Science of the Total Environment 912 (2024) 169269

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Coupling heat wave and wildfire occurrence across multiple ecoregions within a Eurasia longitudinal gradient

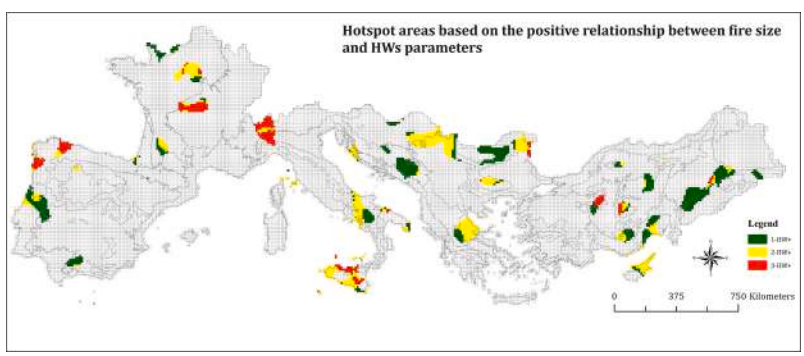
Elia Mario [a], Lafortezza Raffaele [a,g,*], Cappelluti Onofrio [a], Costa-Saura Josè Maria [b,e,f], Bacciu Valentina [c], Giannico Vincenzo [a], Changliang Shao [d], Sanesi Giovanni [a]

[a] *Department of Soil, Plant and Food Sciences, University of Bari Aldo Moro, Via Amendola 165/A, 70126 Bari, Italy*
[b] *Department of Agricultural Sciences, University of Sassari, Sassari 07100, Italy*
[c] *National Research Council of Italy, Institute of Bioeconomy, Sassari 07100, Italy*
[d] *National Hulunber Grassland Ecosystem Observation and Research Station & Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing 10008, China*
[e] *Impacts on Agriculture, Forestry and Ecosystem Services Division, Euro-Mediterranean Center on Climate Changes, Viale Italia, Sassari 07100, Italy*
[f] *National Biodiversity Future Center, Palazzo Steri, Piazza Marina 61, Palermo, 90133, Italy*
[g] *Research Centre of Urban Forestry, Key Laboratory for Silviculture and Forest Ecosystem of State Forestry and Grassland Administration, Beijing Forestry University, Beijing 100083, China*

HIGHLIGHTS

- Characterization of heatwaves (HWs) and fire regime metrics in 37 ecoregions
- No significant differences in terms of intensity, duration and periods of HWs
- High spatial variability of the relationships between fire regime metrics and HWs
- Hotspot areas found in ecoregions characterized by mixed forest ecosystems
- The main HWs metrics guiding the coupling occurrence are the intensity and duration.

GRAPHICAL ABSTRACT



ARTICLE INFO

Guest Editor: Jiaguo Qi

Keywords:
Heat waves
Wildfires
Ecoregions
Euroasia
Fire regime
Risk mitigation

ABSTRACT

Understanding the relationship between heat wave occurrence and wildfire spread represents a key priority in global change studies due to the significant threats posed on natural ecosystems and society. Previous studies have not explored the spatial and temporal mechanism underlying the relationship between heat waves and wildfires occurrence, especially over large geographical regions. This study seeks to investigate such a relationship with a focus on 37 ecoregions within a Eurasia longitudinal gradient. The analysis is based on the wildfire dataset provided by the GlobFire Final Fire Event Detection and the meteorological dataset ERA5-land from Copernicus Climate service. In both cases we focused on the 2001–2019 timeframe. By means of a 12 km square grid, three wildfire metrics, i.e., density, seasonality, and severity of wildfires, were computed as proxy of fire regime. Heat waves were also characterized in terms of periods, duration, and intensity for the same period.

* Corresponding author at: Department of Soil, Plant and Food Science, University of Bari “Aldo Moro”, Via Amendola, 165/A, 70126 Bari, Italy.
E-mail address: raffaele.lafortezza@uniba.it (L. Raffaele).

https://doi.org/10.1016/j.scitotenv.2023.169269
Received 29 September 2023; Received in revised form 5 December 2023; Accepted 8 December 2023
Available online 11 December 2023

Statistical tests were performed to evaluate the different patterns of heat wave and wildfire occurrence in the 37 ecoregions within the study area. By using Geographically Weighted Regression (GWR) we modeled the spatial varying relationships between heat wave characteristics and wildfire metrics. As expected, our results suggest that the 37 ecoregions identified within the Eurasia longitudinal gradient differ in terms of fire regimes. However, the occurrence of heat waves did not show significant differences among ecoregions, but a more evident variability in terms of relationship between fire regime metrics and heat waves within the study area. The outcome of the GWR analysis allowed us to identify the spatial locations (i.e., hotspot areas) where the relationship between heat waves and wildfires is positive and significant. Hence, in hotspots the presence of heat waves can be seen as a driver of wildfire occurrence in forest and steppe ecosystems. The findings from this study could contribute to a more comprehensive assessment of wildfire patterns in this geographical region, thus supporting cross-regional prevention strategies for disaster risk mitigation.

1. Introduction

The global issue of climate change is having tangible effects on the rate of occurrence and intensity of heat waves (HWs) (Meehl and Tebaldi, 2004; Della-Marta et al., 2007; Fischer and Knutti, 2015). The circulation and persistence of large and warm masses of air on specific regions is no longer an exception but rather a recurrent pattern which is leading to the greater likelihood of HW occurrence (Intergovernmental Panel On Climate Change, 2023). Consequently, as global temperatures rise due to the accumulation of greenhouse gases in the atmosphere, heat waves become more frequent, longer-lasting, and extreme (Dean and Green, 2018; Robinson et al., 2021; Xiao et al., 2022). This creates the background for exploring the coupling between HW occurrence and a wide range of associated (natural) risks/hazards. For example, HWs can worsen drought conditions by intensifying evaporation rates and drying out vegetation, making it more susceptible to wildfire ignition and spread. Dry and dead vegetation acts as fuel for wildfires favoring a more rapid and severe spread (Nolan et al., 2016; Rossa, 2017).

Many countries across the globe have experienced the coupling occurrence of wildfires and HWs. During the HW of 2003, >25,000 fire events occurred in the Mediterranean countries of Southern Europe (Portugal, Spain, Italy and France) with severe consequences on woodlands, grasslands, and agricultural areas (Fink et al., 2004). In Greece, three consecutive HWs and severe drought marked 2007 as the worst fire season of the past 50 years: from June to September, over 3000 wildfires burned >270,000 ha of forest, olive groves and croplands (Balafoutis, 2007). In Russia, abnormal Northern Hemisphere HW of 2010, considered as the worst drought in nearly 40 years, favored wildfires throughout the country causing the loss of at least 9 million ha of natural areas (Trenberth and Fasullo, 2012). In the summer of 2017 southern Europe experienced extreme temperatures and unprecedented HWs. Wildfires were detected in Albania, Serbia, Bosnia, Macedonia, Croatia, Greece, and Italy, with several countries evacuating tourists from the affected regions. More than 60 people died from the Pedrógão Grande fire in Portugal that occurred earlier in June 2017 (Leone et al., 2023).

These extreme numbers have led to a growing interest in exploring the coupling occurrence of HWs and wildfires (Page et al., 2010; Fischer and Schär, 2010; Barbero et al., 2015; Fasullo et al., 2018; Vitolo et al., 2019; Hopke, 2020; Ruffault et al., 2020; AghaKouchak et al., 2020; Barriopedro et al., 2023). For example, Rodrigues et al. (2020) analyzed fire-weather typologies promoting large fires in the Iberian Peninsula. The authors found four distinct fire-weather typologies linked to different spatial wildfire occurrence patterns suggesting as burnt areas in Spain are strongly associated with HWs. Parente et al. (2019) provided a characterization of HWs in current and future climate scenarios in Portugal. They found a strong relationship between HWs and temporal and spatial distribution of extreme wildfires. Nojarov and Nikolova (2022) built multiple linear regression models to assess the complex influence of HW characteristics on wildfires in Bulgaria. Their results demonstrated that HWs with longer and higher air temperatures favored conditions for the occurrence and development of wildfire, especially in summer.

However, addressing the coupling occurrence of HWs and wildfires requires a comprehensive knowledge of the two phenomena that encompass both fire regimes and HW patterns in a larger spatial scale. Specifically, the interactions between both the phenomena may be non-linear and change spatially at a broader scale across different landscapes. Assessments of fire regime and HW characteristics based on ecological regions (ecoregions) might be more appropriate (Chuvieco et al., 2008; Archibald et al., 2013; Hanes et al., 2019; Erni et al., 2020; Syphard et al., 2020; Pausas, 2022) as wildfires are strongly linked to vegetation (fuel) and climate conditions, two key factors for the definition of ecoregions.

The present study across multiple ecoregions within a Eurasia longitudinal gradient encompasses Mediterranean countries of southern Europe and the near east (Fig. 1) with the aim to understand the coupling occurrence of HWs and wildfires events. Focusing on this Eurasia longitudinal gradient, our study intends to achieve three main objectives: (i) to characterize and analyze fire regime parameters and HW patterns and (ii) to assess the relationship between HWs and wildfires (iii) to identify hotspots where a significant and positive relationship is found between HW and wildfire occurrence.

Through this study we were able to examine the differences in the wildfire regime and HW patterns across 37 ecoregions including, for example, forest areas, grasslands, and steppes. Up to date, only a few studies have analyzed the coupling occurrence of HWs and wildfires at ecoregional scale, characterized by diverse environmental, biophysical and climate conditions (Fernandes et al., 2016; Ruffault et al., 2020). Addressing this issue across such a large geographical area, which is one of the most fire-affected regions across the globe (San-Miguel-Ayanz et al., 2020), could contribute to support cross-regional prevention strategies for fire disaster risk mitigation.

2. Data

2.1. Study area

The study area includes 37 ecoregions within a Eurasia longitudinal gradient from Portugal to Turkey (Fig. 1) (Olson et al., 2001). The nations involved are Portugal, Spain, France, Luxembourg, Italy, Slovenia, Croatia, Bosnia and Herzegovina, Serbia, Montenegro, Albania, Kosovo, Greece, North Macedonia, Bulgaria, Cyprus, and Turkey.

Ecoregions are defined as large ecologically homogeneous areas within which species and natural communities interact with the biophysical features of the environment (Table 1). Ecoregions describe landscapes with similar potential for climate, physiography, oceanography, hydrography, vegetation, and fauna. Hence, they provide a geographic framework for interpreting ecological processes, disturbance regimes, the spatial distribution of vegetation, and dynamics of ecological systems (Loveland and Merchant, 2004).

According to Olson et al. (2001), Ibss-df (see Table 1) is the largest ecoregion followed by Eamf and Webf, which account for an area >200 * 10^3 km^2. The last two ecoregions are Cmbmf and Sisw which cover an area that does not exceed 4000 km^2.

2.2. Fire and HW data extraction

The spatial domain for this analysis was a 1/8-degree lat/long grid (~12 km resolution) delimited by the geographical boundaries of the ecoregions (Westerling et al., 2011). The result was a set of 2154 grid cells within which wildfire and HW metrics were extracted and modeled at a time range from 2001 to 2019.

