A global view of observed changes in fire weather extremes: uncertainties and attribution to climate change

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Abstract
In many parts of the world, wildfires have become more frequent and intense in recent decades, raising concerns about the extent to which climate change contributes to the nature of extreme fire weather occurrences. However, studies seeking to attribute fire weather extremes to climate change are hitherto relatively rare and show large disparities depending on the employed methodology. Here, an empirical-statistical method is implemented as part of a global probabilistic framework to attribute recent changes in the likelihood and magnitude of extreme fire weather. The results show that the likelihood of climate-related fire risk has increased by at least a factor of four in approximately 40% of the world’s fire-prone regions as a result of rising global temperature. In addition, a set of extreme fire weather events, occurring during a recent 5-year period (2014–2018) and identified as exceptional due to the extent to which they exceed previous maxima, are, in most cases, associated with an increased likelihood resulting from rising global temperature. The study’s conclusions highlight important uncertainties and sensitivities associated with the selection of indices and metrics to represent extreme fire weather and their implications for the findings of attribution studies. Among the recommendations made for future efforts to attribute extreme fire weather events is the consideration of multiple fire weather indicators and communication of their sensitivities.

Keywords Wildfire · Fire weather · Climate change attribution · Extreme value statistics

1 Introduction

Understanding the climatological drivers of wildfires has become an increasingly important area of research with relevance for many parts of the world. In addition to the threats posed to human lives, wildfires are associated with several socioeconomic and environmental impacts (Gill et al. 2013; Tedim et al. 2018; Wang et al. 2021). The recent World Meteorological Organization (WMO) Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes outlined the significant contribution of wildfire events to disaster-incurred economic losses (World Meteorological Organization, 2021).
For instance, across North America, Central America, and Caribbean regions, only tropical storms result in a higher number of reported economic losses than wildfires (World Meteorological Organization, 2021). Notably, the 2019 wildfires in California and Alaska have incurred costs of more than $24bn (World Meteorological Organization, 2021). Environmental impacts include ecosystem degradation and both air and water pollution. Furthermore, the substantial increase in global wildfire activity predicted by the end of the twenty-first century will place enormous stress on the balance between biodiversity and the climate system (Krawchuk et al. 2009; Flannigan et al. 2009; Jolly et al. 2015). To mitigate future risks associated with wildfires, understanding the nature of, and trends in, such events have become an emerging priority, resulting in the necessity to quantify the influence of anthropogenic climate change on wildfire events (Kirchmeier-Young et al. 2017a; Abatzoglou et al. 2019; van Oldenborgh et al. 2021a).

Analysis of wildfires as extreme events tends to be approached similarly to the analysis of extreme heat and cold, drought, extreme rainfall, or other meteorological phenomena. The World Meteorological Organization Atlas, for instance, defines wildfire as ‘climatological’, alongside drought and glacial lake outburst, in its classification of disaster subgroups (World Meteorological Organization, 2021). Strictly speaking, wildfires are not meteorological events — there are other factors at play in their development and the precise link to climate is difficult to quantify (National Academies of Science, Engineering and Medicine, 2016). However, the mechanisms favouring wildfire generation are clearly influenced by climate. Periods of below-average precipitation coupled with high-temperature anomalies are obvious drivers of drought conditions which many of the largest fires are associated (e.g. van Oldenborgh et al. 2021a). Additionally, temperature, wind speed, and humidity play a crucial role in dictating fire spread (Jain et al. 2022), and rainfall has an equally important effect on fire suppression. Climate-related wildfire studies have generally focused on one of three aspects (Hardy, 2005): (i) fire activity itself, which is usually quantified by the number of fires or the extent and intensity of burned area (Campos-Ruiz et al. 2018); (ii) fire risk, which is usually understood to be the climate-related probability of ignition, a function of both hazard and vulnerability (Seneviratne et al. 2021); (iii) fire danger, which typically takes the form of a rating system combining meteorological information, to describe the severity of fires (Deeming et al. 1977; Sharples et al. 2009). However, despite this distinction, advances in the analysis of wildfire extremes in the context of climate change have been limited, partly by the absence of a common framework for best practice.

