Analysis of California Fire-Perimeter Data Using Geographic Information Systems to Examine the Correlation Between Population Density and Acres Burned

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***Abstract*—The number of California wildfires has increased in the past two decades. This change has increased the authors' and policymakers' attention to the factors that affect this phenomenon and how to manage it. Wildfires wreak havoc on the environment by burning large sections of land, housing, animals, and people alike. Wildfires degrade air quality while hindering transportation and communication. They also present a serious threat to the power grid. This study aims to examine the correlation between population density and acres burned which may help understand and manage wildfires in the state. This research study uses California fire-perimeter data, population data, and fire-severity zones extracted from the ArcGIS hub and ScienceBase. In particular, we analyzed five years of fire-perimeter data using a geographic information system ordinary least squares analysis, attributes, and summary statistics to create new layers representing selected features involved in the process. The results show no correlation between the dependent and the explanatory variables. Further analysis suggests that wildfires may be reduced if more awareness campaigns are designed and presented to the public.**

Keywords-Fire perimeter; Wildfires; GIS; ArcGIS.

I. INTRODUCTION

California's hot climate and flammable plants give the state a high wildfire risk [1]. Millions of acres are burned yearly in California wildfires, rendering land unusable for agriculture while destroying habitats and property [2]. California's state government has massive historical data on wildfires, in cooperation with other western US states [2]. For example, in 1910, the historical event "Big Blowup" occurred and affected the Northwest states. As a result, fire-suppression policies were established [3]. In 1889, large parts of Orange County, California, were burned by a great wildfire; the Santiago Canyon Fire [2], estimated at 300,000 acres. More recently, the Matilija (1932, 220,000 acres) and Laguna (1970, 175,000 acres) fires were recorded as the largest and second largest fires in California's history until 2020 [4]. In 2003, a complex fire occurred in Southern California that destroyed 3,719 homes and killed 24 [5]. The 2018 Camp Fire in Butte County, California, damaged 18,804 structures and caused 88 mortalities [6]. In 2020, a collection of large fires broke the state's records [1], burning 4,304,379 acres, destroying 11,116 structures, and killing 33 [7].

Several reasons or factors play critical roles in wildfires' occurrence and severity. Drought increased the chances of the large fires California faced in the last decade. Related to this cause is another critical factor, climate change [2][8][9]. Another natural factor is lightning [10]. Another important factor is humans. As reported by the U.S. Forest Service research data archive, 85% of wildfires in the states are caused by human actions: discarded cigarettes, improperly tended campfires, intentional arson [10], population density [11], and other factors.

Wildfires are a serious threat to the power grid, as they can damage or destroy power lines, transformers, substations, and other infrastructure. Utilities also must sometimes shut off power to prevent sparks from igniting new fires, causing widespread blackouts affecting millions.

At least three smart-grid technologies can help enhance the power grid's wildfire resilience, reliability, and safety. Microgrids—small, localized grids that can operate independently from the main grid—can provide backup power to critical facilities: hospitals, fire stations, and water-treatment plants. Underground power lines, being unexposed to the air, are less vulnerable to damage from wind, trees, animals, and fire and reduce the visual impact and electromagnetic interference of power lines. Sensors and automation, small devices that monitor the condition and performance of the power grid, can automatically detect and isolate faults, such as downed power lines or broken equipment and can also communicate with each other and with the control center to optimize the operation and coordination of the grid. All of these technologies can help prevent or reduce the severity of power outages and restore power more quickly and efficiently after a disruption.

It is essential to analyze all aspects of these fires. Thus, many valuable research studies have been conducted on many aspects of wildfires in California including understanding fire trends [12] and analyzing data to help decision makers [13]. Some researchers have developed simulations to predict where and how fast fire will travel [14]. Researchers have studied previous fires to develop response plans [13], and ways to manage fires [15]. Some of their approaches involve using geographic information systems (GIS) to create simulations with different elements that can impact a fire's spread and severity [16][17]. Researchers have even investigated the root factors of some fires, such as the powerlines [10], to solve that problem and prevent future fires.