Fire boundaries were extracted each year using the GlobFire Final Fire Event Detection Based on MODIS burnt area product Collection 6 (MCD64A1) from the Google Earth Engine Platform (Gorelick et al., 2017) (Fig. S1). The MCD64A1 Version 6 combines Terra and Aqua data to provide a monthly global per-pixel burnt area layer with a spatial resolution of 500 m; a quality assessment layer is also provided (for more details here http://modis-fire.umd.edu/files/MODIS_C6_BA_User_Guide_1.2.pdf). The GlobFire dataset provides further processing on the MODIS data, which defines each wildfire event by merging MODIS pixels in space and time and computing the burnt area of each event (Artés et al., 2019). We then calculated wildfire metrics related to density, seasonality and severity which were associated to the corresponding 12 km^2 grid cells. We calculated the average burnt area per single fire event (i.e., Fire Size see Table 2) (Fernandes et al., 2016). Fire size was considered a density metric for its capacity to characterize the frequency and incidence of wildfire events in each landscape (Morgan et al., 2001; Taylor and Skinner, 2003; Moreno and Chuvieco, 2013; Jiménez-Ruano et al., 2017; Elia et al., 2022). A Fire Season index and the Main season fire (see Table 2) were estimated to account for the seasonality of events across the study area. The last wildfire metric is an index estimating the capacity of fire to heavily damage vegetation such as Stand Replacing Fire. It is a metric of high fire severity based on the capacity of a fire to cause immediate long-term changes that affect soil chemistry, watersheds, wildlife, recreation, livestock and timber uses (Halofsky et al., 2018; Stevens et al., 2017). To calculate this metric the wildfire polygons were overlaid to forest cover losses (Hansen et al., 2013) according to the period and scale of investigation and for each fire polygon we estimated the sum of the pixels that were marked as "loss" in the 3 years following the fire event. Results were then employed to calculate the "stand replacing fire ratio" by dividing it by the total fire polygon area (Elia et al., 2022; Spadoni et al., 2023).

Heatwaves were defined as a period consisting of at least 6 consecutive days with maximum temperatures greater than the 90th percentile (Fischer and Schär, 2010; Parente et al., 2018). Hourly data from the ERA5 land dataset provided by the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/) at a 0.1-degree resolution (~9 km) were used to estimate the spatial occurrence of summer (from June to September) heatwaves.

The Climate Data Operators software, provided by the Max Planck Institute for Meteorology, was used at pixel level to calculate the daily maximum temperatures and the 90th percentile for each Julian day within a 5-day window. Furthermore, we calculated different metrics to characterize the HWs such as duration (in days), intensity (degrees Celsius) and period (Number of HWs within the study period). HW intensity was calculated as the accumulated anomaly (i.e., maximum temperature minus the 90th percentile) for the last 6 days of the HW.

Finally, these metrics were averaged for the study period (see Table 2) and associated to their corresponding 12 km grid cells using a weighted mean that considered the fraction covered by different cells

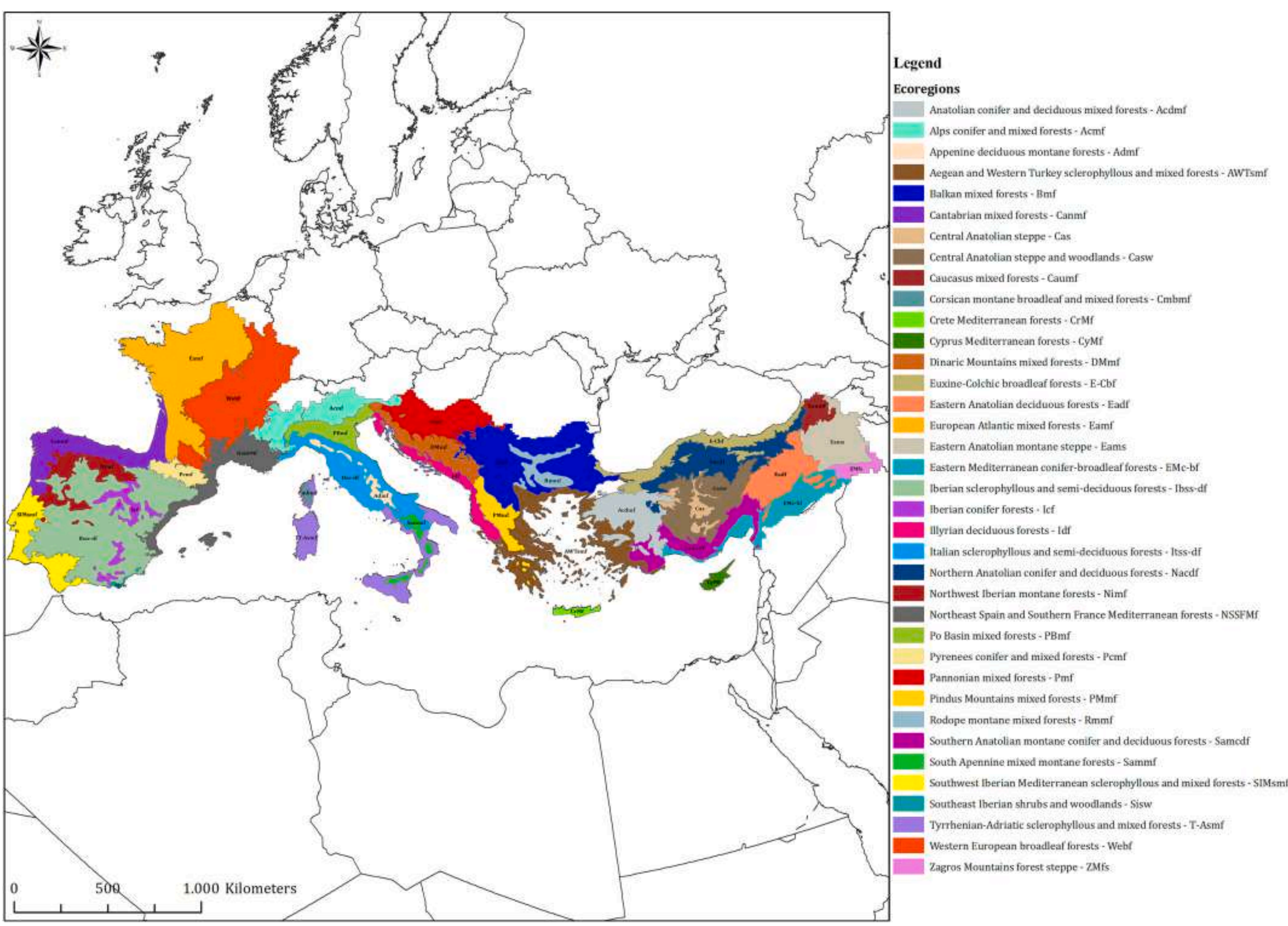


Fig. 1. Map of the study area showing the 37 ecoregions within a Eurasia longitudinal gradient.

Table 1
Codes, names and relative extension (km^2) of the observed ecoregions.

Code	Ecoregion	Area (km^2)
AWTsmf	Aegean and Western Turkey sclerophyllous and mixed forests	133,539.6
Acmf	Alps conifer and mixed forests	82,468.1
Acdmf	Anatolian conifer and deciduous mixed forests	86,392.7
Admf	Apennine deciduous montane forests	16,147.2
Bmf	Balkan mixed forests	194,177.3
Canmf	Cantabrian mixed forests	96,265.2
Caumf	Caucasus mixed forests	21,458.6
Cas	Central Anatolian steppe	24,934.2
Casw	Central Anatolian steppe and woodlands	101,492.5
Cmbmf	Corsican montane broadleaf and mixed forests	3633.6
CrMf	Crete Mediterranean forests	8171.5
CyMf	Cyprus Mediterranean forests	9272.2
DMmf	Dinaric Mountains mixed forests	58,285.8
E-Cbf	Euxine-Colchic broadleaf forests	68,335.1
Eadf	Eastern Anatolian deciduous forests	81,627.5
Eamf	European Atlantic mixed forest	235,784.7
Eams	Eastern Anatolian montane steppe	83,544.4
EMc-bf	Eastern Mediterranean conifer-broadleaf forests	72,539.8
Icf	Iberian conifer forests	34,461.0
Ibss-df	Iberian sclerophyllous and semi-deciduous forests	297,955.7
Idf	Illyrian deciduous forests	40,638.3
Itss-df	Italian sclerophyllous and semi-deciduous forests	102,221.1
NSSFMf	Northeast Spain and Southern France Mediterranean forests	90,850.4
Nacdf	Northern Anatolian conifer and deciduous forests	101,409.6
Nimf	Northwest Iberian montane forests	57,405.9
Pmf	Pannonian mixed forests	88,759.9
PMmf	Pindus Mountains mixed forests	39,583.6
PBmf	Po Basin mixed forests	42,460.7
Pcmf	Pyrenees conifer and mixed forests	25,930.1
Rmmf	Rodope montane mixed forests	31,688.5
Sammf	South Apennine mixed montane forests	13,094.8
Sisw	Southeast Iberian shrubs and woodlands	2867.9
Samcdf	Southern Anatolian montane conifer and deciduous forests	67,775.7
SIMsmf	Southwest Iberian Mediterranean sclerophyllous and mixed forests	71,118.4
T-Asmf	Tyrrhenian-Adriatic sclerophyllous and mixed forests	84,660.2
Webf	Western European broadleaf forests	209,205.8
ZMfs	Zagros Mountains forest steppe	18,779.4

Table 2
Wildfire regime and heat wave metrics with reference units and definitions.

Parameters	Unit	Definition
Wildfire		
Fire size	ha	Average burned area per single fire event
Fire season index	From 0 to 1	Index of fire seasonality, the closer the value is to 1, the more events are concentrated in a single season
Main season fire	–	Seasons in which wildfires occur
Stand replacing fire index	From 0 to 1	Index estimating the capacity of fire to heavily damage vegetation
Heat waves		
Heat waves duration	Days	Mean duration of each heatwave
Heat waves intensity	°C	Cumulated anomaly (i.e., maximum temperature minus the 90th percentile) for the last 6 days of the heatwave
Heat waves period	Heatwaves numbers	Number of heatwaves within the study period

(Fig. S2).

3. Methods

All data from Table 2 (e.g., wildfire and HW metrics) were averaged yearly by cell. To test the significance of the differences among ecoregions, we averaged cell values by ecoregion using boxplots (with medians and percentiles across the years) and a one-way ANOVA followed by Honestly Significant Difference (HSD) Tukey post hoc test.

To assess the relationship between wildfires and HWs and identify hotspots of coupling occurrence, we performed a Geographically Weighted Regression (GWR), which is a statistical method used to model the varying spatial relationships between variables (Fotheringham et al., 2003; Wang et al., 2005; Sá et al., 2011; Martínez-Fernández et al., 2013; Oliveira et al., 2014; Rodrigues et al., 2018; Su et al., 2021). GWR is an extension of traditional global regression models that assume a single set of regression coefficients for the entire study area. In GWR, the regression coefficients are allowed to vary across space, capturing the local variations and spatial heterogeneity in the data. GWR provides a more detailed and localized understanding of the relationships compared to global regression models. The key concept in GWR is the use of spatially adaptive weighting. Each observation in the dataset is assigned a weight based on its proximity to other observations. The weights reflect the influence of nearby observations on the regression estimation at a particular location. This allows GWR to give more emphasis to nearby observations and less weight to distant ones, effectively accounting for the spatial autocorrelation present in many spatial datasets.

