A Global View of Observed Changes in Fire Weather Extremes: Uncertainties and Attribution To Climate Change.

Zhongwei Liu (liuz73@coventry.ac.uk)
Coventry University https://orcid.org/0000-0001-6597-0401
Jonathan M. Eden
Coventry University
Bastien Dieppois
Coventry University
Matthew Blackett
Coventry University

Research Article

Keywords: Wildfire, fire weather, climate change attribution, extreme value statistics

Posted Date: November 23rd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-1054722/v1

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 recent 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 increase 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 fire weather extremes is the consideration of multiple fire weather indicators and communication of their sensitivities.

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). Across the North America, Central America and Caribbean regions for instance, 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 21st 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, specifically through the effects of temperature, wind speed and humidity on fire spread, and the effects of rainfall 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., 1997; 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 (Peterson et al., 2012; Peterson et al., 2013; Herring et al., 2014, 2015, 2016, 2018, 2019, 2020, 2021). Additionally, the evolution of philosophical and methodological approaches in event attribution has been documented in numerous publications (National Academies of Science, Engineering and Medicine, 2016; Stott et al., 2016; Philip et al., 2020; van Oldenborgh et al., 2021b).

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 four sets of results: (i) recent trends in seasonal fire weather statistics; (ii) the relationship between different fire weather indices and burned area; (iii) empirical attribution of worldwide changes in the likelihood of extreme fire danger indices; and (iv) 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 substantially 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 ‘probabilistic’ approach, is used to estimate the probability of a class of events for a given magnitude 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 qualitative analyses instead of quantitative estimations (Clarks 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. 2013) and Australia (Hope et al., 2016), and fire-related extremes in Canada (Kirchmeier-Young et al., 2019), Sweden (Krikken et al., 2019), Australia (van Oldenborgh et al., 2021a). Here, we focus on the direct application of an established statistical technique to reanalysis-derived historical data in order 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 (Philip et al., 2020). As discussed in the introduction, quantifying the relationship between fire and climate is not trivial. The development of specific 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, specifically temperature, relative humidity, surface wind speed and precipitation, that collectively constitute fire-prone conditions, or so-called 'fire weather'. These variables are used to construct a set of 'fuel moisture codes', namely Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), and a subsequent set of 'fire behaviour indices', namely Initial Spread Index (ISI) and Buildup Index (BUI), from which the Fire Weather Index (FWI) is derived. 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, 2019; van Oldenborgh et al., 2021a), other works have justified the use of alternative CFWIS indices. For example, in the western United States, the six ecoregions use DC, FFMC, FWI, BUI and DSR 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). 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 seasonal mean fire weather (section 3.1) and secondly by comparing interannual fire weather variability with burned area (section 3.2). 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. The following CFWIS indices are used: DMC, DC, ISI, BUI and FWI. FFMC is omitted as the constrained upper limit of its range (maximum value: 101) make this index unsuitable for extreme value analysis. In order 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) (resolution; van der Werf et al., 2017) from the period 1996 to 2016.

2.3 Event Definition

The next step is to define the extreme fire weather event in a quantitative way. 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. To represent fire-prone conditions across an area that can feasibly experience consequent wildfires, the annual maximum 5-day average in each CFWIS index is defined for the target event. As the fire behaviours are not independent, and may interact mutually, we smoothed the GFED4 burned area dataset with a quadrilateral curvilinear grid. Then, a burned area mask for all the results is applied according to the region where there existed fires from 1996 to 2015 in the global monthly burned area dataset. Thus, the focus will be on areas of the world that have experienced historic fire activity. In addition, like previous studies (van Oldenborgh et al., 2017; Otto et al., 2018; Eden et al., 2018), a 48-month running mean is also applied to GMST to reduce the effects short-term fluctuations and emphasise longer-term trends. Regarding the spatial extent of extreme events, we pre-defined a grid box () for the centre target grid cell, then all the data in the surrounding grid cells among the grid box is seen as dependent in both temporal and spatial extents.

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; Eden et al., 2016; Eden et al., 2018; Krikken et al., 2019; van Oldenborgh et al., 2021a):

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

where location, scale and shape parameters of the distribution are μ, σ, and ξ, respectively. Here, we fit annual maxima of 5-day running means for each CFWIS index to a GEV distribution across all fire-prone parts of the world in order to quantify the change in likelihood and magnitude in fire weather extremes. 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. Observations are fitted to a non-stationary distribution under the assumption that the σ/μ 'dispersion' ratio and the shape parameter remain constant (Philip et al., 2020). The location and scale parameters and are assumed to vary with an exponential dependency on GMST (van der Wiel et al., 2017):

$$\mu = \mu_0 \cdot exp\frac{\alpha T}{\mu_0} \quad (2)$$

$$\sigma = \sigma_0 \cdot exp\frac{\alpha T}{\mu_0} \quad (3)$$

where μ_0 and σ_0 are the fit parameters of the distribution and α 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 (p1) and that is occurring in the (cooler) climate of 1961 (p0). Change in the likelihood of fire weather extremes is expressed using the 'probability ratio' (PR) p1/p0 (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 3.3) and, more specifically, to collectively attribute a set of exceptional fire weather events observed during recent years (section 3.4).

3. Results

3.1 Recent Trends in seasonal mean fire weather

To identify the potential differences between the CFWIS indices, we first seek to quantify recent trends in seasonal mean fire weather across the world from 1980 to 2018. The tendency and significance (95% confidence level) of trends in December-February (DJF), June-August (JJA) and annual CFWIS means are shown in Fig. 1. Spatial patterns in regions of significant positive and negative change differ substantially between indices. For some indices, most of the globe is associated with a decrease in mean fire weather. For annual DMC and BUI, a negative trend is found at more than 70% of fire-prone grid points, while positive trends are limited to parts of sub-Saharan Africa and Australia. By contrast, a far greater proportion of grid points are associated with positive trends in annual ISI and FWI, including large parts of the Americas, Australia, Europe, central Asia and central and southern Africa. Over 18% of the grid points do not show significant trends in any CFWIS index. For annual mean fire weather, there is consistently a higher proportion of grid points that exhibit a negative trend evident for all indices.

Specifically, looking at the regional trend patterns, for DJF, central and eastern Africa, in addition to parts of Australia, are the only regions showing consistent increasing trends across all fire danger indices (Fig. 1). During the same season, ISI and FWI also show significant increasing trends in southern parts of North America, and in eastern and southern parts of South America, in addition to small parts of western and eastern Asia. In contrast, large parts of the world exhibit significant negative trends in all indices. For JJA, regions showing significant increasing trends extend further into the Northern Hemisphere. North America, the Sahel, and the regions surrounding the Caspian Sea, are the only regions showing consistent increasing trends across all indices in JJA, despite some discrepancies over the spatial extent. Nevertheless, significant increases are also identified in Europe (including Russia), Southern Africa and Eastern South America using ISI and FWI. We thus note a certain degree of discrepancy in the recent trends detected through the five CFWIS indices. Interestingly, northern Canada and Siberia consistently show decreasing or non-significant trends in fire danger, although extreme wildfires have been recorded in these regions in recent years (Kirchmeier-Young et al., 2017a; Witze, 2020).

3.2 Comparison between fire weather and fire activity

To quantify the broad relationship between fire weather and actual fire activity, we examine the correlation between the CFWIS indices and fire-prone grid points, exploring similarities and differences between all CFWIS indices. Fig. 2 shows point-wise Pearson's product moment correlation between annual means in each CFWIS index and annual GFED4 burned area taken from for 1996 to 2016 (95% confidence level).

