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Are Wildfires Coming Closer to Our Doors? Analysis in Spain and California 2007-2015

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Abstract: Wildfires present a significant risk to societies globally due to population growth, con- centrated activities, climate change, and extreme environmental conditions. To establish effective fire suppression and management policies, it is crucial to determine whether the distance between ignition points and urban areas is increasing or decreasing. This study analyses 101,597 fires in Spain and California between 2007 and 2015, using the Mann-Kendall test to determine trends. The study analyses the location and cause of fires to determine their distance from human constructions over time at two spatial scales. The findings suggest that wildfires are not moving away from buildings and, in some areas, are moving significantly closer.

Keywords: wildfire; trends; built-up; ignition points; WUI

1. Introduction

In the year 2022 Senande-Rivera et al. [1] presented a world map of fires and the bleak forecasts for the future. More recently, Calkin et al. [2] reflected on the question of whether the fires affecting urban areas were not forest fires, or at least not the fires to which we are accustomed.

Numerous authors have studied forest fires from various perspectives, including their causes [3–6], effects on soil [7–9], vegetation [10–12], and impact on animal populations [13,14], both positive [15,16] and negative [17]. It is increasingly important to examine the economic and social consequences of forest fires. Studies have been conducted on the impact of fires on the economy [18–22], employment [23,24], and the cost of damage to infrastructure [25–28], buildings [29–31], and homes [32–36]. All of these works, with varying objectives, methodologies, and areas of study, enable us to partially comprehend the causality and consequences of fires.

Previous studies on fires have highlighted the significance of the location or physical space where the fire occurs. Researchers have analyzed various aspects such as the frequency of fires in a particular area [37–43], the danger or risk of wildfires [44–48], and the size and area burned [49–53]. The process of how fire approaches buildings [29] has been a major concern for researchers.

The term wildland-urban interface (WUI) refers to *the urban wildland interface com- munity exists where humans and their development meet or intermix with wildland fuel*. This concept has gained importance since the beginning of the 21st century [54,55], particularly in analyzing the risk of fires and the presence of different types of buildings, vegetation, and factors related to the population. The classification of WUI in the past has been based on the likelihood of fire occurrence and vulnerability [56,57] of settlements. However, these classifications lack generality with regards to the fire regime [58]. Bento-Gonçalves and Vieira [59] provides a comprehensive overview of research on WUI from various perspectives. However, it does not include any papers that analyze the spatiotemporal evolution. In the same year, Intini et al. [60] conducted a review of the variables, standards, and guidelines used to establish WUI zones in different countries and areas of the world.

This review highlighted that fire history is not taken into consideration when defining WUI zones in California or Spain. In a recent paper, Taccaliti et al. [61] reviewed 162 scientific publications from 1983 to 2022 on the definition and interpretation of WUI and its application in different territories. Among these works reviewed, only Tolhurst et al. [62] provides a dynamic definition that accounts for the variability of the interface zone based on weather, fuel, fire scale, and terrain.

The aim of this study is to determine whether the ignition point of fires in two areas, which have been highly affected by fires, has moved closer to or further away from buildings in recent years, based on available data. By

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establishing whether there is a clear pattern of behavior in each territory or if there are spatial and/or temporal changes, we can determine strategies for delimiting the WUI and firefighting with greater precision.

2. Materials and Methods

2.1. Overview of the Study Area

2.1.1. Spain

This work analyses wildfires recorded in Spain from 2007 to 2015. Data were obtained from the General Forest Fire Statistics available at the Spanish Government Data Portal (https://datos.gob.es/en/catalogo/e05068001-estadistica-general-de-incendios-forestales). The dataset covers the period from 1983 to 2015 and provides details on the spatial coordinates and time of ignition for each point, along with information on the cause of the fire, suppression time, and burned area. The regional governments report this data to the Ministry. Before 2007, over half of the regions did not provide coordinate values. Therefore, 2007 was chosen as the starting date for the study. From 2007 to 2015, the regions of the Canary Islands, Cantabria, the Basque Country, Madrid, and Navarre had more than 50% of missing coordinates in one or more years, so they were excluded from the study. The regions studied are those depicted in the Figure 1.

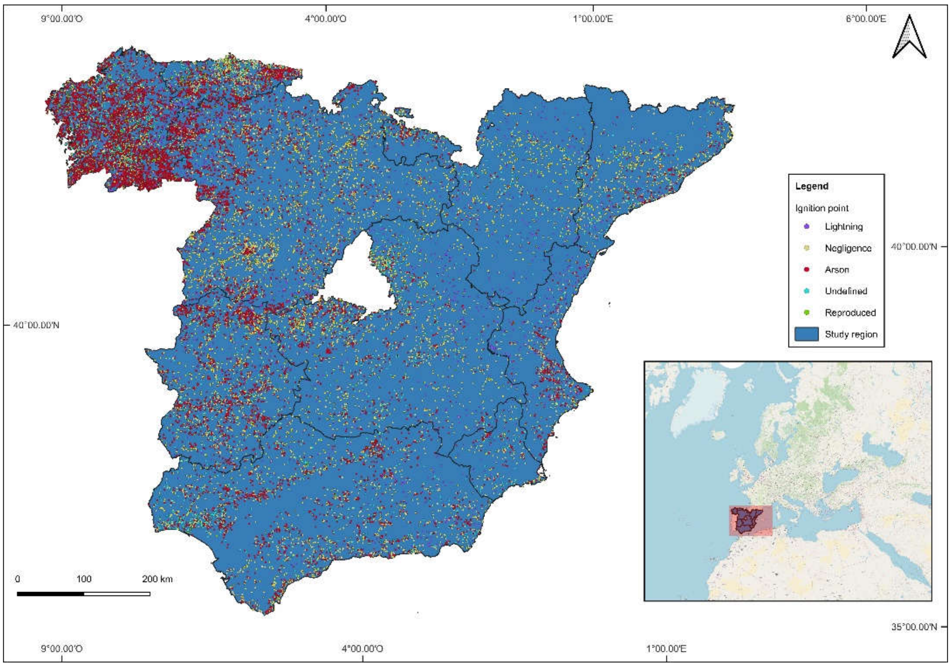

Figure 1. Forest fires occurring between June and October from 2007 to 2015, Spain.

This article focuses on the summer fire season, which lasts from June to October in southern Europe [63]. Wildfires are most concentrated during this period, with the majority of the burned area occurring at this time. The distribution of wildfires in Spain is shown in Table 1.

Table 1. Forest fires 2007-2015, Spain.

Year	Total number of fires	Total burnt area (ha)	Number of fires June- October	Burnt area between June-October (ha)	% of total fires between June-October	% of total area burnt between June and October
2007	5590	53310	2801	39494	50.1	74.1
2008	6552	41870	2604	20825	39.7	49.7
2009	8953	119400	3977	88626	44.4	74.2
2010	6298	47179	3791	35479	60.2	75.2
2011	9893	93248	6369	71505	64.4	76.7
2012	9483	207508	3403	151693	35.9	73.1
2013	6023	61486	4351	52566	72.2	85.5

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2014 5301	41391	2449	21708	46.2	52.4
2015 6716	108806	3521	77935	52.4	71.6

Table 2 displays the distribution of fires according to their causes.

Table 2. Forest fires 2007-2015 by cause, Spain.

Cause	Total number of fires	Total burnt area (ha)	Number of fires June-October	Burnt area between June-October (ha)
Arson	37341	377102	18181 (48.7%)	227841 (60.4%)
Lightning	1669	43319	1489 (89.2%)	40584 (93.7%)
Negligence	18648	290440	9494 (50.9%)	243027 (83.7%)
Repro-duced	1139	20555	818 (71.8%)	15844 (77.1%)
Undefined	6012	42782	3284 (54.6%)	32533 (76.0%)

The data show that forest fires during the period under review were mainly caused by negligence and arson, which together accounted for more than 60% of the total area burnt.

2.1.2. California

The Californian data is sourced from the U.S. Department of Agriculture [64] and shares similar data fields with the Spanish data, including coordinates of ignition points, causes, suppression time, and burnt area. The data has been processed to correspond with the same period as that chosen for Spain, ensuring comparability. See Table 3 and Figure 2 for more information.

Table 3. Forest fires 2007-2015, California.

Year Total number of fires	Total burnt area (ha)	Number of fires June- October	Burnt area between June-October (ha)	% of total fires between June-October	% of total area burnt between June and October
2007 5427	422788	3622	406816	66.7	96.2
2008 5231	578717	3740	548030	71.5	94.7
2009 4069	188592	2957	179186	72.7	95.0
2010 3300	48848	2792	45571	84.6	93.3
2011 4601	77683	3467	72879	75.4	93.8
2012 3868	307801	2700	303423	69.8	98.6
2013 4403	237287	2563	195918	58.2	82.6
2014 2828	221176	1766	206518	62.4	93.4
2015 3061	343332	2215	335022	72.4	97.6

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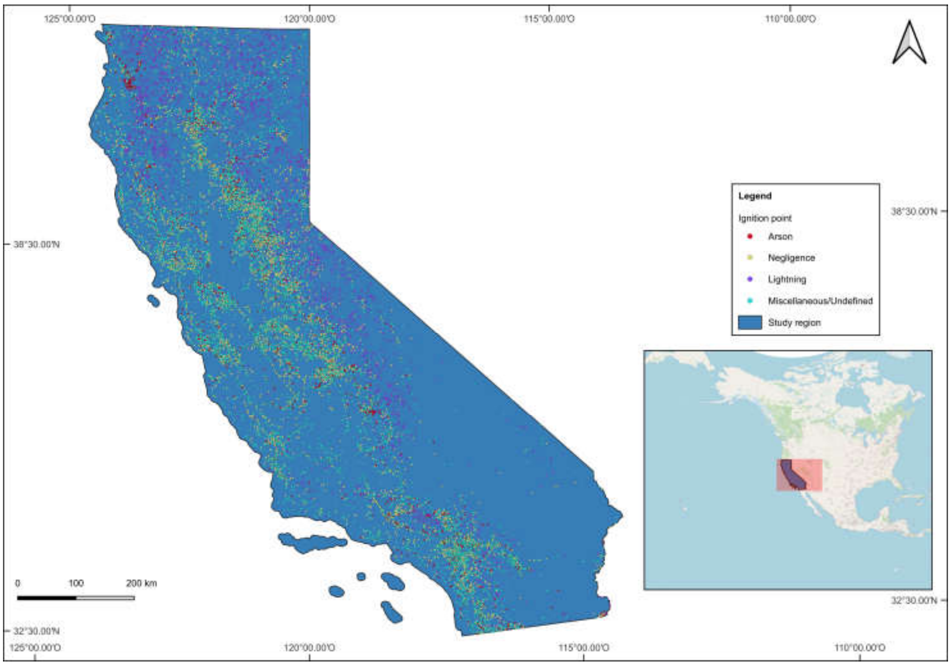

Figure 2. Forest fires occurring between June and October from 2007 to 2015, California.

