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*Article*

# Analysis of Trends in the Distance of Wildfires from Built-Up Areas in Spain and California (USA): 2007–2015

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**Abstract:** Wildfires present a significant risk to societies globally due to population growth, concentrated 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 analyzes 101,597 fires in Spain and California between 2007 and 2015, where ignition points and all built-up areas were precisely geolocated in 2014. The study employs the Mann–Kendall test to determine trends and analyze the relative distance of wildfires to human buildings over time. The results indicate that wildfires are becoming statistically significantly closer in several areas. It is also observed that the majority of wildfires are moving away from buildings, although this is not a significant finding. These results suggest the possibility of further research into the reasons behind these observations and possible future developments and their consequences.

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

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## 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], and also how different building materials and the location on the perimeter of buildings respond to fire [37–40]. 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 [41–47], the danger or risk of wildfires [48–52], and the size and area burned [53–57]. 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 community that exists where humans and their development meet or intermix with wildland fuel*. This concept has gained importance since the beginning of the 21st century [58,59], 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 the WUI in the past has been based on the likelihood of a fire occurrence and the vulnerability [60,61] of settlements. However, these classifications lack generality with regard to the fire regime [62]. Bento-Gonçalves and Vieira [63] provide a comprehensive overview of the research on the WUI from various perspectives. However, it does not include any papers that analyze the spatiotemporal evolution. In the same year, Intini et al. [64] 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. [65] reviewed 162 scientific publications from 1983 to 2022 on the definition and interpretation of the WUI and its application in different territories. Among these works reviewed, only Tolhurst et al. [66] provide 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 the available data. By 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*

In 2014, Moritz published his paper *Learning to Coexist with Wildfires* [67], which made an important contribution to a more integrated understanding of wildfires. Based on the global data, the study focused on three regions where fire-related issues (environmental, social, and economic) were particularly salient. These three regions were the European Mediterranean area, the western United States, and Australia. The authors proposed one of the initial hypotheses as follows: the negative effects of fire that were previously attributed to "distant" fires (e.g., smoke impacts on human health) will become increasingly common, making coexistence with wildfires much more difficult. For the purposes of this study, two sub-regions were selected from the initial study (Spain and California) for which accurate data were available over a sufficiently long period of time to test whether or not fires were becoming less and less distant.

#### 2.1.1. Spain

This work analyzes 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) (accessed on 23 December 2023). 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 Figure 1.

This article focuses on the summer fire season, which lasts from June to October in southern Europe [68]. 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 2 displays the distribution of fires according to their causes.

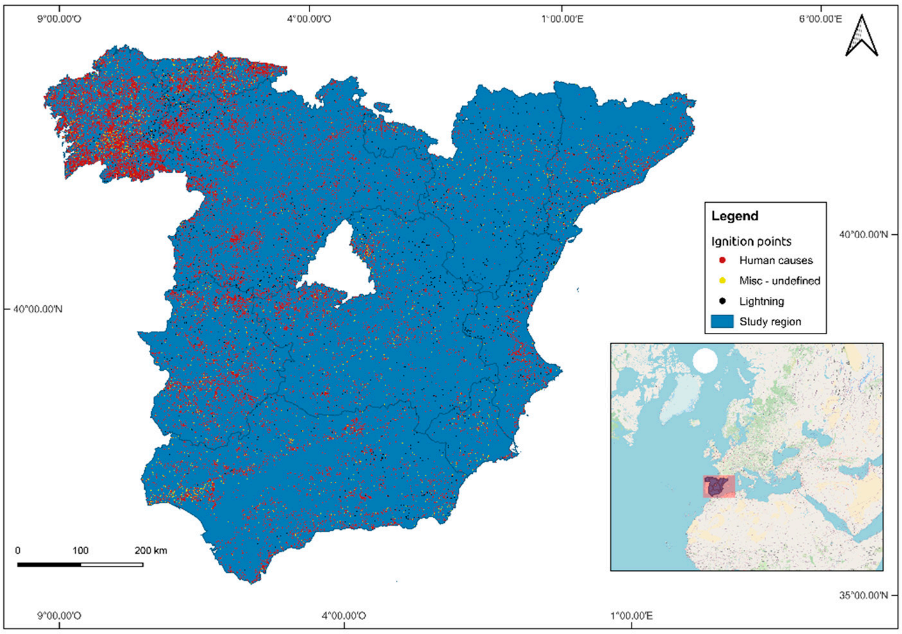



**Figure 1.** Forest fires occurring between June and October from 2007 to 2015 in Spain.

**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 and October (ha) | % of Total Fires between June and October | % of Total Area Burnt between June and October |
|---|---|---|---|---|---|---|
| 2007 | 5590 | 53,310 | 2801 | 39,494 | 50.1 | 74.1 |
| 2008 | 6552 | 41,870 | 2604 | 20,825 | 39.7 | 49.7 |
| 2009 | 8953 | 119,400 | 3977 | 88,626 | 44.4 | 74.2 |
| 2010 | 6298 | 47,179 | 3791 | 35,479 | 60.2 | 75.2 |
| 2011 | 9893 | 93,248 | 6369 | 71,505 | 64.4 | 76.7 |
| 2012 | 9483 | 207,508 | 3403 | 151,693 | 35.9 | 73.1 |
| 2013 | 6023 | 61,486 | 4351 | 52,566 | 72.2 | 85.5 |
| 2014 | 5301 | 41,391 | 2449 | 21,708 | 46.2 | 52.4 |
| 2015 | 6716 | 108,806 | 3521 | 77,935 | 52.4 | 71.6 |

