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Special Section:
Fire in the Earth System

Global and Regional Trends and Drivers of Fire Under Climate Change

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Key Points:

- The frequency and severity of fire weather has increased in recent decades and is projected to escalate with each added increment of warming
- Fire weather is one of the major controls on fire activity, and is the dominant control on variability in burned area (BA) in many mesic forest ecoregions
- Various human and bioclimatic factors also control fire, modulating the relationship between BA and fire weather in many regions

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

Recent wildfire outbreaks around the world have prompted concern that climate change is increasing fire incidence, threatening human livelihood and biodiversity, and perpetuating climate change. Here, we review current understanding of the impacts of climate change on fire weather (weather conditions conducive to the ignition and spread of wildfires) and the consequences for regional fire activity as mediated by a range of other bioclimatic factors (including vegetation biogeography, productivity and lightning) and human factors (including ignition, suppression, and land use). Through supplemental analyses, we present a stocktake of regional trends in fire weather and burned area (BA) during recent decades, and we examine how fire activity relates to its bioclimatic and human drivers. Fire weather controls the annual timing of fires in most world regions and also drives inter-annual variability in BA in the Mediterranean, the Pacific US and high latitude forests. Increases in the frequency and extremity of fire weather have been globally pervasive due to climate change during 1979–2019, meaning that landscapes are primed to burn more frequently. Correspondingly, increases in BA of ~50% or higher have been seen in some extratropical forest ecoregions including in the Pacific US and high-latitude forests during 2001–2019, though interannual variability remains large in these regions. Nonetheless, other bioclimatic and human factors can override the relationship between BA and fire weather. For example, BA in savannahs relates more strongly to patterns of fuel production or to the fragmentation of naturally fire-prone landscapes by agriculture. Similarly, BA trends in tropical forests relate more strongly to deforestation rates and forest degradation than to changing fire weather. Overall, BA has reduced by 27% globally in the past two decades, due in large part to a decline in BA in African savannahs. According to climate models, the prevalence and extremity of fire weather has already emerged beyond its pre-industrial variability in the Mediterranean due to climate change, and emergence will become increasingly widespread at additional levels of warming. Moreover, several of the major wildfires experienced in recent years, including the Australian bushfires of 2019/2020, have occurred amidst fire weather conditions that were considerably more likely due to climate change. Current fire models incompletely reproduce the observed spatial patterns of BA based on their existing representations of the relationships between fire and its bioclimatic and human controls, and historical trends in BA also vary considerably across models. Advances in the observation of fire and understanding of its controlling factors are supporting the addition or optimization of a range of processes in models. Overall, climate change is exerting a pervasive upwards pressure on fire globally by increasing the frequency and intensity of fire weather, and this upwards pressure will escalate with each increment of global warming. Improvements to fire models and a better understanding of the interactions between climate, climate extremes, humans and fire are required to predict future fire activity and to mitigate against its consequences.

Plain Language Summary

In this review, with supplemental data analyses, we focus on the global and regional impacts of climate change on the frequency and intensity of fire weather (conditions conducive to fire ignition and spread) and the consequences for fire activity. We find that significant increases in fire

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weather have occurred in most world regions during recent decades due to climate change. Corresponding increases in the area burned by fires have been seen in some regions, most notably in mesic forests, however, in many regions fire is controlled by a range of other bioclimatic and human factors whose influences mediate or override those of fire weather. Weather conditions affecting vegetation growth and the build-up of fuels, the presence of human ignitions in regions that are not naturally fire-prone, and the fragmentation of fire-prone landscapes by agriculture are key examples of factors that can locally or regionally outweigh fire weather as controls on fire activity. Climate models project that fire weather will become increasingly frequent and intense under future warming, and at an increasing rate with each additional increment of warming. The outcomes for fire activity in future will depend on other regionally important factors that control fire ignition and spread. Existing fire models represent the controls on fire incompletely and so they reproduce observed patterns of fire with only limited success. Models also disagree on historical trends, leading to low confidence in their simulations of future fire activity. Various efforts to improve the representation of fire in models are underway and should yield greater capacity to predict the future of fire activity.

1. Introduction

Fire is a natural phenomenon in the Earth System that has shaped the landscape of many of Earth's biomes for millions of years (Archibald et al., 2013; Bond & Keeley, 2005; Bowman et al., 2009; He et al., 2019; Pausas & Keeley, 2009; Pausas et al., 2017; Shi et al., 2022). Fires burn around 3–5 million km^2 and emit around 8 billion tonnes of CO_2 to the atmosphere on average per year (Chuvieco et al., 2019; Giglio et al., 2018; van der Werf et al., 2017). These fire emissions, and the subsequent sequestration fluxes of around 7 billion tonnes of CO_2 per year resulting from post-fire vegetation recovery, are major fluxes in the carbon cycle (Lasslop et al., 2019; van der Werf et al., 2017; Yin et al., 2020; Yue et al., 2016; Zheng et al., 2021). Globally, fires reduce the quantity of carbon stored in vegetation by around 10% and is thus a major control on atmospheric CO_2 concentrations and climate (Lasslop, Hantson, Harrison, et al., 2020).

Fires are also involved in feedbacks to climate change mainly through their impacts on terrestrial carbon storage, however, they also influence the atmospheric concentration of reflective and absorptive aerosols and alter surface albedo through changes in vegetation cover (Chambers et al., 2005; E. A. Lyons et al., 2008; Harrison et al., 2018; Jin & Roy, 2005; Jones et al., 2019; Lasslop et al., 2019; Potter et al., 2020; Z. Liu et al., 2019; Zou et al., 2020). It has been estimated that climate-carbon cycle feedbacks involving fire cause a 6 ppm increase in atmospheric CO_2 concentration per degree of global mean annual surface temperature (MAT) warming (Harrison et al., 2018) and this positive feedback is only partially offset by the negative feedback associated with increases in surface albedo and reductions in temperature as forest cover reduces (Z. Liu et al., 2019).

The majority of fires do not present immediate risks to society and often contribute to ecosystem health, however, the Centre for Research on the Epidemiology of Disasters (CRED, 2021) estimates that wildfire events that were declared as disasters directly have killed at least 2,500 people, injured 10,500 people and displaced 175,000 people from their homes globally since 1990 (updated after Doerr and Santín (2016)). The economic costs of some fires can also be large. Notably, the total economic cost of the California wildfires in 2020 alone were estimated to be US$149 billion or 1.5% of the states' gross domestic product (GDP), including US$28 billion in capital losses, $32 billion in health costs and $89 billion through suppressed economic activity extending beyond California (Wang et al., 2021). Economists estimated that the Australian wildfires of 2019/2020 caused around US$75 billion losses or 6% of the country's GDP (Read & Denniss, 2020).

The cost of suppressing fires alone is substantial even in non-extreme years in some regions. For example, on average around US$500 million is spent annually on suppressing fires in Canada and around US$1–2 billion is spent in the US (Hope et al., 2016; Jolly et al., 2015; National Interagency Fire Center, 2020; Stocks & Martell, 2016; Tymstra et al., 2020). Fire impacts on society extend beyond their direct destructive force, with exposure to smoke contributing to over 300,000 premature deaths per year (Johnston et al., 2012) particularly in the tropics (Balmes, 2020; Reid et al., 2016). It is estimated that US$1.5 billion was spent treating adverse respiratory health issues due to the smoke emitted by 2019/2020 wildfires in Australia (F. H. Johnston et al., 2021).

The impact of fires on wildlife and ecosystems can also be profound. As a stark example, the Australian 2019/2020 wildfires impacted over 30% of the available habitat of 70 vertebrate species, including 21 endangered species

(Ward et al., 2020). Fire is also a key disturbance mechanism that can prompt change in land cover from forest to non-forest in regions where climate becomes out of phase with the existing vegetation, with various implications for biodiversity, carbon storage and other ecosystem services (Burrell et al., 2020, 2021; He et al., 2019; Hirota et al., 2011; Staver et al., 2011).

Although fires occur naturally and humans have used fire to their advantage for land management throughout the Holocene and even before (Bowman et al., 2009, 2020; Marlon et al., 2008, 2016; Power et al., 2008; Roebroeks et al., 2021), recent fire outbreaks in Amazonia, the Mediterranean, Siberia, southeast Australia, the western US, and Canada have highlighted the risks that fires pose to humans, biodiversity and carbon stocks. Events such as these have led to concern about the impact of climate change on fire activity in many regions (European Environment Agency, 2020; Huf & McLean, 2020; Joint Research Centre et al., 2020; Settele et al., 2014; United Nations Environment Programme, 2022; World Meteorological Organisation, 2021) and about the climate-carbon cycle feedbacks that may reinforce or accelerate climate perturbations (Harrison et al., 2018; Lasslop, Hantson, Harrison, et al., 2020; Lasslop et al., 2019; Pellegrini et al., 2018; Walker et al., 2019; Yin et al., 2020; Zou et al., 2020).

The coexistence and interaction of bioclimatic and human factors is a critical challenge to studying, understanding and communicating the impacts of climate change on fire activity (Abram et al., 2021; Bistinas et al., 2014; Doerr & Santín, 2016; Forkel, Dorigo, et al., 2019; Kelley et al., 2019). It can be difficult to disentangle the impacts of individual drivers on fire activity because fire is the result of the simultaneous occurrence of three factors: a stock of fuel; fire weather conditions that are sufficiently dry to desiccate the fuel; and a human or natural ignition source (Abram et al., 2021; Bistinas et al., 2014; Forkel, Dorigo, et al., 2019; Kelley et al., 2019; Pausas & Ribeiro, 2013; Teckentrup et al., 2019). This nexus of drivers and constraints on fire leads to debate about the causes of major wildfire events and the contributions of bioclimatic and human factors to those events.

Here, we review current understanding of the relationship between fire and climate, with special consideration of the modulating influence of other bioclimatic and human factors that exert important controls on fire activity by influencing the nexus of fuel stocks, fuel dryness and ignitions. Other climatic factors include lightning activity, the primary natural source of ignitions, while other bioclimatic factors include biomass productivity which is a function of climate, natural disturbance regime and land use. Other human factors include the active and pre-emptive suppression of fires, unintended and arson ignitions, and land management affecting connectivity of fuels across natural landscapes.

While our goal was to comprehensively synthesize and review relevant studies published in recent decades, we note that over 8,885 studies published since 1990 matched a combination of the keywords that we consider most relevant to this review ("fire" AND "climate" AND ["population" OR "agriculture" OR "land management" OR "lightning" OR "vegetation" OR "biomass"]), according to the Web of Science (webofknowledge.com; 10th April 2022). A total 75% of all studies were published in the past decade and 50% of all studies were published since 2015, highlighting that the pace of publication on this topic has accelerated and highlights a need for a stocktake of the knowledge generated by this enormous volume of literature.

As well as reviewing the literature, we also report on trends in observed and modeled burned area (BA) and fire weather (weather conditions conducive to the ignition and spread of wildfires) based on published Earth Observation data sets, model simulations and methods (Abatzoglou et al., 2019; Giglio et al., 2018; Jolly et al., 2015; Teckentrup et al., 2019; see Text A in Supporting Information S1 for methods). We further assess relationships between BA and fire weather and a range of other bioclimatic and human controls (Abatzoglou et al., 2018; Andela et al., 2017; Cecil et al., 2014; Spawn et al., 2020). Correlations between BA and each bioclimatic or human control can give valuable insights into the direction and relative strength of the effect of each variable on BA and are used here to highlight regional patterns in the relationship between fire and its controlling factors. However, we note that correlation is not equivalent to causation. Indeed, BA typically correlates with multiple controlling factors and, overall, a spatially varying mixture of factors tend to interact to dictate spatial and temporal patterns of fire rather than a single factor in isolation (Forkel et al., 2017; Kelley et al., 2019).

