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Associations between Wildfire Risk and Socio-Economic-Demographic Characteristics Using GIS Technology

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Abstract

Wildfire is a natural hazard caused mostly by the interaction of human systems and natural phenomena. This research aims to investigate how extreme wildfire events and disasters that occurred in California in the recent three decades are related to socio-economic-demographic characteristics at the levels of census tracts and counties. In addition, this research will use the data of historic wildfires to show counties and census tracts vulnerable to the natural hazard as well as the cyclical changes such as seasonal and annual fluctuations in the wildfire occurrences in the state. To decide how those variables correlate, this research used a Geographic Information System (GIS) designed to collect, analyze, query, and display geographical information. Two types of secondary data were used to conduct the research. One is the geospatial data showing each location of wildfires. The other is the data about such sociodemographic characteristics as race, ethnicity, level of education, and income, which can be collected through the Bureau of Census. In particular, the research employing GIS-based spatial analysis created maps that represent information on the geographic locations of the wildfires at the different geographic levels as well as demographic and socioeconomic factors influenced by the potential risk of wildfires. There are several researching findings. First, this research showed the wildfire-prone communities have comparatively higher level of representation for the populations such as the White and Native Americans. Second, it reveals that Asian people would prefer to reside in communities with a lower level of wildfire risk. In contrast with previous research reporting the Black, Hispanic or Native American people are more vulnerable to wildfire, this research showed only the census tracts with the higher number of the Native Americans are more exposed to the wildfire risk, compared with other census tracts. Third, it revealed that people with a higher level of educational attainment would prefer to reside in communities with a lower level of chemical risk. Forth and lastly, this research indicates that the census tracts that have a higher median household income and median housing price have a negative relationship with the wildfire risk, meaning that people with a higher level of the income or a relatively higher-priced home prefer residing in communities less subject to the natural hazard. Therefore, it can be concluded that associations exist between wildfire risk and certain socio-economic and demographic characteristics.

Keywords

Environmental Hazard, Wildfire Risk, GIS, Disaster, Emergency Management, Risk Analysis

1. Introduction

Environmental disasters have been increasing at an alarming rate alongside a continuous rise in global temperatures [1] [2]. It is expected that certain populations tend to be disproportionately affected by environmental disasters based on numerous socio-economic-demographic characteristics. In particular, minority and poor communities are often most vulnerable to the impacts produced by environmental disasters [3]. The impacts produced by wildfires in the United States are no exception to this, as the extreme wildfire events that have occurred in California in recent decades have brought significant attention to the disproportionate distribution of wildfire vulnerability among different communities across the state. With a steady increase in the number of catastrophic wildfires, along with a substantial rise in the number of houses in the wildland-urban interface, populations have never been more vulnerable to the risks posed by wildfires [4]. The disproportionate distribution of wildfire vulnerability due to socio-economic-demographic characteristics must be understood in order to increase resilience among those groups most vulnerable to the natural hazard.

Prior studies conducted on the potential association between wildfire risk and socio-economic-demographic characteristics focus primarily on the various human factors that generate unequal exposure and susceptibility to wildfires [3] [5]. Findings from these studies suggest that a positive association exists between wildfire hazard exposure and socio-economic disadvantage [6] [7]. Additionally, existing studies found that wildfire vulnerability is spread unequally across race and ethnicity, with census tracts that were majority Black, Hispanic or Native American experiencing much greater vulnerability to wildfire compared to other census tracts. These research findings are meaningful, as they provide a social-ecological perspective of fire-prone landscapes that allows for the identification of areas that are poorly equipped to respond to wildfires [3].

Limitations of existing studies on this topic lie in the fact that many of the assumptions made by researchers about the socio-economic-demographic factors that influence vulnerability to wildfires have not been fully evaluated or tested against objective measures of potential wildfire risk [8]. Further research is needed that utilizes geospatial data to explain the relationships between wildfire risk and select socio-economic-demographic characteristics.

The primary objective of this research is to analyze previously conducted studies and organize the current state of knowledge on existing associations between wildfire risk and socio-economic-demographic characteristics. Specifically, this research aims to investigate potential relationships between socio-economic-demographic characteristics and extreme wildfire events that have occurred in California in recent decades. Therefore, this research has investigated communities and human populations most vulnerable to wildfire hazard and examined how the wildfire risk could negatively influence the different populations such as native, white, black, Asian, and Hispanic people at the county and census tract level in California. In addition, this research has tried to capture how the risk is related to social, economic, and demographic factors such as race, educational attainment, and poverty. Its major goal is to contribute to a research community by providing knowledge about how human-induced hazards can influence different ethnicities. Findings from this research may be useful in developing planning and mitigation measures that can help to increase resilience among populations that are particularly vulnerable to wildfires.

2. Literature Review

2.1. Wildfire Risk Factors and Spatial Pattern of California Wildfires

In order to assess the potential association between wildfire risk and socio-economic-demographic characteristics, the primary factors that contribute to wildfire risk must first be understood. This study focused primarily on wildfire occurrences in California. The State of California is a vast area that spans ten latitudes, and its internal geographical conditions and climate conditions vary widely [9]. Therefore, California wildfires differ greatly in their frequency, size, intensity and extent of damage [10]. The risk that a particular area faces in regard to wildfires is based on several factors including climatic factors (including temperature, humidity, wind), topographic factors (including slope and aspect), vegetation factors (including drought state, vegetation type), and anthropogenic factors (including road network, Wildfire-Urban Interface) [11]. Climatic conditions strongly affect fire risk and behavior, as humidity and temperature determine the rate at which fuels dry [12] [13]. Additionally, wind greatly influences fire behavior, as it dries fuels, provides the fire with oxygen, and governs fire direction and spread rate [14]. Areas that have weather patterns with high temperatures, low relative humidity, and strong surface winds are generally considered to be at a high risk for wildfires [15]. Topography contributes to wildfire risk by influencing the spatial variability of fuels and the biophysical conditions that determine fire spread, intensity, and duration [16]. Additionally, microclimatic conditions such as temperature, precipitation, direct solar radiation, and wind exposure are influenced by topographic factors such as elevation, aspect, and latitude [16]. Areas that contain certain topographical features such as steep slopes are generally considered to be at a high risk for severe wildfires [17] [18]. Vegetation also greatly affects wildfire risk and behavior, as the type of vegetation as well as the spatial pattern and distribution of vegetation determine the probability of fire ignition, fire spread rate, and intensity [19]. Areas in which urban settlements and wildland vegetation intermingle are considered to be at a high risk for wildfires [20]. In addition to climatic factors, topographic factors, and vegetation factors, anthropogenic factors also greatly influence wildfire risk. Proximity to agricultural land, roads, and urban areas affects the wildfire risk of a particular region [11]. Additionally, other factors such as the spatial arrangement and density of buildings in a particular area have been shown to influence wildfire risk [21]. Generally, wildfire density increases in areas that contain many buildings that are densely packed together [22]. It is possible that the presence of the previously noted risk factors in a particular area may correlate with certain socio-economic and demographic characteristics in that area. The socio-economic and demographic characteristics of areas that contain numerous wildfire risk factors should be further explored to determine if an association exists between the two variables.

2.2. Spatial Pattern of California Wildfires and Socio-Economic and Demographic Characteristics of High-Risk Areas

A study conducted by Shu Li and Tirtha Banerjee reported findings on the spatial pattern of wildfires in California from 2000 to 2019. Using data from the wildfire Redbooks published by the California Department of Forestry and Fire Protection (CAL FIRE), this study revealed the specific regions in California that were considered to be at a high risk for wildfires. The study considered both environmental and human-related risk variables, as well as dominant ignition causes of California wildfires. The results from this study showed that due to the complex environmental and terrain conditions in California, the risk of wildfires varies significantly from region to region [22].

Socio-economic and demographic characteristics of areas in California considered to be at a high risk for wildfires were analyzed using data obtained from the United States Census Bureau. Upon analyzing these data, trends in different socio-economic and demographic characteristics among high-risk counties were examined. High-risk counties include those outlined in the previously discussed study on spatial patterns of wildfires in California. Of the 24 counties in California that were considered to be at an increased geographical risk for experiencing severe wildfire events, 18 counties had a poverty rate that was greater than 10%. The county with the highest poverty rate (18%) was Trinity County. Additionally, 8 out of 24 counties had a population that was over 3% African American, 11 out of 24 had a population that was over 3% Native American and Alaska Native, and 22 out of 24 had a population that was over 10% Hispanic or Latino.

There are several examples of specific wildfire events in California that have disproportionately impacted certain socio-economic and demographic groups. For example, Hispanic individuals in Northern California and Santa Barbara were disproportionately impacted during many of the wildfires in the 2017 season as a result of language barriers that prevented these individuals from receiving evacuation notification from authorities [3]. Additionally, the Tubbs Wildfire, Atlas Wildfire, and Nuns Wildfire were all found to disproportionately impact low-income groups [5]. During these fires, it was increasingly difficult for low-income groups to find safe and secure housing. These groups also had limited access to recovery resources following the fires [5]. The Camp Wildfire of 2018 was also found to disproportionately impact certain socio-economic and demographic groups, particularly racial minorities, low-income individuals, and disabled individuals [7].