Table 4 displays the distribution of fires in California according to their causes.

Table 4. Forest fires 2007-2015 by cause, California.

Cause	Total number of fires	Total burnt area (ha)	Number of fires June-October	Burnt area between June-October (ha)
Arson	3075	121108	2307 (75.0%)	118156 (97.6%)
Lightning	3462	1055175	3293 (95.1%)	1045989 (99.1%)
Misc/undefined	18435	776272	13111 (71.1%)	683524 (88.1%)
Negligence	11816	473670	7111 (60.2%)	445694 (94.1%)

The distribution of fires differs significantly from that in Spain. Arson is a residual factor, while lightning has a significant impact on the burnt area, but not on the number of fires.

2.2. Global Human Settlement Layer (GHSL)

The Global Human Settlement Layer [65] project is supported by European Commission, Joint Research Center and Directorate-General for Regional and Urban Policy. As described in project page: *these data contain a multitemporal information layer on built-up presence as derived from Landsat image collections (GLS1975, GLS1990, GLS2000, and ad-hoc Landsat 8 collection 2013/2014). The data have been produced by means of Global Human Settlement Layer methodology in 2015. The main product is the built-up area grid published in the production grid at high resolution, i.e. at around 38m*. The distance from ignition points to the nearest built-up was determined using SQL queries and a postgis database [66]. The layer's overall situation is illustrated in Figure 3 and Figure 4.

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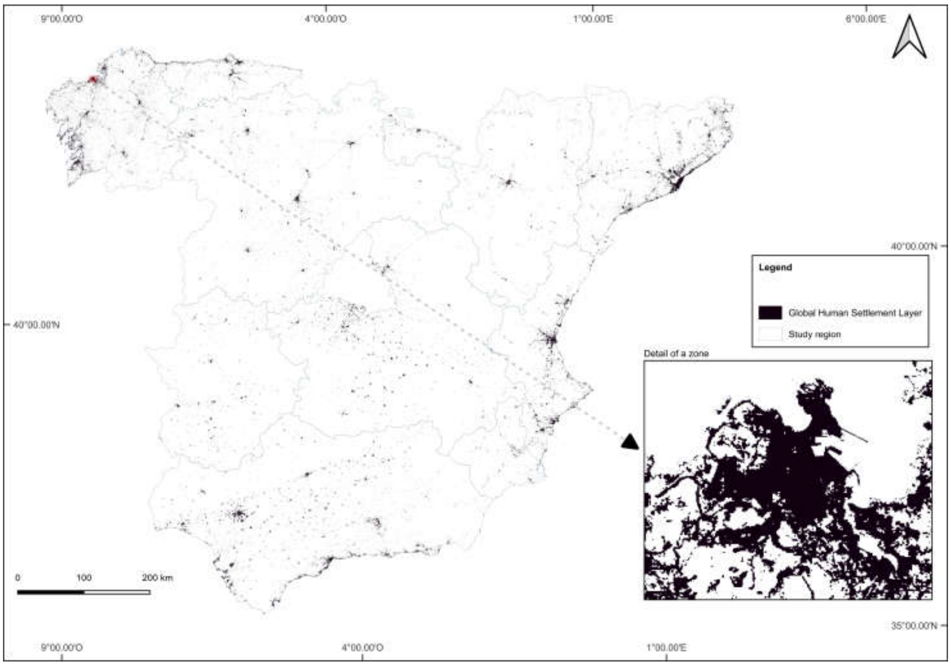


Figure 3. GHL layer, Spain.

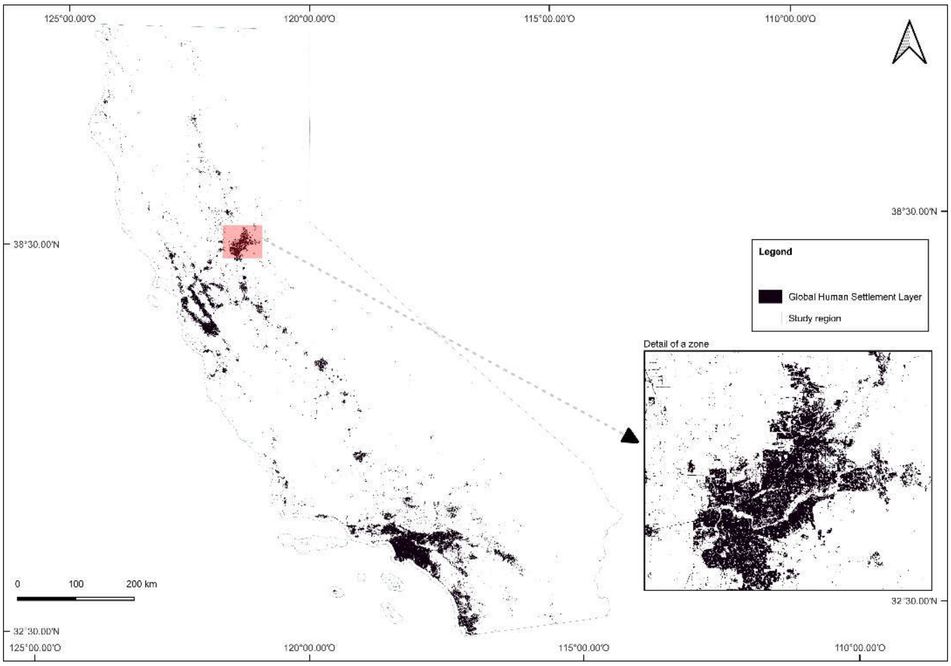


Figure 4. GHL layer, California.

2.3. Discrete Global Grid

As noted by Wang et al. [67], traditional lon/lat grids are unsuitable for global analysis due to problems such as spatial distortions, fractures, inconsistency of spatial relationships, and data overlap. To address these issues, a Discrete Global Grid (DGG) partitions the Earth's surface into uniform cells, each containing a single region. This logical structure avoids the common problems associated with traditional grids [68]. This article analyses temporal trends at different spatial scales using two grids (levels 8 and 9; 7774 and 2591 kms^2 respectively) created by DGGRID [68] with an Icosahedral Snyder Equal Area Aperture 3 Hexagonal Grid. Each cell was assigned the monthly median distance to the nearest building from the ignition points, based on the provided data.

2.4. Methods

The Mann-Kendall test [69,70] was applied to analyze temporal changes in proximity from ignition points to buildings. This test is a non-parametric statistical test that determines the significance of long-term trends without making assumptions about the underlying distribution of data or specifying whether the trend is linear or non-linear. The test checks for the presence of a monotonic upward or downward trend. It is a rank-based procedure, resistant to the influence of extremes, good for use with skewed variables [71] and insensitive to missing values [72]. The Mann-Kendall statistic, S, is calculated as follows: $S = \sum_{k=1}^{n-1}\sum_{j=k+1}^{n} sign(x_j - x_k)$ where:

$$sign(x_j - x_k) = \begin{cases} +1, x_j - x_k > 0 \\ 0, x_j - x_k = 0 \\ -1, x_j - x_k < 0 \end{cases}$$

x represents data points, n the length of the data points and xj represents the data point at time j. The calculation of probability is related to S and n. When n ≥ 10, S is generally in a standard normal distribution and the variance is computed as follows:

$$VAR\ (S) = \frac{n(n-1)(2n+5) - \sum_{j=1}^{m} x_j(x_j-1)(2x_j+5)}{18}$$

where m is the length of the tied group.

The statistic Z is calculated using the following equations:

$$Z \begin{cases} \frac{S-1}{\sqrt{VAR(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{VAR(S)}}, S < 0 \end{cases}$$

The trend is said to be decreasing if Z is negative and the computed probability is greater than the level of significance. The trend is said to be increasing if the Z is positive and the computed probability is greater than the level of significance. If the computed probability is less than the level of significance, no trend is present. In this study, the significance level $\alpha = 0.05$ is applied. Yue and Pilon [73] showed that the Mann-Kendall test and the bootstraped version have the same statistical power. In this study we used the latter. Therefore, we estimated the p-value (p_s) of the S_0 observed sample data using the bootstrap empirical cumulative distribution (BECD~$\hat{S}^*$curve) as:

$$p = \frac{m_S}{M}$$

where M is the total number of bootstrapped resamples (1000 in this study) and m_s is the rank corresponding to the largest value $\hat{S}^* \leq S_0$.

The Mann-Kendall test does not require any assumptions about the data distribution. However, it does require that the data be serially independent, meaning that there is no autocorrelation in the time series. To determine the presence of autocorrelation, we performed a Ljung-Box test [74]. If the test was positive, we used a modified version of the Mann-Kendall test for autocorrelated data [75–78].

Kendall [70] indicated that this test can be used even if N is as low as 10 provided that there are not too many tied values, so cells with low occurrence of wildfires (less than 10 months of data) were excluded.

All the statistical analyses were performed using R and package "modifiedmk" [79].

3. Results

It is important to note that, despite differences in socio-economic factors, land structure, and fire characteristics, there is no area in California or Spain where fires have a statistically significant tendency to begin further away from human-built areas. On the contrary, fires in some areas show a significant tendency to start closer to urbanized zones. However, this effect varies depending on the case.

Figure 5 and Figure 6 show the global results for Spain. Red flags indicate areas where the distance from ignition points to buildings tends to decrease. Consistency in the results was observed at both observation scales in the center of Spain, while differences were found in western and eastern Spain. As cells size decreases, less data is available for each one and may explain this differences, causing an effect similar to the modifiable areal unit problem [80,81].