During the last decade, a growing emphasis has been placed on drawing attention to and understanding changes in the nature of extreme weather and climate events (e.g. Otto et al. 2016; National Academies of Science, Engineering and Medicine, 2016; Philip et al. 2020). There is now a wealth of literature dedicated to the attribution of individual extreme events to climate change, the majority of which have focused on extreme temperature (e.g. Kim et al. 2016) and precipitation events (e.g. Kunkel et al. 2013), in addition to episodes of drought (e.g. Funk et al. 2015; Hoerling et al. 2013), flooding (e.g. van Oldenborgh et al. 2012) and other impacts (e.g. Kirchmeier-Young et al. 2017b; Knutson et al. 2019) that pose substantial societal challenges. A number of these studies have been published during the last decade in the annual special report, ‘Explaining Extreme Events from a Climate Perspective’ from the Bulletin of the American Meteorological Society (BAMS), summarizing substantial outcomes for types of extremes (e.g. Herring et al. 2021). Additionally, the evolution of philosophical and methodological approaches in event attribution has been documented in numerous publications (National Academies of
Event attribution studies allow us to assess and quantify how the nature of individual climate risks has been altered by climate change (e.g., Trenberth et al. 2015; Otto et al. 2016; Knutson et al. 2017). By quantifying the relative contribution of one or more drivers of the observed changes, the classical event attribution approach seeks to determine to what extent the frequency and/or magnitude of extreme events has changed as a result of anthropogenic climate change or, otherwise, long-term changes in global mean temperature (Field et al. 2012). However, while attribution study of extreme heat-related and precipitation events is commonplace, analysis of wildfire or, alternatively, extreme fire weather events are comparatively rare. To date, of the 200 studies published in the BAMS ‘Explaining Extreme Events from a Climate Perspective’ special reports, only eight have been developed for wildfire events (Yoon et al. 2015; Partain et al. 2016; Tett et al. 2018; Hope et al. 2019; Brown et al. 2020; Lewis et al. 2020; Yu et al. 2021; Du et al. 2021). A comprehensive report published by the National Academies of Science, Engineering and Medicine (2016), outlined four components that complicate attribution questions for wildfires (Abatzoglou and Kolden, 2011; Lin et al. 2014; Gauthier et al. 2015): (i) the motivating role of human activities in fire ignitions and suppression, management of forests; (ii) the chaotic nature of small-scale weather systems, such as lightning in igniting large fire outbreaks; (iii) the importance of larger-scale weather in the wildfire spread and growth of fires into major events (e.g., wind and humidity for fire spread, and precipitation for extinguishing fire outbreaks); (iv) the health of the forest condition of burnable vegetation. While some components can be affected by prevailing weather and climate conditions (e.g. likelihood of thunderstorms, long-term droughts), a lack of understanding of the suitability of fire weather indicators limits detailed exploration. Shedding light on these sensitivities and progressing toward a more robust approach for wildfire attribution is, therefore, an important challenge.

Aside from the lack of application to wildfire studies, event attribution faces several broader challenges. Arguably, the most important is reaching a consensus on the way that different types of extreme events should be defined, given that the differences can result in disparate conclusions (Philip et al. 2020). Such definitions should include the goal of the event attribution, the choice of variables, the spatial and temporal extent of the event in question, the specific motivations according to the event types, and researchers or partnerships leading the studies (Philip et al. 2020). Other challenges are relevant to the difficulty in drawing comparisons between studies of similar events using different methods and event definitions (National Academies of Science, Engineering and Medicine, 2016). The application of established attribution methodologies to different event types has the potential to address some of these challenges directly and, in turn, to provide guidance that will support the continued development of robust attribution science.

Here, we assess worldwide observed trends in annual maxima in a range of fire weather indicators and quantify to what extent recent climate change has altered the nature of fire weather extremes. We use an established empirical-statistical methodology as part of a global framework designed to enable the simultaneous attribution of multiple extreme fire weather episodes. Key to this framework is the use of a standardised spatio-temporal event definition, and the quantification of uncertainties associated with the choice of various fire-weather indices. The paper is organized as follows. In Section 2, the methods and data are described. In Section 3, we present three sets of results: (i) recent trends in seasonal fire weather statistics and the relationship between different fire weather indices and burned area; (ii) empirical attribution of worldwide changes in the likelihood of extreme
fire danger indices; and (iii) empirical attribution of a collective of recent ‘exceptional’
fire weather events. In Section 4, we present our conclusions and recommendations for the
framework’s application to climate model ensembles as part of comprehensive attribution
methodologies.

2 Methods and data

2.1 Probabilistic vs. storyline approaches to event attribution

The way an attribution question is framed is an important consideration that can substan-
tially influence a study’s overall results (Philip et al. 2020). Recently, the event attribution
literature has settled on a distinction between two overarching approaches. The ‘probabil-
istic’ approach is used to estimate the probability of a class of events for a given magni-
tude occurring in the past and present climate, regardless of their meteorological cause
(Allen, 2003; Stott et al. 2004). An alternative is the so-called ‘storyline’ approach, which
places an emphasis on the meteorological roots of a given event and aims to deliver qualita-
tive analyses instead of quantitative estimations (Clark et al. 2016; Shepherd, 2016). A
major caveat of storyline-based studies is the general requirement for specialist knowledge
to interpret results, which impedes the ease with which this approach can be applied to
multiple events (Philip et al. 2020). Given our desire for a framework that can be applied
routinely to any event, or indeed multiple events, our study implements a probabilistic
approach. In making this choice, we acknowledge that the probabilistic approach is not
without fault, and its application should be evaluated accordingly.