2.3. Adaptive Capacity

In addition to examining overall wildfire risk in relation to different socio-economic and demographic characteristics, the adaptive capacities of high-risk areas must also be examined in relation to these characteristics. Both wildfire risk and adaptive capacity must be understood in order to adequately assess the vulnerability of certain populations to the effects of severe wildfire events. Populations in geographic areas that are not particularly prone to severe wildfires may still be considered highly vulnerable to wildfire hazards because of their low adaptive capacity. Populations that have low adaptive capacities in geographic areas with elevated wildfire potential are considered to be the most vulnerable to wildfire hazards. Adaptive capacity refers to the ability of a region to absorb and adjust to disturbances, like wildfire, while minimizing damage to life, property, and services [23] [24]. The ability to adapt to hazards is influenced by a number of social and demographic factors, including age, income, strength of social networks, and neighborhood characteristics [3] [25]. Additionally, factors such as education, housing, and transportation affect the adaptive capacity of a particular community. Existing research has found that certain socio-economic and demographic groups are less able to adjust to hazard disturbances than others. A study conducted by Betty Morrow found that economically disadvantaged families, the elderly, disabled people, and residents of high-rise apartments or mobile homes tend to be less adaptable to hazards [26].

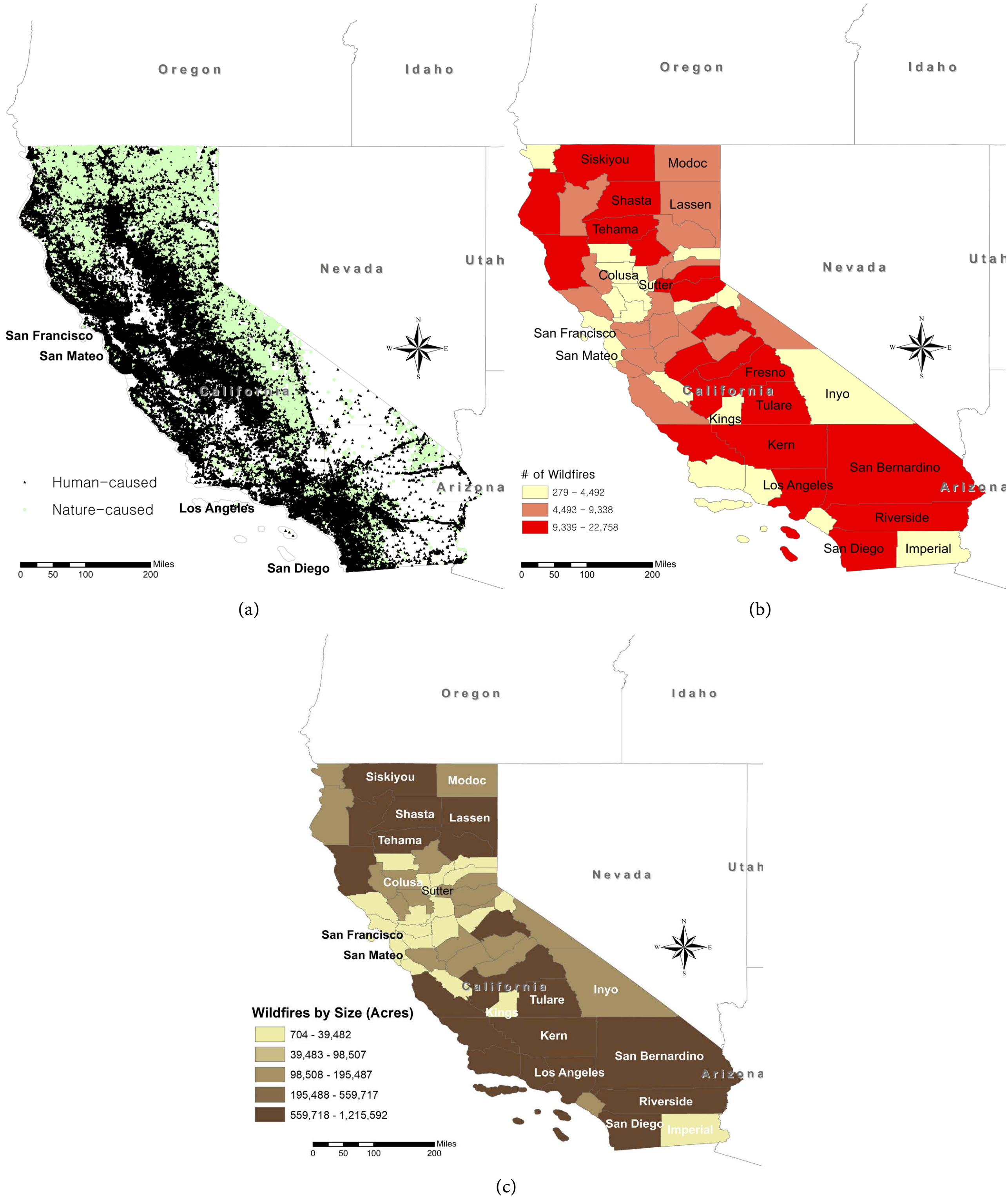
In regard to wildfire-specific hazards, a study conducted by Davies *et al.* displayed that low-income households face several obstacles in preparing for and recovering from these hazards. This study stated that low-income households often cannot afford to pay for fire mitigation services like tree cutting and removal of fire fuels [3] [27]. Additionally, this study found that those living in low-income communities were less likely to have fire insurance and the community firefighting resources needed to extinguish a fire [3] [27] [28]. Adaptive capacity in regard to housing quality and transportation access was also associated with socio-economic status, as economically disadvantaged individuals generally have less access to reliable transportation to evacuate from high-risk areas and they typically have houses that are less able to withstand the impacts of a wildfire [3] [29] [30]. Lower real-estate prices in some fire-prone areas may help explain higher numbers of economically disadvantaged individuals in these locations [3] [31] [32]. Individuals residing in multi-unit housing, such as apartments, are generally considered to be at an increased wildfire risk, as building owners are less likely to pursue fire mitigation on their properties [27] [33]. Additionally, renters are eligible for less federal housing assistance than homeowners, often making it increasingly difficult for them to recover from extreme wildfire events [3]. Low-income households were also found to face more obstacles in rebuilding or finding new housing after a fire, and limited proficiency in English has also been linked to difficulty recovering from disasters [3] [25] [26] [34]. According to previously conducted studies, adaptive capacity to wildfires increases along with increasing education level, as in general, education results in increased access to relevant information, enlarged social networks that can facilitate recovery, and better ability in navigating bureaucratic hurdles [3] [25] [35].

In addition to the previously noted associations, existing research has also found that there is a strong correlation between ethnicity and vulnerability to wildfires. This research has found that generally, the minimum vulnerability to wildfires experienced by communities increases as the proportion of Native Americans and African Americans increases. A similar trend occurs in Hispanic communities. In contrast, as the proportion of Whites and Asians/Pacific Islanders increases, the minimum wildfire vulnerability that these communities experience declines. Native Americans are particularly vulnerable to wildfires, largely due to their historical forced concentration on federal Indian reservations [3]. Native Americans often reside in areas with elevated wildfire potential and they often have a lower adaptive capacity.

3. Study Area and Wildfires in California

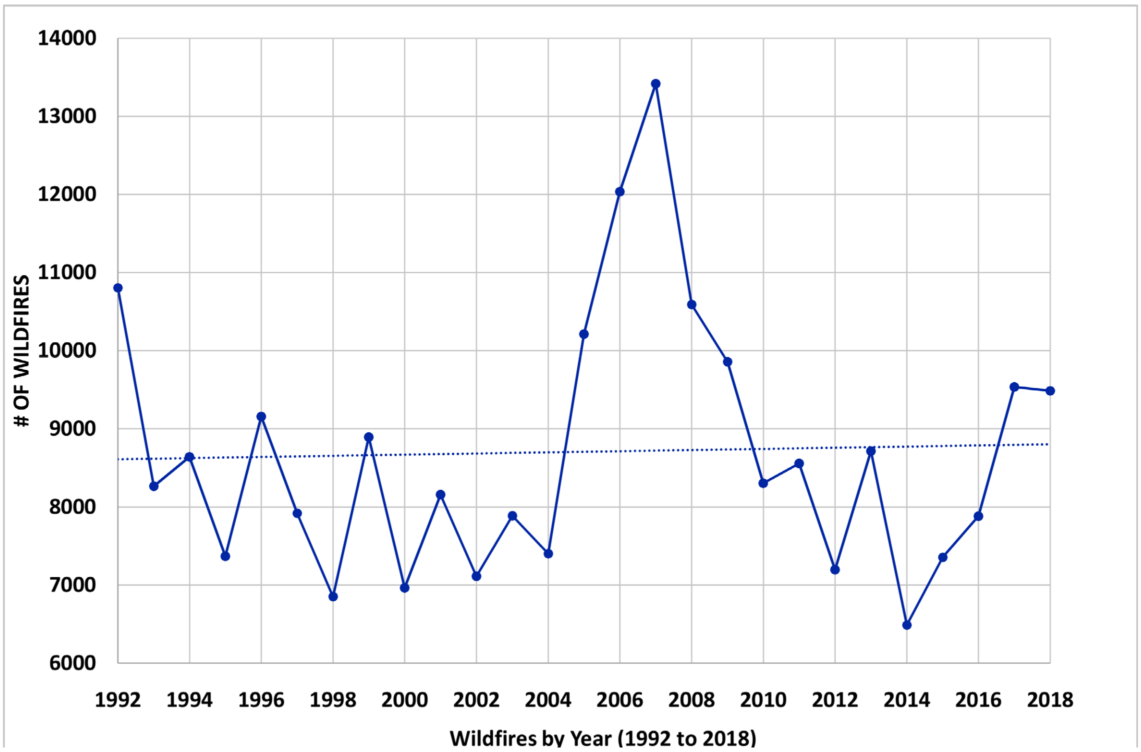
The study area is the entire state of California, which has been plagued with a wide range of very damaging wildfires. In fact, California is known as the most wildfire-prone state accounting for about 12% of the wildfires that occurred in the United States from 1992 to 2018. The state consists of 58 counties and has 24 metropolitan areas, all of which have experienced natural and human-caused wildfires over time. According to the Spatial Wildfire Occurrence Data for the United States, between 1992 and 2018, the state of California recorded a total of 235,032 wildfires, 74% of which were human-caused while 12% were nature-caused and 14% had unknown causes. It seems that there is no evidence that wildfires are continuously increasing. However, it is apparent that human-caused fires occur generally along the west coastline, while nature-caused fires generally occur in the northern and eastern regions of the state (see **Figure**

