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# The intersection of socioeconomic status and wildfire risk: Insights from California



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#### ABSTRACT

Wildfires in California have increased over the past 20 years, raising serious concerns. Due to the significant damage these fires cause to the environment, infrastructure, and communities, it is essential for policymakers and researchers to find effective ways to reduce their impact. This study aims to improve our understanding of wildfires by examining the relationship between population density, wildfire severity, and socioeconomic factors like average household income. The research uses socioeconomic data from the California State Geoportal (CA.gov) and fire severity zones from ArcGIS Hub. Statistical methods, such as ordinary least squares (OLS) regression and correlation analysis, were applied using ArcGIS Pro software from the Environmental Systems Research Institute. This study confirms earlier findings that there is no correlation between population density and wildfire severity. This conclusion is based on a more detailed analysis that moves from the county level to the census tract level. Additionally, we found no connection between socioeconomic status and fire severity, though we did observe a clear link between socioeconomic status and the likelihood of fires starting. Both OLS and correlation analysis supported these results. However, a hot-spot analysis showed that areas with the lowest-income households are also the regions with the most severe wildfires. This suggests a concerning relationship between lower-income communities and increased vulnerability to wildfires. The findings emphasize the need for targeted interventions and a fair distribution of resources to address the socioeconomic inequalities that contribute to wildfire risk.

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# 1. Introduction

The financial burden attributed to wildfires has risen markedly over the last five years, jumping from \$61 million to well over \$400 million per year. This upward trend highlights the increasing pressure on resources allocated for wildfire response and recovery efforts, emphasizing the magnitude of the phenomenon (Fleck, 2022). Trees are densely clustered, reaching up to five times their natural density, leading to wildfires that should foster forest regeneration and transform into devastating infernos. The forests play a crucial role in supplying 60% of the state's developed water; their loss would deprive millions of people of access to clean drinking water (nature.org). Since the 1970s, California has

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experienced a fivefold rise in the yearly scope of wildfires, characterized by exceptionally massive and devastating events (Williams et al., 2019).

The increasing frequency and severity of wildfires in California represents a multifaceted challenge with far-reaching implications for both the environment and communities. As these wildfires continue to devastate landscapes and threaten livelihoods, urgent action is needed to implement robust mitigation strategies and bolster resilience in the face of future fire events. This imperative extends beyond immediate-response efforts to encompass long-term planning and policy aimed at fostering interventions sustainable coexistence with fire-prone ecosystems.

Previous research has explored the connections between population density and wildfire severity in California, alongside investigations into the influence of socioeconomic factors on ignition occurrences (Sultan and Bitar, 2024; Hwang and Meier, 2022; Reilley et al., 2023). This study aims to further our understanding of the correlation between population density and acres burned by narrowing the

geographic focus to the census tract level, thus providing valuable insights into the localized factors influencing wildfire dynamics in California. Additionally, this project expands our comprehension of wildfire dvnamics and socioeconomic impacts. While prior studies (Hwang and Meier, 2022; Reilley et al., 2023) established a direct correlation between ignitions and socioeconomic status, this research extends this inquiry by examining if this correlation leads to higher fire-hazard severity.

Hot-spot analysis helps identify areas at higher risk of severe wildfires based on income levels while also highlighting communities that might be overlooked. often located near wealthier neighborhoods. By using this method, we seek to identify regions that are vulnerable to wildfires due to socioeconomic factors, as well as those that may be marginalized or underserved in terms of fire preparedness. This deeper understanding allows us to create more inclusive and equitable wildfire mitigation strategies that meet the specific needs of at-risk communities throughout California.

Fahey et al. (2016) used geographic information systems (GIS) software to assess a sample of older adults in a home-fire-safety (HFS) study, aiming to identify areas with the highest risk of fire. By comparing census-tract data with participant information based on seven risk factors, the determined the distribution researchers of participants and census tracts among risk categories. Findings revealed that a significant portion of study participants resided in high or severe fire risk areas, indicating successful targeting. Moreover, the study identified additional census tracts suitable for future HFS interventions, highlighting the valuable role of GIS-based fire-risk models in identifying at-risk communities and guiding intervention efforts.

# 2. Literature review

Sultan and Bitar (2024) used GIS methodologies to examine the correlation between population density and fire severity. This approach aimed to understand how variations in population density may impact the severity of wildfires in different regions. Through GIS analysis, these studies provide insights into the spatial patterns of wildfire risk, aiding in the development of targeted mitigation strategies for fire-prone areas.

Sultan and Bitar (2024) employed ordinary least squares (OLS) analysis to explore this correlation, revealing a minimal multiple  $R^2$  value of 0.000009 and an adjusted  $R^2$  of -0.000405. This lack of a significant correlation between population density and fire severity emphasizes the need for a more refined investigation. Narrowing the focus area to the census-tract level offers several advantages. First, census tracts provide a more localized representation of population distribution and landuse patterns compared to counties, allowing for a more precise examination of the relationship between population density and fire severity. Additionally, census tracts offer a balance between granularity and data availability, providing sufficient detail without overwhelming the analysis with excessive complexity.