For the whole period under investigation, we averaged the input data for each cell and performed a regression for each fire metrics (Y values) as a function of the HW variables (X values). Each regression was fitted based on the simple idea of estimating each (local) model using a subset of observations (e.g., neighboring cells) centered on a single center cell.

Fotheringham et al. (1998, 2003) give a general form for the GWR model as:

$$y_i = \beta_{i0} + \sum_{k=1}^{m} \beta_{ik} x_{ik} + \varepsilon_i \tag{1}$$

where y_i is the dependent variable at location i; x_{ik} is the kth independent variable at location i; m is the number of independent variables; β_{i0} is the intercept parameter at location i; β_{ik} is the local regression coefficient for the kth independent variable at location i; and ε_i is the random error at location i.

To determine the best values for the number of neighbor parameters, the golden section search method was employed. This method determines the optimal number of neighbors minimizing the value of the Akaike Information Criterion (AICc). The local statistical significance of the coefficient estimates was assessed with the R^2 values, which give indication of the model fit in each cell and mapped using GIS tools. Even if not one of our aims, by using R^2 and AICc values, we provide a comparison with the performance of Ordinary Least Squares (OLS) to make our analysis more robust. The OLS assumes stationarity and estimates the coefficients for the overall model, while the GWR assumes that the relationships between variables vary in space by calculating regression coefficients at each individual location (Fotheringham et al., 2003; Koutsias et al., 2010; Sá et al., 2011).

The following step included the identification of hotspots. For each HW and fire metric R^2 was calculated using GWR. Subsequently, a threshold was established based on the 68th percentile of R^2 value distribution. Using the threshold above the 68th percentile as reference, fire metrics with a positive correlation with one or more HW metrics were identified and represented a hotspot. In statistics the 68th percentile, as well as the 95th and 99.7th, known as the empirical rule, is a shorthand used to remember the percentage of values that lie within an interval estimate in a normal distribution (Pukelsheim, 1994).

Once a positive correlation between HWs and fire metrics was determined, a spatial representation of hotspots was generated, indicating the locations where the positive coupling occurrence between HWs and fire metrics occurs. This spatial representation highlights the areas where the relationship is significant and positive and can be considered of "first level" if only one HW parameter is significantly correlated with the response variable (i.e., 1-HW+), "second level" if two HWs parameters are positively correlated with the response variable (i.e., 2-HW+), and "third level" if all the three HWs parameters are significantly and positively correlated with the fire response variable (i.e., 3-HW+). Overall, this process aims to explore the relationship between HW and fire metrics at the local level by identifying those fire metrics which are positively affected by the occurrence of HWs and by visualizing the corresponding hotspots. We further estimated the percentage of each level for the single hotspot detected within each ecoregion.

4. Results

4.1. Fire regime parameters and heat wave patterns

The one-way ANOVA followed by the Honestly Significant Difference (HSD) Tukey post hoc test allowed us to shed light on the potential significant differences between ecoregions in terms of wildfire regime and HW metrics (Figs. 2 and 3, respectively). The differences among ecoregions were significant ($P < 0.05$) for all the wildfire metrics, but surprisingly not significant for the HW metrics.

Fire size did not present significant differences among ecoregions except for EMc-bf, Samcdf and SIMsmf. Thirty-four of 37 ecoregions reported similar values in terms of yearly average burnt area per single event according to the statistical test. As expected, we found main differences among the ecoregions for the Fire Season Index and the Stand Replacing Fire Index. In the case of fire seasonality, the gradient from east to west seemed to have an influence on the main season of fire. The majority of ecoregions (24) exhibited a concentration of the fire events in summer, while only one ecoregion (Pcmf) showed fire events in the winter, one in the spring (Cymf) and four in the fall season. Particular mention should be made regarding the 9 ecoregions with a double seasonality in fire occurrence, as for example Eams and SIMsmf. In terms of Stand replacing fire index, the analysis revealed more heterogeneity among ecoregions, with high values for Acdmf and the lowest values for Casw, PBmf e Rmmf. The index showed no values for the Caumf ecoregion.

4.2. Relationship between HWs and wildfires

To assess the relationship between wildfires and HWs we developed a Geographically Weighted Regression. The GWR showed a better performance compared to OLS across the entire study area and for all the three response variables (Table 3), with a significant improvement of R^2 and AICc values respectively. Our findings suggested that the highest average R^2 is obtained for the Fire size dependent variable with a value of 0.38 (Table 3), while the highest values of R^2 is obtained for the Stand replacing fire index (0.59) (Fig. 6a). The spatial distribution of R^2 values exhibited a high heterogeneity across the study area for the Fire size and Fire season index (Figs. 4a and 5a). The ecoregions in central Europe (Balkans, Italy, Greece and Turkey) and the extreme borders of the study area (Portugal and Cyprus) showed the highest values of R^2 reaching 0.57 both for Fire size and Fire season index. The distribution of R^2 for the Stand replacing fire index displayed a more clustered pattern, with the highest values found in the Iberian ecoregions and Aegean and western Turkey sclerophyllous forest (Fig. 6a).

4.3. Identification of hotspots

Figs. 4b, 5b and 6b show the distribution of hotspots across the study area according to the three response variables (i.e., wildfire metrics).

Fire size hotspots areas were distributed homogeneously along the study area from west to east (Fig. 4b). The ecoregions mostly affected by third level hotspots (i.e., all the three HW parameters are significantly and positively correlated with the fire response variable, 3-HW+) were the PBmf and Acmf located in Italy (Fig. 4b), covering 94 % and 81 % of the entire hotspot surface, respectively. Ecoregions with >50 % of the hotspots characterized by 3-HW+ were: Webf and Canmf in the western part of Europe and Acdmf and Cas in Turkey (Fig. S3). Of 37 ecoregions only 15 included 3-HW+ hotspots, 16 were affected by first and second level hotspots, while the remaining 6 (i.e., Caumf, Cmbmf, CrMf, Icf, NSSFMf, Sisw) did not show any hotspot (Fig. 4b).

Fire seasonal index hotspots were fewer compared to those of Fire size and located mainly in western Europe (Fig. 5b). Only Itss-df showed a hotspot with >50 % of its area affected by a third level relationship between the response variable (i.e., Fire season index) and the three HW metrics (Fig. S3). The percentage for six ecoregions (AWTsmf, Nimf, Eamf, DMmf, Ibss-df, and Webf) was >20 %. Of 37 ecoregions, only 9 included third level hotspots, while 15 did not exhibit any hotspot.

Stand replacing fire index hotspots were drastically fewer compared to the previous response variables (i.e., Fire size and Fire season index). Only 2 ecoregions showed 3-HW+ hotpots, mainly located in the Iberian Peninsula, particularly Ibss-df and Nimf, with 32 % and 27 % of their areas characterized by a full relationship between the response variable and the three HW metrics (Fig. S3).

5. Discussion

Future projections of climate change worldwide foresee an ever greater increase in intensity of HWs, along with an increasing probability of their co-occurrence with other natural phenomena, such as wildfires (Ruffault et al., 2020; Grünig et al., 2023; Turco et al., 2023; Yuan et al., 2023). While it is broadly acknowledged that heat waves alter fire regime, uncertainties remain on the coupling occurrence of HWs and wildfires.

While it is broadly acknowledged that HWs alter fire regimes, uncertainties remain with regard to the coupling occurrence of HWs and wildfires. In this study, we analyzed the metrics related to fire regime which are significantly and positively affected by HWs, and how the intensity, duration, and amount of HWs influence such metrics. We further identified potential hotspots at ecoregional scale in a time window of approximately 20 years.

High-pressure systems, like the so-called African subtropical anticyclone, have been expanding northward in recent decades, generating the occurrence of HWs (Ventura et al., 2023). As temperatures continue to warm up, changes in atmospheric circulation patterns can lead to increased drought and water shortage, maximum temperatures and warmer air (Nojarov and Nikolova, 2022). Russo et al. (2014) found that the percentage of global area affected by HWs has increased in recent decades. Lhotka and Kyselý (2022) discovered that the 83 % of the entire European continent has experienced severe heat waves in the past two decades (2002–2021), setting a new record across most of Europe. Croitoru et al. (2016) provided evidence of a rise in HWs frequency in Romania, which was particularly severe in its western and central regions. Similarly, Unkašević and Tošić (2015) observed a growing trend in the frequency and duration of HWs in Serbia from 1949 to 2012.

Although our analysis found no significant differences among ecoregions in terms of intensity, duration and periods of HWs, the data revealed greater variability in terms of relationships between fire regime metrics and HWs within the study area. HWs provide the perfect weather conditions for wildfires to ignite and rapidly spread. Indeed, our analysis suggested a more evident variability of fire regime metrics within the study area. We found differences among ecoregions (see Fig. 2) as did other authors in their studies. For example, Pausas (2022) found that fire regime parameters varied across different environments within the western Palearctic. He observed distinctive fire regime characteristics for each biome, with a tendency for greater fire activity in warmer environments. Nolè et al. (2022) found that fire severity exhibited spatial differences and interannual variability across biogeographic regions of Europe. Galizia et al. (2021) identified four large-scale pyroregions describing a meaningful segmentation of fire regimes across Europe. A large body of studies (Ascoli and Bovio, 2010; Moreno and Chuvieco, 2013; Curt et al., 2016; Chergui et al., 2018; Rodrigues et al., 2019) is also found at a lower scale highlighting the