Positive correlation between CFWIS and fire-prone grid points (r>0.5) is found across North and South America, eastern Europe, equatorial and South Africa, southeast Asia and southern Australia (Fig. 2). Interestingly, areas of significant correlation 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., 2019). Also, significant 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 isolated points in central and southern Asia. Overall, there are few differences between the CFWIS index in terms of their relationship with fire-prone areas. In terms of choosing an index as the most appropriate fire weather indicator as part of an attribution analysis, there is little to suggest that any particular index would prove more suitable than any other, at least on a global scale.

3.3 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. Here, the GEV-scaling method is applied to annual maxima in each CFWIS index. Global maps showing probability ratio (PR) and change in magnitude (%MAG) at each grid point are shown in Fig.3.

Overall, there are a number of similarities in spatial patterns of both PR and %MAG across the five CFWIS indices (Fig. 3). A 4-fold 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 magnitude of around 20%, ranging from 15.5% in DC to 25.5% in DMC. Regions with increasing likelihoods in %MAG are mainly similar with 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, 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 are 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 an increasing trend or no significant change in likelihoods (Fig. 3). 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. 1), and that are also poorly correlated with fire-prone area (i.e., eastern parts of South America for FWI, East Asia and Western Australia; Fig. 2). As these regions are also data-scarce regions (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.

In order 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). Fig. 4 shows the proportion of grid points that exhibit significant increases and decreases in likelihood in the five CFWIS 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 with the exception of 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. 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 in 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.

3.4 Attribution of recent exceptional fire weather events

As highlighted in Section 1, the last decade has witnessed a sharp increase in attribution of 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. Events are defined as ‘exceptional’ where the index value of an annual CFWIS index maxima, 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.5.

According to Fig. 5, exceptional fire weather events occurred prevalently in multiple locations around the world between 2014 and 2018. Four of the five CFWIS indices show that events associated with a significant increase in likelihoods is more than 50%; the exception is DC, which is the only index 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 sensitivity of the index choice is revealed by the fact that different indices present disparate distributions of exceptional events. In Alaska, ISI and FWI events that exceed the magnitude of the previous maxima by more than 50% are observed and associated with an increase in likelihood. However, exceptional events in other indices are either not evident or, in the case of DMC extremes, associated with a 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 (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 attribution multiple events collectively. Fig. 6 summaries the number of exceptional fire weather events in the five CFWIS indices, and corresponding averaged PR, across the 14 GFED fire regions. The largest number of exceptional events are found in BOAS (540) for DMC only, while CEAS (244 by using DMC), SHSA (204 by using DMC), NHAF (186 by using BUI) and TENA (91 by using BUI). Also, for those five of the 14 fire regions, there is a large overall increase in likelihood in exceptional events identified across all indices (averaged PR>8). Only one fire region (SEAS) shows a general decrease in likelihood (PR<0.5) in exceptional ISI, BUI and FWI events. Again, though most fire regions present similar trends of significant increase and decrease among five fire weather indices, those in CEAM, NHSA, CEAS, EQAS and AUST present substantial differences in PR changes as a result of globally warming temperature.

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 index for fire weather representation, particularly in the context of extreme event attribution.

The first part of the analysis pertaining to seasonal 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. At the global scale, a decreasing trend was found in the seasonal mean of each index. 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.

More importantly, despite a decreasing trend in mean fire weather, we found the probability of extreme climate-related wildfire risk has increased substantially as a response to globally warming temperature 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 in 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 in order to: (i) understand and communicate the sensitivity of the results to the chosen index or metric; (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 on the basis of 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). In this sense, this study serves as a reference point for the evaluation and bias correction of climate models, and ultimately to improve the accuracy of attribution findings generated from models (van Oldenborgh et al., 2016). 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 United States 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 (McArthur, 1967).

Declarations

Acknowledgements

The research leading to these results received funding from the Coventry University Trailblazer PhD studentship scheme.

Statements and Declarations

Ethical Approval:

Conflicts of interest: The research leading to these results received funding from the Coventry University Trailblazer PhD studentship scheme.

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.

Consent to Publish: We agreed with the content and gave explicit consent to submit to the Journal and Publisher.

Authors Contributions: Z. Liu, J. M. Eden and B. Dieppois carried out the analysis. Z. Liu, J. M. Eden, B. Dieppois and M. Blackett drafted the manuscript, reviewed and approved the final manuscript.

Funding: The research leading to these results received funding from the Coventry University Trailblazer PhD studentship scheme.

Competing Interests: We declare that we have no competing interests.

Availability of data and materials: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

References

1. Abatzoglou, J. T., & Kolden, C. A. (2011). Relative importance of weather and climate on wildfire growth in interior Alaska. *International Journal of Wildland Fire*, *20*(4), 479-486.
2. Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences*, *113*(42), 11770-11775.
3. Abatzoglou, J. T., Williams, A. P., & Barbero, R. (2019). Global emergence of anthropogenic climate change in fire weather indices. *Geophysical Research Letters*, *46*(1), 326-336.
4. Acharya, S. C., Nathan, R., Wang, Q. J., Su, C. H., & Eizenberg, N. (2019). An evaluation of daily precipitation from a regional atmospheric reanalysis over Australia. *Hydrology and Earth System Sciences*, *23*(8), 3387-3403.
5. Ager, A. A., Preisler, H. K., Arca, B., Spano, D., & Salis, M. (2014). Wildfire risk estimation in the Mediterranean area. *Environmetrics*, *25*(6), 384-396.
6. Allen, M. (2003). Liability for climate change. *Nature*, *421*(6926), 891-892.
7. Bhatt, U.S., Lader, R.T., Walsh, J.E., Bieniek, P.A., Thoman, R., Berman, M., Borries-Strigle, C., Bulock, K., Chriest, J., Hahn, M., Hendricks, A.S., Jandt, R., Little, J., McEvoy, D., Moore, C., Rupp, T.S., Schmidt, J.,

Stevens, E., Strader, H., Waigl, C., White, J., York, A., Ziel, R. (2021). Emerging Anthropogenic Influences on the Southcentral Alaska Temperature and Precipitation Extremes and Related Fires in 2019. *Land*, *10*(1), 82.