Previous research has also extensively employed GIS science and tools to delve into the relationships between socioeconomic factors and ignition occurrences (Hwang and Meier, 2022; Reilley et al., 2023). That research provides significant insights into the methodologies employed to analyze socioeconomic factors in relation to wildfires, offering valuable guidance on approaches for conducting similar analyses. Furthermore, these studies offer practical insights into identifying vulnerable communities and high-risk areas prone to wildfire ignition, helping formulate targeted strategies.

Hwang and Meier (2022) conducted a descriptive statistical analysis of variables, including the number of wildfires and socioeconomic characteristics. The findings revealed no linear relationship between wildfire occurrences and demographic variables at the county level (USCB, 2022), whereas at the census tract level, all demographic variables showed moderate and significant correlations with wildfire occurrence. Specifically, variables related to race/ethnicity, such as Hispanic, Black, and Asian, negativelv correlated with were wildfire occurrences, suggesting lower wildfire presence in areas with higher representation of these populations. Conversely, White and Native American populations showed positive correlations with wildfire incidence, indicating higher wildfire risk in these areas. Additionally, higher levels of educational attainment, median household income, and median housing price were associated with lower wildfire ignitions at the census tract level.

Reilley et al. (2023) examined the causes of wildfire ignitions and evaluated the influence of biophysical and socioeconomic factors on human and natural ignitions across distinct fire regimes in Oregon and Washington (U.S.). Using a dataset spanning from 1992 to 2018, the research finds that socioeconomic factors such as income, employment, population density, and age significantly correlate with human ignitions. The study highlights regional differences in the importance of socioeconomic factors on human ignitions, particularly between the west and east sides of the Cascade Range in the Pacific Northwest. Additionally, the findings emphasize the role of escaped fires from recreation or debris and open burning activities as major contributors to human ignitions, suggesting opportunities for tailored wildfire-prevention efforts to mitigate higher-risk activities and reduce accidental ignitions.

Previous studies typically employed generalized linear regression techniques such as multiple linear regression, logistic regression, or Poisson and negative-binomial regressions to analyze ignition occurrence (Costafreda-Aumedes et al., 2017). Reilley et al. (2023) used a response variable representing counts of ignitions normalized by the area of each county subdivision to create a measure of ignition density, accommodating variations in subdivision sizes. While the Poisson distribution is commonly used for count data, their data exhibited overdispersion, where variance exceeded the mean, a common occurrence in fire datasets. Therefore, they opted for the negative binomial distribution, which is suitable for over-dispersed count data and has been used in other fire-occurrence studies (Chas-Amil et al., 2015; Pozo et al., 2022; Su et al., 2019).

## 3. Methods

#### 3.1. Data selection and acquisition

Population data, boundaries, and household income data were sourced from a unified polygon dataset provided by CA Open Data (lab.data.ca.gov). California's fire-severity zone data is delineated into three distinct levels of hazard within the responsibility areas: moderate, high, and very high. These zones were established by assigning a hazard score, drawing from various factors, including fire history, natural vegetation, terrain, blowing embers, predicted flame length, and typical fire weather in the area (hub.arcgis.com). Both datasets were imported into ArcGIS Pro as feature layers.

## 3.2. Analysis

ArcGIS Pro, developed by the Environmental Systems Research Institute, served as the primary tool for analysis in a Windows environment. The analysis used the OLS linear regression tool with correlation and hot-spot analyses after consolidating all data into a single layer.

In preparing for the analysis using the OLS tool in ArcGIS Pro, we had to ensure that the table was formatted appropriately. This involved using numerical values for both the independent and dependent variables. Additionally, the data had to be organized in rows, with each row representing a distinct observation, and the corresponding values for each variable aligned correctly in the columns. This meticulous arrangement was essential to ensure the accuracy of the analysis and the tool's ability to effectively examine the relationships between the variables. The variables for population density were categorized into three groups: low medium population, population, and high population. Similarly, fire severity was classified into three levels: medium, high, and very high (Fig. 1).

A similar methodology was employed to conduct an OLS analysis examining the relationship between fire severity and economic status. Fire severity remained categorized as medium, high, and very high, while economic status was divided into five groups according to the Pew Research definition of income (ktla.com). These groups were assigned numerical values ranging from 1 for the lowest income category to 5 for the highest. These variables constituted the basis for the statistical analysis (Fig. 2). To validate the outcomes of this OLS analysis, we performed a correlation analysis using Python (Fig. 3). The objective of this analysis was to evaluate the strength and direction of the relationships between the variables. By employing correlation analyses, we aimed to further substantiate the findings derived from the OLS analysis, thus enhancing the reliability of our conclusions.