Probabilistic application to attribution study typically involves the use of empirical-
statistical methods applied to observations and climate model outputs. Examples include
the rainfall-related extremes in America (Eden et al. 2016; van Oldenborgh et al. 2017)
and Netherlands (Eden et al. 2018), heat-related extremes in America (Mera et al. 2015)
and Australia (Hope et al. 2016), and fire-related extremes in Canada (Kirchmeier-Young
et al. 2019), Sweden (Krikken et al. 2021) and Australia (van Oldenborgh et al. 2021a).
Here, we focus on the direct application of an established statistical technique to reanal-
ysis-derived historical data to estimate how climate change has affected the likelihood or
magnitude of particular types of fire weather events (Stott et al. 2016).

2.2 Sensitivity to the representation of fire weather

The index chosen to represent fire weather is often circumstance, and location, dependent.
There remains considerable uncertainty surrounding the potential sensitivity of trends and
attribution metrics to the definition of fire weather. As discussed in the introduction, quan-
tifying the relationship between fire and climate is not trivial. The development of spe-
cific indices for ‘fire weather’, particularly the widely used approach of the Canadian Fire
Weather Index System (CFWIS) (Van Wagner, 1987), has set a benchmark for drawing
quantifiable links between climate and fire. The CFWIS uses meteorological variables, spe-
cifically temperature, relative humidity, surface wind speed, and precipitation, that collec-
tively constitute fire-prone conditions, or so-called ‘fire weather’. These variables are firstly
used to construct a set of ‘fuel moisture codes’ depending on the fuel consistency (Vitolo
et al. 2019): Fine Fuel Moisture Code (FFMC) is an indicator of the moisture content, and
therefore relative flammability and combustibility, of fine fuels, and is characterised by
their rapid response to weather changes; Duff Moisture Code (DMC) represents a numerical rating of the averaged moisture content of decomposed organic material, and is characterised by a medium-term response to weather changes; Drought Code (DC) represents the averaged moisture content of the soil at depth; and is characterised by long-term response to weather changes. Subsequently, a set of ‘fire behaviour indices’, is calculated (Vitolo et al. 2019): Initial Spread Index (ISI) represents a numerical rating of the spread potential of a fire in the early stages shortly after ignition; Buildup Index (BUI) represents a numerical rating of the total amount of fuel available for combustion and is an estimate of potential heat release in heavier fuels and a weighted combination of current DMC and DC. The final calculation is the Fire Weather Index (FWI), which represents a numerical rating of the general fire intensity and therefore a general index of fire danger (Vitolo et al. 2019).

Although initially developed for application in Canada, FWI has been used to describe fire-climate relationships in other parts of the world, such as France, Italy and Portugal (Viegas et al. 1999), New Zealand (Dudfield, 2004), southeast Australia (de Groot et al. 2006), southeast Asia (de Groot et al. 2007), and Greece (Dimitrakopoulos et al. 2011). These studies assume that FWI is an appropriate metric for fire weather, but a systematic worldwide comparison of multiple indices is lacking in the literature. While FWI has been the most widely used metric to describe fire-climate relationships (Cortez and Morais, 2007; Ager et al. 2014; Pinto et al. 2020), and as the basis of some attribution studies (Abatzoglou and Williams, 2016; Krikken et al. 2021; van Oldenborgh et al. 2021), other works have justified the use of alternative CFWIS indices. For example, in the western USA, the six ecoregions use DC, FFMC, FWI, BUI, and the Daily Severity Rating (an additional component of CFWIS; Van Wagner, 1987) to present individual fire danger risks separately (Spracklen et al. 2009). Similarly, the derived monthly DC has been employed in northern Europe, northern Asia, and Canada (de Groot et al. 2007), while the daily BUI has been utilised in Alaska (Bhatt et al. 2021). Furthermore, Jain et al. (2022) used ISI alongside FWI and vapour pressure deficit as the basis to assess global trends in extreme fire weather. Though these studies widely applied different indices, robust justifications for the choice of an index for each region are not critically developed, and a systematic worldwide comparison of multiple indices is lacking in the literature, which motivates our desire to quantify the sensitivity of different indices.