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However, to our knowledge, this is the first study that examines the correlation between population density and acres burned using GIS. Thus, the main aim of this research is to analyze that correlation. We hypothesize a strong correlation between population density and acres burned. Correlation analysis is used to test the hypothesis through GIS to analyze several scenarios and testing the hypothesis by applying ordinary least squares (OLS). This research study answers only one question: What is the correlation between population density and acres burned?

The remainder of the paper is organized as follows. Section II presents the literature review focused on the recent studies conducted in California state. Section III describes the methodology, which includes a clear description of the data and the analytical techniques used. The remaining two sections illustrate the results, discussion, conclusion, limitations, and suggestions for future work.

II. Literature Review

Several research studies have used GIS science and tools to analyze, understand, manage, and develop solutions for many issues including natural disasters, including earthquakes [18] and flood risk [19]. Also, GIS has been used to analyze California wildfire data, as is the focus of the current research study, to develop useful solutions that may help decision makers and communities or develop a deeper understanding of the problem, such as knowing the associated factors [16][17].

For example, [5] answered three main questions focusing on evacuation orders during wildfires to enhance community safety: “Who is at risk?” “How long will it take to evacuate?” “How much time is available?” The authors used fire-spread modeling with GIS to answer these questions, to determine the trigger point, and to recommend evacuation if the fire is nearby a certain landmark (point) [5]. The authors’ techniques were based on a buffer to determine the evacuation trigger, so they applied three steps: 1) modeling the fire spread, 2) generating a fire-spread network, and 3) originating a wildfire-evacuation-trigger buffer. They argued that there is no need to have any particular information about the fire’s location and their techniques could be used in a long-term strategic or short-term operational plan [5]. Reference [13] enhanced the wildfire-trigger modeling that used a buffer by combining traffic- and fire-simulation models to set a trigger. The authors proposed a three-step method with spatiotemporal GIS. The framework helps evaluate the generated trigger. The results from the framework showed that the dynamic representation of the evacuation traffic during the wildfire is improved and linked to a better understanding of the decision making and evacuation time [13].

Reference [12] used data from the NASA RECOVER Historic Fires Database (HFD) and GIS to support decision making related to fire trends in the western United States. ArcGIS Pro helped analyze wildfires’ spatiotemporal patterns, characterizing changes in fire size, severity, and frequency over time. The results showed that the mean size of a fire that occurred in 1950 was less than the mean size of fires occurring more recently in 2010 and 2019. Fire frequency showed a slight increase, and fire severity was stable [12].

Responding to the destructive Camp Fire wildfire in Butte County, California, [6] created pre- and postwildfire maps representing elementary evacuation data and mitigation plans. This study used GIS and machine learning techniques. To map the pre- and postwildfire conditions, the authors applied Landsat-8 and Sentinel-2 imagery. To classify the pre- and postwildfire map, the authors compared a hybrid model, a support vector machine (SVM) optimized by the imperialist competitive algorithm with the unoptimized SVM algorithm. The hybrid model produced better accuracy compared with the unoptimized SVM. A total of eight pre–postwildfire burn-area maps could be used to assess the area affected by the Camp Fire wildfire to develop a well-established mitigation plan in the future [6].

Reference [20] examined the statistical correlation between weather and wildfire in 2020 while mining the available online California climate and historical spatial data from 1992 until 2011 using GIS. The authors investigated the correlation between drought conditions and wildfire number per forest unit area in California and visualized the results using GIS computing technology. They found such a correlation where no correlation between the wildfire and wind existed [20].

In 2021, [21] conducted case-study research in Southern California to prioritize wildfire restoration by applying GIS-based ordered-weight averaging (OWA). They assessed the efficacy of OWA and GIS-based multicriteria decision analysis (MCDA) techniques in determining the wildfire areas that need restoration priority. The combination of the GIS–MCDA process and the OWA technique helps develop and compare several decision maps. These maps show the restoration with prioritization and different spatial distributions. The authors concluded their research by highlighting the power of the GIS-MCDA technique as a core tool in spatial decision making [21].

