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Biophysical controls over fire regime properties in Central Portugal

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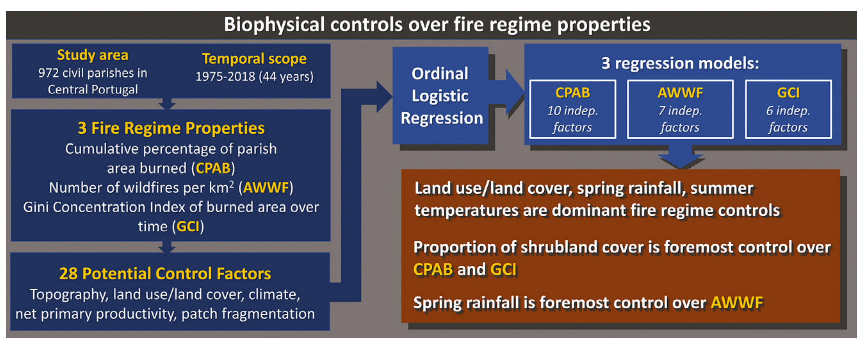
HIGHLIGHTS

- Fire regime is characterized for a 44-year period using three properties.
- Ordinal logistic regression is applied to assess fire regime controls at local scale.
- Land use/land cover and climate are the predominant fire regime controls.
- Extensive burned area is mostly controlled by the proportion of shrubland cover.
- Wildfire frequency is mostly controlled by spring rainfall.

GRAPHICAL ABSTRACT



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ABSTRACT

The concept of fire regime can be used to describe, with different degrees of complexity, the spatial and temporal patterns of fires and their effects within a given area and over a given period. In this work, we explore the relations between fire regime and a set of potential biophysical controls at a local scale, for 972 civil parishes in central Portugal. The fire regime was characterized with reference to a 44-year period (1975–2018) using three properties: cumulative percentage of parish area burned, area-weighted total number of wildfires, and the Gini concentration index of burned area over time. Potential control variables included topography, seasonal temperature and rainfall, and land use/land cover type and patch fragmentation. Ordinal logistic regression was used to model the relations between the fire regime properties and the potential control factors. Results show that the fire regime properties have important spatial contrasts within the study area, and that land use/land cover distribution, spring rainfall and summer temperatures are the major controls over their variability. The percentage of each parish occupied by shrubland and spontaneous herbaceous vegetation is the single most important factor influencing cumulative percentage of parish area burned and the Gini concentration index of burned area, whereas spring rainfall is the foremost factor regarding area-weighted total number of wildfires. Along with the role of spring rainfall in promoting fuel availability later in the year, our results highlight the importance of the speed of regrowth of shrubland and spontaneous herbaceous vegetation after burning, pointing out the need of tailoring fuel management strategies to the properties of each parish.

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1. Introduction

Wildfires account for substantial damages worldwide, as shown by the destructiveness of recent wildfire events in such distinct areas as Australia, the USA, Greece, or Canada (Khorshidi et al., 2020; Nolan et al., 2020; Ribeiro et al., 2020). Fire-prone Mediterranean-like landscapes, such as those of southern Europe, suffer extensive burned areas on a yearly basis. These are likely to increase in the future according to climate change projections (Bowman et al., 2017; San-Miguel-Ayanz et al., 2018). Among the southern European countries, Portugal is one of the most affected by wildfires, despite its relatively small area (89,015 km^2 for mainland Portugal). Between 1980 and 2019, this country burned an average of 115,024 ha per year, being only surpassed in absolute numbers by Spain (San-Miguel-Ayanz et al., 2020). Wildfire incidence and characteristics are not homogenous throughout the Portuguese territory. Most ignitions and burned area are concentrated in the northern half of the country (north of the river Tagus), characterized by an irregular topography and a predominance of forest and semi-natural areas, with a secondary concentration in the southernmost region of the country (Algarve) (Nunes et al., 2016; Oliveira et al., 2020; Tonini et al., 2017). The lowlands that dominate the southern half of the country, dominated by agricultural and agro-forestry land uses, show a much lower wildfire incidence. The largest burned areas tend to occur in the forest-and-shrubland dominated central sector of the country, whereas the other areas with high wildfire ignition density (the suburban areas of the northwest and the Lisbon regions) have mostly smaller wildfires (Tonini et al., 2017). These different patterns of wildfire occurrence result from the spatial variation of wildfire drivers and their multiple combinations, namely fuel, topography, and weather conditions (Fernandes et al., 2016), often categorized as 'bottom-up' and 'top-down' controls (Fernandes et al., 2014; Parks et al., 2012).

The spatial and temporal patterns of fires and their effects within a given area and over a given period, including their intensity and severity, can be encompassed under the concept of "fire regime" (Oddi, 2018). This can assume different definitions and has been studied under different approaches with varying degrees of complexity (Krebs et al., 2010). Nevertheless, authors have often adopted a relatively simple conceptual approach, describing fire regime in terms of one or more spatial and temporal variables such as wildfire size, frequency, or annual burned areas, and comparing them with different potential control factors. For example, Calheiros et al. (2020) defined regions of similar fire regime (pyro-regions) in the Iberian Peninsula, using monthly values of normalized burned area, comparing them in view of the incidence of different components of the Canadian Forest Fire Weather Index System. Syphard et al. (2007), used the annual number of fires and the area burned to describe the fire regime in counties in California (western USA), and then assessed the effect of different drivers over their evolution between 1960 and 2000. In Portugal, Nunes et al. (2016) characterized the incidence of wildfires among Portuguese municipalities using ignition density and burned area, then assessing the relations between these properties and a set of biophysical and anthropogenic potential explanatory variables. Fernandes et al. (2019), on the other hand, analysed the effect of the expansion of Eucalyptus plantations over burned area, wildfire size, and wildfire hazard and severity in mainland Portugal over a period of 38 years.

Regardless of the approach, understanding particular properties of a fire regime in a specific time and space is crucial to decision-making regarding wildfire management (Pausas and Fernández-Muñoz, 2012). In this framework, this study has two objectives. The first is characterizing the fire regime within a regional-sized study area in Central Portugal over a 44-year period by using three complementary properties describing the tendency for burning extensively, for burning frequently, and for the temporal concentration of damage. The second is to analyse the relations between these properties of the fire regime and a set of potential biophysical control factors.

The approach adopted presents two novel aspects. Regarding the adopted fire regime attributes, it is, to our knowledge, the first time that an indicator of the temporal concentration of burn damage is combined with burned area and wildfire frequency indicators. By integrating these three parameters, we intended to obtain a more nuanced perspective about fire regime and its controls. The way the data was structured and analysed was also innovative, as other work tends to employ daily to annual data values or individual wildfires as units of analysis (Arpaci et al., 2014; Fernandes et al., 2016, 2019; Hoinka et al., 2009; Marcos et al., 2015; Silva et al., 2019; Slocum et al., 2010; Urbieta et al., 2015). In our case, each fire regime variable and each potential control factor pertained to the whole 44-year study period, which allowed taking into consideration fire regime properties that can only be detected over time, such as the temporal concentration of burned area. An underlying assumption of this approach is that the behaviour of the adopted fire regime properties and their drivers has not significantly changed throughout the study period, in spite of the fact that both are subject to changes and temporal trends (Silva et al., 2019; Syphard et al., 2007).

2. Data and methods

2.1. Study area

The studied area is a region comprising 28,199 km^2 within central mainland Portugal (Fig. 1-A), heterogeneous in terms of climate, topography, and LULC patterns. Elevation increases from the coast in its western limit to its eastern sector (Fig. 1-B). The Central Mountain System (*Cordilheira Central*), a SW-NE-oriented mountain range, is located within the study area, including the highest point in mainland Portugal (1993 m). Slope values increase eastward from the flatter seacoast in the west to the mountainous areas in the central sector (Fig. 1-C), decreasing afterwards in the direction of the plateau that limits the region in the east. Mean annual rainfall ranges from slightly below 600 mm, mostly in the southernmost sector of the study area, up to 1834 mm, in the highest areas of the Central Mountain System (Fig. 1-D; reference period 1970–2000). Mean monthly temperature varies between 6.6 and 16.8 °C (Fig. 1-E; reference period 1970–2000). The lowest values occur along the northernmost limit of the study area, whereas the highest values concentrate mostly along its southernmost limit.