1(a)). The largest number of wildfires took place in 2007, after which the incidence rate declined until 2014 (see Figure 2). Figure 3 shows that July has the



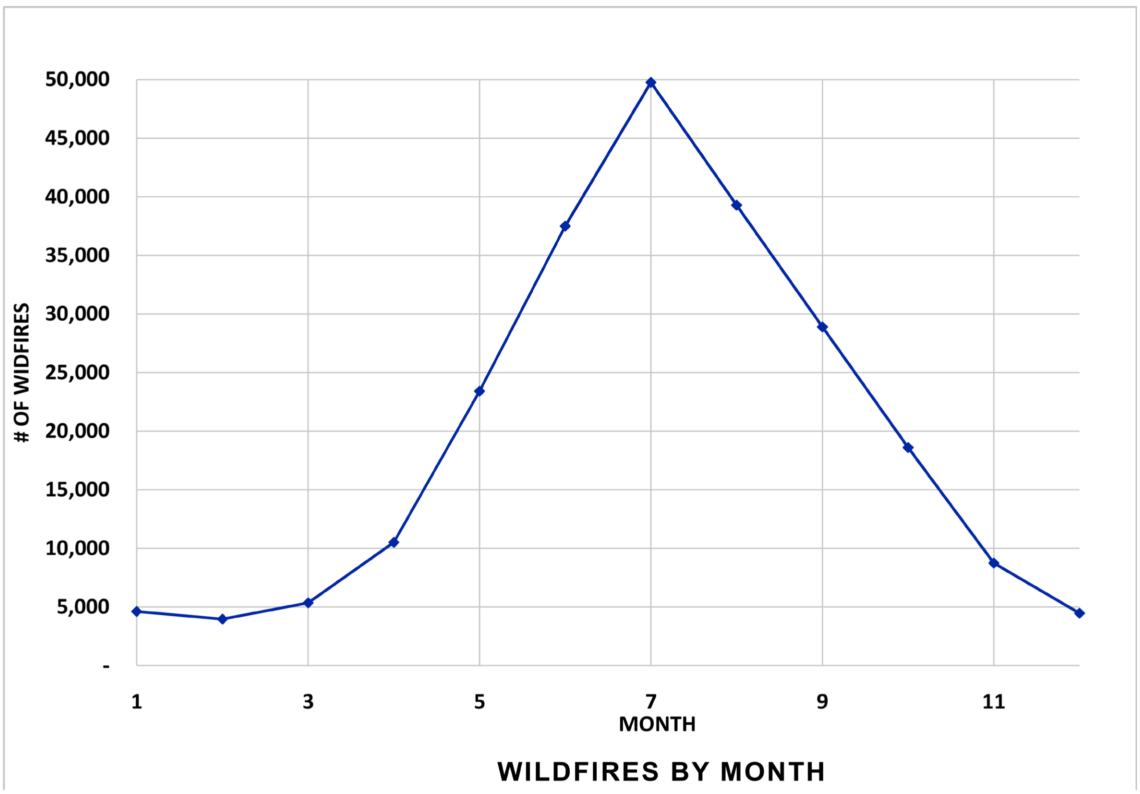
NOTE: These maps and graphs used in Figures 1-3 were created using data developed by the United States Forest Service.

Figure 1. (a) Causes of Wildfires; (b) Wildfires by County; (c) Wildfires by Size.



NOTE: These maps and graphs used in Figures 1-3 were created using data developed by the United States Forest Service.

Figure 2. Wildfire by Year (1992 to 2018).



NOTE: These maps and graphs used in Figures 1-3 were created using data developed by the United States Forest Service.

Figure 3. Wildfire by Month.

largest number of wildfires while the winter period (*i.e.*, December to March) has the lowest number. In California, Riverside County ranked first with 22,758 wildfires, followed by Los Angeles County with 12,124 and Sand Diego County with 11,676. San Francisco County, which had 279 wildfires for that time period, was found to be the least vulnerable to wildfire, followed by Kings County with 415 and Colusa County with 440 (see **Figure 1(b)**). In terms of fire size, Sand Diego County ranked first with over 1.2 million acres, followed by Los Angeles County with over 1.05 million acres and Siskiyou County with over 0.9 million acres. San Francisco County had the smallest fire size with 703 acres, followed by San Mateo County with 2,050 acres and Sutter County with 2538 acres (see **Figure 1(c)**). California's dry and windy weather conditions as well as changing climate and increasing fuel loads in the forest make fires hard to manage, which may lead to a significant risk of wildfires, threatening public health and safety, damaging properties, and disrupting the natural and man-made environment.

4. Data Collection and Analytical Methods

Two major types of datasets were collected to conduct the research. One is the geospatial data showing each location of the wildfires that occurred in the state of California. To this end, the Spatial Wildfire Occurrence Data for the United States, 1992-2018, administered by the United States Forest Service were used.

The other is the dataset about sociodemographic characteristics such as race, ethnicity, level of education, and income, which were collected through the Bureau of Census the datas*et* also includes census tract and county boundaries, both of which should contain information about sociodemographic characteristics (e.g., race ethnicity, educational attainment, and income level) as attributes in each of the data tables. The attributes come from the 2010 ACS (American Community Survey) 5 Year estimates.

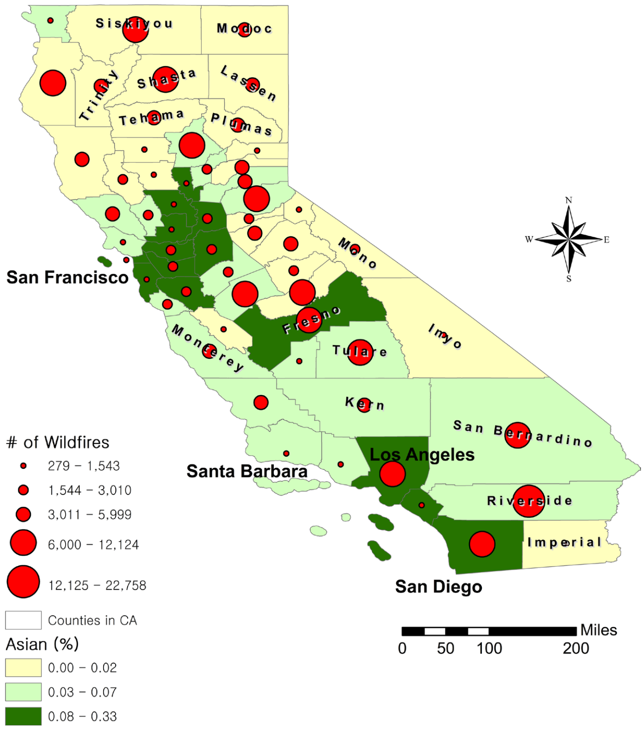
These data, which were imported into ArcMap for geospatial analysis and projected into the UTM Zone 10N coordinate system, helped to analyze the effects of the potential wildfire risk on the communities in California through GIS-based spatial analysis. Various analytical methods that were employed include geoprocessing operations (such as Summarize, Table Join, and Spatial Join). The results of this geospatial analysis created maps that represent information on the geographic locations of the wildfires as well as human populations and socioeconomic and demographic factors that can be influenced by the potential risk.

5. Results

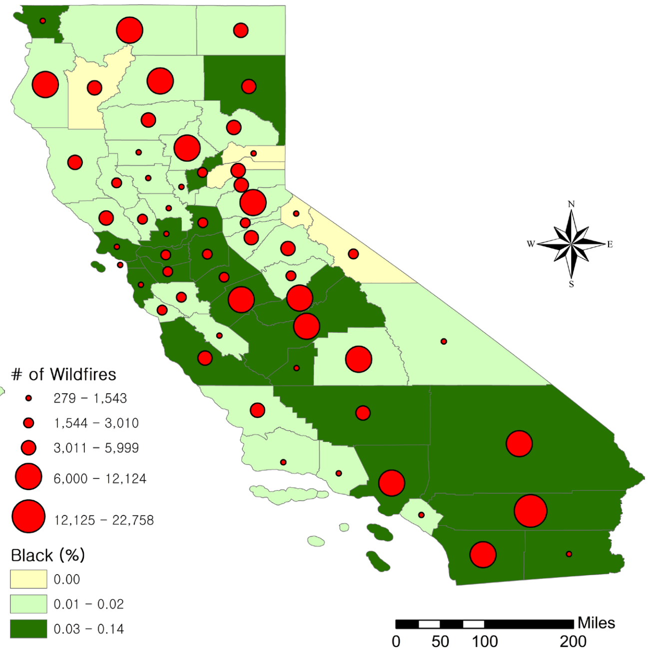
5.1. Relationships between Demographic Variables and Wildfires by County in California

Figure 4(a) through **Figure 4(h)** show relationships between wildfire incidents and socio-economic-demographic characteristics (*i.e.*, race, educational attainment, median household income, and median housing price) at the county level.