8. Brown, T., Leach, S., Wachter, B., & Gardunio, B. (2020). The extreme 2018 northern California fire season. *Bulletin of the American Meteorological Society*, *101*(1), S1-S4.
9. Burton, C., Rifai, S., & Malhi, Y. (2018). Inter-comparison and assessment of gridded climate products over tropical forests during the 2015/2016 El Niño. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1760), 20170406.
10. Campos-Ruiz, R., Parisien, M. A., & Flannigan, M. D. (2018). Temporal patterns of wildfire activity in areas of contrasting human influence in the Canadian boreal forest. *Forests*, *9*(4), 159.
11. CFWIS, 2021. *Canadian Wildland Fire Information System | Canadian Forest Fire Danger Rating System (CFFDRS).* [online] Available at: https://cwfis.cfs.nrcan.gc.ca/background/summary/fdr [Accessed 11 June 2021].
12. Clark, M.P., Wilby, R.L., Gutmann, E.D., Vano, J.A., Gangopadhyay, S., Wood, A.W., Fowler, H.J., Prudhomme, C., Arnold, J.R. and Brekke, L.D. (2016). Characterizing uncertainty of the hydrologic impacts of climate change. *Current Climate Change Reports*, *2*(2), 55-64.
13. Cohen, J. D. (1985). *The national fire-danger rating system: basic equations* (Vol. 82). US Department of Agriculture, Forest Service, Pacific Southwest Forest and Range Experiment Station.
14. Coles, S., Bawa, J., Trenner, L., & Dorazio, P. (2001). *An introduction to statistical modeling of extreme values* (Vol. 208, p. 208). London: Springer.
15. Cortez, P., & Morais, A. D. J. R. (2007). A data mining approach to predict forest fires using meteorological data.
16. Deeming, J. E., Burgan, R. E., & Cohen, J. D. (1977). *The national fire-danger rating system--1978* (Vol. 39). Intermountain Forest and Range Experiment Station, Forest Service, US Department of Agriculture.
17. Dimitrakopoulos, A. P., Bemmerzouk, A. M., & Mitsopoulos, I. D. (2011). Evaluation of the Canadian fire weather index system in an eastern Mediterranean environment. *Meteorological Applications*, *18*(1), 83-93.
18. Du, J., Wang, K., & Cui, B. (2021). Attribution of the Extreme Drought-Related Risk of Wildfires in Spring 2019 over Southwest China. *Bulletin of the American Meteorological Society*, *102*(1), S83-S90.
19. Dudfield, M. (2004). Art and science of forest and rural fire management. *Understanding the Variables that Affect Australian Hardwood Woodchip Export Performance–Perceptions and Lessons from the International Business Management*, 79.
20. de Groot, W.J., Goldammer, J.G., Keenan, T., Brady, M.A., Lynham, T.J., Justice, C.O., Csiszar, I.A. and O'Loughlin, K. (2006). Developing a global early warning system for wildland fire. *Forest Ecology and Management*, *234*(1), p.S10.
21. de Groot, W. J., Field, R. D., Brady, M. A., Roswintiarti, O., & Mohamad, M. (2007). Development of the Indonesian and Malaysian fire danger rating systems. *Mitigation and Adaptation Strategies for*

Global Change, *12*(1), 165-180.

22. Eden, J. M., Wolter, K., Otto, F. E., & Van Oldenborgh, G. J. (2016). Multi-method attribution analysis of extreme precipitation in Boulder, Colorado. *Environmental Research Letters*, 11(12), 124009.
23. Eden, J. M., Kew, S. F., Bellprat, O., Lenderink, G., Manola, I., Omrani, H., & van Oldenborgh, G. J. (2018). Extreme precipitation in the Netherlands: An event attribution case study. *Weather and climate extremes*, *21*, 90-101.
24. Efron, B., & Tibshirani, R. (1998). The problem of regions. *Annals of Statistics*, *26*(5), 1687-1718.
25. Field, C. B., Barros, V., Stocker, T. F., & Dahe, Q. (Eds.). (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change*. Cambridge University Press.
26. Field, R.D., Spessa, A.C., Aziz, N.A., Camia, A., Cantin, A., Carr, R., De Groot, W.J., Dowdy, A.J., Flannigan, M.D., Manomaiphiboon, K. and Pappenberger, F. (2015). Development of a global fire weather database. *Natural Hazards and Earth System Sciences*, *15*(6), 1407-1423.
27. Flannigan, M. D., Krawchuk, M. A., de Groot, W. J., Wotton, B. M., & Gowman, L. M. (2009). Implications of changing climate for global wildland fire. *International journal of wildland fire*, *18*(5), 483-507.
28. Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A. and Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data*, *2*(1), 1-21.
29. Gauthier, S., Bernier, P., Kuuluvainen, T., Shvidenko, A. Z., & Schepaschenko, D. G. (2015). Boreal forest health and global change. *Science*, *349*(6250), 819-822.
30. Gill, A. M., Stephens, S. L., & Cary, G. J. (2013). The worldwide “wildfire” problem. *Ecological applications*, *23*(2), 438-454.
31. Gillett, N. P., Weaver, A. J., Zwiers, F. W., & Flannigan, M. D. (2004). Detecting the effect of climate change on Canadian forest fires. *Geophysical Research Letters*, *31*(18).
32. GISTEMP Team (2021) GISS Surface Temperature Analysis (GISTEMP), version 4. NASA Goddard Institute for Space Studies. Dataset accessed 2021-05-27 at https://data.giss.nasa.gov/gistemp/.
33. Gleixner, S., Demissie, T., & Diro, G. T. (2020). Did ERA5 improve temperature and precipitation reanalysis over East Africa?. *Atmosphere*, *11*(9), 996.
34. Global Fire Emissions Database. (2021). Retrieved 14 June 2021, from https://www.globalfiredata.org/data.html.
35. Hall, B. L., T. J. Brown, L. S. Bradshaw, W. M. Jolly, and R. Nemani. (2003). National standardized Energy Release Component (ERC) forecasts. *Second International Wildland Fire Ecology and Fire Management Congress and Fifth Symposium on Fire and Forest Meteorology*, 16-20 November 2003, Orlando, FL [program volume and electronic resource]. American Meteorological Society, Boston, MA. p. 172, http://ams.confex.com/ams/FI.

36. Hardy, C. C. (2005). Wildland fire hazard and risk: problems, definitions, and context. *Forest ecology and management*, *211*(1-2), 73-82.
37. Herring, S. C., Hoerling, M. P., Peterson, T. C., & Stott, P. A. (Eds.). (2014). Explaining extreme events of 2013 from a climate perspective. *Bulletin of the American Meteorological Society*, *95*(9), Si-S97.
38. Herring, S. C., Hoerling, M. P., Kossin, J. P., Peterson, T. C., & Stott, P. A. (2015). Explaining extreme events of 2014 from a climate perspective. *Bulletin of the American Meteorological Society*, *96*(12), S1-S172.
39. Herring, S. C., Hoell, A., Hoerling, M. P., Kossin, J. P., Schreck III, C. J., & Stott, P. A. (2016). Explaining extreme events of 2015 from a climate perspective. *Bulletin of the American Meteorological Society*, *97*(12), S1-S145.
40. Herring, S. C., Christidis, N., Hoell, A., Kossin, J. P., Schreck III, C. J., & Stott, P. A. (2018). Explaining extreme events of 2016 from a climate perspective. *Bulletin of the American Meteorological Society*, *99*(1), S1-S157.
41. Herring, S. C., Christidis, N., Hoell, A., Hoerling, M. P., & Stott, P. A. (2019). Explaining Extreme Events of 2017 from a Climate Perspective. *Bulletin of the American Meteorological Society*, 100(1), S1–S11.
42. Herring, S. C., Christidis, N., Hoell, A., Hoerling, M. P., & Stott, P. A. (2020). Explaining Extreme Events of 2018 from a Climate Perspective. *Bulletin of the American Meteorological Society*, 101(1), S1–S128, doi:10.1175/BAMS-ExplainingExtremeEvents2018.1.
43. Herring, S. C., Christidis, N., Hoell, A., Hoerling, M. P., & Stott, P. A. (2021). Explaining Extreme Events of 2019 from a Climate Perspective. *Bulletin of the American Meteorological Society*, *102*(1), S1-S116.
44. Hoerling, M., Kumar, A., Dole, R., Nielsen-Gammon, J.W., Eischeid, J., Perlwitz, J., Quan, X.W., Zhang, T., Pegion, P. and Chen, M. (2013). Anatomy of an extreme event. *Journal of Climate*, *26*(9), 2811-2832.
45. Hope, P., Black, M. T., Lim, E. P., Dowdy, A., Wang, G., Fawcett, R. J., & Pepler, A. S. (2019). On Determining the Impact of Increasing Atmospheric CO2 on the Record Fire Weather in Eastern Australia in February 2017. *Bulletin of the American Meteorological Society*, *100*(1), S111-S117.
46. Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., & Bowman, D. M. (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature communications*, *6*(1), 1-11.
47. Keetch, J. J. and Byram, G. M. (1968). A drought index for forest fire control. *USDA Forest*
48. *Service*, Research Paper SE-38.
49. Kim, Y. H., Min, S. K., Zhang, X., Zwiers, F., Alexander, L. V., Donat, M. G., & Tung, Y. S. (2016). Attribution of extreme temperature changes during 1951–2010. *Climate dynamics*, *46*(5-6), 1769-1782.
50. Kirchmeier-Young, M. C., Zwiers, F. W., Gillett, N. P., & Cannon, A. J. (2017a). Attributing extreme fire risk in Western Canada to human emissions. *Climatic Change*, *144*(2), 365-379.