Another research study was conducted to investigate the association between California’s extreme wildfire events that happened in the last three decades and the socioeconomic characteristics focusing on the census tracts and county levels [15]. The authors used two secondary data types, wildfire geospatial data and the sociodemographic characteristics collected from the Bureau of Census that include, for example, ethnicity and educational level. They employed GIS-based spatial analysis to create a map representing the wildfire geolocations for several geographic levels with the socioeconomic and demographic factors that affected the potential wildfire risk. The results showed that more-educated people and people who have higher to median income prefer to live in a community with low crime levels and fewer natural hazards. Also, census tracts with more Native American citizens are more exposed to wildfire compared to other census tracts [15].

III. Methods

A. Data Selection and Acquisition

Three datasets were used in this current research study. The main dataset had information about fire perimeters in California [22]. These data came from the ArcGIS hub and

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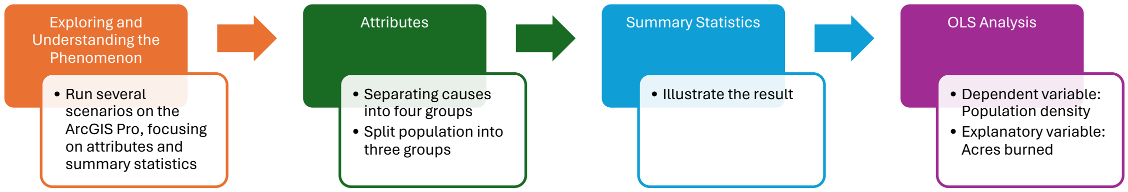

Figure 1. Used techniques and tools during the analysis phase.

were uploaded into ArcGIS Pro. The population data came from ScienceBase [23], representing the total number of people in each county. This dataset helped analyze the correlation using population information and perimeter size information for each fire. The final dataset contains California's fire-severity zones with three levels of hazard in the responsibility areas: moderate, high, and very high. The zones were developed by assigning a hazard score based on such factors as fire history, natural vegetation, terrain, blowing embers, predicted flame length, and typical fire weather in the area [22]. We used a total of 2,418 records in this study.

B. *Analysis Phase*

We used ArcGIS Pro, a full-featured professional desktop GIS application from the Environmental Systems Research Institute, Inc. (Esri), to run the analyses in a Windows environment. The OLS linear regression tool was used in the analysis after entering all data in one layer. However, before that, to explore and understand the phenomenon, several investigations and analyses were performed using ArcGIS Pro software focusing on attributes and summary statistics (see Figure 1).

To conduct the OLS analysis between population density and acres burned, we first split the population density into three groups, signified by color. Next, we ran a one-to-many spatial-join operation to combine the fire-perimeter and population-density layers to enable the extraction of the county where the fires took place. With all data in one layer, we conducted the analysis using OLS with the population as the dependent variable and the acres burned as the explanatory field. The attributes tool enabled the selection of some rows from the data that contained a certain number or a certain string in a column. After selecting the required data, we created a new map layer. This tool helped separate the causes into four groups: 1) unknown/other causes, 2) human causes, 3) natural causes, and 4) industrial causes. The attributes tool also split the population density into 1) high, 2) medium, and 3) low. This splitting facilitated the analysis to understand the correlation as discussed in the results and discussion section.

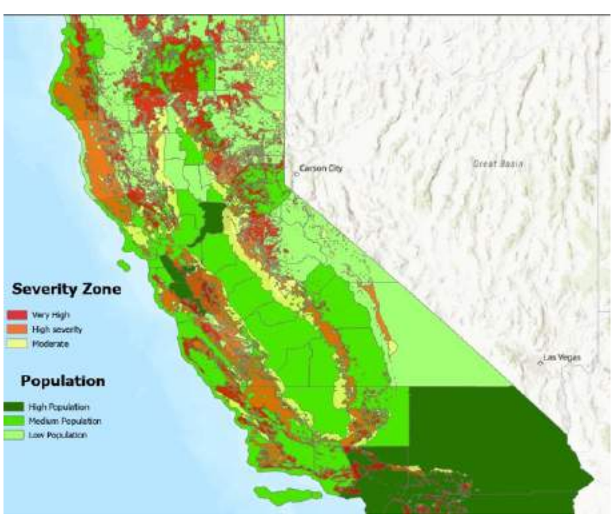

Figure 2. Fire-severity zones with the population data.

