgeog.2013.11.002.
[90] L. Greiman, Data Limitations in the American Community Survey: the Impact on Rural Disability Research, The University of Montana Rural Institute for Inclusive Communities, Missoula, Montana, 2017. https://scholarworks.umt.edu/ruralinst_independent_living_community_participation/45/.