We make an initial assessment of the sensitivity of fire weather analysis to the choice of CFWIS index, firstly by comparing trends in annual mean fire weather and secondly by comparing interannual fire weather variability with area burned (Section 3.1). Historical fire weather data is derived from the Global Fire Danger Reanalysis (0.25° resolution; Vitolo et al. 2019), produced by the Copernicus Emergency Management Service for the European Forest Fire Information System, for the period 1980–2018. While the calculation of all indices closely follows the CFWIS methodology outlined by Van Wagner (1987) and Lawson and Armitage (2008), a worldwide application across different climates and fire regimes means it is necessary to note some caveats. There is some debate on whether the fuel moisture codes, particularly DC, should be reset to a start-up value ahead of the fire season or ‘overwintered’ to account for the effects of inter-seasonal drought (McElhinny et al. 2020). The calculations of ISI, BUI, and FWI in the Global Fire Danger Reanalysis are reset to zero at locations with greater than 20% snow cover, but the calculation of the FFMC, DC, and DMC is not suspended (Vitolo et al. 2019). By default, the Global Fire Danger Reanalysis thus does not implement overwintering. Instead, the start and duration of the fire season are determined by the user (Vitolo et al. 2019).

Our analysis used the following CFWIS indices: DMC, DC, ISI, BUI, and FWI. FFMC is omitted as the constrained upper limit of its range (maximum value: 101), which is
frequently reached in many parts of the subtropics, making this index unsuitable for extreme value analysis. DC has a probable maximum value of around 800 but even the most extreme drought conditions do not reach this upper limit (de Groot, 1987; National Wildfire Coordinating Group, 2022). To limit the analysis to parts of the world that are prone to fire, monthly burned area dataset is taken from the fourth version of the Global Fire Emissions Database (GFED4; Global Fire Emissions Database, 2021) for which data is available between 1996 and 2016 (0.25° resolution; van der Werf et al. 2017).

2.3 Event definition

The next step is to define the extreme fire weather event quantitatively. The event definition is crucial within the event attribution process; overall results can be dramatically influenced by the definition itself (van Oldenborgh et al. 2021b). As stated earlier, we take a class-based approach to estimate the likelihoods of the occurrence of a given event in the real world and present climate. The event class would typically be defined in spatio-temporal terms according to the meteorological anatomy of the target event. The framework used here necessitates a definition that can be applied globally. Previous efforts to attribute fire weather extremes have focused on 5-day (e.g. Lewis et al. 2020) or 7-day (e.g. Krikken et al. 2021) averages, while analysis of soil moisture as a fire risk indicator found little difference between 3-day, 5-day and 7-day anomalies preceding fire occurrences (Thomas Ambadan et al. 2020). Here, in order to best account for extreme events occurring on shorter timescales and ensure inter-index comparability, we focus on annual maxima in 5-day averages in each CFWIS index. The definition must also declare the spatial extent of the extreme event; at each target grid cell, we consider all information within a pre-defined 5 × 5 (1.25° × 1.25°) surrounding grid box. Finally, to limit our analysis to areas of the world that can be considered fire-prone on the basis of historic fire activity, we smoothed the GFED4 data with a quadrilateral curvilinear grid and masked all grid points at which burned area was recorded between 1996 and 2016.

2.4 Attributing changes in event likelihood

The generalized extreme value (GEV) distribution (Coles, 2001) fitted to block maxima has been widely applied to estimate the return period of extreme events (van Oldenborgh et al. 2015, 2021a; Eden et al. 2016, 2018; Krikken et al. 2021):

\[
F(x) = \exp \left[ -\left(1 + \xi \frac{x - \mu}{\sigma}\right)^{-1/\xi} \right]
\]

(1)

where location, scale, and shape parameters of the distribution are \(\mu\), \(\sigma\), and \(\xi\), respectively. Here, we fit the annual maxima of 5-day running means for each CFWIS index to a GEV distribution across all fire-prone parts of the world to quantify the change in likelihood and magnitude in fire weather extremes. While it may be more appropriate for regional analysis to consider maxima during a period representative of the regional fire season, we choose to focus on the calendar year (January–December) in line with a consistent approach designed for global applicability. To account for possible changes due to climate change over time, we assume the GEV fit is scaled linearly to annual global mean surface temperature (GMST), taken from the Goddard Institute for Space Studies Surface Temperature Analysis (GISTEMP Team, 2021) and smoothed with a 48-month running mean,
as a representation of global warming. This approach is consistent with similar application in previous work (van Oldenborgh et al. 2018; Otto et al. 2018; Eden et al. 2018). Observations are fitted to a non-stationary distribution under the assumption that the $\sigma/\mu$ ‘dispersion’ ratio and the shape parameter $\xi$ remain constant (Philip et al. 2020). The location and scale parameters $\mu$ and $\sigma$ are assumed to vary with an exponential dependency on GMST (van der Wiel et al. 2017): $\mu$ and $\sigma$ are assumed to vary with an exponential dependency on GMST (van der Wiel et al. 2017):