After splitting the data causes and severity zones, the summary-statistics tool was used to illustrate the number of entries in the data, the sum of all the acres burned, and the average acres burned. The summary-statistics tool presented the data in a table which helps understand and make comparisons.

IV. RESULTS AND DISCUSSION

Interesting findings have been discovered after analyzing the data. First, the analysis of the population data and the fire-severity zones helped find zones with higher or lower populations. The results from the analysis show few patterns emerge between population and severity zones (see Figure 2): High and moderate fire-severity zones appear within medium- and low-population areas.

Another analysis was conducted to further investigate the proposed correlation: Only larger fire data were included, those that burned at least 5,000 acres, and compared with population. Figures 3 and 4 illustrate where most of the huge fires took place from 2016 to 2021, mostly in Northern California (see Figure 3). Figure 4 shows no patterns exist between the bigger fires and the population as the most huge fires occurred in medium- or even low-population zones.

Another analysis focused on the four main causes of fires and acres burned (see Figure 5). The most apparent causes on the map are the natural and unknown/other causes. To get a deeper understanding, we used the summary statistics tool to return the frequency of the fires per cause, the sum of all the acres burned for that cause, and the average in each fire with that cause (Table 1).

As illustrated in Table 1, the unknown/other cause is responsible for most fires. However, the unknown/other cause is just a third of the mean of acres burned. Also, interesting was that natural causes were first for the average acres burned, which means that the natural causes created fewer but more destructive fires.

Following the exact technique above, we broke the human-causes attribute into five unique associated types (Figure 6). As shown in Table 2, equipment use is a more frequent cause of fire with 298, but its mean acres is just 481.3095. Campfire burned the most acre (180,044.4) and the highest mean (3,830.73). The least cause is smoking where the frequency is 14 and the mean of acres is 78.8814.

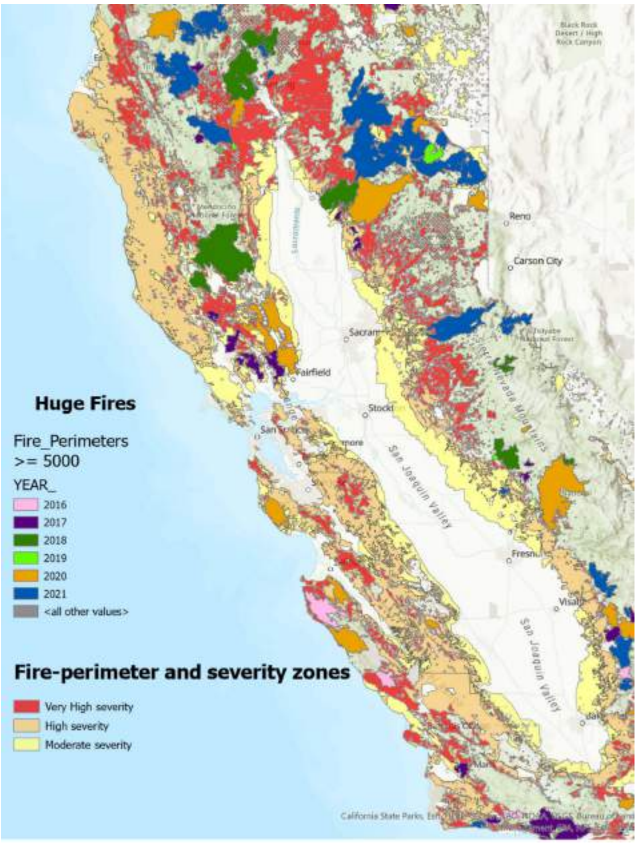

Figure 3. Huge fire locations.

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Two subcauses of the natural causes were debris and lighting. We created a new layer for each cause based on the selection in ArcGIS Pro. The separate layers help visualize fires based on their specific causes. Lighting is the most common natural cause with also higher means of acres compared to debris (Figure 7 and Table 3).

Using the same techniques for the industrial revealed five unique cause types (Figure 8 and Table 4). The most frequent cause is vehicle while the higher mean of acres is powerlines. The least frequent are both railroad and aircraft causes while the acres mean for the railroad is higher than aircraft.