Our analyses are applied to consistent world regions, allowing the regional results of previously published analyses to be related across compatible domains. Specifically, we performed all analyses on three regional layers (Figure 1): first, for each of 14 macroregions used by the Global Fire Emissions Database (GFED; Giglio, 2006; van der Werf et al., 2006); second, for 10 biogeographical focus ecoregions selected from Olson et al. (2001), and;

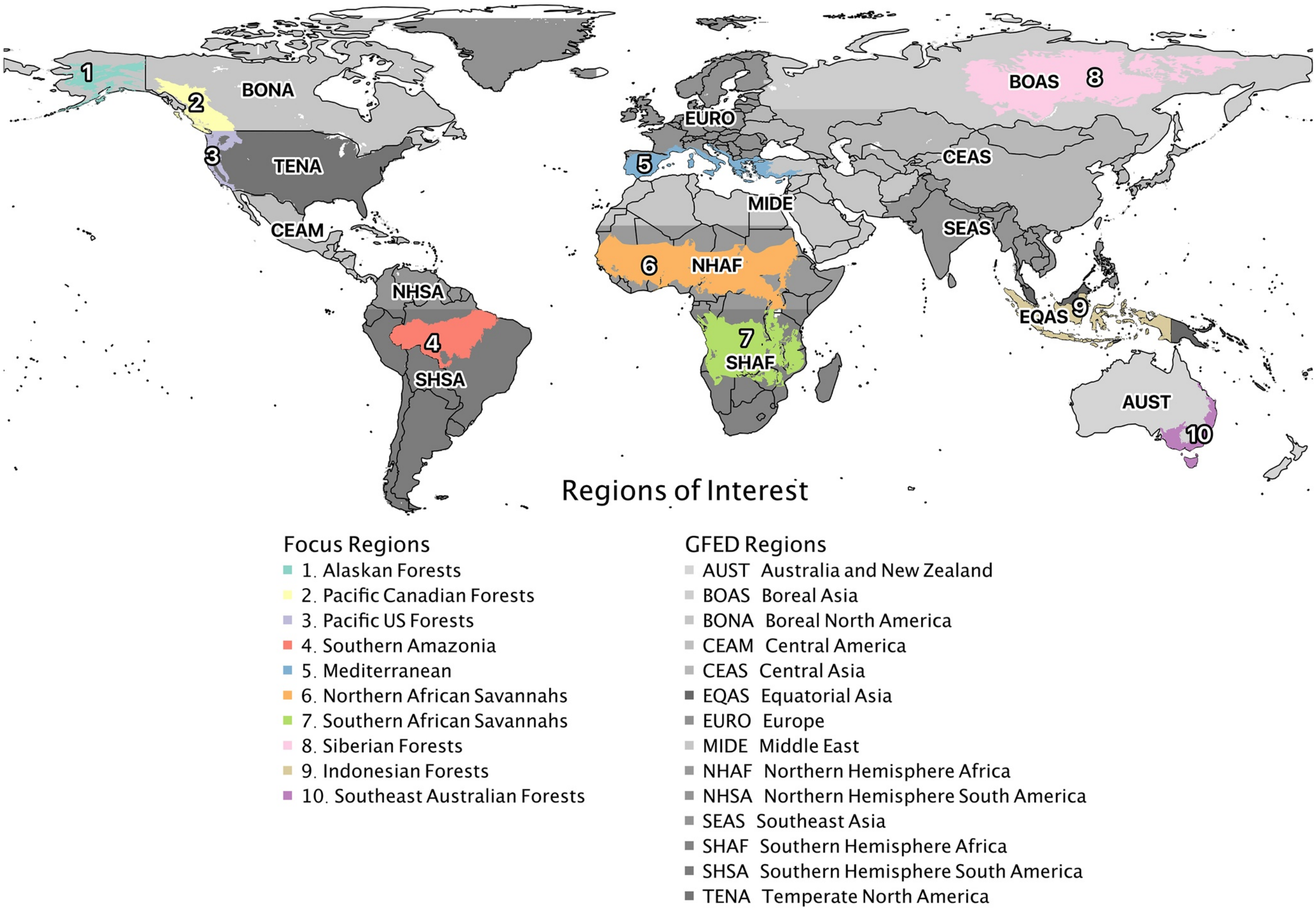

Figure 1. Map of the regions used in our study including Global Fire Emissions Database macroregions (shades of gray) (van der Werf et al., 2006), focus ecoregions (colored and numbered) (Olson et al., 2001), and countries (outlined) (EU GISCO, 2020). Results and statistics are provided in Data Set S1 for all regions shown.

third, for countries (EU GISCO, 2020). Our methods are described in Text A in Supporting Information S1, and the results for all regions are provided in Data Set S1 (see Text B in Supporting Information S1 for a summary of the data set).

We begin by summarizing the key technological advances and conceptual foundations that have facilitated important leaps in the understanding of the patterns, trends and controls on fire during recent decades (Section 2). In Section 3, we describe global and regional changes in fire weather and BA observed in recent decades, as well as the strength of the relationship between variability in fire weather and BA. In Section 4, we discuss the relationship between fire activity and other bioclimatic controls including vegetation productivity and lightning ignitions globally and across regions. In Section 5, we consider the influence of in situ human activities on global patterns of fire through their impact on ignitions, their use of fire as a tool of agriculture, land stewardship, and deforestation, and their direct and indirect suppression of fire through firefighting and fragmentation of natural landscapes. Sections 4 and 5 highlight the regional nuances surrounding the relationship between climate and fire activity, which arise because vegetation productivity, natural and human ignition opportunities, and human impacts on land cover and fragmentation strongly modulate the relationship between BA and fire weather. In Section 6, we focus on historical and projected changes in fire weather and review the current capacity of fire models to reproduce historical trends and patterns of BA, and in Section 7, we highlight key opportunities to bolster the existing model capacity over the coming years.

2. Technological Advances and Conceptual Foundations of Fire Science

2.1. Expansion of Earth Observations

One of the most critical advances in fire science in recent decades has been the development of operational satellite products that detect BA and active fires, particularly since the late 2000s (Chuvieco et al., 2020; Giglio & Roy, 2020; Roy et al., 2019; Wooster et al., 2021). Satellite observations of fire commenced in the 1970s and, since the 1980s, the NOAA advanced very-high-resolution radiometer has been used to generate fire products with variable success (Giglio & Roy, 2020). Systematic global fire products based on the NASA moderate resolution imaging spectroradiometer (MODIS) sensors with dedicated fire monitoring capabilities commenced in the early 2000s (Justice et al., 2002) and have been refined through time (Chuvieco et al., 2018; Giglio et al., 2018). Other early fire products were based on the Along Track Scanning Radiometer sensor (Arino et al., 2012; Simon, 2004). In addition, National or jurisdictional fire databases, such as those from forestry services, have often been used to reconstruct fire history, however, these have important limitations for global-scale research questions, not least their partial spatial coverage (Mouillot & Field, 2005). They are not available for all countries or regions, they are derived by different methods in different countries, their quality falls with antecedence, and they tend to include only a subset of fire types (Bowman et al., 2009; Giglio, Descloitres, et al., 2003; Mouillot & Field, 2005).

Two strategies are predominantly employed in algorithms designed to detect fires in satellite observations. In the first, BA is mapped according to temporal changes to the spectral signature of fire-affected land surfaces between consecutive satellite images (Boschetti et al., 2004; Giglio et al., 2018; Roy et al., 2005, 2008; Simon, 2004). In the second, active fires are detected according to satellite retrievals of the energy released from fires in the infrared wavelengths (Dwyer et al., 2000; Giglio, Kendall, et al., 2003; Giglio et al., 2016, 2009; Mota et al., 2006; Randerson et al., 2012; Schultz, 2002), with the added benefit that the day-to-day progression can be tracked due to the high frequency of active fire observations (Andela et al., 2019). The intensity and severity of fires, typically referring to energy release and the quantity of biomass consumed, respectively, can also be estimated from satellite observations of radiative energy release from the fire or through changes in spectral ratios across the optical-to-infrared spectrum (Chuvieco et al., 2020; Keeley, 2009; Laurent et al., 2018; Roy et al., 2006; Schroeder et al., 2010).

Satellite products that are purely based on BA detection have historically omitted many small fires that occur below the ~500 m spatial resolution of the satellite data, and consequently they provide a conservative estimate of BA (Chuvieco et al., 2018; Giglio et al., 2010, 2016; Hall et al., 2016; Hawbaker et al., 2017; Ramo et al., 2021; Randerson et al., 2012; Roteta et al., 2019). The latest BA products are addressing this issue by merging active fire detections with BA detections to correct for small fires that are not detected through spectral changes (Chuvieco et al., 2018; Giglio et al., 2018; Roy et al., 2019; van der Werf et al., 2017). Observations from radar sensors are also increasingly employed alongside optical sensors to assist in the detection of fires, including under forest canopies (Belenguer-Plomer et al., 2019; Mathieu et al., 2019). The present is a period of transition to higher resolution (below ~30 m) satellite imagery from a variety of sensors, including Landsat-8 and Sentinel-2, which are increasingly being harnessed to detect small fires based on spectral changes (Coops et al., 2018; Goodwin & Collett, 2014; Hawbaker et al., 2017; Ramo et al., 2021; Roteta et al., 2019, 2021; Roy et al., 2019; Verhegghen et al., 2016; White et al., 2017). For example, Roy et al. (2019) demonstrated that algorithms applied to Landsat-8 and Sentinel-2 captured a greater BA and more detail about the size distribution of fires than a MODIS BA product, and that improvements in detectability vary seasonally depending on the timing of specific fire types.

While the ongoing developments to global BA detection products are helping to overcome or lessen historical challenges with the global detection of fires, especially small fires, a variety of limitations remain (Chuvieco et al., 2019). For example, clouds and smoke can obscure the land surface during sequential satellite overpasses, presenting a persistent challenge to the detection of spectral changes or thermal hotspots by the satellite sensors. BA products based on different satellite sensors, methods, and algorithms also span different time periods, all of them relatively short, and inconsistencies can prevent a robust merging of multiple products (Giglio & Roy, 2020; Otón et al., 2021). Moreover, the accuracy of BA products is known to vary across land covers such that trends and variability in BA can be assessed with greater confidence in some regions than others. Detections made by moderate-resolution global BA data sets such as MODIS have been evaluated for omission errors (false-negatives) and commission errors (false-positives), albeit not uniformly across the globe. Targeted evaluations have been conducted in specific regions (e.g., Chuvieco et al., 2008; D. Cheng et al., 2013; Hall et al., 2016; Libonati et al., 2015; Roy & Boschetti, 2009; Vetrita et al., 2021) and some global studies have evaluated the accuracy of MODIS BA detections using a stratified random sampling approach to select fires in a manner that equitably represents biomes and seasons (Boschetti et al., 2016, 2019; Padilla et al., 2014, 2015, 2017). For example, Boschetti et al. (2019) evaluated the MODIS BA product MCD64A1 and estimated commission and omission errors to be 40% and 73%, respectively, at the global scale. The lowest errors were observed in the boreal forest biome where fires tend to be relatively large and long, and highest errors were observed in the tropical and temperate forests and Mediterranean biomes where small cropland fires, which tend to be underdetected, are common. Other products show differences in global and regional accuracy, while many of the higher-resolution BA products that have emerged in recent years are yet to be the subject of the most intensive validation protocols (Roy et al., 2019).

Overall, despite the known limitations to accuracy and inconsistencies across products, satellite BA products have built a valuable global picture of fire activity at increasingly detailed resolution, which could not have been achieved through incomplete national or regional inventories of fire activity. This new capacity has transformed the study of fire's occurrence, patterns, trends and controls (Andela et al., 2017, 2019; Archibald et al., 2009; Forkel, Andela, et al., 2019; Forkel, Dorigo, et al., 2019; Kelley et al., 2019; Y. Chen et al., 2017).

Here, we use satellite observations of BA based on the MODIS BA data (MCD64A1; Giglio et al., 2018) to illustrate the global distribution of fire and examine how fire occurrence has been changing regionally over recent decades (see Text A in Supporting Information S1 for methods).

2.2. Indexing the Climatic Controls on Landscape Flammability

Alongside developments in fire observation, the ability to assess how weather conditions influence the probability of fire has been growing, with attention mostly focusing on how changes in multiple weather and climate variables affect fire risk by altering the frequency of fire-prone weather conditions. Weather observations have become richly available during recent decades at the global scale and have underpinned the development of several meteorological reanalyzes, which combine observations from a variety of sources in a way that conserves the integrity of the physical laws embodied within atmospheric models (Dee et al., 2011; Gelaro et al., 2017; Hersbach et al., 2020; Kobayashi et al., 2015; Saha et al., 2014).

For historical and future centuries, state-of-the-art climate models which contribute to the coupled model intercomparison project (CMIP) provide the output variables required to assess climate change impacts on the frequency of fire-prone weather conditions (Abatzoglou et al., 2019; Eyring et al., 2016; Meehl et al., 2009; Taylor et al., 2012). These climate models are driven by historical observations of atmospheric composition including CO_2 concentration. For the future period, the climate models are driven by a variety of Special Report on Emissions Scenarios (SRES) or representative concentration pathways (RCPs), which prescribe the effect of plausible emission scenarios on atmospheric composition (Meinshausen et al., 2011), or by shared socioeconomic pathways which represent plausible emissions trajectories that influence atmospheric composition within the models (Riahi et al., 2017).

Many indices of "fire weather" or "fire danger" have been devised and applied to observations from meteorological stations and reanalysis data sets, with each index seeking to "rate" the combined effects of multiple weather variables on the flammability of the landscape (Jolly et al., 2015). Fire weather conceptually refers to the contemporaneous influence of temperature, precipitation, humidity, and wind on vegetation dryness (Bedia et al., 2015; Field et al., 2015; Jolly et al., 2015; M. D. Flannigan et al., 2009, 2016). Fire weather or fire danger rating systems predominantly rely on inputs of meteorological variables and occasionally soil moisture to represent the contemporaneous and interacting influences of weather on vegetation flammability (Abatzoglou et al., 2018; Abatzoglou & Kolden, 2013; Bedia et al., 2015; de Groot et al., 2013; Field et al., 2015; M. D. Flannigan et al., 2005). They may also account for some lagged impacts of precipitation in recent days to weeks to inform vegetation moisture levels, although fuel (vegetation) load itself is not usually considered.