51. Kirchmeier-Young, M. C., Zwiers, F. W., & Gillett, N. P. (2017b). Attribution of extreme events in Arctic sea ice extent. *Journal of Climate*, *30*(2), 553-571.
52. Kirchmeier-Young, M. C., Gillett, N. P., Zwiers, F. W., Cannon, A. J., & Anslow, F. S. (2019). Attribution of the influence of human-induced climate change on an extreme fire season. *Earth's Future*, *7*(1), 2-10.
53. Knutson, T., Kossin, J., Mears, C., Perlwitz, J., & Wehner, M. (2017). Detection and attribution of climate change.
54. Knutson, T., Camargo, S.J., Chan, J.C., Emanuel, K., Ho, C.H., Kossin, J., Mohapatra, M., Satoh, M., Sugi, M., Walsh, K. and Wu, L. (2019). Tropical cyclones and climate change assessment: Part I: Detection and attribution. *Bulletin of the American Meteorological Society*, *100*(10), 1987-2007.
55. Krawchuk, M. A., Moritz, M. A., Parisien, M. A., Van Dorn, J., & Hayhoe, K. (2009). Global pyrogeography: the current and future distribution of wildfire. *PloS one*, *4*(4), e5102.
56. Krikken, F., Lehner, F., Haustein, K., Drobyshev, I., & van Oldenborgh, G. J. (2019). Attribution of the role of climate change in the forest fires in Sweden 2018. *Natural Hazards and Earth System Sciences Discussions*, 1-24.
57. Kunkel, K.E., Karl, T.R., Brooks, H., Kossin, J., Lawrimore, J.H., Arndt, D., Bosart, L., Changnon, D., Cutter, S.L., Doesken, N. and Emanuel, K. (2013). Monitoring and understanding trends in extreme storms: State of knowledge. *Bulletin of the American Meteorological Society*, *94*(4), 499-514.
58. Lewis, S.C., Blake, S.A., Trewin, B., Black, M.T., Dowdy, A.J., Perkins-Kirkpatrick, S.E., King, A.D. and Sharples, J.J. (2020). Deconstructing factors contributing to the 2018 fire weather in Queensland, Australia. *Bulletin of the American Meteorological Society*, *101*(1), S115-S122.
59. Lin, H.W., McCarty, J.L., Wang, D., Rogers, B.M., Morton, D.C., Collatz, G.J., Jin, Y. and Randerson, J.T. (2014). Management and climate contributions to satellite-derived active fire trends in the contiguous United States. *Journal of Geophysical Research: Biogeosciences*, *119*(4), 645-660.
60. Liu, Z., Liu, Y., Wang, S., Yang, X., Wang, L., Baig, M.H.A., Chi, W. and Wang, Z. (2018). Evaluation of spatial and temporal performances of ERA-Interim precipitation and temperature in mainland China. *Journal of Climate*, *31*(11), 4347-4365.
61. McArthur, A. G. (1967). Fire Behaviour in Eucalypt Forests. *Department of National Development Forestry and Timber Bureau*, *Canberra*, Leaflet 107.
62. Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E., & Houston, T. G. (2012). An Overview of the Global Historical Climatology Network-Daily Database, *Journal of Atmospheric and Oceanic Technology*, *29*(7), 897-910.
63. Mera, R., Massey, N., Rupp, D. E., Mote, P., Allen, M., & Frumhoff, P. C. (2015). Climate change, climate justice and the application of probabilistic event attribution to summer heat extremes in the California Central Valley. *Climatic Change*, *133*(3), 427-438.
64. National Academies of Sciences, Engineering, and Medicine. (2016). *Attribution of extreme weather events in the context of climate change*. National Academies Press. Washington DC.
65. Nwcg, 2020. Fire Weather Index (FWI) System | NWCG. [online] Available at: https://www.nwcg.gov/publications/pms437/cffdrs/fire-weather-index-system [Accessed 13 Jun

2021].

66. Otto, F. E., Van Oldenborgh, G. J., Eden, J., Stott, P. A., Karoly, D. J., & Allen, M. R. (2016). The attribution question. *Nature Climate Change*, *6*(9), 813-816.
67. Otto, F.E., Wolski, P., Lehner, F., Tebaldi, C., Van Oldenborgh, G.J., Hogesteeger, S., Singh, R., Holden, P., Fučkar, N.S., Odoulami, R.C. and New, M. (2018). Anthropogenic influence on the drivers of the Western Cape drought 2015–2017. *Environmental Research Letters*, *13*(12), 124010.
68. Partain Jr, J.L., Alden, S., Bhatt, U.S., Bieniek, P.A., Brettschneider, B.R., Lader, R.T., Olsson, P.Q., Rupp, T.S., Strader, H., Thoman Jr, R.L. and Walsh, J.E. (2016). An assessment of the role of anthropogenic climate change in the Alaska fire season of 2015. [in "Explaining Extremes of 2015 from a Climate Perspective"]. *Bulletin of American Meteorological Society*, 97(12), S14 –S18.
69. Peterson, T. C., Stott, P. A., & Herring, S. (2012). Explaining extreme events of 2011 from a climate perspective. *Bulletin of the American Meteorological Society*, *93*(7), 1041-1067.
70. Peterson, T. C., Hoerling, M. P., Stott, P. A., & Herring, S. (2013). Explaining extreme events of 2012 from a climate perspective. *Bulletin of the American Meteorological Society*, *94*(9), S1-S74.
71. Philip, S., Kew, S., van Oldenborgh, G.J., Otto, F., Vautard, R., van der Wiel, K., King, A., Lott, F., Arrighi, J., Singh, R. and van Aalst, M. (2020). A protocol for probabilistic extreme event attribution analyses. *Advances in Statistical Climatology, Meteorology and Oceanography*, *6*(2), 177-203.
72. Pinto, M. M., DaCamara, C. C., Hurduc, A., Trigo, R. M., & Trigo, I. F. (2020). Enhancing the fire weather index with atmospheric instability information. *Environmental Research Letters*, *15*(9), 0940b7.
73. Seneviratne, S.I., X. Zhang, M. Adnan, W. Badi, C. Dereczynski, A. Di Luca, S. Ghosh, I. Iskandar, J. Kossin, S. Lewis, F. Otto, I. Pinto, M. Satoh, S.M. Vicente-Serrano, M. Wehner, and B. Zhou, 2021: Weather and Climate Extreme Events in a Changing Climate. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson- Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press. In Press.
74. Sharples, J. J., McRae, R. H., Weber, R. O., & Gill, A. M. (2009). A simple index for assessing fire danger rating. *Environmental Modelling & Software*, *24*(6), 764-774.
75. Shepherd, T. G. (2016). A common framework for approaches to extreme event attribution. *Current Climate Change Reports*, *2*(1), 28-38.
76. Spracklen, D. V., Mickley, L. J., Logan, J. A., Hudman, R. C., Yevich, R., Flannigan, M. D., & Westerling, A. L. (2009). Impacts of climate change from 2000 to 2050 on wildfire activity and carbonaceous aerosol concentrations in the western United States. *Journal of Geophysical Research: Atmospheres*, *114*(D20).
77. Stott, P. A., Stone, D. A., & Allen, M. R. (2004). Human contribution to the European heatwave of 2003. *Nature*, *432*(7017), 610-614.