$$\mu = \mu_0 \cdot \exp \frac{\alpha T}{\mu_0}$$

$$\sigma = \sigma_0 \cdot \exp \frac{\alpha T}{\sigma_0}$$

where $\mu_0$ and $\sigma_0$ are the fit parameters of the distribution and $\alpha$ is the trend in fire indicator maxima as a function of smoothed GMST anomaly $T$. To estimate the uncertainty, a 1000-sample non-parametric bootstrapping method with a moving-block approach is applied (Efron and Tibshirani, 1998; van der Wiel et al. 2017). At each grid point, we evaluate return time, and hence the probability, of an extreme fire weather event defined by the 95th percentile occurring in the climate of 2018 ($p_1$) and that is occurring in an ‘alternative climate’ associated with a reduced anthropogenic forcing ($p_0$). Here, the year 1961 is chosen to represent an ‘alternative climate’ to capture the full extent of global warming witnessed since the 1970s (IPCC, 2021). Several previous attribution studies have used 1961 as a reference year for ‘alternative climate’ (e.g. Zhou et al. 2017; Eden et al. 2018); Kirchmeier-Young et al. (2019) used a similar period, noting that the extent of global temperature change between the 1960s and the 2010s is similar to the difference between fully and natural-forced simulations of the second-generation Canadian Earth System Model (CanESM2). Change in the likelihood of fire weather extremes is expressed using the ‘probability ratio’ (PR) $p_1/p_0$ (also known as the ‘risk ratio’). We also quantify the percentage change of a recent fire weather event and an event of equivalent likelihood occurring in a past climate (%MAG). This empirical-statistical method is applied to attribute extreme fire weather worldwide (Section 3.2) and, more specifically, to collectively attribute a set of exceptional fire weather events observed during recent years (Section 3.3; IPCC, 2021).

3 Results

3.1 Recent trends in seasonal mean fire weather and links to fire activity

To identify the potential differences between the CFWIS indices, we first seek to quantify recent trends in fire weather and its relationship with fire activity. It is important for a global analysis to consider regional variability in the timing of the period of greatest fire risk. As stated in Section 2.2, the Global Fire Danger Reanalysis encourages a user-driven definition of the start and duration of the fire season (Vitolo et al. 2019). Here, given our emphasis on extreme fire weather, and specifically on annual fire weather maxima, the fire season is defined at each grid point by the set of months that experienced the highest 5-day CFWIS average in each year between 1980 and 2018.

The tendency and significance (95% confidence level) of trends in CFWIS seasonal means from 1980 to 2018 are shown in Fig. 1a. Spatial patterns in regions of significant
positive and negative change exhibit differences between indices. For all five indices, most of the globe is associated with an increase in mean fire weather. For all indices, a significant positive trend is found at more than 25% of fire-prone grid points, and at more than 30% of grid points for ISI and FWI, including large parts of the Americas, Australia, Europe, central Asia, and central and southern Africa. Negative trends are limited to parts of sub-Saharan Africa, southern Asia, and southwestern Australia. The results indicate a certain degree of discrepancy in the recent trends detected in the five CFWIS indices. Additionally, trends are generally weaker in the high latitudes of the Northern Hemisphere, most notably in central Canada where negative trends are found, despite the occurrence of extreme wildfires in these regions in recent years (Kirchmeier-Young et al. 2017a; Witze, 2020).

Point-wise Pearson’s product-moment correlation between seasonal means in each CFWIS index and corresponding GFED4 burned area (for which data is available between 1996 and 2016) is shown in Fig. 1b. Positive correlation between seasonal CFWIS and burned area is found across North and South America, eastern Europe, equatorial Africa, southeast Asia, and southern Australia. Significant positive correlations ($p < 0.05; r > 0$) are found at between 19.8% (for DC) and 26% (for FWI) of all grid points. Interestingly, areas of relatively strong positive correlation ($r > 0.4$) between FWI and burned area are somewhat limited across northern and western Europe, where FWI has been frequently used as an indicator for fire risk (Viegas et al. 1999; Tanskanen et al. 2008; Krikken et al. 2021). Negative correlations tend to be detected over dry and/or data-scarce regions (Menne et al. 2012), including parts of Australia and sub-Saharan Africa, in addition to the isolated points in central Asia. Overall, positive correlations between fire weather conditions and burned area are witnessed in most regions of the world, while there are few inter-index differences in the relationship between each CFWIS index and fire-prone areas. In terms of choosing an index as the most appropriate fire weather indicator as part of attribution analysis, there is little to suggest that any particular index would prove more suitable than any other, at least on a global scale.