Many indices of fire weather have been formulated and prominent examples include the Canadian Fire Weather Index (FWI; Van Wagner, 1987), Australian McArthur Forest Fire Danger Index (Noble et al., 1980), US National Fire-Danger Rating System (Bradshaw et al., 1984), Swedish Angstrom Index (Chandler et al., 1983) and Nesterov Index (used in parts of Europe and Russia; Nesterov, 1949). These indices have origins in operational fire management and were typically developed by national agencies to assess daily fire risks and inform resource requirements. The Canadian FWI and its sub-components, such as its drought code or fuel moisture codes, have been employed particularly widely to study the influence of weather conditions on vegetation flammability and fire risk in many regions of the world (Abatzoglou et al., 2018; Bedia et al., 2015; Field et al., 2015; M. D. Flannigan et al., 2005, 2009, 2016). Vapor pressure deficit (VPD) is conceptually aligned with fuel moisture codes in that it focuses on the impact of atmospheric dryness on vegetation moisture levels (Williams et al., 2019).

Since fire weather indices chiefly account for the contemporaneous meteorological controls on fire risk, they give greatest insight into the likelihood of fire in regions where fire is limited by fuel dryness (Abatzoglou et al., 2018; Bedia et al., 2015), as opposed to those regions where fire is limited by fuel productivity (Archibald et al., 2009; Boer et al., 2016; Kelley et al., 2019). Within and before a fire season, prolonged moisture deficits or droughts during preceding months and seasons can reduce soil moisture reserves and make vegetation less resilient to peaks in fire weather (Abatzoglou & Kolden, 2013; Abatzoglou et al., 2018; Abram et al., 2021). Consequently, adaptations have been proposed to account for the compounding effects of contemporaneous fire weather and longer-term antecedent conditions on fire ignition and spread (McElhinny et al., 2020).

Increases in fire weather represent an increase in the likelihood of fire if fuels are available, with drier, hotter, windier, and less humid conditions priming vegetation to burn. Shifts toward a warmer and more drought-prone climate can act as a key driver of increase in the likelihood of fire, at least up to the point where the system becomes productivity-limited. The Intergovernmental Panel on Climate Change (IPCC) has identified several climate trends that could promote the increasing frequency or extremity of fire weather (Fischer et al., 2021; Jia et al., 2019; Settele et al., 2014): global increases in mean annual surface air temperature (MAT); global increases in the frequency and intensity of heatwaves, and; regional increases in the frequency and intensity of droughts. Consequently, the potential for climate change to influence fire activity by increasing the frequency and severity of fire weather has been investigated using observations and climate models (Abatzoglou et al., 2019; Bedia et al., 2015; Burton et al., 2018; Jain et al., 2017; Jolly et al., 2015; M. D. Flannigan et al., 2005).

Here, we examine past and future change in fire weather on regional scales by exploring some of the available observations of FWI from the ERA5 meteorological data set (1979–2019; Hersbach et al., 2020; Vitolo et al., 2020) and an ensemble of 17 climate models (Abatzoglou et al., 2019; see Text A in Supporting Information S1 for methods).

2.3. Conceptualizing the Bioclimatic Interactions Between Climate, Vegetation, and Fire

A key concept that has emerged in recent decades is that the world's ecoregions can be arranged along a climatic gradient of productivity-dryness that determines the key limitations on fire (Archibald et al., 2009; Kelley et al., 2019; Parisien & Moritz, 2009; Pausas & Keeley, 2009; Pausas & Ribeiro, 2013). This is because, in the presence of ample ignition sources, fires depend on both weather conditions conducive to fuel dryness *and* sufficient vegetation stocks available to burn. Consequently, fire occurs most frequently in regions with intermediate moisture availability, where dry conditions are sufficiently frequent to intermittently desiccate the available vegetation but not consistently dry enough to limit fuel production. On the other hand, fire is a less common phenomenon in consistently wet/humid regions where vegetation is often highly productive but also infrequently affected by drought, and also in consistently dry regions where climatic conditions inhibit the accumulation of fuels. Hence, fire occurrence is determined by a delicate balance between vegetation productivity (fuel production) and the frequency of dry conditions (fuel moisture).

On evolutionary timescales, climate and fire have shaped the biogeographical distribution of ecoregions, and the vegetation of different ecoregions bears various traits and employs survival strategies that influence the flammability of the landscape (Archibald et al., 2013; Bond & Keeley, 2005; Bowman et al., 2009; Harrison et al., 2021; He et al., 2019; Pausas & Ribeiro, 2013; Pausas et al., 2017; Rogers et al., 2015). Meanwhile, variability in weather on interannual and sub-decadal timescales influences vegetation productivity and moisture levels on shorter timescales, thus determining the availability and dryness of fuels during any particular fire season (Alvarado et al., 2020; Forkel et al., 2017; Kelley et al., 2019; Y. Chen et al., 2017).

Operating on decadal to centennial timescales, climate change is shifting the global climate zones and affecting both fire weather frequency and the productivity and biogeography of vegetation (Keenan et al., 2014; Piao et al., 2020; Sitch et al., 2015). Hence, the impact of climate change on fire activity is complicated because increases in fire weather can be either compounded or countered by changes in vegetation productivity. Moreover, trends in atmospheric CO_2 and land use change also influence vegetation cover, productivity and connectivity and thus modulate the response of vegetation productivity to climate. The overall effect of changes in climate and CO_2 has been to increase biomass in many high latitude ecoregions (Berner et al., 2020; Bistinas et al., 2014; C. Chen et al., 2019; Forkel et al., 2016; Jong et al., 2012; Piao et al., 2020; Zhu et al., 2016), whereas the combination of global changes in CO_2 concentration, climate change and land use has elsewhere caused complex and regionalised changes in vegetation productivity and biomass storage (Burrell et al., 2020; D'Odorico et al., 2013; Fensholt et al., 2012; Jong et al., 2012; Park et al., 2018; Sherwood & Fu, 2014).

Here, we use a harmonized data set of aboveground carbon stocks (Spawn et al., 2020) to explore the relationships between BA and tree biomass, non-tree biomass and total biomass with a particular focus on the effects of vegetation biogeography (see Text A in Supporting Information S1).

2.4. Improvements to the Observation and Modeling of Lightning Ignitions

The routine observation of lightning activity by satellites and networks of ground sensors are beginning to enable a more detailed understanding of the role of lightning activity as a driver of fire (Cecil et al., 2014; Christian, 2003; Styger et al., 2018; Veraverbeke et al., 2017; Y. Chen et al., 2021). Lightning is the dominant natural cause of fire ignitions and a particularly important ignition source for fires in regions of low human impact (Abatzoglou et al., 2016; Balch et al., 2017; Stocks et al., 2002; Veraverbeke et al., 2017). Electrification of the atmosphere occurs when charged ice and graupel particles collide in clouds, and rates of such collisions are determined by atmospheric weather conditions, including some that are affected by climate trends (Finney et al., 2018; Romps, 2019). Temperature, pressure and humidity all influence in-cloud convection, the vertical movement of particles and the rates of collision between charged ice and graupel particles (Latham et al., 2007).

The relationship between lightning activity and climate has been investigated through its relationship with convective available potential energy (CAPE; a measure of the buoyancy force required for uplift of air masses in the atmosphere; Romps, 2019; Romps et al., 2014; Tippett et al., 2019), convective fluxes of ice in clouds (Finney et al., 2014, 2018), or the intensity of in-cloud updrafts as determined by convective cloud top height (C. Price & Rind, 1992, 1994). Increases in atmospheric temperature both enhance rates of convection and suppress the formation of cloud ice, and these complexities mean that the impact of rising temperature on electrification of the atmosphere is currently unclear and model-dependent (Finney et al., 2018; Romps, 2019).

Lightning occurs in an instant that is challenging to predict. Moreover, the ignition efficiency of lightning strikes can vary strongly in space and time because other controls such as fire weather influence the flammability and receptiveness of vegetation (M. D. Flannigan & Wotton, 1991; Krawchuk et al., 2009; Sedano & Randerson, 2014; Wierzchowski et al., 2002). Distinct ignition behavior is shown by lightning that is accompanied by precipitation at ground level ("wet lightning") and lightning that is not accompanied by precipitation ("dry lightning"), the latter of which occurs because falling droplets evaporate before reaching ground level (Dowdy & Mills, 2012; Nash & Johnson, 1996; Rorig & Ferguson, 2002; Perez-Invernon et al., 2021). Precipitation that accompanies wet lightning can suppress the ignition and spread of fire by increasing the moisture content of the vegetation. Hence, dry lightning that strikes a fuel bed that has dried under fire weather conditions can result in widespread ignitions (Rorig & Ferguson, 2002). The highly stochastic nature of lightning ignitions presents major challenges for fire prediction and severely inhibits the management of wildfires in remote regions.

Nonetheless, the availability of lightning strike observations has been growing rapidly in recent years and is helping to build a better understanding of patterns and trends in lightning. Lightning emits radio energy at very low frequencies that are increasingly observable thanks to the expansion of networks of ground sensors and to the launch of satellites. Networks of ground sensors have been in place for several decades in some countries, including Canada and the US (Orville et al., 2002), and various products are now available globally (Abarca et al., 2010; Holzworth et al., 2021; Kaplan & Lau, 2021; Orville, 2008; Rodger et al., 2006; Said et al., 2010; S. D. Rudlosky & Shea, 2013; S. D. Rudlosky et al., 2017; S. Rudlosky, 2015; Virts et al., 2013). In addition, several orbiting and geostationary satellites are fitted with lightning sensors, providing good coverage of the Americas and global tropics (Blakeslee et al., 2020; Cecil et al., 2014; Goodman et al., 2013; S. D. Rudlosky et al., 2019). The short time series of lightning detections has historically limited analyses of fire ignition rates in many regions to the past decade. Nonetheless, the observational time series has grown in recent years and is now sufficient to reveal increases in lightning activity as the climate warms in some regions, including the Arctic (Holzworth et al., 2021).

Here, we use a prominent climatological data set of lightning activity, which is based on satellite observations (Cecil et al., 2014), to explore the seasonal relationship between BA and lightning activity at the global scale (see Text A in Supporting Information S1 for methods).

2.5. Understanding Complex Human-Fire Relationships and Their Historical Origins

Contemporary human fire ignition patterns must be understood, at least in part, as the product of regional history. The practices of fire use by Indigenous civilizations continue to influence human uses of fire in the modern period, although they have been variably modified or superseded by colonial attitudes toward fire management. There is substantial evidence that Indigenous and traditional burning of landscapes was widespread on every continent except Antarctica, and particularly in subtropical, Mediterranean, and temperate semi-arid biomes, prior to the onset of colonialism (Trauernicht et al., 2015). Indigenous peoples used landscape and cultural fire intentionally for a wide range of purposes. Highly localized, small-scale fire use facilitated communication and increased abundance of culturally important plants and the production of food, fiber, and medicines, while broader landscape application of fire supported hunting, crop cultivation, land clearing, maintenance of travel routes, and reduced risk of wildfires around communities (Kimmerer & Lake, 2001). Meta-analyses of Indigenous fire use make clear that many groups globally viewed and understood complex ecosystems holistically, and used fire in myriad ways to achieve sustainability and resilience (Trauernicht et al., 2015).

Over the past 500 years, European colonialism in North and South America, Australia, and southern Africa brought vast changes to traditional land practices, including a dramatic reduction in or outright banning of Indigenous fire practices across colonial states, widespread grazing, and the spread of intensive agriculture that fragmented natural landscapes (Klein Goldewijk et al., 2011; Marlon et al., 2008). The loss of regular application of fire in many ecosystems that evolved with it has had wide-ranging consequences for contemporary societies, and these consequences have been compounded by land use practices and anthropogenic climate change. Concurrent to the reduction of Indigenous and traditional fire use, the forces of globalization introduced fire to facilitate deforestation and agriculture in regions where landscape fire was rare prior to colonization, such as in Amazonia and other tropical rainforests (Bowman et al., 2011).

Arguably, the role of humans is the greatest source of complexity in our understanding and model representation of modern fire patterns (Ford et al., 2021). Human relationships with fire are as long as human history itself, and they are also regionally complex due to the diverse regional histories of controlling and using fire (Bowman et al., 2011). Humans ignite landscape fires intentionally for the purpose of land use change (chiefly deforestation) and land management, as well as through arson and unwanted ignitions such as escape of controlled fires and accidents. Elsewhere, humans reduce fire activity through active fire suppression or preemptive fuel management, and also indirectly by excluding fires from managed areas, urbanization, and by modifying the density and connectivity of landscape fuels through land use (Andela et al., 2017; Arora & Melton, 2018; Bowman et al., 2017; Doerr & Santín, 2016; Lasslop & Kloster, 2017). Human activities do not only affect the spatial patterns of fire but also the interannual variability. For example, interannual variability in BA tends to increase with economic development especially in the tropics (Chuvieco et al., 2021).