**Table 2.** Forest fires 2007–2015 by cause in Spain.

| Cause | Total Number of Fires | Total Burnt Area (ha) | Number of Fires June–October | Burnt Area between June and October (ha) |
|---|---|---|---|---|
| Human causes | 55,989 | 667,542 | 27,675 (49.4%) | 470,869 (70.5%) |
| Lightning | 1669 | 63,337 | 1489 (89.2%) | 48,377 (76.4%) |
| Misc/undefined | 7151 | 43,319 | 4102 (57.4%) | 40,584 (93.7%) |

The data indicate that the area burned during the period under review was indeed concentrated in the months analyzed.

### 2.1.2. California

The Californian data are sourced from the U.S. Department of Agriculture [69] and share similar data fields with the Spanish data, including coordinates of ignition points, causes, suppression time, and burnt area. The data have 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 and October (ha) | % of Total Fires between June and October | % of Total Area Burnt between June and October |
|---|---|---|---|---|---|---|
| 2007 | 5427 | 422,788 | 3622 | 406,816 | 66.7 | 96.2 |
| 2008 | 5231 | 578,717 | 3740 | 548,030 | 71.5 | 94.7 |
| 2009 | 4069 | 188,592 | 2957 | 179,186 | 72.7 | 95.0 |
| 2010 | 3300 | 48,848 | 2792 | 45,571 | 84.6 | 93.3 |
| 2011 | 4601 | 77,683 | 3467 | 72,879 | 75.4 | 93.8 |
| 2012 | 3868 | 307,801 | 2700 | 303,423 | 69.8 | 98.6 |
| 2013 | 4403 | 237,287 | 2563 | 195,918 | 58.2 | 82.6 |
| 2014 | 2828 | 221,176 | 1766 | 206,518 | 62.4 | 93.4 |
| 2015 | 3061 | 343,332 | 2215 | 335,022 | 72.4 | 97.6 |

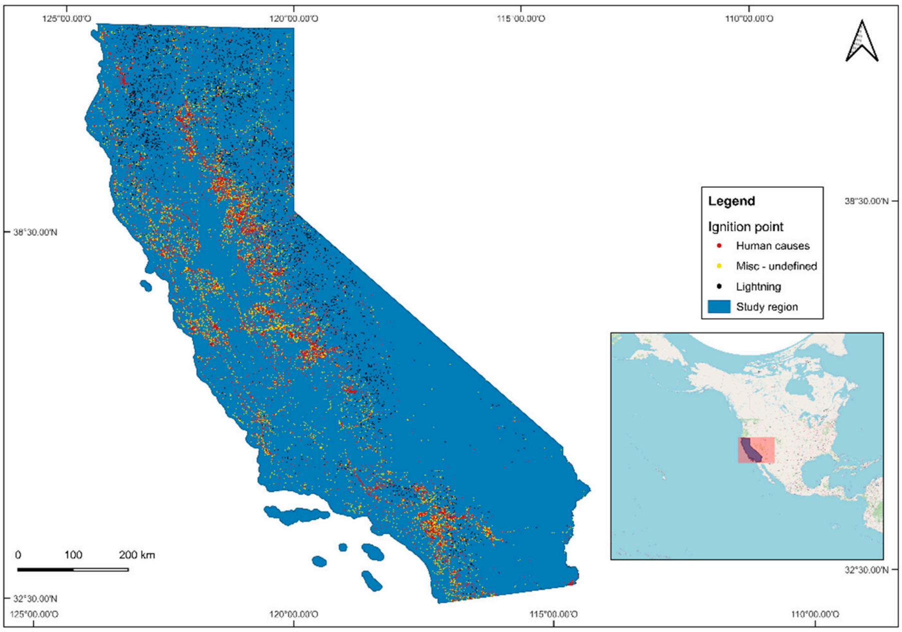



**Figure 2.** Forest fires occurring between June and October from 2007 to 2015 in California.

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

**Table 4.** Forest fires 2007–2015 by cause in California.

| Cause | Total Number of Fires | Total Burnt Area (ha) | Number of Fires June–October | Burnt Area between June and October (ha) |
|---|---|---|---|---|
| Human causes | 14,891 | 594,778 | 9418 (63.2%) | 563,851 (94.8%) |
| Lightning | 3462 | 1,055,175 | 3293 (95.1%) | 1,045,989 (99.1%) |
| Misc/undefined | 18,435 | 776,272 | 13,111 (71.1%) | 683,524 (88.1%) |

The distribution of fires in this region differs significantly from that observed in Spain. While the number of lightning strikes is relatively low, they have a significant impact on the burnt area. Furthermore, the burnt area is even more concentrated in the months analyzed than in the Spanish case.