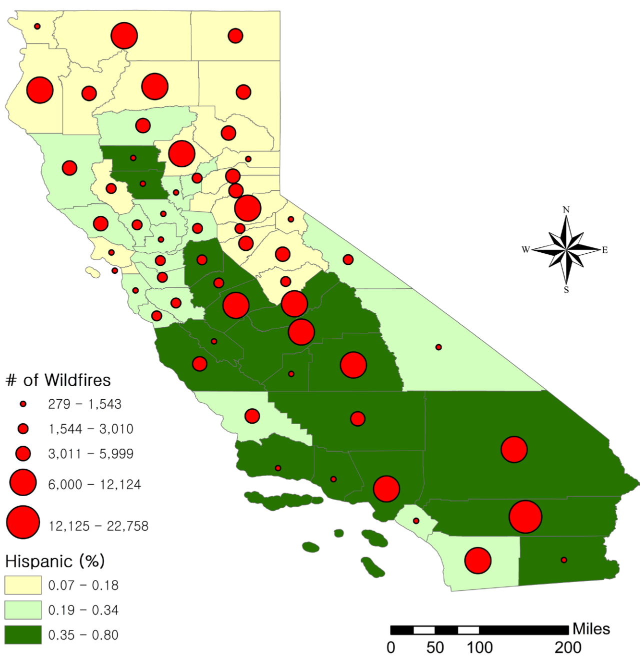
Each of the map layers representing demographic characteristics was dissolved into three classes (or indices) based on the Quantile Method where features (*i.e.*, 58 counties) were aggregated in equal numbers (*i.e.*, 19 counties each) in each class (or index) and plotted on each map as shown in Figures 4(a)-(h) above. The quantities of wildfires were assigned to each county in California. Each of Figures 4(a)-(e) provides a color-coded map layer showing the percentage



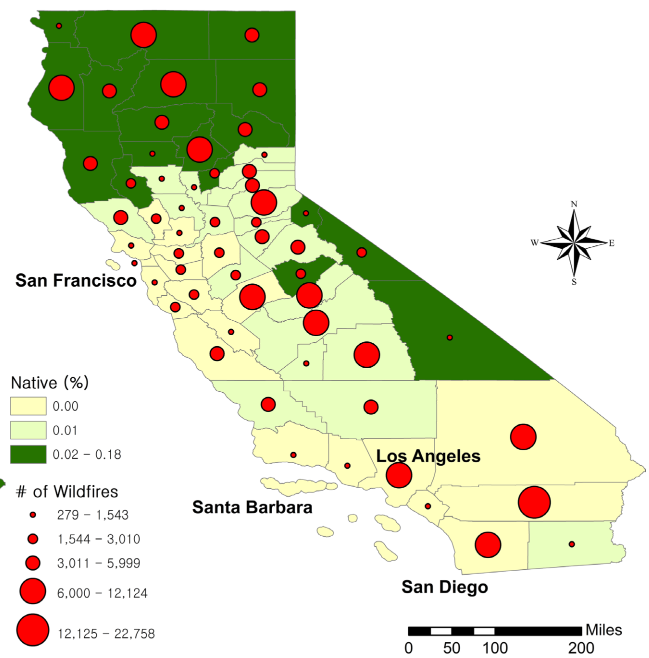
(a)



(b)



(c)



(d)

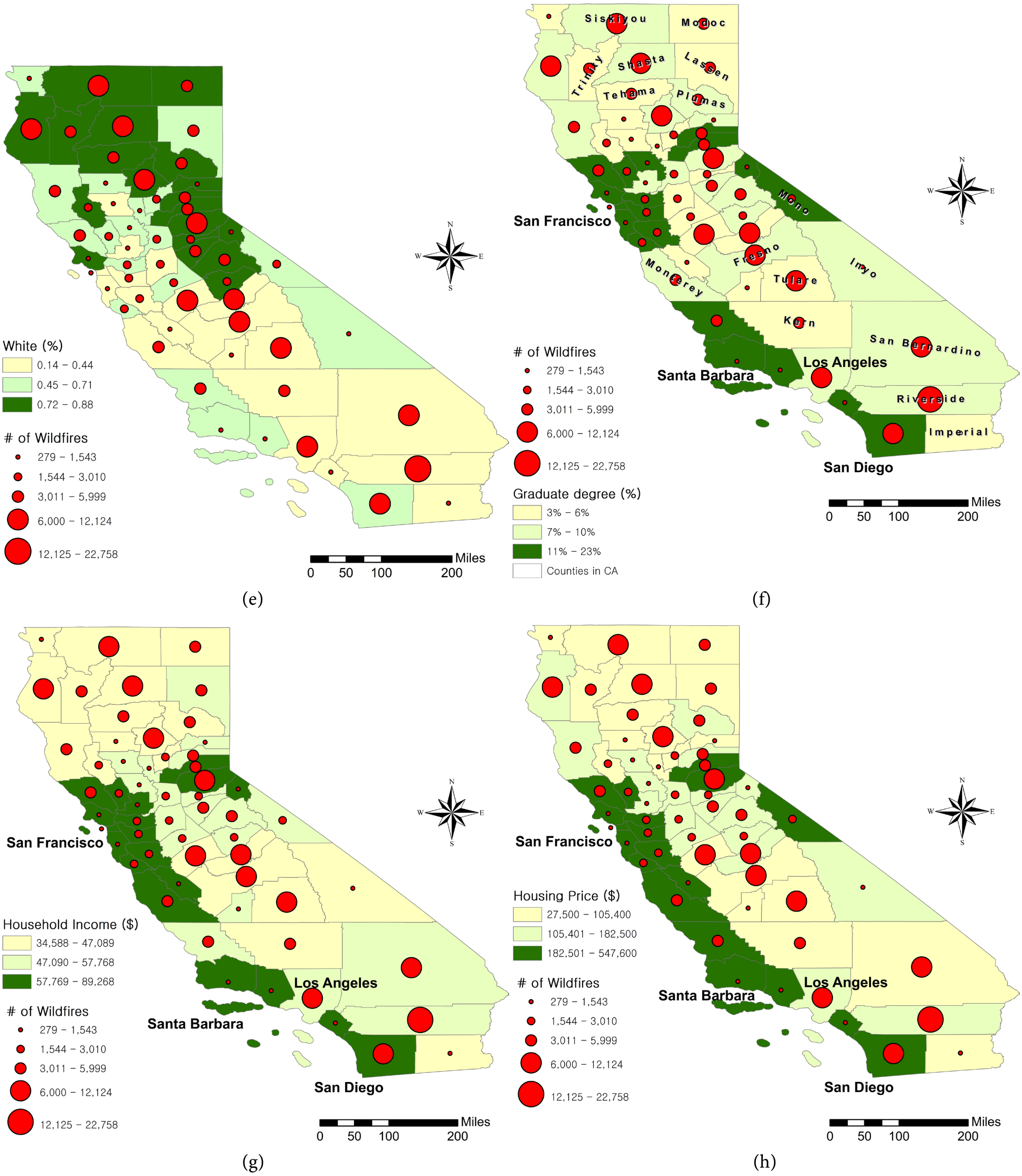


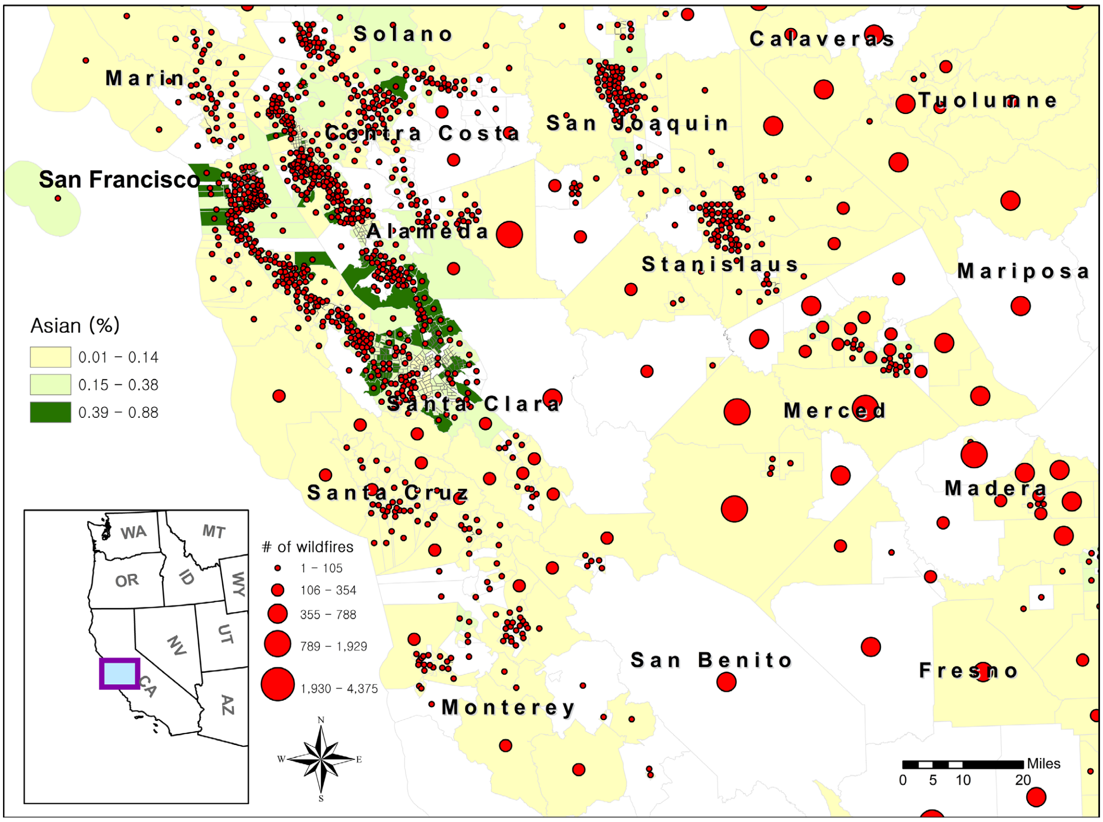
Figure 4. Relationships between demographic variables and wildfires at the county level.

of the Asian, Black, Native American, Hispanic, and White populations by county in California, respectively, each of which is overlaid with another layer showing the number of wildfires that occurred during the period 1992-2018 to represent relationships between race/ethnicity and the wildfire risk. These maps give a quick overview of where both a certain population group and the hot spots of the wildfire occurrences are concentrated. It appears that the Los Angeles and San Francisco metro areas have the highest numeric Asian population in CA, while its northern region has the largest White and Native American population. Meanwhile, the Black and Hispanic population are relatively concentrated in its middle and southern regions. In general, Figure 4(a), Figure 4(c), and Figure 4(e) seemingly show no correlations between the Asian population and the incidence rate of wildfires; between the Hispanic population and the rate; and between the White population and the rate, respectively. On the other hand, it appears that Figure 4(b) and Figure 4(d) show that the higher the representation of the black or Native people, the higher the wildfire risk. This means that the Black and Native people tend to reside in a county with a higher level of wildfire risk while the Asian, Hispanic, and White people tend to reside in other areas, regardless of wildfire risk.