Much of the unexplained variability in fire-climate relationships and predictive models stems from the patterns and (un)predictability of human relationships with fire, and how they have diverged over time (Ford et al., 2021). Hence, it is increasingly appreciated that more must be done to represent human-fire relationships with quantitative variables that have potential to aid diagnostic models of fire activity and to be implemented within predictive models of future fire activity (Bowman et al., 2009; Ford et al., 2021; Forkel et al., 2017; Glikson, 2013; Kelley et al., 2019; Lasslop & Kloster, 2017; Pechony & Shindell, 2009).

Here, we assess correlations between BA and population density following Andela et al. (2017) and average these correlations within world regions (see Text A in Supporting Information S1 for methods).

2.6. Representing Complex and Interacting Controls on Fire in Global Models

The growing availability of Earth observation data and understanding of the multiple controls on fire have enabled the development of empirical fire models and improvements to the representation of fire in process-based models, such as those used in dynamic global vegetation models (DGVMs) and Earth System models

(ESMs). These models have already been used for global-scale simulation of historical trends in fire activity (Arora & Melton, 2018; Kloster & Lasslop, 2017; Knorr et al., 2016; Teckentrup et al., 2019), and in few cases for future periods (Kloster & Lasslop, 2017; Knorr et al., 2016). A key limitation to the application of both empirical and process-based models is that their reliability is unclear when extrapolated far outside the limited range (∼2 decades) of direct observational data used to parameterize and evaluate them.

A range of empirical models have been developed to relate fire activity to its drivers and constraints (Hantson et al., 2016). Thonicke et al. (2001) introduced an empirical model (GlobFIRM) which predicted BA as a function of fine fuel moisture, without explicitly accounting for the presence or absence of ignition sources. Later models introduced human ignitions and suppression of fire as functions of population density and replaced fine fuel moisture with VPD or precipitation indices as the key climatological determinant of fire's likelihood (Pechony & Shindell, 2009, 2010), which have carried through to later models (e.g., the INFERNO model; Mangeon et al., 2016). Knorr et al. (2014) introduced another model whereby BA was predicted as a function of weather variables, vegetation properties and population density. Many other empirical models, constructed on global or regional scales, show promise in reproducing observed patterns and variability in BA based on similar input data (Archibald et al., 2009; Balshi et al., 2009; Forkel et al., 2017; Huang et al., 2015; Krawchuk et al., 2009; Moritz et al., 2012; Turco, Jerez, et al., 2018).

Empirical models trained on observational data have been used in a standalone fashion to predict fire activity under predicted changes in climate (Archibald et al., 2009; Balshi et al., 2009; Krawchuk et al., 2009; Moritz et al., 2012; Pechony & Shindell, 2010; Turco, Rosa-Cánovas, et al., 2018; Turco et al., 2014). Most empirical fire models use pre-defined predictor variables and functional relationships to simulate fire activity and hence reflect the current understanding of the controls of fire activity. Alternative approaches based on machine learning models allow the use of a variety of potential climate, vegetation, and human-related predictors and hence to quantify the importance of the various controls on fire activity (Archibald et al., 2009; Forkel, Andela, et al., 2019; Forkel et al., 2017). Empirical fire models often outperform process-based fire models in reproducing observed patterns and dynamics of fire activity because they have been trained against observational data, although their reliability is unclear when extrapolating outside the range of the training data. The majority of empirical fire models simulate only one target variable (e.g., BA) and do not synchronously simulate fire size, intensity and severity which are important to accurately simulate fire effects on atmospheric composition and ecosystem dynamics. Additionally, a limitation of stand-alone empirical models is that they omit transient vegetation responses to changes in CO_2 and climate, such that they have limited potential to represent important interactions and feedbacks to climate change in their simulations of fire activity (Hantson et al., 2016; Harrison et al., 2018; Lasslop et al., 2019; Rabin et al., 2017; Williams & Abatzoglou, 2016).

In process-based fire models, both the ignition and spread of fires is modeled mechanistically as well as the emission of carbon through fuel combustion (Hantson et al., 2016). Lenihan et al. (1998) introduced a model (MCFIRE) that simulates the ignition of fire as a function of drought conditions tied to fine fuel moisture and also the spread of fire from the point of ignition (Lenihan & Bachelet, 2015; Rogers et al., 2011). Venevsky et al. (2002) also introduced a model (RegFIRM) that simulates fire count as a function of the Nesterov FWI and fire spread as a function of wind and fuel bed conditions, which has since been adapted to better represent ignition sources (Arora & Boer, 2005; Arora & Melton, 2018; Melton & Arora, 2016) and suppression (Li et al., 2013). Thonicke et al. (2010) built on RegFIRM in their development of the SPITFIRE model, which has been further developed to include lightning and human ignitions in a variety of ways (Kelley et al., 2014; Le Page et al., 2014, 2015; Pfeiffer et al., 2013; Prentice et al., 2011). In additional model developments, emphasis has been placed on better representing fire processes associated with land use change (Kloster et al., 2010; Li et al., 2013). Diverse process-based models are now in existence with many sharing or inheriting elements from earlier models (Hantson et al., 2016). Overall, the process-based models provide a range of representations of the physical processes of fire ignition, spread and other fire dynamics with parameter values that lie within the current boundaries of process understanding.

Both empirical and process-based models have been employed within a range of DGVMs (Hantson et al., 2016, 2020; Lasslop et al., 2019; Teckentrup et al., 2019), which are the terrestrial component of the ESMs used for climate simulation. Nonetheless, most ESMs that contributed to the climate model intercomparison project's fifth (CMIP5; Kloster & Lasslop, 2017; Taylor et al., 2012) and sixth phases (CMIP6; Eyring et al., 2016; Lasslop, Hantson, Brovkin, et al., 2020), and which supported the IPCC's fifth assessment report on climate change impacts (Settele et al., 2014), have excluded fire processes. ESMs that have included fire processes were found to reproduce satellite observations of BA poorly. Indeed, Kloster and Lasslop (2017) concluded that "fire occurrence is poorly represented in ESMs that participated in CMIP5 and that there is no consensus on how fire occurrence changed over the past and might change in the future." The development of the fire models used in CMIP5 was broadly completed before globally consistent BA data sets based on satellite observations became available, and hence fire models may have been trained on outdated or incomplete (regional) observations. In addition, the development of the fire components of the DGVMs used in CMIP5 models also preceded many of the key developments in fire modeling discussed above, in particular excluding key improvements to the representation of human ignitions and suppression. Given the poor performance of the CMIP5 models against satellite observations of BA, the IPCC relied chiefly on statistical predictions in its recent assessment reports and highlighted the considerable uncertainty in future trends in fire activity (Jia et al., 2019; Settele et al., 2014).

The results of the CMIP5 fire modeling effort exposed a critical need to improve the representation of fire in DGVMs and triggered major efforts, embodied by the Fire Model Intercomparison Project (FireMIP), to improve the process representation and parameterization of fire models and advance their capability to represent observed patterns of fire in the Earth system (Hantson et al., 2016; Rabin et al., 2017). FireMIP has driven progress in modeling by cross-comparing the methods that are currently employed within models (Hantson et al., 2016), designing an experimental framework to evaluate and compare model representation of key processes (Rabin et al., 2017), and most recently employing that framework, comparing model estimates of BA, identifying key parameters that are the root causes of spread across the model ensemble (Lasslop et al., 2019; Li et al., 2019; Teckentrup et al., 2019) and benchmarking model performance against observations (Forkel, Andela, et al., 2019; Hantson et al., 2020). The FireMIP has already helped to encourage developments in fire-enabled DGVMs (Burton et al., 2019; Lasslop, Hantson, Harrison, et al., 2020), as well as new research into future changes under various emission scenarios (Burton, Kelley, et al., 2021). Future aims are to be able to project the future of BA in a fully coupled Earth System configuration through the employment of fire models within ESMs.

Here, we explore model outputs from six FireMIP models (Hantson et al., 2020; Teckentrup et al., 2019) to illustrate the current understanding of how the global distribution of fire activity has changed over the past century (see Text A in Supporting Information S1 for methods).

3. Decadal-Scale Observations of Change in Fire Weather and Burned Area

3.1. Fire-Prone Conditions Are on the Rise Globally

Fire weather seasons have extended and extreme fire weather conditions have become more common at the global scale in recent decades, enhancing the flammability of vegetation and pre-conditioning many landscapes to burn more frequently. Jolly et al. (2015) showed that fire weather season length (FWSL) lengthened across 25% of the Earth's vegetated surface during 1979–2013, leading to a 19% increase in global mean FWSL. The trends were shown to hold across different meteorological data sets and metrics of fire weather, with the increasing trends in FWSL in the range of 5%–7% decade^{-1} (Jolly et al., 2015). Using the methods of Jolly et al. (2015) applied to the ERA5 meteorological reanalysis (Hersbach et al., 2020; Vitolo et al., 2020), we analyzed the observed trends in fire weather for the regions shown in Figure 1 (see Text A in Supporting Information S1 for methods). We observed that annual FWSL increased by 14 days year^{-1} during 1979–2019 (+27%) and that the frequency of 95th percentile extreme fire weather (FWI_{95d}) increased by 10 days year^{-1} (+54%) globally (Table 1). The decadal trend in FWSL seen here (~+7% decade^{-1}) lies in the range reported by Jolly et al. (2015) for various combinations of meteorological data set and index. In our gridded analysis (Figure 2), we see fewer regional examples of reductions in fire weather than in the study of Jolly et al. (2015), which may be because we present the trends based on one meteorological reanalyzes and one FWI in contrast to the average of three meteorological reanalyzes and three fire weather/danger indices as presented by Jolly et al. (2015). Jain et al. (2021) have recently diagnosed the underlying drivers of increasing FWI_{95d} for continents and ecoregions, finding that either humidity or temperature trends were dominant in most regions while changes in wind speed or daily precipitation have been the dominant driver in very few regions.

We also found significant positive trends in both FWSL and FWI_{95d} in the majority of GFED macroregions (Figure 2; Table 1). At these macroregional scales, increases in FWSL have been proportionally greatest in Europe, central and boreal Asia, southern hemisphere South America and temperate North America. Increases

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Table 1
Annual Fire Weather Season Length (FWSL; Days Year^{-1}) and the Frequency of 95th Percentile Fire Weather (FWI_{95d}; Days Year^{-1}), Change in FWSL and FWI_{95d} (Days Year^{-1} and %), and Significance of Those Trends in Each Global Fire Emissions Database (GFED) Macroregion and Focus Ecoregion Based on ERA5 Fire Weather Index (FWI) Data for the Period 1979–2019 (Hersbach et al., 2020; Vitolo et al., 2020)

Region		Fire Weather Season Length (FWSL)				Annual days exceeding the 95th percentile FWI value (FWI_{95d})		
		Mean FWSL (days year^{-1})	Absolute Change (days year^{-1})	Relative Change (%)	Significance ($p < 0.05$)	Absolute Change (days year^{-1})	Relative Change (%)	Significance ($p < 0.05$)
Global		53	14	27.22	*	10	54.3	*
GFED	BONA	12	4	30.45	*	6	25.1	*
	TENA	44	20	45.17	*	13	64.8	*
	CEAM	80	39	48.90	*	13	70.2	*
	NHSA	27	10	38.25		9	33.2	
	SHSA	48	30	62.40	*	26	118.7	*
	EURO	17	12	67.05	*	13	66.6	*
	MIDE	96	19	19.47	*	21	97.3	*
	NHAF	163	22	13.78	*	16	81.7	*
	SHAF	105	32	30.50	*	24	117.7	*
	BOAS	11	4	39.57	*	8	37.0	*
	CEAS	31	18	57.72	*	16	78.0	*
	SEAS	62	-12	-19.76	*	-6	-28.7	*
	EQAS	10	4	36.12		1	4.5	
	AUST	130	27	20.78	*	11	56.3	*
Ecoregions	Alaskan Forests	10	7	69.13	*	11	59.4	*
	Pacific Canadian Forests	12	9	70.26	*	12	58.5	*
	Pacific US Forests	86	37	43.20	*	37	166.0	*
	Southern Amazonia	41	39	94.37	*	37	162.6	*
	Mediterranean	52	29	54.74	*	29	136.2	*
	North African Savannahs	202	16	7.78	*	11	57.0	*
	South African Savannahs	103	25	24.47	*	20	100.3	*
	East Siberian Forests	13	4	27.24		3	16.9	
	Indonesian Forests	12	6	48.18		4	21.1	
	Southeast Australian Forests	50	24	48.04	*	11	51.5	

Note. Absolute change is calculated as the trend (days year^{-2}) multiplied by the 41 years in the period 1979–2019 (see Figures 3 and 4). Relative change in burned area (BA) is the absolute change (days year^{-1}) divided by the mean annual BA (days year^{-1}). Trends are based on the Theil-Sen estimator, which is insensitive to outliers, and asterisks denote significant trends ($p < 0.05$) according to Mann-Kendall tests. Colors represent the strength of positive (brown) and negative (purple) trends in fire weather as in Figure 5. See methods in Text A in Supporting Information S1.