LULC also shows a marked heterogeneity (Fig. 1-E); the central sector of the study area is dominated by coniferous and eucalyptus forests, the latter concentrated in a distinctive N-S oriented section. A separate coniferous-dominated area also extends along the shoreline, comprising a consolidated maritime pine forest that occupies over 10,000 ha. The highest sector of the Central Mountain System shows a concentration of shrubland and unvegetated or sparsely vegetated terrain, whereas a combination of shrubland and agriculture/agro-forestry dominates the eastern and southwestern sectors of the study area.

Civil parishes were used as terrain units for analysis. They correspond to the smallest administrative unit in Portugal with management responsibilities over its territory, where residents share infrastructures and services and follow common procedures (Oliveira and Zêzere, 2020). The study area includes 972 civil parishes, varying from a minimum area of 1.98 km^2 to a maximum of 373.50 km^2 (Fig. 1-A). The parish boundaries are the ones defined in the official administrative map of Portugal (CAOP), produced by the Portuguese Directorate-General of the Territory (DGT).

2.2. Data collection and pre-processing

Both the variables describing the fire regime (dependent variables) and their potential controlling factors (independent variables) were calculated for each civil parish, by combining different data with the boundaries of parishes. ArcMAP 10.7.1 (ESRI Inc.) software was used for all spatial analysis operations. Whenever raster operations were performed, a 25 m pixel was employed, following the resolution of the topographic data. This was the finer resolution among the data used (see Section 2.2.2), and allowed to maintain the detail of the topographic data for further analysis.

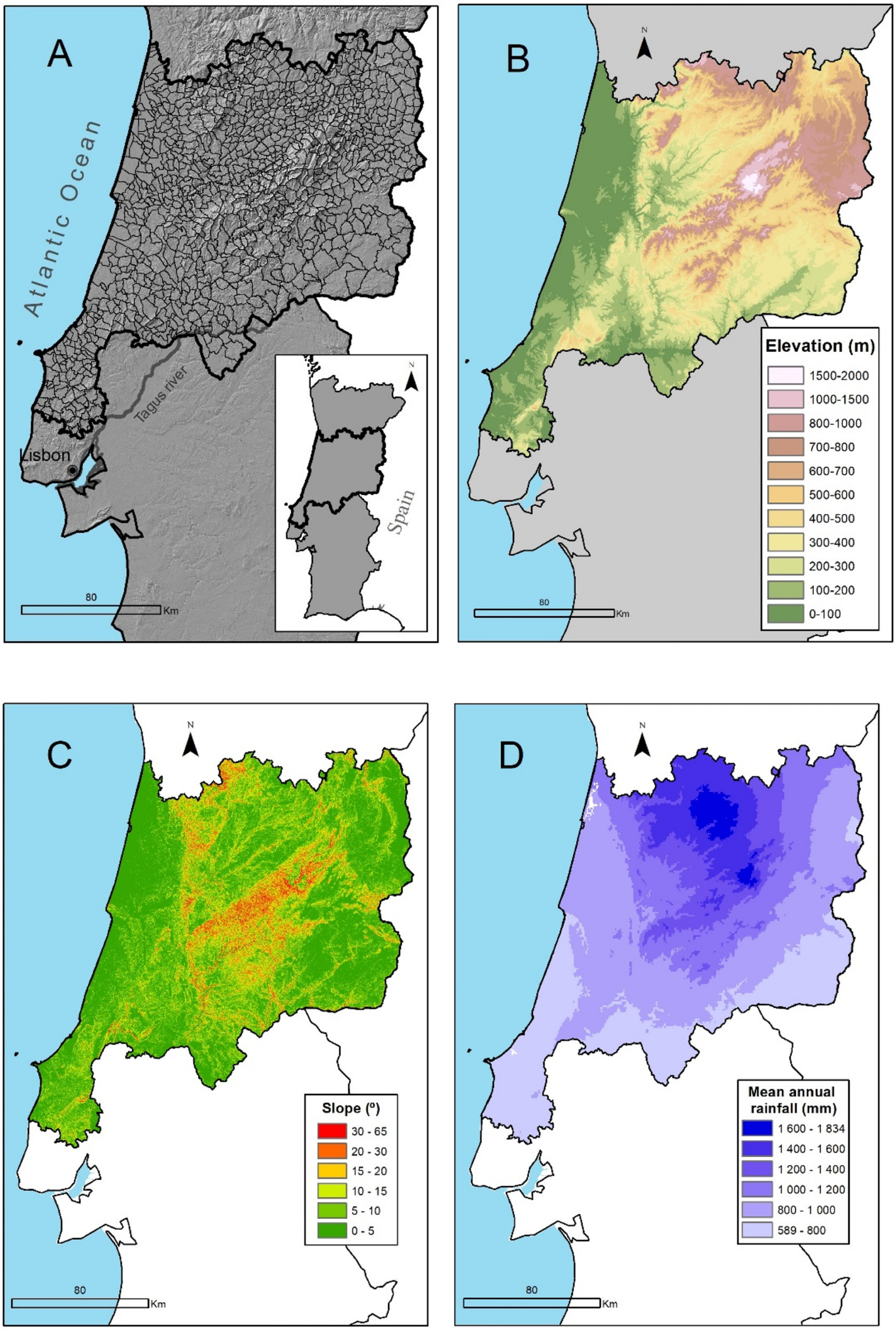

Fig. 1. A – Location and limits of the study area within mainland Portugal (NUTS II Central Region), including parish limits; B – Elevation (m); C – Slope (degrees); D – Mean annual rainfall (mm); E - Land use/land cover (2018); F – Mean monthly temperature (°C). Data Sources: elevation was obtained from the European Environmental Agency's Digital Surface Model, with a 25 m pixel (https://www.eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-eu-dem). Mean annual rainfall and mean monthly temperature (both 1970–2000) were obtained from the Worldclim database at https://www.worldclim.org/ (Fick and Hijmans, 2017), with a pixel of 30 s (about 1 km^2 resolution). Land use/land cover was obtained from the 2018 Land Cover Map (*Carta de Ocupação do Solo*) produced by the General Directorate of the Territory (*Direção-Geral do Território*).