### 3.2 Empirical attribution of extreme fire weather

As previously mentioned, an empirical-statistical method is utilized to attribute the changes in likelihoods of extreme fire weather, namely, the annual maximum of 5-day running mean to each CFWIS index. Here, the GEV-scaling method is applied to the annual maxima in each CFWIS index. Global maps showing the goodness of the GEV fit by using Kolmogorov–Smirnov test, probability ratio (PR), and change in magnitude (%MAG) at each grid point are presented in Fig. 2. We also present global maps showing the quality of the GEV fit following the Kolmogorov–Smirnov goodness of fit test. The assumption that the distribution of annual maxima can be approximated well by the GEV can be made throughout most of the world’s fire-prone regions; for FWI for instance, the Kolmogorov–Smirnov test statistic falls within the critical value of 95% significance at 70% of fire-prone grid points.
There are some exceptions, including parts of Mediterranean Europe, and we recommend exercising a degree of caution in the interpretation of the attribution results in such regions.

Overall, there are several similarities in spatial patterns of both PR and %MAG across the five CFWIS indices (Fig. 2). A fourfold increase in likelihood (PR > 4) in response to globally warming temperature is found in approximately 40% of the world’s fire-prone grid points. This corresponds to an increase in the magnitude of around 20%, ranging from 15.5% in DC to 25.5% in DMC. Regions with increasing likelihoods in %MAG are mainly similar to that in PR. Such increases in the likelihood of extreme fire danger are particularly strong in temperate North America, Europe, Africa, Boreal, and Central Asia. On the contrary, extreme fire weather appears to be less likely across all CFWIS indices in South Asia, Southeast Asia, Northern Hemisphere South America, Western West Africa,
and Southern and Eastern Africa, as suggested by a decrease in the likelihood in response to globally warming temperature (PR < 1). The proportion of regions showing a significant decrease in likelihoods is relatively lower by employing the %MAG metric than the PR.

Across the CFWIS indices, spatial patterns are generally similar, but certain regions show contrasting results. For instance, by choosing either BUI or FWI as the reference index for western Australia, we may find either a positive trend or no significant change in likelihoods (Fig. 2). Similarly, in eastern Africa, significant increases in likelihood (PR > 1) of ISI and FWI extremes are found, while for DC and BUI extremes, significant decreases are found (PR < 1) in DC and BUI extremes are found. Moreover, the largest discrepancies in both PR and %MAG between CFWIS indices are found in regions with large inter-index differences in recent trends (Fig. 1a), and that are also poorly correlated with the fire-prone area (i.e., eastern parts of South America for FWI, East Asia and Western Australia; Fig. 1b). As these regions are also data-scarce (Menne et al. 2012), the observed differences could be due to the low reliability of the reanalysis product there (Burton et al. 2018; Liu et al. 2018; Acharya et al. 2019; Gleixner et al. 2020). Alternatively, this could also highlight that, in hot and humid tropical regions, relative humidity and precipitation are more important than temperature in driving changes in fire weather indices.

To summarise the results of our empirical-statistical attribution analysis on the regional scale, PR results are amalgamated across the 14 GFED Basis Regions (identified according to annual emission estimates; van der Werf et al. 2017). Figure 3 shows the proportion of grid points that exhibit significant increases and decreases in likelihood in the five CFWIS

![Diagram of regional summaries of PR results across the 14 GFED fire regions. Pie charts for each CFWIS index show the proportion of fire-prone grid points associated with positive (red; PR > 1), negative (blue; PR < 1), and no change (grey) at the 95% confidence level.]

Fig. 3 Regional summaries of PR results across the 14 GFED fire regions. Pie charts for each CFWIS index show the proportion of fire-prone grid points associated with positive (red; PR > 1), negative (blue; PR < 1), and no change (grey) at the 95% confidence level.
indices in each of the 14 fire regions. Notably, for four of the fire regions (TENA, SHSA, NHAF, and CEAS), an increase in the likelihood of extremes in all indices is found in more than 50% of grid points; for a fifth region (BOAS), the same results are found for each index except for DC. Similarly, for CEAM, EURO, and SHAF, increasing likelihoods are dominant in general, while BONA and MIDE predominantly show non-significant changes in likelihoods. Conversely, the NHSA and EQAS region exhibit decreasing likelihoods in extremes of all indices in up to approximately 50% of grid points. Meanwhile, only the SEAS region shows a homogeneous and consistent decrease in likelihood at more than 50% of the grid points, with the highest proportions evident for DMC and BUI. Efforts to attribute extreme heat in this region have been inconclusive; van Oldenborgh et al. (2018) were unable to detect trends in the highest maximum temperatures in India since the 1970s, noting the counteracting effect on global warming of (i) increased irrigation and resultant evaporative cooling and (ii) the blocking of sunlight by aerosols as a result of increased air pollution. Though most fire regions present similar proportions of grid points with significant increase and decrease among all CFWIS indices, that in AUST present inter-index differences in PR. In AUST, among the five indices, DC, DMC, and BUI present increasing likelihoods over 70%; ISI and FWI display the increasing likelihoods around 50% with decreasing likelihoods around 20%.