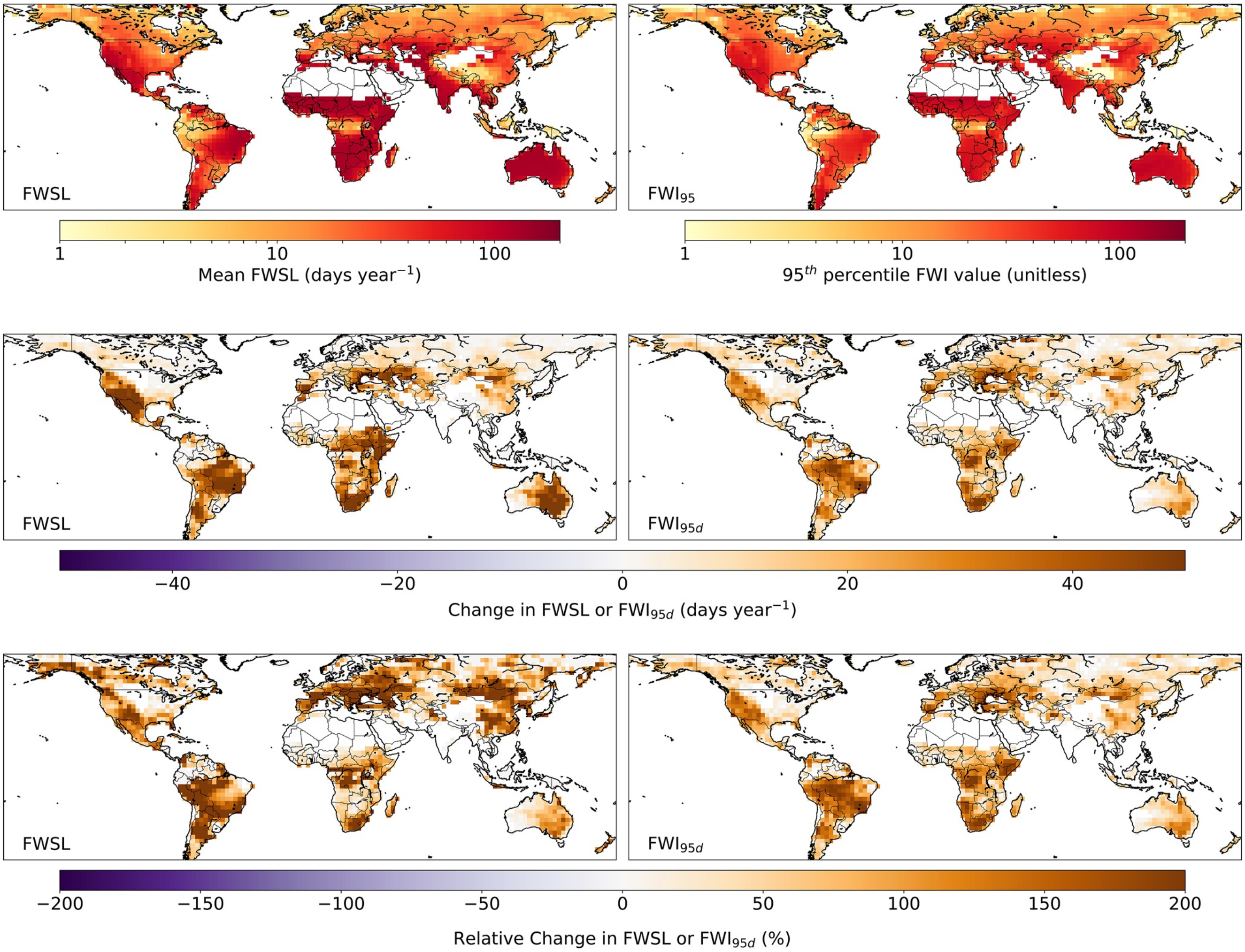

Figure 2. Global patterns and trends in fire weather during 1979–2019 based on ERA5 reanalysis data (Hersbach et al., 2020; Vitolo et al., 2020). (Left panels) include (top) mean, (middle) absolute change and (bottom) relative change in annual fire weather season length (FSWL) during 1979–2019. (Right panels) include (top) the 95th percentile daily value of fire weather index (FWI) threshold value during 1979–2019, (middle) the absolute change in annual days with FWI values exceeding the 95th percentile and (bottom) the relative change. Absolute change (days year^{-1}) is calculated as the trend (days year^{-2}) multiplied by the length of the time series (41 years). The relative change is the absolute change divided by the mean.

in FWI_{95d} have been most pronounced in southern hemisphere South America, central Asia and across Africa. Trends in extreme fire weather have notably outpaced trends in FWSL in southern hemisphere South America and Africa, whereas trends in FWSL have been more pronounced in Europe and boreal Asia (Table 1).

On ecoregional scales, the *western US* is perhaps the region in which trends in fire weather and related climatological indicators of vegetation dryness have been studied most widely. Abatzoglou and Kolden (2013) showed that significant increases in extreme fire weather occurred during 1979–2012 across much of the western US. Abatzoglou and Williams (2016) reported that, during 1979–2015, the extent of western US forests experiencing high VPD grew by 75% along with an average of nine additional days of extreme VPD each year. Williams et al. (2019) further reported that temperatures on warm-season days trended upwards by 1.4°C warmer since the 1970s in California, triggering a significant increase in VPD. However, both increased VPD and decreased fire-season precipitation have been implicated as the key driver of fire weather trends in this region (Holden et al., 2018). Goss et al. (2020) found that a 1°C increase in autumn temperature and a 30% decline in autumn precipitation since the 1980s drove a 20% increase in autumn mean FWI and a doubling of FWI_{95d} in California. In strong agreement with the preceding literature, our analysis indicated that FWSL rose significantly by 43%

(+37 days $year^{-1}$) and FWI_{95d} by 166% (+37 days $year^{-1}$) in Pacific US forests during 1979–2019 (Figures 2–4; Table 1).

Studies of fire weather in *Canadian forests* have revealed large, but often statistically insignificant, trends during the twentieth century, and they have also highlighted the spatial heterogeneity of the fire weather trends across Canada (Amiro et al., 2004; Girardin et al., 2004, 2009; Jain et al., 2017; L. M. Johnston et al., 2020; X. Wang et al., 2015). The prevailing explanation for the absence of significant trends in fire weather is that interannual variability is so large that even substantial trends are difficult to isolate robustly in this region (Amiro et al., 2004; Jain et al., 2017). Nonetheless, some recent studies have shown significant increases in the extreme values of FWI that are considered most dangerous for fire spread by fire management practitioners (e.g., FWI >20), especially in western Canadian forests (Kirchmeier-Young et al., 2017, 2019; X. Wang et al., 2015). In support of these studies, our analysis also indicates that FWSL and FWI_{95d} rose insignificantly by +70% (9 days $year^{-1}$) and +59% (+12 days $year^{-1}$), respectively, during 1979–2019 (Figures 2–4, Table 1).

Trends in fire weather have been studied less extensively in *other high latitude regions*. Several studies have highlighted the links between fire weather and fire activity in Alaskan forests (e.g., Barrett et al., 2016; Duffy et al., 2005), yet to our knowledge the trend in fire weather has not been reported. Our analysis indicates that FWSL and FWI_{95d} rose significantly in Alaskan forests by +69% (7 days $year^{-1}$) and +59% (11 days $year^{-1}$), respectively, during 1979–2019 (Figures 2–4, Table 1). In the Eurasian boreal region including Siberia, Girardin et al. (2009) reported a significant increase in the forest area experiencing extreme drought codes during 1901–2002. Groisman et al. (2007) also reported significant increases in various indices of fire weather in east Siberia during the twentieth Century, which principally aligned with temperature increases in the region. Justino et al. (2021) reported positive trends in potential weather fire index version 2 (PFIv2) during 2000–2016 across northern high- and mid-latitudes, with peaks in central Eurasia and Siberia, driven predominantly by low precipitation anomalies. In our analysis, we observed increases in FWSL (+27%; 4 days $year^{-1}$) and FWI_{95d} (+17%; 3 days $year^{-1}$) in east Siberian forests during 1979–2019 (Figures 2–4, Table 1). Across all North American conifer forests (including high latitude forests in Alaska and Canada, temperate forests in the western US, and subtropical forests in the southeast US), Jolly et al. (2015) reported a significant increase in FWSL of 6 days $year^{-1}$ during 1979–2015 based on multiple meteorological reanalyzes and fire weather indices.

In *the Mediterranean*, Venäläinen et al. (2014) observed significant increases in average FWI during 1980–2012 and an increase in the probability of regional extreme FWI values (FWI >45) by around 5%. Others have similarly highlighted increases in fire weather extremes in the Mediterranean. Bedia et al. (2012) identified significant trends in the seasonal severity rating, which is based on FWI values across annual fire seasons, on the Iberian Peninsula during 1989–2011. Fréjaville and Curt (2015) showed that there had been a significant increase in fire weather severity in southern France, especially during spring. Recently, Giannaros et al. (2021) revealed significant positive trends in the frequency of fire weather extremes in the Iberian Peninsula and eastern Balkans during 1987–2016. The number of days with FWI values over 30, which are deemed to support extreme fire spread, increased by 1 day $year^{-1}$ in these regions. In our analysis, we observed large and significant increases in FWSL (+55%; +29 days $year^{-1}$) and FWI_{95d} (+136%; +29 days $year^{-1}$) in the Mediterranean during 1979–2019 (Figures 2–4, Table 1). Jolly et al. (2015) reported a significant, but smaller, increase in FWSL of 10 days $year^{-1}$ in the Mediterranean during 1979–2015 based on multiple meteorological reanalyzes and fire weather indices.

In *southeast Australia*, numerous studies have identified large increases in FWSL and the frequency of extreme fire weather during the observational record, however, most of these studies also show that there is strong interannual variability that largely precludes these trends from reaching significance thresholds (Abram et al., 2021; H. Clarke et al., 2013; Sharples et al., 2016). The interannual variability is specifically attributed to large-scale oceanic oscillations in the Pacific (El Niño Southern Oscillation [ENSO]), Southern (Southern Annular Mode) and Indian oceans (Indian Ocean Dipole), which strongly influence synoptic-scale variability in temperature and precipitation in southeast Australia, promoting large interannual variability in fire weather (Abram et al., 2021; H. Clarke et al., 2013; Harris & Lucas, 2019; Sharples et al., 2016; Williamson et al., 2016). Clarke et al. (2013) showed that despite high interannual variability at the regional scale, significant increases in fire weather and extreme fire weather could be seen at ~40% and ~60% of meteorological stations in Australia, respectively, with the majority of significant trends seen in stations in the southeast of the country. New analyses with multiple fire weather indices show a shift toward high occurrence of extreme fire weather days in the southeast of Australia since around the year 2000 (Canadell et al., 2021; Richardson et al., 2021). Hence, there are strong indications