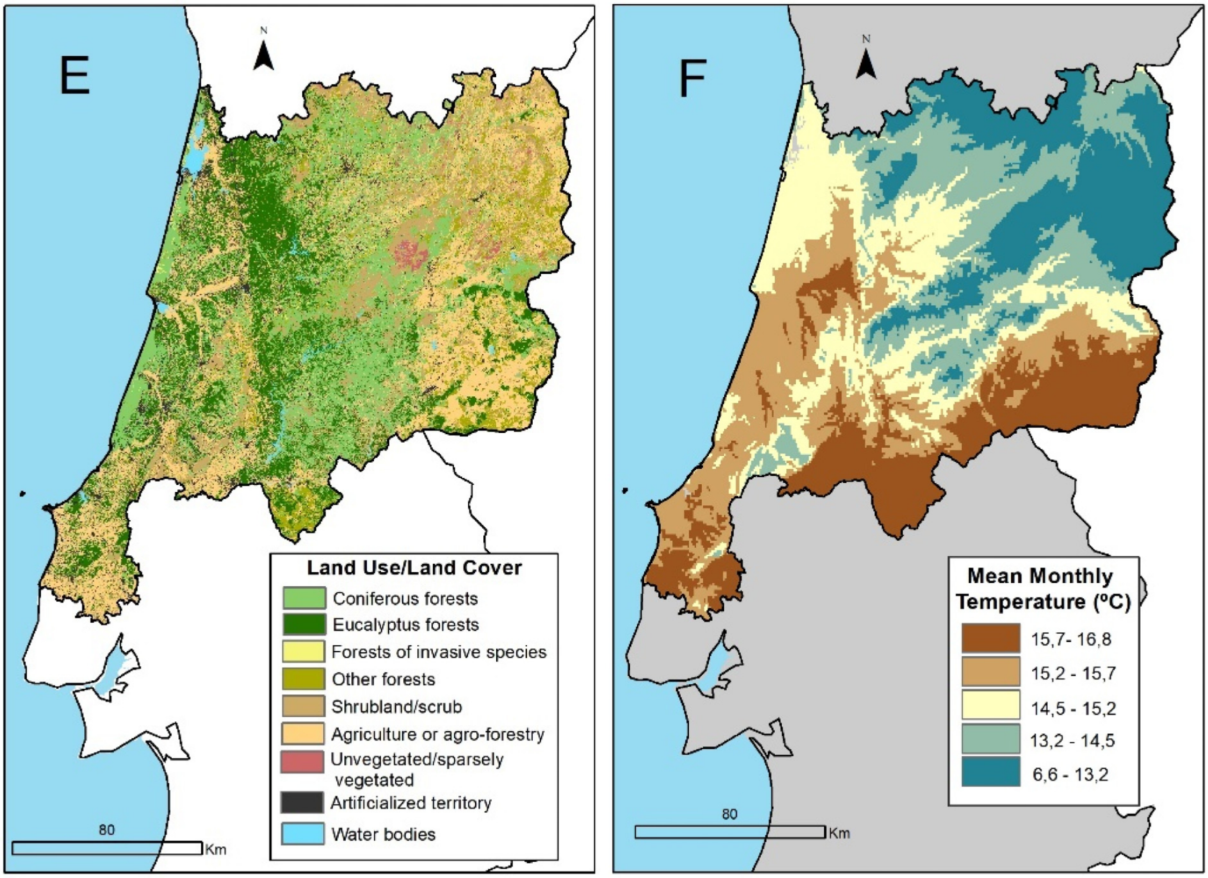

Fig. 1 (*continued*).

2.2.1. Fire regime variables

The fire regime characterizing each parish, during the period 1975–2018, was represented by three complementary variables, all obtained from the annual burned area maps, produced in vector format by the National Forests Service (Portuguese Institute for the Conservation of Nature and Forests - ICNF). The first variable expresses the dimension of wildfires and measures the general tendency of each parish to burn extensively over time. It was obtained from the cumulative percentage of parish area burned (CPAB) over the 44-year period (Oliveira and Zêzere, 2020).

The second variable is a general measure of wildfire frequency in each parish, and it was calculated as the total number of wildfires recorded within the parish over the study period. This value was divided by the parish area (in km^2), to avoid scale effects due to the contrasting parish sizes, in practice resulting in the number of wildfires per km^2 over the 44-year study period, or area-weighted wildfire frequency (AWWF). To obtain this variable, each polygon falling within the parish limits in each annual burnt area map between 1975 and 2018 (produced by the Portuguese Institute for the Conservation of Nature and Forests - ICNF) was quantified as a single wildfire event. The total number of such events was calculated for the totality of the studied period, and this number was divided by the parish area.

The third variable is linked with the temporal distribution of the total burned area in each civil parish. It corresponds to the Gini Concentration Index (GCI), applied to the burned areas of each parish over the studied period. The GCI corresponds to the Gini coefficient when expressed in percentage. The Gini coefficient G can be formulated as (Brown, 1994):

$$G = 1 - \sum_{i=0}^{K-1} (X_{i+1} - X_i)(Y_{i+1} + Y_i) \quad (1)$$

where k is the total number of years (44), X is the cumulative percentage of years associated to the ith year, and Y is the cumulative percentage of burnt area associated to the same year. The value of G was multiplied by 100, converting it into GCI. By quantifying between 0 and 100 the level of temporal concentration of the burned area for each parish, this index allows to differentiate parishes where most burned area is concentrated in a small number of years (high GCI), from those where the burned area is more regularly distributed over time (low GCI). The Gini Concentration Index was originally developed for the economic domain (Gini, 1921) and has been used to measure the concentration of wildfire damage over wildfire events (Díaz-Delgado et al., 2004; Loepfe et al., 2010; Miralles Ortega, 2015), or as the basis for concentration indexes with the same purpose (Royé et al., 2020). Barreal and Jannes (2020) employed it to measure both the temporal and spatial concentration of the number of wildfires and burned areas in Galicia (NW Spain). It is noteworthy that the GCI by itself does not quantify the magnitude of the concentrated or distributed burned area, and hence its complementarity with the first variable. For example, two parishes may show the same high concentration of burned area over a small number of years but contrasting CPAB. In a parish with a high CPAB, the results will indicate a fire regime marked by a relatively small number of years with very extensive wildfires, whereas in a parish with a low CPAB the results will indicate a fire regime marked by both low-frequency and low-extensiveness wildfires.

2.2.2. Potential control factors

A set of variables related to topography, weather and climate, LULC/biomass, and LULC fragmentation were used as potential drivers of the fire regime indicators (Table 1).

2.2.2.1. Topography. Topographic features have been shown to influence the variation in burned area in Portugal, mainly slope gradient and elevation (Nunes et al., 2016; Oliveira et al., 2020; Verde and Zêzere, 2010), which influence available fuel types, wind speed, rainfall (and therefore fuel moisture), accessibility to the areas (thus influencing fire suppression) and fire behaviour. High slopes have a direct influence on fire propagation, by promoting faster wildfire spread uphill through increased heating of fuels (Carmo et al., 2011; Díaz-Delgado et al., 2004; Gralewicz et al., 2012; Leuenberger et al., 2018; Oliveira et al., 2020). Elevation (in metres) and slope (in degrees) were obtained from the European Environmental Agency's Digital Surface Model, with a 25 m pixel (https://www.eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-eu-dem). Both were used to calculate the 50th, 75th, 80th, 90th and 95th percentiles for each parish.

2.2.2.2. Weather and climate. Rainfall influences wildfires in two ways: through its influence over the types of available fuel, and its effect over their flammability. Spring and summer rainfall exert a well-known influence over the occurrence of wildfires in Portugal and other areas with Mediterranean climate. For example, Viegas and Viegas (1994), focusing on the period 1975–1992, established an inverse relation between rainfall occurring between June and September and annual burned areas, which can be explained through the role of rainfall over fuel flammability. Pereira et al. (2005) confirmed this relation using precipitation between May and August, for the period 1980–2000. Pausas (2004) established a similar relation between summer rainfall and annual burned area in the region of Valencia (Eastern Spain). Oliveira et al. (2012) observed a relation between rainfall off the summer season (June–September) and wildfire occurrence in Southern Europe, likely related to the positive influence of spring rainfall on fuel accumulation. In this work, we used three variables to represent the potential influence of rainfall over the characteristics of fire regimes. Mean annual rainfall was employed as a general indicator of the availability of water for enabling fuel production. Mean cumulative rainfall during the spring months (April–June) was employed to focus on its potential effect over the flammability of existing fuel during spring, as well as on the production of fuel that becomes available to burn in the following summer season. Finally, mean cumulative rainfall recorded between July and September was used to represent the effect of rainfall on fuel flammability during summer, the most critical season regarding wildfire occurrence in Portugal. All three variables are expressed in mm and pertain to the period 1970–2000. Data were obtained from the Worldclim database at https://www.worldclim.org/ (Fick and Hijmans, 2017) in the form of raster maps of approximately 30 s (about 1 km^2 resolution), which were resampled to a 25 m pixel. For mean annual rainfall, we calculated the mean among the pixels that comprise each parish. For mean cumulative rainfall during the spring (April–June) and summer (July–September) seasons, we summed the three corresponding monthly maps, and subsequently calculated the mean value among the pixels of each parish.