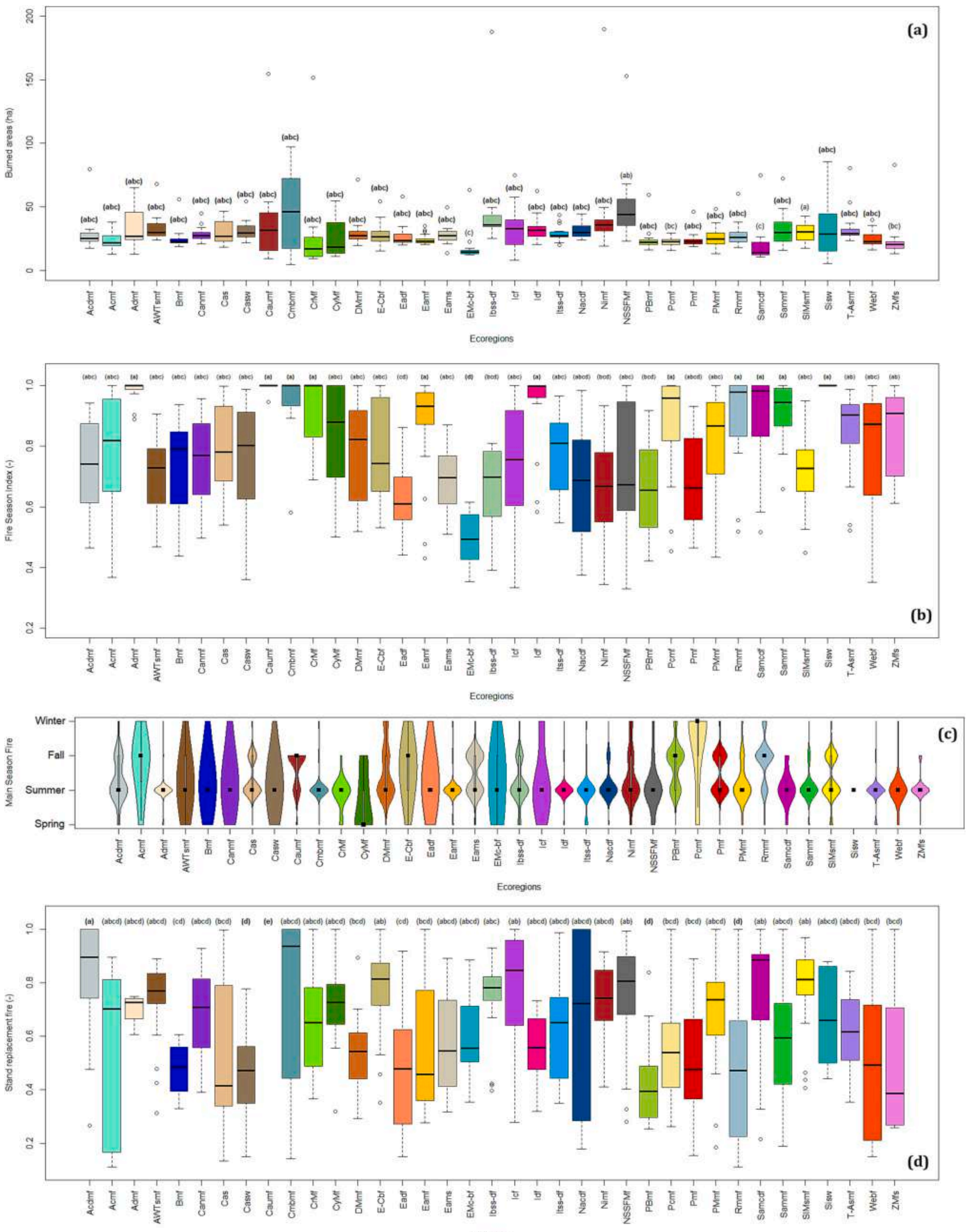


Fig. 2. Box plots showing the distribution of values for each wildfire regime metrics (a) Fire size, (b) Fire season index, and (d) Stand replacing fire index. For each plot, an ecoregion was assigned to a specific group represented by a letter above each box, according to Honestly Significant Difference (HSD) Tukey post hoc test. Ecoregions indicated with the same letters were not significantly different (P < 0.05). Violin plots describe the distribution of fire events during different seasons; (c) Main fire season.

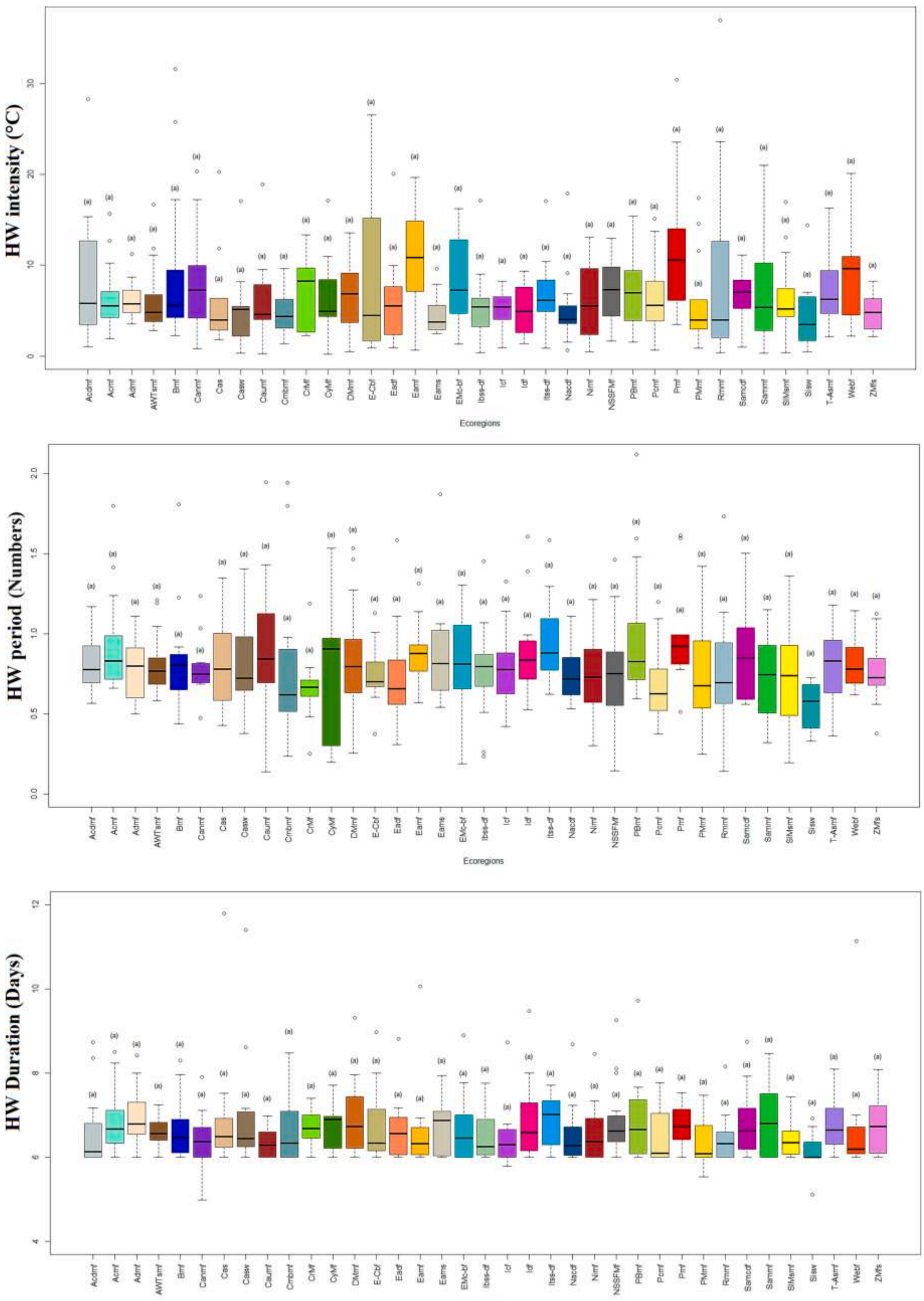


Fig. 3. Box plots showing the distribution of values for each HW metrics: (a) intensity, (b) period, (c) duration. For each plot, an ecoregion was assigned to a specific group represented by letters above each box, according to Honestly Significant Difference (HSD) Tukey post hoc test. Ecoregions indicated with the same letters were not significantly different (P < 0.05).

Table 3
Comparison of R^2 and AICc values between the OLS and GWR models.

Response variables	OLS model		GWR model		
	R^2	AICc	R^2	AICc	Neighboring cells
Fire size	0.006	277,698.19	0.38	267,901.94	37
Fire season index	0.008	26,409.34	0.31	19,334.01	31
Stand replacing fire index	0.006	4033.72	0.33	−3793.6	31

AICc: Akaike information criterion; OLS: ordinary least square; GWR: geographically weighted regression.

variability of fire regime metrics across landscapes of Mediterranean region. For example, Elia et al. (2022) reported that a significant variability of wildfire regime metrics in Italy was largely explained by climate variables such as increasing temperatures and exposure to drought. Conedera et al. (2018) found a clear differentiation between the high fire density of the southern slope of the Alps and the lower proportion of burnt areas registered in the north. Moreno and Chuvieco (2016) suggested that environmental gradients shaped fire regimes across the Iberian Peninsula. A strong positive relationship between seasonal temperature fluctuations and fire is the one of the key links of wildfire density and seasonality.

As stated above by the authors, the evidence is clear regarding the influence of climate variables on fire regimes as well as the relationship between HWs and wildfires, especially in the warmer areas of Mediterranean countries (Brotons et al., 2013; Ruffault et al., 2018; Bowman et al., 2020; Sutanto et al., 2020). Our study revealed hotspots where the above-mentioned relationship is significant and reaches higher R^2 values. The areas in red (see Figs. 4a, 5a and 6a) represents the highest positive correlation between the three HW metrics and the metrics related to density, seasonality and fire severity, respectively. The analysis revealed hotspots not only in the ecoregions of Turkey, Greece, Italy, France, and Iberian Peninsula but also in the Balkan area. These findings are consistent with other studies. For example, Unal et al. (2013) found coefficients of correlation between the number of days of HW and fires ranging from 0.4 to 0.6 in most of western Turkey. Koutsias et al. (2012) observed a significant correlation (0.66) between the average maximum temperature of HWs and wildfires, in vegetated landscapes of Greece. Nojarov and Nikolova (2022) explored the relationship between the average duration of HWs and forest fires in Bulgaria. They modeled a positive and statistically significant relationship in four of the six areas studied explaining up to 60 % of the variations of forest fires in Bulgaria.

Our findings further highlight that hotspots 3-HW+ are found in ecoregions characterized by mixed forest ecosystems (Fig. S3). Alps conifer and mixed forests (Acmf), Anatolian conifer and deciduous mixed forests (Acdmf), Cantabrian mixed forests (Canmf), Caucasus mixed forests (Caumf), and Po Basin mixed forests (PBmf) ranked in the first five positions of the ecoregions mostly covered by 3-HW+ hotspots in terms of fire size response to HW metrics. Aegean and Western Turkey