*2.2. Global Human Settlement Layer (GHSL)*

The Global Human Settlement Layer [70] project is supported by the European Commission, Joint Research Center, and Directorate-General for Regional and Urban Policy. As described on the 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 the 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 38 m*. The distance from ignition points to the nearest built-up was determined using SQL queries and a Postgis database [71]. The layer's overall situation is illustrated in Figures 3–5.

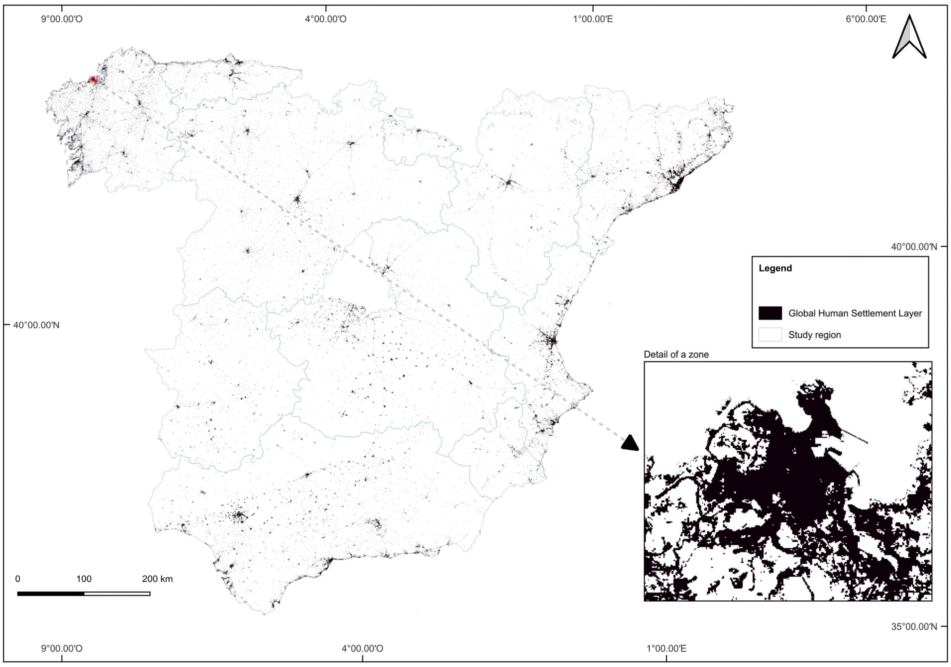



**Figure 3.** GHL layer, Spain.

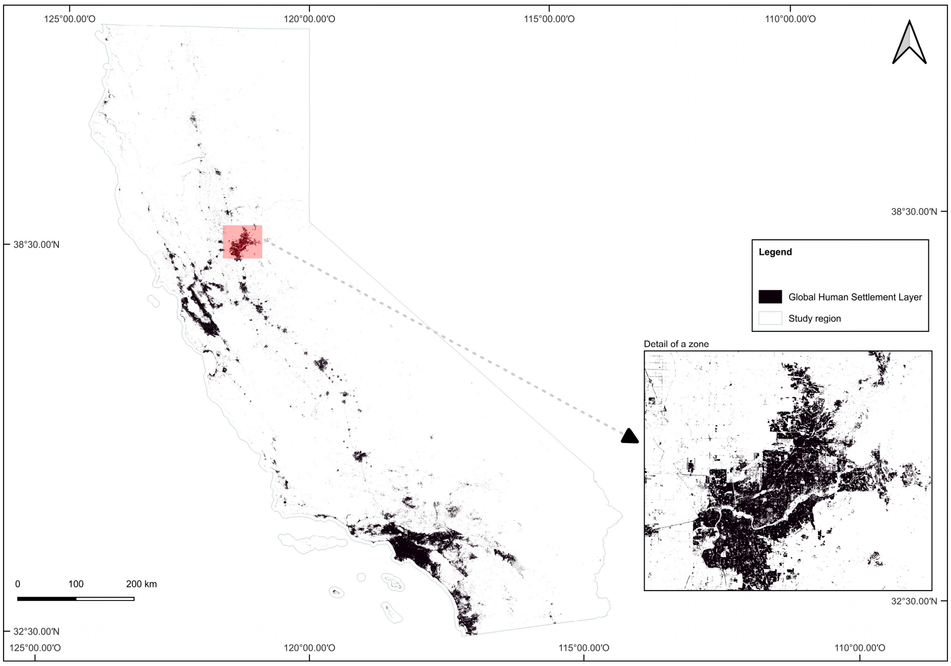



**Figure 4.** GHL layer, California.

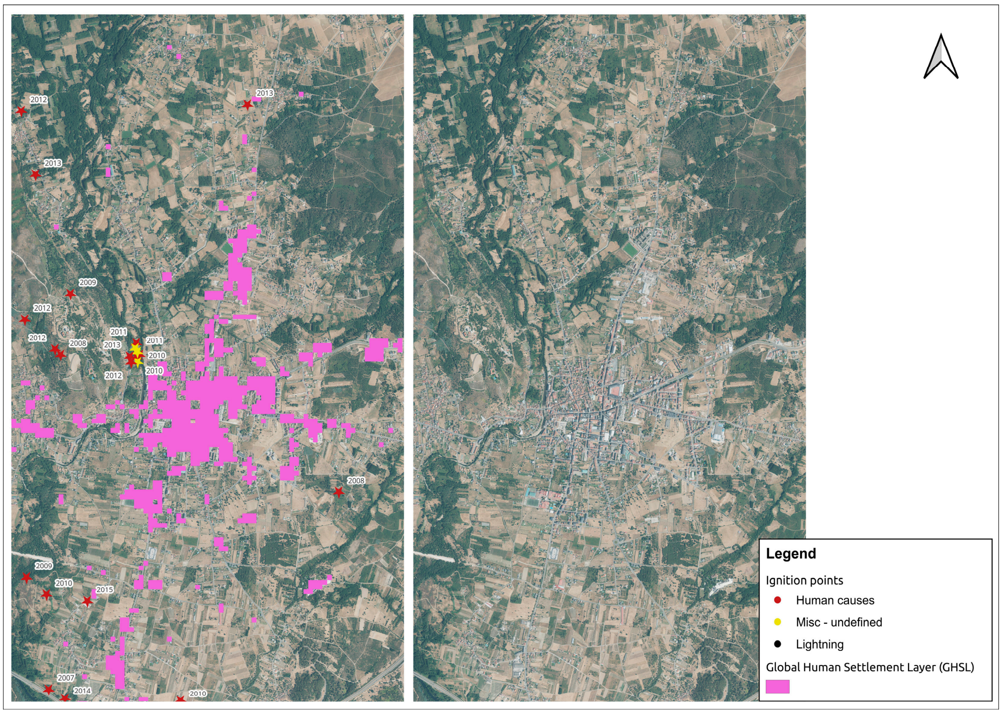



**Figure 5.** Example of the data that has been used.

### 2.3. Discrete Global Grid

As noted by Wang et al. [72], traditional long/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 [73]. This article analyzes temporal trends using a grid (level 8, cells with an area of 7774 km $s^2$) created by DGGRID [73] 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 [74,75] was applied to analyze the temporal changes in proximity from the 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 [76], and insensitive to missing values [77]. 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 the data points, $n$ is 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 $n \geq 10$, S is generally in a standard normal distribution, and the variance is computed as follows:

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

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 smaller than the level of significance. Conversely, the trend is said to be increasing if the $Z$ is positive and the computed probability is smaller than the level of significance. Finally, if the computed probability is higher than the level of significance, no trend is present. In this study, the significance level $\alpha$ = 0.05 is applied. Yue and Pilon [78] showed that the Mann–Kendall test and the bootstrapped version have the same statistical power. In this study, we used the