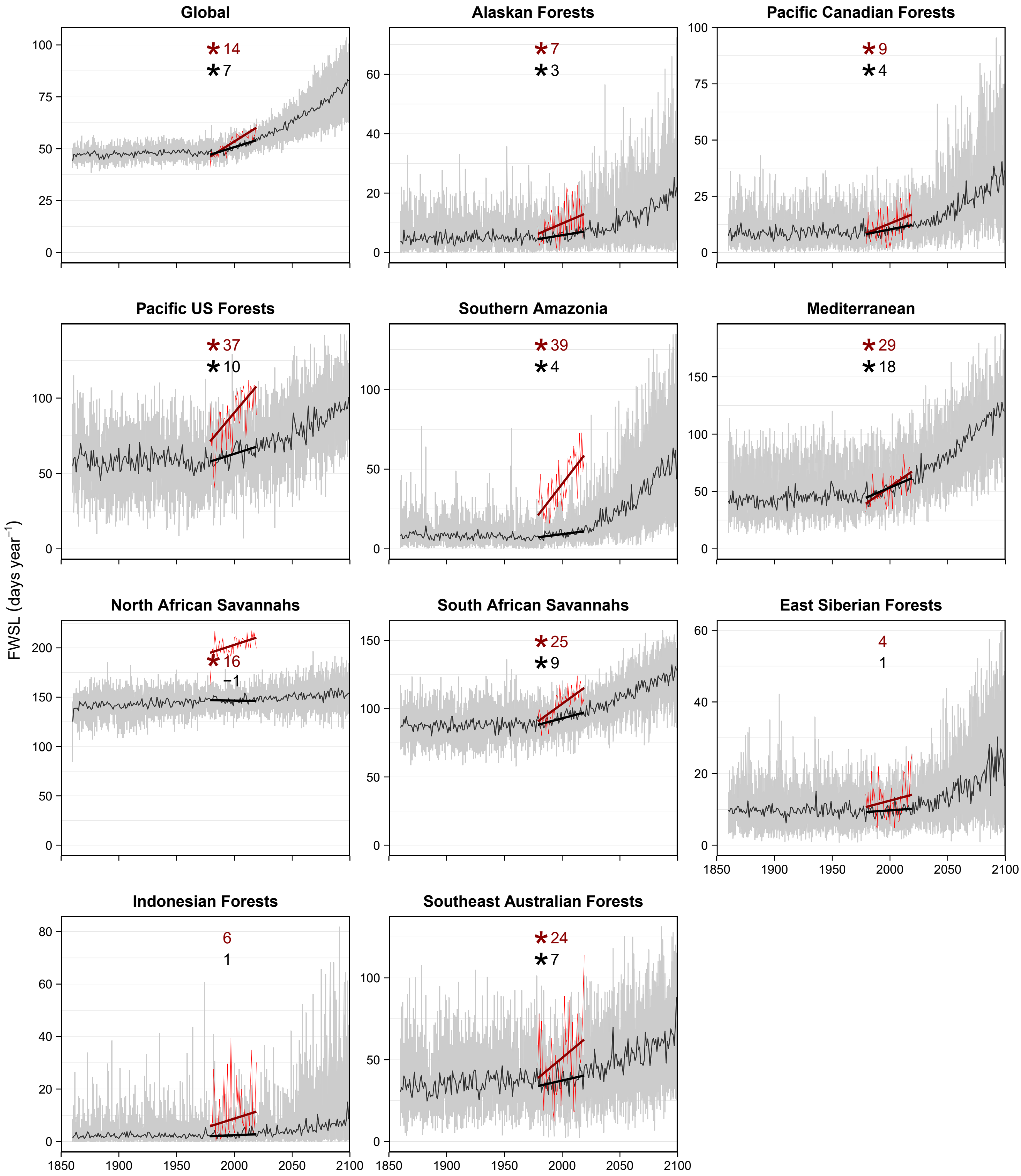

Figure 3. Time series of global and regional estimates of mean fire weather season length (FWSL) from ERA5 (thin red lines; Hersbach et al., 2020; Vitolo et al., 2020) and CMIP5 models running RCP8.5 (gray lines; Abatzoglou et al., 2019). Thin black lines mark the multi-model mean estimate from the CMIP5 models. Linear trends in the period 1979–2019 are shown for the ERA5 (thick red lines) and CMIP5 (thick black lines), with corresponding numbers marking the change in annual FWSL during the period (the slope integrated over the period 1979–2019) and corresponding asterisks denoting significant changes at the 95% confidence interval. Differences between modeled and observed FWSL can be explained by differences in the resolution of the models (2.5°) versus the observations (0.25°), since FWSL is partly determined by the maximum value FWI and this is reduced through spatial averaging.

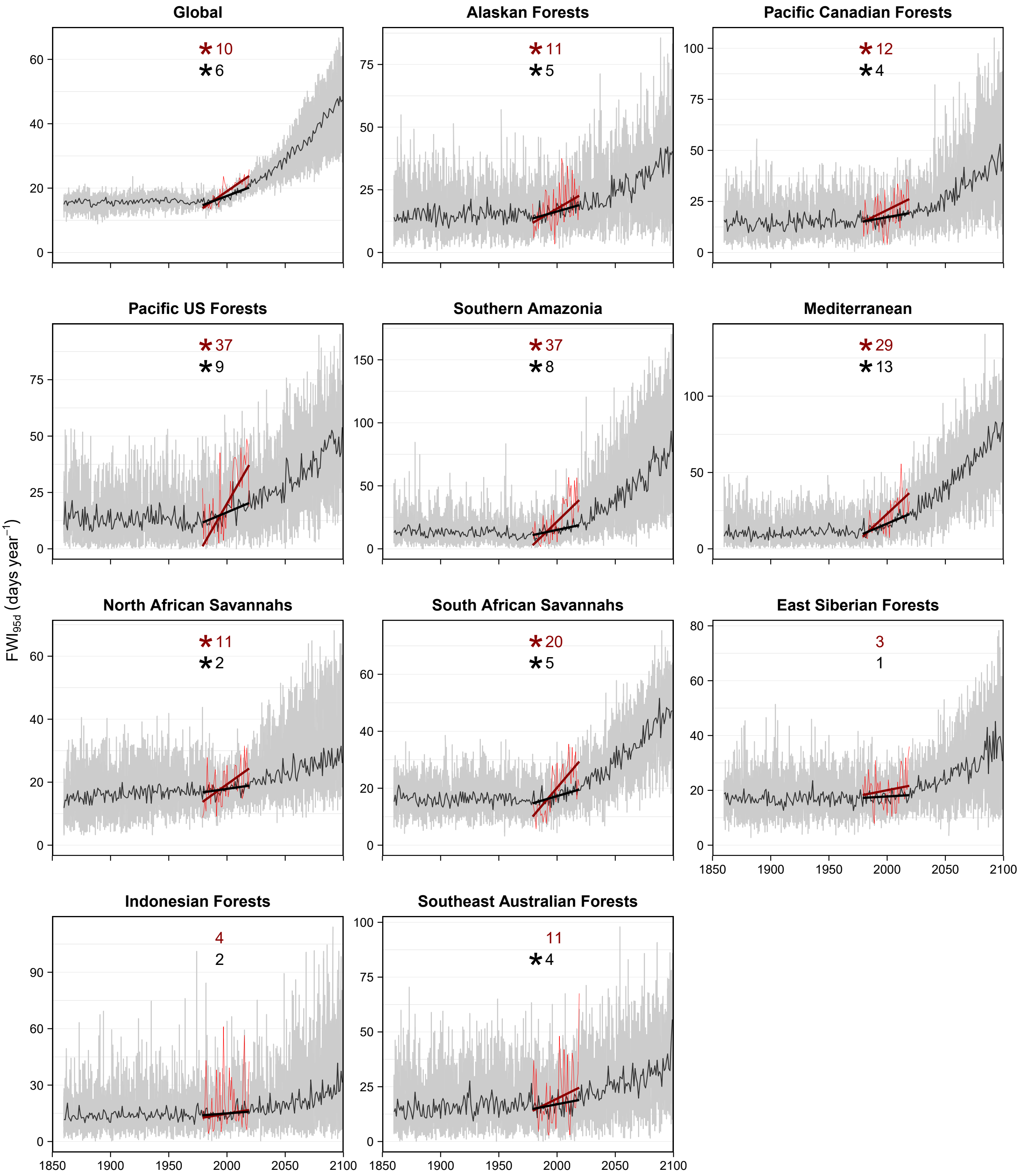

Figure 4. Time series of global and regional estimates of mean FWI_{95d} from ERA5 (thin red lines; Hersbach et al., 2020; Vitolo et al., 2020) and CMIP5 models running RCP8.5 (gray lines; Abatzoglou et al., 2019). Thin black lines mark the multi-model mean estimate from the CMIP5 models. Linear trends in the period 1979–2019 are shown for the ERA5 (thick red lines) and CMIP5 (thick black lines), with corresponding numbers marking the change in annual FWSL during the period (the slope integrated over the period 1979–2019) and corresponding asterisks denoting significant changes at the 95% confidence interval.

that FWSL and the frequency of extreme fire weather are increasing in southeast Australia, but interannual variability is superimposed on those trends and complicates their robust detection (Abram et al., 2021; van Oldenborgh et al., 2021; Williamson et al., 2016). In our analysis, we observed significant trends in FWSL (+48%; 24 days year^{-1}) and non-significant increases in FWI_{95d} (+52%; 11 days year^{-1}) in southeast Australian forests during 1979–2019 (Table 1, Figures 3 and 4), consistent with the previous studies in the region. Jolly et al. (2015) similarly reported no significant trend in FWSL during 1979–2015 in Australian forests.

Among the most important atmospheric factors contributing to an elevated probability of fire in southeast Australia is the development of unstable "pyroconvective" conditions associated with frontal systems (Abram et al., 2021; Canadell et al., 2021; Dowdy & Mills, 2012; Sharples et al., 2016). The likelihood of pyroconvective conditions is raised by offshore cold fronts that draw dry and warm winds toward southeast Australia from the interior of the continent (Di Virgilio et al., 2019; Dowdy & Pepler, 2018; Dowdy et al., 2019; Reeder et al., 2015). These winds foster rapid surface drying and significantly enhance heat convection from the land surface, which leads to instability in the lower atmosphere and promotes sustained flaming combustion, as well as the updraft of embers and production of lightning that can ignite further fires (Abram et al., 2021; Dowdy & Pepler, 2018; Khaykin et al., 2020; McRae et al., 2015). The continuous C-Haines index of pyroconvection has often been used as a complement to fire weather indices to quantify fire risk in Australia. Dowdy and Pepler (2018) showed that there have been significant increases in the frequency of spring and summer days with 95th percentile C-Haines index values and compound events when both fire weather and C-Haines are in their 95th percentiles in parts of southeast Australia during 1979–2016. The compounding effect of pyroconvection on likelihood of fire have also been highlighted in the Mediterranean (Pinto et al., 2020; Tatli & Türkeş, 2014).

According to our analysis, *Amazonia* was the region with the greatest proportional increases in FWSL (+94%; +39 days year^{-1}) and also among the largest increases in FWI_{95d} (+163%; +37 days year^{-1}) during 1979–2019 (Table 1, Figures 3 and 4). Various studies have identified trends in precipitation and drought indices and highlighted their relevance to wildfire activity (Alencar et al., 2015; Aragão et al., 2018; Brando et al., 2014; D. Nepstad et al., 2004; Lewis et al., 2011; Nogueira et al., 2017). The significant trends in fire weather corroborate with reductions in dry season precipitation, increases in the duration of the dry season, and increases in the frequency of drought conditions that have been reported for the region (Marengo & Espinoza, 2016; Marengo et al., 2011, 2018; Nogueira et al., 2017). Historically, the most pronounced seasons of drought-driven fire in Amazonia have been associated with natural variability in precipitation associated with El Niño events or sea surface temperatures in the North Atlantic (Aragão et al., 2018; Brando et al., 2014; Jiménez-Muñoz et al., 2016; Lewis et al., 2011; Marengo & Espinoza, 2016; Marengo et al., 2018; Panisset et al., 2018). Despite various studies of changes in primary climate variables in the region, study of trends in fire weather have been rare. Jolly et al. (2015) reported that FWSL increased by 33 days year^{-1} during 1979–2015 across a broader region encompassing tropical and subtropical forests, grasslands and savannas in South America.

3.2. Burned Area Trends Are Diverse and Region-Specific

Despite the increases in fire weather seasons and fire weather extremes that have been observed in virtually all world regions, BA has shown a range of regional trends. Andela et al. (2017) previously reported a 24% decline in global BA in the period 1998–2015 and that this global decline is predominantly driven by a decline in BA in the savannah-grassland systems, where 55% of global BA occurs in the average year (Table 2). In contrast, BA in forests has not declined globally and, since forest fires emit more carbon per unit area than fires in other land covers, emissions of carbon from fires have reportedly been stable or increased globally despite the decline in global BA (van der Werf et al., 2017; Zheng et al., 2021). We extended the analysis by Andela et al. (2017) to the period 2001–2019 based on updated BA observations (Giglio et al., 2018; see methods in Text A in Supporting Information S1) and found that the BA fell globally by 27% during 2001–2019, with significant declines in African savannahs (Figures 5 and 6, Table 2).

On macroregional scales, the negative trends were found to be significant only in Africa (NHAF and SHAF), Europe (EURO), and central Asia (CEAS; Table 2), while in our focus ecoregions the negative trends in BA were found to be significant only in northern and southern African savannahs. The decline in BA is most pronounced in northern African savannahs, where BA fell by 41% during 2001–2019. Of total global reductions in BA, 59% have occurred in the two African GFED macroregions and 50% have occurred in African savannahs (Figures 5

Table 2
Mean Annual Burned Area (BA) and Change in BA During the Period 2001–2019, and Significance of Those Changes in Each Global Fire Emissions Database (GFED) Macroregion and Focus Ecoregion Based on Moderate Resolution Imaging Spectroradiometer (MODIS)-Derived BA Data (Giglio et al., 2018)

Region		Mean BA (km² year⁻¹)	Absolute Change in BA (km² year⁻¹)	Mean BA Fraction (% year⁻¹)	Absolute Change in BA Fraction (% year⁻¹)	Relative Change (%)	Significance ($p < 0.05$)
Global	Global	4,136,411	-1,124,368.9	2.78	-0.75	-27.18	*
GFED	BONA	23,673	3,362.3	0.19	0.03	14.20	
	TENA	27,955	11,670.8	0.35	0.15	41.75	
	CEAM	27,383	135.7	0.87	0.00	0.50	
	NHSA	53,407	-8,391.3	1.70	-0.27	-15.71	
	SHSA	285,497	-78,750.2	1.88	-0.52	-27.58	
	EURO	10,427	-6,504.1	0.13	-0.08	-62.38	*
	MIDE	14,702	5,329.8	0.12	0.04	36.25	
	NHAF	1,251,796	-466,972.7	8.40	-3.13	-37.30	*
	SHAF	1,500,145	-221,380.9	14.89	-2.20	-14.76	*
	BOAS	93,057	391.0	0.59	0.00	0.42	
	CEAS	191,974	-145,343.4	1.04	-0.79	-75.71	*
	SEAS	138,418	31,379.8	1.94	0.44	22.67	
	EQAS	15,352	-1,387.5	0.40	-0.04	-9.04	
	AUST	501,705	-241,216.6	5.97	-2.87	-48.08	
Ecoregions	Alaskan Forests	2,994	18.3	0.59	0.00	0.61	
	Pacific Canadian Forests	2,192	1,389.9	0.25	0.16	63.40	
	Pacific US Forests	4,133	2,022.2	0.71	0.35	48.93	
	Southern Amazonia	39,355	-19,479.2	1.35	-0.67	-49.50	
	Mediterranean	4,799	-3,775.3	0.40	-0.32	-78.66	
	North African Savannahs	1,093,069	-447,987.0	15.24	-6.25	-40.98	*
	South African Savannahs	1,168,509	-137,811.7	27.07	-3.19	-11.79	*
	East Siberian Forests	22,987	21,353.2	0.55	0.51	92.89	
	Indonesian Forests	11,011	-1,435.5	0.58	-0.08	-13.04	
	Southeast Australian Forests	10,290	-2,048.5	1.23	-0.25	-19.91	

Note. Absolute change in BA (and BA fraction) is calculated as the trend in 1,000 km^2 year^{-2} (% year^{-2}) multiplied by the 19 years in the period 2001–2019 (see examples in Figure 6). Relative change in BA is the absolute change (1,000 km^2 year^{-1}) divided by the mean annual BA (1,000 km^2 year^{-1}). Trends are based on the Theil-Sen estimator, which is insensitive to outliers, and asterisks denote significant trends ($p < 0.05$) according to Mann-Kendall tests. See methods in Text A in Supporting Information S1.