TABLE I. CAUSES AND BURNING ACRES

Cause	*Frequency*	*Sum of acres*	*Mean of acres*
Unknown/other	1,189	3,023,862.61	2,543.20
Human	525	464,800.54	885.33
Natural	495	2,845,918.36	5,749.33
Industrial	355	1,609,638.03	4,534.19

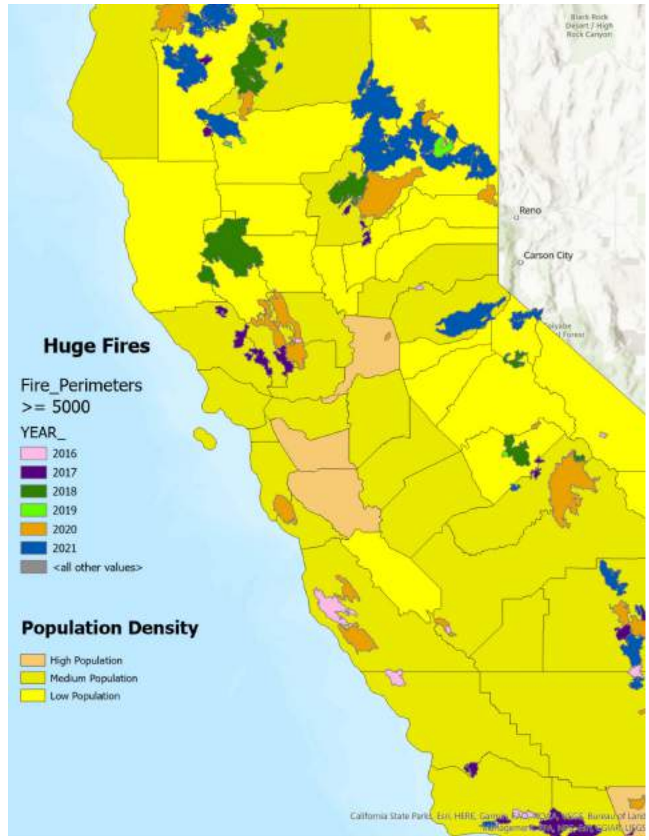

Figure 4. Huge fire with the population.

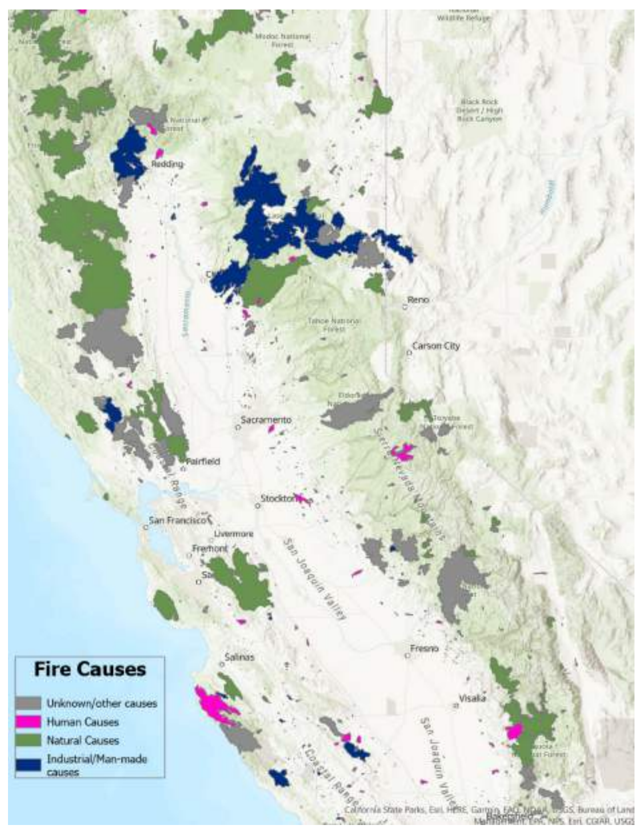

Figure 5. Causes and acres burned.

Figure 6. Human causes.

Figure 7. Natural causes.