In summary, fire weather events have become more likely and greater in magnitude in most regions of the world. In some regions, particularly within the tropics and the high latitudes of the northern hemisphere, there is evidence that the likelihood of extremes has decreased as global temperatures have risen. In addition, we note that sensitivities in the choice of indices are particularly strong in Australia, while they are relatively small in other regions of wildfire prominence, such as North and Central America and much of Asia.

### 3.3 Attribution of recent exceptional fire weather events

As highlighted in Section 1, the last decade has witnessed a sharp increase in efforts to attribute individual events. Studies related to wildfire or, alternatively, extreme fire weather are relatively rare. Here, we extend the application of our approach to a set of recent extreme fire weather episodes in the observational record that would have been considered as ‘exceptional’ and, in principle, would have been an appropriate focus of an event attribution study. We demonstrate that classifying extreme weather events according to the same strict event definition allows for collective conclusions to be drawn from the attribution of multiple events.

Our analysis defines events as ‘exceptional’ where the index value of an annual maximum, occurring between 2014 and 2018, exceeds the previous maxima (recorded since 1980) by more than 20%. The geographical distribution, comparative magnitude, and PR tendency (at the 95% confidence level) of those exceptional events are shown in Fig. 4. Exceptional fire weather events occurred prevalently in multiple locations around the world between 2014 and 2018. Four of the five CFWIS indices show that more than 50% of events were associated with a significant increase in likelihoods; the exception is DC, which is the only index that is, in principle, constrained by a maximum probable value (de Groot, 1987) with an upper limit. DMC and BUI were associated with the largest number of exceptional events, which were mostly associated with positive changes in PR. On the contrary, DC, ISI and FWI show relatively fewer exceptional events, but those are still strongly related to an increase in likelihood. Specifically, the largest exceptional fire weather events (i.e. those exceeding the previous maxima by 50%) are detected in coastal North America, central
and southeast South America, central and southern Africa, and boreal Asia, in addition to parts of Europe and Australia. Almost all of these occurrences are linked to a significant increase in likelihood (PR > 1). Nevertheless, some exceptional events are associated with a decrease in likelihood (PR < 1), particularly extremes in DMC in the Pacific Northwest of North America and central Europe, extremes in DMC and BUI in northern parts of South America, and extremes in BMC, DC, and BUI in equatorial Asia.

The fact that different indices present disparate distributions of exceptional events highlights the sensitivity of a fire weather event study to the index used to define the event in question. There are several instances in which such sensitivity is strongly evident. In Alaska, several ISI and FWI events are observed that exceed the magnitude of the previous maxima by more than 50% and are associated with a significant increase in likelihood. However, exceptional events in other indices are either not evident or, in the case of DMC extremes, associated with a significant decrease in likelihood. In South America, there is a large number of exceptional DMC and BUI events spanning the entire continent, but relatively few exceptional DC, FWI and ISI events are found outside of the northern region. In central Africa, extreme ISI events of lesser exceptionality

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**Fig. 4** Global distribution of recent fire weather events (2014–2018), defined by each CFWIS index, for which the magnitude exceeds any previous annual maxima by more than 20%. Point size is representative of the exceptionality of each event. Point colour is representative of the corresponding PR: events associated with a significant increase (PR > 1) and decrease (PR < 1) in likelihood are shown in red and blue respectively; events associated with no significant change are shown in grey. Numbers in the bottom-left corner of each panel shows the percentage of events associated with a significant increase in likelihoods.
(no more than 30% greater than the previous maxima) compared to other indices, but in all cases, those events are associated with increasing PR. Europe is associated with particularly exceptional events, but those events are linked with negative PR in the Scandinavian region and positive PR over the rest of Europe. In Northern and East Asia, there are numerous exceptional DMC and BUI events (> 50%), but far fewer for other indices.