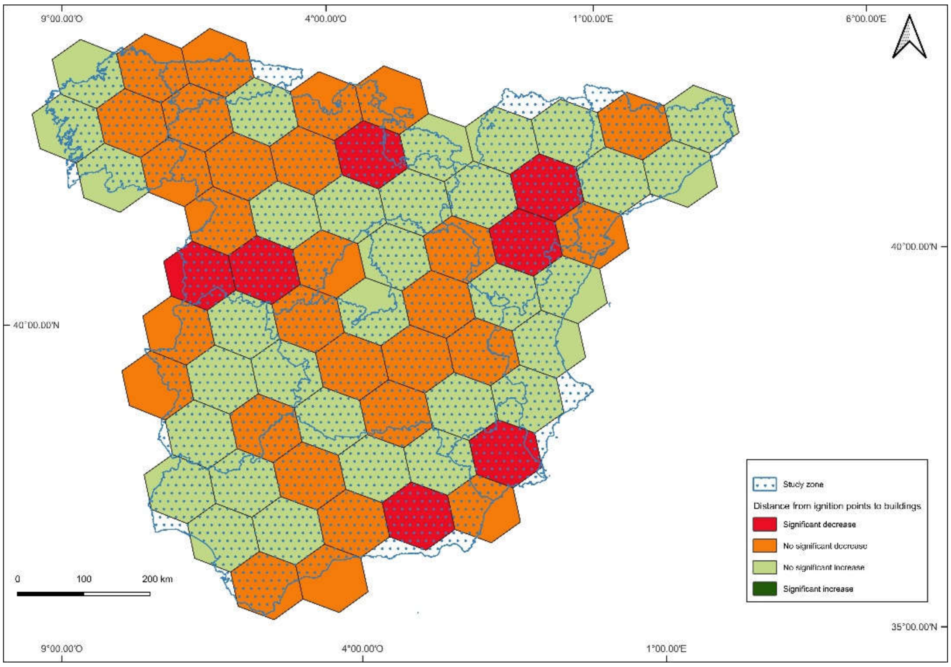


Figure 5. Mann-Kendall test, Spain, Resolution 8.

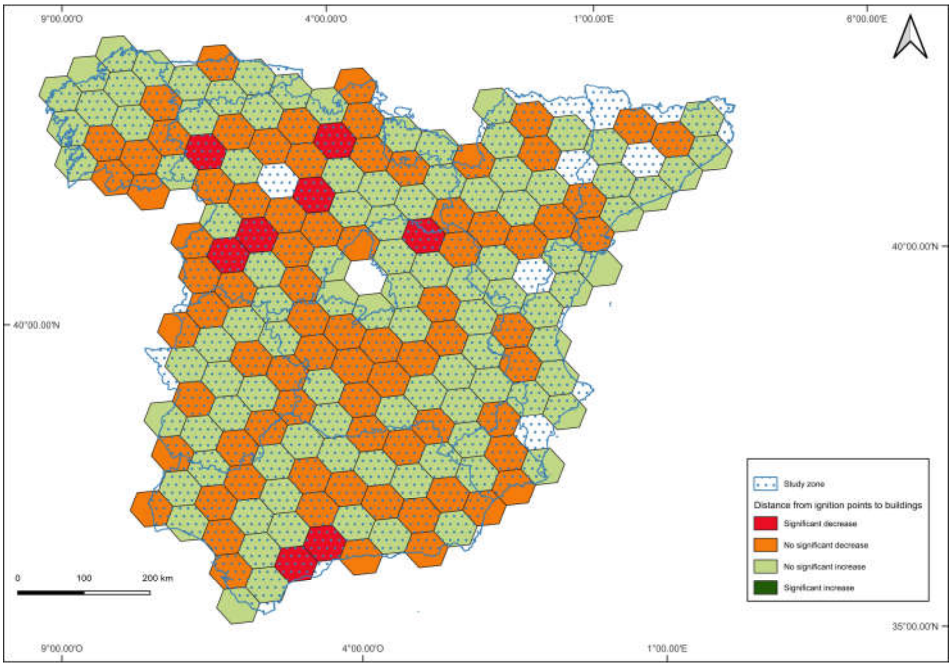
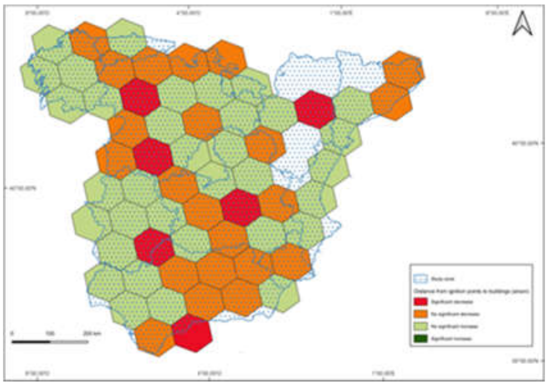


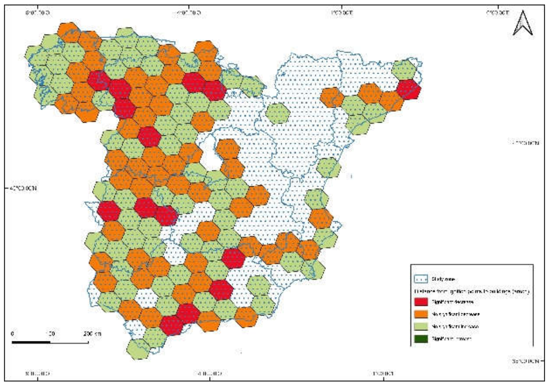
Figure 6. Mann-Kendall test, Spain, Resolution 9.

When analyzing the results of the Mann-Kendall test for Spain segmented by cause, it is observed that for arson fires (Figure 7a and Figure 7b), there are several areas in the west where the tendency to start closer to human constructions is statistically significant for both scales of observation. Figure 1 illustrates that this is where arson is most significant. However, in the central and eastern regions, there are extensive areas with such a low occurrence of this type of fire that analysis at resolution 9 is not feasible. Furthermore, there is no correlation between the findings of the two maps in these regions. For negligent fires, significant downward trends are found at 6.0% of total area in resolution 8, decreasing to

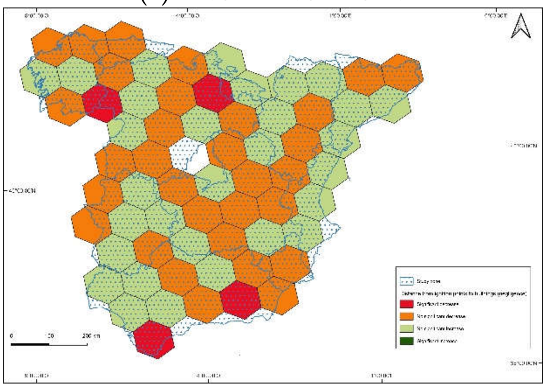
3.9% in resolution 9. Lightning caused, reproduced and unknown fires are too sparse and infrequent to be analyzed.



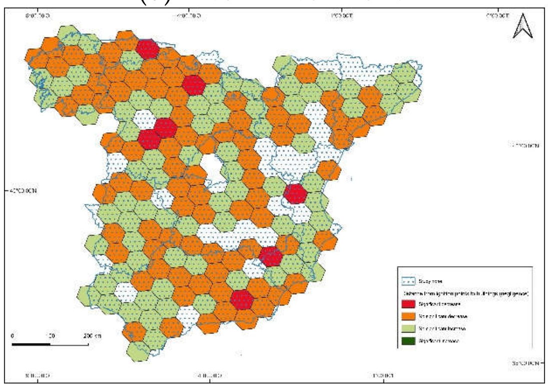
(**a**) Arson. Resolution 8



(**b**) Arson. Resolution 9



(**c**) Negligence. Resolution 8



(**d**) Negligence. Resolution 9

Figure 7. Mann-Kendall test by cause, Spain.

The Mann-Kendall test results for California (see Table 5 and Figure 8 through Figure 10h) show differences between zones and spatial scales. As can be seen in Figure 2 the distribution of fires by cause in California is not uniform and appears to be the source of these differences.

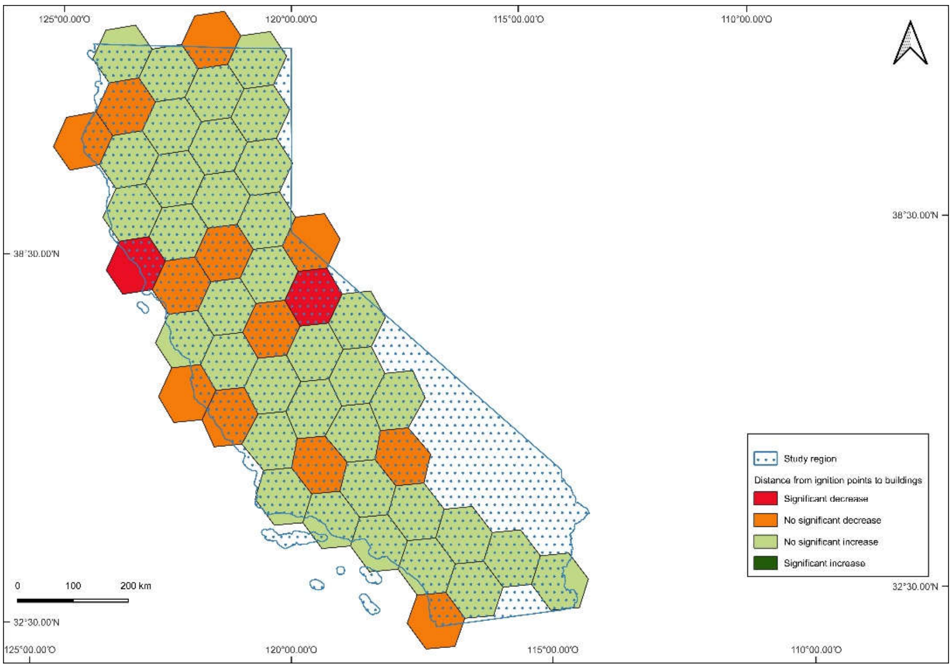


Figure 8. Mann-Kendall test, California, Resolution 8.