78. Stott, P. A., Christidis, N., Otto, F. E., Sun, Y., Vanderlinden, J. P., van Oldenborgh, G. J., ... & Zwiers, F. W. (2016). Attribution of extreme weather and climate-related events. *Wiley Interdisciplinary Reviews: Climate Change*, *7*(1), 23-41.
79. Tanskanen, H., & Venäläinen, A. (2008). The relationship between fire activity and fire weather indices at different stages of the growing season in Finland. *Boreal Environment Research*, 13(4), 285-302.
80. Tedim, F., Leone, V., Amraoui, M., Bouillon, C., Coughlan, M.R., Delogu, G.M., Fernandes, P.M., Ferreira, C., McCaffrey, S., McGee, T.K. and Parente, J. (2018). Defining extreme wildfire events: difficulties, challenges, and impacts. *Fire*, *1*(1), 9.
81. Tett, S.F., Falk, A., Rogers, M., Spuler, F., Turner, C., Wainwright, J., Dimdore-Miles, O., Knight, S., Freychet, N., Mineter, M.J. and Lehmann, C.E. (2018). Anthropogenic forcings and associated changes in fire risk in Western North America and Australia during 2015/16. *Bulletin of the American Meteorological Society*, *99*(1), S60-S64.
82. Trenberth, K. E., Fasullo, J. T., & Shepherd, T. G. (2015). Attribution of climate extreme events. *Nature Climate Change*, *5*(8), 725-730.
83. van der Werf, G.R., Randerson, J.T., Giglio, L., Leeuwen, T.T.V., Chen, Y., Rogers, B.M., Mu, M., Van Marle, M.J., Morton, D.C., Collatz, G.J. and Yokelson, R.J. (2017). Global fire emissions estimates during 1997–2016. *Earth System Science Data*, *9*(2), 697-720.
84. van Oldenborgh, G. J., Van Urk, A., & Allen, M. (2012). The absence of a role of climate change in the 2011 Thailand floods. *Bull. Amer. Meteor. Soc*, *93*, 1047-1049.
85. van Oldenborgh, G.J., Stephenson, D.B., Sterl, A., Vautard, R., Yiou, P., Drijfhout, S.S., Von Storch, H. and Van Den Dool, H. (2015). Drivers of the 2013/14 winter floods in the UK. *Nature Climate Change*, *5*(6), 490-491.
86. van Oldenborgh, G.J., Van Der Wiel, K., Sebastian, A., Singh, R., Arrighi, J., Otto, F., Haustein, K., Li, S., Vecchi, G. and Cullen, H. (2017). Attribution of extreme rainfall from Hurricane Harvey. *Environmental Research Letters*, 12(12), 124009.
87. van Oldenborgh, G.J., Krikken, F., Lewis, S., Leach, N.J., Lehner, F., Saunders, K.R., van Weele, M., Haustein, K., Li, S., Wallom, D. and Sparrow, S. (2021a). Attribution of the Australian bushfire risk to anthropogenic climate change. *Natural Hazards and Earth System Sciences*, *21*(3), 941-960.
88. van Oldenborgh, G.J., van der Wiel, K., Kew, S., Philip, S., Otto, F., Vautard, R., King, A., Lott, F., Arrighi, J., Singh, R. and van Aalst, M. (2021b). Pathways and pitfalls in extreme event attribution. *Climatic Change*, *166*(1), 1-27.
89. Van Wagner, C.E (1987). Development and Structure of the Canadian Forest Fire Weather Index System, Forestry Technical Report, Canadian Forestry Service Headquarters, Ottawa.
90. Viegas, D. X., Bovio, G., Ferreira, A., Nosenzo, A., & Sol, B. (1999). Comparative study of various methods of fire danger evaluation in southern Europe. *International Journal of wildland fire*, *9*(4), 235-246.
91. Vitolo, C., Di Giuseppe, F., Krzeminski, B., & San-Miguel-Ayanz, J. (2019). A 1980–2018 global fire danger re-analysis dataset for the Canadian Fire Weather Indices. *Scientific data*, *6*(1), 1-10.

92. Wang, D., Guan, D., Zhu, S., Mac Kinnon, M., Geng, G., Zhang, Q., Zheng, H., Lei, T., Shao, S., Gong, P. and Davis, S.J. (2021). Economic footprint of California wildfires in 2018. *Nature Sustainability*, *4*(3), 252-260.
93. Witze, A. (2020) The Arctic is burning like never before-and that's bad news for climate change, *Nature*, *585*(7825), 336-337.
94. World Meteorological Organization. (2021). The Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes (1970-2019). World Meteorological Organization, Geneva, Switzerland, 90pp
95. Wotton, B. M. (2009). Interpreting and using outputs from the Canadian Forest Fire Danger Rating System in research applications. *Environmental and Ecological Statistics*, *16*(2), 107-131.
96. Yoon, J. H., Kravitz, B., Rasch, P. J., Simon Wang, S. Y., Gillies, R. R., & Hipps, L. (2015). Extreme fire season in California: A glimpse into the future. *Bulletin of the American Meteorological Society*, *96*(12), S5-S9.
97. Yu, Y., Dunne, J. P., Shevliakova, E., Ginoux, P., Malyshev, S., John, J. G., & Krasting, J. P. (2021). Increased risk of the 2019 Alaskan July fires due to anthropogenic activity, [in "Explaining Extremes of 2019 from a Climate Perspective"]. B*ulletin of the American Meteorological Society*, 102(1), S1–S7.

