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Open Access Earth System Science Data Discussions

A global database of extreme fire events from satellite data from 2003 to 2022

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Abstract. Extreme fires represent a significant threat due to their impacts on climate, ecosystems, and society. Despite their increasing prevalence, their definition remains controversial, as their characteristics vary depending on the region considered. In this article, we present the first version of the Extreme Fire Events (EFEs) database, a global dataset of extreme fires in NetCDF format containing monthly rasters on a regular grid with a spatial resolution of 0.25 degrees. The database includes the period 2003-2022, when a consistent satellite record was available. The basic unit of analysis is a cell-month event (CME), which represents aggregated fire activity within a grid cell during a given month. The identification of extreme events was based on two main satellite-derived variables: Burned Area (BA) from the European Space Agency's FireCCI51 dataset and Fire Radiative Power (FRP) obtained from the NASA MCD14ML active fire product. Both variables were derived from the MODIS sensor. They were aggregated to the spatial and temporal scale defined for the CMEs and were used to compute standardised anomalies within each of the 55 defined regions, in order to account for spatial and seasonal differences in fire activity in the main global biomes. A CME was classified as an EFE when it presented anomalous values in both variables according to the established regional thresholds. Further, for each EFE, the database also indicates if any fire perimeter from the FRY v2.0 dataset identified as extreme by a certain attribute (fire size, duration, mean FRP, rate of spread and severity) overlapped with the CME. The database includes 19,951 EFEs between 2003 and 2022, with the highest frequency in 2010 and 2007, and the lowest in 2013. The dataset is intended for climate and Earth System modellers aiming to understand the causes and impacts of EFEs, as well as to forecast their occurrence under future scenarios or include them in broader Earth System models.

1 Introduction

Wildfires have significant impacts on the climate, ecosystems, and society, including effects on vegetation, soil, water resources, and human health (Bell et al., 2018; Bowman et al., 2020a). Recent global trends show a decrease in total burned area (BA), mainly attributed to land-use changes and human management in savannas and grasslands (Andela et al., 2017). Paradoxically, recent studies also indicate that extreme wildfires (here understood as unusually large or intense events) are

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becoming more frequent across many regions of the world (Cunningham et al., 2024; Abatzoglou et al., 2025; Cunningham et al., 2025a). Indeed, extraordinary fire seasons have been observed across different regions of the world over the past few years. For example, in 2017, the wildfire in Pedrógão Grande, Portugal, devastated over 9,000 hectares and caused 66 fatalities, becoming the deadliest wildfire in the country's history and one of the most tragic in Europe (Pinto et al., 2022). Shortly thereafter, the 2019-2020 "Black Summer" fire season in Australia was unprecedented in both scale and intensity (Abram et al., 2021), with many areas in the South East of the country burning around eight times more than in the previous 18 years (Bowman et al., 2020b). Following this trend, in 2021, almost 8.5 million hectares of forests burned in Yakutia, Siberia, marking one of the largest wildfires in Russia and globally for that year (Desyatkin et al., 2024). Together, these events illustrate some of the impacts of extreme wildfires within the period covered by our study.

The occurrence of these extreme fire events (EFEs) and their disproportionate impacts on humans, ecosystems and the climate, have led to an increasing number of scientific publications (Bowman et al., 2017; Tedim et al., 2018; Linley et al., 2022; Cunningham et al., 2024). However, there is still no unique approach to defining or characterising extreme events. Indeed, different criteria have been proposed to characterise these events, considering parameters such as fire size (Tedim et al., 2018; Linley et al., 2022), intensity (Cunningham et al., 2024), or even the capacity to suppress the fire (Bowman et al., 2017; Tedim et al., 2018; Linley et al., 2022). For example, to simplify the characterization, some authors proposed the use of thresholds of fire size (e.g., > 10,000 ha) to consider an individual fire event, or a cluster of fires, as extreme (Linley et al., 2022, 2025; Ghasemiazma et al., 2026). However, even if the mechanisms underlying fire behaviour might be universal, the typical patterns of fire differ considerably between regions of the world due to specific ecological and climatic conditions (Archibald et al., 2013; García et al., 2022; Yin et al., 2026). Consequently, the use of unique global thresholds may not be suitable to characterize EFEs essentially because large or intense fires that may be relatively common in some regions may have disastrous impacts in others (Tedim et al., 2018; Jones et al., 2024). In addition, fires in fuel-limited regions (e.g., deserts or agricultural areas) may never reach large extents (e.g., fire sizes above 10,000 ha), even under a strong climatic influence on interannual fire variability, which limits the applicability of global fire behaviour thresholds (Bowman et al., 2017; Gincheva et al., 2024). Many of the most EFEs that occurred in the last few years have taken place in regions with high fuel availability, leading to long-lasting large-scale disturbances that can alter vegetation structure, species composition and ecosystem dynamics over long periods (Duane et al., 2021). Consequently, EFEs can contribute to amplifying climate change by releasing large amounts of greenhouse gases and particles (Peterson et al., 2021; Kelley et al., 2025) and causing large impacts on water (Adams, 2013) and air quality (Kelley et al., 2025). Therefore, even though extreme fires occur sporadically, these events can play a disproportionate role in shaping landscapes (Meyn et al., 2007; Jones et al., 2022).

In recent years, several global products on fire activity derived from satellite observations have been released (Chuvieco et al., 2020), thus facilitating the analysis of fire impacts and drivers (Jones et al., 2024; Kelley et al., 2025). However, the analysis of EFEs remains limited, due to both the lack of a standard definition of their characteristics and the absence of a dedicated database that would facilitate the analysis of different fire event typologies and drivers. This was the main objective of the XFires project (European Space Agency, 2026), funded under the cross-ECV (Essential Climate Variables) activities of the

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European Space Agency (ESA). The aim of this paper is to present the first version of this global EFEs database. The database covers the period 2003-2022 and is based on satellite-derived BA and Fire Radiative Power (FRP), aggregated to a monthly 0.25-degree grid, where the fire activity of each grid cell in each month constitutes a fire event (hereafter called cell-month events, CMEs). The period was selected to ensure the use of consistent long-term datasets and to include years with different global fire characteristics. CMEs were identified as extreme using regionally standardized anomalies of BA and FRP, and the resulting EFEs database includes information on monthly values of both variables, as well as auxiliary data derived from the analysis of fire perimeters, indicating which characteristics such as size, duration, mean FRP, rate of spread, or severity of the fire event stand out as extreme. This allows the database to retain CMEs as the main analytical unit while providing supplementary information on fire event characteristics within the associated fire perimeters. This provides a consistent framework for assessing extreme fire activity, both spatially and temporally.

2 Methods

Figure 1 presents the workflow used to construct the EFEs database for the period 2003-2022. The dataset is based on BA and FRP derived from satellite observations, aggregated monthly on a 0.25° grid, capturing complementary aspects of fire activity: BA reflects the spatial extent of fires over a CME, while the sum of FRP represents an estimate of the rate of radiative energy release and fire intensity. To account for regional variability, the world was divided into 55 regions corresponding roughly to continental biomes. Thresholds of BA and sum of FRP were then calculated independently for each region and fire variable using standardised anomalies. Finally, a CME was considered to be an EFE when both its BA and the sum of FRP values exceeded their corresponding regional thresholds. In addition to CMEs, fire perimeters were assessed for extreme characteristics using the same standardised anomaly approach. For each EFE (i.e., an extreme CME), overlapping fire patches were examined to determine whether they were extreme for any given attribute. The database records this information as a binary indicator of extremeness for size, duration, mean FRP, rate of spread, or burn severity, rather than providing the quantitative values. Fire perimeters information was extracted from the FRY v2.0 dataset (Laurent et al., 2018; Chen, 2025).

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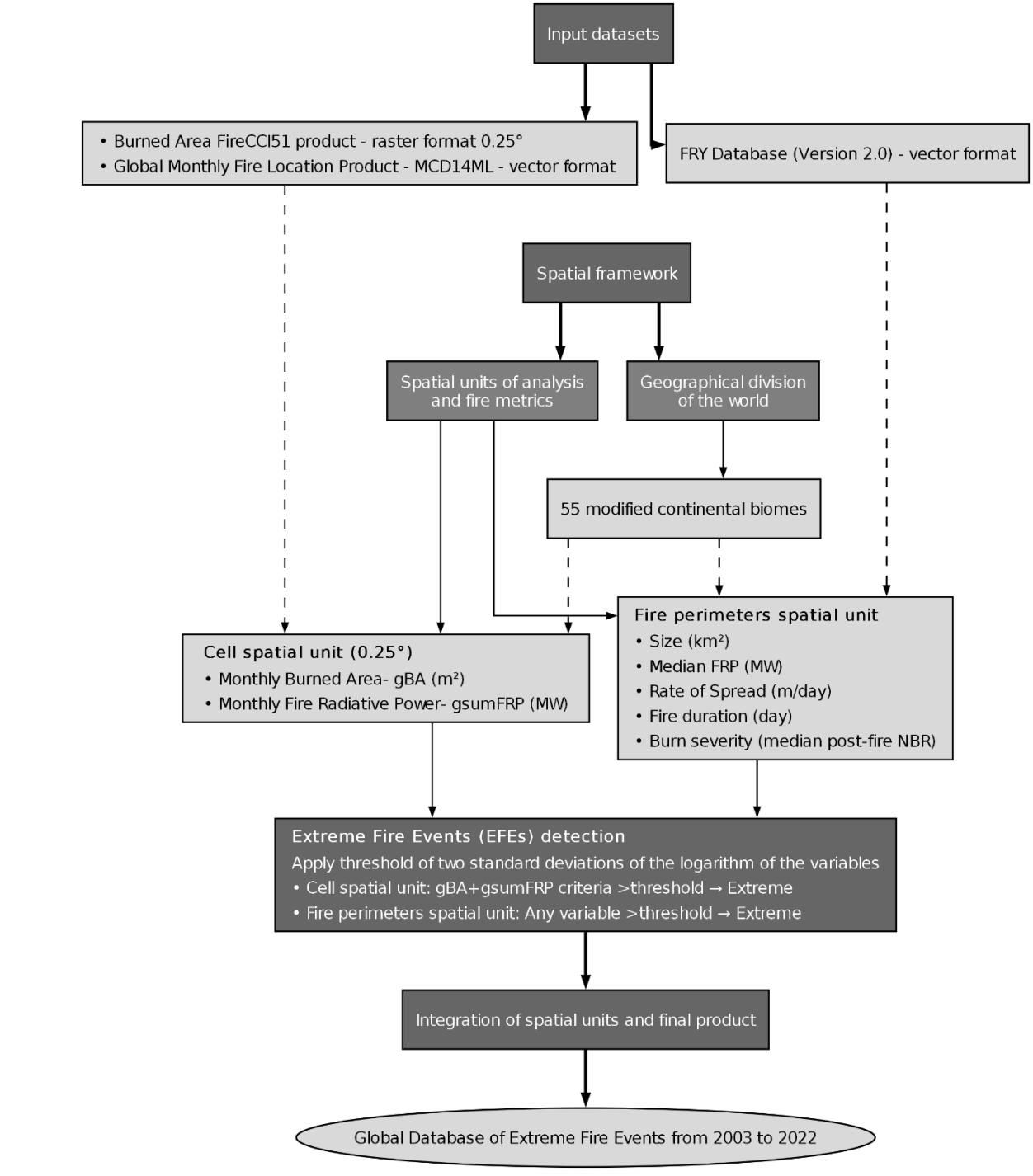

Figure 1: Workflow for constructing the database of global Extreme Fire Events (EFEs) in the period 2003 to 2022.