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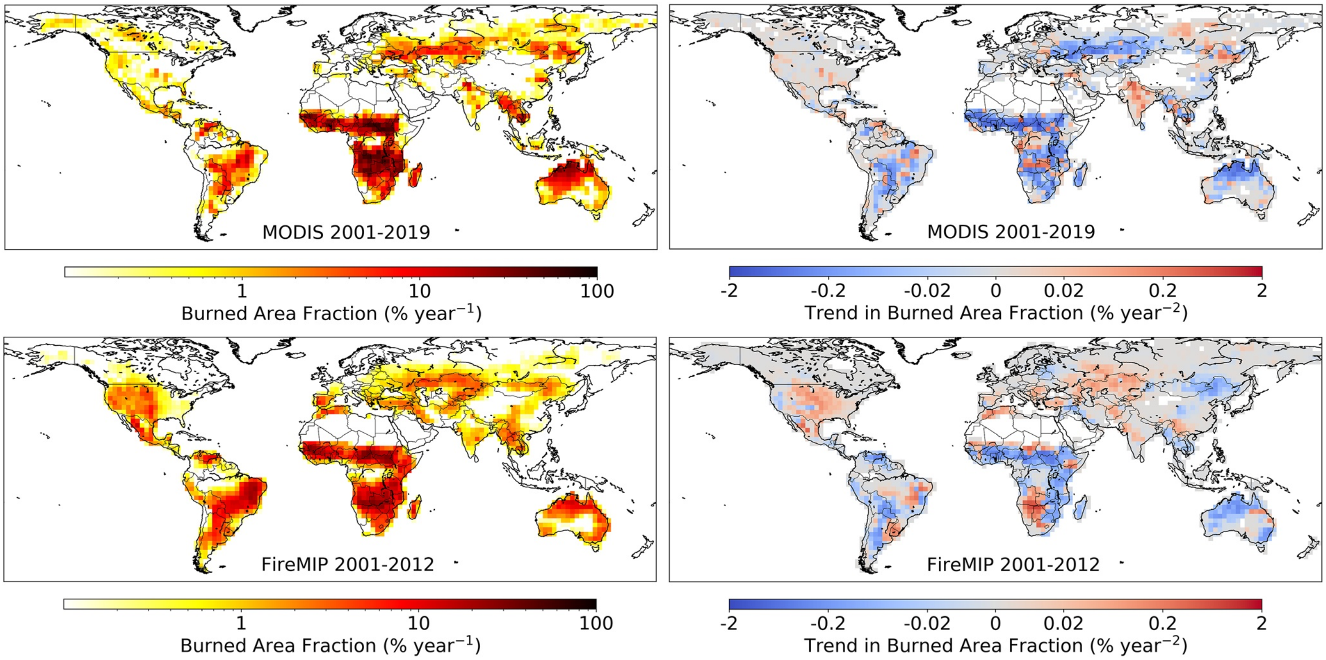

Figure 5. Global observed and modeled burned area (BA) fraction and their trends during the periods shown, gridded at 2.5° resolution (Giglio et al., 2018; Teckentrup et al., 2019). Plots show (left panels) annual mean BA fraction (% year^{-1}) and (right panels) trend in BA fraction (% year^{-2}) since 2001 period for (upper panels) moderate resolution imaging spectroradiometer BA (2001–2019) and (lower panels) six Fire Model Intercomparison Project (FireMIP) models (2001–2012). Year 2012 is the final year for which FireMIP simulations are available. The slope is calculated as the Theil-Sen estimator, which is insensitive to outliers.

and 6, Table 2). Our results support the conclusion of Andela et al. (2017) and others (Forkel, Dorigo, et al., 2019) that African savannahs have an exceptional influence on global trends in BA.

The significant declines in BA in *African savannahs* have occurred despite significant increases in fire weather, and especially extreme fire weather, in the region (Section 3.1), signaling that the trends in fire activity are decoupled from trends in fire weather in African savannahs and caused by other bioclimatic or human factors. This is expected as savannah fires are known to be limited foremost by fuel availability and strongly influenced by land management such as the fragmentation of the natural fire-prone landscape and exclusion of fire from agricultural regions (Alvarado et al., 2020; Andela & van der Werf, 2014; Archibald et al., 2009, 2010, 2012; Rosan et al., 2022). Andela et al. (2017) concluded that the observed decline in BA in African savannahs has been caused by the expansion of high-capital agriculture. They used a statistical model built by Andela and van der Werf (2014) to show that the decline in BA during 1998–2016 could be reproduced by statistical models even after trends in precipitation were accounted for, especially in northern hemisphere Africa. Nonetheless, others have concluded that reductions in vegetation productivity (fuel build-up) driven by changes to the hydrological balance of the region are the predominant determinant driver of the BA trend (Zubkova et al., 2019). Indeed, various studies employing statistical or machine learning models have shown that both hydrological and human factors contribute to spatial and temporal variability in BA in most parts of African savannah biome, and that there are few sub-regions where either of these factors are the exclusive driver of variability in fire activity (Alvarado et al., 2020; Andela & van der Werf, 2014; Archibald et al., 2010; Forkel et al., 2017; van der Werf et al., 2008). See Sections 4.1 and 5.4 for further discussion of the bioclimatic and human drivers of fire in African savannahs.

Although a large portion of the global decline in BA is explained by the declining BA in African savannahs, declines in BA are also seen in other regions both in previous studies and in our analyses (Figures 5 and 6, Table 2). In the *Mediterranean*, Turco et al. (2016) observed a ~66% reduction in BA in the Mediterranean between 1985 and 2011, with the most pronounced trends in Spain and France. Urbieta et al. (2019) and Silva et al. (2019) similarly noted a decrease in BA in most regions of Spain during 1975–2013, while Fréjaville and Curt (2017) reported that BA declined in southern France during 1976–2009. Trends in wildfires in Portugal have been spatially varied and have tended to relate to regional contrasts in population and land use dynamics (Oliveira et al., 2017; Silva et al., 2019; Turco et al., 2016). Our analysis indicates a 79% reduction in BA in the

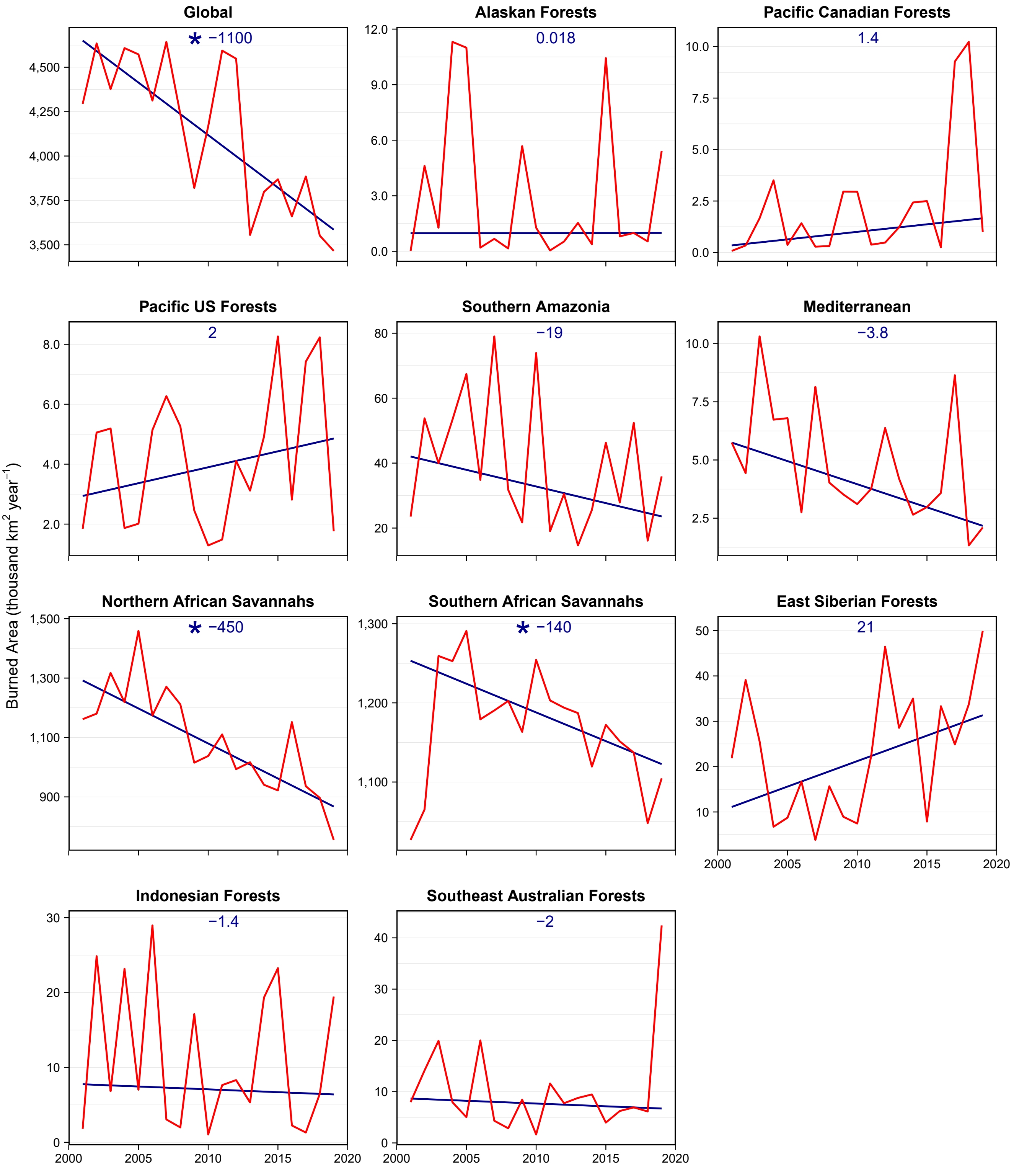

Figure 6. Trends in annual burned area (BA) globally and for ecoregions shown in Figure 1 (Giglio et al., 2018). Red lines show annual BA (1,000 km^2 year^{-1}), blue lines the linear trend (1,000 km^2 year^{-2}) and blue numbers the change in annual BA during the period (1,000 km^2 year^{-1}; the trend in 1,000 km^2 year^{-2} multiplied by the 19 years in the period 2001–2019). The slope is calculated as the Theil-Sen estimator, which is insensitive to outliers, and blue asterisks denote significant changes in BA at the 95% confidence interval according to Mann-Kendall tests (see Text A in Supporting Information S1 for methods).

Mediterranean during 2001–2019, though this was not found to be significant (Figures 5 and 6, Table 2). The declines in BA in the Mediterranean have occurred despite significant increases in FWSL and FWI_{95d} (Figures 2–4, Table 1), and they have generally been associated with increased suppression of fires by humans since the 1980s (Brotons et al., 2013; Ruffault & Mouillot, 2015; Silva et al., 2019; Turco, Jerez, et al., 2018; Turco et al., 2016; Urbieta et al., 2019). Nonetheless, several extreme and deadly wildfires have been linked to extreme fire weather conditions during major droughts in the region in recent decades, underscoring the importance of fire weather extremes for dangerous fire activity in the region (Lagouvardos et al., 2019; Ruffault et al., 2018, 2020; Turco et al., 2019).