Figure 4(f) indicates that the higher the number of people with graduate degrees, the lower the wildfire risk. Similarly, according to Figure 4(g) and Figure 4(h), the counties with higher median household income or higher median housing price have relatively a lower wildfire risk. However, it should be noted that this naked-eye-based detection of the relationships between these variables has limitations and does not necessarily determine whether such results are statistically meaningful. Therefore, a bivariate correlation analysis was conducted to quantify the power of the linear relationship between those variables, and the next section describes the results.

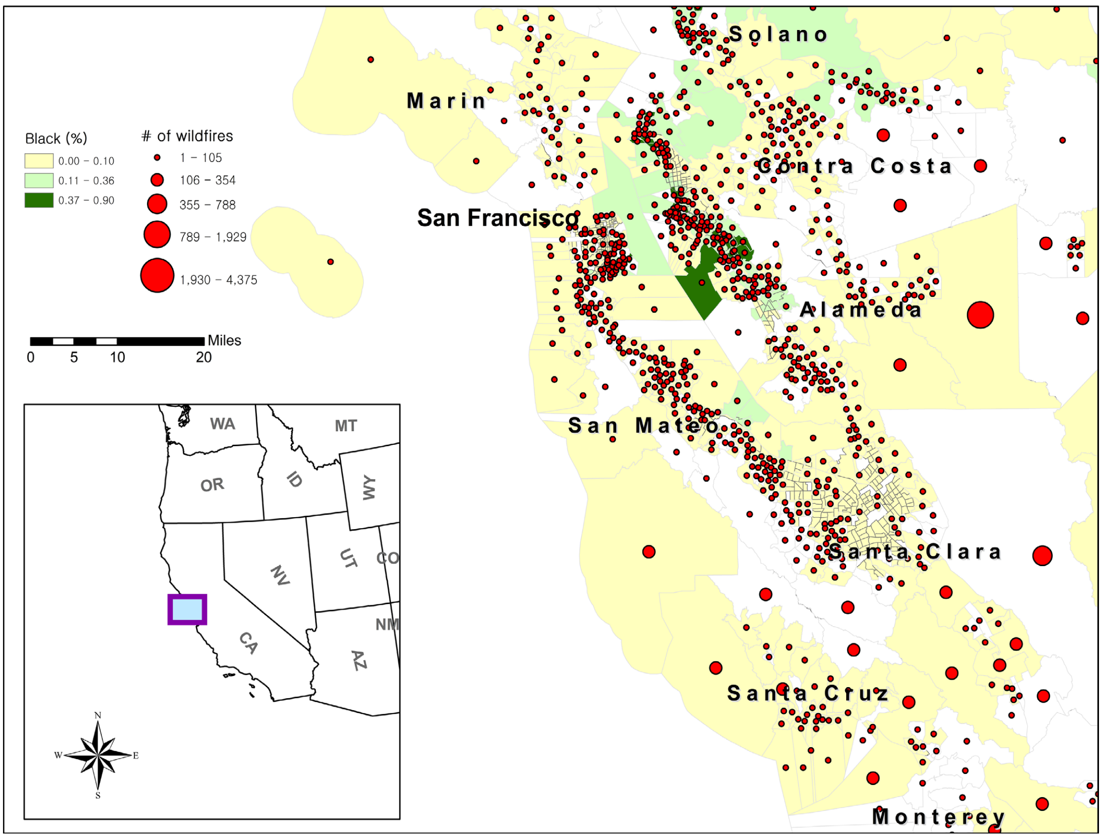
5.2. Relationships between Demographic Variables and Wildfires by Census Tract

A more in-depth geospatial analysis was conducted to see if there is any difference between variables discussed in the previous section at the census tract level. Figures 5(a)-(h) show relationships between wildfire risk spots and socio-economic-demographic characteristics at the census tract level. The quantities of wildfires were assigned to each census tract. Census tracts, each of which generally consists of 1200 to 8000 people with different sizes relying on the settlement density, are subdivisions of a county. These maps show slightly different results as opposed to those discussed in the section titled "Relationships between Demographic Variables and Wildfires by County in California". To be more specific, according to Figure 5(a) and Figure 5(c), the majority of the Asian and Hispanic people tend to avoid the census tracts at the wildfire hot spots, even though there are some of those people in areas with a higher risk of wildfires because those populations are disproportionally concentrated in the census tracts with a higher level of wildfire risk. On the contrary, most of the Native Americans and White people, as shown in Figure 5(d) and Figure 5(e), tend to reside in those counties where the higher or highest number of the wildfires occurred. Meanwhile, as shown in Figure 5(b), it seems to be difficult to determine if there is any linear relationship between the wildfire risk and the concentration of Black people; the map shows that there is a weak relationship between the Black



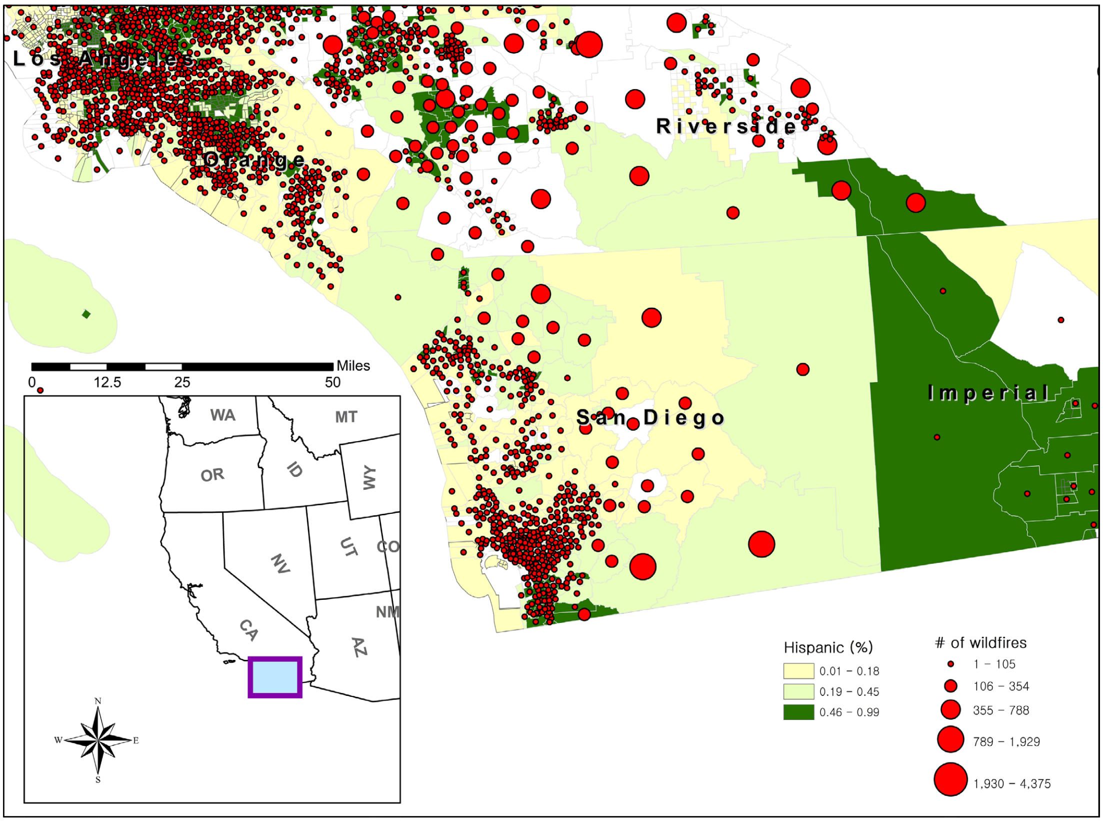
Solano
Marin
Calaveras
Tuolumne
Contra Costa
San Joaquin
San Francisco
Alameda
Stanislaus
Mariposa
Asian (%)
0.01 – 0.14
0.15 – 0.38
0.39 – 0.88
Santa Clara
Merced
Santa Cruz
Madera
# of wildfires
1 – 105
106 – 354
355 – 788
789 – 1,929
1,930 – 4,375
WA
MT
OR
ID
WY
NV
UT
CA
AZ
San Benito
Fresno
Monterey
Miles
0 5 10 20

(a)