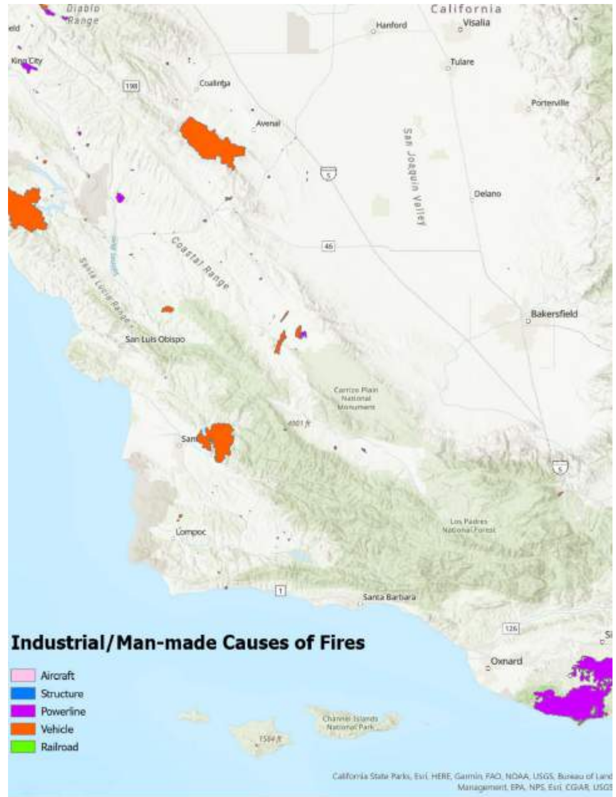

Figure 8. Industrial causes.

TABLE II. HUMAN CAUSES

Cause	*Frequency*	*Sum of acres*	*Mean of acres*
Equipment Use	298	143,430.2	481.3095
Smoking	14	1,104.34	78.8814
Campfire	47	180,044.4	3,830.73
Arson	125	135,449.9	1,083.6
Playing with fire	26	2,325.25	89.4327
Escaped prescribed burn	15	2,446.46	163.0973

TABLE III. NATURAL CAUSE TYPES

Cause	*Frequency*	*Sum of acres*	*Mean of acres*
Lightning	393	4,620,219.4	11,756.28
Debris	102	62,338	611.157

TABLE IV. INDUSTRIAL CAUSE TYPES

Cause	*Frequency*	*Sum of acres*	*Mean of acres*
Railroad	3	427	142.3333
Vehicle	198	368,135.4	1,859.27
Powerline	144	1,240,273.5	8,613.01
Structure	7	502.15	71.7357
Aircraft	3	300	100

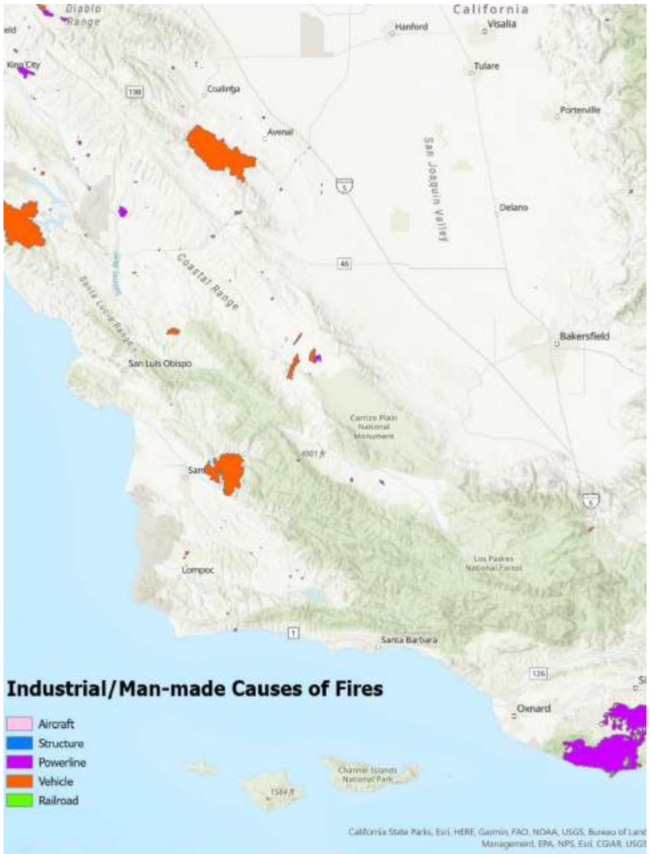

Figure 9. Fire-perimeter and severity zones.