## 4. Results and discussion

The analysis of the relationship between population density and fire severity yielded intriguing results: a multiple  $R^2$  value of 0.000074 and an adjusted  $R^2$  value of 0.000032. While these values are slightly higher than previous estimates, they still indicate an extremely low level of explained variance in acres burned based on population at both the county and census tract levels. This suggests that population density alone does not significantly account for variations in acres burned. Moreover, the adjusted  $R^2$  values, although positive, do not provide substantial explanatory power, hinting at potential limitations such as multicollinearity or model complexity relative to the available data. Overall, these findings underscore the persistent absence of a meaningful correlation between acres burned and population density.

The correlation analysis conducted through Python scripting revealed a correlation coefficient of 0.04496774817734328 between wildfire severity and income level. This finding indicates a very weak positive correlation between the two variables. In practical terms, this suggests little to no linear relationship between income level and wildfire severity in the study area. These results imply that other factors beyond income level may play a more significant role in wildfire severity. Further exploration of these additional factors is warranted to gain a comprehensive understanding of the dynamics driving wildfire severity in the region.

The hot-spot analysis tool revealed a compelling pattern: lower-income communities, identified as cold spots, predominantly inhabit areas classified as fire hazard zones, particularly those with the highest severity levels. Notably, within these high-risk zones, specific census tracts exhibit an average income below \$35,000, underscoring the socioeconomic disparities within regions highly susceptible to wildfires. This nuanced understanding highlights the multifaceted nature of the relationship between socioeconomic status and fire risk, transcending a singular focus on income. It underscores the imperative for targeted interventions aimed at enhancing economic equity and fostering community resilience to mitigate the impact of wildfires.

Fig. 4 illustrates the results of the hot-spot analysis, with blue indicating cold spots and red indicating hot spots in income disparities across the fire severity layer, particularly in regions where the severity risk is moderate or higher. Circles on the map represent areas where the average household income is \$35,000 or less, coinciding with the most severe fire hazard zones. Larger circles denote communities with fewer financial resources, highlighting their increased vulnerability to wildfire hazards and limited capacity for recovery and protection measures.



Fig. 1: Fire-severity zones with the population data





import arcpy import pandas as pd
# Specify the path to the input table input_table = r"path_to_input_table"
# Convert the input table to a pandas DataFrame dg = pd.DataFrame(arcpy.da.TableToNumPyArray(input_table, ["Variable_A", "Variable_B"]))
# Calculate the correlation matrix correlation_matrix = dg.corr()
# Extract the correlation coefficient between the variables correlation_coefficient = correlation_matrix.loc["Variable_A", "Variable_B"]
# Print the correlation coefficient print("Correlation Coefficient:", correlation_coefficient)
Fig. 3: Python script for correlation analysis

**Fig. 3:** Python script for correlation analysis



Fig. 4: Hot-spot analysis with low-income families in high fire-severity areas

## **5.** Conclusion

This study delves into California's escalating wildfire trend over the past two decades. Wildfires' substantial threats to various aspects of society, from the environment to infrastructure and communities, raise an urgent call for effective mitigation strategies. By focusing on the correlation between population density, wildfire severity, and socioeconomic factors, this research aims to deepen our comprehension of wildfire dynamics. Leveraging socioeconomic data sourced from the California Energy Commission and fire-severity zones from ArcGIS Hub, the study employs rigorous statistical analyses, including OLS regression and correlation analysis, to explore potential relationships among these variables. Refining the analysis from the county level to the more detailed census-tract level reaffirmed the absence of a correlation between population density and fire severity, as well as fire severity and socioeconomic factors. This finding was further supported by correlation analysis and OLS regression. In contrast, a hot-spot analysis revealed a troubling association between areas with the lowestincome households and regions of heightened fire severity. This underscores the imperative for targeted interventions and equitable resource allocation to address socioeconomic disparities exacerbating wildfire vulnerability.

Previous studies have established a direct correlation between socioeconomic status and wildfire ignitions in California (Hwang and Meier, 2022). However, this analysis delved deeper into these findings and revealed that this economic factor does not influence the severity of the fires. This is the first known study to investigate this relationship. It also reveals an interesting finding: More ignitions do not always lead to greater fire severity. This challenges the idea that areas with more fires will suffer more damage.

Future research could delve deeper into the nuanced relationship between socioeconomic factors and wildfire severity, exploring additional variables and employing more advanced analytical techniques. Additionally, longitudinal studies tracking changes over time could provide valuable insights into the evolving dynamics of wildfires and their socioeconomic impacts. Furthermore, comparative analyses across different regions or states could offer a broader perspective on the factors influencing wildfire risk and resilience.

# **Compliance with ethical standards**

#### **Conflict of interest**

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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