Fire is routinely used for land clearing in *Amazonia* and consequently BA shares a close association with deforestation rates in this region (Aragão et al., 2008; van Wees et al., 2021). Deforestation rates declined overall during 2001–2019 in Amazonia following peak rates in the late 1990s and early 2000s (Aragão et al., 2018; Silva Junior et al., 2021; Libonati et al., 2021). However, this decline in BA has not been uniform and the recent history of economic and environmental policy has led to several shifts in the BA trend within the period (Aragão et al., 2018; Silva Junior et al., 2021; Libonati et al., 2021). Several decades of federal investment in infrastructure led to improved road access to the Brazilian Amazon and resulted in the highest recorded rates of deforestation in Amazonia during the 1990s and early 2000s (Cochrane, 2003; D. C. Nepstad et al., 1999; D. Nepstad et al., 2001). Legislation implemented to prevent deforestation later led to a 75% decline in deforestation rates during the period 2005–2015 (Aragão et al., 2018; Silva Junior et al., 2021; D. Nepstad et al., 2014; Tyukavina et al., 2017). Since 2015, deforestation rates have increased in the Amazon (Libonati et al., 2021; Silva Junior et al., 2021) with 2019 and 2020 being extraordinary years for deforestation fire in the context of the past decade (Silva Junior et al., 2021; Kelley et al., 2021; Trancoso, 2021). Silva Junior et al. (2021) suggest that controversial changes to the Brazilian Forest Code in 2012 and a weakening of the code's enforcement have enabled a resurgence of illegal land-grabbing in Amazonia during recent years.

In addition to deforestation fires, wildfires associated with drought have superimposed substantial inter-annual variability on the BA trend in Amazonia. Droughts in the region in 2005, 2010, and 2015 have led to substantial peaks in fire activity (Aragão et al., 2018; D. C. Nepstad et al., 2008; Lewis et al., 2011; Morton et al., 2013). There have been numerous reports that the area burned by wildfires in Amazonia has increased in recent decades, predominantly during droughts and despite contemporaneous reductions in deforestation fire (Aragão et al., 2018; Brando, Macedo, et al., 2020; Brando, Soares-Filho, et al., 2020; Jiménez-Muñoz et al., 2016; Marengo & Espinoza, 2016; Marengo et al., 2018). Aragão et al. (2018) suggested that increases in drought frequency and intensity are an increasingly important driver of fire activity in Amazonia, particularly affecting forest edges that are disturbed by adjacent land use. However, this "decoupling" of fire incidence from deforestation activity does not emerge robustly across all data sets (Libonati et al., 2021). Deforestation fires and drought-driven fires are not mutually independent because deforestation has a legacy effect on the susceptibility of forest edges to drought (Brando et al., 2014; Cochrane, 2003; Silva Junior et al., 2018, 2021). In our analysis, BA was found to decline in southern Amazonian forests by ~50% during the period 2001–2019 (Figures 5 and 6, Table 2), though this trend was not significant and masks alternating sub-decadal trends; the trend was positive pre-2005, negative during 2005–2015 and positive once more post-2015 (Figure 6), mirroring changes in deforestation rates (Silva Junior et al., 2021).

Other regions of the world have seen substantial increases in fire activity and BA in recent decades. In *western US forests*, Westerling (2006, 2016) found that there had been *a* >10-fold increase in BA in Western US forests between 1973–1982 and 2003–2012 based on fire records from federal agencies. Other studies have since reported a fourfold increase in BA in western US forests during 1984–2015 (Abatzoglou & Williams, 2016) and a fivefold increase in BA in California during 1972–2018 (Williams et al., 2019) based on a mixture of federal fire records and MODIS BA detections. The frequency of large fires has also been rising (Dennison et al., 2014) and shows an exponential relationship with vegetation dryness (Williams et al., 2019). Parks and Abatzoglou (2020) showed that the area burned by severe fires increased eightfold in western US forests during 1985–2017. Large and severe fires are becoming more common in the region and imprinting also upon total BA. Trends in BA in the western US forests have occurred amidst increases in fire weather (Williams et al., 2019) and variability in fire activity holds an especially strong relationship with fire weather in the region (Abatzoglou & Williams, 2016; Goss et al., 2020), although the important roles of ignition sources and fuel stocks have also been highlighted. In our analysis, we observed shallower (and non-significant) increases in BA of 49% in the Pacific US forests, which likely reflects our consideration of total BA as opposed to the area burned by the large fires as captured by agency statistics (Figures 5 and 6, Table 2). In the modern day, BA is comparable to the estimated annual BA for western US forests during the early twentieth century (Littell et al., 2009), highlighting the extent to which humans have suppressed fire in the region during the mid-to-late twentieth century through wildland firefighting and land conversion to agriculture (see Section 5).

Increases in BA have also been reported for *Canada and Alaska*, though the statistical robustness of these trends has varied. Stocks et al. (2002) compiled a database of large fires based on wildfire reports to fire management agencies in Canada, observing an increase in BA and fire counts during 1959–1997, though they noted that inter-annual variability in BA exceeds the magnitude of the trends. Nonetheless, expanding these records to Alaska, Kasischke and Turetsky (2006) reported that annual BA doubled across the North American boreal zone during 1959–1999, principally due to increases in the frequency of large fires. Kasischke et al. (2010) later reported that BA in Alaska was greater during the decade of the 2000s than in any decade since the 1940s, based on records from fire management agencies, and identified a trend towards greater area burned by late-season fires. Veraverbeke et al. (2017) blended agency records and satellite observations to show that BA increased in the Northwest Territories at a rate of 7% year^{-1} during 1975–2015, but no significant increase was seen in the Alaskan interior forests. Coops et al. (2018) identified no significant trends in BA across Canada during 1985–2015, however, several western boreal forest regions showed significant trends since 2006 on the order of 13%–26%. Hanes et al. (2019) updated and synthesised various agency-based data sets of BA for Canada, and reported significant increases in BA and the number of large fires during 1959–2015. In our analysis, we observed a non-significant increase in BA of 63% in Pacific Canadian forests during 2001–2019 and no substantial change in BA in Alaskan forests (Figures 5 and 6, Table 2). Variability in BA in Canada is considered to predominantly result from variability in fire weather extremes (Jain et al., 2017; Kasischke et al., 2010; Kirchmeier-Young et al., 2017), although changes in lightning and human ignitions are also implicated as important factors affecting BA (Hanes et al., 2019; Veraverbeke et al., 2017). As in Pacific US forests, the increases in total BA seen in our analysis appear to mask more prominent increases in the frequency and extent of large fires as reported elsewhere based on agency statistics.

Recent severe wildfires in east *Siberian forests* have fetched interest because large stocks of carbon are held in the boreal forests, permafrost soils and peatlands of the region (Bowman et al., 2020; Kim et al., 2020; Scholten et al., 2021; Veraverbeke et al., 2017, 2021; Walker et al., 2019; Y. Chen et al., 2021). These fires are an example of the increased Arctic vegetation available as fuel that previously would not have been dry enough to burn, suggesting fire regimes are invading formerly fire-resistant landscapes (J. L. McCarty et al., 2020). Yet trends in BA in the region have been studied less extensively than in boreal North America (García-Lázaro et al., 2018; Ponomarev et al., 2016). Soja et al. (2007) showed an increase in BA across all Siberian forests (east of the Ural mountains) during 1980–2006 based on Russian forest agency records, though this trend was not reported to be significant. Krylov et al. (2014) observed no significant trends in BA during 2002–2011 based on satellite detections across all Russian forests. Kukavskaya et al. (2016) showed that, for one region of southeast Siberia, the decadal number of forest fires increased by 165% during 1970–2010 according to Russian forest agency records, whereas BA observed by satellites and agency records showed no significant trend during 1996–2015. On the other hand, Ponomarev et al. (2016) observed a significant increase on the order of 80%–100% in both fire count and BA in a large latitudinal transect of central Siberia during 1996–2015. García-Lázaro et al. (2018) developed a long-term BA product based on multiple satellite sensors and showed high variability in BA in northeast Siberia during 1982–2015, with trends on the order of 60% visible on decadal timescales. Tomshin and Solovyev (2021) report a non-significant positive trend in BA over Siberia during 2001–2020, with regional variability including both significant negative and positive trends in parts of Western Siberia and Eastern Siberia, respectively. Recent severe fires in Siberia began very early in the fire season, prior to the time of year when vegetation and soils normally become flammable, which may be the result of "overwintering" fires that smolder in organic soils beneath the ground surface (J. L. McCarty et al., 2020; Scholten et al., 2021). In our analysis, we saw a 93% increase in BA in east Siberian forests during 2001–2019, which was non-significant (Table 2, Figures 5 and 6).

Despite the rich availability of research showing increased likelihood of wildfire in *southeast Australia* as a result of changes in fire weather (Abram et al., 2021; Di Virgilio et al., 2019; Dowdy et al., 2019; Sharples et al., 2016), a limited number of studies have reported on trends in BA for the region. Most notably is a continental-wide analysis of forest BA (mostly concentrated in the southeast of Australia) that shows an annual linear increase over the past 32 years, and an exponential increase in forest BA during the cooler seasons of autumn and winter (Canadell et al., 2021). Based on a compilation of ground-based data since 1930, the authors also showed a fire regime shift from the year 2000 onwards with a jump in the number of mega fire years burning more than 1 million hectares of forests. Other studies have focused on specific regions in Australia such as the state of Victoria, for which Lindenmayer and Taylor (2020) showed that there has been a long-term increase in BA during 2001–2020 versus 1950–2000 due to the occurrence of several years with extreme wildfire outbreaks in the state since 2000. Bowman et al. (2020) presented a visually similar time series of BA data for New South Wales, as did L. Collins et al. (2021) and Abram et al. (2021) for broader parts of southeast Australia, but trends in BA were not reported in those cases. In our analysis, we observed no significant change in annual BA in southeast Australian forests during 2001–2019 (Table 2, Figures 5 and 6), although we note that the selected region also includes grass dominated rangelands and open woodlands with different fire regimes and drivers of fire activity from those of forests. Fuel dryness, influenced by contemporaneous fire weather and antecedent drought, is considered the principal limitation to fire in southeast Australian forests, and there are clear relationships between extreme fire weather and extreme forest fires in the region (Abram et al., 2021; Dowdy, 2018; van Oldenborgh et al., 2021). The 2019/2020 bushfires epitomized the effect of fire weather on fire risk in southeast Australia, with the forests primed to burn during the most extreme fire weather since observational records began in 1950 (Abram et al., 2021). Extreme fire weather conditions seen during the 2019/2020 bushfires can occur naturally when several ocean-atmosphere oscillations align at peak amplitude (ENSO, Southern Annular Mode and Indian Ocean Dipole) (Abram et al., 2021; Harris & Lucas, 2019). However, background increases in average fire weather due to anthropogenic climate change led to *a* >30% increase in the likelihood of 2019/2020 fire weather conditions (van Oldenborgh et al., 2021).

3.3. Fire Weather Is a Pervasive Enabler of Fire

Numerous studies have evaluated the co-variability of BA and FWI at global and regional scales. At the global scale, Bedia et al. (2015) showed that the relationship between BA and FWI varies regionally, and is strongest in biomass-rich environments where fuel moisture, rather than fuel availability, is the dominant limitation to fire. Specifically, BA is most sensitive to FWI in ecosystems with low-to-moderate mean annual FWI. On the other hand, BA is relatively insensitive to variability in fire weather in xeric grasslands and shrublands because these are fuel-productivity limited systems (Bedia et al., 2015). Abatzoglou et al. (2018) similarly identified the strongest relationships between BA and FWI in boreal forests and North American temperate forests with ample fuels. Earlier work showed that fire activity is most sensitive to weather variables in zones with intermediate precipitation, where ample fuels are generally available but moisture deficits can lead to sufficient fuel drying (Archibald et al., 2009; Bradstock, 2010; Krawchuk et al., 2009; van der Werf et al., 2008).

In our analysis of the relationship between BA and FWI (see Text A in Supporting Information S1 for methods), we found that monthly BA correlates positively and significantly with monthly FWI in the majority of world regions (Table 3, Figure 7). In addition, the total BA in a fire season correlates positively with the mean FWI during the fire season in all regions except for NHAF and northern African savannahs, and the correlations were significant in Alaskan forests, pacific Canadian forests, pacific US Forests, Indonesian forests and the Mediterranean (Table 3, Figure 7). These results emphasize the global-scale robustness of the relationship between fire weather and BA, with the strongest relationships broadly observed in mesic ecoregions (Table 3, Figure 7). The correlations between BA and FWI do not preclude the important influences of other bioclimatic and human controls on fire, but rather suggest that fire weather acts as a pervasive upwards pressure on BA that can nonetheless be modulated by other factors. No other fire driver shares such a consistent relationship with fire activity at the global scale (Sections 5 and 6), underscoring the key role of fire weather as a pervasive enabler of fire.

A particular wealth of studies have revealed the critical influence of fire weather on fire activity in the *western US forests*. The combination of fire weather indices with variables representing long-term moisture balance is often found to show strong predictive capacity in the region. Littell et al. (2009) found that most of the interannual variability in BA in the forested mountains of the western US could be explained by variability in antecedent precipitation, a drought index, and temperature, with large fires predominantly occurring under extreme fire weather conditions. Abatzoglou and Kolden (2013) highlighted that atmospheric conditions during the fire season predominantly influence the flammability of fuels, and that these effects are reinforced in years with droughts preceding the fire season. Abatzoglou and Williams (2016) observed that 76% of the interannual variability in BA

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Table 3
Spearman's Correlations (ρ) Between Burned Area (BA) and Fire Weather Index (FWI) for the Period 2001–2019

Region		Seasonal: Monthly Mean FWI vs. