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Exploring Drivers of Wildfires in Spain

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Abstract: Wildfires play a dual role in ecosystems by providing ecological benefits while posing catastrophic events; they also inflict non-catastrophic damage and yield long-term effects on biodiversity, soil quality, and air quality, among other factors, including public health. This study analysed the key determinants of wildland fires in Spain using openly available spatial data from 2008 to 2021, including fire perimeters, bioclimatic variables, topography, and socioeconomic datasets, at a resolution of 1 km^2. Our methodology combined principal component analysis (PCA), linear regression analysis, and one-way analysis of variance (ANOVA). Our findings show that scrub/herbaceous vegetation (average 63 $\pm$ 1.45% SE) and forests (average 19 $\pm$ 0.76% SE) have been highly susceptible to wildfires. The population density exhibited a robust positive correlation with wildfire frequency (R^2 = 0.88, p < 0.0001). Although the study provides insights into some fire-related climatic drivers over Spain, it includes only temperature- and precipitation-based variables and does not explicitly consider fuel dynamics. Therefore, a more advanced methodology should be applied in the future to understand the local specifics of regional wildfire dynamics. Our study identified that scrub/herbaceous areas and forests near densely populated regions should be prioritised for wildfire management in Spain, particularly under changing climate conditions.

Keywords: wildfires; land cover; driving factors; burned area; PCA

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1. Introduction

Wildland fires are considered a natural phenomenon worldwide [1] and are one of the major disasters that have altered the environmental conditions of the southern part of Europe [2]. Wildland fires provide many ecological functions, including maintaining ecosystem health, helping forest regeneration, and controlling insect outbreaks and disease damage [3]. However, despite their ecological benefits, these fires can lead to catastrophic events that result in the loss of biodiversity and forest resources. Moreover, they pose significant socioeconomic challenges by causing infrastructure destruction and endangering human life and health, particularly in densely populated regions [4,5]. In Euro-Mediterranean (EU-MED) countries such as France, Greece, Italy, Portugal, and Spain, over 95% of fire incidents were caused by anthropogenic activities (such as purposefully, arsonistically, or deliberately), and the remaining 5% are naturally caused by lightning and other unknown factors [6,7]. However, over 60,000 fires occur in the EU-MED region each year, consuming more than 500,000 hectares of land [8]. This indicates the enormous number of land cover distributions lost to wildfires, altering their overall ecosystem functioning.

On a European basis, EU-MED countries have the highest frequency of fires and the greatest number of burned areas because of extreme wildfire episodes [9–11], whereas Spain had the second-highest number of wildfire episodes after Portugal. Moreover, the impact of climate change has altered the climatic conditions of the Mediterranean Basin, with temperature increases in summers, a reduction in precipitation in springs and autumns, and wetter and milder climates in winters [12–15]. As mentioned earlier, these circumstances exacerbate high heatwave episodes, which in turn generate wildland fire ignitions, resulting in severe fire activity and fatalities [16]. Nevertheless, studies have discovered that several factors, such as meteorological variables, topographical characteristics, and factors related to socioeconomic conditions, have an important role in increasing the frequency and extent of wildland fires during wildfire seasons [17–19]. Hence, the annual burned areas in Mediterranean countries of Europe have seen an increase over the past two decades, attributed to intensified climate change coupled with other environmental factors [20].

Importantly, understanding the distribution of land use/cover (LUC) in the Mediterranean region is critical because it could provide fire experts with a clear picture of how wildfires might affect communities based on climate and human-induced factors influencing fire dynamics [21,22]. Over the decades, wildland fires have been changing the states of LUC types in the Mediterranean basin [6]. Therefore, to gain insights into the trends of wildfire occurrences, we analysed CORINE land-cover (CLC) maps of 2006, 2012, and 2018. These maps provide valuable information about the historical, present, and potential future patterns of wildfires. Hence, accurate data can assist in understanding the current situation and distribution of various land-cover types [21,22]. However, it is crucial to note that not all land cover types are equally flammable, as [22] discovered that forests and agricultural lands burn more than shrublands and grasslands due to the accumulation of fuel loads, sources of fire ignition, and climatic circumstances. At the country level, Spain has witnessed significant LUC changes as a result of human activity in recent years [23].

Machine learning techniques, such as principal component analysis (PCA), have become crucial for understanding the underlying factors of wildfires [24,25]. In the realm of wildfire research, these approaches are gradually gaining recognition and relevance. Numerous studies have been conducted using PCA to determine the underlying factors influencing fires [25,26]. Indeed, among the many algorithms available, PCA is becoming a powerful tool for predicting the driving factors of wildland fires, the number of fires, and burned areas at all levels [25,27–31]. Additionally, some authors have demonstrated that the PCA model produces better results as compared to other approaches [29,30,32,33]. Consequently, PCA models have been widely employed in identifying wildfire drivers at global and continental scales; however, there has been minimal research at the national and provincial levels. Concisely, the motivation behind this research is to contribute to the body of knowledge of leveraging artificial intelligence methods such as PCA to build appropriate fire propagation measures and management strategies that would help mitigate the danger of wildland fires in Mediterranean-type regions.

This paper presents a temporal, spatial, and statistical analysis of factors driving wildfires across various LUC types and regions in Spain. The study explores the use of PCA combined with linear regression and analysis of variance (ANOVA) to identify the primary factors influencing wildfires within the area of study. The research sets three objectives: (i) to analyse the spatial and temporal patterns of fire incidents and the extent of burned areas, (ii) to determine which LUC types (agricultural areas, forests, others, scrub/herbaceous vegetation and wetlands) are most susceptible to wildfires, and (iii) to pinpoint the main factors driving wildfires at both national and provincial levels. The Materials and Methods section provides detailed descriptions and information on the datasets used. Consequently, this research aids in understanding the factors that drive wildland fires, thereby enabling predictions of their behaviour and spread patterns for specific periods and locations. This study offers insights that can inform the development of effective fire suppression strategies, the establishment of emergency warning systems, and the strategic allocation of resources to combat and suppress future wildfires.

2. Materials and Methods

2.1. Study Area

The study areas comprise all autonomous communities of Spain with the exclusion of the Canary Islands territory (UTM projection of ETRS89, latitude of 40.4637° N, and longitude of 3.7492° W). Therefore, the remaining total land area of the study site was approximately 498,497 km^2. Figure 1 depicts the study area and land cover distribution map of Spain and the percentage of each land cover type across the country. The climate of the Iberian Peninsula of Spain varies considerably. It is characterised by moderate winter cycles, extremely drier and unbearably hot in the summer period, and wetter and cooler in the mountain areas. Annually, the average temperature ranges from 0 °C to 18 °C, annual precipitation ranges from 150 mm to 2500 mm, and the average wind speed is 7.9 miles per hour. As of the end of 2020, the demographic population density of Spain is estimated to be 66,229,715 people, with Andalucia having the highest population density of approximately 11,796,105 people residing in the region. Within study periods, our study discovered 3430 fire events, and these events damaged more than 867,500 hectares caused by wildfires between 2008 to 2021. Notably, 266 wildfires were reported in 2012, resulting in the loss of 178,504 hectares of land. In addition, when considering land cover types, about 257 fires occurred in 2017, destroying around 112,892 hectares of scrub/herbaceous vegetation.

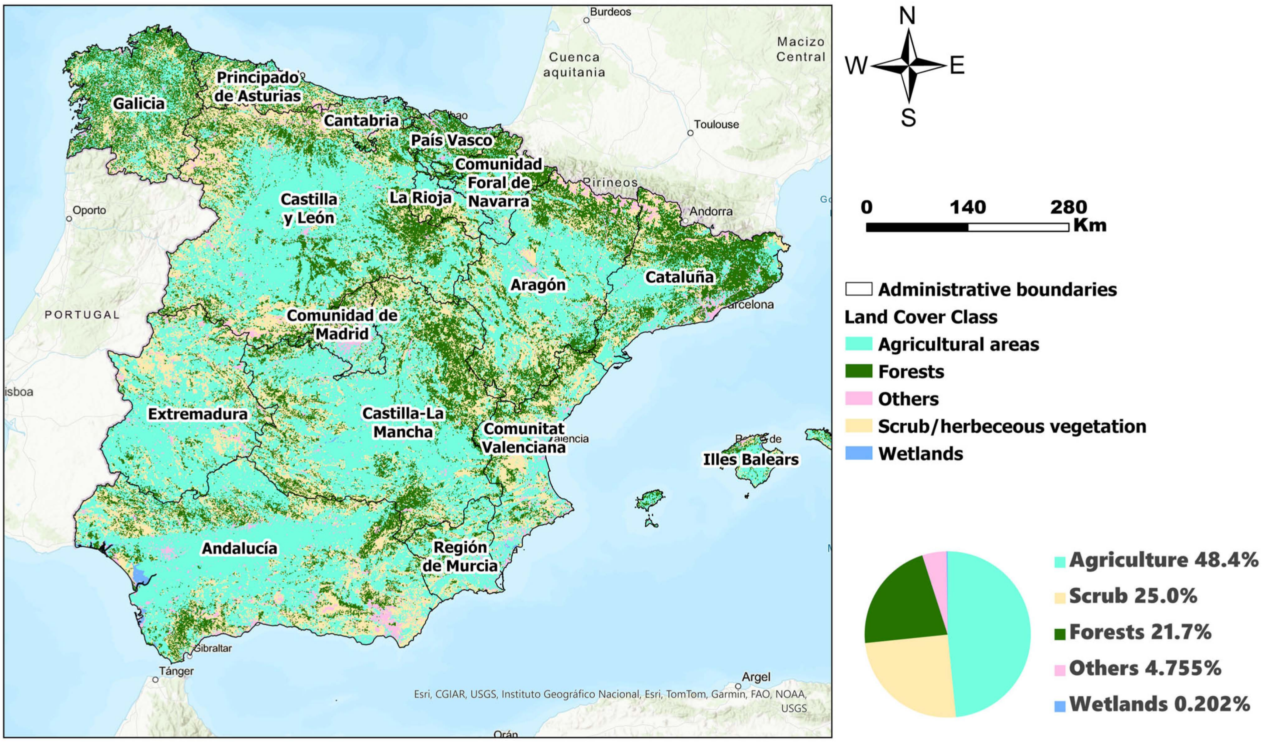


Figure 1. Study area. The percentage of each landcover type per municipality is indicated in the pie chart.

2.2. Data Sources

2.2.1. Bioclimatic, Socioeconomic, and Topographic Variables

Several studies have identified temperature and precipitation as critical factors affecting moisture availability and fire propagation [25,34], with fuel moisture found to be crucial to assessing fire danger [35] due to the positive response of fire activity, such as fire frequency and spread, to increasing forest fuel dryness [36,37]. Therefore, this study incorporates 19 bioclimatic variables (bio-1 to bio-19) from the WorldClim database [38,39], with 11 variables describing temperature-related metrics and 8 variables related to precipitation. From our observations, the line graph shows that July and August experience the highest peak temperatures, averaging 23 °C. Additionally, Shuttle Radar Topography

Mission (SRTM V.2.1) [40] elevation data at ~30 s (1 km^2) spatial resolution of the Universal Transverse Mercator (UTM) resolution grid was downloaded from WorldClim [38] and processed in ArcGIS version 10.7 to obtain topographic features such as elevation and distance from the streams in the study area. Table 1 shows the explanatory codes of the 19 bioclimatic variables, including elevation and streams.

Table 1. Explanatory code for bioclimatic, topographic, and socio-economic variables.

S/N	Code	Meaning	Unit	Source
		Bioclimatic variables		
1	bio1	Annual Mean Temperature	°C	WorldClim version 2.1
2	bio2	Mean Diurnal Range (Mean of monthly (max temp—min temp))	°C	WorldClim version 2.1
3	bio3	Isothermality (Bio2/Bio7) (×100)	%	WorldClim version 2.1
4	bio4	Temperature Seasonality (standard deviation ×100)	°C	WorldClim version 2.1
5	bio5	Max Temperature of Warmest Month	°C	WorldClim version 2.1
6	bio6	Min Temperature of Coldest Month	°C	WorldClim version 2.1
7	bio7	Temperature Annual Range (BIO5-BIO6)	°C	WorldClim version 2.1
8	bio8	Mean Temperature of Wettest Quarter	°C	WorldClim version 2.1
9	bio9	Mean Temperature of Driest Quarter	°C	WorldClim version 2.1
10	bio10	Mean Temperature of Warmest Quarter	°C	WorldClim version 2.1
11	bio11	Mean Temperature of Coldest Quarter	°C	WorldClim version 2.1
12	bio12	Annual Precipitation	mm/year	WorldClim version 2.1
13	bio13	Precipitation of Wettest Month	mm/month	WorldClim version 2.1
14	bio14	Precipitation of Driest Month	mm/month	WorldClim version 2.1
15	bio15	Precipitation Seasonality	%	WorldClim version 2.1
16	bio16	Precipitation of Wettest Quarter	mm/quarter	WorldClim version 2.1
17	bio17	Precipitation of Driest Quarter	mm/quarter	WorldClim version 2.1
18	bio18	Precipitation of Warmest Quarter	mm/quarter	WorldClim version 2.1
19	bio19	Precipitation of Coldest Quarter	mm/quarter	WorldClim version 2.1
		Topographic variables		
20	elevation	Elevation	m	WorldClim version 2.1
21	stream	Distance to streams	m	WorldClim version 2.1
		Socio-economic variables		
22	population	Population density	People/km^2	SEDAC database
23	life exp	Life expectancy	yearly	Global data lab
24	hdi	Human development index	-	Global data lab
25	gni	Gross national income	EUR	Global data lab
26	income index	Income index	-	Global data lab

In terms of topographic variables, hydrological analysis was performed on the elevation data to obtain the stream order and distances of the fire points around the streams across the study area. The elevation data were filled to raise the cells with shallow pixel values and prevent broken streamlines. Subsequently, a flow-direction raster was created using the filled elevation data, and areas with higher accumulations (areas greater than 1% of the highest accumulation) corresponding to stream channels were obtained using the flow-direction raster. Euclidean distances around the streamlines were obtained, and pixel values were extracted into the fire database to obtain the distance between each fire point and the nearest stream channel.

Regarding socioeconomic variables, the population density data were acquired from the Socioeconomic Data and Application Centre database (SEDAC—https://sedac.ciesin.columbia.edu/, accessed on 19 June 2023), a data centre in NASA's Earth Observing System Data and Information System (EOSDIS). The data provide a gridded population density raster at a 1 km^2 resolution. The population ranges from 2010 to 2020, with a 5-year gap. The data consists of the world's population density derived from the country's census counts and adjusted to match the total population of the United Nations country totals [41]. The raster files were masked to Spain, and each cell value corresponding to the population density of each year was extracted into a point feature of the burned areas to obtain the corresponding population density. Compared to raster data, vector data, such as point features, allow further analysis and comparison of population densities across the years and use the figures to understand the relationships between wildland fires and population. Each population year within the fire period was selected as the corresponding period. For example, the 2010 population was used for all fires between 2008 and 2011. This allowed for an objective representation of the population density across wildland fire occurrences over the study period. In addition, life expectancy, human development index (HDI), gross national income (GNI), and income index were obtained from Global Data Lab (https://globaldatalab.org/, accessed on 19 June 2023). These variables are within the study period spanning from 2008 to 2021.

2.2.2. Fire Dataset Acquisition and Processing

The spatial wildfire data used for this analysis on the European scale were obtained from the European Forest Fire Information System (EFFIS database—https://effis.jrc.ec.europa.eu/, accessed on 19 June 2023) as provided by [42]. The collection and documentation of forest fires across European countries date back to the 1970s. Still, the lack of harmonisation of these datasets has limited a collaborative approach to regional wildfire prevention [43]. As a result, the EFFIS was developed as a collaborative effort by the European Commission services (Directorate General Environment and the Joint Research Centre) and the relevant fire services across the countries (forest fires and civil protection services) to provide data needed by agencies such as the European Parliament and the European Commission Services [2]. The fire dataset in the EFFIS database is a comprehensive analysis that covers the complete forest management cycle, including fire prevention and post-fire damage analysis, and receives comprehensive forest fire information from countries across European and Mediterranean regions [6]. The study period for fire record information is 14 years (2008–2021), which comprises burned area per hectare (ha), sources of ignition, start and end dates, size of the fire occurrence, and location of each wildfire. The UTM resolution was readjusted to 1 km^2 resolution to be consistent with the other datasets used in this project. The limitation in the use of this dataset is the exclusion of small-size fires as the data do not capture fires with burned areas below 30 Ha. However, while only a fraction of the total number of fires is mapped in the EFFIS dataset, the burned areas of size larger than 30 ha represent 75% to 80% of the total EU burned areas (http://effis.jrc.ec.europa.eu/about-effis/data-license/, accessed on 19 June 2023), thus, making it suitable to assess country-level fire behaviour.

2.2.3. Land Cover Classification

The land cover maps for 2006, 2012, and 2018 were obtained from the Copernicus website (https://land.copernicus.eu/pan-european/corine-land-cover, accessed on 19 June 2023). The CORINE Land Cover (CLC) database is a European Programme coordinated by the European Environment Agency (EEA) that provides consistent information on land cover and land cover changes across Europe. Initially, the original data were masked to Spain and reclassified from 15 classes at level 2 and 44 land-cover types at levels 3 to 7 using map algebra with incorporated Python function code in ArcGIS version 10.7.

Furthermore, individual classes were dissolved to obtain five reclassified land cover types. The polygon was rasterised to extract cell values corresponding to the land-cover type in the fire database. To this end, we reclassified land use and land cover types into five distinct classes: agricultural areas, forests, scrub/herbaceous vegetation, wetland, and others (see Table 2 for complete details and information).

Table 2. CORINE and reclassified land-cover types.

S/N	Reclassified Land-Cover Type	CORINE Land-Cover Type
1	Agricultural area	Non-irrigated and permanent irrigated land, rice fields, vineyards, fruit trees and berry plantations, olive groves, pastures, annual crops associated with permanent crops, agriculturally dominant land with significant natural vegetation, and agro-forestry areas.
2	Forest	Broad-leaved forest, coniferous forest, and mixed forest.
3	Others	Built-up areas, beaches, dunes, sands, bare rocks, sparsely vegetated areas, burnt areas and glaciers, and perpetual snow.
4	Scrub/herbaceous vegetation	Natural grasslands, moors and heathland, sclerophyllous vegetation, and transitional woodland shrubs.
5	Wetland	Inland and salt marshes, peat bogs, salines, and intertidal flats

Source: Copernicus.

2.3. Methods

We developed a methodology to examine the temporal and spatial patterns of wildfires in Spain, focusing on the frequency of fires and the extent of burned areas. A flowchart of the stepwise methodology is presented in detail in the diagram below (Figure 2). Initially, the process involved consolidating all datasets into a unified database to define criteria for fire size, enabling the evaluation of burned areas and fire counts. We conducted spatial and statistical analyses on historical bioclimatic variables, wildfire perimeters from 2008 to 2021, CORINE land cover data for 2006, 2012, and 2018 at six-year intervals, population density figures for 2010, 2015, and 2020 at five-year intervals, and digital elevation model (DEM) data. Linear regression and one-way ANOVA were employed for all datasets to investigate variable correlations. Then, PCA was applied in the second phase to establish connections between dependent and independent variables. Data processing, analysis, and visualisation were performed using ArcGIS version 10.7 and R software version 4.3.1.

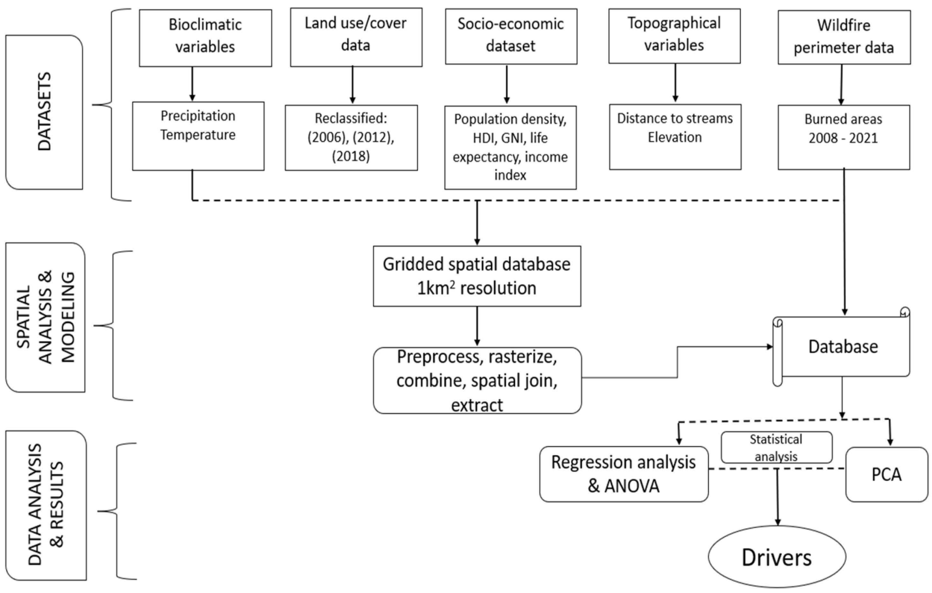


Figure 2. A Stepwise methodology flowchart.

2.4. Statistical Analysis

For statistical analysis, we used PCA to determine the association between the dependent variable (fire perimeter data) and the independent variables (bioclimatic variables, CORINE land cover, elevation, distance to stream, life expectancy, HDI, GNI, income index, and gridded population data). In this study, PCA was employed to gain insights into and identify the drivers of wildland fires in Spain. Hence, PCA is a useful method that allows the interpretation of variance within the original data to effectively lower the dimensionality of the datasets. Additionally, we used a linear regression model to make predictions among the predictors and explanatory variables to test for statistical relationships. These statistical analyses and PCA tests were performed using R software version 4.3.1 [44] using the following library packages: ggrepel, ggplot2, factoextra, FactoMineR, janitor, lubridate, magrittr, pcaMethods, raster, and tidyverse.

3. Results

3.1. Trends in Number of Fires and Burned Areas

The number of fires and the size of burned areas in Spain due to wildfires varied considerably across the study period, both within different land-cover types and regions. Generally, the total number of fires increased significantly within the study period from 32 fire events in 2008 to 850 in 2021 (Figure 3 left, Appendix A: Table A2). Specifically, scrub/herbaceous vegetation accounts for the highest number of fires across the various land-cover types with a mean of 153 ± 37 (1 standard error of the mean), as shown in Appendix A: Table A2). Forests have the second highest number of wildfires, with a mean of 47 ± 12, while agriculture stands at a mean of 31 ± 8 fires (Appendix A: Table A2). The highest number of wildfires in a single year per land-cover class occurred in scrub/herbaceous vegetation, with a total of 528, accounting for ~62% of the total wildfires in 2021 (Appendix A: Table A2). Relatedly, scrub/herbaceous vegetation has the highest burned areas through the study period with a mean of 36,552 ± 7239 ha, with forest and agriculture areas having mean values of 11,397 ± 2381 ha and 9456 ± 2608 ha, respectively (Appendix A: Table A3), having second and third highest burned areas within the study period. The highest total burned area was in 2012, with a total area of 178,504 ha (Appendix A: Table A3, Figure 3 right). The total burned areas significantly differ on the scrub/herbaceous land compared to other land cover classes, with other land cover classes showing interrelatedness in the extent of yearly burned areas. However, when the proportion is considered, scrubland significantly differs from all the land cover classes, while the proportion of forest burned is not different from agricultural lands but differs significantly from other land cover classes, as revealed by the corresponding letter in the boxplots. Similar to the highest number of fires per year per land-cover type, the highest burned area per year also occurred in the scrub/herbaceous vegetation with a total of 101,727 ha, making ~57% of total burned areas in 2012 (Appendix A: Table A3).

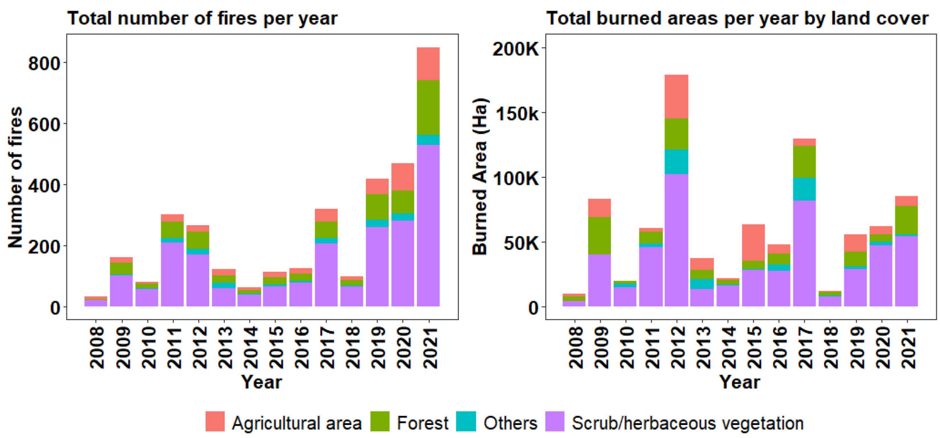


Figure 3. Change in number of fires (for fires with burned area ≥ 30 Ha) per year by land cover (**left**) and burned areas (**right**) per year by land cover classes in Spain through the study period (2008–2021).

Expectedly, others (land cover class as described in Table 2 and wetland land category are the land cover types with the lowest burned areas (see Appendix A: Table A3, for complete details and information) and number of fires (Appendix A: Table A2), respectively. Additionally, during the study period (2008–2021), the year 2017 had the second-highest total burned areas of 129,434 ha. Notably, both 2012 and 2017 correspond to the period of El Nino events, which resulted in the increase in temperatures across Spain (Figure 3 right). Overall, ~63% of total wildfires in Spain occurred in scrub/herbaceous vegetation; forest areas are responsible for ~19%, while agricultural areas accounted for ~13% of total wildfires in Spain (Appendix A: Table A2).

The number of fires per month shows two distinct periods of high wildfires, specifically during spring (February to April) and summer (July to October), as shown in Figure 4, left. This depicts that major fire events are not limited to the summer period when there is less rainfall and intense heat but in the late winter and early spring when the temperature is relatively low. This can also be attributed to the increasing winter temperature, which favours fire events across different land-cover classes in Spain. Furthermore, while March has the highest number of wildfire events within the study period, with a total of 648, the distribution across the study period is positively skewed, as shown in Figure 5, with more fires, on average, occurring during the summer periods.

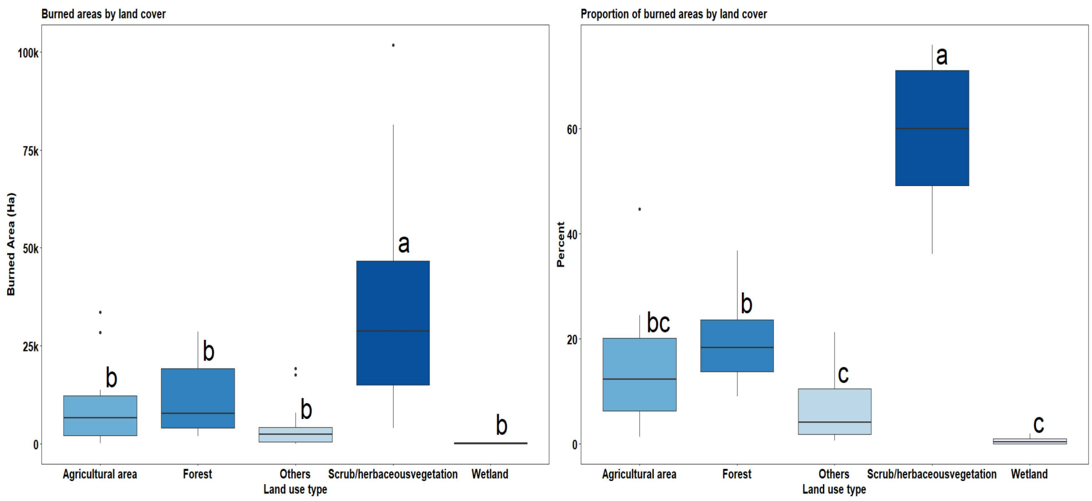


Figure 4. Boxplot of distribution of total burned areas in Spain by land cover types (**left**) and proportion of land cover burned (**right**) through the study period (2008–2021). The land cover types whose means are statistically different at $\alpha = 0.05$ are in different letters, while colour transparency denotes a difference in median values.

The monthly burned areas show the concentration of large fires towards the summer periods (from July to October). Unlike the number of fires that show two distinct periods, the monthly burned areas' distribution shows a higher number of burned areas in the summer, which peaks in August (Figure 5, right). Therefore, while the summer and spring seasons drive the number of wildfires, the size of fires is more favoured during the summer.

The number of fires and the extent of burned areas were not evenly distributed across all regions in Spain (Figure 6). Hence, some areas experienced a higher number of fire events than others. Moreover, weather patterns across different regions of Spain also vary significantly, which can further complicate the management and prevention of fires. Interestingly, autonomous communities such as Principado de Asturias, Galicia, and Castilla y León have the highest number of fire events, with 754, 732, and 576 fires, respectively (Appendix A: Table A4, Figures 7 and 8). However, provinces like Galicia, Castilla y León, and Andalucía have the highest burned areas with a total of 170,370 ha, 168,845 ha, and 115,384 ha, respectively (Figure 9). The total burned areas per region did not reveal the complete information about burned areas, as some autonomous regions are considerably more extensive in size compared to others. The larger burned areas may be due to the size of the region; therefore, the percentage of region burned areas across the study period (2008–2021) was calculated using Equation (1). The result shows Cantabria, Principado de Asturias, and Galicia as having the highest burned areas relative to the region's size (Figure 9). This is important, especially when compared to the total burned area; Cantabria has a total burned area of 34,450, less than Galicia, Castilla y León, and Andalucía (regions with the highest total burned area), but higher in proportion. This is due to the size, which is considerably smaller. While we observed differences in burned proportion across Spain regions, further studies could explore the difference in burned proportion based on the available wildland and compare the results with ours to understand variations. Similarly, regions like Castilla y León and Andalucía have a higher total burned areas; however, the proportion, relative to the size, is lower (Figure 9; Table A4).

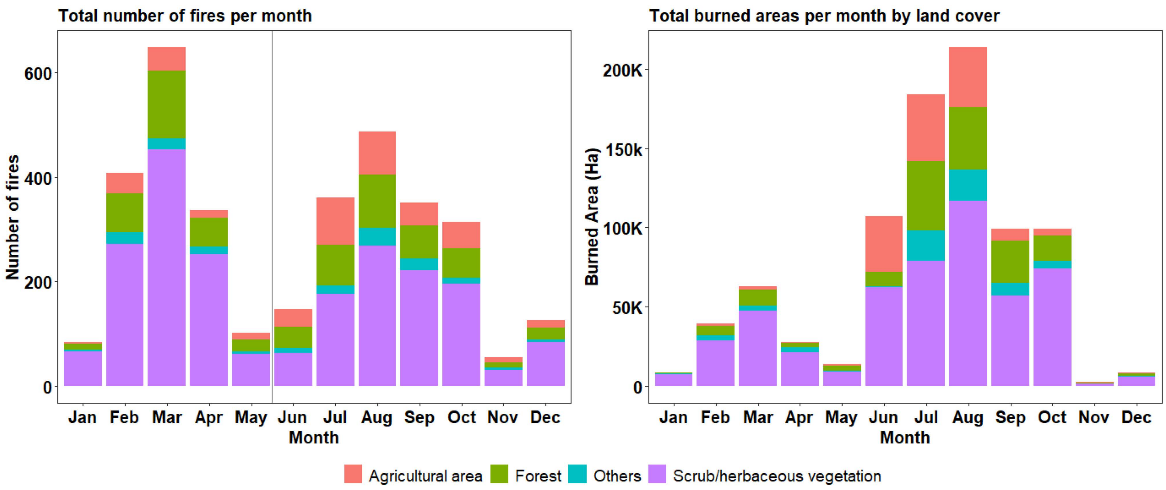


Figure 5. The seasonality of fire activity of the total number of fires per month (**left**) from January to December (the line showing two distinct periods of an increasing number of wildfires) and the total burned area per month (**right**). For each month, we have the distribution of a historical number of fires over 2008–2021 (14 periods per month). The data describe fires with burned area $\geq$ 30 ha.

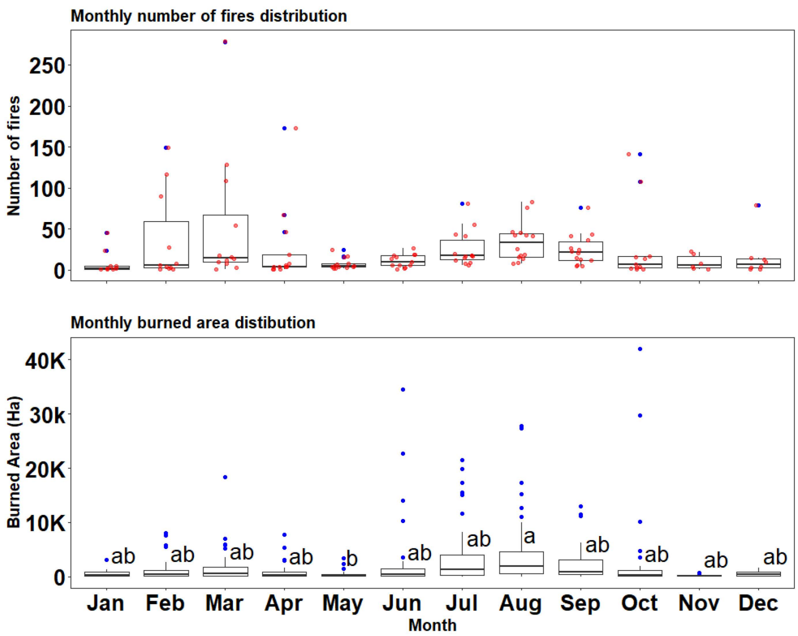


Figure 6. Distribution of monthly fire frequencies (**top**) and burned areas (**bottom**) in Spain (red dots represent observations while outliers are in blue). For each month, we have a distribution of a historical number of fires and burned areas over 2008–2021. The burned areas whose means are statistically different at α = 0.05 are in different letters.

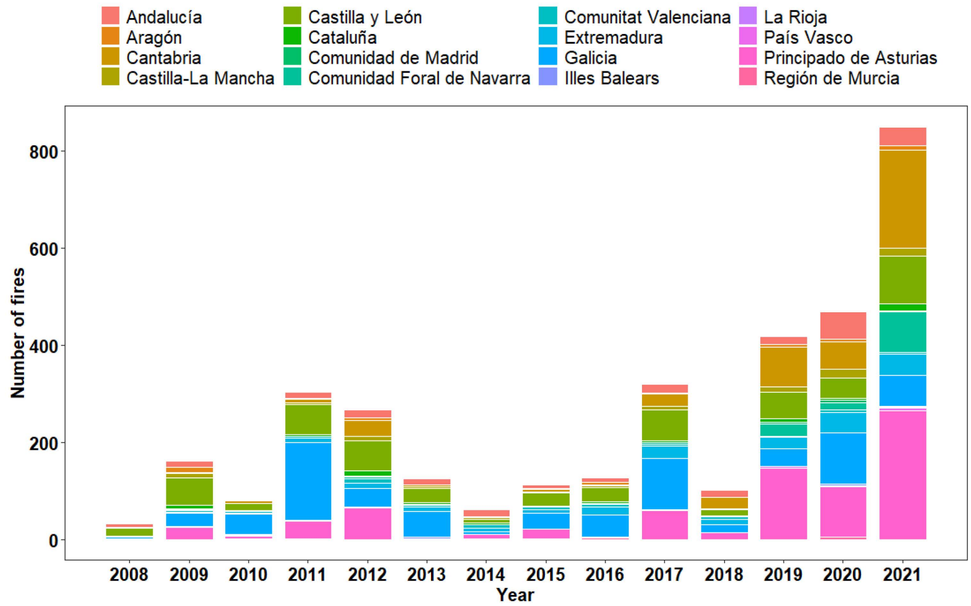


Figure 7. Temporal sequence of the total number of fires (fires with burned area ≥ 30 ha) per region during the study period from 2008 to 2021, with each colour denoting the specific fire count for each region.

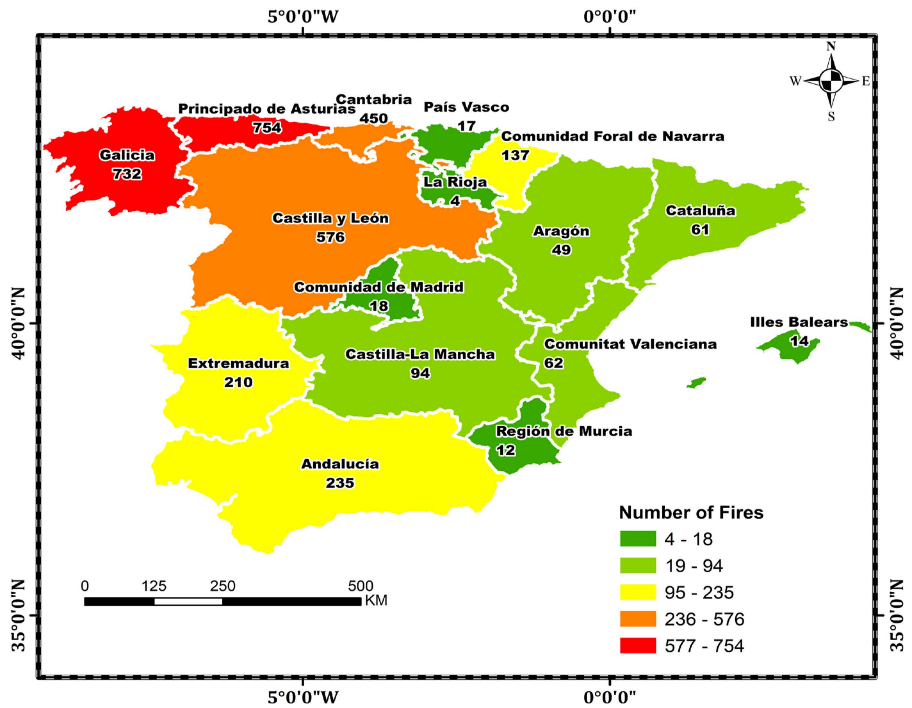


Figure 8. Spatial pattern of the number of fires per region between 2008 and 2021 in the study area.

While further exploring the relationship between burned areas and the number of fires in each region, we found a moderate relationship, which shows that the extent of burned areas is not necessarily dependent on the number of fire events within a particular region. For example, 51,595 ha of land cover was burned in Aragon, corresponding to 49 fire events, while Cantabria, with a total of 450 fires, had just 34,450 ha of burned areas. Additionally, regression analysis between the number of fires and burned areas per region (Figure 10 shows a significant relationship, with the number of fires explaining 74% of variations in burned areas with an R^2 of 0.74 and a p-value of 0.001. However, when the number of fires is examined while factoring the land cover types, it explains 77% of the variation in yearly burned areas within the regions with an R^2 of 0.77 and *p*-value < 0.001 (Figure 11) and 85% variation in monthly burned areas with an R^2 of 0.85 and *p*-value < 0.001 (Figure 12).

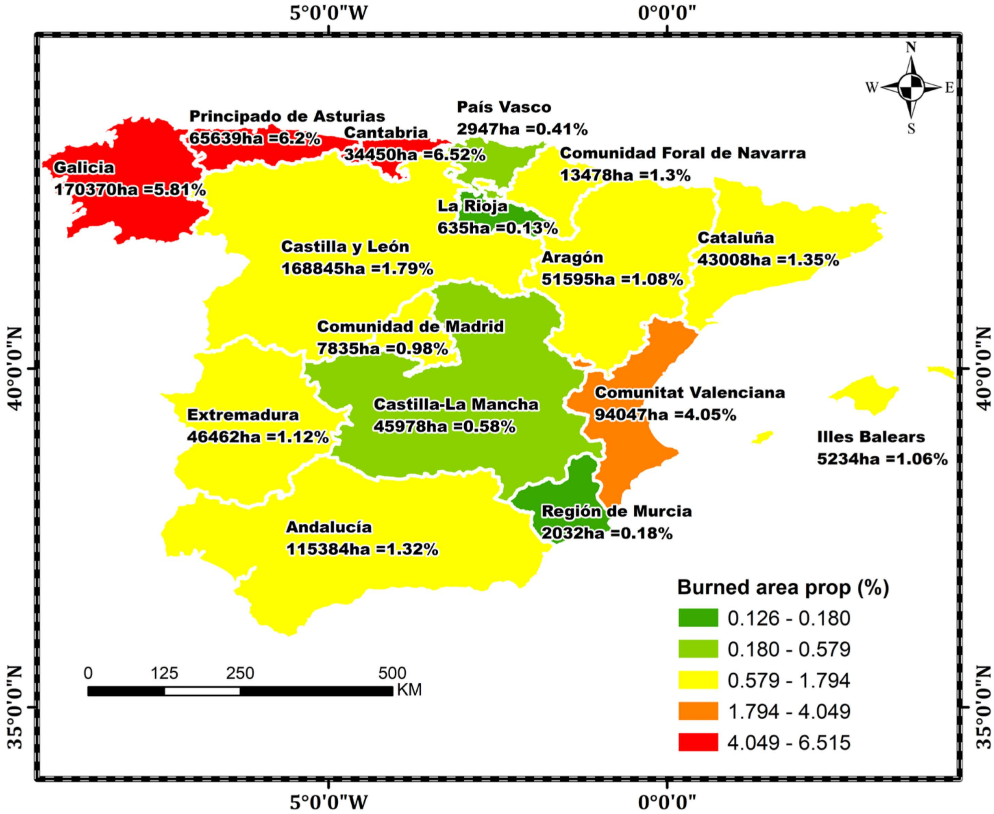


Figure 9. Spatial distribution of total burned area (in percentage) per region between 2008 and 2021 in the study area.

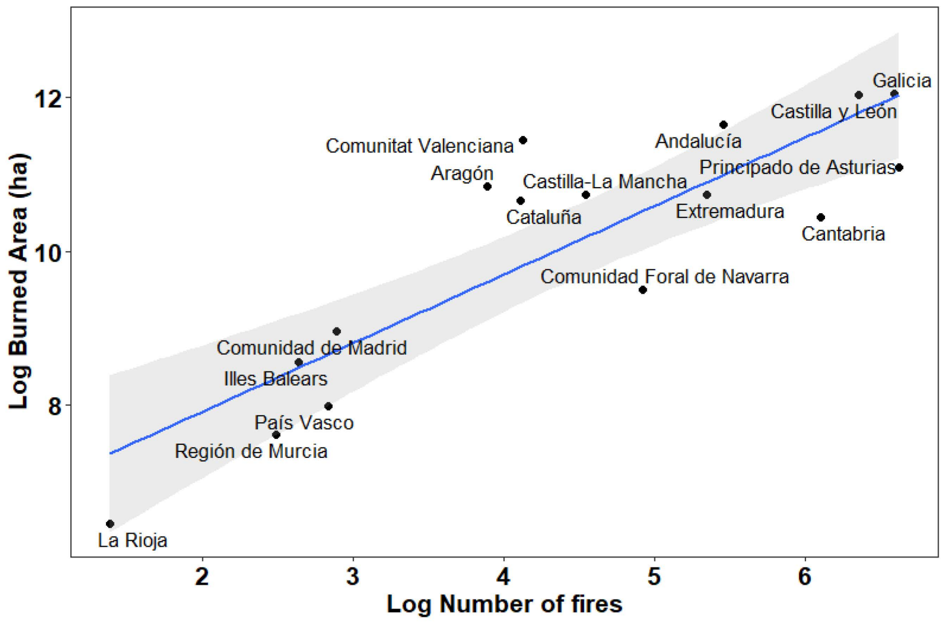


Figure 10. Regression relationship between the number of fires and burned areas per region (point shows the total burned areas within each region) and regression formulae and scale has been log transformed to address heteroskedasticity. The blue line shows the regression line while the shaded grey area represents the standard error.

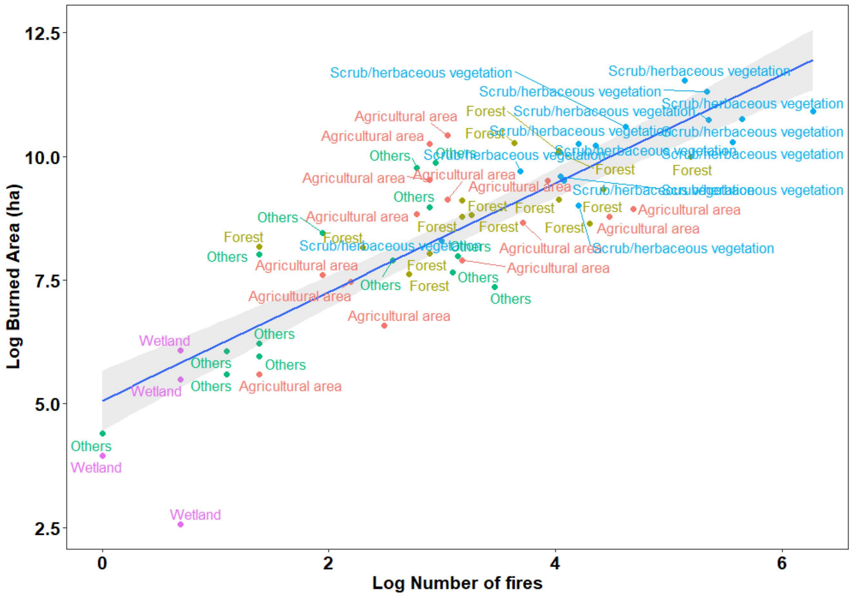


Figure 11. Regression relationship between the yearly burned areas and the number of fires factoring different land cover types (points and colours show the land cover types). The blue line shows the regression line while the shaded grey area represents the standard error.

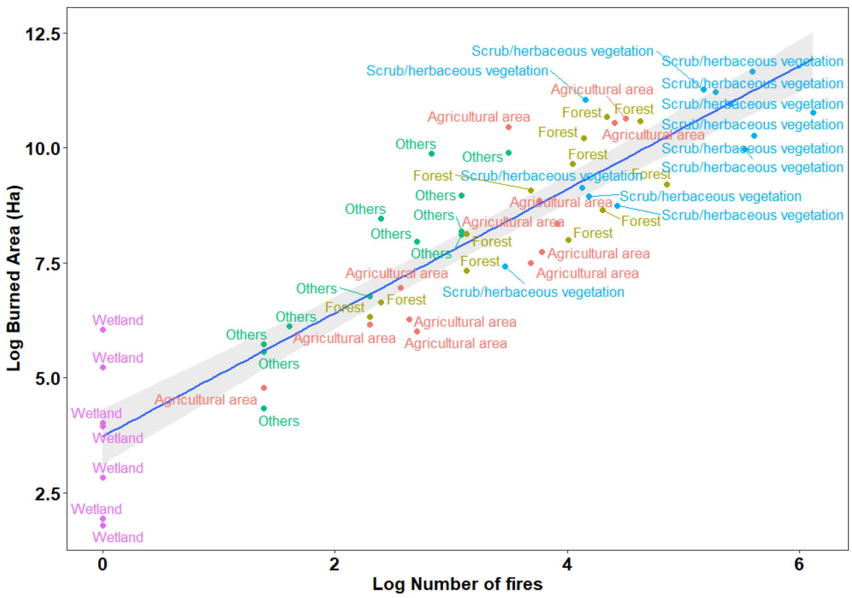


Figure 12. Regression relationship between the monthly burned areas and the number of fires factoring different land cover types (points and colours show the land cover types; the blue line shows the regression line while the shaded grey area represents the standard error).

We calculated the percentage of burned areas in each municipality per year, as shown in Table A4 and Figure 9.

$$\%BA = \frac{\sum BA_{ry}}{A_r} \times 100 \quad (1)$$

where

$\%BA$ = percentage of burned area in each region;
BA_{ry} = Burned areas in each region per year;
A_r = Area of a region in hectares.

3.2. Wildfire Variability

Andalucía, Cataluña, and Comunidad de Madrid are the regions with the highest population, with a mean population of 11,884,485, 11,365,403, and 9,834,728, respectively. While this does not directly relate to wildfires, population within points of fire occurrences will better describe the influence on wildfires. Therefore, the total population within 1 km^2 grids (spatial resolution of the gridded population data) of fire points was used to analyse the relationship between the number of fires, burned areas, and population. A strong association was found between the total population and the number of fires, showing population as a significant driver of wildfires in Spain. Examining the relationship between population and the total number of fires per year through linear regression, an R^2 of 0.88 and a p-value of <0.001 show a significant positive relationship with population, explaining 88% variations in yearly wildfires in Spain (Figure 13), showing the importance of increasing population to fire frequency.

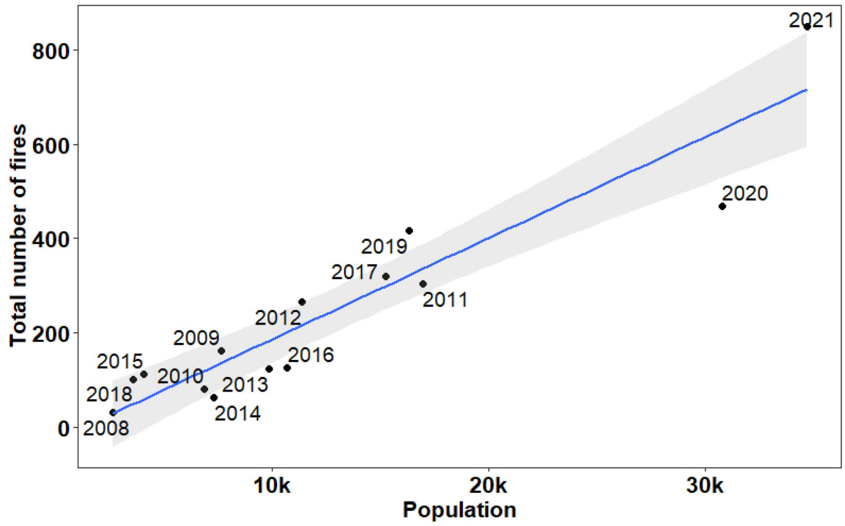


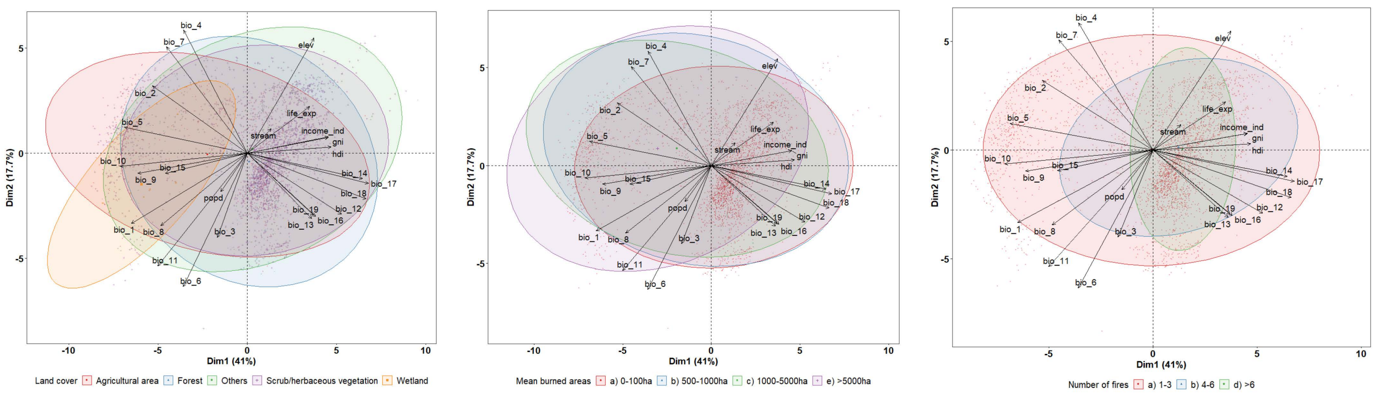
Figure 13. Regression relationship between total population and number of fires per year (point shows the total number of fires in each year). The number of fires refers to fires with a burned area ≥30 ha. The blue line shows the regression line while the shaded grey area represents the standard error.

Based on our findings across the different land cover classes, a high relationship was observed between burned areas and the number of fires across each period. The number of fires was found to significantly influence burned areas across each land cover type, with a p-value < 0.001 (Appendix A: Table A7). Furthermore, two years, corresponding to 2012 and 2017, witnessed a significant increase in burned areas during the period of study, with p-values of 0.001 and 0.03, respectively (Appendix A: Table A7 highlighted). This is due to the significant increase in temperature and drought events within these two years. This reveals the importance of temperature change in driving the extent of burned areas across Spain, with increasing temperature significantly increasing the burned areas.

On a monthly basis, there was an observed variability in the extent of burned areas and the number of fires (refer to Figure 5). The relationship between both, across different land cover classes, shows that the monthly fire ignition across different land cover classes significantly influenced burned areas, with a p-value < 0.001 (Appendix A: Table A8). While a strong relationship was observed between monthly number of fires and burned areas across different land cover classes with an R^2 of 0.74, June, July, and August are months with larger burned areas, with p-values of 0.03, 0.01, and 0.009, respectively (Appendix A: Table A8 highlighted). This further reinforces the importance of the summer periods, characterised by rising temperatures and decreased rainfall, in influencing the spread of fires post-ignition.

3.3. Factors That Influence Wildfires

The biplot of PCA results showed different driving factors in wildland fires in various regions of Spain. Generally, the first three principal components account for approximately 80% of the total variability in the wildfire dataset (Appendix A: Table A7). Our results identified key drivers of wildfires based on land cover (Figure 14a), burned areas (Figure 14b), and number of fires (Figure 14c). To begin, on the one hand, the land cover distribution shows a difference in fire drivers. Fires in wetlands are driven by temperature-related variables (annual mean temperature, mean diurnal range, max temperature of warmest month, mean temperature of wettest quarter, mean temperature of driest quarter, mean temperature of warmest quarter, and mean temperature of coldest quarter). On the other hand, wildfires in scrub/herbaceous vegetation were mainly driven by elevation and temperature (i.e., temperature seasonality and temperature annual range). Population density, elevation, and stream variables influence fires in all the land cover types except wetlands. In agricultural areas, temperature-related variables are primarily the main drivers of fires. Specifically, the analysis shows a temperature-driven increasing burned areas, with elevation contributing to the rising burned areas as seen in Figure 14a. Small areas respond to all bioclimatic variables, with growing burned areas favoured by temperature variables (temperature seasonality, temperature annual range, minimum temperature of coldest month, and mean temperature of coldest quarter) and elevation (Figure 14b). To this end, the number of fires shows differences in drivers for increasing reoccurrence of wildfire events. To obtain the number of wildfire recurrences, the fire dataset was spatially joined to know the count of overlapping fire polygons, thus examining the number of times a polygon was burned within the study period. From the analysis, small recurrent fires (1–3 times) are influenced by all variables (Figure 14c). However, Precipitation-related variables were observed to influence the increasing recurrence of fires within the study period.



(**a**) (**b**) (**c**)

Figure 14. Bi plot of PCA result. (**a**) Land cover type, (**b**) the mean of burned areas in hectares, (**c**) the number of fires for the study area for the period of 14 years (2008–2021).

4. Discussion

A combination of climatic, socioeconomic, and topographic variables has been significantly influencing the occurrence of fires and the extent of burned areas in Spain [23,25,32,45–47] and other Mediterranean countries such as Greece [48], the south-eastern part of France [30], Italy [31], and Portugal [29]. Regions in Spain show a large variability in the wildfire patterns and the extent of burned areas across different land cover types. Our study focused on the analysis of wildfire variability across different land cover types in Spain within the study period (2008–2021), where autonomous communities of Castilla y León, Galicia, and Andalucía experienced the most burned areas, with 17,0162 ha, 168,845 ha, and 115,379 ha, respectively. Based on the analysis of the land cover dynamics in relation to wildfire activity, we found that scrub/herbaceous vegetation (encompassing grassland, sclerophyllous vegetation, and transitional woodland-shrubs after reclassifying land cover types) and forests are susceptible to most wildfires in Spain. This is in line with the study on wildfires in the European Mediterranean region [6] showing that forests experienced a more frequent occurrence of fires than other LUC types. This finding also closely aligns with a recent study conducted by [49] in Italy, which suggests that shrubland and forests, particularly coniferous forests, are prone to burning within the Mediterranean biome. The increased risk is attributed to such factors as species composition, fuel accumulations, and the impact of drier and hotter climate conditions during the fire seasons. Furthermore, our study demonstrated that agricultural-related land cover types, i.e., agricultural landscapes, were not affected by large fires across the regions in Spain. This is evident when comparing the landcover types of regions with the highest burned areas, which reveals an inverse relationship between burned areas and the percentage of agricultural areas across three regions (Galicia, Castilla y León, and Andalucía). This result supports the study [45], which asserted that agricultural-related fires might be becoming less significant in Spain.

Population density is identified as one of the key socioeconomic factors impacting wildfires in the framework of our study, which is in agreement with previous studies conducted in Spain [50]. We found a positive correlation between yearly dynamics of population and the number of fires, as well as monthly population and burned areas, confirming the role of human factors as drivers of fire dynamics [17,50].

In our study, we used Principal Component Analysis (PCA). Recently, PCA has been applied to investigate the diverse drivers of wildfires, encompassing climatic, socioeconomic, and topographical factors on different eco-biome types around the world [25,29,30,49]. Many studies have compared the patterns of association between wildfires and environmental [17,51] or human-caused [23,52] drivers of wildfires in the EU-MED region. For example, Montoya et al. [25] used PCA to determine the drivers of wildfires in different eco-biome types in Mexico, and results showed that grasslands, hydrophilic vegetation, and temperate forests had the highest burned areas, accounting for 42% of the total land cover areas. PCA was used to identify specific fire regime zones in south-eastern France and found that wildfire drivers in the research area are based on fuel loads, population density, topography, and inadequate fire-fighting capacity [30]. Similarly, Jiménez-Ruano et al. [28] identified regions of fire activity in Spain using PCA and Ward's hierarchy clustering models based on the spatial-temporal framework of their key fire characteristics. PCA was applied in Portugal [29] to identify the most vulnerable locations for wildfires, revealing that wildfires are more likely to occur in the central and southernmost areas of Portugal in the future. However, while many machine learning algorithm methods like PCA coupled with different mathematical models have been commonly employed to identify wildfire drivers or predict burned areas using climate, socioeconomic, and topographic factors (some of which are listed in this study), few studies have considered these factors combined [53,54].

In our modelling work, we considered the temperature- and precipitation-related bioclimatic drivers of fire events. The summer months in Spain over the last decades have witnessed a major increase in extreme heat waves and drought conditions [55,56]. Our analysis showed that fires are driven by population, elevation, distance to streams, and extreme precipitation-related variables such as the precipitation of the wettest month, the precipitation of the driest month, the precipitation of the wettest quarter, and the precipitation of the coldest quarter. More specific analysis is needed to understand the impacts of precipitation since fuel dynamics was not explicitly analysed in this study. On the one hand, decreasing precipitation in combination with other weather variables could lead to lower fuel moisture. On the other hand, the increasing precipitation favours forest growth and biomass accumulation through increased photosynthesis [57], leading to a higher fuel load in the forest landscapes. Therefore, we need to track precipitation dynamics in high temporal frequency. Fuel availability and dry conditions make the forest susceptible to fire ignition during wildfire seasons, especially in the presence of a large population density, which has been found to relate positively to the number of fires. Temperature-related variables, especially extreme events such as temperature seasonality, temperature annual range, minimum temperature of the month, mean temperature of the coldest quarter, and maximum temperature of the warmest month, were found significant in explaining the extent of burned areas across different land covers. It is evident that Spain experienced a notable temperature increase during the summer months (between June and September), with an average temperature of 23 °C (Appendix A: Figure A1).

In order to fully estimate the impacts of weather dynamics on wildfire, a more sophisticated methodology should be applied, including an assessment of evapotranspiration rates [58] based on a number of climatic variables, e.g., temperature, precipitation, wind speed, and relative humidity [59]. Although our study used simplified methods, based only on the temperature- and precipitation-based bioclimatic indicators, it still captures climate impacts on the persistently high summer burned areas in Spain over the study period. Obviously, weather drives fire-favourable conditions being combined with human ignitions, which result in extensive burned areas during fire season [60]. The years 2012 and 2017 recorded the highest burned areas. The extreme drought conditions of 2012 [61] and the intense summer heat of 2017 in Southern Europe [62,63] resulted in a significantly higher burned area in these two periods as compared to the average burned areas over the study period. Furthermore, the yearly number of fires showed an abrupt increase in 2019. Prior to 2019, the number of fires and burned areas (except the years with extreme temperature and drought events) has reduced, and this can be attributed to efficiency in emergency response [64] and successful risk prevention in some regions within Spain [65]. However, several studies [2,53] have predicted an increase in wildfire activities resulting from climate change and an increase in fuel load due to socio-economic activities. To explain the sudden increase in the number of fires and burned areas within Spain in recent years, more factors should be analysed, including human activities and fuel dynamics.

In future work, our study would use a more advanced methodology, such as a processed-based wildfire model [66,67], to take into account interactions of several fire-related variables. Moreover, deep analysis of local dynamics using expert knowledge across Spain should be performed, while our study proposed a large-scale simplified framework based on openly available datasets for weather, land cover, and population density.

5. Conclusions

Wildfire activity in Spain is driven by both biophysical factors and human activities. Notably, the frequency and intensity of these wildfires vary depending on the type of land cover in different regions of the country. Our findings show that scrub/herbaceous vegetation (average 63 ± 1.45% SE) and forests (average 19 ± 0.76% SE) have been highly susceptible to wildfires. The population density exhibited a robust positive correlation with fire frequency ($R^2 = 0.88$, $p < 0.0001$). Our study identified that scrub/herbaceous areas and forests near densely populated regions should be prioritised for wildfire management in Spain, particularly under changing climate conditions.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Population density per region for the years 2010, 2015, and 2020 (Source: SEDAC).

Region	2010	2015	2020
Andalucía	12,018,458	11,838,892	11,796,105
Aragon	2,090,960	2,039,021	2,009,465
Cantabria	906,758	880,430	863,829
Castilla-La Mancha	3,150,617	3,192,516	3,278,849
Castilla y Leon	3,984,571	3,739,480	3,547,574
Cataluña	11,257,884	11,322,140	11,516,185
Comunidad de Madrid	9,759,432	9,800,253	9,944,499
Comunidad Foral de Navarra	1,017,229	1,006,902	1,007,139
Comunidad Valenciana	7,576,683	7,671,928	7,853,461
Extremadura	1,669,162	1,573,393	1,498,768
Galicia	4,275,564	4,000,854	3,784,052
Islas Baleares	1,588,246	1,675,667	1,786,431
La Rioja	497,134	494,062	496,160
Pais Vasco	3,447,363	3,261,408	3,118,903
Principado de Asturias	1,723,194	1,598,815	1,498,964
Region de Murcia	2,121,432	2,163,402	2,229,332
Total	67,084,689	66,259,164	66,229,715

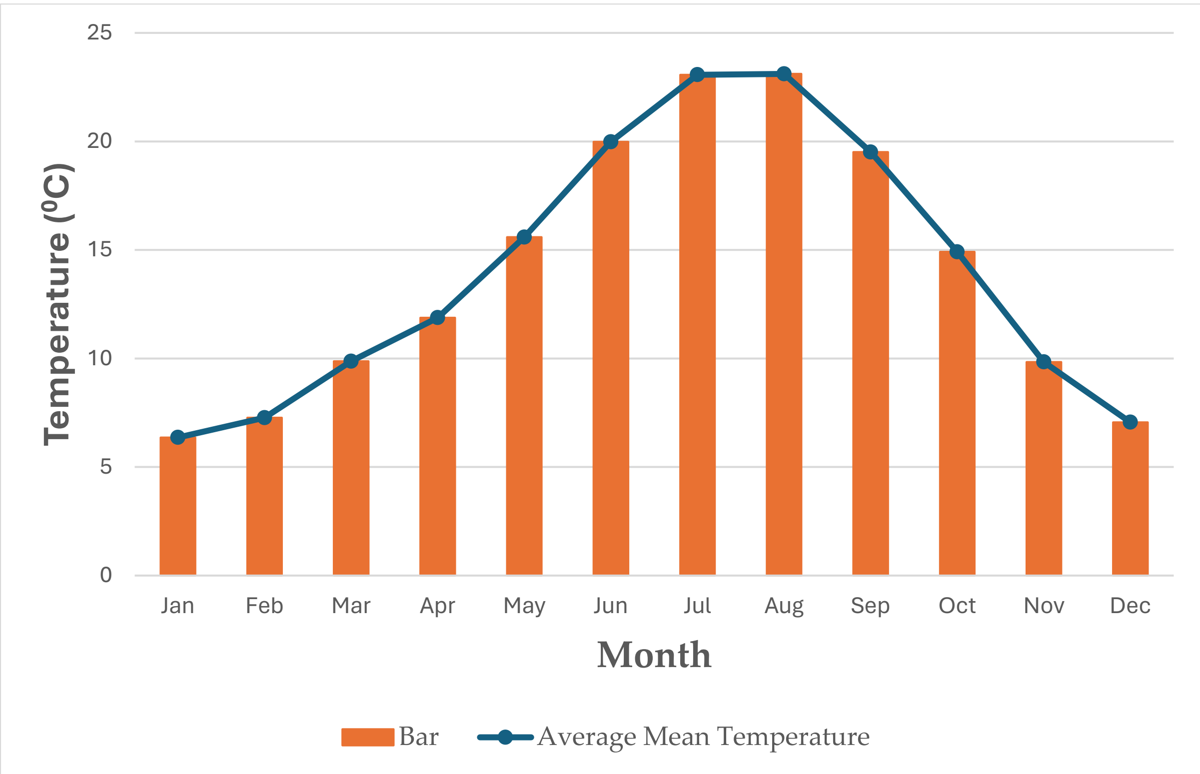

Figure A1. Seasonal trend in average monthly temperature. Changes during the summer period correspond to increasing burned areas in the summer period (source: World Bank Climate Knowledge Bank).

Table A2. Number of fires across different land-cover types in Spain between 2008 and 2021. Land cover types whose means are statistically different at (α = 0.05) are in different letters.

Year	Agriculture		Forest		Scrub/Herbaceous Vegetation		Wetlands		Others		Total
	Total	%	Total	%	Total	%	Total	%	Total	%	
2008	7	21.88	4	12.50	20	62.50	NA	NA	1	3.13	32
2009	18	11.18	38	23.60	101	62.73	NA	NA	4	2.48	161
2010	4	5.00	15	18.75	57	71.25	NA	NA	4	5.00	80
2011	24	7.92	56	18.48	210	69.31	NA	NA	13	4.29	303
2012	21	7.89	56	21.05	170	63.91	NA	NA	19	7.14	266
2013	21	16.94	26	20.97	59	47.58	NA	NA	18	14.52	124
2014	9	14.52	10	16.13	40	64.52	NA	NA	3	4.84	62
2015	18	15.93	24	21.24	67	59.29	NA	NA	4	3.54	113
2016	16	12.70	24	19.05	78	61.90	1	0.79	7	5.56	126
2017	41	12.81	56	17.50	207	64.69	NA	NA	16	5.00	320
2018	12	11.76	18	17.65	67	65.69	2	1.96	3	2.94	102
2019	51	12.23	83	19.90	261	62.59	NA	NA	22	5.28	417
2020	88	18.76	74	15.78	282	60.13	2	0.43	23	4.90	469
2021	108	12.71	180	21.18	528	62.12	2	0.24	32	3.76	850
Mean	31 ± 8^{b}	13 ± 1.20^{c}	47 ± 12^{b}	19 ± 0.76^{b}	153 ± 37^{a}	63 ± 1.45^{a}	0.5 ± 0.23^{b}	0.24 ± 0.15^{e}	12 ± 3^{b}	5 ± 0.79^{d}	245 ± 59.07

%—Percentage.