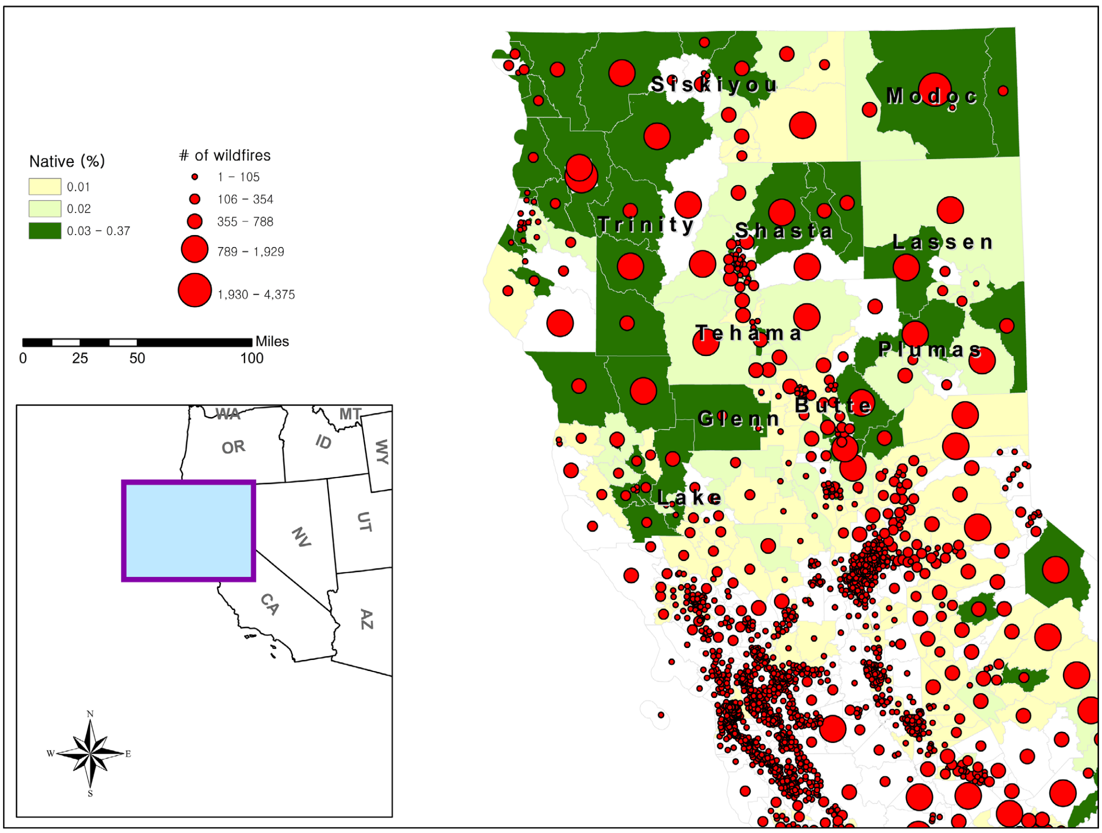


Solano
Marin
Black (%)
0.00 – 0.10
0.11 – 0.36
0.37 – 0.90
# of wildfires
1 – 105
106 – 354
355 – 788
789 – 1,929
1,930 – 4,375
Contra Costa
San Francisco
Alameda
Miles
0 5 10 20
San Mateo
WA
MT
OR
ID
WY
NV
UT
CO
NM
CA
AZ
Santa Clara
Santa Cruz
Monterey

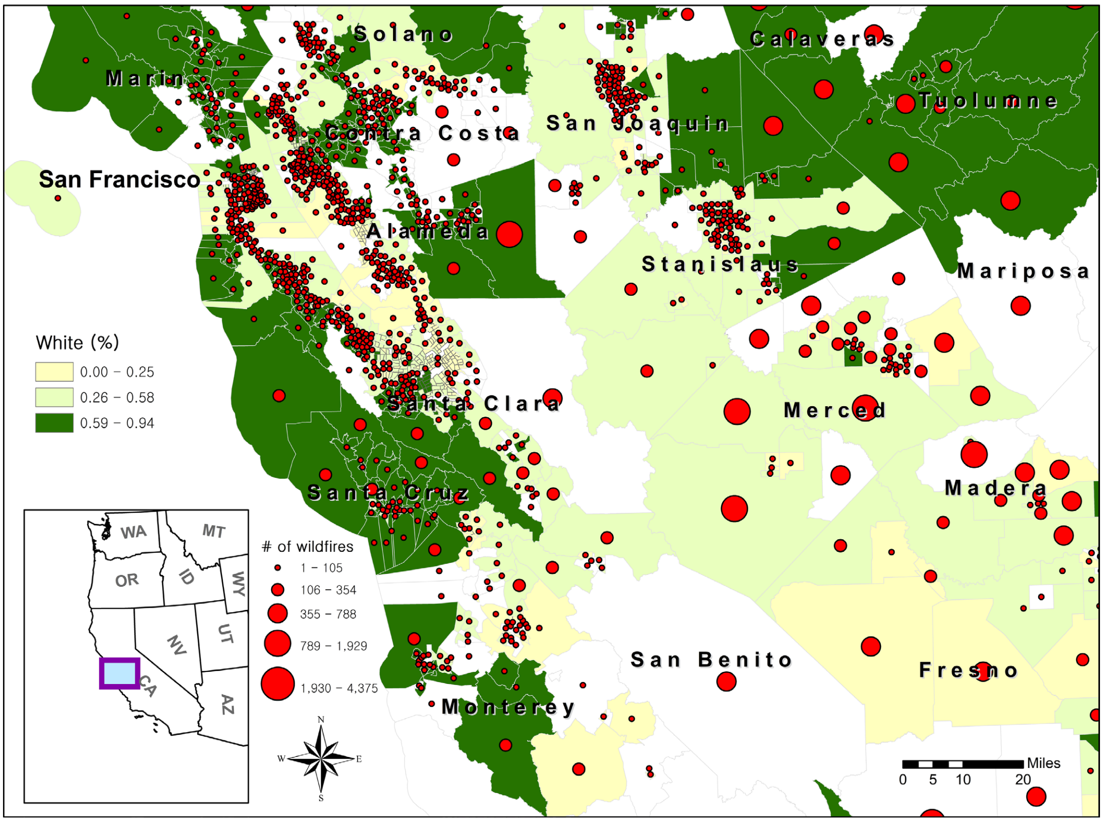
(b)


Los Angeles
Orange
Riverside
San Diego
Imperial
Miles
0
12.5
25
50
WA
MT
OR
ID
WY
NV
UT
CO
CA
NM
AZ
Hispanic (%)
0.01 - 0.18
0.19 - 0.45
0.46 - 0.99
# of wildfires
1 - 105
106 - 354
355 - 788
789 - 1,929
1,930 - 4,375

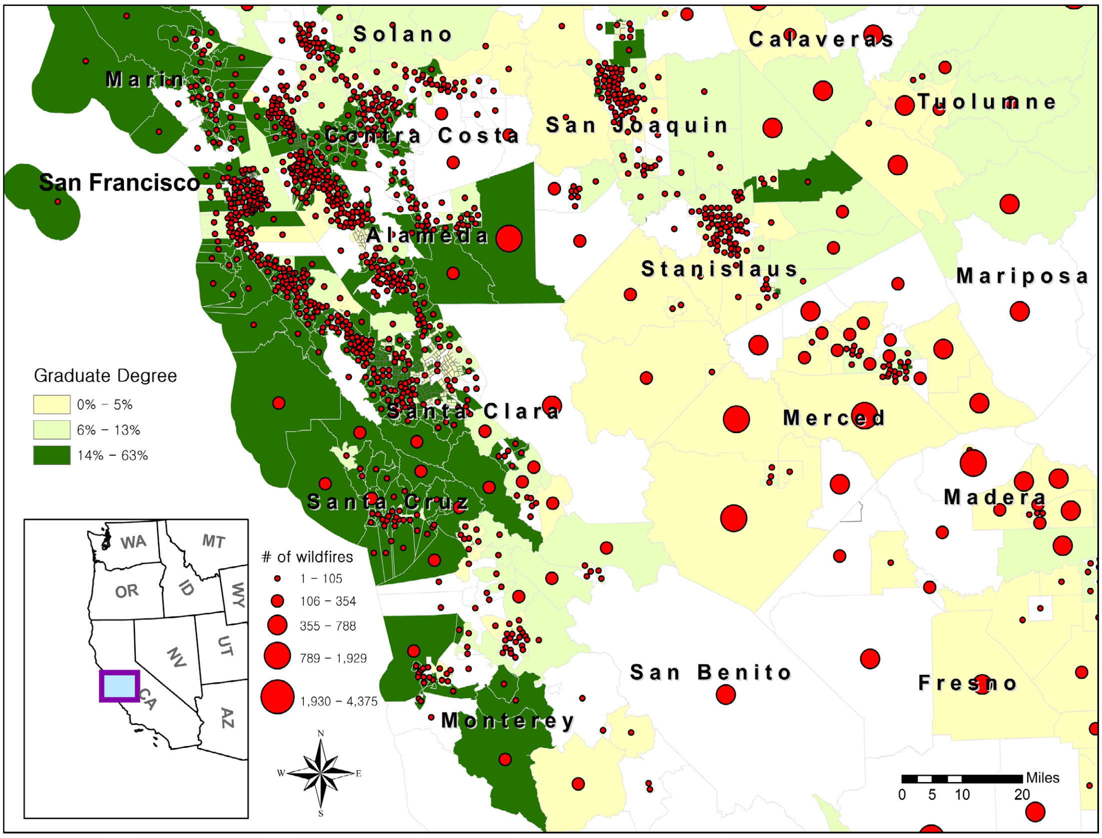
(c)


Siskiyou
Modoc
Trinity
Shasta
Lassen
Tehama
Plumas
Glenn
Butte
Lake
Native (%)
0.01
0.02
0.03 - 0.37
# of wildfires
1 - 105
106 - 354
355 - 788
789 - 1,929
1,930 - 4,375
Miles
0
25
50
100
WA
MT
OR
ID
WY
NV
UT
CA
AZ