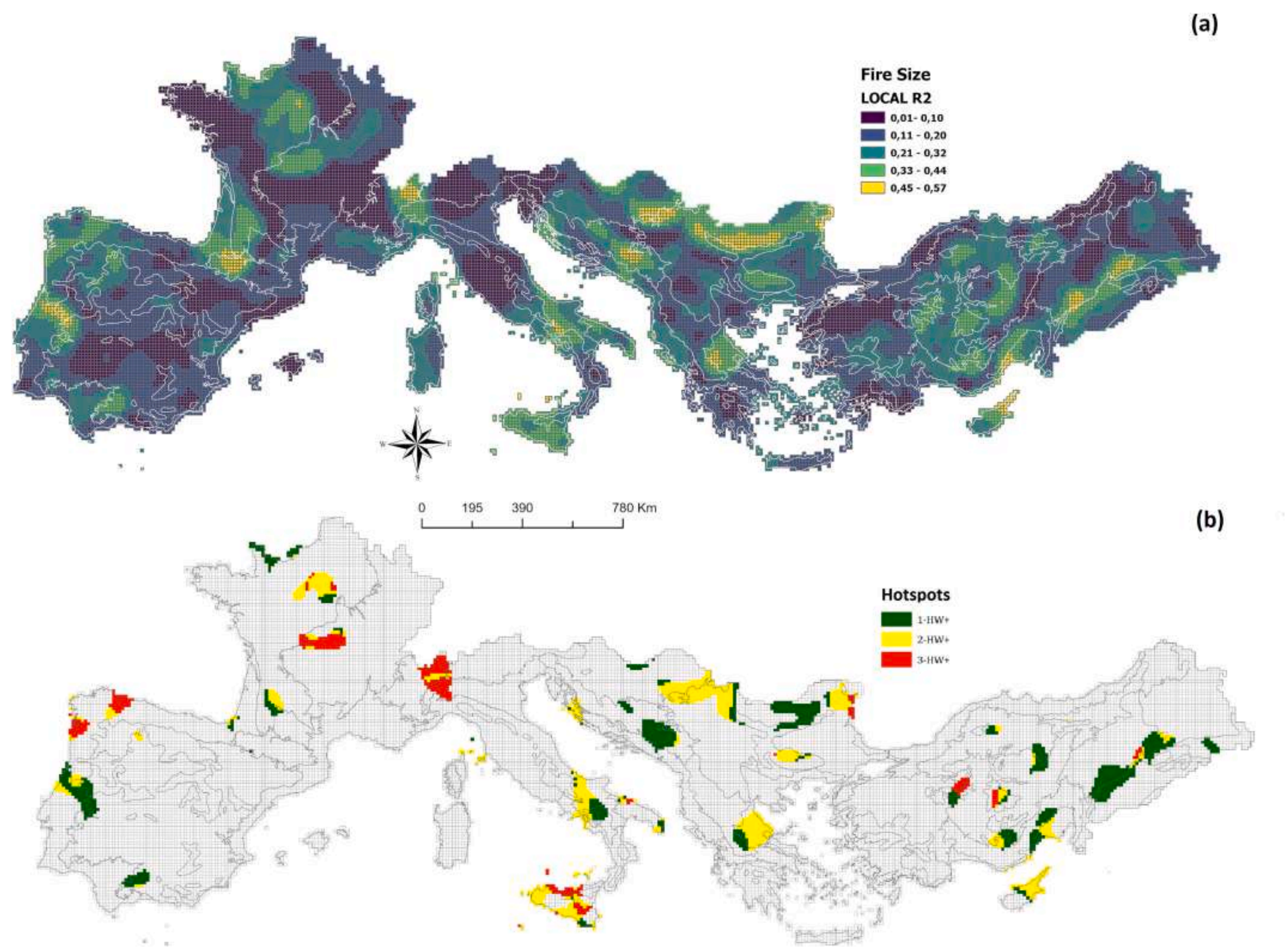


Fig. 4. Relationship between fire size and heat waves (HWs) across the study area: (a) Distribution of geographically weighted regression local R^2 values for the Fire size response variable; and (b) identification of hotspots based on the positive relationship between fire size and HW parameters at each level.

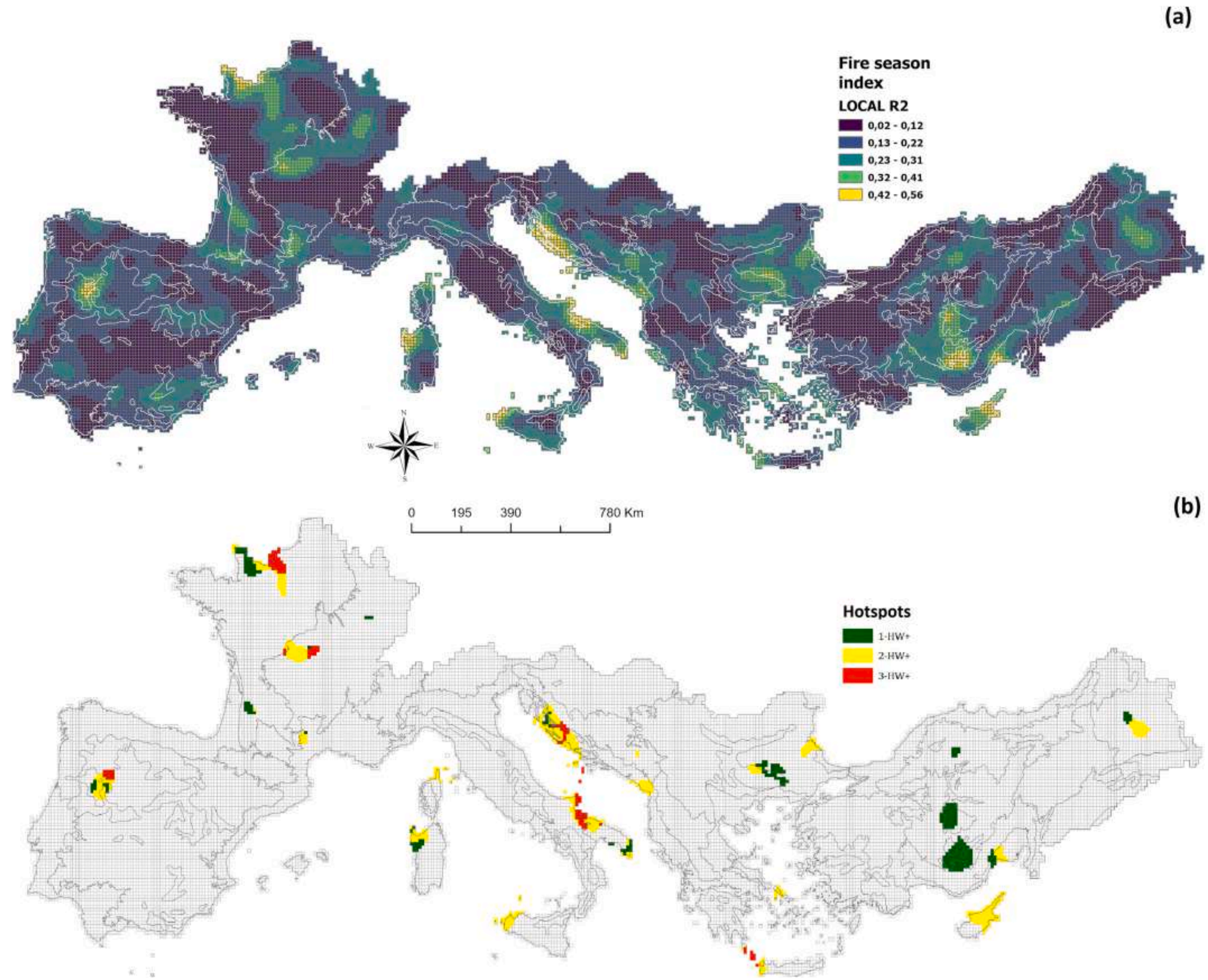


Fig. 5. Relationship between the Fire season index and HWs across the study area: (a) Distribution of geographically weighted regression local R^2 values for the Fire season index response variable; and (b) identification of hotspots based on the positive relationship between the Fire season index and HW parameters at each level.

sclerophyllous and mixed forests (AWTsmf) and Dinaric Mountains mixed forests (DMmf) ranked in second position as the ecoregions mostly covered by 3-HW+ hotspots in terms of the Fire seasonal index in response to HW metrics. Although Oliveira et al. (2013) found that the forest-type land covers show intermediate values of fire selectivity, we believe that future work is needed to gain a deeper understanding of whether certain forest categories (i.e., mixed forest) are more susceptible to the coupling occurrence of HWs and fires. For other ecoregions characterized by broadleaf, shrubland and steppe, except for Western European broadleaf forests (Webf), our analysis demonstrates that hotspots are mostly represented by first and second level relationships. In these cases, the main HW metrics guiding the coupling occurrence are intensity and duration (Tables S1, S2, S3). Steppe and grasslands exhibit a higher susceptibility to wildfires because of their inherent flammability traits, such as ignitability (Qu et al., 2016; Cromartie et al., 2020; Erdős et al., 2022). High HW intensity can increase the likelihood of fires in these regions, posing risks to both natural habitats and human communities. The combination of dry vegetation, high temperatures, low humidity, strong winds, and potential ignition sources during HWs creates a highly conducive environment for wildfire occurrence in steppe ecosystems (Dong et al., 2011; Twidwell et al., 2013; Schubert et al., 2014; Stavi, 2019).

The diverse ecoregional characteristics, ignition patterns, and management practices applied to different vegetation types, as well as firefighting strategies all represent factors that could contribute to a comprehensive understanding of how effectively HWs are responsible for these differences in fire regime metrics. However, our findings can be applied in landscape management models or decision support systems aimed at reducing the likelihood and severity of wildfires, even in real time when a HW occurs (Mermoz et al., 2005; Moreira et al., 2011, 2020).

In the near future, the mounting occurrence of more intense and prolonged HWs will probably induce Europe to plan proactive measures to mitigate the potential coupling occurrence of HWs and wildfires (Vanderplanken et al., 2021). The Mediterranean region, in particular, will face the dual challenge of escalating heat extremes and the coupled risk of forest fires as outlined by the European Environment Agency report (EEA, 2023) on climate change impacts. The data also reveals a substantial uptick in the occurrence of wildfires during years marked by extreme HW conditions.

Despite the important results found in our study across such a large area, we recognize the existence of certain limitations. For example, we explored the coupling occurrence of HWs and fires on the basis of only a certain number of metrics. Fire metrics were employed because they are

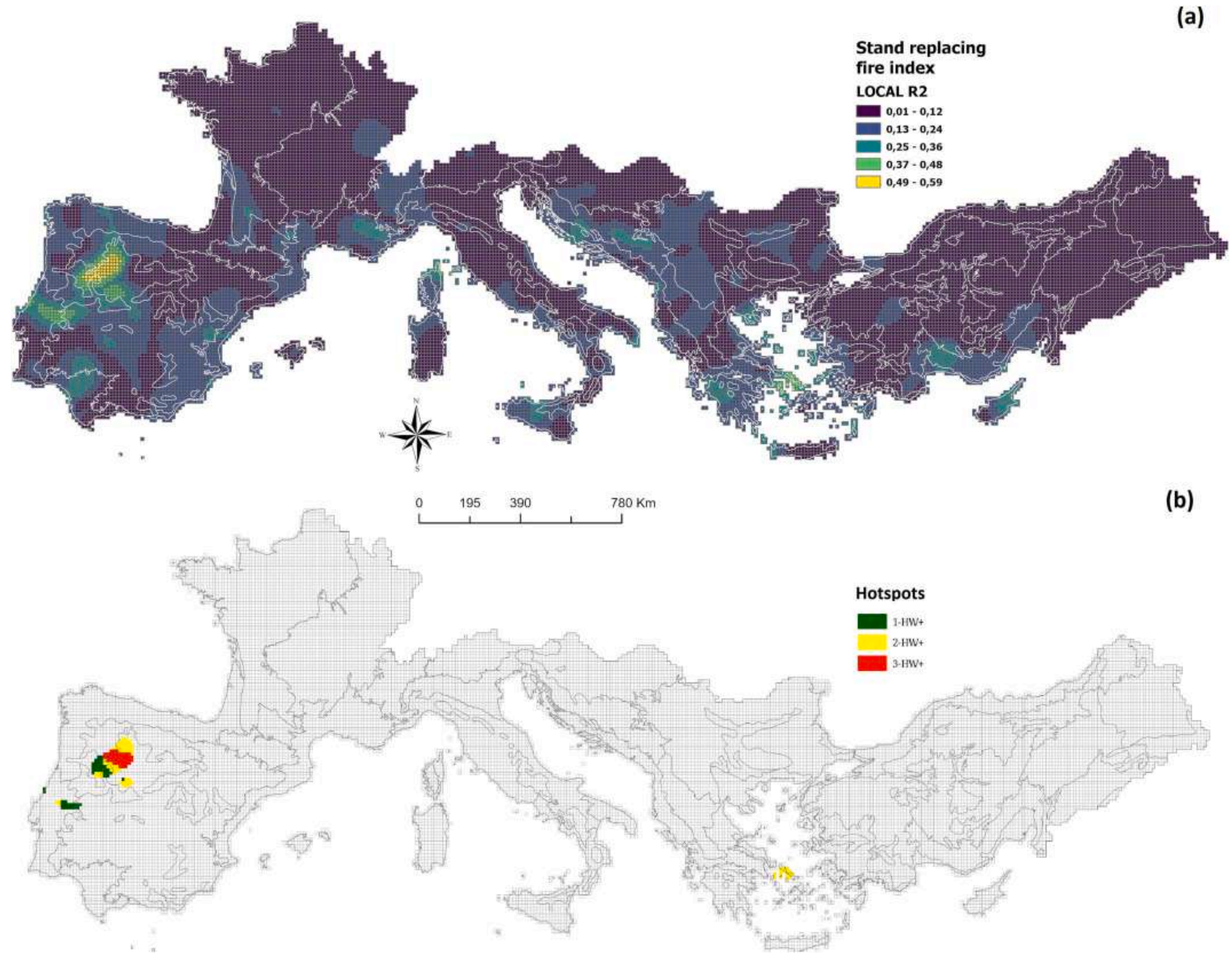


Fig. 6. Relationship between the Stand replacing fire index and HWs across the study area: (a) Distribution of geographically weighted regression local R^2 values for the Stand replacing fire index response variable; and (b) identification of hotspots based on the positive relationship between Stand replacing fire index and HW parameters at each level.

frequently used in fire-related studies and describe key aspects of fire regimes (Boulanger et al., 2014; Jiménez-Ruano et al., 2020; Rodrigues et al., 2020). Future studies including other wildfire regime components (not available in our dataset) could provide additional knowledge for understanding the coupling occurrence of HWs and wildfires across the Eurasia region at large.

We also adopted widely accepted threshold-based values, drawing on established methods and practices found in the scientific literature to compute the three specific HW metrics. This resulted in the 90th percentile employed for HW estimation. The choice of a higher or lower threshold can yield disparate outcomes. For instance, employing a different threshold value for HW estimation, such as the 95th percentile, as seen in studies by Guerreiro et al. (2018) and Di Napoli et al. (2019), would impact the occurrence of HWs. It is essential to note that elevated temperatures cannot be automatically qualified as HWs. In line with the typical approach in HW-related research, as established by (Perkins and Alexander, 2013), the percentiles used in our study to define a HW hazard are derived from climatology and tailored to each grid cell and day. This results in geographically and daily variable thresholds. Consequently, the 90th percentile for air temperature in northern Europe is lower than the corresponding percentile in southern Europe, which may potentially lead to HWs in northern Europe being associated with lower temperatures compared to southern Europe.

6. Conclusion

Heatwave occurrence potentially triggers significant influence on wildfire regimes. This study aimed to explore the relationship between HWs and wildfires encompassing 37 ecoregions within a Eurasia longitudinal gradient. Our findings displayed no significant differences among ecoregions in terms of HW intensity, duration and periods, but at the same time showed a greater variability of the relationship between fire regime metrics and HWs within the study area. Our GWR model locally exhibited good performance in the local prediction of such a relationship, reaching values of R2 near to the 0.6.

Hotspots were identified largely for an area stretching from west to east Europe. For the wildfire metrics related to density and seasonality, the identified hotspots are distributed along the entire gradient covering mostly ecoregions characterized by mixed forest ecosystems. This result can be considered as room of improvement for the near future at aim to deeply understand why, within this forest typology, there such a strong relationship between HWs and wildfire occurrence is. Future studies should be addressing this topic. Mention needs to be done for the hotspot locations derived by the Stand Replacing Fire index, which are markedly different by the other two fire metrics. The analysis found only four hotspots, the most important of which are in the Iberian Peninsula. This is one of the most wildfire prone area across the globe, which experienced in the past dramatic and fatal events such as Pedrógão Grande (2017). In that occasion an intense HW occurred before the fires, with many areas of Portugal seeing temperatures >40 °C (104 °F). In this regard, our analysis suggested that the main HW metrics guiding the relationship between HWs and wildfires are the intensity and duration.

In conclusion, this work is one of the first study that aims to provide a valuable cross-ecoregional insight for the coupling occurrence of two different natural risk. It presents a consolidate approach for the identification of hotspots and the evaluation of hazard patterns that can be useful to determine relationships among natural hazards. The results of this study offer valuable insights for shaping strategies aimed at adapting to and mitigating the impacts of heatwaves, particularly concerning human health and wildfires.

Furthermore, it's important to note that global and regional climate models effectively simulate warm air masses, which means that we can confidently predict the occurrence of HWs in space and time. These valuable data can be harnessed to establish warning systems for vulnerable populations exposed to wildfire risk. Moreover, it can facilitate communication regarding risks and prevention measures, in line with the IPCC (Intergovernmental Panel On Climate Change, 2023) recommendations. This information is particularly relevant for institutions responsible for forest and fire management, enabling them to plan activities, allocate resources, and prepare for firefighting efforts during periods and in areas affected by heatwaves.

CRediT authorship contribution statement

Elia Mario: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lafortezza Raffaele:** Writing – review & editing, Supervision. **Cappelluti Onofrio:** Methodology, Formal analysis, Data curation. **Costa-Saura Josè Maria:** Writing – original draft, Methodology, Data curation. **Bacciu Valentina:** Writing – review & editing. **Giannico Vincenzo:** Writing – review & editing, Data curation. **Changliang Shao:** Writing – review & editing. **Sanesi Giovanni:** Writing – review & editing, Supervision.

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.

Data availability

Data will be made available on request.

Acknowledgements

This study was carried out within the Agritech National Research Center and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4 – D.D. 1032 17/06/2022, CN00000022). This manuscript reflects only the authors' views and opinions; neither the European Union nor the European Commission can be considered responsible for them.

This study was carried out within the PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) Missione 4 "Istruzione e Ricerca" - Componente C2 Investimento 1.1, "Fondo per il Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale (PRIN)" - FIRE-BOX – Essential tools for wildland fire risk management in Italy (P2022MXRK9). This manuscript reflects only the authors' views and opinions; neither the European Union nor the European Commission can be considered responsible for them.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.169269.

References

AghaKouchak, A., Chiang, F., Huning, L.S., Love, C.A., Mallakpour, I., Mazdiyasni, O., Moftakhari, H., Papalexiou, S.M., Ragno, E., Sadegh, M., 2020. Climate extremes and compound hazards in a warming world. Annu. Rev. Earth Planet. Sci. 48, 519–548. https://doi.org/10.1146/annurev-earth-071719-055228.

Archibald, S., Lehmann, C.E.R., Gómez-Dans, J.L., Bradstock, R.A., 2013. Defining pyromes and global syndromes of fire regimes. PNAS 110, 6442–6447. https://doi.org/10.1073/pnas.1211466110.

Artés, T., Oom, D., de Rigo, D., Durrant, T.H., Maianti, P., Libertà, G., San-Miguel-Ayanz, J., 2019. A global wildfire dataset for the analysis of fire regimes and fire behaviour. Sci. Data 6, 296. https://doi.org/10.1038/s41597-019-0312-2.

Ascoli, D., Bovio, G., 2010. Tree encroachment dynamics in heathlands of north-west Italy: the fire regime hypothesis. iForest Biogeosci. Forest. 3, 137. https://doi.org/10.3832/ifor0548-003.

Balafoutis, C.J., 2007. The Recent Heatwaves Over Balkans as an Indicator of Climate Change and a Signal for New Planning Decisions.

Barbero, R., Abatzoglou, J.T., Larkin, N.K., Kolden, C.A., Stocks, B., 2015. Climate change presents increased potential for very large fires in the contiguous United States. Int. J. Wildland Fire 24, 892–899. https://doi.org/10.1071/WF15083.

Barriopedro, D., García-Herrera, R., Ordóñez, C., Miralles, D.G., Salcedo-Sanz, S., 2023. Heat waves: physical understanding and scientific challenges. Rev. Geophys. 61, e2022RG000780 https://doi.org/10.1029/2022RG000780.

Boulanger, Y., Gauthier, S., Burton, P.J., 2014. A refinement of models projecting future Canadian fire regimes using homogeneous fire regime zones. Can. J. For. Res. 44, 365–376. https://doi.org/10.1139/cjfr-2013-0372.

Bowman, D.M.J.S., Kolden, C.A., Abatzoglou, J.T., Johnston, F.H., van der Werf, G.R., Flannigan, M., 2020. Vegetation fires in the Anthropocene. Nat. Rev. Earth Environ. 1, 500–515. https://doi.org/10.1038/s43017-020-0085-3.

Brotons, L., Aquilué, N., Cáceres, M. de, Fortin, M.-J., Fall, A., 2013. How fire history, fire suppression practices and climate change affect wildfire regimes in Mediterranean landscapes. PloS One 8, e62392. https://doi.org/10.1371/journal.pone.0062392.

Chergui, B., Fahd, S., Santos, X., Pausas, J.G., 2018. Socioeconomic factors drive fire-regime variability in the Mediterranean Basin. Ecosystems 21, 619–628. https://doi.org/10.1007/s10021-017-0172-6.

Chuvieco, E., Giglio, L., Justice, C., 2008. Global characterization of fire activity: toward defining fire regimes from Earth observation data. Glob. Chang. Biol. 14, 1488–1502. https://doi.org/10.1111/j.1365-2486.2008.01585.x.

Conedera, M., Krebs, P., Valese, E., Cocca, G., Schunk, C., Menzel, A., Vacik, H., Cane, D., Japelj, A., Muri, B., Ricotta, C., Oliveri, S., Pezzatti, G.B., 2018. Characterizing Alpine pyrogeography from fire statistics. Appl. Geogr. 98, 87–99. https://doi.org/10.1016/j.apgeog.2018.07.011.

Croitoru, A.-E., Piticar, A., Ciupertea, A.-F., Roşca, C.F., 2016. Changes in heat waves indices in Romania over the period 1961–2015. Global Planet. Change 146, 109–121. https://doi.org/10.1016/j.gloplacha.2016.08.016.

Cromartie, A., Blanchet, C., Barhoumi, C., Messager, E., Peyron, O., Ollivier, V., Sabatier, P., Etienne, D., Karakhanyan, A., Khatchadourian, L., Smith, A.T., Badalyan, R., Perello, B., Lindsay, I., Joannin, S., 2020. The vegetation, climate, and fire history of a mountain steppe: a Holocene reconstruction from the South Caucasus, Shenkani, Armenia. Quaternary Sci. Rev. 246, 106485 https://doi.org/10.1016/j.quascirev.2020.106485.

Curt, T., Fréjaville, T., Lahaye, S., Curt, T., Fréjaville, T., Lahaye, S., 2016. Modelling the spatial patterns of ignition causes and fire regime features in southern France: implications for fire prevention policy. Int. J. Wildland Fire 25, 785–796. https://doi.org/10.1071/WF15205.

Dean, A., Green, D., 2018. Climate change, air pollution and human health in Sydney, Australia: a review of the literature. Environ. Res. Lett. 13, 053003 https://doi.org/10.1088/1748-9326/aac02a.