The role of temperature in wildfires is mostly related to its effect over evapotranspiration, and therefore over the fuels' moisture content and flammability (Aldersley et al., 2011; Ventura and Vasconcelos, 2006). This was expressed in the form of two variables; mean monthly temperature during the spring months (Apr–Jun) was adopted due to its effect over fuel flammability during spring, as well as its possible role in potentiating fuel flammability in the subsequent summer period. Mean monthly temperature in the summer months (Jul–Sep) was adopted due to its direct effect over fuel flammability during the summer, when most of the wildfire damage takes place in Portugal (Pereira et al., 2005, 2013). Both variables pertain to the period 1970–2000 and were calculated from 30-second resolution mean monthly temperature raster maps extracted from the Worldclim database, resampled to a 25 m pixel size. To obtain values for each parish, we began by calculating the mean among each set of three months data (one set for spring and another for summer) in the form of a new map, and then calculated the mean value among the pixels of this map that were comprised in each parish using the Zonal Statistics tool.

2.2.2.3. Land use/land cover and biomass. Land use/land cover (LULC) is a crucial wildfire factor because of its direct relation to the type and abundance of burnable vegetation and its influence in wildfire behaviour parameters, such as flame propagation (Barros and Pereira, 2014; Moreira et al., 2009; Nunes et al., 2005). Data on LULC was obtained from the official Land Use/Land Cover Map (*Carta de Uso e Ocupação do Solo*) for the years 1990, 1995, 2007, 2010, 2015 and 2018, produced by the Portuguese General-Directorate of the Territory (*Direção-Geral do Território*). This information is made available in the form of a digital vector map, with a minimum mapped area of 1 ha. Eight class aggregations were used (Table 1), representing areas with similar features regarding vegetation and land occupation, and they were all expressed as the percentage of the area of the parish occupied by each LULC class.

AGR consisted of the aggregation of all agricultural classes. It included temporary dryland and irrigated cultures, rice paddies, vineyards, orchards, olive groves, permanent pastures, temporary cultures and/or pastures associated to permanent cultures, and complex land parcel and cultivation systems. SHR included areas occupied by shrubland and spontaneous herbaceous vegetation. Shrubland is well-known to be the most fire-prone LULC type in Portugal (Carmo et al., 2011; Marques et al., 2011; Moreira et al., 2009; Nunes et al., 2005), as well as in Mediterranean region in general (Curt et al., 2013; Oliveira et al., 2012).

The remaining six aggregations are forest-based. According to the technical specification of the land cover maps used, the designation "forest" implies the presence of trees with a minimum of 5 m height and covering a minimum of 30% of the ground (Caetano et al., 2018).

PIN class included forests of both maritime pine (*Pinus pinaster*) and stone pine (*Pinus pinea*). OAK class included cork oak (*Quercus suber*) and holm-oak (*Quercus rotundifolea*) forests, while EUC included eucalyptus (mostly *Eucalyptus globulus*) forests. CON class included forests of coniferous species other than maritime or stone pine. These include, for example, other species of the genus *Pinus* (e.g. *Pinus halepensis*), as well as species in genuses as *Larix*, *Picea* or *Abies*. BRD class included forests of broadleaved species other than eucalyptus, cork oak and holm oak. It includes species such as chestnut oak (*Castanea sativa*), Pyrenean oak (*Quercus pyrenaica*) and European oak (*Quercus robur*), as well as species of the genus *Salix*, *Populus* or *Platanus*. INV class aggregated all forests of invasive species (e.g., *Acacia dealbata* or *Ailanthus altissima*).

The definition of these forest classes was based on recent studies regarding their fire proneness in the Portuguese context; maritime pine, eucalyptus and cork oak are the dominant forest species in the country, with the latter being regarded as less fire-prone, contrarily to pines and eucalyptus. In recent years, invasive species such as those in the genus *Acacia* and *Ailanthus* have spread in the country and are becoming more fire prone. The other forest groups show varying relationships with fire occurrence, depending on the years and the regions affected (Meneses et al., 2018; Oliveira et al., 2020).

As LULC changed over time, and since we obtained compatible data, we combined the six existing land cover maps that are included in the study period (1990, 1995, 2007, 2010, 2015, 2018). After calculating each LULC variable in each of the six dates, we defined the final value for each parish as the mean of the six values, weighted by the number of years during which the LULC maps were valid. Taking as example the variable AGR, we began by calculating the value using each of the six LULC maps. We then calculated the weighted mean of the six values, using as weights the number of years that each map represents: 5 years for 1990 (1990–1994); 12 years for 1995 (1995–2006); 3 years for 2007 (2007–2009); 5 years for 2010 (2010–2014); 3 years for 2015 (2015–2017); and a single year for 2018 (2018 itself). The final calculation was done as follows:

$$AGR_{1990-2018} = (AGR_{1990} * 5 + AGR_{1995} * 12 + AGR_{2007} * 3 + AGR_{2010} * 5 + AGR_{2015} * 3 + AGR_{2018})/29 \quad (2)$$

The same procedure was applied for the remaining LULC variables.

Table 1
Synthetic description of the potential fire regime control variables. Variables identified with * passed the preliminary multicollinearity analysis and were used as inputs in the modeling process (see Section 2.3).

Type	Variable code	Variable	Temporal extent	Original spatial Resolution	Units
Topography	ELE50, ELE75, ELE80, ELE90, ELE95	Elevation (percentiles 50, 75, 80, 90, 95)	n.a.	25 m	m
	SLO50, SLO75, SLO80*, SLO90, SLO95	Slope (percentiles 50, 75, 80, 90, 95)	n.a.	25 m	o
Climate	RF	Mean annual rainfall	1970–2000	Approx. 1000 m	mm
	RFAJ*	Mean cumulative rainfall April–June			
	RFJS	Mean cumulative rainfall July–September			
	TPAJ	Mean monthly temperature April–June			°C
	TPJS*	Mean monthly temperature July–September			
Biomass	NPP*	Net Primary Productivity	2000–2014	500 m	KgC/m^2
Land use/Land cover	AGR*	Percentage of parish area occupied by agriculture	1990–2018	Vector data. Minimum mapped area 1 ha	%
	PIN	Percentage of parish area occupied by maritime pine and stone pine forests			
	OAK*	Percentage of parish area occupied by cork-oak and holm-oak forests			
	EUC*	Percentage of parish area occupied by eucalyptus forests			
	INV*	Percentage of parish area occupied by forests of invasive species	1995–2018		
	CON*	Percentage of parish area occupied by forests of coniferous species other than maritime or stone pine	1990–2018		
	BRD*	Percentage of parish area occupied by forests of broadleaved species other than eucalyptus, cork-oak and holm-oak			
	SHR*	Percentage of parish area occupied by shrubland and spontaneous herbaceous vegetation			
Fragmentation	FRAGF*	Fragmentation of forest patches	1995–2018		no. of centroids/ha of forest or forest and shrubland
	FRAGFS	Fragmentation of forest and shrubland patches			

Net Primary Productivity (NPP), which can be defined as the difference between the rate at which plants in an ecosystem produce useful chemical energy (Gross Primary Productivity) and the rate at which they expend some of that energy for respiration, describes the photosynthetic accumulation of carbon by plants (Potter et al., 2012). It can therefore be employed as a proxy for biomass, and hence fuel availability (Pausas and Ribeiro, 2013). Annual maps of NPP (in KgC/m^2) between 2000 and 2014 (the available period) were extracted from NASA's Earth Science Data Systems database (https://lpdaac.usgs.gov/products/mod17a3hgfv006/) and resampled from the original 500 m pixel to the 25 m pixels that compose the civil parishes. Mean annual values were then calculated from the 15 available years. Finally, the mean NPP value among the pixels within each parish was retrieved using the Zonal Statistics tool.

2.2.2.4. Land use/land cover fragmentation. We incorporated two variables representing the fragmentation of LULC patches, as fuel fragmentation is a well-known control over the capacity of wildfire to efficiently propagate (Curt et al., 2013; Fernandes et al., 2016; Gralewicz et al., 2012; Turner and Romme, 1994).

With the purpose of analysing the relative influence of forest and shrubland, we considered both forest patches alone (*FragF*), and the result of their agglomeration with shrubland patches (*FragFS*). To obtain each variable, all the relevant LULC classes (all forest types; all forest types plus shrubland/spontaneous herbaceous vegetation) were merged and then divided into individual unconnected polygons. The centroid of each of these polygons was subsequently generated. The number of individual centroids comprised within each parish was quantified, and then divided by the area of the parish (in ha) associated to forest (in the case of *FragF*) or forest and shrubland (in the case of *FragFS*). The final values quantify the mean number of disconnected patches comprised in each hectare of forest or forest and shrubland, used as general indicators of fragmentation.