Table A3. Burned areas (Ha) across different land-cover types in Spain between 2008 and 2021. Land cover types whose means are statistically different at (α = 0.05) are in different letters.

Year	Agriculture		Forest		Scrub/Herbaceous Vegetation		Wetlands		Others		Total
	Total	%	Total	%	Total	%	Total	%	Total	%	
2008	1990	20.61	3547	36.74	4036	41.81	NA	NA	81	0.84	9654
2009	13,686	16.52	28,683	34.63	39,954	48.24	NA	NA	498	0.60	82,821
2010	271	1.36	2045	10.27	14,552	73.08	NA	NA	3045	15.29	19,913
2011	2689	4.45	9133	15.11	45,908	75.97	NA	NA	2697	4.46	60,427
2012	33,643	18.85	23,811	13.34	101,727	56.99	NA	NA	19,323	10.82	178,504
2013	9143	24.53	6691	17.95	13,504	36.23	NA	NA	7935	21.29	37,273
2014	1750	7.93	3467	15.72	16,406	74.38	NA	NA	433	1.96	22,056
2015	2844	44.71	6513	10.23	28,284	44.45	NA	NA	390	0.61	63,636
2016	6898	14.35	8978	18.67	27,470	57.14	52	0.11	4680	9.73	48,078
2017	5721	4.42	24,805	19.16	81,359	62.86	NA	NA	17,549	13.56	129,434
2018	717	5.78	3087	24.88	8089	65.20	243	1.96	271	2.18	12,407
2019	13,369	23.88	11,308	20.20	29,203	52.16	NA	NA	2102	3.75	55,982
2020	6477	10.37	5698	9.12	46,919	75.11	439	0.7	2935	4.70	62,468
2021	7583	8.89	21,793	25.55	54,320	63.69	13	0.02	1577	1.85	85,286
Mean	9456 ± 2608^{b}	15 ± 2^{bc}	$11,397 \pm 2381^{b}$	19 ± 2.2^{b}	$36,552 \pm 7239^{a}$	59 ± 3.3^{a}	187 ± 45^{b}	0.2 ± 0.14^{c}	4537 ± 1614^{b}	7 ± 1.68^{c}	$61,996 \pm 12,060$

%—Percentage.

Table A4. Burned area per region in hectares.

S/N	Region	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
1	Andalucía	1695	11,460	72	1817	11,566	1535	8673	13,162	2715	19,007	2860	5295	20,581	14,946	115,384
2	Aragon	2498	21,425	NA	200	9095	NA	NA	14,904	1324	240	30	1209	577	93	51,595
3	Cantabria	NA	91	562	919	4037	299	263	582	308	2056	1284	8109	3684	12,256	34,450
4	Castilla y León	4489	19,379	4284	8804	32,568	9634	1553	7562	7861	30,866	1610	7624	3654	28,957	168,845
5	Castilla-La Mancha	525	5286	NA	570	11,281	3053	5448	1087	1690	4830	326	4523	1691	5668	45,978
6	Cataluña	NA	7278	121	553	21,026	671	1150	1149	846	626	NA	7045	56	2487	43,008
7	Comunidad de Madrid	NA	41	NA	NA	2033	766	NA	NA	156	NA	NA	3593	1203	43	7835
8	Comunidad Foral de Navarra	NA	1086	86	NA	1151	NA	922	85	3617	306	75	1168	1163	3819	13,478
9	Comunitat Valenciana	53	3096	5496	1870	64,972	1141	1013	2510	6277	2003	3532	929	563	592	94,047
10	Extremadura	170	3533	105	1370	2278	3595	1271	11,228	4211	4887	737	1987	7070	4020	46,462
11	Galicia	145	4439	7433	36,574	7950	14,032	519	8056	18,248	48,347	1306	4556	14,735	4030	170,370
12	Illes Balears	NA	NA	323	1920	NA	2481	NA	NA	NA	69	NA	NA	436	5	5234
13	La Rioja	NA	NA	NA	NA	NA	NA	NA	166	NA	53	NA	NA	NA	416	635
14	Pais Vasco	NA	2099	501	NA	27	NA	51	NA	NA	NA	34	133	69	33	2947
15	Principado de Asturias	NA	3608	497	5466	10,520	66	1045	2912	565	16,144	613	9811	6471	7921	65,639
16	Region de Murcia	79	NA	433	364	NA	NA	148	233	260	NA	NA	NA	515	NA	2032

NA indicates the absence of fire.

Table A5. Yearly number of fires per region.

S/N	Region	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
1	Andalucía	7	13	1	12	16	11	15	8	8	19	15	15	56	39	235
2	Aragon	1	10	NA	2	5	NA	NA	2	5	2	1	6	6	9	49
3	Cantabria	NA	2	6	8	33	5	2	5	2	25	23	81	56	202	450
4	**Castilla y León**	17	57	14	63	62	29	8	26	29	63	13	56	41	98	**576**
5	Castilla-La Mancha	1	9	NA	3	9	4	4	3	5	8	2	11	19	16	94
6	Cataluña	NA	7	1	3	10	3	2	2	3	3	NA	7	4	16	61
7	Comunidad Foral de Navarra	NA	2	1	NA	4	NA	1	1	1	4	2	24	15	82	137
8	Comunidad de Madrid	NA	1	NA	NA	3	2	NA	NA	1	NA	NA	4	5	2	18
9	Comunitat Valenciana	1	5	4	4	8	4	7	4	6	3	4	2	5	5	62
10	Extremadura	1	2	1	8	11	8	7	8	15	27	11	25	42	44	210
11	**Galicia**	3	27	41	160	39	54	5	32	46	104	17	36	106	62	**732**
12	Illes Balears	NA	NA	3	3	NA	2	NA	NA	NA	1	NA	NA	3	2	14
13	La Rioja	NA	NA	NA	NA	NA	NA	NA	1	NA	1	NA	NA	NA	2	4
14	Pais Vasco	NA	1	1	NA	1	NA	1	NA	NA	NA	1	3	3	6	17
15	**Principado de Asturias**	NA	25	6	36	65	2	9	20	2	60	13	147	104	265	**754**
16	Region de Murcia	1	NA	1	1	NA	NA	1	1	3	NA	NA	NA	4	NA	12

NA indicates the absence of a fire event.

Table A6. Relationship between burned areas and number of fires across different land cover, factoring the different years (highlighted years have a significant relationship between burned areas and number of fires at (α = 0.05)). The strength of statistical significance at α = 0.05 is represented by the * symbol where * represent weak significance and *** represent strong significance.

	Std. Error	**t-Value**	***p*-Value**
Intercept	5551.07	0.191	0.849400
Number of fires	18.92	8.943	1.53×10^{-11} ***
2009	7871.16	1.631	0.109919
2010	7850.77	0.068	0.945999
2011	7951.44	0.155	0.877557
2012	7925.12	4.078	**0.001183** ***
2013	7859.53	0.383	0.703180
2014	7848.77	0.233	0.816526
2015	7856.83	1.282	0.206525
2016	7451.88	0.576	0.567475
2017	7964.80	2.230	**0.030751** *
2018	7448.47	−0.273	0.786475
2019	8055.93	−0.583	0.562479
2020	7619.64	−0.582	0.563473
2021	8050.81	−1.585	0.119937
$R^2 = 0.77$			

Table A7. Relationship between burned areas and number of fires across the different land cover, factoring the different months (highlighted months have a significant relationship between burned areas and the number of fires at (α = 0.05)). The strength of statistical significance at α = 0.05 is shown by the * symbol where * represent weak significance and *** represent strong significance.

	Std. Error	**t-Value**	***p*-Value**
Intercept	6369.97	−0.241	0.81056
Number of fires	24.12	8.067	4.52×10^{-10} ***
February	9751.56	−0.856	0.39675
March	9389.23	−1.179	0.24512
April	9071.18	−0.666	0.50937
May	9536.77	0.011	0.99146
June	9546.32	2.212	**0.03243** *
July	9086.72	2.666	**0.01084** *
August	9195.12	2.748	**0.00881** **
September	9079.80	0.855	0.39722
October	9648.61	1.140	0.26075
November	8990.46	−0.013	0.98984
December	9540.90	−0.251	0.80301
$R^2 = 0.74$			

Table A8. Principal component proportion of variables.

	PC1	**PC2**	**PC3**
Eigen value	3.1171	2.1374	1.8138
Variance proportion	0.4417	0.2077	0.1495
Cumulative proportion	0.4417	0.6493	0.7988
Eigen Vectors			
	PC1	**PC2**	**PC3**
bio_01	−0.26107	−0.2047	0.07949
bio_02	−0.21309	0.195398	−0.03959
bio_03	−0.06702	−0.24503	0.074376
bio_04	−0.14305	0.357966	−0.10285
bio_05	−0.27611	0.075055	−0.03163

Table A8. *Cont.*

	Eigen Vectors		
	PC1	**PC2**	**PC3**
bio_06	−0.14448	−0.38913	0.096607
bio_07	−0.1817	0.309396	−0.08949
bio_08	−0.19443	−0.211	0.243545
bio_09	−0.24586	−0.05895	−0.0395
bio_10	−0.28584	−0.0387	0.02777
bio_11	−0.20106	−0.32872	0.114453
bio_12	0.212475	−0.17779	−0.2721
bio_13	0.145219	−0.19	−0.35575
bio_14	0.259897	−0.07402	0.143008
bio_15	−0.18383	−0.05831	−0.34313
bio_16	0.153736	−0.18453	−0.35577
bio_17	0.273353	−0.0883	0.078039
bio_18	0.267866	−0.13356	0.049617
bio_19	0.149444	−0.18057	−0.36546
elevation	0.15051	0.334696	−0.17638
population	−0.05943	−0.11166	0.036238
stream	0.05364	0.070701	0.03835
life exp	0.140634	0.135563	0.156159
hdi	0.188716	0.017598	0.256821
gni	0.18264	0.046171	0.276279
income index	0.18206	0.047027	0.273631

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