Della-Marta, P.M., Haylock, M.R., Luterbacher, J., Wanner, H., 2007. Doubled length of western European summer heat waves since 1880. J. Geophys. Res. Atmos. 112 https://doi.org/10.1029/2007JD008510.

Di Napoli, C., Pappenberger, F., Cloke, H.L., 2019. Verification of heat stress thresholds for a health-based heat-wave definition. J. Appl. Meteorol. Clim. 58 (6), 1177–1194.

Dong, G., Guo, J., Chen, J., Sun, G., Gao, S., Hu, L., Wang, Y., 2011. Effects of spring drought on carbon sequestration, evapotranspiration and water use efficiency in the songnen meadow steppe in northeast China. Ecohydrology 4, 211–224. https://doi.org/10.1002/eco.200.

EEA, 2023. EEA Signals 2023 — health and environment in Europe — European Environment Agency [WWW Document]. URL. https://www.eea.europa.eu/publications/eea-signals-2023 (accessed 9.27.23).

Elia, M., Giannico, V., Ascoli, D., Argañaraz, J.P., D'Este, M., Spano, G., Lafortezza, R., Sanesi, G., 2022. Uncovering current pyroregions in Italy using wildfire metrics. Ecol. Process. 11, 15. https://doi.org/10.1186/s13717-022-00360-6.

Erdős, L., Török, P., Veldman, J.W., Bátori, Z., Bede-Fazekas, Á., Magnes, M., Kröel-Dulay, G., Tölgyesi, C., 2022. How climate, topography, soils, herbivores, and fire control forest–grassland coexistence in the Eurasian forest-steppe. Biol. Rev. 97, 2195–2208. https://doi.org/10.1111/brv.12889.

Erni, S., Wang, X., Taylor, S., Boulanger, Y., Swystun, T., Flannigan, M., Parisien, M.-A., 2020. Developing a two-level fire regime zonation system for Canada. Can. J. For. Res. 50, 259–273. https://doi.org/10.1139/cjfr-2019-0191.

Fasullo, J.T., Otto-Bliesner, B.L., Stevenson, S., 2018. ENSO's changing influence on temperature, precipitation, and wildfire in a warming climate. Geophys. Res. Lett. 45, 9216–9225. https://doi.org/10.1029/2018GL079022.

Fernandes, P.M., Barros, A.M.G., Pinto, A., Santos, J.A., 2016. Characteristics and controls of extremely large wildfires in the western Mediterranean Basin. J. Geophys. Res. Biogeo. 121, 2141–2157. https://doi.org/10.1002/2016JG003389.

Fink, A.H., Brücher, T., Krüger, A., Leckebusch, G.C., Pinto, J.G., Ulbrich, U., 2004. The 2003 European summer heatwaves and drought-synoptic diagnosis and impacts: European heatwave - impacts. Weather 59, 209–216. https://doi.org/10.1256/wea.73.04.

Fischer, E.M., Knutti, R., 2015. Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes. Nat. Clim. Change 5, 560–564. https://doi.org/10.1038/nclimate2617.

Fischer, E.M., Schär, C., 2010. Consistent geographical patterns of changes in high-impact European heatwaves. Nat. Geosci. 3, 398–403. https://doi.org/10.1038/ngeo866.

Fotheringham, A.S., Charlton, M.E., Brunsdon, C., 1998. Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. Environ. Plan. A 30, 1905–1927.

Fotheringham, A.S., Brunsdon, C., Charlton, M., 2003. Geographically Weighted Regression: The Analysis of Spatially Varying Relationships. John Wiley & Sons.

Galizia, L.F., Curt, T., Barbero, R., Rodrigues, M., Galizia, L.F., Curt, T., Barbero, R., Rodrigues, M., 2021. Understanding fire regimes in Europe. Int. J. Wildland Fire 31, 56–66. https://doi.org/10.1071/WF21081.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031.

Grünig, M., Seidl, R., Senf, C., 2023. Increasing aridity causes larger and more severe forest fires across Europe. Glob. Chang. Biol. 29, 1648–1659. https://doi.org/10.1111/gcb.16547.

Guerreiro, S.B., Dawson, R.J., Kilsby, C., Lewis, E., Ford, A., 2018. Future heat-waves, droughts and floods in 571 European cities. Environ. Res. Lett. 13, 034009 https://doi.org/10.1088/1748-9326/aaaad3.

Halofsky, J.S., Donato, D.C., Franklin, J.F., Halofsky, J.E., Peterson, D.L., Harvey, B.J., 2018. The nature of the beast: examining climate adaptation options in forests with stand-replacing fire regimes. Ecosphere 9, e02140. https://doi.org/10.1002/ecs2.2140.

Hanes, C.C., Wang, X., Jain, P., Parisien, M.-A., Little, J.M., Flannigan, M.D., 2019. Fire-regime changes in Canada over the last half century. Can. J. For. Res. 49, 256–269. https://doi.org/10.1139/cjfr-2018-0293.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853. https://doi.org/10.1126/science.1244693.

Hopke, J.E., 2020. Connecting extreme heat events to climate change: media coverage of heat waves and wildfires. Environ. Commun. 14, 492–508. https://doi.org/10.1080/17524032.2019.1687537.

Intergovernmental Panel On Climate Change, 2023. Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 1st ed. Cambridge University Press. https://doi.org/10.1017/9781009157896.

Jiménez-Ruano, A., Rodrigues Mimbrero, M., de la Riva Fernández, J., 2017. Exploring spatial–temporal dynamics of fire regime features in mainland Spain. Nat. Hazards Earth Syst. Sci. 17, 1697–1711. https://doi.org/10.5194/nhess-17-1697-2017.

Jiménez-Ruano, A., de la Riva Fernández, J., Rodrigues, M., 2020. Fire regime dynamics in mainland Spain. Part 2: a near-future prospective of fire activity. Sci. Total Environ. 705, 135842 https://doi.org/10.1016/j.scitotenv.2019.135842.

Koutsias, N., Martínez-Fernández, J., Allgöwer, B., 2010. Do factors causing wildfires vary in space? Evidence from geographically weighted regression. GIScience Remote Sensing 47, 221–240. https://doi.org/10.2747/1548-1603.47.2.221.

Koutsias, N., Xanthopoulos, G., Founda, D., Xystrakis, F., Nioti, F., Pleniou, M., Mallinis, G., Arianoutsou, M., Koutsias, N., Xanthopoulos, G., Founda, D., Xystrakis, F., Nioti, F., Pleniou, M., Mallinis, G., Arianoutsou, M., 2012. On the relationships between forest fires and weather conditions in Greece from long-term national observations (1894–2010). Int. J. Wildland Fire 22, 493–507. https://doi.org/10.1071/WF12003.

Leone, V., Elia, M., Lovreglio, R., Correia, F., Tedim, F., 2023. The 2017 extreme wildfires events in Portugal through the perceptions of volunteer and professional firefighters. Fire 6, 133. https://doi.org/10.3390/fire6040133.

Lhotka, O., Kyselý, J., 2022. The 2021 European heat wave in the context of past major heat waves. Earth Space Sci. 9, e2022EA002567 https://doi.org/10.1029/2022EA002567.

Loveland, T.R., Merchant, J.M., 2004. Ecoregions and ecoregionalization: geographical and ecological perspectives. Environ. Manag. 34, S1–S13. https://doi.org/10.1007/s00267-003-5181-x.

Martínez-Fernández, J., Chuvieco, E., Koutsias, N., 2013. Modelling long-term fire occurrence factors in Spain by accounting for local variations with geographically weighted regression. Nat. Hazards Earth Syst. Sci. 13, 311–327. https://doi.org/10.5194/nhess-13-311-2013.

Meehl, G.A., Tebaldi, C., 2004. More intense, more frequent, and longer lasting heat waves in the 21st century. Science 305, 994–997. https://doi.org/10.1126/science.1098704.

Mermoz, M., Kitzberger, T., Veblen, T.T., 2005. Landscape influences on occurrence and spread of wildfires in Patagonian forests and shrublands. Ecology 86, 2705–2715. https://doi.org/10.1890/04-1850.

Moreira, F., Viedma, O., Arianoutsou, M., Curt, T., Koutsias, N., Rigolot, E., Barbati, A., Corona, P., Vaz, P., Xanthopoulos, G., Mouillot, F., Bilgili, E., 2011. Landscape – wildfire interactions in southern Europe: implications for landscape management. J. Environ. Manage. 92, 2389–2402. https://doi.org/10.1016/j.jenvman.2011.06.028.

Moreira, F., Ascoli, D., Safford, H., Adams, M.A., Moreno, J.M., Pereira, J.M.C., Catry, F. X., Armesto, J., Bond, W., González, M.E., Curt, T., Koutsias, N., McCaw, L., Price, O., Pausas, J.G., Rigolot, E., Stephens, S., Tavsanoglu, C., Vallejo, V.R., Wilgen, B.W.V., Xanthopoulos, G., Fernandes, P.M., 2020. Wildfire management in Mediterranean-type regions: paradigm change needed. Environ. Res. Lett. 15, 011001 https://doi.org/10.1088/1748-9326/ab541e.

Moreno, M.V., Chuvieco, E., 2013. Characterising fire regimes in Spain from fire statistics. Int. J. Wildland Fire 22, 296–305. https://doi.org/10.1071/WF12061.

Moreno, M.V., Chuvieco, E., 2016. Fire regime characteristics along environmental gradients in Spain. Forests 7, 262. https://doi.org/10.3390/f7110262.

Morgan, P., Hardy, C.C., Swetnam, T.W., Rollins, M.G., Long, D.G., 2001. Mapping fire regimes across time and space: understanding coarse and fine-scale fire patterns. Int. J. Wildland Fire 10, 329–342. https://doi.org/10.1071/wf01032.

Nojarov, P., Nikolova, M., 2022. Heat waves and forest fires in Bulgaria. Nat. Hazards 114, 1879–1899. https://doi.org/10.1007/s11069-022-05451-3.

Nolan, R.H., Boer, M.M., Resco de Dios, V., Caccamo, G., Bradstock, R.A., 2016. Large-scale, dynamic transformations in fuel moisture drive wildfire activity across southeastern Australia. Geophys. Res. Lett. 43, 4229–4238. https://doi.org/10.1002/2016GL068614.

Nolè, A., Rita, A., Spatola, M.F., Borghetti, M., 2022. Biogeographic variability in wildfire severity and post-fire vegetation recovery across the European forests via remote sensing-derived spectral metrics. Sci. Total Environ. 823, 153807 https://doi.org/10.1016/j.scitotenv.2022.153807.

Oliveira, S., Moreira, F., Boca, R., San-Miguel-Ayanz, J., Pereira, J.M., 2013. Assessment of fire selectivity in relation to land cover and topography: a comparison between Southern European countries. Int. J. Wildland Fire 23 (5), 620–630.

Oliveira, S., Pereira, J.M.C., San-Miguel-Ayanz, J., Lourenço, L., 2014. Exploring the spatial patterns of fire density in Southern Europe using geographically weighted regression. Appl. Geogr. 51, 143–157. https://doi.org/10.1016/j.apgeog.2014.04.002.