(d)


Solano
Marin
Calaveras
Tuolumne
San Joaquin
Contra Costa
San Francisco
Alameda
Stanislaus
Mariposa
White (%)
0.00 – 0.25
0.26 – 0.58
0.59 – 0.94
Santa Clara
Merced
Santa Cruz
Madera
# of wildfires
1 – 105
106 – 354
355 – 788
789 – 1,929
1,930 – 4,375
WA
MT
OR
ID
WY
NV
UT
CA
AZ
San Benito
Fresno
Monterey
Miles
0 5 10 20

(e)


Solano
Marin
Calaveras
Tuolumne
San Joaquin
Contra Costa
San Francisco
Alameda
Stanislaus
Mariposa
Graduate Degree
0% – 5%
6% – 13%
14% – 63%
Santa Clara
Merced
Santa Cruz
Madera
# of wildfires
1 – 105
106 – 354
355 – 788
789 – 1,929
1,930 – 4,375
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WY
NV
UT
CA
AZ
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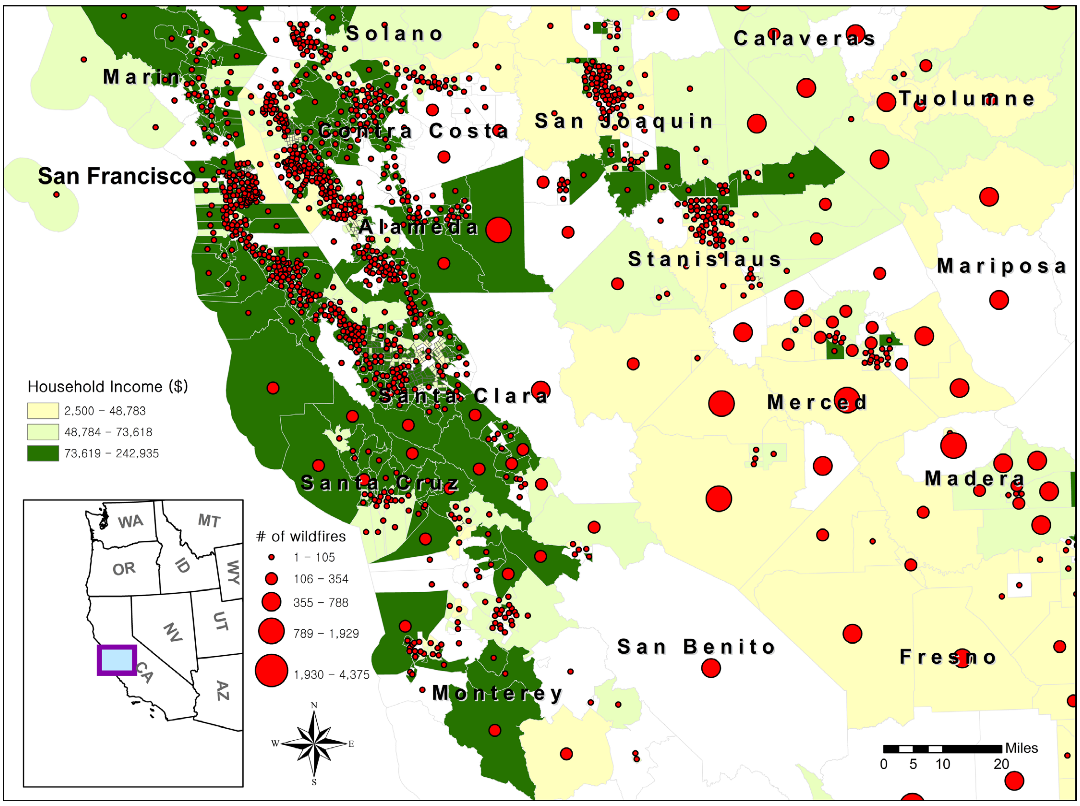
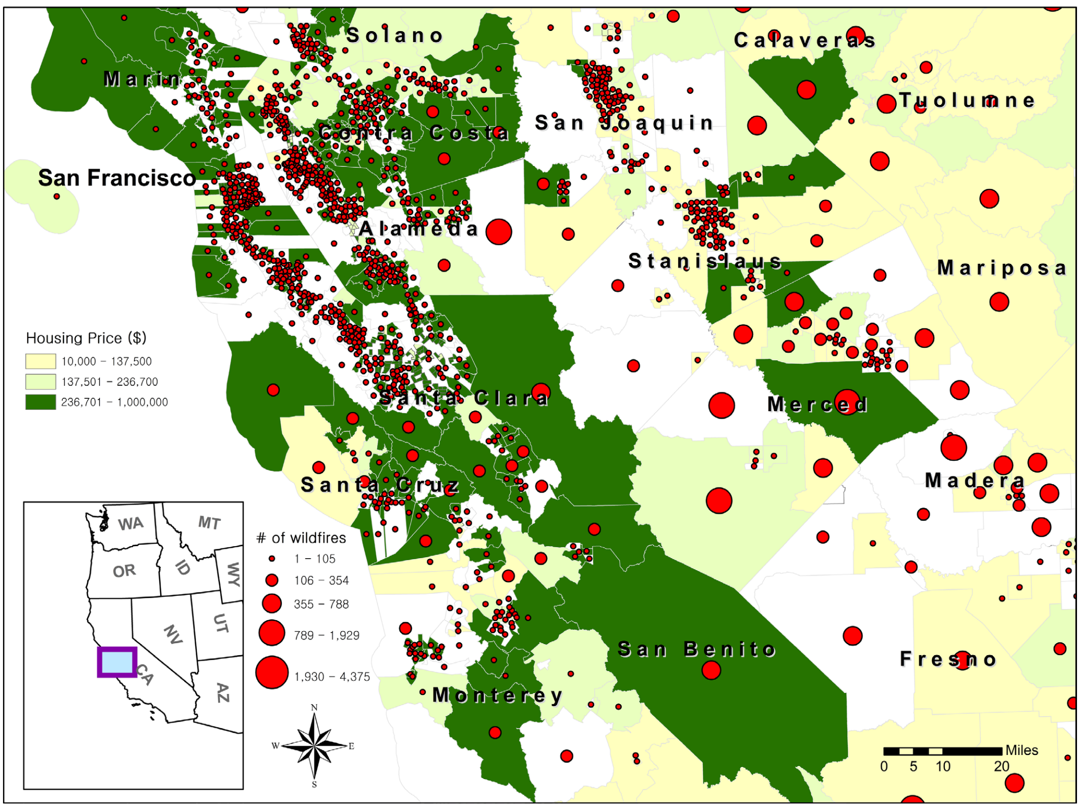
Fresno
Monterey
Miles
0 5 10 20

(f)



(g)



(h)

Figure 5. Relationships between demographic variables and wildfires at the census tract level.

population and the scientifically measured wildfire risk, considering that many areas with a higher and medium level of representation for the people have a higher level of wildfire risk.

As seen in the relationship between the wildfire risk and educational attainment, **Figure 5(f)** exhibits that the census tracts with the greater number of people with graduate degrees is generally associated with a lower the wildfire risk. In a similar manner, it appears that **Figure 5(g)** and **Figure 5(h)** reveals that the higher the median household income or median housing price, the lower the wildfire risk. What should be noticeable is that these judgements made based on naked eyes would not guarantee the strength of the linear relationship between those variables. Therefore, refer to the correlation analysis and results in the next section.

5.3. Statistical Analysis

Table 1 displays descriptive statistics of the variables used in this research, including the number of wildfires and socio-economic-demographic characteristics (*i.e.*, race, educational attainment, median household income, and median housing price) at the county and census tract levels. Wildfire datasets and demographic variables were put into the spreadsheet in SPSS for correlational analysis. In these correlations, the socio-economic-demographic characteristics were compared with the variable representing the wildfire occurrences. Appendix 1 supports no linear relationship between wildfire occurrences and any demographic variables at the county level. To the contrary, as seen in Appendix 2, all demographic variables at the census tract level are moderately and significantly correlated with the wildfire variable. To be more specific, race/ethnicity-related variables such as Hispanic, Black, Asian were negatively related to the number of wildfires, indicating that the more the representation of these populations, the

Table 1. Descriptive statistics.

	County			Census Tract		
	Mean	Std. Deviation	N	Mean	Std. Deviation	N
# of Fires	4052	4041.76	58	33.36	134.77	7049
Hispanic (%)	28	0.17	58	36	0.26	5922
White (%)	57	0.19	58	41	0.27	5922
Black (%)	3	0.03	58	6	0.1	5922
Native (%)	2	0.03	58	1	0.01	5922
Asian (%)	7	0.08	58	13	0.15	5922
Graduate Degree (%)	9	4.66	58	11	10.22	5931
Household Income ($)	55,266	13,421	58	65,483	31,054	5935
Housing Price ($)	177,241	115,040	58	227,103	167,163	4514

less the number of wildfires present in the given census tracts. One thing that is notable, taking into consideration each coefficient of those variables, is that compared with the Black and Hispanic populations which are marginally in relation with the fire variable, the Asian people were more negatively correlated with the Wildfire variable. On the other hand, the statistics show that the White and Native Americans had a positive correlation with the fire incidence rate, meaning that their populations may be found in the areas with the higher risk of wildfires. Once again, compared with the White people who are related to the wildfire hazard to a slight extent, the Native Americans have a stronger correlating with the wildfire variable.

Additionally, the statistical results indicate that the census tracts with the greater number of graduate degrees (*i.e.*, the percentage of the population with a master or Ph.D. degree) are slightly in a negative association with the wildfire occurrence, indicating that people with the higher educational degree appear to avoid the wildfire risk. In the same manner, the correlations show that the median household income and median housing price are negatively related to the wildfire risk at the census tract level, meaning that people with a higher level of income or a relatively higher-priced home may be reluctant to live in a census tract with a higher level of wildfire risk.