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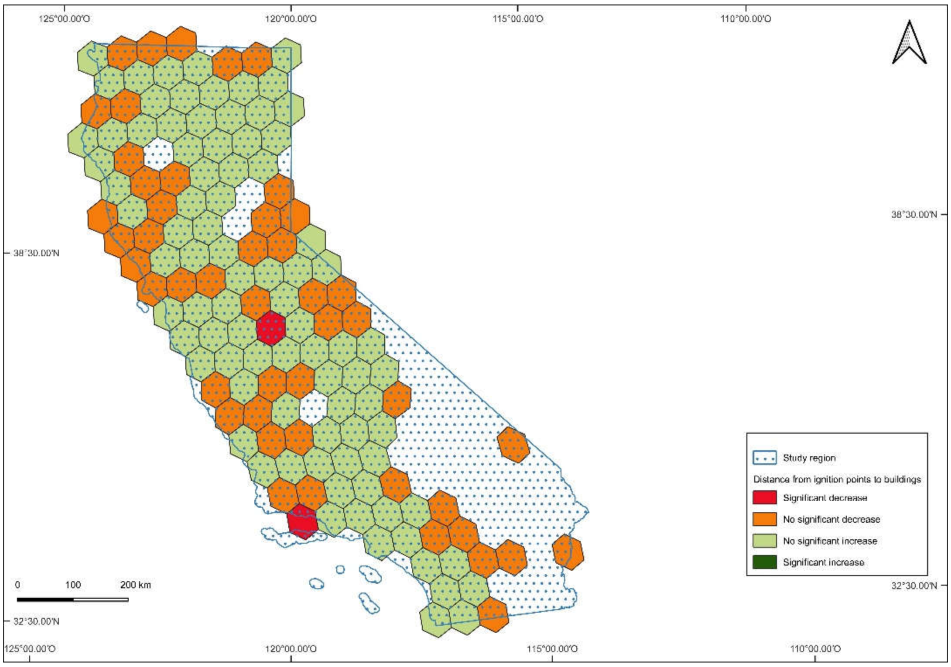
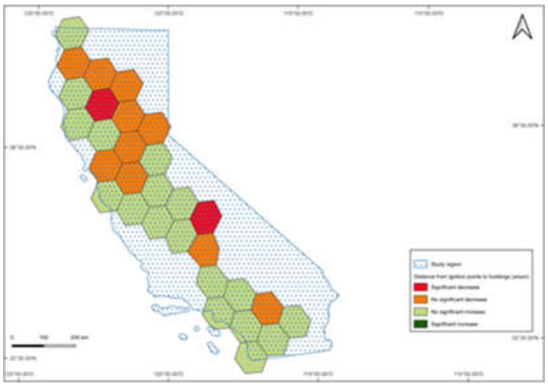
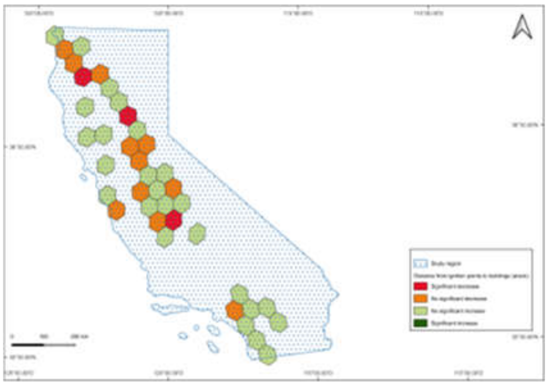


Figure 9. Mann-Kendall test, California, Resolution 9.

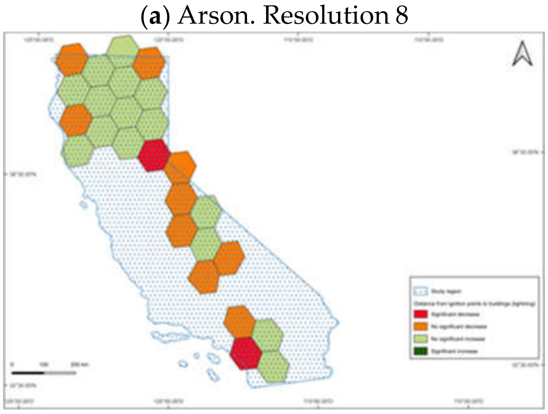
It is noteworthy that the areas where arson tends to start progressively closer to the buildings (Figure 10a and Figure 10b) are located on the edge of populated cities.



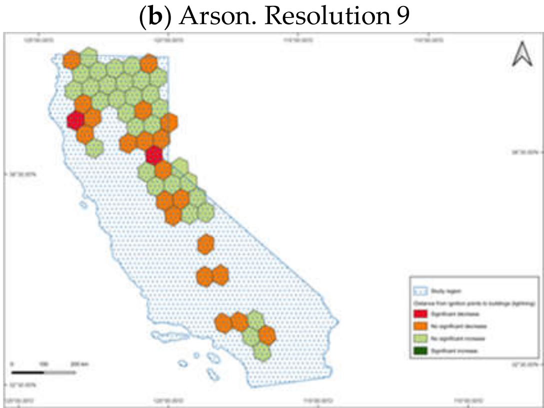
(**a**) Arson. Resolution 8



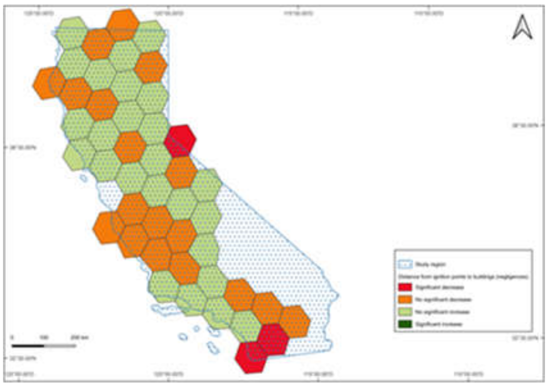
(**b**) Arson. Resolution 9



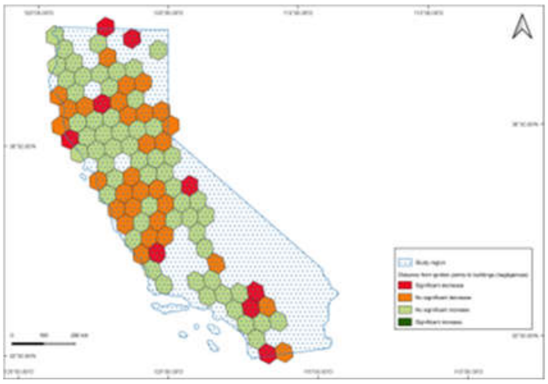
(**c**) Lightning. Resolution 8



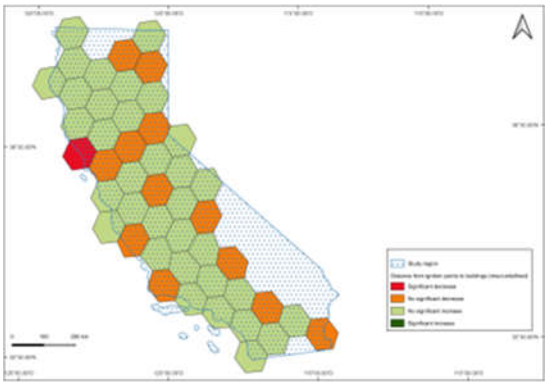
(**d**) Lightning. Resolution 9



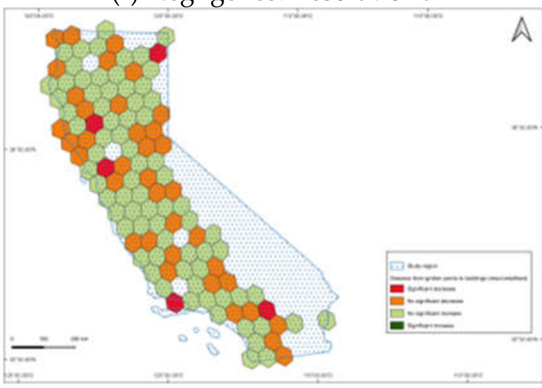
(**e**) Negligence. Resolution 8



(**f**) Negligence. Resolution 9



(**g**) Miscellaneous/undefined. Resolution 8



(**h**) Miscellaneous/undefined. Resolution 9

Figure 10. Mann-Kendall test by cause, California.

Table 5. Mann-Kendall test results, significant downward trend ($p_s < 0.05$), California.

Cause	% of area at resolution 8	% of area at resolution 9
All causes	3.8	1.4
Arson	6.3	7.0
Lightning	7.4	3.5
Misc/undefined	2.0	4.2
Negligence	6.2	9.3

4. Discussion

Our research is unique in that it compares fire trends in two geographically distant regions with similarities and differences in their relationship to fire. To the best of our knowledge, this type of analysis has no scientific precedent. Previous studies on forest fires have either focused on general patterns at global scale [82,83] or on a continental or subcontinental level [84,85] but not in the evolution of relative positions of fire and built up areas.

Previous studies at subregional scales, such as [5,37,43,86] or [87], and for the entire study region, such as [50,88–92], have analyzed fire statistics using various techniques. This allows us to make partial comparisons with our results. In general, summer fires exhibit a spatial distribution throughout the study period with certain irregularities in both regions. This is a common occurrence in Mediterranean climate zones, as previously noted by authors such as Calheiros et al. [93] in the case of Spain and Yadav et al. [94] for California. These authors attribute the occurrence of more or fewer fires in summer to climatic variability [95,96], which is a fundamental factor. They also note that other socio-economic variables [5,6,24], irregularly distributed across the territory, are associated with increased fire activity.

The scientific community [97] has been discussing the selection of a spatial scale for studying wildfire forecasting. The spatial scale of distribution-based approaches varies from fine-scale grids, which are typically 1 km x 1 km or smaller [98–101], to larger scales of approximately 10 km x 10 km [102–104], multiscalar [105,106] or by using computerized and artificial intelligence techniques [107,108]. Throughout the work, we aim to ensure the robustness of our results by validating them at different spatial scales, which is a crucial aspect of classical landscape analysis [109,110]. The limits of the analysis were motivated by the lack of data in some cells, either generally or for certain fire causalities. When

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comparing our results to the scheme presented in Parisien and Moritz [111] on the dominant factors affecting fire at multiple spatial and temporal scales, we observe that the results remain relatively constant even when changing the spatial scale. Several authors have conducted spatio-temporal studies of fires using different methods and window sizes [37]. The authors have recently conducted a study on a wider region [5], differentiating between fire causality. They found notable differences in the spatio-temporal behavior of arson and negligence, with clustering patterns that change over time. In contrast, natural patterns maintain a constant distribution. For this region, we analyzed the evolution of fire-causing conflict behavior using both zero-one-inflated structured additive beta regression techniques [98]. We found that the behavior evolved spatially and temporally.

The analysis revealed that there were no cells in the different scales examined for the two regions where fires were significantly moving away from buildings. This result partially supports Calkin et al. [2] proposal that fires are increasingly encroaching on buildings, highlighting the need for us to prepare for living with fire [112]. The findings do not provide a clear indication of the fires' approach to the buildings. Instead, the situation can be described as spatially stable with a tendency for some areas to become closer. In both California and Spain, there are few zones that show significant values of approach over time, demonstrating the stability of the affected areas. Chen and Jin [113] demonstrated that fires in California follow consistent patterns in terms of their probability of occurring in specific areas of the territory, but differ in terms of their causality. Galizia et al. [114] explained the distribution of fires at a European scale and identified the areas where they were more frequent. Bugallo et al. [92] used zero-inflated negative binomial mixed model techniques to identify fire behavior patterns and explanatory variables in Spain. Boubeta et al. [115] also used mixed models, specifically Poisson, to predict constant fire behavior in fire areas. These findings are consistent with previous research indicating that fires tend to occur repeatedly in the same areas, albeit in smaller numbers. Our contribution enables us to determine whether more detailed behavioral patterns exist that explain the relationship between fire and human infrastructure, which has not been adequately studied and compared in two regions such as Spain and California.

In terms of cause distribution, there is an issue with the varying classifications between California and Spain. In Spain, lightning or natural fires are infrequent [5,116,117], making analysis unfeasible due to a lack of data. Therefore, the Spanish fires analyzed are of the arson or negligence type. Regarding arson, it has been observed that fires tend to occur closer to buildings in areas where fires are not frequent and where structural reasons cannot explain the cause of arson [95,118,119]. These are areas where fires occur occasionally, and their origin is often due to conjunctural reasons, such as negligence [120], which can give rise to a certain random character while maintaining a certain spatial pattern. In their analysis of the Galicia region, where half of Spain's fires occur, Marey-Perez et al. [5] found that the distribution of natural wildfires remained stable over the years, with a high incidence in summer and in the eastern area of Galicia. Arson wildfires exhibit aggregated patterns, with a strong interaction between outbreaks and fires. Their distribution varied both over and within years, with high incidence shifting between the southern and western areas. High hazard was observed in early spring and late summer. Negligence wildfire patterns show short-distance aggregation, and their spatial distribution also varied between and within years.

In California, fire causes are classified more broadly. When compared to Li and Banerjee [50] study of all fires by cause between 1920 and 2019, it becomes clear that natural and human-caused fires follow different patterns in time and space. Natural fires are primarily concentrated in the northern part of the state, whereas arson and human-caused fires tend to occur in a north-south direction along the Central Valley and the Sierra Nevada area, between Plumas and Tulare counties. These fires have caused significant damage to buildings [121,122]. Chen et al. [123] found that population density and its increase were significant factors in explaining a large number of arson fires. Yadav et al. [94] suggested that sociodemographic characteristics of the population could also explain fire behavior. It is worth noting that cells in which fires had a significant approach to buildings were relatively rare, but they were located in areas where more fires occurred. For natural fires, the situation is concentrated in the north, specifically in Humboldt to Modoc counties, which are generally less affected by fires [124]. Fires caused by natural causes in California follow more random patterns [121], although there are explanatory factors, such as the presence of mixed conifer forests, that facilitate the spread of fires when the right environmental conditions are present.

5. Conclusions

Summer wildfires are a significant environmental, social, and economic problem in many regions of the world, including Spain and California. It is necessary to establish methodologies and conduct scientific research to help reduce the problem. It is of great interest to determine rigorously the evolution of the distance between the point of origin of forest fires and human constructions. Our work makes an interesting contribution in this regard.

Based on all fires located and classified by cause, the results obtained allow us to draw a clear conclusion: summer fires in Spain and California are not moving away from human constructions during the analyzed period. It is not possible to assert with the same level of certainty that there is a statistically significant trend towards approximation in a general sense. However, certain trends of approximation have been observed globally, in specific areas or by cause, which should be considered and subject to further analysis.

In the future, research teams, including ours, can conduct a detailed analysis of the reasons and explanations for the persistence of fires and their occurrence in specific areas and under certain conditions. Such results will advance the science of forest fires and improve citizen safety.

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Abbreviations

The following abbreviations are used in this manuscript:

WUI Wildland-urban interface

References

1. Senande-Rivera, M.; Insua-Costa, D.; Miguez-Macho, G. Spatial and temporal expansion of global wildland fire activity in response to climate change. *Nature Communications* **2022**, *13*, 1208. https://doi.org/10.1038/s41467-022-28835-2.
2. Calkin, D.E.; Barrett, K.; Cohen, J.D.; Finney, M.A.; Pyne, S.J.; Quarles, S.L. Wildland-urban fire disasters aren't actually a wildfire problem. *Proceedings of the National Academy of Sciences* **2023**, *120*, e2315797120. https://doi.org/10.1073/pnas.2315797120.
3. González-Olabarria, J.R.; Mola-Yudego, B.; Coll, L. Different Factors for Different Causes: Analysis of the Spatial Aggregations of Fire Ignitions in Catalonia (Spain). *Risk Analysis* **2015**, *35*, 1197–1209. https://doi.org/10.1111/risa.12339.
4. Castro, A.C.M.; Nunes, A.; Sousa, A.; Lourenço, L. Mapping the Causes of Forest Fires in Portugal by Clustering Analysis.*Geosciences* **2020**, *10*, 53. https://doi.org/10.3390/geosciences10020053.
5. Marey-Pérez, M.F.; Fuentes-Santos, I.; Saavera-Nieves, P.; González-Manteiga, W. Non-parametric comparative analysis of the spatiotemporal pattern of human-caused and natural wildfires in Galicia. *International Journal of Wildland Fire* **2022**, *32*, 178–194. https://doi.org/10.1071/WF22030.
6. Sari, F. Identifying anthropogenic and natural causes of wildfires by maximum entropy method-based ignition susceptibility distribution models. *Journal of Forestry Research* **2023**, *34*, 355–371. https://doi.org/10.1007/s11676-022-01502-4.
7. Certini, G.; Nocentini, C.; Knicker, H.; Arfaioli, P.; Rumpel, C. Wildfire effects on soil organic matter quantity and quality in two fire-prone Mediterranean pine forests. *Geoderma* **2011**, *167-168*, 148–155. https://doi.org/10.1016/j.geoderma.2011.09.005.
8. Caon, L.; Vallejo, V.R.; Ritsema, C.J.; Geissen, V. Effects of wildfire on soil nutrients in Mediterranean ecosystems. *Earth-Science Reviews* **2014**, *139*, 47–58. https://doi.org/10.1016/j.earscirev.2014.09.001.
9. Agbeshie, A.A.; Abugre, S.; Atta-Darkwa, T.; Awuah, R. A review of the effects of forest fire on soil properties. *Journal of Forestry Research* **2022**, *33*, 1419–1441. https://doi.org/10.1007/s11676-022-01475-4.
10. Levin, N.; Levental, S.; Morag, H. The effect of wildfires on vegetation cover and dune activity in Australia's desert dunes: a multisensor analysis. *International Journal of Wildland Fire* **2012**, *21*, 459. https://doi.org/10.1071/WF10150.
11. Foster, C.N.; Barton, P.S.; Robinson, N.M.; MacGregor, C.I.; Lindenmayer, D.B. Effects of a large wildfire on vegetation structure in a variable fire mosaic. *Ecological Applications* **2017**, *27*, 2369–2381. https://doi.org/10.1002/eap.1614.
12. Or, D.; Furtak-Cole, E.; Berli, M.; Shillito, R.; Ebrahimian, H.; Vahdat-Aboueshagh, H.; McKenna, S.A. Review of wildfire modeling considering effects on land surfaces. *Earth-Science Reviews* **2023**, *245*, 104569. https://doi.org/10.1016/j.earscirev.2023.104569.
13. Schaffer, K.E.; Hedwall, S.J.; Jr., W.F.L., Fire and animal interactions. In *Fire in California´s ecosystems*; Sugihara, N.G.; van Wagendonk, J.W.; Schaffer, K.E.; Fites-Kaufman, J.; Thode, A.E., Eds.; University of California, 2006; pp. 118–144.
14. González, T.M.; González-Trujillo, J.D.; Muñoz, A.; Armenteras, D. Effects of fire history on animal communities: a systematic review. *Ecological Processes* **2022**, *11*, 11. https://doi.org/10.1186/s13717-021-00357-7.
15. Jolly, C.J.; Dickman, C.R.; Doherty, T.S.; van Eeden, L.M.; Geary, W.L.; Legge, S.M.; Woinarski, J.C.Z.; Nimmo, D.G. Animal mortality during fire. *Global Change Biology* **2022**, *28*, 2053–2065. https://doi.org/10.1111/gcb.16044.
16. Isaza, D.F.G.; Cramp, R.L.; Franklin, C.E. Fire and rain: A systematic review of the impacts of wildfire and associated runoff on aquatic fauna. *Global Change Biology* **2022**, *28*, 2578–2595. https://doi.org/10.1111/gcb.16088.