Figures

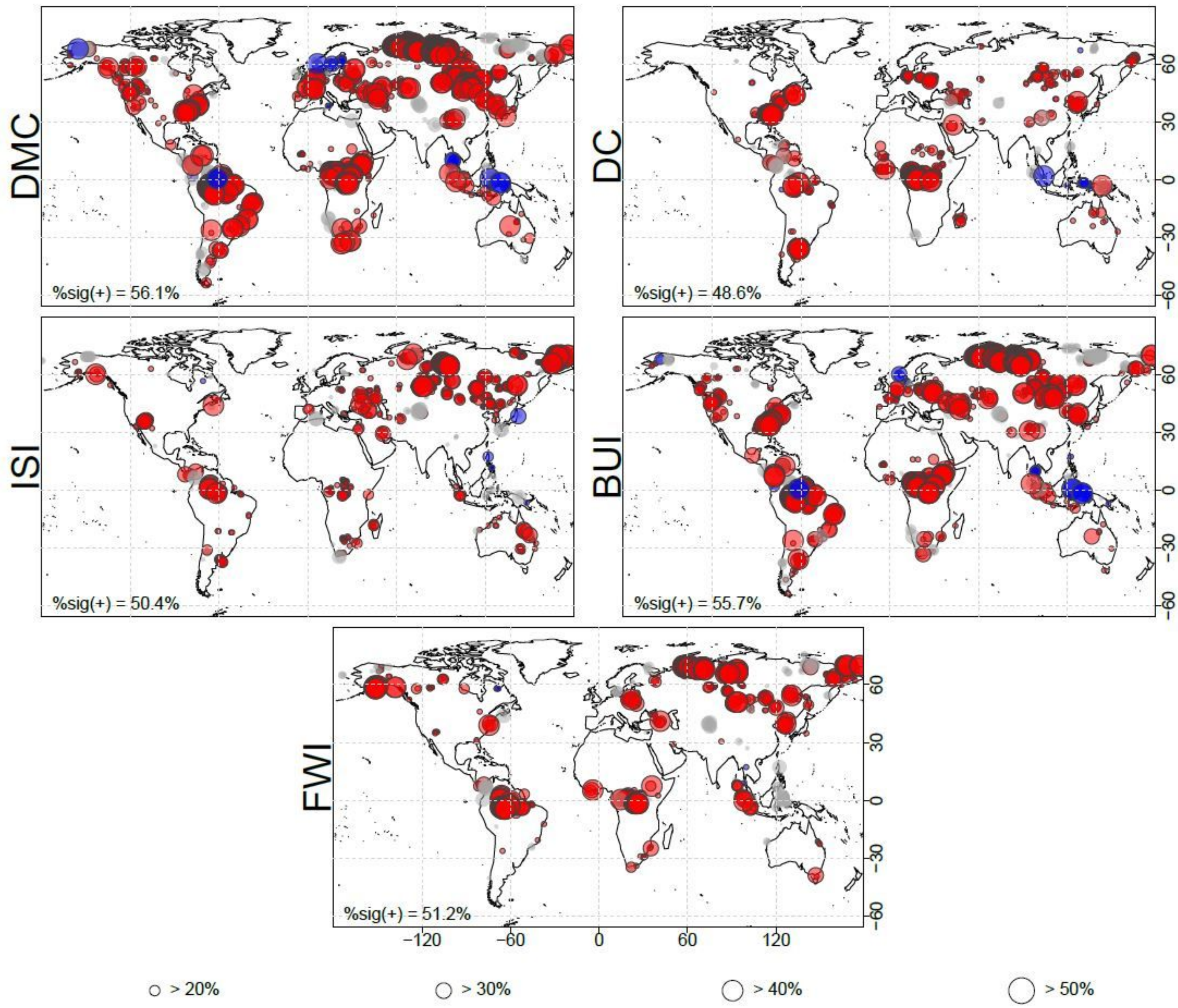


Figure 1

Seasonal mean trends in five CFWIS indices take from the Global Fire Danger Reanalysis (Vitolo et al., 2019) for the period 1980-2018. Fire-prone regions where a significant increase is detected are shown in red; regions of significant decrease are shown in blue; regions of where no significant change is detected are shown in grey. Values in the bottom-left corner of each panel show the percentage of grid points that show significant increase (red) and decrease (blue) respectively.

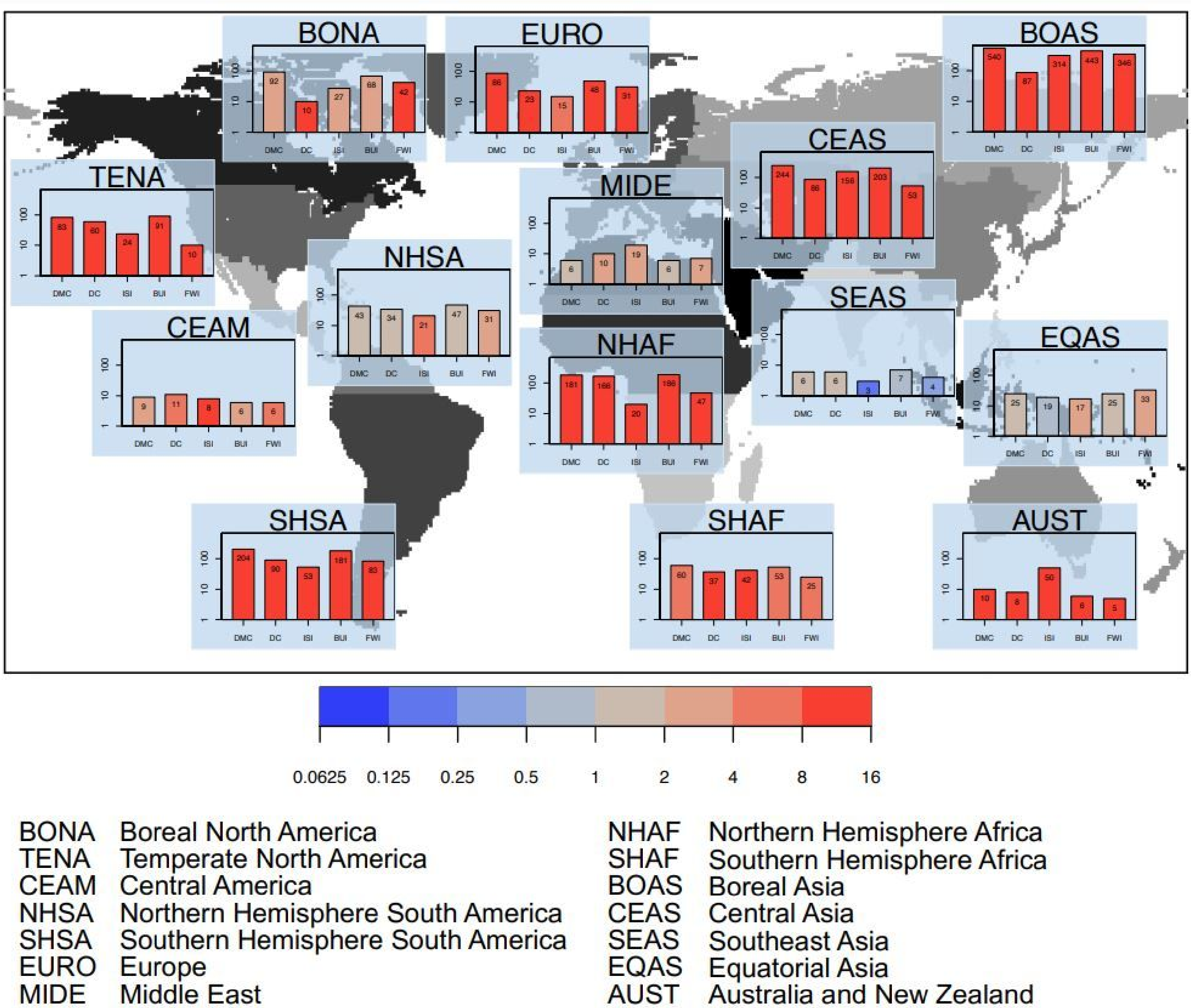
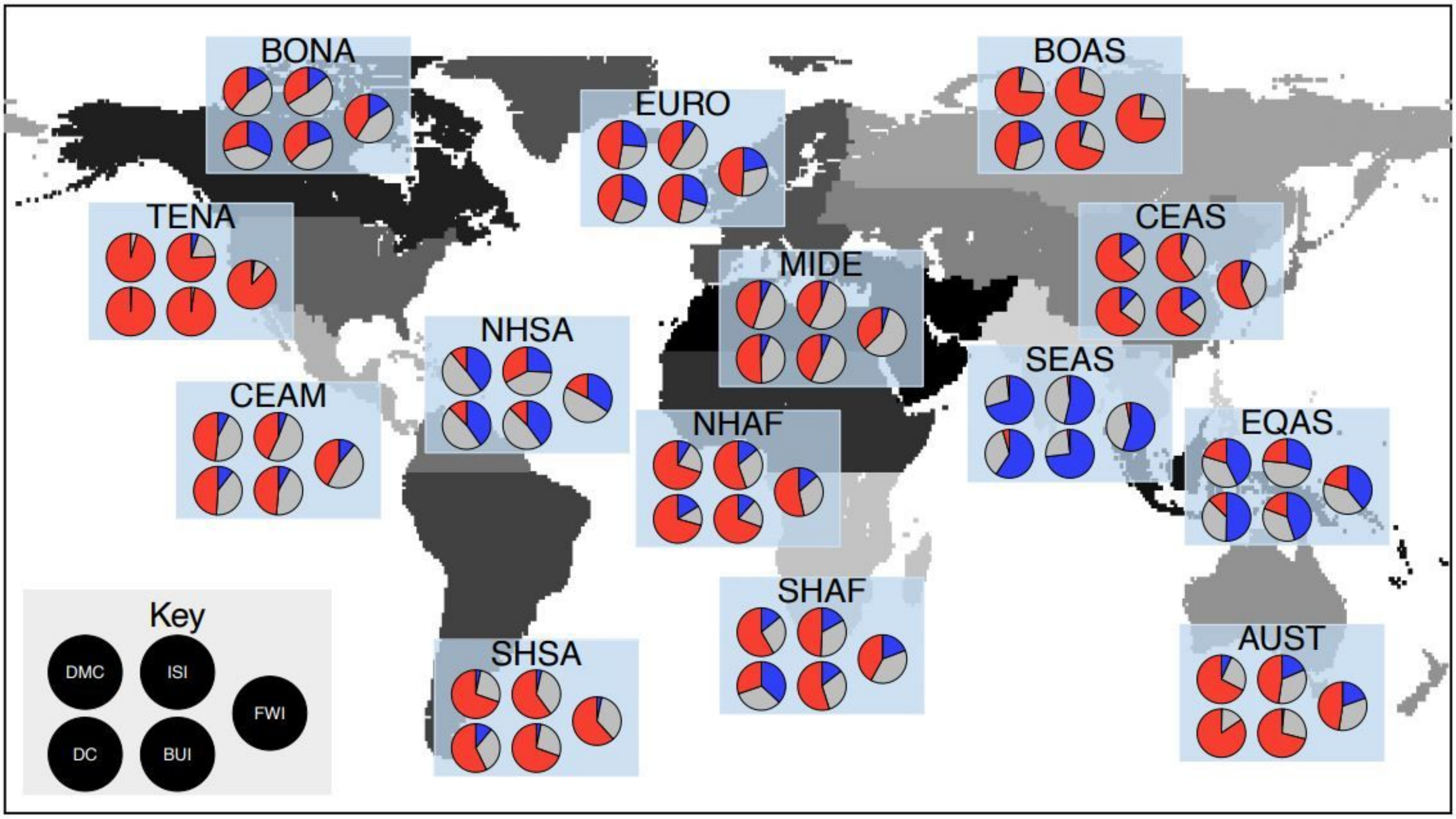


Figure 2

Correlation between the annual means of each CWFIS index and GFED burned area at all fire-prone grid points from 1996 to 2016. Regions where the correlation does not exceed the critical value associated with a 95% confidence level (±0.267) are shown in grey.



BONA	Boreal North America	NHAF	Northern Hemisphere Africa
TENA	Temperate North America	SHAF	Southern Hemisphere Africa
CEAM	Central America	BOAS	Boreal Asia
NHSA	Northern Hemisphere South America	CEAS	Central Asia
SHSA	Southern Hemisphere South America	SEAS	Southeast Asia
EURO	Europe	EQAS	Equatorial Asia
MIDE	Middle East	AUST	Australia and New Zealand

Figure 3

Global view of probability ratio (PR; left) and percentage change (%MAG; right) with reference to the target event at each grid point for five CFWIS indices. Numbers in the bottom-left corner represent globally averaged PR and %MAG, and the percentage of the grid points for which PR and %MAG results are significant.

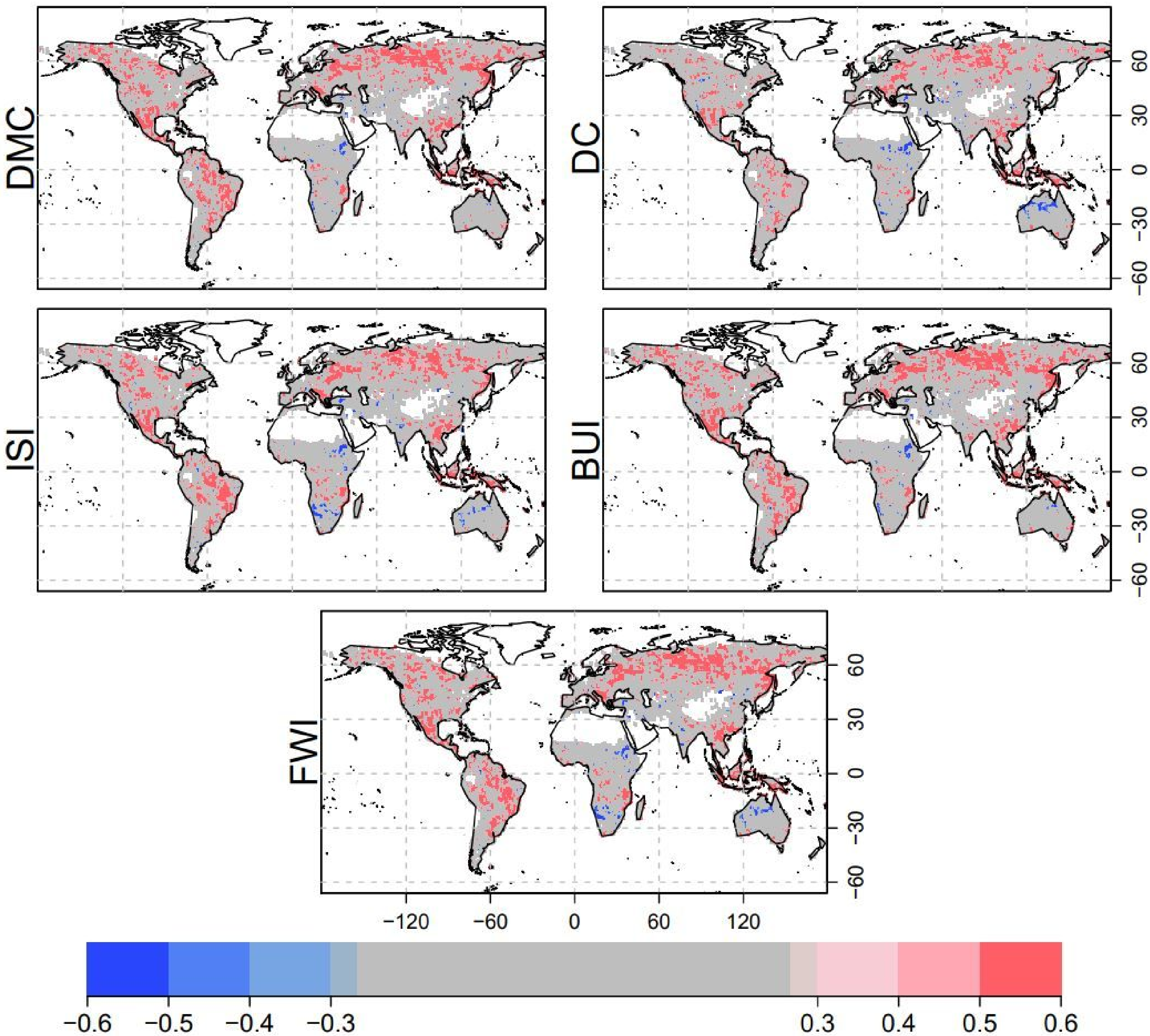


Figure 4

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.