In a similar manner to the LULC variables described above, this procedure was performed separately for the land cover maps of 1995, 2007, 2010, 2015 and 2018. The 1990 map was not included, as it possesses positioning errors derived from being based on non-orthorectified aerial photos (Caetano et al., 2018) which could influence the results of spatial arrangement-oriented analyses. The values for the five different dates were finally combined as a weighted mean, with the numbers of valid years for each land cover map serving as weight: 12 for 1995 (1995–2006); 3 for 2007 (2007–2009); 5 for 2010 (2010–2014); 3 for 2015 (2015–2017) and one for 2018, in a total of 24 years.

A synthetic description of all potential control variables is presented in Table 1.

2.3. Data analysis

A preliminary analysis was carried out in two successive steps to detect multicollinearity and thus possible redundances between the independent variables using SPSS 24 software (IBM Corp.).

Firstly, bivariate correlations between all variables were analysed to detect strong correlations (Pearson correlation coefficients above 0.7 or below −0.7, significant at the $p < 0.05$ level) (results presented as supplementary material in Table S.1). This analysis revealed that all elevation variables were strongly correlated among themselves, the same happening with the slope variables. In each case, we selected the variable with the highest correlation coefficients in relation to the others in the same group (thus being the best suited to represent it): ELE80 and SLO80. The same criterium led to the selection of RFAJ from among the rainfall variables. Both temperature variables TPAJ and TPJS were strongly correlated ($r = 0.764, p \leq 0.01$). As TPAJ was also strongly correlated to the elevation variables, we selected TPJS for its greater independence. FRAGF and FRAGFS were also strongly correlated ($r = 0.796, p \leq 0.01$). As FRAGFS was also strongly correlated with AGR ($r = 0.776, p \leq 0.01$), we opted by keeping FRAGF, thus leaving a total of 14 potential control factors.

A second step of the analysis focused on the possibility that the behaviour of some variables can be expressed as a linear combination of a set of other variables, instead of one. We therefore calculated the Variance Inflation Factor (VIF) associated to each one of the independent variables. This indicator can be calculated as $1/(1 - R^2)$, where R^2 is the determination coefficient of a multiple linear regression model with the variable under analysis as dependent as all others as independents (Maroco, 2007; Weisberg, 2005). All variables with VIF values above 5 were considered to suffer from multicollinearity (following Maroco, 2007). The analysis was performed iteratively. After calculating all VIFs, the variable with the highest value above 5 was excluded, and the process repeated for the remaining variables until no values above 5 remained. This allowed to eliminate PIN (VIF = 11.9) in a first iteration, and then ELE80 (VIF = 6.6) in a second one. A third calculation showed that no values over 3.0 remained, resulting in a final set of 12 independent variables to be used in the regression analysis (identified in Table 1).

The relations between each of the fire regime characteristics (dependent variables) and the 12 potential control factors were tested and quantified with ordinal logistic regression. Unlike multiple linear regression, this technique has the advantages of not assuming linear relations between dependent and independent variables and of not requiring the independent variables to be normally distributed. It also is less sensitive to outliers (Maroco, 2007). Ordinal logistic regression has been used in the wildfire literature, for example, to analyse the effect of environmental controls over the severity of wildfires in spring and summer in NE China by Fan et al. (2017).

For a dependent variable *y*, expressed as *c* classes, and for a set of *p* independent variables *X*, the ordinal logistic regression model can be formalized as (Azen and Walker, 2011):

$$logit\left[P\left(Y_j \le j\right)\right] = \ln\left[\frac{P(y \le j)}{P(y > j)}\right] = \alpha_j + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \qquad (3)$$

where *j* varies from 1 to *c*-1. According to this formulation, when the regression coefficient β of an independent variable is >0, an increase in that variable's value leads to an increase in the probability that *Y* belongs to a lower class. Contrarily, when β < 0, the probability that *Y* belongs to a higher class increases. As this relation between β and the variation of *Y* runs contrary to the typical interpretation of the sign of β in regression, the ordinal logistic regression model can be re-written as (Agresti, 2010; Maroco, 2007):

$$logit\left[P\left(Y_j \le j\right)\right] = \ln\left[\frac{P(y \le j)}{P(y > j)}\right] = \alpha_j - \beta_1 X_1 - \beta_2 X_2 - \ldots - \beta_p X_p \qquad (4)$$

This is the formulation employed by statistical analysis software packages such as SPSS (IBM Corp.), used in this work, according to which, when β > 0, the likelihood that *Y* belongs to a higher class increases, and vice-versa (Agresti, 2010).

Prior to their integration into the regression models, the dependent variables were classified into five classes using quintiles, thus adopting an ordinal data scale. All potential control factors were converted into z-scores, to allow a clearer assessment of their relative importance in the models using their regression coefficients. The Logit link function was chosen to build the regression models, as it is suitable for datasets where the classes of Y have a uniform distribution (Maroco, 2007). A significance level of 0.05 in the Wald test was adopted as threshold for considering a potential control factor as significant in explaining the fire regime variations.

Regression models were constructed using each of the three fire regime parameters as the dependent variable. Each model was constructed from a randomly selected subset of the data comprising 60% of the parishes in each quintile (testing sample). The remaining 40% of the data were used to perform an independent validation (validation sample), by applying the resulting model to predict the quintile of each parish that was not included in the testing sample. Each model was built iteratively, with the least statistically significant variables being excluded one by one at successive runs until a final model with significant variables only ($p < 0.05$) was obtained.

The quality of each model was quantified using pseudo-R^2 statistics obtained using Cox and Snell's, Nagelkerke's and McFadden's methods. Cox and Snell's method is based on the difference between the log likelihood for the full model compared to the log likelihood for a baseline (intercept-only) model. It has the disadvantage of having a theoretical maximum value of less than 1. Nagelkerke's pseudo-R^2 is an adaptation of Cox & Snell's that adjusts the scale of the statistic to cover the full range from 0 to 1. McFadden's is an alternative version of the Pseudo-R^2 statistic, based on the ratio between the full estimated model and the baseline model (Maroco, 2007).

3. Results

3.1. Fire regime properties

A preliminary analysis of the results showed that 35 out of the 972 parishes had no wildfires during the 44-year studied period. These parishes, corresponding to areas dominated by urban settlements and agriculture, were removed from all analyses. The descriptive statistics for the fire regime properties within the remaining 937 parishes are shown in Table 2, and their spatial distributions within the study area are presented in Fig. 2.

Regarding cumulative percentage of burned area (CPAB) (Fig. 2-A), low values dominate almost exclusively along the coast in the west and in the southeast sector, with greater heterogeneity and high values occurring in the centre and northeast parts of the study area.

Area-weighted wildfire frequency (AWWF) (Fig. 2-B) shows a similar concentration of low values along the coast and in the southeast sector (although more homogeneously low). However, in this case the highest values are concentrated in the NE sector, with the centre of the study area being marked by a concentration of middle-range values.

Unlike the previous variables, the Gini concentration index of burned area (GCI) (Fig. 2-C) shows a remarkable concentration of the highest values along a N-S area near the coast. More heterogenous patterns occur in the remaining study area, with the medium-to-very-high classes dominating in the south and southeast, and the medium-to-very-low in the north and northeast parishes.

A bivariate correlation analysis was performed for the three variables, showing that CPAB and AWWF are positively correlated ($r = 0.648$) and that both are negatively correlated to GCI, with a stronger correlation in the case of AWWF ($r = -0.711$) than in that of CPAB ($r = -0.592$) (all coefficients significant at the 0.01 level).

3.2. Regression models

3.2.1. Cumulative percentage of area burned (CPAB model)

The final model using CPAB as dependent variable was obtained in the third run, after the successive elimination of INV ($p = 0.973$) and FRAGF (0.975). The −2 log-likelihood Chi-Square test (Table 3) indicates that the model is overall highly significant, i.e., that at least one of the independent variables exerts effect over the dependent one. Pseudo-R^2 values indicate that the independent variables explain between 61% and 64% of the variance of CPAB among the studied parishes (considering Cox and Snell's and Nagelkerke's test), with McFadden's test producing a lower value of 29%. The model correctly predicted the quintile of 51.5% of all parishes in the independent subsample of the data.

The regression coefficients (Table 4) show that, among the LULC-related factors, shrubland and spontaneous herbaceous vegetation (SHR) is the most important, exerting a positive effect over CPAB. The second most important LULC factor is the percentage of parish area dedicated to agriculture (AGR), which exerts a negative effect. These two are the most important of all independent variables in the model.

Increasing effects over CPAB are associated to forests of broadleaves other than eucalyptus, cork oak and holm oak (BRD) and eucalyptus (EUC). Contrarily, a decreasing effect was found in association to forests of cork oak and holm oak (OAK) and of non-pine coniferous species (CON). Regarding climatic factors, both spring rainfall (RFAJ) and summer

Table 2
Descriptive statistics for the three fire regime properties. CPAB – Cumulative percentage of parish area burned; AWWF – Area-weighted wildfire frequency; GCI – Gini concentration index of burned area. SD – standard deviation; P25 and P75 – 25th and 75th percentiles, respectively. *N* = 937.

	Min	Max	Mean	SD	P25	P75
CPAB	0.006	486.799	95.845	87.532	20.923	144.416
AWWF	0.185	6.487	1.001	0.973	0.308	1.345
GCI	61.539	97.727	88.324	7.737	83.962	94.505

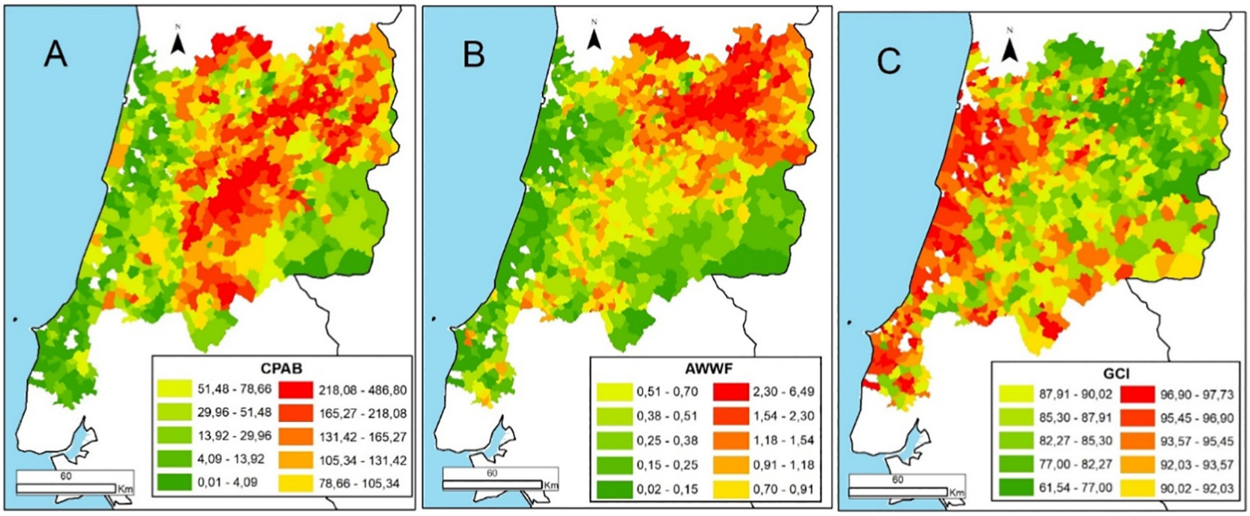

Fig. 2. Spatial distribution of the fire regime properties within the study area. A – Cumulative percentage of area burned (CPAB); B – Area-weighted wildfire frequency (AWWF); C – Gini concentration index of burned area (GCI). All maps were classified using deciles.

temperatures (TPJS) are positively related to CPAB, with the latter exerting a slightly stronger effect.

The regression coefficient obtained for net primary productivity (NPP) shows that it is negatively related to CPAB. A relatively weak positive effect was associated to slope (SLO80).

3.2.2. Area-weighted wildfire frequency (AWWF model)

The final model using AWWF as dependent was obtained in the 6th run, after the successive eliminations of INV ($p = 0.901$), SLO80 (0.499), CON (0.349), FRAGF (0.212) and EUC (0.154). The final model includes 7 independent variables (Table 4). According to the results of the -2 log-likelihood Chi-Square test (Table 3), at least one of the independent variables significantly influence AWWF among the studied parishes. Cox and Snell's and Nagelkerke's Pseudo-R^2 values indicate that the behaviour of the independent variables explains approximately 55% and 57% of the variance of the dependent among the studied parishes, with McFadden's producing a lower value of about 25%. The model was able to correctly predict the quintile of 44.9% of the parishes in the independent subsample of the data.

The regression coefficients (Table 4) show that the most important factor controlling AWWF is spring rainfall (RFAJ), followed by the percentage of shrubland and spontaneous herbaceous vegetation (SHR). Other LULC variables include, by decreasing order of importance, other broadleaves (BRD), with a positive effect, cork oak and holm oak forests (OAK) with a negative effect, and agriculture (AGR), with a relatively weak positive effect.

Regarding climatic factors, summer temperature (TPJS) exerts a positive influence, although mush weaker than spring rainfall (RFAJ). Finally, net primary productivity (NPP) exerts a relatively weak negative influence over AWWF.

Table 3
Overall model significance, Pseudo-R^2 and accuracy values for the final models with CPAB, AWWF and GCI respectively as dependents.

			Chi-square	Sig.
CPAB	Model significance (-2 log-likelihood)		528.735	0.000
	Pseudo-R^2	Cox and Snell	0.610	
		Nagelkerke	0.635	
		McFadden	0.292	
	Model accuracy (independent sample)			51.5%
			Chi-square	Sig.
AWWF	Model significance (-2 log-likelihood)		444.053	0.000
	Pseudo R^2	Cox and Snell	0.546	
		Nagelkerke	0.569	
		McFadden	0.245	
	Model accuracy (independent sample)			44.9%
			Chi-square	Sig.
GCI	Model significance (-2 log-likelihood)		362.128	0.000
	Pseudo R^2	Cox and Snell	0.475	
		Nagelkerke	0.495	
		McFadden	0.200	
	Model accuracy (independent sample)			44.5%

Table 4
Regression coefficients, Wald statistics and significance levels for the final models with CPAB, AWWF, and GCI as dependent. The regression coefficients are organized in decreasing order of absolute value.

Indep. variable	Coefficient	Wald	Sig.
CPAB			
SHR	1.408	101.295	0.000
AGR	−0.973	65.369	0.000
TPJS	0.791	41.397	0.000
RFAJ	0.732	38.105	0.000
NPP	−0.384	10.889	0.001
SLO80	0.380	10.926	0.001
BRD	0.367	14.970	0.000
OAK	−0.285	6.867	0.009
CON	−0.246	4.201	0.040
EUC	0.229	5.308	0.021
AWWF			
RFAJ	1.325	126.545	0.000
SHR	1.075	84.541	0.000
BRD	0.486	28.355	0.000
OAK	−0.462	10.032	0.002
TPJS	0.442	15.665	0.000
NPP	−0.416	14.503	0.000
AGR	0.305	11.348	0.001
GCI			
SHR	−1.388	121.422	0.000
RFAJ	−0.665	47.229	0.000
NPP	0.415	15.103	0.000
TPJS	−0.256	6.290	0.012
EUC	−0.239	7.344	0.007
BRD	−0.228	5.812	0.016

3.2.3. Gini concentration index of burned area (GCI model)

The final regression model was obtained in the 7th run, after the successive elimination of SLO80 ($p = 0.894$), INV (0.355), OAK (0.347), CON (0.167), AGR (0.121), and FRAGF (0.160).

Results of the −2 log-likelihood Chi-Square test (Table 3) indicate that at least one the independent variables significantly influence GCI. Cox and Snell's and Nagelkerke's Pseudo-R^2 values indicate that the behaviour of the independent variables explains approximately 48% and 50% of the variance of GCI among the studied parishes, with McFadden's producing a lower value of about 20%. The model was able to correctly predict the quintile of 44.5% of the independent subsample of the data.

The percentage of shrubland/herbaceous vegetation (SHR) is the single most important factor influencing GCI, as shown by the regression coefficients (Table 4). Notably, the same factor dominates the CPAB regression model. However, in the case of GCI, the influence is negative: higher SHR leads to a lower temporal concentration of the burned area. The other two LULC classes integrated in the model were the ones representing eucalyptus forests (EUC) and broadleaves other than eucalyptus, cork oak and holm oak (BRD), both with negative coefficients.

Regarding climatic factors, both spring rainfall (RFAJ) and summer temperature (TPJS) were shown to exert a negative effect on the temporal concentration of burned area. Spring rainfall is the second most important variable in the model, whereas TPJS exerts a weaker influence. Finally, net primary productivity (NPP) was shown to have a positive association with GCI.

4. Discussion

In the central region of Portugal, three major subtypes of fire regime could be identified. One subtype refers to areas where wildfires are infrequent and of low extensiveness, with a concentration of the total damage in only a few years, as found along the coastline. Other suggested subtype of fire regime includes parishes with very high values of CPAB and middle-range values of AWWF and GCI, characterizing the central sector of the study area. These values denote a tendency for very extensive and somewhat frequent wildfires, with the damage being relatively dispersed through time when compared to the previous regime. Yet a third subtype characterizes the NE sector of the study area, where high CPAB and high AWWF combine with low-to-middle range values of GCI, suggesting a regime with both very extensive and very frequent wildfires, and a high dispersion of the damage through time when compared to the previous two regimes. Overall, our findings show that the parishes that accumulated more burned area in proportion to their size (higher CPAB) are also those that burned more frequently (higher AWWF). These parishes also tend to have the total amount of damage dispersed through time (lower GCI), instead of concentrated in few relatively severe years.

Each of the three adopted fire regime properties are associated with several control factors. LULC factors exert a major control, especially the percentage covered by shrubland/spontaneous herbaceous vegetation (SHR), which is the single most important variable affecting CPAB and GCI, and the second most important regarding AWWF. On the other hand, topography was shown to have only a minor influence: slope (SLO80) has a statistically significant, although relatively weak, effect only over the cumulative percentage of area burned (CPAB), which can be attributed to its effect in promoting fire spread (Marques et al., 2011; Oliveira et al., 2020). The apparently weak effect of topography in our models may be related to the scale of application: within the Central region studied, most spatial units analysed (parishes) are dominated by irregular topography, which can reduce the power of this variable in distinguishing the parishes. Indeed, in contrast with our results, in a model applied at the national level in Portugal, slope was found to be the second most important biophysical variable promoting elevated CPAB (Oliveira and Zêzere, 2020). As such, the influence of slope in wildfire occurrence must be considered according to the specific environmental context and scale of application.

4.1. Land use/land cover factors

Area burned (here measured by CPAB) is promoted by shrubland/spontaneous herbaceous vegetation, by broadleaved species other than eucalyptus, cork and holm oak (BRD), and by eucalyptus (EUC). This is in accordance with the well-established tendency of most of these species to burn (Moreira et al., 2009; Nunes et al., 2005; Oliveira et al., 2014, 2020). It is also in accordance with the results recently obtained by Oliveira and Zêzere (2020), who determined the percentage of shrubland to be the foremost LULC factor promoting CPAB on a country-wide scale. The same authors also found a positive relation between CPAB and the percentage area of broadleaves (including the classes EUC and BRD adopted in this work). Meneses et al. (2018) specifically assessed the relations between LULC classes and probability of wildfire recurrence, noting that shrubland stood out for having the maximum values, followed by eucalyptus and maritime pine.

In opposition to other forest types, a decreasing effect over CPAB was found in association to forests of cork oak and holm oak (OAK), and those of coniferous species other than stone and maritime pine (CON). Cork oak and holm oak forests have been shown to be less susceptible to wildfire than all other forest types in Portugal with the exception of stone pine forests (aggregated in this study with maritime pine) (Oliveira et al., 2020). In the case of the coniferous species other than stone and maritime pine, several of the species included in this forest class (*Larix* sp., *Abies* sp., *Pinus sylvestris*) are considered relatively less flammable than eucalyptus or maritime pine (Xanthopoulos et al., 2012).

The second most important LULC factor affecting CPAB is agriculture (AGR), and the regression model showed that increases in agricultural area decrease CPAB. Oliveira and Zêzere (2020) also determined agriculture to be the second most important LULC factor and the foremost LULC constraint on CPAB on the whole of continental Portugal. Moreira et al. (2009) demonstrated that annual and permanent crops have the lowest fire selection ratios of all LULC classes within the study area, a result later confirmed by Oliveira et al. (2014) for mainland Portugal.

Regarding wildfire frequency (AWWF), shrubland/spontaneous herbaceous vegetation is the second most important variable within the model. Its strong positive effect over wildfire frequency can be attributed to its relatively high rate of post-fire regeneration in relation to other LULC classes, allowing for fuel availability year after year (Meneses et al., 2018). Three other significant variables appear: forests of broadleaved species other than eucalyptus, cork oak and holm oak (including species as *Salix* sp., *Populus* sp., *Platanus* sp. or *Alnus glutinosa*), as well as agriculture, are linked with higher wildfire frequency. Contrarily, forests of cork oak and holm oak coincide with areas of lower frequency, which may be related to anthropic variables that were not considered in this study. This is very possibly the case with agriculture, which is likely to be associated to increased human presence in comparison to forests (Catry et al., 2009), and to activities that often result in wildfire ignition, such as the burning of agricultural waste (Catry et al., 2009; Pereira et al., 2006).

Unlike CPAB and AWWF, the temporal concentration of damage (GCI) decreases with the increasing coverage of shrubland-type vegetation (SHR). It also decreases with the importance of eucalyptus forests, and of other broadleaves (BRD). In the case of SHR and EUC, this effect can be attributed to the relatively high rates of post-fire regeneration of these two LULC classes in relation to other classes; in addition, shrubland-type vegetation is known to rapidly colonize recently burned areas and abandoned farmland (Pereira et al., 2014). These conditions allow for more frequent burning and are, therefore, reflected in the temporal dispersion of damage over time.

4.2. Weather and climate factors

All three fire regime parameters were influenced by meteorological factors. Summer temperature (TPJS) and spring rainfall (RFAJ) both exert a positive influence over the tendencies to burn extensively (CPAB) and to burn frequently (AWWF), with TPJS promoting optimal conditions for wildfire spread and RFAJ promoting fuel availability throughout the rest of the year. However, the importance of their effects over CPAB and AWWF contrasts greatly. Both spring rainfall and summer temperature exert similar effects over CPAB, with the latter predominating, whereas with AWWF, spring rainfall is the single most important factor, with summer temperature having about a fourth of its importance. This is expectable, as spring rainfall can be considered a proxy for fuel availability from the spring on throughout the rest of the year (Oliveira et al., 2012; Xystrakis et al., 2014), whereas the effect of summer temperature, as a promoter of fuel flammability, is necessarily more constrained in time.

GCI was negatively influenced by both RFAJ and TPJS. Abundant spring rainfall will make fuel available for fires later in the year, promoting wildfire frequency and dispersing the damage over time. Likewise, high summer temperatures will promote the occurrence of regular summer wildfires, also leading to a dispersion of burn damage over the years. The importance of temperature and rainfall in wildfire regimes is well recognized. Pereira et al. (2005) defined two major atmospheric controls over annual burned area in Portugal: the amount of precipitation during spring, and the occurrence of synoptic conditions that induce very hot and dry conditions over western Iberia during the summer. Oliveira et al. (2012) observed precipitation off the summer season to be a major influence over wildfire density in the European Mediterranean region, ascribing it to the role of spring rainfall in promoting fuel accumulation. A significant relation between annual burned area and spring rainfall was also described in Greece by Xystrakis et al. (2014). Regarding temperature, our results can be explained in terms of its effect over the moisture content of fuels and thus over their fire-proneness, with warmer summers implying better conditions for wildfire spread (Viegas, 2006; Viegas et al., 2004).

4.3. Net primary productivity

Net primary productivity (NPP) influenced all three fire regime parameters. In the cases of the tendency of parishes to burn extensively (CPAB) and to burn frequently (AWWF), its negative effect seems at first to contradict our working hypothesis that increases in biomass will imply higher fuel availability. However, shrubland/spontaneous herbaceous vegetation is the dominant LULC class in burned areas in Portugal (Oliveira et al., 2020; Pereira et al., 2006). As this type of vegetation has lower NPP values than forests, high-CPAB and high-AWWF parishes with a high percentage of shrubland/spontaneous herbaceous vegetation tend to have lower NPP values than forest-rich parishes (as shown by the negative correlation between NPP and SHR; see Table S.1 in the Supplementary Material), leading to a negative regression coefficient in the final model.

Unlike CPAB and AWWF, the temporal concentration of wildfire damage (GCI) has a positive relation with NPP. This can be related to the regeneration period of vegetation, since NPP is higher for slowly regenerating forest cover than for quickly regenerating shrubland/spontaneous herbaceous vegetation. Parishes with more extensive forests will take more time to regenerate between wildfires, leading to a higher temporal concentration of wildfire damage when compared to parishes with more coverage of shrublands, which will be available to burn in few years.

4.4. Limitations and uncertainties

There are two sources of uncertainty that should be noted in relation to the used datasets, both imposed by data availability constraints. The first results from the disparities between the period used to characterize the fire regime (1975–2018, 44 years) and the periods covered by the data for its different potential control factors: 1970–2000 (31 years) for all climate variables, 1990–2018 (29 years) for most LULC classes, 1995–2018 (24 years) for the LULC patch fragmentation indicators, and 2000–2014 (15 years) for NPP (Table 1). Our combined use of these datasets implies the assumption that they represent the whole 44-year studied period. The second factor of uncertainty is the disparity between the original resolutions of the datasets, which varied from 25 m for topography to about 1000 m to the climatic variables (Table 1), entailing contrasting degrees of generalization in the data.

Regarding the limitations of this work, the values of the pseudo-R^2 for the three regression models (Table 3) show that an important part of the variances of the adopted fire regime variables is dependent on other factors not considered in this analysis, possibly of a socioeconomic nature. The relatively low accuracy values obtained from the application of the models to independent subsets of the data confirm this notion, regardless of being largely superior to what could be expected from a random classification. A recent country-wide study, also using parishes as units of analysis (Oliveira and Zêzere, 2020), demonstrated that socioeconomic factors had a significant effect over CPAB, although biophysical factors were observed to be predominant. Moreover, the influence of human factors such as road or population density over wildfire patterns has been well demonstrated in the literature (Nunes et al., 2016; Oliveira et al., 2017; Pausas and Fernández-Muñoz, 2012; Rogers et al., 2020; Syphard et al., 2007). It is possible that the positive effect over wildfire frequency found in association to some of our LULC classes may be, at least in part, a result of associations between these classes and population density. This is specially the case of agricultural land, which requires active population to thrive in any area.

Another limitation of the employed approach regards the possibility that a part of the wildfire patterns in each parish may be determined by wildfires originating elsewhere. This issue is not captured by the models, which assume that the fire regime in any parish is a function of the biophysical factors specific to it. Given the spatial behaviour inherent to wildfire, future approaches at such detailed scale should address the effect of neighbouring conditions over a spatial unit's fire regime.

4.5. Implications to wildfire management

The analysis of specific fire regime properties within a large region allowed to distinguish areas with diverse patterns and to identify the dominant biophysical factors which influence these patterns. Such type of analysis is crucial to further understand the interaction between wildfire occurrence and territorial conditions at different scales, and to adequately adjust prevention and mitigation strategies that are urgent to implement. The new National Plan for Integrated Rural Fire Management, published in June 2020 (AGIF, 2020), fosters the integration of multiple measures and actions adapted to the fire regime of each region, as the complexity of the wildfire phenomenon in the country cannot be solved with a single approach. Our findings indicate that, within the Central region, wildfire management strategies should be spatially tailored to cope with the control factors that predominate at sub-regional level, defining priorities. In areas where high wildfire frequency is linked to farming activities, such as the parishes in the northeast, traditional practices and knowledge must be regulated and integrated in landscape management strategies. For example, the use of fire as a tool to renovate pastures must be combined with preventive measures to avoid the spread of uncontrolled fires to neighbouring land; also, when feasible, grazing activities can be further promoted to decrease fuel loads. In areas characterized by high burned area, as the parishes in the central sector, the creation of fuel discontinuities and the promotion of diversified landscapes must be considered, an approach that requires a landscape-level vision that goes beyond the parish boundaries. The parishes located in the coastal area do not burn frequently, but when they do the damage is very high. These results mirror the exceptional year of 2017, when the national and protected pine forest that spreads over that area has burned extensively, fuelled by extreme weather conditions. Landscape restoration of this area must be steered by the creation of fuel discontinuities for the protection of both the natural and human assets that coexist there, together with the prevention of ignitions through behavioral changes and the implementation of mitigation strategies that improve the coping capacity and self-protection abilities of residents in case a large fire occurs. All these potential strategies, and other alternatives, are legally framed by the recently created System of Integrated Management of Rural Fires, published in the Decree-Law 82/2021, of 13th October. The local and sub-regional level of analysis is, therefore, important to fine-tune wildfire management to the particular features of each area.

5. Conclusions

We showed that the three properties used to describe the fire regime in the central region of mainland Portugal show contrasting spatial distributions. The tendency to burn extensively (CPAB) is concentrated both on the centre and NE sectors of the study area. Wildfire frequency (AWWF) is overwhelmingly concentrated in the NE sector, whereas the concentration of wildfire damage over time (GCI) dominates in the parishes located along the seacoast. Different types of biophysical controls exert significant effects over the fire regime parameters, with land use / land cover (LULC) distribution, spring rainfall and summer temperature playing the foremost role in all three models. Regarding LULC, the percentage of parish area occupied by shrubland/spontaneous herbaceous vegetation is in all cases the most relevant factor. Other classes have differing degrees of influence over the fire regime parameters. Agriculture, cork-oak and holm-oak forests, forests of other broadleaves, and eucalyptus forests exert the next strongest effects over the tendency to burn extensively, with this role being associated to forests of other broadleaves, forests of cork-oak and holm-oak and agriculture in the case of wildfire frequency, and to forests of eucalyptus and of other broadleaves in the case of the temporal concentration of damage. Regarding weather and climate factors, both spring rainfall and summer temperature were shown to be major influences on the three fire regime variables, with spring rainfall being the foremost driver in the case of wildfire frequency, the second most important regarding the temporal concentration of damage, and the fourth most important in the case of cumulative percentage of area burned. Slope was shown to have only a minor influence over the cumulative percentage of area burned.

Based on our results, future work should be focused on two major avenues. One regards the exploration of the roles played by other potential control variables, as it was demonstrated that a significant part of the behaviour of our fire regime parameters could not be accounted for, most especially in the case of the tendency for the concentration of burned area over time. These variables include both those of a socioeconomic nature and those related to the potential effect of the conditions in neighbouring parishes.

The other avenue for further work regards the differentiation of fire regime subtypes within our study area, which is suggested by the definite spatial contrasts shown by the three fire regime parameters. This could be approached using quantitative techniques, such as cluster analysis, to aggregate parishes based on their similarity regarding these parameters, and then investigating the external controls of such groupings. Such an approach would allow integrating the three fire regime properties that were separately analysed and modelled in this work. Furthermore, it could enable tailoring of fire prevention and suppression strategies and policies to the specificity of the fire regime characterizing each group of parishes.

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CRediT authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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