17. Brown, D.J.; Baccus, J.T.; Means, D.B.; Forstner, M.R.J. Potential Positive Effects of Fire on Juvenile Amphibians in a Southern USA Pine Forest. *Journal of Fish and Wildlife Management* **2011**, *2*, 135–145. https://doi.org/10.3996/062011-JFWM-037.
18. Mercer, D.E.; Pye, J.M.; Prestemon, J.P.; Butry, D.T.; Holmes, T.P.; Wildfires, F. *Economic Effects of Catastrophic Wildfires: Assessing the Effectiveness of Fuel Reduction Programs for Reducing the Economic Impacts of Catastrophic Forest Fire Events*; 2000.
19. Davis, E.J.; Moseley, C.; Nielsen-Pincus, M.; Jakes, P.J. The Community Economic Impacts of Large Wildfires: A Case Study from Trinity County, California. *Society & Natural Resources* **2014**, *27*, 983–993. https://doi.org/10.1080/08941920.2014.905812.
20. Molina, J.R.; González-Cabán, A.; y Silva, F.R. Wildfires impact on the economic susceptibility of recreation activities: Application in a Mediterranean protected area. *Journal of Environmental Management* **2019**, *245*, 454–463. https://doi.org/10.1016/j.jenvman.2019.05.131.
21. Kim, E.; Kwon, Y.J. Analyzing indirect economic impacts of wildfire damages on regional economies. *Risk Analysis* **2023**, *43*, 2631–2643. https://doi.org/10.1111/risa.14106.
22. Meier, S.; Elliott, R.J.R.; Strobl, E. The regional economic impact of wildfires: Evidence from Southern Europe. *Journal of Environmental Economics and Management* **2023**, *118*, 102787. https://doi.org/10.1016/j.jeem.2023.102787.
23. Luo, T. Labor market impacts of destructive California wildfires. *Monthly Labor Review* **2023**.
24. Walls, M.A.; Wibbenmeyer, M. How Local are the Local Economic Impacts of Wildfires?
25. Sfetsos, A.; Giroud, F.; Clemencau, A.; Varela, V.; Freissinet, C.; LeCroart, J.; Vlachogiannis, D.; Politi, N.; Karozis, S.; Gkotsis, I.; et al. Assessing the Effects of Forest Fires on Interconnected Critical Infrastructures under Climate Change. Evidence from South France. *Infrastructures* **2021**, *6*, 16. https://doi.org/10.3390/infrastructures6020016.
26. Rad, A.M.; Abatzoglou, J.T.; Kreitler, J.; Alizadeh, M.R.; AghaKouchak, A.; Hudyma, N.; Nauslar, N.J.; Sadegh, M. Human and infrastructure exposure to large wildfires in the United States. *Nature Sustainability* **2023**, *6*, 1343–1351. https://doi.org/10.1038/s41893-023-01163-z.
27. Park, H.; Nam, K.; Lim, H. Is critical infrastructure safe from wildfires? A case study of wildland-industrial and -urban interface areas in South Korea. *International Journal of Disaster Risk Reduction* **2023**, *95*, 103849. https://doi.org/10.1016/j.ijdrr.2023.103849.
28. Sayarshad, H.R.; Ghorbanloo, R. Evaluating the resilience of electrical power line outages caused by wildfires. *Reliability Engineering & System Safety* **2023**, *240*, 109588. https://doi.org/10.1016/j.ress.2023.109588.
29. Papathoma-Köhle, M.; Schlögl, M.; Garlichs, C.; Diakakis, M.; Mavroulis, S.; Fuchs, S. A wildfire vulnerability index for buildings. *Scientific Reports* **2022**, *12*, 6378. https://doi.org/10.1038/s41598-022-10479-3.
30. Kasraee, N.K.; Hawbaker, T.J.; Radeloff, V.C. Identifying building locations in the wildland–urban interface before and after fires with convolutional neural networks. *International Journal of Wildland Fire* **2023**, *32*, 610–621. https://doi.org/10.1071/WF22181.
31. Radeloff, V.C.; Mockrin, M.H.; Helmers, D.; Carlson, A.; Hawbaker, T.J.; Martinuzzi, S.; Schug, F.; Alexandre, P.M.; Kramer, H.A.; Pidgeon, A.M. Rising wildfire risk to houses in the United States, especially in grasslands and shrublands. *Science* **2023**, *382*, 702–707. https://doi.org/10.1126/science.ade9223.
32. Duff, T.J.; Penman, T.D. Determining the likelihood of asset destruction during wildfires: Modelling house destruction with fire simulator outputs and local-scale landscape properties. *Safety Science* **2021**, *139*, 105196. https://doi.org/10.1016/j.ssci.2021.105 196.
33. Hawbaker, T.J.; Henne, P.D.; Vanderhoof, M.K.; Carlson, A.R.; Mockrin, M.H.; Radeloff, V.C. Changes in wildfire occurrence and risk to homes from 1990 through 2019 in the Southern Rocky Mountains, USA. *Ecosphere* **2023**, *14*, e4403. https://doi.org/10.100 2/ecs2.4403.
34. Fitch, R.A.; Mueller, J.M.; Meldrum, J.; Huber, C. Estimating proximity effects to wildfire fuels treatments on house prices in Cibola National Forest, New Mexico, USA. *Landscape and Urban Planning* **2023**, *238*, 104838. https://doi.org/10.1016/j. landurbplan.2023.104838.
35. Costa, R.; Baker, J.W. A methodology to estimate postdisaster unmet housing needs using limited data: Application to the 2017 California wildfires. *Risk Analysis* **2023**. https://doi.org/10.1111/risa.14206.
36. Coile, R.V.; Lucherini, A.; Chaudhary, R.K.; Ni, S.; Unobe, D.; Gernay, T. Economic Impact of Fire: Cost and Impact of Fire Protection in Buildings **2023**.
37. Fuentes-Santos, I.; Marey-Pérez, M.F.; González-Manteiga, W. Forest fire spatial pattern analysis in Galicia (NW Spain). *Journal of Environmental Management* **2013**, *128*, 30–42. https://doi.org/10.1016/J.JENVMAN.2013.04.020.
38. Elia, M.; Giannico, V.; Spano, G.; Lafortezza, R.; Sanesi, G. Likelihood and frequency of recurrent fire ignitions in highly urbanised Mediterranean landscapes. *International Journal of Wildland Fire* **2020**, *29*, 120. https://doi.org/10.1071/WF19070.
39. Tuyen, T.T.; Jaafari, A.; Yen, H.P.H.; Nguyen-Thoi, T.; Phong, T.V.; Nguyen, H.D.; Le, H.V.; Phuong, T.T.M.; Nguyen, S.H.; Prakash, I.; et al. Mapping forest fire susceptibility using spatially explicit ensemble models based on the locally weighted learning algorithm. *Ecological Informatics* **2021**, *63*, 101292. https://doi.org/10.1016/j.ecoinf.2021.101292.
40. D'Este, M.; Ganga, A.; Elia, M.; Lovreglio, R.; Giannico, V.; Spano, G.; Colangelo, G.; Lafortezza, R.; Sanesi, G. Modeling fire ignition probability and frequency using Hurdle models: a cross-regional study in Southern Europe. *Ecological Processes* **2020**, *9*, 54. https://doi.org/10.1186/s13717-020-00263-4.
41. Son, R.; Wang, S.Y.S.; Kim, S.H.; Kim, H.; Jeong, J.H.; Yoon, J.H. Recurrent pattern of extreme fire weather in California.*Environmental Research Letters* **2021**, *16*, 94031. https://doi.org/10.1088/1748-9326/ac1f44.
42. Fernández-Guisuraga, J.M.; Marcos, E.; Calvo, L. The footprint of large wildfires on the multifunctionality of fire-prone pine ecosystems is driven by the interaction of fire regime attributes. *Fire Ecology* **2023**, *19*, 32. https://doi.org/10.1186/s42408-023-0 0193-4.
43. de Diego, J.; Fernández, M.; Rúa, A.; Kline, J.D. Examining socioeconomic factors associated with wildfire occurrence and burned area in Galicia (Spain) using spatial and temporal data. *Fire Ecology* **2023**, *19*, 18. https://doi.org/10.1186/s42408-023-00173-8.

44. Uyttewaal, K.; Prat-Guitart, N.; Ludwig, F.; Kroeze, C.; Langer, E.R. Territories in Transition: how social contexts influence wildland fire adaptive capacity in rural Northwestern European Mediterranean areas. *Fire Ecology* **2023**, *19*, 13. https://doi.org/10.1186/s42408-023-00168-5.
45. Trucchia, A.; Meschi, G.; Fiorucci, P.; Provenzale, A.; Tonini, M.; Pernice, U. Wildfire hazard mapping in the eastern Mediterranean landscape. *International Journal of Wildland Fire* **2023**, *32*, 417–434. https://doi.org/10.1071/WF22138.
46. Rivière, M.; Lenglet, J.; Noirault, A.; Pimont, F.; Dupuy, J.L. Mapping territorial vulnerability to wildfires: A participative multi-criteria analysis. *Forest Ecology and Management* **2023**, *539*, 121014. https://doi.org/10.1016/j.foreco.2023.121014.
47. Pandey, P.; Huidobro, G.; Lopes, L.F.; Ganteaume, A.; Ascoli, D.; Colaco, C.; Xanthopoulos, G.; Giannaros, T.M.; Gazzard, R.; Boustras, G.; et al. A global outlook on increasing wildfire risk: Current policy situation and future pathways. *Trees, Forests and People* **2023**, *14*, 100431. https://doi.org/10.1016/j.tfp.2023.100431.
48. Zacharakis, I.; Tsihrintzis, V.A. Integrated wildfire danger models and factors: A review. *Science of The Total Environment* **2023**,*899*, 165704. https://doi.org/10.1016/j.scitotenv.2023.165704.
49. Pausas, J.G.; Keeley, J.E. Wildfires and global change. *Frontiers in Ecology and the Environment* **2021**, *19*, 387–395. https://doi.org/10.1002/fee.2359.
50. Li, S.; Banerjee, T. Spatial and temporal pattern of wildfires in California from 2000 to 2019. *Scientific Reports* **2021**, *11*, 8779. https://doi.org/10.1038/s41598-021-88131-9.
51. Fernandez-Anez, N.; Krasovskiy, A.; Müller, M.; Vacik, H.; Baetens, J.; Hukic´, E.; Solomun, M.K.; Atanassova, I.; Glushkova, M.; Bogunovic´, I.; et al. Current Wildland Fire Patterns and Challenges in Europe: A Synthesis of National Perspectives. *Air, Soil and Water Research* **2021**, *14*, 117862212110281. https://doi.org/10.1177/11786221211028185.
52. Richards, J.; Huser, R.; Bevacqua, E.; Zscheischler, J. Insights into the Drivers and Spatiotemporal Trends of Extreme Mediterranean Wildfires with Statistical Deep Learning. *Artificial Intelligence for the Earth Systems* **2023**, *2*. https://doi.org/10.1175/AIES-D-22-0095.1.
53. Regos, A.; Pais, S.; Campos, J.C.; Lecina-Diaz, J. Nature-based solutions to wildfires in rural landscapes of Southern Europe: let's be fire-smart! *International Journal of Wildland Fire* **2023**, *32*, 942–950. https://doi.org/10.1071/WF22094.
54. Cohen, J.D. Preventing Disaster: Home Ignitability in the Wildland-Urban Interface. *Journal of Forestry* **2000**, *98*, 15–21. https://doi.org/10.1093/JOF/98.3.15.
55. Winter, G.J.; Fried, J.S. Estimating Contingent Values for Protection from Wildland Fire Using a Two-Stage Decision Framework.*Forest Science* **2001**, *47*, 349–360. https://doi.org/10.1093/FORESTSCIENCE/47.3.349.
56. Asiyanbi, A.; Davidsen, C. Governing Wildfire Risk in Canada: The Rise of an Apparatus of Security. *Annals of the American Association of Geographers* **2023**, *113*, 1207–1223. https://doi.org/10.1080/24694452.2023.2175638.
57. Bramwell, L. Understanding Wildfire in the Twenty-First Century: The Return of Disaster Fires. *Environmental History* **2023**,*28*, 467–494. https://doi.org/10.1086/725396.
58. Beltrán-Marcos, D.; Calvo, L.; Fernández-Guisuraga, J.M.; Fernández-García, V.; Suárez-Seoane, S. Wildland-urban interface typologies prone to high severity fires in Spain. *Science of The Total Environment* **2023**, *894*, 165000. https://doi.org/10.1016/j.scitotenv.2023.165000.
59. Bento-Gonçalves, A.; Vieira, A. Wildfires in the wildland-urban interface: Key concepts and evaluation methodologies. *Science of The Total Environment* **2020**, *707*, 135592. https://doi.org/10.1016/j.scitotenv.2019.135592.
60. Intini, P.; Ronchi, E.; Gwynne, S.; Bénichou, N. Guidance on Design and Construction of the Built Environment Against Wildland Urban Interface Fire Hazard: A Review. *Fire Technology* **2020**, *56*, 1853–1883. https://doi.org/10.1007/s10694-019-00902-z.
61. Taccaliti, F.; Marzano, R.; Bell, T.L.; Lingua, E. Wildland–Urban Interface: Definition and Physical Fire Risk Mitigation Measures, a Systematic Review. *Fire* **2023**, *6*, 343. https://doi.org/10.3390/fire6090343.
62. Tolhurst, K.; Duff, T.; Chong, D.M. From "Wildland-Urban Interface" to "Wildfire Interface Zone" using dynamic fire modelling. In Proceedings of the MODSIM2013 20th International Congress on Modelling and Simulation, 2013, pp. 1–6.
63. Ganteaume, A.; Barbero, R.; Jappiot, M.; Maillé, E. Understanding future changes to fires in southern Europe and their impacts on the wildland-urban interface. *Journal of Safety Science and Resilience* **2021**, *2*, 20–29. https://doi.org/10.1016/J.JNLSSR.2021.01.001.
64. Short, K.C. Spatial wildfire occurrence data for the United States, 1992-2015 [FPA_FOD_20170508] (4th Edition). *Fort Collins, CO: Forest Service Research Data Archive* **2017**. https://doi.org/https://doi.org/10.2737/RDS-2013-0009.4.
65. Pesaresi, M.; Ehrlich, D.; Florczyk, A.; Freire, S.; Julea, A.; Kemper, T.; Soille, P.; Syrris, V. GHS-BUILT R2015B - GHS built-up grid, derived from Landsat, multitemporal (1975, 1990, 2000, 2014). *European Commission, Joint Research Centre (JRC)* **2015**.
66. The PostGIS Development Group. PostGIS 3.1.2dev Manual, 2020.
67. Wang, W.; Zhou, H.; Zheng, S.; Lü, G.; Zhou, L. Ocean surface currents estimated from satellite remote sensing data based on a global hexagonal grid. *International Journal of Digital Earth* **2023**, *16*, 1073–1093. https://doi.org/10.1080/17538947.2023.2192003.
68. Sahr, K. Central Place Indexing: Hierarchical Linear Indexing Systems for Mixed-Aperture Hexagonal Discrete Global Grid Systems. *Cartographica: The International Journal for Geographic Information and Geovisualization* **2019**, *54*, 16–29. https://doi.org/10.3138/cart.54.1.2018-0022.
69. Mann, H.B. Nonparametric Tests Against Trend. *Econometrica* **1945**, *13*, 245. https://doi.org/10.2307/1907187.
70. Kendall, M.G. *Rank correlation methods.*, 4 ed.; Charles Griffin: London, 1975.
71. Lins, H.F.; Slack, J.R. Streamflow trends in the United States. *Geophysical Research Letters* **1999**, *26*, 227–230. https://doi.org/10.1029/1998GL900291.
72. Wu, H.; Soh, L.K.; Samal, A.; Chen, X.H. Trend analysis of streamflow drought events in Nebraska. *Water Resources Management* **2008**, *22*, 145–164. https://doi.org/10.1007/S11269-006-9148-6/METRICS.

73. Yue, S.; Pilon, P. A comparison of the power of the t test, Mann-Kendall and bootstrap tests for trend detection. *Hydrological Sciences Journal* **2004**, *49*, 21–37. https://doi.org/10.1623/HYSJ.49.1.21.53996.
74. Ljung, G.M.; BOX, G.E.P. On a measure of lack of fit in time series models. *Biometrika* **1978**, *65*, 297–303. https://doi.org/10.1093/biomet/65.2.297.
75. Hamed, K.H.; Ramachandra Rao, A. A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology* **1998**,*204*, 182–196. https://doi.org/10.1016/S0022-1694(97)00125-X.
76. Hamed, K.H. Enhancing the effectiveness of prewhitening in trend analysis of hydrologic data. *Journal of Hydrology* **2009**,*368*, 143–155. https://doi.org/10.1016/J.JHYDROL.2009.01.040.
77. Sa'adi, Z.; Shahid, S.; Ismail, T.; Chung, E.S.; Wang, X.J. Trends analysis of rainfall and rainfall extremes in Sarawak, Malaysia using modified Mann–Kendall test. *Meteorology and Atmospheric Physics* **2019**, *131*, 263–277. https://doi.org/10.1007/S00703-017-0564-3/TABLES/3.
78. Alashan, S. Combination of modified Mann-Kendall method and S¸en innovative trend analysis. *Engineering Reports* **2020**,*2*, e12131. https://doi.org/10.1002/ENG2.12131.
79. Patakamuri, S.K.; O'Brien, N. *modifiedmk: Modified Versions of Mann Kendall and Spearman's Rho Trend Tests*, 2021. R package version 1.6.
80. Openshaw, S.; Taylor, P.J. The modifiable areal unit problem. *Quantitative geography: a British view* **1981**. https://doi.org/10.1002/9781118526729.ch3.
81. Wong, D.W. Modifiable Areal Unit Problem. *International Encyclopedia of Human Geography* **2009**, pp. 169–174. https://doi.org/10.1016/B978-008044910-4.00475-2.
82. Shi, K.; Touge, Y. Characterization of global wildfire burned area spatiotemporal patterns and underlying climatic causes.*Scientific Reports* **2022**, *12*, 644. https://doi.org/10.1038/s41598-021-04726-2.
83. Yang, X.; Zhao, C.; Zhao, W.; Fan, H.; Yang, Y. Characterization of global fire activity and its spatiotemporal patterns for different land cover types from 2001 to 2020. *Environmental Research* **2023**, *227*, 115746. https://doi.org/10.1016/j.envres.2023.115746.
84. Weber, K.T.; Yadav, R. Spatiotemporal Trends in Wildfires across the Western United States (1950–2019). *Remote Sensing* **2020**,*12*, 2959. https://doi.org/10.3390/rs12182959.
85. Li, H.; Vulova, S.; Rocha, A.D.; Kleinschmit, B. Spatio-temporal feature attribution of European summer wildfires with Explainable Artificial Intelligence (XAI). *Science of The Total Environment* **2024**, *916*, 170330. https://doi.org/10.1016/j.scitotenv.2024.170330.
86. Moreno, M.; Bertolín, C.; Arlanzón, D.; Ortiz, P.; Ortiz, R. Climate change, large fires, and cultural landscapes in the mediterranean basin: An analysis in southern Spain. *Heliyon* **2023**, *9*, e16941. https://doi.org/10.1016/j.heliyon.2023.e16941.
87. Schmidt, J. Defensible Space, Housing Density, and Diablo-North Wind Events: Impacts on Loss Rates for Homes in Northern California Wildfires **2023**.
88. Watson, G.L. *On Model Determination, Prediction and Statistical Learning: The Case of Space-Time Data*; 2021.
89. Dwomoh, F.K.; Auch, R.F.; Brown, J.F.; Tollerud, H.J. Trends in tree cover change over three decades related to interannual climate variability and wildfire in California. *Environmental Research Letters* **2023**, *18*, 24007. https://doi.org/10.1088/1748-9326/acad15.
90. Ostertag, S.; Rice, M.; Qu, J.J. Investigating spatiotemporal trends of large wildfires in California (1950–2020). *Advances in Cartography and GIScience of the ICA* **2023**, *4*, 1–9. https://doi.org/10.5194/ica-adv-4-16-2023.
91. MacDonald, G.; Wall, T.; Enquist, C.A.F.; LeRoy, S.R.; Bradford, J.B.; Breshears, D.D.; Brown, T.; Cayan, D.; Dong, C.; Falk, D.A.; et al. Drivers of California's changing wildfires: a state-of-the-knowledge synthesis. *International Journal of Wildland Fire* **2023**, *32*, 1039–1058. https://doi.org/10.1071/WF22155.
92. Bugallo, M.; Esteban, M.D.; Marey-Pérez, M.F.; Morales, D. Wildfire prediction using zero-inflated negative binomial mixed models: Application to Spain. *Journal of Environmental Management* **2023**, *328*, 116788. https://doi.org/10.1016/j.jenvman.2022.116788.
93. Calheiros, T.; Nunes, J.P.; Pereira, M.G. Recent evolution of spatial and temporal patterns of burnt areas and fire weather risk in the Iberian Peninsula. *Agricultural and Forest Meteorology* **2020**, *287*, 107923. https://doi.org/10.1016/j.agrformet.2020.107923.
94. Yadav, K.; Escobedo, F.J.; Thomas, A.S.; Johnson, N.G. Increasing wildfires and changing sociodemographics in communities across California, USA. *International Journal of Disaster Risk Reduction* **2023**, *98*, 104065. https://doi.org/10.1016/j.ijdrr.2023.104065.
95. Rodrigues, M.; Jiménez-Ruano, A.; de la Riva, J. Fire regime dynamics in mainland Spain. Part 1: Drivers of change. *Science of The Total Environment* **2020**, *721*, 135841. https://doi.org/10.1016/j.scitotenv.2019.135841.
96. Dong, L.; Leung, L.R.; Qian, Y.; Zou, Y.; Song, F.; Chen, X. Meteorological Environments Associated With California Wildfires and Their Potential Roles in Wildfire Changes During 1984–2017. *Journal of Geophysical Research: Atmospheres* **2021**, *126*, e2020JD033180. https://doi.org/10.1029/2020JD033180.
97. Oliveira, S.; Rocha, J.; Sá, A. Wildfire risk modeling. *Current Opinion in Environmental Science & Health* **2021**, *23*, 100274. https://doi.org/10.1016/j.coesh.2021.100274.
98. Ríos-Pena, L.; Kneib, T.; Cadarso-Suárez, C.; Klein, N.; Marey-Pérez, M. Studying the occurrence and burnt area of wildfires using zero-one-inflated structured additive beta regression. *Environmental Modelling & Software* **2018**, *110*, 107–118. https://doi.org/10.1016/j.envsoft.2018.03.008.
99. Oliveira, S.; Gonçalves, A.; Zêzere, J.L. Reassessing wildfire susceptibility and hazard for mainland Portugal. *Science of The Total Environment* **2021**, *762*, 143121. https://doi.org/10.1016/j.scitotenv.2020.143121.
100. Prapas, I.; Kondylatos, S.; Papoutsis, I.; Camps-Valls, G.; Ronco, M.; Fernández-Torres, M.Á.; Guillem, M.P.; Carvalhais, N. Deep Learning Methods for Daily Wildfire Danger Forecasting **2021**.

101. Qiu, L.; Chen, J.; Fan, L.; Sun, L.; Zheng, C. High-resolution mapping of wildfire drivers in California based on machine learning.*Science of The Total Environment* **2022**, *833*, 155155. https://doi.org/10.1016/j.scitotenv.2022.155155.
102. Rodrigues, M.; Costafreda-Aumedes, S.; Comas, C.; Vega-García, C. Spatial stratification of wildfire drivers towards enhanced definition of large-fire regime zoning and fire seasons. *Science of The Total Environment* **2019**, *689*, 634–644. https://doi.org/10.1016/j.scitotenv.2019.06.467.
103. Wang, S.S.C.; Wang, Y. Quantifying the effects of environmental factors on wildfire burned area in the south central US using integrated machine learning techniques. *Atmospheric Chemistry and Physics* **2020**, *20*, 11065–11087. https://doi.org/10.5194/acp- 20-11065-2020.
104. Woolford, D.G.; Martell, D.L.; McFayden, C.B.; Evens, J.; Stacey, A.; Wotton, B.M.; Boychuk, D. The development and implementation of a human-caused wildland fire occurrence prediction system for the province of Ontario, Canada. *Canadian Journal of Forest Research* **2021**, *51*, 303–325. https://doi.org/10.1139/cjfr-2020-0313.
105. Monjarás-Vega, N.A.; Briones-Herrera, C.I.; Vega-Nieva, D.J.; Calleros-Flores, E.; Corral-Rivas, J.J.; López-Serrano, P.M.; Pompa-García, M.; Rodríguez-Trejo, D.A.; Carrillo-Parra, A.; González-Cabán, A.; et al. Predicting forest fire kernel density at multiple scales with geographically weighted regression in Mexico. *Science of The Total Environment* **2020**, *718*, 137313. https://doi.org/10.1016/j.scitotenv.2020.137313.
106. Wang, X.; Zhao, H.; Zhang, Z.; Yin, Y.; Zhen, S. The Relationship between Socioeconomic Factors at Different Administrative Levels and Forest Fire Occurrence Density Using a Multilevel Model. *Forests* **2023**, *14*, 391. https://doi.org/10.3390/f14020391.
107. Zhang, C.; Li, X. Land Use and Land Cover Mapping in the Era of Big Data. *Land* **2022**, *11*, 1692. https://doi.org/10.3390/land11101692.
108. Malik, K.; Robertson, C.; Roberts, S.A.; Remmel, T.K.; Long, J.A. Computer vision models for comparing spatial patterns: understanding spatial scale. *International Journal of Geographical Information Science* **2023**, *37*, 1–35. https://doi.org/10.1080/13658816.2022.2103562.
109. Diaz-Varela, E.R.; Marey-Pérez, M.F.; Rigueiro-Rodriguez, A.; Álvarez-Álvarez, P. Landscape metrics for characterization of forest landscapes in a sustainable management framework: Potential application and prevention of misuse. *Annals of Forest Science* **2009**, *66*, 301. https://doi.org/10.1051/forest/2009004.
110. Díaz-Varela, E.R.; Marey-Pérez, M.F.; Riveiro-Valiño, J.A.; Alvarez-Lopez, C.J. Preservation of Spatial Information in Rasterization Processes: A Practical Approach Using Real Categorical Data and Landscape Metrics. *GIScience & Remote Sensing* **2010**, *47*, 425–442. https://doi.org/10.2747/1548-1603.47.3.425.
111. Parisien, M.A.; Moritz, M.A. Environmental controls on the distribution of wildfire at multiple spatial scales. *Ecological Monographs* **2009**, *79*, 127–154. https://doi.org/10.1890/07-1289.1.
112. Thompson, M.P.; MacGregor, D.G.; Dunn, C.J.; Calkin, D.E.; Phipps, J. Rethinking the Wildland Fire Management System. *Journal of Forestry* **2018**, *116*, 382–390. https://doi.org/10.1093/jofore/fvy020.
113. Chen, B.; Jin, Y. Spatial patterns and drivers for wildfire ignitions in California. *Environmental Research Letters* **2022**, *17*, 55004. https://doi.org/10.1088/1748-9326/ac60da.
114. Galizia, L.F.; Curt, T.; Barbero, R.; Rodrigues, M. Understanding fire regimes in Europe. *International Journal of Wildland Fire* **2021**,*31*, 56–66. https://doi.org/10.1071/WF21081.
115. Boubeta, M.; Lombardía, M.J.; Marey-Pérez, M.; Morales, D. Poisson mixed models for predicting number of fires. *International Journal of Wildland Fire* **2019**, *28*, 237. https://doi.org/10.1071/WF17037.
116. Nieto, H.; Aguado, I.; García, M.; Chuvieco, E. Lightning-caused fires in Central Spain: Development of a probability model of occurrence for two Spanish regions. *Agricultural and Forest Meteorology* **2012**, *162-163*, 35–43. https://doi.org/10.1016/j.agrformet.2012.04.002.
117. Vecín-Arias, D.; Castedo-Dorado, F.; Ordóñez, C.; Rodríguez-Pérez, J.R. Biophysical and lightning characteristics drive lightning-induced fire occurrence in the central plateau of the Iberian Peninsula. *Agricultural and Forest Meteorology* **2016**, *225*, 36–47. https://doi.org/10.1016/j.agrformet.2016.05.003.
118. Viedma, O.; Urbieta, I.R.; Moreno, J.M. Wildfires and the role of their drivers are changing over time in a large rural area of west-central Spain. *Scientific Reports* **2018**, *8*, 17797. https://doi.org/10.1038/s41598-018-36134-4.
119. Rodrigues, M.; Jiménez-Ruano, A.; Peña-Angulo, D.; de la Riva, J. A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using Geographically Weighted Logistic Regression. *Journal of Environmental Management* **2018**, *225*, 177–192. https://doi.org/10.1016/j.jenvman.2018.07.098.
120. Calviño-Cancela, M.; Chas-Amil, M.L.; García-Martínez, E.D.; Touza, J. Wildfire risk associated with different vegetation types within and outside wildland-urban interfaces. *Forest Ecology and Management* **2016**, *372*, 1–9. https://doi.org/10.1016/j.foreco.2016.04.002.
121. Wong, S.D.; Broader, J.C.; Shaheen, S.A.; Org, E. Review of California Wildfire Evacuations from 2017 to 2019 **2020**. https://doi.org/10.7922/G29G5K2R.
122. Buechi, H.; Weber, P.; Heard, S.; Cameron, D.; Plantinga, A.J. Long-term trends in wildfire damages in California. *International Journal of Wildland Fire* **2021**, *30*, 757–762. https://doi.org/10.1071/WF21024.
123. Chen, B.; Jin, Y.; Scaduto, E.; Moritz, M.A.; Goulden, M.L.; Randerson, J.T. Climate, Fuel, and Land Use Shaped the Spatial Pattern of Wildfire in California's Sierra Nevada. *Journal of Geophysical Research: Biogeosciences* **2021**, *126*, e2020JG005786. https://doi.org/10.1029/2020JG005786.
124. Schwartz, M.W.; Syphard, A.D. Fitting the solutions to the problems in managing extreme wildfire in California. *Environmental Research Communications* **2021**, *3*, 81005. https://doi.org/10.1088/2515-7620/ac15e1.

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