Olson, D.M., Dinerstein, E., Wikramanayake, E.D., Burgess, N.D., Powell, G.V.N., Underwood, E.C., D'amico, J.A., Itoua, I., Strand, H.E., Morrison, J.C., Loucks, C.J., Allnutt, T.F., Ricketts, T.H., Kura, Y., Lamoreux, J.F., Wettengel, W.W., Hedao, P., Kassem, K.R., 2001. Terrestrial ecoregions of the world: a new map of life on earth. BioScience 51, 933. https://doi.org/10.1641/0006-3568(2001)051[0933:TEOTWA]2.0.CO;2.

Page, Y.L., Oom, D., Silva, J.M.N., Jönsson, P., Pereira, J.M.C., 2010. Seasonality of vegetation fires as modified by human action: observing the deviation from eco-climatic fire regimes. Glob. Ecol. Biogeogr. 19, 575–588. https://doi.org/10.1111/j.1466-8238.2010.00525.x.

Parente, J., Pereira, M.G., Amraoui, M., Fischer, E.M., 2018. Heat waves in Portugal: current regime, changes in future climate and impacts on extreme wildfires. Sci. Total Environ. 631-632, 534–549.

Parente, J., Amraoui, M., Menezes, I., Pereira, M.G., 2019. Drought in Portugal: current regime, comparison of indices and impacts on extreme wildfires. Sci. Total Environ. 685, 150–173. https://doi.org/10.1016/j.scitotenv.2019.05.298.

Pausas, J.G., 2022. Pyrogeography across the western Palaearctic: a diversity of fire regimes. Glob. Ecol. Biogeogr. 31, 1923–1932. https://doi.org/10.1111/geb.13569.

Perkins, S.E., Alexander, L.V., 2013. On the measurement of heat waves. J. Climate 26, 4500–4517. https://doi.org/10.1175/JCLI-D-12-00383.1.

Pukelsheim, F., 1994. The three sigma rule. Am. Stat. 48, 88–91. https://doi.org/10.1080/00031305.1994.10476030.

Qu, L., Chen, J., Dong, G., Jiang, S., Li, L., Guo, J., Shao, C., 2016. Heat waves reduce ecosystem carbon sink strength in a Eurasian meadow steppe. Environ. Res. Provision Ecosyst. Services Response Glob. Change 144, 39–48. https://doi.org/10.1016/j.envres.2015.09.004.

Robinson, A., Lehmann, J., Barriopedro, D., Rahmstorf, S., Coumou, D., 2021. Increasing heat and rainfall extremes now far outside the historical climate. npj Clim. Atmos. Sci. 4, 1–4. https://doi.org/10.1038/s41612-021-00202-w.

Rodrigues, M., Jiménez-Ruano, A., Peña-Angulo, D., de la Riva, J., 2018. A comprehensive spatial-temporal analysis of driving factors of human-caused wildfires in Spain using geographically weighted logistic regression. J. Environ. Manage. 225, 177–192. https://doi.org/10.1016/j.jenvman.2018.07.098.

Rodrigues, M., Costafreda-Aumedes, S., Comas, C., Vega-García, C., 2019. Spatial stratification of wildfire drivers towards enhanced definition of large-fire regime zoning and fire seasons. Sci. Total Environ. 689, 634–644. https://doi.org/10.1016/j.scitotenv.2019.06.467.

Rodrigues, M., Trigo, R.M., Vega-García, C., Cardil, A., 2020. Identifying large fire weather typologies in the Iberian Peninsula. Agric. For. Meteorol. 280, 107789 https://doi.org/10.1016/j.agrformet.2019.107789.

Rossa, C.G., 2017. The effect of fuel moisture content on the spread rate of forest fires in the absence of wind or slope. Int. J. Wildland Fire 26, 24–31. https://doi.org/10.1071/WF16049.

Ruffault, J., Martin-StPaul, N., Pimont, F., Dupuy, J.-L., 2018. How well do meteorological drought indices predict live fuel moisture content (LFMC)? An assessment for wildfire research and operations in Mediterranean ecosystems. Agric. For. Meteorol. 262, 391–401. https://doi.org/10.1016/j.agrformet.2018.07.031.

Ruffault, J., Curt, T., Moron, V., Trigo, R.M., Mouillot, F., Koutsias, N., Pimont, F., Martin-StPaul, N., Barbero, R., Dupuy, J.-L., Russo, A., Belhadj-Khedher, C., 2020. Increased likelihood of heat-induced large wildfires in the Mediterranean Basin. Sci. Rep. 10, 13790. https://doi.org/10.1038/s41598-020-70069-z.

Russo, S., Dosio, A., Graversen, R.G., Sillmann, J., Carrao, H., Dunbar, M.B., Singleton, A., Montagna, P., Barbola, P., Vogt, J.V., 2014. Magnitude of extreme heat waves in present climate and their projection in a warming world. J. Geophys. Res. Atmos. 119, 12,500–12,512. https://doi.org/10.1002/2014JD022098.

Sá, A.C.L., Pereira, J.M.C., Charlton, M.E., Mota, B., Barbosa, P.M., Stewart Fotheringham, A., 2011. The pyrogeography of sub-Saharan Africa: a study of the spatial non-stationarity of fire–environment relationships using GWR. J. Geogr. Syst. 13, 227–248. https://doi.org/10.1007/s10109-010-0123-7.

San-Miguel-Ayanz, F., et al., 2020. Forest Fires in Europe, Middle East and North Africa 2019 [WWW Document]. EU Science Hub - European Commission. URL. https://ec.europa.eu/jrc/en/publication/forest-fires-europe-middle-east-and-north-africa-2019 (accessed 4.21.21).

Schubert, S.D., Wang, H., Koster, R.D., Suarez, M.J., Groisman, P.Y., 2014. Northern Eurasian heat waves and droughts. J. Climate 27, 3169–3207. https://doi.org/10.1175/JCLI-D-13-00360.1.

Spadoni, G.L., Moris, J.V., Vacchiano, G., Elia, M., Garbarino, M., Sibona, E., Tomao, A., Barbati, A., Sallustio, L., Salvati, L., Ferrara, C., Francini, S., Bonis, E., Dalla Vecchia, I., Strollo, A., Di Leginio, M., Munafò, M., Chirici, G., Romano, R., Corona, P., Marchetti, M., Brunori, A., Motta, R., Ascoli, D., 2023. Active governance of agro-pastoral, forest and protected areas mitigates wildfire impacts in Italy. Sci. Total Environ. 890, 164281 https://doi.org/10.1016/j.scitotenv.2023.164281.

Stavi, I., 2019. Wildfires in grasslands and shrublands: a review of impacts on vegetation, soil, hydrology, and geomorphology. Water 11, 1042. https://doi.org/10.3390/w11051042.

Stevens, J.T., Collins, B.M., Miller, J.D., North, M.P., Stephens, S.L., 2017. Changing spatial patterns of stand-replacing fire in California conifer forests. For. Ecol. Manage. 406, 28–36. https://doi.org/10.1016/j.foreco.2017.08.051.

Su, Z., Zheng, L., Luo, S., Tigabu, M., Guo, F., 2021. Modeling wildfire drivers in Chinese tropical forest ecosystems using global logistic regression and geographically weighted logistic regression. Nat. Hazards 108, 1317–1345. https://doi.org/10.1007/s11069-021-04733-6.

Sutanto, S.J., Vitolo, C., Di Napoli, C., D'Andrea, M., Van Lanen, H.A.J., 2020. Heatwaves, droughts, and fires: exploring compound and cascading dry hazards at the pan-European scale. Environ. Int. 134, 105276 https://doi.org/10.1016/j.envint.2019.105276.

Syphard, A.D., Keeley, J.E., Syphard, A.D., Keeley, J.E., 2020. Mapping fire regime ecoregions in California. Int. J. Wildland Fire 29, 595–601. https://doi.org/10.1071/WF19136.

Taylor, A.H., Skinner, C.N., 2003. Spatial patterns and controls on historical fire regimes and forest structure in the Klamath Mountains. Ecol. Appl. 13, 704–719. https://doi.org/10.1890/1051-0761(2003)013[0704:SPACOH]2.0.CO;2.

Trenberth, K.E., Fasullo, J.T., 2012. Climate extremes and climate change: the Russian heat wave and other climate extremes of 2010. J. Geophys. Res. Atmos. 117 https://doi.org/10.1029/2012JD018020.

Turco, M., Abatzoglou, J.T., Herrera, S., Zhuang, Y., Jerez, S., Lucas, D.D., AghaKouchak, A., Cvijanovic, I., 2023. Anthropogenic climate change impacts exacerbate summer forest fires in California. Proc. Natl. Acad. Sci. 120, e2213815120 https://doi.org/10.1073/pnas.2213815120.

Twidwell, D., Fuhlendorf, S.D., Taylor Jr., C.A., Rogers, W.E., 2013. Refining thresholds in coupled fire–vegetation models to improve management of encroaching woody plants in grasslands. J. Appl. Ecol. 50, 603–613. https://doi.org/10.1111/1365-2664.12063.

Unal, Y.S., Tan, E., Mentes, S.S., 2013. Summer heat waves over western Turkey between 1965 and 2006. Theor. Appl. Climatol. 112, 339–350. https://doi.org/10.1007/s00704-012-0704-0.

Unkašević, M., Tošić, I., 2015. Seasonal analysis of cold and heat waves in Serbia during the period 1949–2012. Theor. Appl. Climatol. 120, 29–40. https://doi.org/10.1007/s00704-014-1154-7.

Vanderplanken, K., van den Hazel, P., Marx, M., Shams, A.Z., Guha-Sapir, D., van Loenhout, J.A.F., 2021. Governing heatwaves in Europe: comparing health policy and practices to better understand roles, responsibilities and collaboration. Health Res. Policy Syst. 19, 20. https://doi.org/10.1186/s12961-020-00645-2.

Ventura, S., Miró, J.R., Peña, J.C., Villalba, G., 2023. Analysis of synoptic weather patterns of heatwave events. Climate Dynam. https://doi.org/10.1007/s00382-023-06828-1.

Vitolo, C., Di Napoli, C., Di Giuseppe, F., Cloke, H.L., Pappenberger, F., 2019. Mapping combined wildfire and heat stress hazards to improve evidence-based decision making. Environ. Int. 127, 21–34. https://doi.org/10.1016/j.envint.2019.03.008.

Wang, Q., Ni, J., Tenhunen, J., 2005. Application of a geographically-weighted regression analysis to estimate net primary production of Chinese forest ecosystems. Glob. Ecol. Biogeogr. 14, 379–393. https://doi.org/10.1111/j.1466-822X.2005.00153.x.

Westerling, A.L., Bryant, B.P., Preisler, H.K., Holmes, T.P., Hidalgo, H.G., Das, T., Shrestha, S.R., 2011. Climate change and growth scenarios for California wildfire. Clim. Change 109, 445–463. https://doi.org/10.1007/s10584-011-0329-9.

Xiao, X., Xu, Y., Zhang, X., Wang, F., Lu, X., Cai, Z., Brasseur, G., Gao, M., 2022. Amplified upward trend of the joint occurrences of heat and ozone extremes in China over 2013–20. Bull. Am. Meteorol. Soc. 103, E1330–E1342. https://doi.org/10.1175/BAMS-D-21-0222.1.

Yuan, X., Wang, Y., Ji, P., Wu, P., Sheffield, J., Otkin, J.A., 2023. A global transition to flash droughts under climate change. Science 380, 187–191. https://doi.org/10.1126/science.abn6301.