6. Conclusions

The major goal of this research was to identify the location and extent of areas subject to the wildfire hazard and to reveal how race, ethnicity, income levels, and educational attainments are related to the risk of the hazard at the county and census tract levels in the state of California. This research provides no evidence that there are relationships between the demographic variables discussed in the previous sections and the risk of wildfire risk at the county level. However, demographic variables are related to wildfire risk at a more detailed geographical level, such as the census tract level. First, this research shows the wildfire-prone communities are ones with a comparatively higher level of representation for the populations such as the White and Native Americans. In particular, the Native Americans are more significantly correlated with the wildfire risk. It appears that they are more likely to live in the areas more vulnerable to wildfires. Second, in contrast, this research reveals that some ethnicity or races, such as Asian people would prefer to reside in communities with a lower level of wildfire risk. Additionally, this research shows only the census tracts with the higher number of the Native Americans are more exposed to the wildfire risk, compared with other census tracts. Third, people with a higher level of educational attainment would prefer to reside in communities with a lower level of chemical risk. Forth and lastly, this research indicates that the census tracts that have a higher median household income and median housing price have a negative relationship with the wildfire risk, meaning that people with a higher level of the income or a relatively higher-priced home prefer residing in communities less subject to the natural hazard. Therefore, it can be concluded that associations exist between wildfire risk and certain socio-economic and demographic characteristics.

Research on the potential associations between wildfire risk and certain socio-economic and demographic characteristics in California has many implications in the field of emergency management. The study results can be used as a basis for future decisions of policymakers to prevent or reduce impacts of a future wildfire disaster on communities. Additionally, the geographical patterns explored in the study will help develop and calibrate the regulation of wildfires. In addition, findings from this research may be useful in developing a comprehensive emergency management plan including mitigation measures that increase resilience among populations that are particularly vulnerable to wildfires. Additionally, this research may be beneficial in implementing strategies that increase the adaptive capacity of vulnerable populations to the effects of extreme wildfire events. Furthermore, this research may have implications in regard to wildfire management practices and future land use planning in California. This research would be of great assistance in the formulation of future targeted wildfire emergency plans and planning related to local response and relief organizations, as it would allow for sufficient consideration of high-risk groups with low adaptability.

7. Future Directions

Further research is warranted on the topic of wildfire risk as it relates to socio-economic and demographic characteristics of populations in California. Currently, there is not an abundance of research that exists on this topic, and the research that has been conducted on this topic could certainly be expanded. Increased research is needed to fully understand the correlation between socio-economic-demographic factors and wildfire risk and vulnerability. This correlation must be adequately understood in order to implement emergency management strategies that effectively reduce wildfire risk and increase resilience in vulnerable populations.

Future research directions related to this topic that may be considered include evaluating socio-economic-demographic factors of populations against the presence of different wildfire risk factors. Additionally, information related to this topic would greatly benefit from expansion of research that utilizes geospatial data to explain the relationships between wildfire risks and select socio-economic-demographic characteristics. Furthermore, research is warranted on the effectiveness of existing programs (such as educational programs and cost-sharing programs) aimed at reducing wildfire potential and increasing adaptive capacity in vulnerable communities. Research on the various environmental justice issues that surround this topic could also be expanded.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix 1. Correlations at the County Level

		# of Fires	Hispanic (%)	White (%)	Black (%)	Native (%)	Asian (%)	Graduate	Income	Housing Price
# of Fires	Pearson Correlation	1	0.176	−0.12	0.137	−0.131	−0.092	−0.161	−0.179	−0.246
	Sig. (2-tailed)		0.185	0.371	0.306	0.325	0.493	0.227	0.18	0.063
	N	58	58	58	58	58	58	58	58	58
Hispanic (%)	Pearson Correlation	0.176	1	−0.870**	0.222	−0.361**	0.062	−0.24	−0.042	−0.055
	Sig. (2-tailed)	0.185		<0.001	0.094	0.005	0.646	0.069	0.752	0.683
	N	58	58	58	58	58	58	58	58	58
White (%)	Pearson Correlation	−0.12	−0.870**	1	−0.536**	0.364**	−0.506**	−0.044	−0.212	−0.157
	Sig. (2-tailed)	0.371	<0.001		<0.001	0.005	<0.001	0.744	0.11	0.238
	N	58	58	58	58	58	58	58	58	58
Black (%)	Pearson Correlation	0.137	0.222	−0.536**	1	−0.292*	0.491**	0.081	0.232	0.03
	Sig. (2-tailed)	0.306	0.094	<0.001		0.026	<0.001	0.547	0.08	0.821
	N	58	58	58	58	58	58	58	58	58
Native (%)	Pearson Correlation	−0.131	−0.361**	.364**	−0.292*	1	−0.334*	−0.106	−0.297*	−0.265*
	Sig. (2-tailed)	0.325	0.005	0.005	0.026		0.01	0.428	0.024	0.045
	N	58	58	58	58	58	58	58	58	58
Asian (%)	Pearson Correlation	−0.092	0.062	−0.506**	0.491**	−0.334*	1	0.617**	0.608**	0.575**
	Sig. (2-tailed)	0.493	0.646	<0.001	<0.001	0.01		<0.001	<0.001	<0.001
	N	58	58	58	58	58	58	58	58	58
Graduate Degree	Pearson Correlation	−0.161	−0.24	−0.044	0.081	−0.106	0.617**	1	0.799**	0.855**
	Sig. (2-tailed)	0.227	0.069	0.744	0.547	0.428	<0.001		<0.001	<0.001
	N	58	58	58	58	58	58	58	58	58
Median Household Income	Pearson Correlation	−0.179	−0.042	−0.212	0.232	−0.297*	0.608**	0.799**	1	0.844**
	Sig. (2-tailed)	0.18	0.752	0.11	0.08	0.024	<0.001	<0.001		<0.001
	N	58	58	58	58	58	58	58	58	58
Median Housing Price	Pearson Correlation	−0.246	−0.055	−0.157	0.03	−0.265*	0.575**	0.855**	0.844**	1
	Sig. (2-tailed)	0.063	0.683	0.238	0.821	0.045	<0.001	<0.001	<0.001	
	N	58	58	58	58	58	58	58	58	58

**: Correlation is significant at the 0.01 level (1-tailed). *: Correlation is significant at the 0.05 level (1-tailed).

Appendix 2. Correlations at the Census Tract Level

		# of Fires	Hispanic (%)	White (%)	Black (%)	Native (%)	Asian (%)	Graduate	Income	Housing Price
# of Fires	Pearson Correlation	1	−0.086**	0.185**	−0.089**	0.447**	−0.150**	−0.091**	−0.078**	−0.105**
	Sig. (2-tailed)		<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	N	7049	5922	5922	5922	5922	5922	5931	5935	4514
Hispanic (%)	Pearson Correlation	−0.086**	1	−0.781**	0.026*	−0.100**	−0.303**	−0.652**	−0.556**	−0.433**
	Sig. (2-tailed)	<0.001		0	0.048	<0.001	<0.001	0	0	<0.001
	N	5922	5922	5922	5922	5922	5922	5918	5922	3724
White (%)	Pearson Correlation	0.185**	−0.781**	1	−0.354**	0.164**	−0.235**	0.548**	0.491**	0.340**
	Sig. (2-tailed)	<0.001	0		<0.001	<0.001	<0.001	0	0	<0.001
	N	5922	5922	5922	5922	5922	5922	5918	5922	3724
Black (%)	Pearson Correlation	−0.089**	0.026*	−0.354**	1	−0.051**	−0.086**	−0.164**	−0.247**	−0.171**
	Sig. (2-tailed)	<0.001	0.048	<0.001		<0.001	<0.001	<0.001	<0.001	<0.001
	N	5922	5922	5922	5922	5922	5922	5918	5922	3724
Native (%)	Pearson Correlation	0.447**	−0.100**	0.164**	−0.051**	1	−0.162**	−0.119**	−0.143**	−0.175**
	Sig. (2-tailed)	<0.001	<0.001	<0.001	<0.001		<0.001	<0.001	<0.001	<0.001
	N	5922	5922	5922	5922	5922	5922	5918	5922	3724
Asian (%)	Pearson Correlation	−0.150**	−0.303**	−0.235**	−0.086**	−0.162**	1	0.243**	0.243**	0.254**
	Sig. (2-tailed)	<0.001	<0.001	<0.001	<0.001	<0.001		<0.001	<0.001	<0.001
	N	5922	5922	5922	5922	5922	5922	5918	5922	3724
Graduate Degree	Pearson Correlation	−0.091**	−0.652**	0.548**	−0.164**	−0.119**	0.243**	1	0.643**	0.654**
	Sig. (2-tailed)	<0.001	0	0	<0.001	<0.001	<0.001		0	0
	N	5931	5918	5918	5918	5918	5918	5931	3731	3731
Median Household Income	Pearson Correlation	−0.078**	−0.556**	0.491**	−0.247**	−0.143**	0.243**	0.710**	1	0.643**
	Sig. (2-tailed)	<0.001	0	0	<0.001	<0.001	<0.001	0		0
	N	5935	5922	5922	5922	5922	5922	5931	5935	3731
Median Housing Price	Pearson Correlation	−0.105**	−0.433**	0.340**	−0.171**	−0.175**	0.254**	0.654**	0.643**	1
	Sig. (2-tailed)	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0	0	
	N	4514	3724	3724	3724	3724	3724	3731	3731	4514

**: Correlation is significant at the 0.01 level (1-tailed). *: Correlation is significant at the 0.05 level (1-tailed).