latter, which is the denominated *Bootstrap-based MK (BS-MK) test* in [78]. The Mann–Kendall statistic ($S_0$) of the sample data, X, is computed and used. The significance of $S_0$ can be assessed based on the null distribution of the bootstrap Mann–Kendall statistic, BECD $\hat{S}^*$ , which is derived from the bootstrapped sample data. 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:

$$p_s = \frac{m_s}{M}$$

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 [79]. If the test was positive, we used a modified version of the Mann–Kendall test for the autocorrelated data [80–83].

Kendall [75] 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 a low occurrence of wildfires (less than 10 months of data) were excluded.

All the statistical analyses were conducted using R and package "modifiedmk" [84], which provides functions for calculating regular and modified versions of the Mann–Kendall and Spearman's Rho tests for the trend. This allows the influence of serially correlated data to be removed, if necessary, thus ensuring the reliability of the results.

## 3. Results

It is important to note that, despite differences in socioeconomic 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 6 shows the global results for Spain. The absence of dark green cells over the entire surface is noteworthy, indicating that in no area has there been a movement of fires away from buildings over time. In contrast, there are a total of seven red cells (10.5% of the surface) in which there is a significant approach of the ignition points to the buildings. These areas are not characterized by many forest fires. The observed pattern can be attributed to the existence of distinct dynamics of fire activity, which are influenced by localized factors. In terms of non-significant results, there is a balance between the two options. In 41% of the territory, the fire moves away from the buildings compared to 47%, where it moves closer. This indicates a situation of balance throughout the 2007–2015 series in the overall calculation, with the aforementioned differences at the local scale.

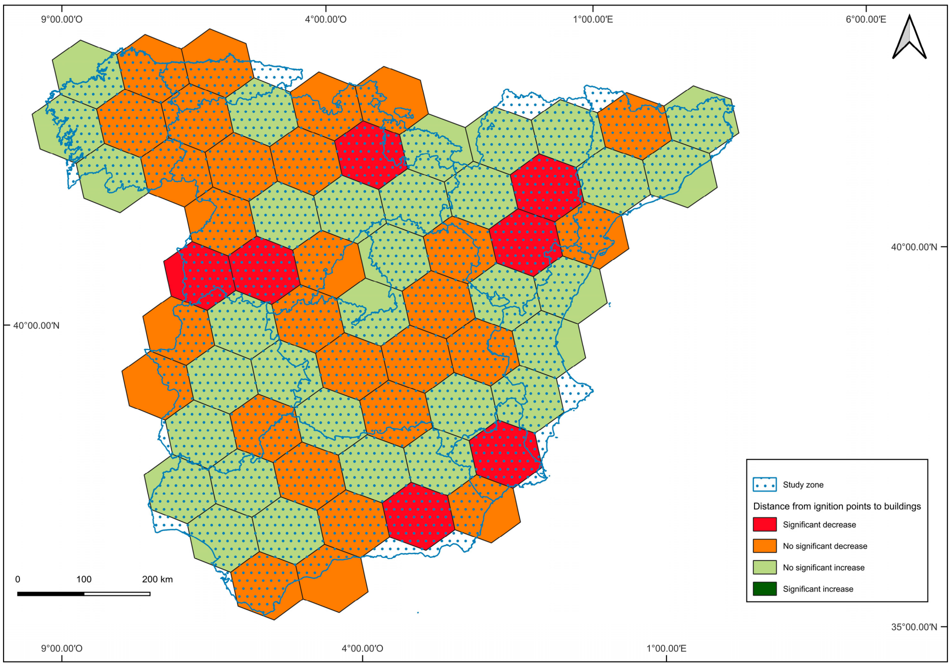


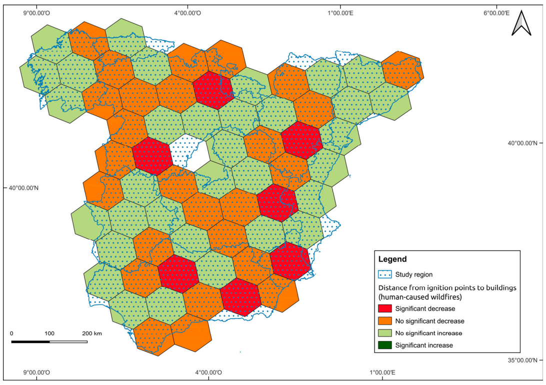

**Figure 6.** Mann–Kendall test, Spain, Resolution 8.

When analyzing the results of the Mann–Kendall test for Spain, segmented by cause, it is worth noting that summer fires of human origin (Figure 7a) account for 83.2% of all fires in Spain between June and October. This partial result is in line with the overall result. On a national scale, there is a balance: in 50.7% of the territory, fires of this cause move away from buildings, while in 49.3%, they move closer to buildings. However, only in 10.4% of cases do they do so in a statistically significant way. These areas largely align with the global results.

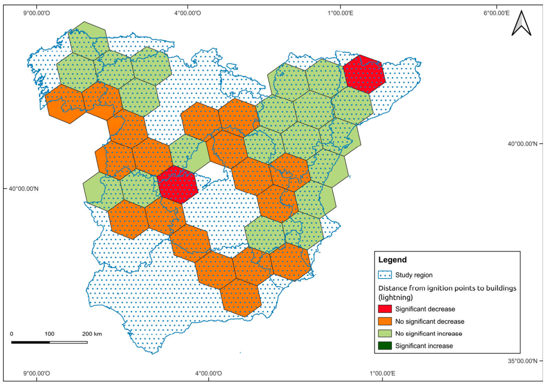
It has been established that fires of unknown cause (Figure 7c) account for 12.3% of the summer fires. Furthermore, sufficient data are available for analysis in 54 of the 67 cells. In 46.3% of the cases, there is a non-significant distancing, while in the remaining 53.7% of the cases, the fires are becoming closer to buildings. Of these, 7.4% of the area is statistically significant in this regard. From the perspective of territorial distribution, there is no discernible tendency for fires of this type to move closer or further away in areas where they are most prevalent. However, the situation in Asturias (North) is noteworthy, exhibiting a notable tendency to move closer to built-up areas.

Fires caused by lightning (Figure 7b) represent only 4% of the total number of fires analyzed. This low percentage indicates that only 40 cells have the minimum data necessary to carry out the analysis. In approximately half of the cases, fires caused by lightning are moving closer from built-up areas, but only in 5% of the territory is this trend statistically significant. It is notable, however, that there is a significant trend to move closer in the north (Pyrenees area), which is a mountainous region that is highly susceptible to fires due to dry summer storms.

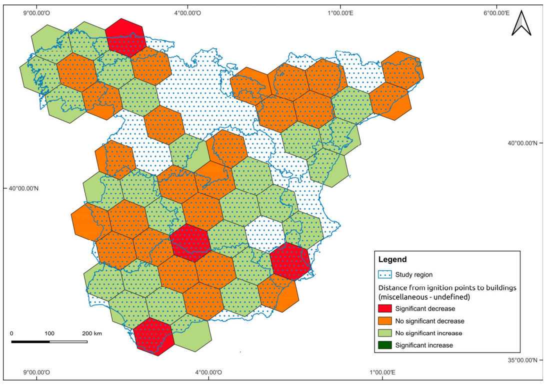
In a manner analogous to that observed in Spain, in California (Figure 8), there are no areas with a significant tendency for wildfires to move away from buildings. Conversely, in 4% of the territory (2 of the 50 cells), there is a significant approach of fire to buildings. These are two areas not particularly affected by fire and with very different characteristics. In contrast to the distribution observed in Spain, the non-significant results are not evenly distributed across the area. In fact, 72% (36 out of 50 cells) of the area shows a non-significant tendency for fires to move away from human buildings, while 24% (12 out of 50 cells) show a tendency for fires to move closer to them. These results may indicate that, on the whole, fires are moving away from buildings. However, as they do not do so significantly, it is not possible to say with certainty.




(**a**) Human-caused




(**b**) Lightning




(**c**) Miscellaneous, undefined

**Figure 7.** Mann–Kendall test by cause, Spain.

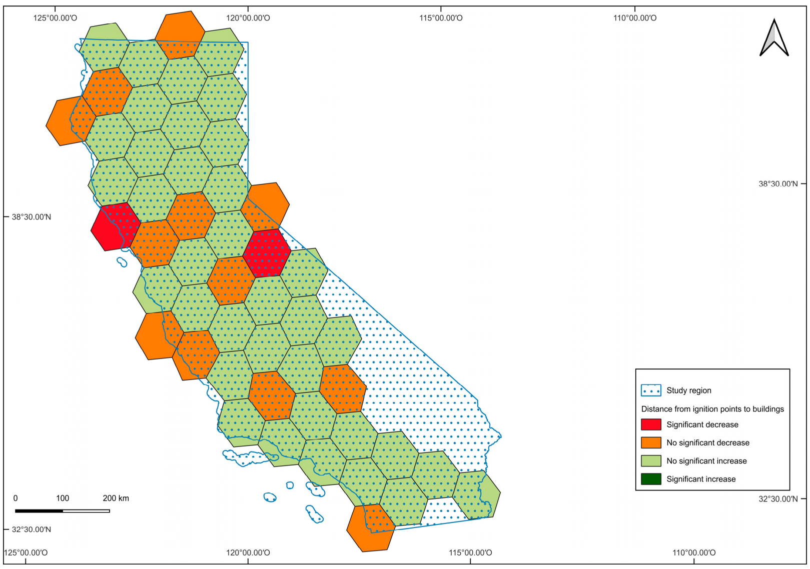
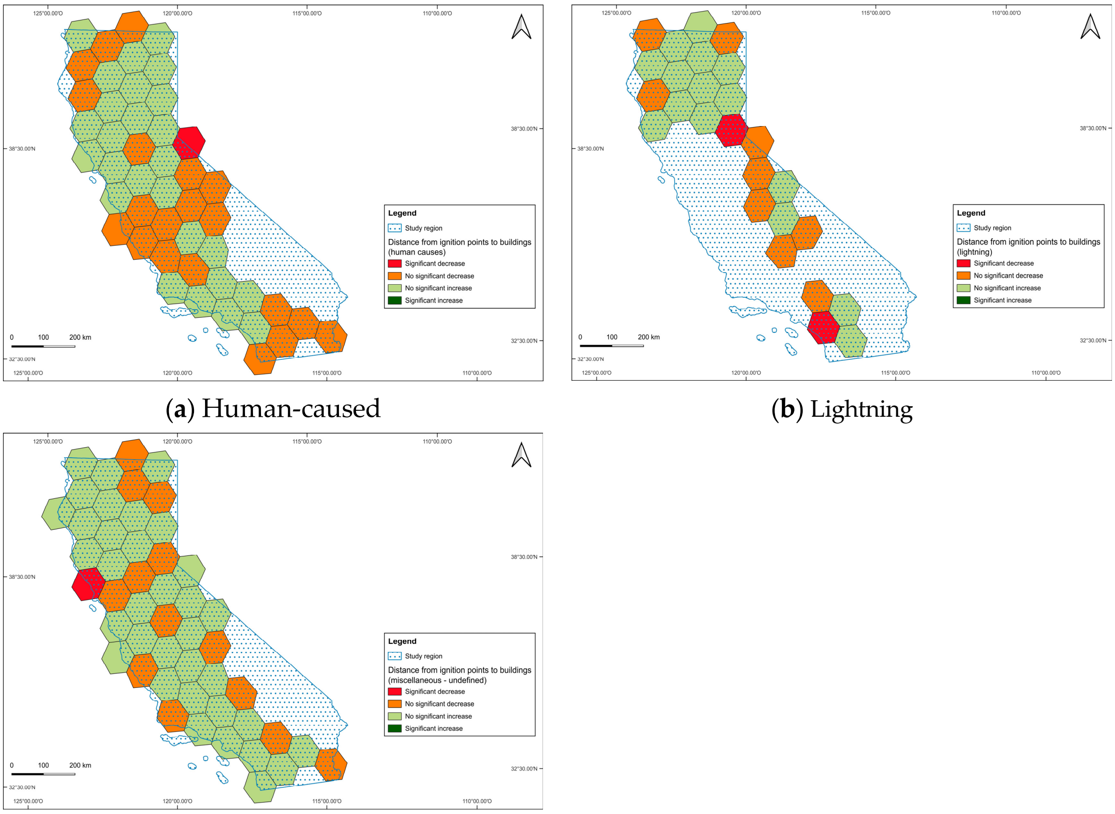