TABLE V. FIRE-PERIMETER AND SEVERITY ZONES

Severity	*Frequency*	*Sum of acres*	*Mean of acres*
Moderate	633	149,997.29	236.96
High	608	207,325.72	340.99
Very High	1,323	7,586,896.53	5,734.62

Another investigation joined the fire-perimeter and severity zones (Figure 9). After the joining, the summary-statistics tool was used to learn how frequently the fires occurred in the area, the sum of acres burned in the severity zone, and the average acres burned per zone (Table 5).

The results showed that the very-high-severity zone accounted for over half of the fires that had occurred with a mean of acres of 5,734.62. It also had a very high sum of acres burned compared to the moderate- and high-severity zones.

To test the hypothesis, correlation analysis through OLS was conducted between population density and the number of acres burned. The results showed that the multiple R^2, which reflects the model performance, is 0.000009, a significantly low value. The adjusted R^2, which reflects the model significance, is −0.000405. This means that no correlation exists between the population density and the number of acres burned, rejecting the research hypothesis.

Multiple studies have been conducted related to wildfires in California [4][21][24]. However, most of these studies used different techniques and methods and had different aims compared to this study. For example, in 2022, [25] performed a study to mainly evaluate the grazing effect on burn probability in California. The authors combined fire time series from 2001 through 2017 with environmental and socioeconomic covariate and grazing data. To analyze the data, they applied preregression matching and mixed-effects regression. The results show that a decrease in annual burn properties is linked to livestock grazing [25].

Since the risk associated with wildfires caused by smoke is a major concern across the United States including the Wildland–Urban Interfaces (WUI), [26] focused on the fire-danger trends over time. The authors used ArcGIS to perform their study including data from 1990 to 2010 [26] and concluded that the fire danger has increased over time during the peak season in the United States. This growth affects the WUI area as well as the people who live there. The authors also examined the relationship between fire danger and population density, finding that fire danger is increased in all medium and high densities whereas a decrease in fire danger occurred in the lowest population density [26]. This is in contrast to one of our analysis results focused on the population data and fire-severity zones. In this current study, the results indicate no pattern or relation between these two variables. One reason could be that in [26], the authors included all populations from the WUI area and others, which may affect their results. Also, different data in their study and this current study may also contribute to different results.

There is a need to develop proactive measures to prevent wildfires in California and elsewhere, which have increased in the last two decades. Reference [27] conducted a detailed analysis across California of the spatiotemporal distribution of the larger wildfires, concentrating on the human causes and others [27] using CAL FIRE data for the past two decades (2000–2019). The study showed that even though the total burned area increased, the mean burned area was still stable. Most of the wildfires were caused by humans. Natural factors were also common causes of wildfires in California. Far away from the human community, climate, and vegetation cover were the most important factors, especially the areas with heavy grass coverage, high temperature, and high vapor-pressure deficit [27]. The results are aligned with the findings in this study: Human, industrial, and natural are major causes. Hopefully, that can be managed by increasing public awareness campaigns.

V. CONCLUSION, LIMITATIONS, AND FUTURE WORK

The increased number of wildfires in California and the consequences of these fires have caused several researchers to study the phenomena for better understanding or to find useful solutions. In this research, the main aim is to examine the correlation between population density and the number of acres burned in an area. We conducted analysis in ArcGIS Pro and with OLS spatial Statistics tool. Fire-perimeter cause data were further analyzed in multilabel scenarios at different layers. The main findings are that there is no correlation between population density and acres burned (R^2 = 0.000009) where more wildfires are caused by humans than by nature. However, population density does not affect fire severity. More awareness campaigns must be conducted at the state level and might help reduce the number of acres burned. Thus, policy and decision makers must focus more on that activity.

One of the research limitations is the data used for the analysis since some causes were classified as unknown/other. If the causes were known, the results may change. Thus, as a future direction, interviews may be conducted to classify those causes, or other data may be used. Another future direction is to change the analysis techniques by, for example, using the Kernel density estimation (KDE) Spatial Analyst tool within ArcPro and/or other techniques to create a map of statistically significant hot spots for wildfires.

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