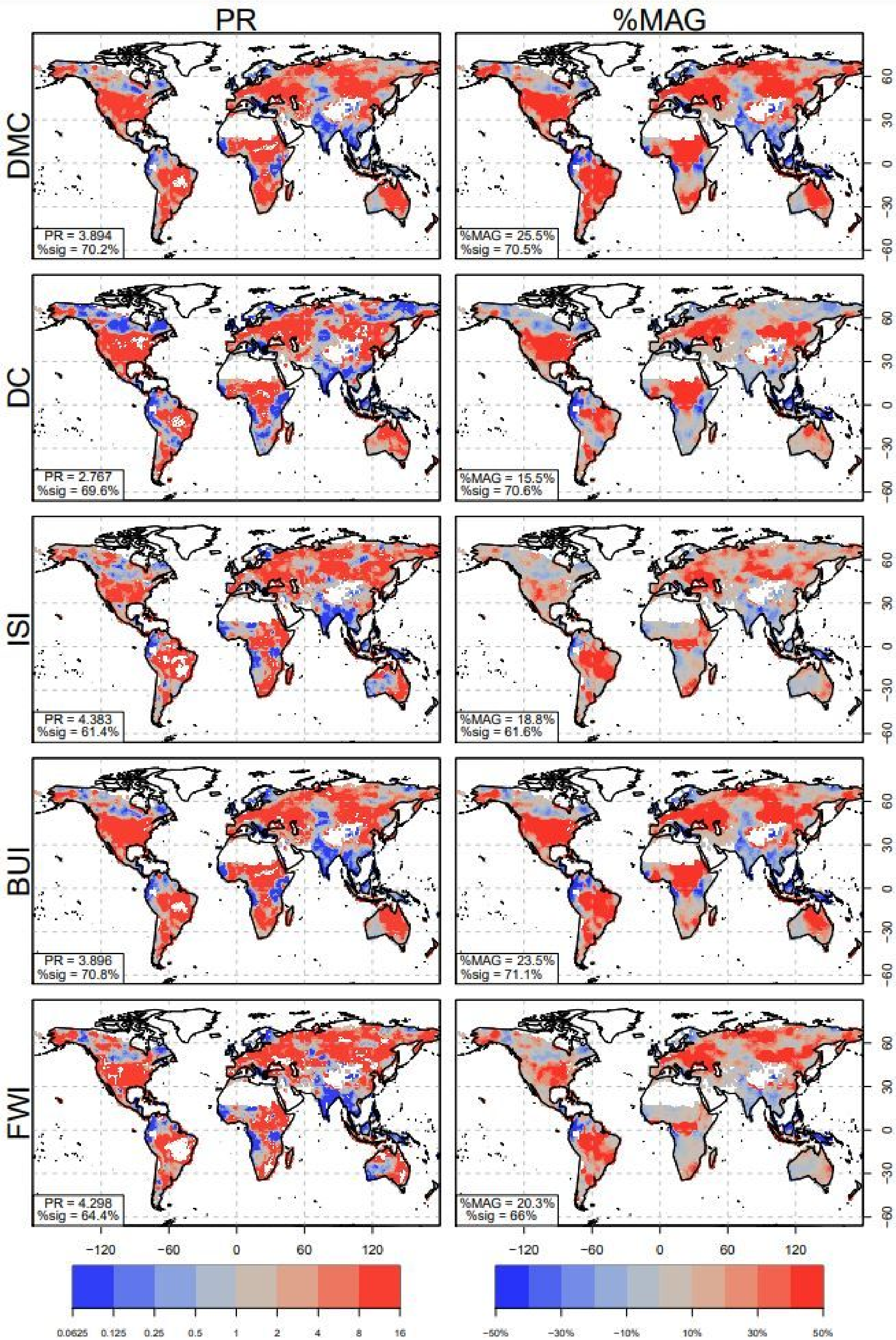


Figure 5

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 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.

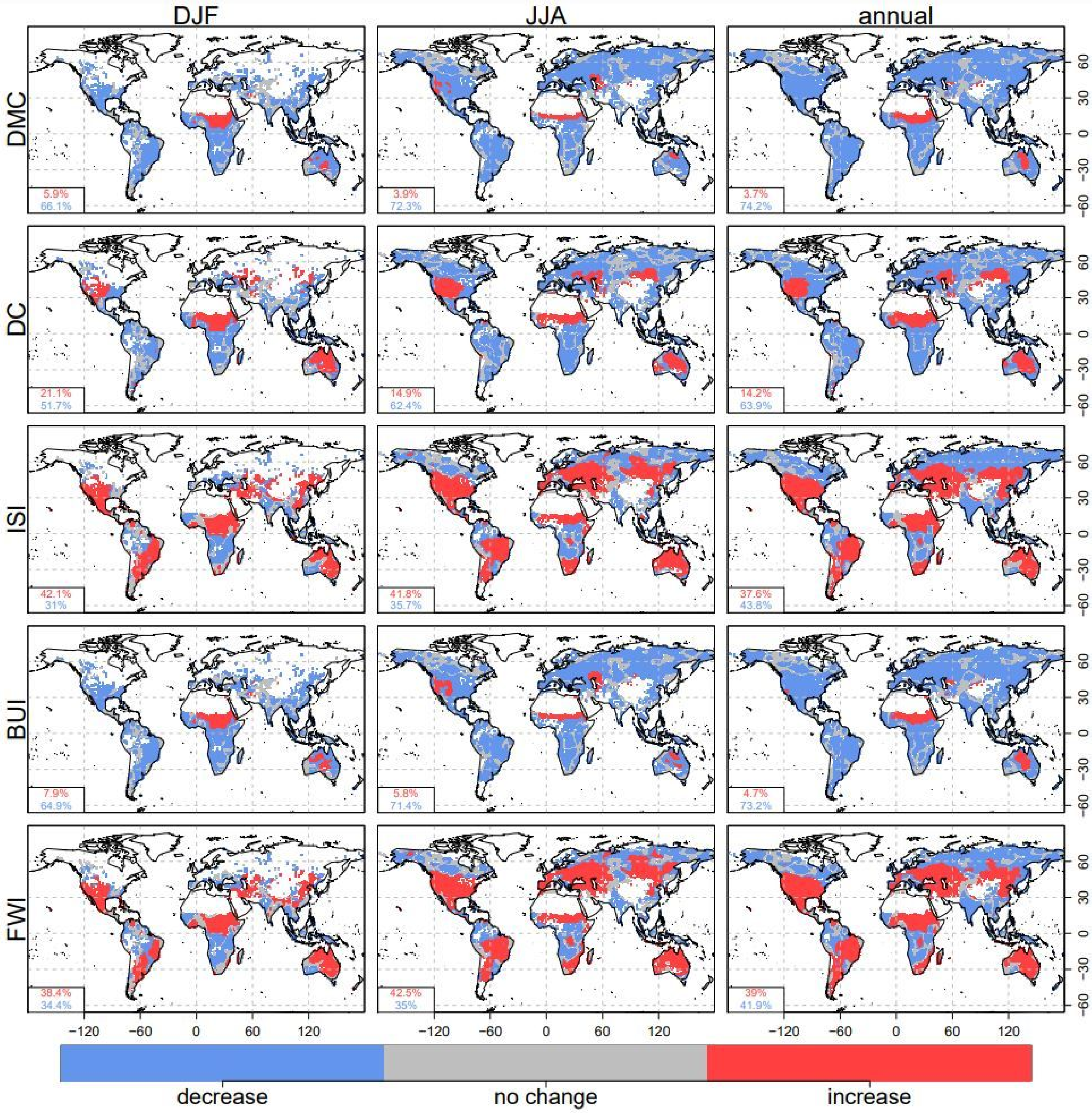


Figure 6

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 at the 95% confidence level.