The use of a consistent spatiotemporal event definition presents the possibility to attribute multiple events collectively, which we do by averaging the PR of all exceptional fire weather events across the 14 GFED fire regions. Figure 5 summarises the PR averaged across each region for each CFWIS index. Exceptional fire weather events recorded in six regions (BOAS, TENA, CEAS, SHAF, NHAf, and AUST) exhibit the largest collective increase in likelihood (average PR > 8) irrespective of the index used to define them. For TENA and NHAf specifically, the increase in likelihood is exhibited for more than 95% of events used to construct the averages. By contrast, there are examples where the average PR differs substantially between indices. The recent exceptional BUI, ISI, and FWI events occurring in SEAS collectively exhibit an averaged decrease in likelihood (PR < 0.5), whereas an increase is found for DMC and DC events. There are also some notable inter-index differences among the exceptional events occurring in

![Fig. 5 Regional summaries of exceptional event attribution across the 14 GFED fire regions. Bar charts for each CFWIS index show PR averaged across all the exceptional fire weather events identified for each CFWIS index. The size of each bar represents the number of exceptional events; the colours of each bar represent average PR; bars shown in bold and with an asterisk indicate where over 95% of exceptional events agree on either an increase (PR > 1) or decrease (PR < 1) in likelihood.](image-url)
4 Discussion and conclusions

This study has identified trends in fire weather extremes and quantified to what extent climate change has altered their likelihood and magnitude. Following a probabilistic approach, an established empirical-statistical method was used to construct a globally applicable framework to attribute worldwide extreme fire weather events. The results provide clarification on uncertainties and sensitivities associated with the choice of an index for fire weather representation, particularly in the context of extreme event attribution.

The first part of the analysis of fire weather trends and correlation analysis presents preliminary knowledge about the performance of fire weather indicators in the form of the CFWIS indices across the world’s fire-prone regions. A positive trend was found in the seasonal mean of each index in most fire-prone regions of the world, and broadly in line with the present understanding of global fire weather and its relationship with climate change (Jain et al. 2022). Reflecting on correlation with the occurrence of fire activity (in the form of burned area data), while inter-index differences are modest, there are several examples of substantial differences at the regional scale. Notably, we found that FWI is not systematically the closest match to fire activity, suggesting that other indices could potentially be more appropriate proxies for fire risk in specific regions.

The probability of extreme climate-related wildfire risk has increased substantially as a response to globally warming temperatures in large parts of the world. This is, however, not the case in some regions, such as Southeast Asia. While our results are based on a relatively short record (39 years from 1980 to 2018), it is possible to conclude that the greater maximum daily temperature may not be the major driver of fires in these areas, which means other factors (i.e. precipitation, humidity and surface wind) should play an important role in attribution methodologies. Since climate change effects at the regional scale are associated not only with warming temperatures but also with changes to precipitation and atmospheric moisture content, this does not imply that such extreme fire weather events are unrelated to anthropogenic climate change. Generally, these results are consistent irrespective of the index used to define extreme fire weather. However, there are some notable exceptions (e.g. Australia and sub-Saharan Africa), where attribution results show a strong sensitivity to the choice of index.

It is evident that while the CFWIS indices used here form part of a common wildfire information system, different indices can lead to disparate results with respect to changes in the nature of fire weather extremes in various regions of the world. Therefore, as highlighted in recent work (Philip et al. 2020; van Oldenborgh et al. 2021b), it is crucial to explore the availability and merits of indices or metrics that may be used to represent fire weather, and to fully justify their application in the context of event attribution. As illustrated through our analysis of recent exceptional events, attribution of changes in the likelihood of events in response to warming global temperature can be significantly different depending on the choice of index. With respect to future efforts to attribute fire weather extremes, we recommend the consideration of a full variety of indices or metrics to (i) understand and communicate the sensitivity of the results to the chosen index or metric and (ii) better understand the effect of climate change on different combinations of the
meteorological components of fire weather (temperature, precipitation, wind speed, and atmospheric moisture content).

Empirical attribution analysis provides important preliminary knowledge of changing extreme fire weather based on observations, but robust attribution of extreme events requires the complementary application of similar methods to the outputs of climate model ensembles (van der Wiel et al. 2017). We anticipate that the results presented here will serve as a benchmark against which results from climate models can be compared, and ultimately serve to improve the accuracy of attribution findings generated from models (van Oldenborgh et al. 2021b). In future studies, it may also be beneficial to include more indices from other risk assessment systems in a similar framework, such as the Keetch-Byram drought index (KBDI) from the US Department of Agriculture’s Forest Service (Keetch and Byram, 1968), the energy release component (ERC) calculated from the US National Fire Danger Rating System (NFDRS; Deeming et al. 1977), and the McArthur forest fire danger index (FFDI) from the Centre for Australia Weather and Climate Research (MacArthur, 1967).

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Research involving human participants and/or animals This article does not contain any studies with human or animal participants performed by any of the authors.

Informed consent We confirm that this article does not contain any studies with human or animal participants performed by any of the authors.

Consent to participate We confirmed that this article does not contain any studies with human or animal participants performed by any of the authors.

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