**Figure 8.** Mann–Kendall test, California, Resolution 8.

A similar analysis of causality was conducted in the case of Spain. It should be noted that the numerical importance differs. The fires of human origin (Figure 9a) identified accounted for a total of 9418 fires, which represents 36.47% of the total. They were distributed in 47 cells, with only one (2%) exhibiting a significant approach to buildings. In the majority of cases (26 out of 47 cells, representing 55.3% of the area), the fires did not move significantly away from the buildings. In the opposite case, where the fires approached non-significantly, this occurred in 20 out of 47 cells, representing 42.55% of the cases. Spatially, this occurs in the northernmost and southernmost areas, as well as a central strip where fires identified as human-caused appear to be approaching.




(**a**) Human-caused (**b**) Lightning

(**c**) Miscellaneous, undefined

**Figure 9.** Mann–Kendall test by cause, California.

Fires of unknown cause (Figure 9c) account for 50.77% of the summer fires, and sufficient data are available for analysis in 49 of the 50 cells. In 35 of the 49 cells, 71.4% of the cases show a non-significant tendency to move away from buildings. This is a highly relevant result, as the tendency is also very homogeneous throughout the territory. The opposite tendency to move closer to human constructions is observed in only one cell (2%) with statistical significance. In 13 cells (26.5%), this occurs in a non-significant way. The results indicate that, for this type of causation in California, fires are moving away from buildings.

Fires caused by lightning (Figure 9b) account for 12.77% of the total number of fires analyzed. A total of 26 out of 50 cells have minimal data available for analysis. Of these, 15 cells (57.7% of the total surface area) indicate that wildfires caused by lightning strikes are moving away from buildings in a non-significant way. Conversely, 11 cells show a tendency for wildfires to move closer to buildings, with 1 cell exhibiting a significant result. As an intriguing outcome, in Northern California, a region historically renowned for its abundance of lightning, the prevailing tendency appears to be to move away from buildings.

## 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 a global scale [85,86] or on a continental or subcontinental level [87,88] but not on the evolution of relative positions of fire and built-up areas. As this is a pioneering study, it is challenging to make comparisons with previous studies. Another limitation is that the mapping of the WUI zones for each region is not available, as it has not been carried out or published. This limits the ability to contrast the information obtained on the evolution of fires with the legal and technical delimitations established by the administrations.

Previous studies at subregional scales, such as [5,41,47,89,90], and for the entire study region, such as [54,91–95], 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. [96] in the case of Spain and Yadav et al. [97] for California. These authors attribute the occurrence of more or fewer fires in summer to climatic variability [98,99], which is a fundamental factor. They also note that other socioeconomic variables [5,6,24], irregularly distributed across the territory, are associated with increased fire activity.

The scientific community [100] 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 [101–104], to larger scales of approximately 10 km $\times$ 10 km [105–107], multiscalar [108,109] or by using computerized and artificial intelligence techniques [110,111]. Initially, two scale levels were selected: level 8 (7774 km $s^2$) and level 9 (2591 km $s^2$). The lack of data in many of the cells, especially when analyzed for causality, indicated that level 8 was the most appropriate for this analysis. When comparing our results to the scheme presented in Parisien and Moritz [112] on the dominant factors affecting fire at multiple spatial and temporal scales, we observed 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 [41]. 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 the zero-one-inflated structured additive beta regression techniques [101]. We found that the behavior evolved spatially and temporally.