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2.1 Input datasets

To construct the EFEs database, we used data from three main datasets providing information on fire activity at a global scale.

2.1.1 FireCCI51 global burned area dataset

FireCCI51 (Lizundia-Loiola et al., 2020) is a global BA dataset developed under the ESA FireCCI project (European Space Agency, 2025a) provided in pixel (~250 m and daily) and grid (0.25º and monthly) format. Both pixel and grid datasets provide consistent global BA records for the period 2001-2022 using advanced detection algorithms and improved uncertainty characterisation (European Space Agency, 2025a) and are publicly available through the Centre for Environmental Data Analysis (CEDA) Archive catalogue (Chuvieco et al., 2019). FireCCI51 pixel product algorithm combines spectral information from the MODIS sensor, integrating near-infrared (NIR) reflectance bands (~250 m) with the detection of active fires (AFs) from mid-infrared and thermal channels. This approach is developed in two phases: first, it identifies pixels affected by fires through thermal anomalies, and then it expands the detection by considering the reduction in near-infrared reflectance between images taken before and after the event, allowing for a more precise delimitation of the BAs (Lizundia-Loiola et al., 2020). In this study, we used the FireCCI51 grid product, which is provided as monthly NetCDF files, representing monthly and spatially aggregated BAs of the FireCCI51 pixel product to a regular grid with a spatial resolution of 0.25°. We used BA for the period 2003-2022, corresponding to the years of stable operation of the Terra (launched in December 1999) and Aqua (launched in May 2002) satellites to ensure the continuity and temporal reliability of the series of burned areas analysed (Lizundia-Loiola et al., 2020).

2.1.2 Global Monthly Fire Location and FRP Product - MCD14ML

The MCD14ML is a satellite product based on data from MODIS sensors aboard NASA's Terra and Aqua satellites (Collection 6.1) providing detections of AFs globally (Giglio et al., 2021). The daily MOD14 (Terra) and MYD14 (Aqua) products provide these individual detections with a spatial resolution of approximately 1 km per pixel at nadir (Giglio et al., 2016). The MODIS AFs detection algorithm identifies thermal anomalies on the Earth's surface and determines which ones correspond to fires. Each MCD14ML record corresponds to an AF pixel and includes coordinates, acquisition time, thermal source type, and confidence level. The thermal source type is numerically coded: suspected vegetation fire (0), active volcano (1), other static terrestrial source (2), and maritime source (3) (Giglio et al., 2021). Further, MCD14ML also includes an estimate of the FRP of the AF, estimated in megawatts (MW), which quantifies the instantaneous thermal energy emitted by a fire at the satellite overpass, and is commonly used to estimate the intensity of the fire (Giglio et al., 2021).

2.1.3 FRY Database (Version 2.0)

As a complementary information to the CMEs, we incorporated into the EFE database burned perimeters information derived from the FRY v2.0 dataset (Laurent et al., 2018; Chen, 2025). This product provides detailed information on different

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characteristics of individual fire patches in vector format (Laurent et al., 2018). Each fire perimeter is identified by applying a 'flood-fill' clustering algorithm (Archibald and Roy, 2009) to draw fire polygons and characterise their features (Laurent et al., 2018). The algorithm considers contiguous burned pixels to be part of the same perimeter if they coincide within a temporal period below a set "cut-off" value (Laurent et al., 2018). FRY provides fire perimeters using two temporal cut-off values, 6 and 12 days (Chen, 2025). In regions such as the tropical and subtropical savannas of Africa, very large fire perimeters can result from the thresholds applied by the FRY algorithm, as multiple adjacent fires occurring within a short period may be aggregated into a single patch (Figure S1). In this study, we used fire perimeters derived from the FireCCI51 product with the 12-day cut-off, to account for the uncertainty associated with the day of detection of the fires identified by FireCCI51 (Lizundia-Loiola et al., 2020). The FRY dataset is provided in the form of annual shapefiles of fire perimeters, which includes a set of morphological attributes and fire behaviour variables describing individual fires. We considered fire size (in km²); median fire FRP (in MW); median burn severity, derived from the MODIS Burn Severity dataset (MOSEV; Alonso-González and Fernández-García (2021)); fire duration; and rate of spread (ROS), defined by the FRY dataset as fire size divided by duration. These variables capture different dimensions of fire (spatial magnitude, energy intensity, temporal dynamics, and ecological severity), which are and have been identified as key metrics for characterising fires on a global scale (Laurent et al., 2018).

2.2 Spatial units of analysis and fire metrics

The construction of the EFEs database was based on two primary variables derived from satellite observations: BA and the sum of FRP within a 0.25° grid cell and month (hereafter referred to as gBA and gsumFRP, respectively). These variables were selected because they capture complementary dimensions of fire activity. BA is a primary metric for monitoring fire extent and is extensively used in studies of large-scale fire activity (Mouillot et al., 2014), while the sum of FRP values from AFs represents an estimation of the radiative energy released by the fire and has previously been used to characterise fire intensity and extreme fire behaviour (Bowman et al., 2017; Cunningham et al., 2024).

As the EFEs database is targeted at climate and Earth System modellers, we identified extreme fire activity on a regular 0.25º grid cell to facilitate its analysis with biophysical and socio-economic variables, which are also available in grid format. The BA and FRP were aggregated in monthly periods. While the FireCCI51 BA product in grid format is directly provided with these spatial and temporal resolutions, we aggregated the FRP values from the filtered AFs from MODIS into monthly FRP sums. Therefore, we define CMEs as those grid cells with some fire activity in terms of BA or the sum of FRP in a certain month. This approach allows a certain flexibility in characterising extreme fire activity, as extreme CMEs may correspond either to a single extraordinary large and intense fire or to the anomalous accumulation of several individual fires that, together, correspond to a large extent and energy emitted (Beverly and Schroeder, 2024). Aggregating fire activity at the monthly scale offers a compromise between very short temporal resolutions (such as daily observations) which can artificially fragment prolonged fire events and overestimate fire frequency, and the need to define broader temporal windows such as fire seasons, whose duration varies considerably among regions (Archibald et al., 2013).

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Moreover, grid-based approaches at comparable spatial scales to the one used here have been widely adopted in large-scale fire studies, where fire activity is aggregated to grid cells over a certain period and considered as "fire events" (Bowman et al., 2017; Cunningham et al., 2024). Monthly grid-based resolutions are also standard in global fire, climate, and vegetation modelling frameworks, including Dynamic Global Vegetation Models (DGVMs) and Earth System Models (ESMs) that incorporate fire components (Hantson et al., 2016; Hantson et al., 2020). In addition, recent global reconstructions of fire activity designed to support modelling applications have likewise adopted grid-based datasets at monthly resolution (Guo et al., 2025; Williams et al., 2026).

Before calculating gsumFRP, we applied three quality filters to minimise errors associated with scan geometry and thermal source types (Li et al., 2018; Chen et al., 2023): we only used AF pixels with confidence level ≥ 30%, thermal type equal to 0 (vegetation fire), a positive FRP value, and scan angle ≤ 24° to reduce geolocation errors (Li et al., 2018). Next, we calculated the sum of the FRP values of the remaining AFs in each CME.

2.3 Geographic division of the world

Fire occurrence and its characteristics vary across the world in terms of size, frequency, intensity and seasonality, in patterns of activity that are commonly known as fire regimes or pyromes (Archibald et al., 2013). Consequently, the geographical division of the world used to explore fire dynamics will influence the identification of EFEs (Jones et al., 2024; Kelley et al., 2025). For example, some regions like the tropical and subtropical savannas present much higher burned areas than other regions (Andela et al., 2017), while individual fires tend to be large and long-lasting in boreal regions (Andela et al., 2019). Similarly, some areas present higher fire intensities (i.e., FRP values) than others (Cunningham et al., 2024, 2025b). Therefore, identifying EFEs by comparing fire metrics within a geographical area with similar fire characteristics can reduce the potential problems of global biases. Because we aim to create a database of CME that can be considered extreme in different areas of the world, we used a geographical reference 55 regions based on the global biomes proposed by Dinerstein et al. (2017), subdivided by continent to better capture the social, ecological, and climatic heterogeneity leading to different fire regimes. Continental biomes with an area equal to or less than 125,000 km² were merged with ecologically or geographically close regions. We also merged the Mediterranean ecosystems of Europe, Western Asia, and Northern Africa, thus creating an independent region for the Southern African Mediterranean biome. Further, we divided the African and South American savannas and deserts into their northern and southern hemisphere regions. Hereafter, we refer to these regions as modified continental biomes (MCBs, see a complete description of these regions, including their names, delimitation criteria, and location in Table S1, and their geographical distribution in Fig. 2).

All 0.25° grid cells and FRY fire perimeters were assigned to an MCB according to their geographical location. When a grid cell or fire perimeter overlapped with more than one MCB, it was assigned to the MCB with the largest area overlap. EFEs were identified on a per-MCB basis. This approach made it possible to minimise the underestimation of EFE identification in biomes that present fire regimes with typically smaller burned areas and lower intensities, and the overestimation of EFE identification in others.

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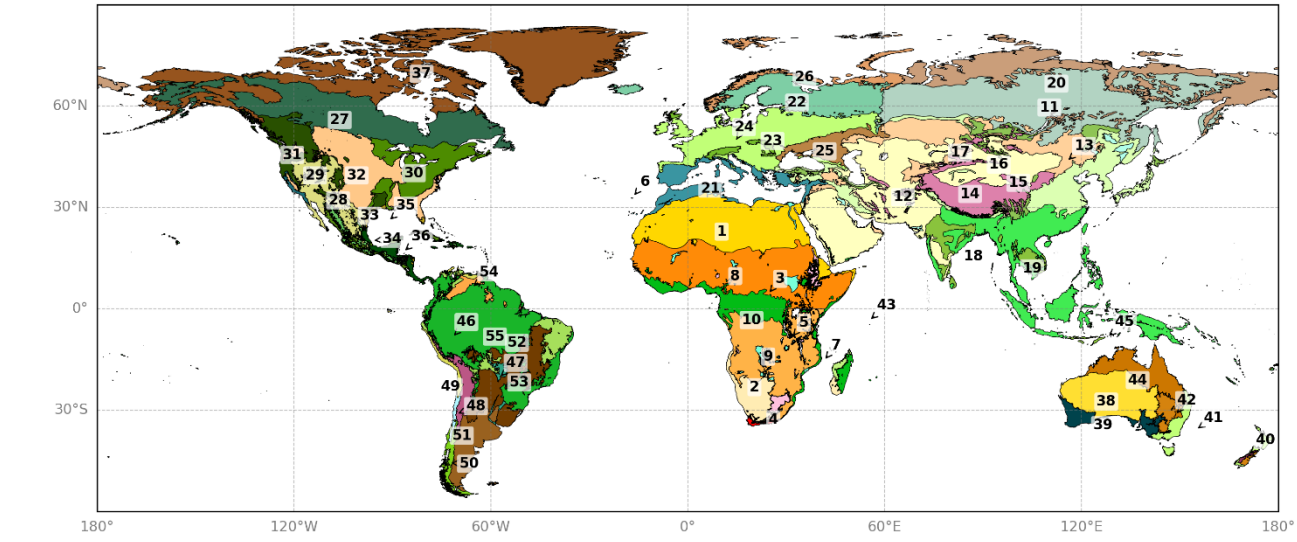

Figure 2: Delimitation of the 55 modified continental biomes (MCBs) used for the classification of extreme fire events (EFEs) at a global scale. Each polygon represents a unique combination of biome and continent, with a region identifier (ID) from 1 to 55 (see Table S1 for a complete definition). This regionalization is based on Dinerstein et al. (2017) global biomes, adapted and delimited at the continental level with some additional modifications.

2.4 Identification of EFEs

EFEs were identified by the gBA and gsumFRP values using a standardisation approach (based on standard deviations from the mean), that aimed to separate normal and extreme fire activity. This approach is commonly employed in the literature to detect climatic and ecological anomalies. This method has been applied in different contexts, adjusting the standardization to the variable of interest, for example, to detect anomalies in vegetation cover using the Normalised Difference Vegetation Index (NDVI) (Yool, 2001; Peters et al., 2002), or to gauge anomalous fire seasons in terms of BA and fire counts (number of AFs) in comparison to previous fire seasons (Jones et al., 2024; Kelley et al., 2025). It has also been applied to define extreme daily fires based on deviations from the regional average of the area burned daily (Balik et al., 2024), to assess daily fire spread rates and their relationship to fire occurrence patterns at the landscape scale (McFarland et al., 2025), and also to characterize precipitation anomalies using the Standardised Precipitation Index (SPI) with the same standardization approach (McKee et al., 1993).

In our analysis, we first applied a logarithmic transformation to each gBA and gsumFRP values to normalise the input variables, as they present a skewed distribution. Then, for each variable and MCB separately, we calculated the Z scores for each CME, which was considered extreme if both transformed variables (gBA and gsumFRP) exceeded 2 standard deviations from the regional MCB mean. In other words, EFEs were defined as events that simultaneously present large BA and high FRP values.

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This requirement of simultaneity in extreme values is referred to in this paper as the gBA+gsumFRP criterion. This approach was adopted to provide a more comprehensive definition of extreme events: while FRP reflects fire intensity, BA reflects fire extent, and both aspects are relevant to assessing anomalous fire impacts within a given biome. Previous studies (e.g., Bowman et al., 2017; Cunningham et al., 2024) typically consider only one variable, but we consider it essential to incorporate both to better capture the full scope of EFEs.

As mentioned previously, we complemented the CME analysis by evaluating fire perimeters from the FRY database to identify those with extreme characteristics. Fire perimeters presenting extreme characteristics were identified using the same standardised anomaly approach applied to CMEs evaluating each of the FRY fire variables (size, duration, median FRP, rate of spread, or severity) independently. Before calculating the anomalies, all fire perimeters variables were log-transformed to reduce skewness. While CMEs were classified as extreme based on the combined gBA+gsumFRP criterion, a the EFE database incorporated dedicated fields to indicate whether an extreme CME was also overlapping an extreme fire perimeter, using any of the five FRY variables to allow database users to select and explore which variable or combination of variables to use when studying EFEs. For doing that, each fire perimeter identified as extreme for at least one FRY variable was projected onto the grid, identifying the EFEs with which it overlapped. Next, the temporal component was considered, associating a fire perimeter with an EFE if the duration of the perimeter overlapped temporally, even partially, with the corresponding month. For example, the information of a fire perimeter identified as extreme with a duration from September 23 to November 16, 2009, would be assigned to the spatially overlapping EFEs of September, October, and November of that year.

When an EFE overlapped with one or more fire perimeters with extreme characteristics, the variables for which those perimeters were classified as extreme were recorded as binary descriptors of the corresponding EFE (1 = extreme, 0 = not extreme).

The final database therefore integrates, for each CME, its classification as an extreme fire according to the combined gBA+gsumFRP criterion, together with information derived from FRY perimeters specifying which variables were extreme within the same spatial and temporal boundaries. This structure preserves CMEs as the principal spatial unit of analysis while using fire perimeters as complementary information that provide additional context on the extreme CME.

3 Results

3.1 Structure of the EFEs database

EFEs database (Solano-Romero and Segura-Garcia, 2025) consists of a set of NetCDF files, corresponding to each month of the period 2003-2022. The files use the WGS84 geographic coordinate system and are systematically named according to the year and month of the record (i.e., *EFEs_dataset_<year><month>.nc*).

Each file contains 11 layers comprising information on extreme fires (Table 1). The main layer (*efes_id*) classifies each CME into three categories: 0, no fire activity; 1, CME identified as EFE according to the combined criterion *gBA+gsumFRP*; and 2, CME with fire activity (gBA > 0 and/or gsumFRP > 0) but not considered extreme under this criterion. In addition, seven

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additional layers are included indicating whether any of the gBA, gsumFRP or the five FRY variables were classified as extreme for each grid cell in that particular month. These layers indicate whether each grid cell presented extreme gBA or gsumFRP values (coded as 1 if extreme values, and otherwise as 0); and whether it overlaps (1, otherwise 0) with at least one extreme patch for each variable.

The files also include three additional layers, which provide basic information for each CME: *burned_area*, which indicates the total BA (gBA, in m²); *sum_frp*, which represents the sum of the filtered FRP values (gsumFRP, in MW) and *region_ID*, an integer from 0 to 55 that identifies the MCB region to which the cell belongs (Table S1).

Table 1: Description of the layers included in the extreme fire events (EFEs) database, covering the period 2003 to 2022. The main layer, efes_id, identifies whether a cell-month event (CME) had fire activity and whether it was classified as an EFE according to combined criteria of burned area (gBA) and total radiative power (gsumFRP). Layers with the prefix efes_FRY represent the different characteristics of extreme events, such as size, median FRP, rate of spread, severity, and duration, according to the extreme fire perimeters. Other layers provide information on the total burned area, total FRP, and the modified continental biomes (MCBs) region assigned to each CME.

Extreme Fire Events (EFEs) Database	
Format	NetCDF
EPSG	4326
Spatial Resolution	0.25º
Time Period	2003-2022 - Monthly.
Statistical method of analysis	Two standard deviations on the logarithm of the variables.
Layer name	**Description**
efes_id	**Main layer.** Indicates whether the CME showed any fire activity and whether it was classified as extreme based on the combined gBA and gsumFRP criteria: • **0**: no fire activity (gBA = 0 and gsumFRP = 0). • **1**: extreme event, identified because **both** variables (gBA and gsumFRP) exceeded the threshold simultaneously. • **2**: fire activity detected (gBA > 0 and/or gsumFRP > 0), but not classified as extreme because both thresholds were not met simultaneously.
efes_gBA	Binary variable. **1** if the CME was classified as extreme by gBA (derived from the FireCCI51 grid product); **0** otherwise.
efes_gsumFRP	Binary variable. **1** if the CME was classified as extreme by gsumFRP (sum of FRP from MCD14ML); **0** otherwise.
efes_FRYsize	Binary variable. **1** if any FRY fire perimeter identified as extreme by size overlaps with the CME; **0** otherwise.
efes_FRYmedfrp	Binary variable. **1** if any FRY fire perimeter identified as extreme by median FRP overlaps with the CME; **0** otherwise.
efes_FRYros	Binary variable. **1** if any FRY fire perimeter identified as extreme by Rate Of Spread (ROS) overlaps with the CME; **0** otherwise.
efes_FRYseverity	Binary variable. **1** if any FRY fire perimeter identified as extreme by burn severity overlaps with the CME; **0** otherwise.

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efes_FRYduration	Binary variable. **1** if any FRY fire perimeter identified as extreme by duration overlaps with the CME; **0** otherwise.
burned_area	Total BA (m^2) in the CME (gBA), derived from the FireCCI51 grid product.
sum_frp	Total FRP (MW) in the CME, derived from MCD14ML after filtering certain MODIS active fire detections.
region_ID	Integer from 0 to 55 indicating the modified continental biome the CME belongs to (Table S1).

Spatio-temporal analysis of EFEs

Figure 3 shows the spatial distribution of CMEs according to the presence of fire activity and their classification as EFEs based on the combined gBA and gsumFRP criterion. EFEs were detected in most biomes, with particularly high frequencies in tropical seasonally dry ecosystems, temperate and boreal forests, and semi-arid grasslands and shrublands. The EFE database identified 19,951 extreme CMEs during the analysed period (2003-2022). Of these EFEs, approximately 96% coincided spatially and temporally with at least one fire perimeter classified as extreme according to the FRY variables (fire size, duration, median FRP, ROS or severity). In addition, Figure 4 shows the distribution of events according to the combinations of FRY variables associated with the EFEs. The most frequent combination was that of extremes in fire perimeter duration and size (27.6%), followed by the combination of duration, ROS and size (20.0%), and by the combination of ROS and size (10.5%).

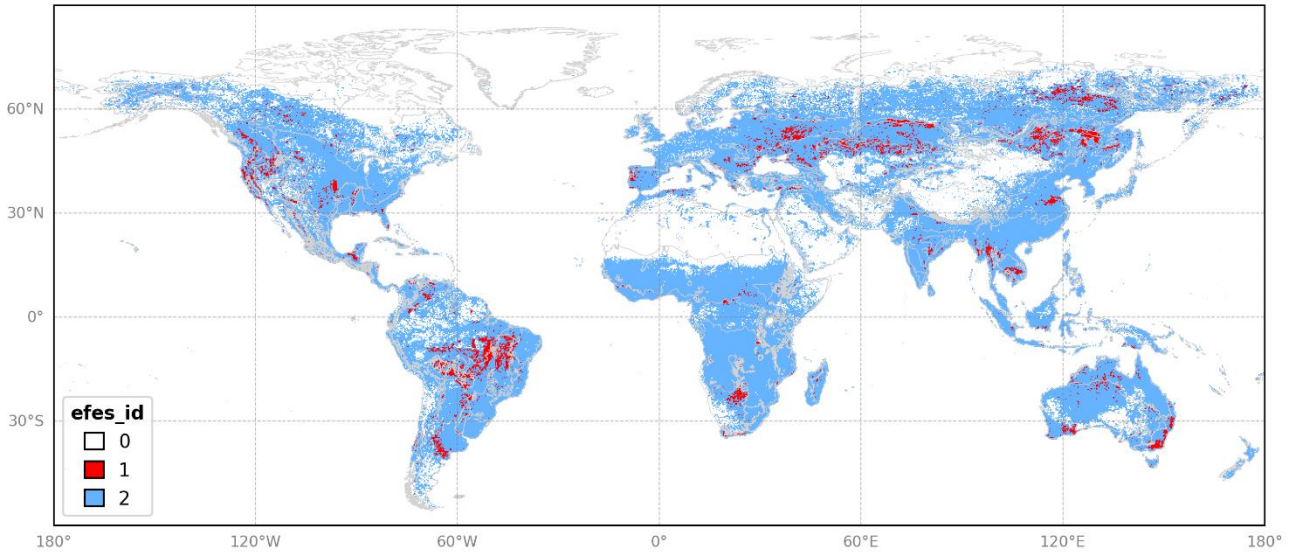

Figure 3: Visualization of the efes_id layer for the 2003-2022 time series. Category 0 represents cell-month events (CMEs) with no fire activity during the entire period (in white). Category 1 (in red) corresponds to CMEs identified as extreme fire events (EFEs) in at least one month of the series, according to the combined gBA+gsumFRP criterion. Category 2 (in blue) includes CMEs that had fire activity at least once during the period but were not classified as EFEs.

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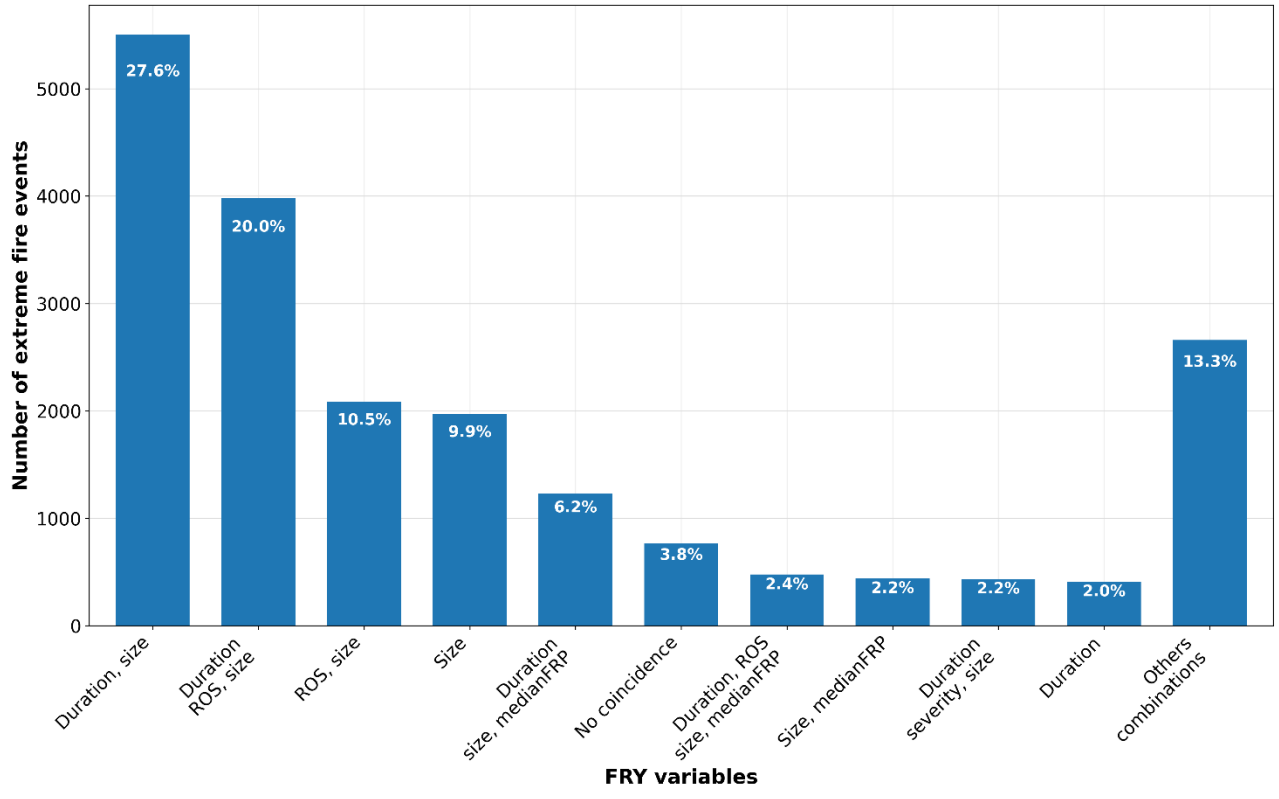

Figure 4: Combination of extreme fire events (EFEs) and FRY variables in which fire patches were also identified as extreme. The bar chart shows the 10 combinations of variables with the highest number of extreme events, plus an aggregate category called 'Other combinations' that groups all the remaining combinations. The "No coincidence" bar represents the EFEs that did not match any extreme FRY variable. The percentages within each bar represent the proportion of events relative to the total number of EFEs.

At the global scale, the EFEs identified in the database showed marked temporal variability (Fig. 5). Specifically, Figure 5a shows that interannual counts varied substantially during 2003-2022, with a mean of 997.5 events per year and no clear temporal trend. The maximum value was recorded in 2010, with 1,572 EFEs, whereas the minimum was observed in 2013, with 448 EFEs. In turn, Figure 5b reflects a well-defined seasonality in the monthly distribution of EFEs. The highest values were concentrated in August and September, which accumulated 3,898 and 4,121 events, respectively, and together accounted for around 40% of the total recorded during the analysed period. At some distance, April ranked third, with 2,120 events, followed by July (1,583) and January (1,434). At the opposite end, November and December showed the lowest cumulative numbers of EFEs, with 400 and 510 events, respectively. This pattern is consistent with the superposition of different seasonal fire regimes at the global scale. In particular, the predominance of events in late boreal summer is consistent with the high fire

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activity observed across extensive temperate and boreal regions of the Northern Hemisphere, while also coinciding with the dry season in several tropical and subtropical regions of the Southern Hemisphere, as shown by the spatial patterns described by Lizundia-Loiola et al. (2020).

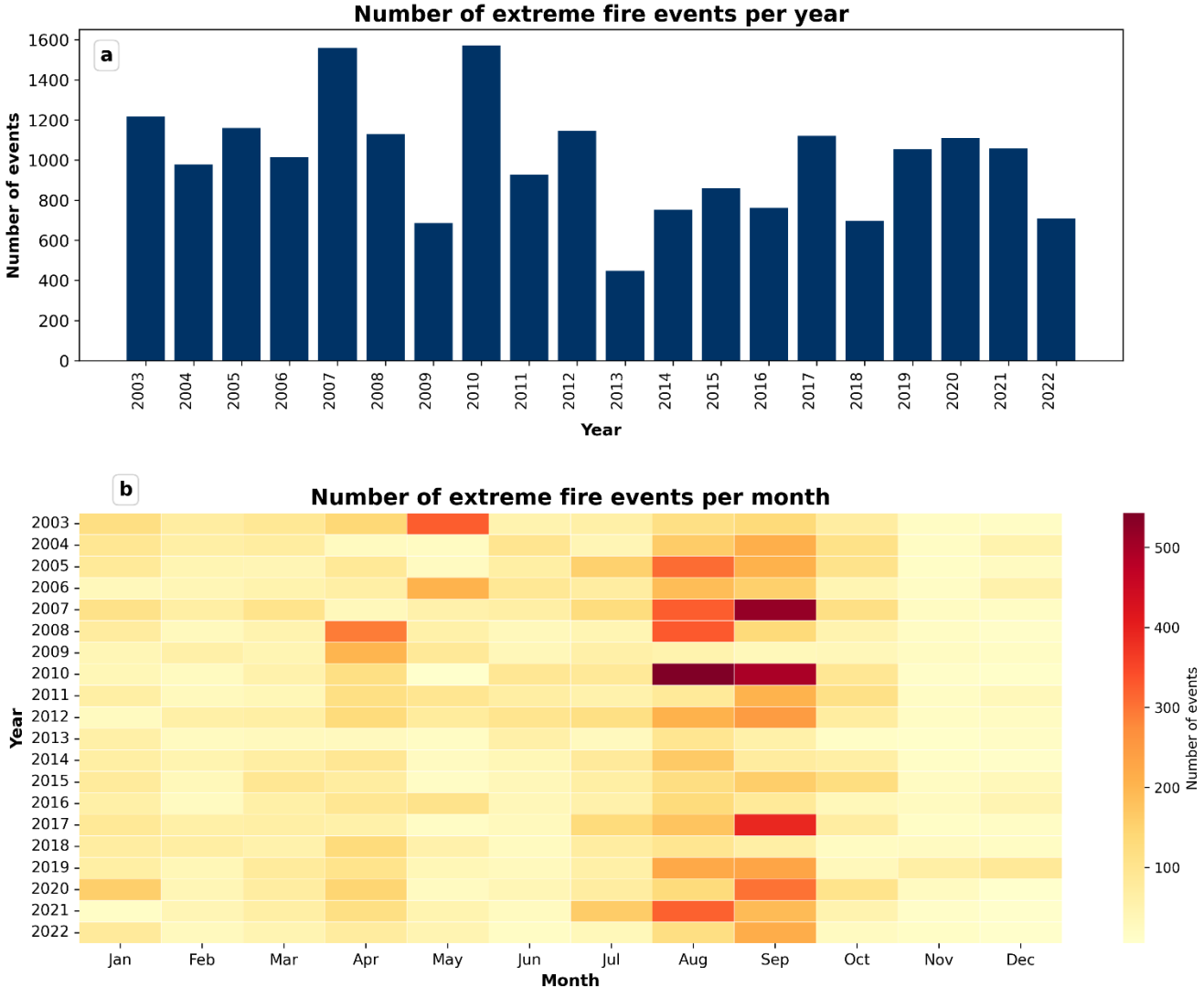

Figure 5: **Number of extreme fire events (EFEs) identified in the database. Panel (a) shows the annual total of EFEs globally. Panel (b) shows the global monthly number of EFEs.**

The distribution of EFEs across continental biomes was highly uneven (Fig. 6). Of the 55 continental biomes considered, 52 recorded at least one EFE during the study period, while only three did not present any extreme event: Africa-Flooded Grasslands & Savannas (ID 3), Africa-Temperate Broadleaf & Mixed Forests (ID 6), and Australia-Oceania-Montane Grasslands & Shrublands (ID 40). Approximately 50% of all EFEs were concentrated in just six regions. The largest

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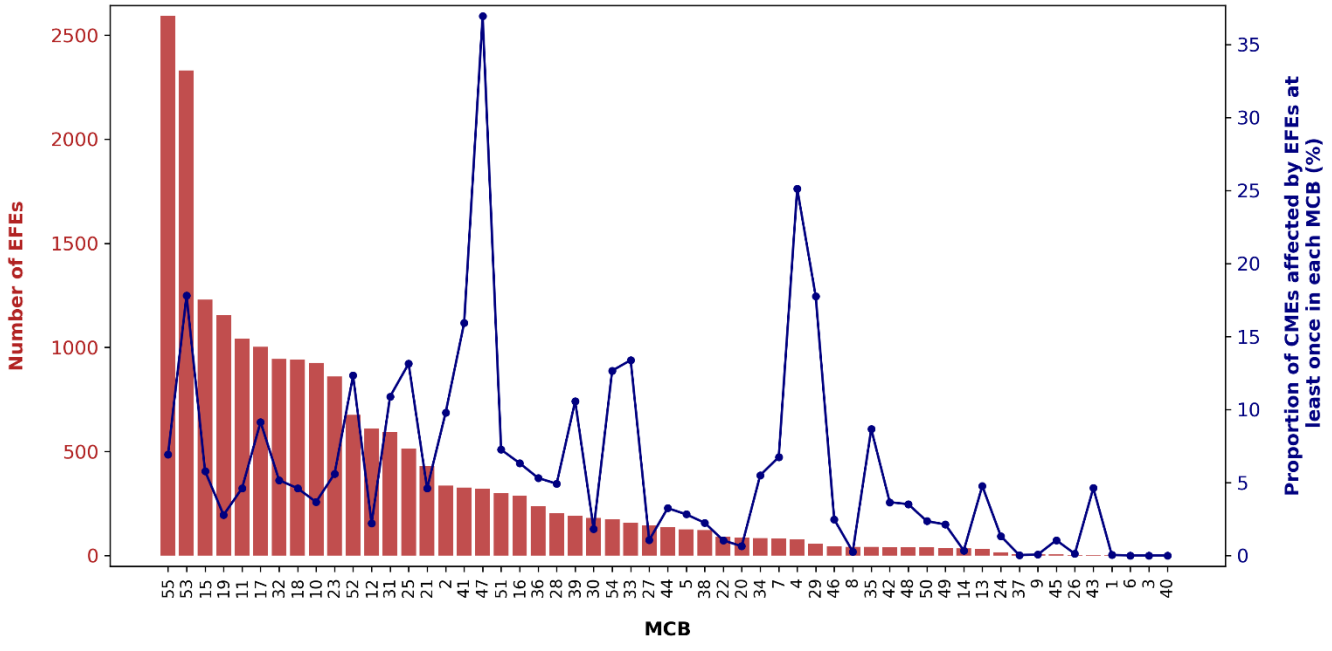
297 contributions corresponded to South America-Tropical & Subtropical Moist Broadleaf Forests (ID 55) and South America-
298 Tropical & Subtropical Grasslands, Savannas & Shrublands-Southern Hemisphere (ID 53), with 2,591 and 2,331 EFEs,
299 respectively (Fig. 6). These were followed by several Asian biomes, in particular Asia-Temperate Broadleaf & Mixed Forests
300 (ID 15), Asia-Tropical & Subtropical Moist Broadleaf Forests / Mangroves / Tropical & Subtropical Grasslands, Savannas &
301 Shrublands (ID 19), and Asia-Boreal Forests/Taiga (ID 11), together with Asia-Temperate Grasslands, Savannas & Shrublands
302 (ID 17) and North America-Temperate Grasslands, Savannas & Shrublands (ID 32). In contrast, 30 regions contributed less
303 than 10% of the total EFEs, reinforcing the idea that the occurrence of extreme events is strongly concentrated in a limited
304 number of continent-biome combinations (See Fig. S2 for a spatial interpretation of the number of EFEs by MCB). However,
305 this pattern changes when considering the proportion of CMEs that were affected by at least one EFE within each MCB. From
306 this perspective, the highest values corresponded to South America-Flooded Grasslands & Savannas (ID 47), with 37% of its
307 CMEs affected at least once, and Africa-Mediterranean Forests, Woodlands & Scrub-Southern Hemisphere (ID 4), with 25%.
308 South America-Tropical & Subtropical Grasslands, Savannas & Shrublands-Southern Hemisphere (ID 53) and North America-
309 Mediterranean Forests, Woodlands & Scrub (ID 29) also stood out, with 18% in both cases. At a second level, Australia /
310 Oceania-Temperate Broadleaf & Mixed Forests / Montane Grasslands & Shrublands (ID 41) reached 16%. This shows that
311 the absolute number of EFEs and their relative spatial extent do not always coincide.
312



313

314 **Figure 6: Number and proportion of extreme fire events (EFEs) per modified continental biomes (MCB). Bars**
315 **represent the total number of EFEs in each MCB across the entire time series, including repeated occurrences in the**

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same cells, while the line shows the proportion of cell-month events (CMEs) that have been classified as EFEs at least once in each MCB.

At the continental scale, the temporal distribution of EFEs showed marked differences among biomes and regions (Fig. 7). Each panel represents the biome and the period in which a given continent recorded the highest concentration of EFEs. The solid line identifies the continent with the greatest number of EFEs in that biome during the study period, while the dashed lines correspond to the remaining continents. In Africa, the highest concentration of EFEs was recorded in the Deserts & Xeric Shrublands biome, mainly in the Southern Hemisphere, with notable peaks in August 2010 and August 2011 (Fig. 7a). In Asia, the most prominent biome was Boreal Forests/Taiga, where a very pronounced peak was observed in August 2021, clearly exceeding those recorded in other continents sharing this biome (Fig. 7b). In Europe and Australia, the most affected biome was Temperate Broadleaf & Mixed Forests, although during different periods. In Europe, the highest EFE activity was concentrated between 2007 and 2010, with particularly intense peaks in August 2008 and a second relevant maximum in 2009 (Fig. 7c). In contrast, in Australia, peak activity in this same biome occurred between 2018 and 2021, with a very strong concentration of events between November and December 2019 and January 2020 (Fig. 7d). In North America, the highest number of EFEs was recorded in the Temperate Grasslands, Savannas & Shrublands biome, with well-defined peaks in April 2009 and April 2011 (Fig. 7e). Finally, in South America, the highest concentration of extreme events was observed in Tropical & Subtropical Grasslands, Savannas & Shrublands, particularly in the Southern Hemisphere, with very pronounced maxima in September 2007 and September 2010 (Fig. 7f).

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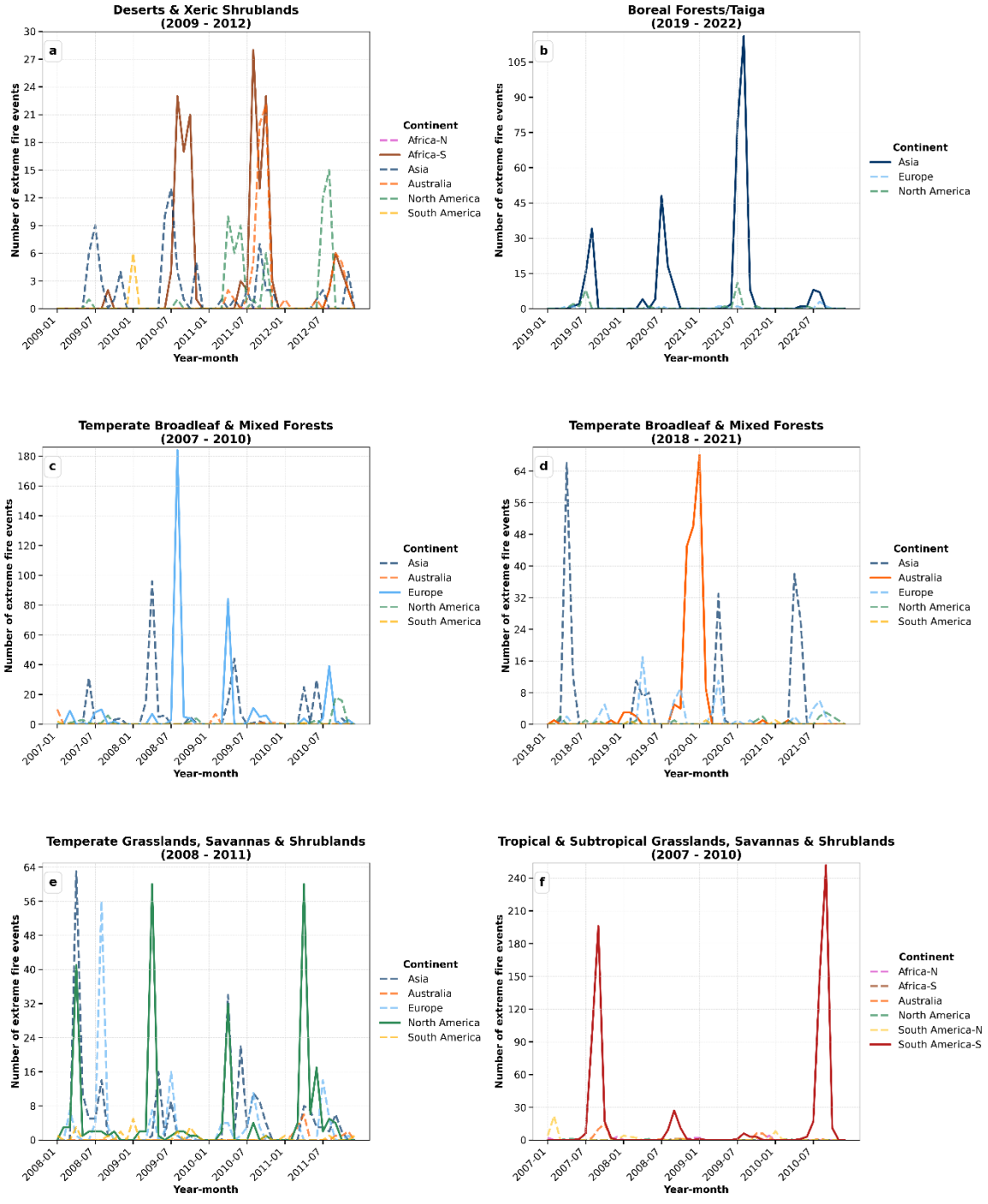

Figure 7: Biome and time interval in which a continent recorded the highest concentration of extreme fire events (EFEs). Within each panel, the lines represent the monthly evolution of the number of EFEs. The solid line indicates

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the continent that recorded the highest number of EFEs, while the dashed lines correspond to the remaining continents. The labels -N and -S indicate the subdivision of some continents into the Northern and Southern Hemispheres, respectively.

This temporal variability across continents and biomes is accompanied by a clear pattern of spatial recurrence in extreme fire activity (Fig. 8). Based on the frequency with which each grid cell was identified as extreme, distinct recurrence patterns emerge at the global scale. A limited number of cells exhibited high recurrence, with EFEs recorded in more than 15 different years over the study period. These recurrent EFEs tend to show higher annual values of gBA and gsumFRP than other non-recurrent EFEs, and other CMEs in the same MCB that were not classified as extreme according to the gBA+gsumFRP criterion (Fig. S3 and Fig. S4).

Furthermore, we found that fire activity frequency (defined as the number of months in which a CME exhibited any fire activity) is consistently among the highest in cells with recurrent EFEs, compared to all grid cells that experienced fire at any point (Fig. S5). Specifically, EFEs recorded over a period of 15 years or more tend to exhibit more frequent fire activity and, overall, higher intensity than other cells within the same MCB. Recurrent EFEs were mainly observed in landscapes with low levels of transformation, where high levels of non-extreme fire activity are also commonly recorded, as is the case, for example, in Temperate Grasslands, Savannas & Shrublands in North America. However, recurrent EFEs were also detected in highly anthropised landscapes, such as Deserts & Xeric Shrublands in some regions of Asia.

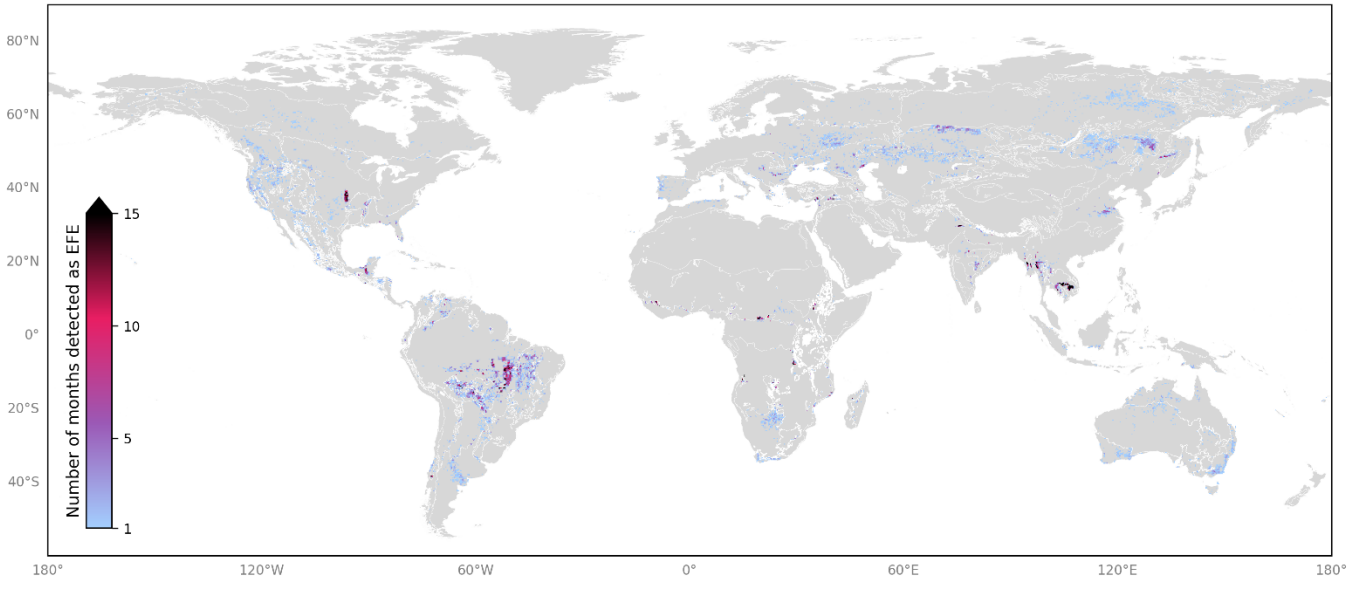

Figure 8: Monthly spatial distribution of the frequency of extreme fire events (EFEs) during the period 2003-2022. The colors represent the number of months in which at least one EFE was recorded in each cell-month events (CMEs). CMEs with no

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detected EFEs are shown in gray color. The color scale is visually limited to 15 events; however, the actual maximum frequency reaches 30. Values above 15 are represented with the maximum color intensity.

3.2 Intercomparison analysis

Given that there is no pre-existing global database of extreme fires, and a lack of consensus in the literature on the definition of 'extreme fire' to validate our product, we compared our database against a list of events that we have identified in the scientific literature. We conducted the search in Google Scholar using the following combinations of keywords: 'extreme wildfire events', 'megafires', 'large fire events', 'catastrophic wildfires', along with terms related to the climate and environmental context ('fire behaviour', 'fire season', 'climate change', 'carbon emissions' and 'satellite-derived burned area'). We also included in our search the names of affected regions, such as Australia, Amazonia, Canada, Chile, Portugal, Indonesia, Siberia and the United States, to ensure a globally representative coverage of extreme fires.

We selected twenty representative events (Table S2) that documented large-scale fires in different ecosystems, climatic and socio-economic contexts within the study period. To assess whether these events were present in our EFE database, we compared the geographic area described in each article with the records in the database. An event was considered mapped if it coincided with the reported location and with the same months in the database.

Using this procedure, the EFE database identified 18 of the 20 EFEs identified in the literature, which include some of the worst fire events on record in the last decades, such as the Black Summer in Australia (2019-2020), Amazonia (2019), Canada (2014), Chile (2017), Portugal (2003 and 2017), Indonesia (2015), Siberia (2003 and 2021) and the western United States (2018 and 2020). The two events that were not detected by our database were the Mati fire (Greece, 2018) and the Marshall fire (Colorado, 2021). The Mati fire, which occurred in July 2018, caused the deaths of 103 people and the destruction of some 4,000 homes, as well as thousands of vehicles (Bitek and Erenoğlu, 2022). The Marshall fire, in December 2021, originated in the state of Colorado (USA) and was notable for its rapid spread, driven by winds of up to 160 km/h, which caused the destruction of more than 1,000 homes and significant economic damage (Benjamin et al., 2023; Balch et al., 2024). In both cases, fires were highly destructive in terms of human and material impact, but relatively small in size, extending over approximately 1,500 ha in Mati (Bitek and Erenoğlu, 2022) and 2,400 ha in Marshall (Benjamin et al., 2023). At a spatial resolution of 0.25°, these areas represent a very small fraction of a grid cell, probably explaining why we did not identify them as extreme events according to our identification criteria.

The EFE database presented here provides an assessment of extreme events based on their size and energy release. However, the social impacts of fires are not always linked to these characteristics, but rather to where and when fires occur, particularly when happening in the vicinity of densely populated areas (Teymoor Seydi et al., 2025). The difficulty of obtaining consistent global-scale information on the social impacts of fires restricts the conceptualization and posterior identification of extreme fire events in relation to these impacts; while fire variables associated with fire activity and behaviour can be approached from satellite datasets across space and time. Still extreme socio-economic impacts from fire are of course a subject of paramount importance and need to be evaluated whenever consistent data are available.

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4 Data and code availability

EFEs database is publicly available in the Consorcio Madroño repository under the main folder *Extreme_Fire_Events_EFEs_database*, which contains the subfolder *EFEs_dataset_2003-2022* with the full database (https://edatos.consorciomadrono.es/previewurl.xhtml?token=94b577ad-c940-4042-9a4e-239102294a4e, Solano-Romero and Segura-Garcia, 2025).

The compilation of the EFEs dataset was based on three external data inputs, all of which are publicly available. The **Fire_cci Burned Area v5.1 (FireCCI51) grid product** is available at the European Space Agency Climate Change Initiative. CEDA Catalogue: https://catalogue.ceda.ac.uk/uuid/3628cb2fdba443588155e15dee8e5352/ *Period:* 2001-2022. *Last accessed:* 9 October 2025 (European Space Agency, 2025b). The global database of fire patch functional traits **FRY version 2.0 (provisional)** is available at OSF repository: https://osf.io/rjvz5/. *Last accessed:* 9 October 2025 (Chen, 2025). Finally, **MCD14ML Active Fire Product (MODIS)** was accessed through the University of Maryland SFTP server (FUOCO). *Last accessed:* 9 October 2025 (University of Maryland, 2020).

All datasets are open access and can be freely downloaded from their respective repositories.

The codes used for the development of the EFEs database (Solano-Romero and Segura-Garcia, 2025) are freely available in the Consorcio Madroño repository under the main folder *Extreme_Fire_Events_EFEs_database*, which contains the subfolder *Codes* with all scripts used for data processing and analysis, in line with the FAIR Guiding Principles (Wilkinson et al., 2016).

5 Discussion and conclusions

EFEs database presented here represents, to the best of our knowledge, the first global dataset specifically designed to characterize extreme fire activity. Developed under the ESA Climate Change Initiative (CCI) as part of the XFires project, the database contributes to the project's goal of improving the understanding of extreme fires and their environmental impacts by providing essential data for climate modelers. While previous studies have addressed extreme fires at global scales (e.g., Bowman et al., 2017; Cunningham et al., 2024), they have generally relied on a single metric, such as cell-level FRP (Cunningham et al., 2024), without explicitly accounting for the variability of fire regimes across different biomes. In this context, the EFEs database provides a novel approach by combining BA and FRP with additional descriptive variables derived from fire perimeters and by using continental biomes as the geographical reference framework for characterizing extremes. This dataset enables a more comprehensive representation of extreme fire activity and broadens its utility both for analyzing historical patterns during the reference period and for incorporation as predictive variables in Earth System Models (ESMs), Dynamic Global Vegetation Models (DGVMs), and other meteorological, emission, and global fire models.

The selection of FireCCI51 as the burned area data source was guided not only by considerations of data quality and temporal consistency, but also by the methodological framework within which this database has been developed, closely linked to the products generated under ESA's CCI projects. From this perspective, the priority was to define a robust, homogeneous, and methodologically stable reference period on which extreme events could be characterized consistently across regions and

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biomes. Global accuracy assessments indicate that FireCCI51 presents lower omission errors between 2017 and 2019 than alternative products such as MCD64A1 (Franquesa et al., 2022), with global Dice Coefficient values for these three years of 66.7% for FireCCI51 compared to 62.5% for MCD64A1, making it a more reliable source for detecting extreme events over long time series. However, because FireCCI51 is based on MODIS data and the more recent development of the FireCCI project has led to a new burned area product based on Sentinel-3, FireCCIS311 (Lizundia-Loiola et al., 2022), a consistency issue arises between the two series. In particular, FireCCI51 and FireCCIS311 do not detect exactly the same burned area, meaning that a direct extension of the EFEs database beyond 2022 could introduce artificial discontinuities in the identification and characterization of extreme events. For this reason, this study limited the database to the 2003–2022 period, defined from a single burned area source and therefore internally consistent for the comparison of extremes across regions and biomes. Future advances in the harmonization of both products may facilitate the extension of this database to more recent periods without compromising the consistency of the reference framework. In addition, we used FRY v2.0 for the EFEs database because it provides detailed descriptive metrics and, by using the version derived from the FireCCI51 burned area product, ensures consistency in temporal coverage, allowing fire perimeters-level and cell-level analyses to be comparable across the reference period.

The use of the EFE database can provide valuable insights into the typology of EFEs, thus complementing the analysis being currently conducted on BA and FRP trends (Kelley et al., 2025; Abatzoglou et al., 2025; Ghasemiazma et al., 2026). Some EFEs are identified as extreme recurrently, which reflects the high variability of fire activity within certain MCBs. These areas contain CMEs with much higher and more recurrent fire activity than others. As a result, these EFEs are almost annually classified as extreme relative to the surrounding cells, rather than necessarily indicating a particular ecological or land management pattern. This methodological characteristic should be considered when interpreting spatial patterns in the database or performing regional comparisons. The analysis of the EFE database, along with climate, vegetation and socio-economic drivers may provide new explanation models on the drivers leading these types of extreme anomalies.

Overall, the EFEs database represents a novel and useful tool for the study of EFEs at global scales. Its combination of complementary fire variables, cell-month temporal resolution, and integration with fire perimeter-level descriptors allows for detailed characterisation of extreme events while maintaining consistent global coverage. This resource will support modelers, ecosystem studies, and fire management applications by providing a standardised reference of extreme fire activity from 2003 to 2022.

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Supplement link

Supplementary material is attached

Author contributions

ESR: Conceptualization, Methodology, Software, Analysis, Data curation, Investigation, Validation, Writing - original draft, Writing - review and editing. CSG: Conceptualization, Methodology, Software, Analysis, Data curation, Investigation, Writing - review and editing. MLP: Conceptualization, Project administration, Writing - review and editing. AK: Conceptualization, Writing - review and editing. MÁTV: Conceptualization, Writing - review and editing. ECh: Supervision, Project administration, Conceptualization, Writing - review and editing, Funding acquisition.

Competing interest

The authors declare no competing interests

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References

Abatzoglou, J. T., Kolden, C. A., Cullen, A. C., Sadegh, M., Williams, E. L., Turco, M., and Jones, M. W.: Climate change has increased the odds of extreme regional forest fire years globally, Nature Communications, 16, 6390, 10.1038/s41467-025-61608-1, 2025.

https://doi.org/10.5194/essd-2026-236
Preprint. Discussion started: 11 May 2026
© Author(s) 2026. CC BY 4.0 License.

Abram, N. J., Henley, B. J., Sen Gupta, A., Lippmann, T. J., Clarke, H., Dowdy, A. J., Sharples, J. J., Nolan, R. H., Zhang, T., and Wooster, M. J.: Connections of climate change and variability to large and extreme forest fires in southeast Australia, Communications Earth & Environment, 2, 8, 10.1038/s43247-020-00065-8, 2021.

Adams, M. A.: Mega-fires, tipping points and ecosystem services: Managing forests and woodlands in an uncertain future, Forest Ecology and Management, 294, 250-261, 10.1016/j.foreco.2012.11.039, 2013.

Alonso-González, E. and Fernández-García, V.: MOSEV: a global burn severity database from MODIS (2000–2020), Earth System Science Data, 13, 1925-1938, 10.5194/essd-13-1925-2021, 2021.

Andela, N., Morton, D. C., Giglio, L., Paugam, R., Chen, Y., Hantson, S., Van Der Werf, G. R., and Randerson, J. T.: The Global Fire Atlas of individual fire size, duration, speed and direction, Earth System Science Data, 11, 529-552, 10.5194/essd-11-529-2019, 2019, 2019.

Andela, N., Morton, D. C., Giglio, L., Chen, Y., van der Werf, G. R., Kasibhatla, P. S., DeFries, R. S., Collatz, G., Hantson, S., and Kloster, S.: A human-driven decline in global burned area, Science, 356, 1356-1362, 10.1126/science.aal4108, 2017.

Archibald, S. and Roy, D.: Identifying individual fires from satellite-derived burned area data, 2009 IEEE International Geoscience and Remote Sensing Symposium, Cape Town, South Africa, III-160-III-163, 10.1109/IGARSS.2009.5417974,

Archibald, S., Lehmann, C. E., Gómez-Dans, J. L., and Bradstock, R. A.: Defining pyromes and global syndromes of fire regimes, Proceedings of the National Academy of Sciences, 110, 6442-6447, 10.1073/pnas.1211466110, 2013.

Balch, J. K., Iglesias, V., Mahood, A. L., Cook, M. C., Amaral, C., DeCastro, A., Leyk, S., McIntosh, T. L., Nagy, R. C., and St. Denis, L.: The fastest-growing and most destructive fires in the US (2001 to 2020), Science, 386, 425-431, 10.1126/science.adk5737, 2024.

Balik, J. A., Coop, J. D., Krawchuk, M. A., Naficy, C. E., Parisien, M.-A., Parks, S. A., Stevens-Rumann, C. S., and Whitman, E.: Biogeographic patterns of daily wildfire spread and extremes across North America, Frontiers in Forests and Global Change, 7, 1355361, 10.3389/ffgc.2024.1355361, 2024.

Bell, J. E., Brown, C. L., Conlon, K., Herring, S., Kunkel, K. E., Lawrimore, J., Luber, G., Schreck, C., Smith, A., and Uejio, C.: Changes in extreme events and the potential impacts on human health, Journal of the Air & Waste Management Association, 68, 265-287, 10.1080/10962247.2017.1401017, 2018.

Benjamin, S. G., James, E. P., Szoke, E. J., Schlatter, P. T., and Brown, J. M.: The 30 December 2021 Colorado Front Range windstorm and Marshall Fire: Evolution of surface and 3D structure, NWP guidance, NWS forecasts, and decision support, Weather and Forecasting, 38, 2551-2573, doi.org/10.1175/WAF-D-23-0086.1, 2023.

Beverly, J. L. and Schroeder, D.: Alberta's 2023 wildfires: context, factors, and futures, Canadian Journal of Forest Research, 55, 1-19, 10.1139/cjfr-2024-0099, 2024.

Bitek, D. and Erenoğlu, R. C.: Forest Fire Analysis with Sentinel-2 Satellite Imagery: The Case of Mati (Greece) in 2018, Academic Platform Journal of Natural Hazards and Disaster Management, 3, 85-98, 10.52114/apjhad.1211651, 2022.

Bowman, D. M., Kolden, C. A., Abatzoglou, J. T., Johnston, F. H., van der Werf, G. R., and Flannigan, M.: Vegetation fires in the Anthropocene, Nature Reviews Earth & Environment, 1, 500-515, 10.1038/s43017-020-0085-3, 2020a.

https://doi.org/10.5194/essd-2026-236
Preprint. Discussion started: 11 May 2026
© Author(s) 2026. CC BY 4.0 License.

Bowman, D. M., Williamson, G. J., Abatzoglou, J. T., Kolden, C. A., Cochrane, M. A., and Smith, A. M.: Human exposure and sensitivity to globally extreme wildfire events, Nature ecology & evolution, 1, 0058, 10.1038/s41559-016-0058, 2017.

Bowman, D. M., Williamson, G., Yebra, M., Lizundia-Loiola, J., Pettinari, M. L., Shah, S., Bradstock, R., and Chuvieco, E.: Wildfires: Australia needs national monitoring agency, Nature, 584, 188-191, 10.1038/d41586-020-02306-4, 2020b.

Chen, W.: FRY version 2.0 provisional, OSF [dataset], 2025.

Chen, Y., Hall, J., van Wees, D., Andela, N., Hantson, S., Giglio, L., van der Werf, G. R., Morton, D. C., and Randerson, J. T.: Multi-decadal trends and variability in burned area from the fifth version of the Global Fire Emissions Database (GFED5), Earth System Science Data, 15, 5227-5259, 10.5194/essd-15-5227-2023, 2023.

Chuvieco, E., Pettinari, M. L., Lizundia Loiola, J., Storm, T., and Padilla Parellada, M.: ESA Fire Climate Change Initiative (Fire_cci): MODIS Fire_cci Burned Area Grid product, version 5.1 (5.1), Centre for Environmental Data Analysis (CEDA) [dataset], 10.5285/3628cb2fdba443588155e15dee8e5352, 2019.

Chuvieco, E., Aguado, I., Salas, J., García, M., Yebra, M., and Oliva, P.: Satellite remote sensing contributions to wildland fire science and management, Current Forestry Reports, 6, 81-96, 10.1007/s40725-020-00116-5, 2020.

Cunningham, C., Williamson, G. J., Abatzoglou, J., Kolden, C., Jones, M. W., Fromm, M., Peterson, D. A., Tedim, F., Flannigan, M., and Johnston, F. H.: Pyrogeography of extraordinary wildfires, 10.31223/X5T187, 2025a.

Cunningham, C. X., Williamson, G. J., and Bowman, D. M.: Increasing frequency and intensity of the most extreme wildfires on Earth, Nature ecology & evolution, 8, 1420-1425, 10.1038/s41559-024-02452-2, 2024.

Cunningham, C. X., Williamson, G. J., and Bowman, D. M.: Reply to: Increases in the world's most extreme wildfire events probably driven by fire size and simultaneity, Nature Ecology & Evolution, 1-4, 10.1038/s41559-025-02742-3, 2025b.

Desyatkin, A., Okoneshnikova, M., Fedorov, P., Ivanova, A., Filippov, N., and Desyatkin, R.: The Impact of catastrophic forest fires of 2021 on the light soils in Central Yakutia, Land, 13, 1130, 10.3390/land13081130, 2024.

Dinerstein, E., Olson, D., Joshi, A., Vynne, C., Burgess, N. D., Wikramanayake, E., Hahn, N., Palminteri, S., Hedao, P., and Noss, R.: An ecoregion-based approach to protecting half the terrestrial realm, BioScience, 67, 534-545, 10.1093/biosci/bix014, 2017.

Duane, A., Castellnou, M., and Brotons, L.: Towards a comprehensive look at global drivers of novel extreme wildfire events, Climatic Change, 165, 43, 10.1007/s10584-021-03066-4, 2021.

Fire project — Climate Change Initiative: https://climate.esa.int/en/projects/fire/, last access: 9 October 2025.

ESA Climate Change Initiative Open Data Portal: https://catalogue.ceda.ac.uk/uuid/3628cb2fdba443588155e15dee8e5352/, last access: 9 October 2025.

XFires: https://climate.esa.int/en/Cross_ECV_Projects/xfires/, last access: 24 March 2026.

Franquesa, M., Lizundia-Loiola, J., Stehman, S. V., and Chuvieco, E.: Using long temporal reference units to assess the spatial accuracy of global satellite-derived burned area products, Remote Sensing of Environment, 269, 112823, 10.1016/j.rse.2021.112823, 2022.

https://doi.org/10.5194/essd-2026-236
Preprint. Discussion started: 11 May 2026
© Author(s) 2026. CC BY 4.0 License.

García, M., Pettinari, M. L., Chuvieco, E., Salas, J., Mouillot, F., Chen, W., and Aguado, I.: Characterizing global fire regimes from satellite-derived products, Forests, 13, 699, 10.3390/f13050699, 2022.

Ghasemiazma, F., Tonini, M., Fiorucci, P., and Turco, M.: Megafires in Mediterranean Europe: the compound role of fire weather and drought, npj Natural Hazards, 3, 33, 10.1038/s44304-026-00197-5, 2026.

Giglio, L., Schroeder, W., and Justice, C. O.: The collection 6 MODIS active fire detection algorithm and fire products, Remote sensing of environment, 178, 31-41, 10.1016/j.rse.2016.02.054, 2016.

Giglio, L., Schroeder, W., Hall, J. V., and Justice, C. O.: MODIS collection 6 and collection 6.1 active fire product user's guide, National Aeronautical and Space Administration—NASA: Washington, DC, USA, 64, 2021.

Gincheva, A., Pausas, J. G., Torres-Vázquez, M. Á., Bedia, J., Vicente-Serrano, S. M., Abatzoglou, J. T., Sánchez-Espigares, J. A., Chuvieco, E., Jerez, S., and Provenzale, A.: The interannual variability of global burned area is mostly explained by climatic drivers, Earth's Future, 12, e2023EF004334, 10.1029/2023EF004334, 2024.

Guo, Z., Li, W., Ciais, P., Sitch, S., van der Werf, G. R., Bowring, S. P., Bastos, A., Mouillot, F., He, J., and Sun, M.: Reconstructed global monthly burned area maps from 1901 to 2020, Earth System Science Data Discussions, 2025, 1-28, 10.5194/essd-17-3599-2025, 2025.

Hantson, S., Arneth, A., Harrison, S. P., Kelley, D. I., Prentice, I. C., Rabin, S. S., Archibald, S., Mouillot, F., Arnold, S. R., and Artaxo, P.: The status and challenge of global fire modelling, Biogeosciences, 13, 3359-3375, 10.5194/bg-13-3359-2016, 2016.

Hantson, S., Kelley, D. I., Arneth, A., Harrison, S. P., Archibald, S., Bachelet, D., Forrest, M., Hickler, T., Lasslop, G., and Li, F.: Quantitative assessment of fire and vegetation properties in historical simulations with fire-enabled vegetation models from the Fire Model Intercomparison Project, Geoscientific Model Development Discussions, 2020, 1-25, 10.5194/gmd-13-3299-2020, 2020.

Jones, M. W., Abatzoglou, J. T., Veraverbeke, S., Andela, N., Lasslop, G., Forkel, M., Smith, A. J., Burton, C., Betts, R. A., and van der Werf, G. R.: Global and regional trends and drivers of fire under climate change, Reviews of Geophysics, 60, e2020RG000726, 10.1029/2020RG000726, 2022.

Jones, M. W., Kelley, D. I., Burton, C. A., Di Giuseppe, F., Barbosa, M. L. F., Brambleby, E., Hartley, A. J., Lombardi, A., Mataveli, G., and McNorton, J. R.: State of wildfires 2023–2024, Earth System Science Data, 16, 3601-3685, 10.5194/essd-16-3601-2024, 2024.

Kelley, D. I., Burton, C., Di Giuseppe, F., Jones, M. W., Barbosa, M. L., Brambleby, E., McNorton, J. R., Liu, Z., Bradley, A. S., and Blackford, K.: State of Wildfires 2024–2025, Earth System Science Data, 17, 5377-5488, 10.5194/essd-17-5377-2025, 2025.

Laurent, P., Mouillot, F., Yue, C., Ciais, P., Moreno, M. V., and Nogueira, J. M.: FRY, a global database of fire patch functional traits derived from space-borne burned area products, Scientific Data, 5, 1-12, 10.1038/sdata.2018.132, 2018.

Li, F., Zhang, X., Kondragunta, S., and Csiszar, I.: Comparison of fire radiative power estimates from VIIRS and MODIS observations, Journal of Geophysical Research: Atmospheres, 123, 4545-4563, 10.1029/2017JD027823, 2018.

https://doi.org/10.5194/essd-2026-236
Preprint. Discussion started: 11 May 2026
© Author(s) 2026. CC BY 4.0 License.

Linley, G. D., Jolly, C. J., Doherty, T. S., Geary, W. L., Armenteras, D., Belcher, C. M., Bliege Bird, R., Duane, A., Fletcher, M. S., and Giorgis, M. A.: What do you mean,'megafire'?, Global Ecology and Biogeography, 31, 1906-1922, 10.1111/geb.13499, 2022.

Linley, G. D., Jolly, C. J., Doherty, T. S., Geary, W. L., Armenteras, D., Belcher, C. M., Bliege Bird, R., Duane, A., Fletcher, M. S., and Giorgis, M. A.: 'Megafire'—You May Not Like It, But You Cannot Avoid It, Global Ecology and Biogeography, 34, e70032, 10.1111/geb.70032, 2025.

Lizundia-Loiola, J., Franquesa, M., Khairoun, A., and Chuvieco, E.: Global burned area mapping from Sentinel-3 Synergy and VIIRS active fires, Remote Sensing of Environment, 282, 113298, 10.1016/j.rse.2022.113298, 2022.

Lizundia-Loiola, J., Otón, G., Ramo, R., and Chuvieco, E.: A spatio-temporal active-fire clustering approach for global burned area mapping at 250 m from MODIS data, Remote Sensing of Environment, 236, 111493, 10.1016/j.rse.2019.111493, 2020.

McFarland, J. R., Coop, J. D., Balik, J. A., Rodman, K. C., Parks, S. A., and Stevens-Rumann, C. S.: Extreme fire spread events burn more severely and homogenize postfire landscapes in the southwestern United States, Global Change Biology, 31, e70106, 10.1111/gcb.70106, 2025.

McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, Proceedings of the 8th Conference on Applied Climatology, Anaheim, California, 179-183,

Meyn, A., White, P. S., Buhk, C., and Jentsch, A.: Environmental drivers of large, infrequent wildfires: the emerging conceptual model, Progress in Physical Geography, 31, 287-312, 10.1177/0309133307079365, 2007.

Mouillot, F., Schultz, M. G., Yue, C., Cadule, P., Tansey, K., Ciais, P., and Chuvieco, E.: Ten years of global burned area products from spaceborne remote sensing—A review: Analysis of user needs and recommendations for future developments, International Journal of Applied Earth Observation and Geoinformation, 26, 64-79, 10.1016/j.jag.2013.05.014, 2014.

Peters, A. J., Walter-Shea, E. A., Ji, L., Vina, A., Hayes, M., and Svoboda, M. D.: Drought monitoring with NDVI-based standardized vegetation index, Photogrammetric engineering and remote sensing, 68, 71-75, 2002.

Peterson, D. A., Fromm, M. D., McRae, R. H., Campbell, J. R., Hyer, E. J., Taha, G., Camacho, C. P., Kablick III, G. P., Schmidt, C. C., and DeLand, M. T.: Australia's Black Summer pyrocumulonimbus super outbreak reveals potential for increasingly extreme stratospheric smoke events, NPJ climate and atmospheric science, 4, 38, 10.1038/s41612-021-00192-9, 2021.

Pinto, P., Silva, Á. P., Viegas, D. X., Almeida, M., Raposo, J., and Ribeiro, L. M.: Influence of convectively driven flows in the course of a large fire in Portugal: the case of Pedrógão Grande, Atmosphere, 13, 414, 10.3390/atmos13030414, 2022.

Solano-Romero, E. and Segura-Garcia, C.: Extreme Fire Events EFEs database (Preliminar), Consorcio Madroño [dataset], 10.21950/TK9BXK, 2025.

Tedim, F., Leone, V., Amraoui, M., Bouillon, C., Coughlan, M. R., Delogu, G. M., Fernandes, P. M., Ferreira, C., McCaffrey, S., and McGee, T. K.: Defining extreme wildfire events: Difficulties, challenges, and impacts, Fire, 1, 9, 10.3390/fire1010009, 2018.

https://doi.org/10.5194/essd-2026-236
Preprint. Discussion started: 11 May 2026
© Author(s) 2026. CC BY 4.0 License.

Teymoor Seydi, S., Abatzoglou, J. T., Jones, M. W., Kolden, C. A., Filippelli, G., Hurteau, M. D., AghaKouchak, A., Luce, C. H., Miao, C., and Sadegh, M.: Increasing global human exposure to wildland fires despite declining burned area, Science, 389, 826-829, 10.1126/science.adu6408, 2025.

University of Maryland: MCD14ML Active Fire Product (MODIS Collection 6) (Collection 6) [dataset], 2020.

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.-W., da Silva Santos, L. B., and Bourne, P. E.: The FAIR Guiding Principles for scientific data management and stewardship, Scientific data, 3, 1-9, 10.1038/sdata.2016.18, 2016.

Williams, A. P., Hansen, W. D., Juang, C. S., Abatzoglou, J. T., Radeloff, V. C., Wang, B., Hall, J., Buch, J., and Madakumbura, G. D.: The Western United States Large Forest-Fire Stochastic Simulator (WULFFSS) 1.0: a monthly gridded forest-fire model using interpretable statistics, Geoscientific Model Development, 19, 1157-1191, 10.5194/egusphere-2025-2934, 2026.

Yin, C., Abatzoglou, J. T., Jones, M. W., Cullen, A. C., Sadegh, M., Wang, J., and Liu, Y.: Increasing synchronicity of global extreme fire weather, Science Advances, 12, eadx8813, 10.1126/sciadv.adx881, 2026.

Yool, S. R.: Enhancing fire scar anomalies in AVHRR NDVI time-series data, Geocarto International, 16, 7-14, 2001.