The analysis revealed that there were no cells for the two regions where fires were significantly moving away from buildings. This result partially supports Calkin et al.'s [2] proposal that fires are increasingly encroaching on buildings, highlighting the need for us to prepare for living with fire [113]. A more detailed analysis of the results reveals that, although not statistically significant, there is a clear trend away from building fires over the time series in both areas and for the different causes of wildfires. This opens up an interesting debate that has not been addressed by other authors and may be related to the efficiency of legal measures or fire awareness.

Chen and Jin [114] 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. [115] explained the distribution of fires on a European scale and identified the areas where they were more frequent. Bugallo et al. [95] used the zero-inflated negative binomial mixed model techniques to identify fire behavior patterns and explanatory variables in Spain. Boubeta et al. [116] also used mixed models, specifically Poisson, to predict the constant fire behavior in fire areas. These findings are consistent with the previous research that indicates 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 the cause distribution, there is an issue with the varying classifications between California and Spain that we have overcome by the homogeneous aggregation of cases in both areas. For the Spanish wildfires' arson or negligence type, grouped into human causes, 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 [98,117,118]. These are areas where fires occur occasionally, and their origin is often due to conjunctural reasons, such as negligence [119], 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 the eastern area of Galicia. Human-caused wildfires exhibit aggregated patterns, with a strong interaction between outbreaks and fires. Their distribution varied both over and within years, with a high incidence shifting between the southern and western areas. A 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.

The classification of wildfires in California is highly diverse. In this study, they have been grouped for comparison with wildfires in Spain. As in the case of Spain, there are no cells in which fires move away from buildings in a statistically significant way. Furthermore, the general trend is to move away in most of the cells in which the analysis could be performed due to the presence of data. When compared to Li and Banerjee's [54] 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 areas between the Plumas and Tulare counties. These fires have caused significant damage to buildings [120,121]. Chen et al. [122] found that the population density and its increase were significant factors in explaining a large number of arson fires. Yadav et al. [97] suggested that sociodemographic characteristics of the population could also explain fire behavior. It is worth noting that the 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 the Humboldt to Modoc counties, which are generally less affected by fires [123]. Fires caused by natural causes in California follow more random patterns [120], 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.

This pioneering work can and should be completed in the future through two lines of action. The first is to complete the historical series of data, for which the forestry administrations must make the databases available. The second consists of incorporating other variables or covariables into the analysis, such as the area affected, the intensity of the fire, or the simultaneity in each area. The results obtained demonstrate, as has been demonstrated on numerous occasions, that forest fires present a random pattern in the case of natural fires and spatial aggregation in the case of those of human origin. When analyzed from the perspective of their temporal evolution on a general scale (Spain and California), in general, the behavioral pattern tends to remain stable. This implies that those responsible for establishing forest policy and fighting forest fires, as well as forest firefighters, should establish plans for the location of resources and stable action programs across the majority of the territory. The prevalence of the light green color (wildfires tending to begin further away from built-up areas in a non-significant manner) in both study regions is particularly noteworthy, as it may indicate that firefighting policies and actions may not only be reducing fires but also moving them away from urban and inhabited areas, although in neither case in a significant manner. It is important to note that the speed of detection and rapid response to extinguish fires is a crucial factor in the success of firefighting, particularly when fires are in close proximity to residential or industrial areas.

## 5. Conclusions

It can be demonstrated that scientific reference works on forest fires indicate the severity of the problem. It is evident that societies around the world, particularly urban societies in developed countries, are aware of the issue when fires occur in their vicinity. Our contribution to the field of fire research is that we have conducted the first analysis of the tendency for fires to start closer to buildings in two regions, namely Spain and California. These are two regions where a substantial amount of fire research is conducted and where there is a high level of awareness of the importance of the problem.

The methodology employed is based on the rigorous control of information from the ignition points, forest fire protection services, and buildings. Regardless of the causes, the results obtained allow us to draw three conclusions. The first is that there are no areas with a significant trend of fires moving away from buildings in Spain and California between 2007 and 2015. The second conclusion is somewhat contradictory to the previous one, as it can be stated that there is a non-significant tendency in most of the cells analyzed for fires, depending on their ignition point, to be increasingly further away from buildings. Both conclusions are generalizable for the fires analyzed by cause. Thirdly, although we have observed statistically significant evidence of the cells where fires are becoming closer to buildings, in both areas, this category is very much in the minority.

The work presented opens an interesting line of research that can be further explored through statistical techniques such as generalized linear mixed models (GLMMs) or other models that allow the introduction of variables and covariates related to aspects related to fire behavior or the environmental conditions in which it develops. This will enable a better understanding of this phenomenon, both on a local level and at larger scales of analysis. This work can be of great benefit to the decision-making at the level of fire planning or actions on a specific date when several fires occur simultaneously.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| WUI | Wildland–urban interface |

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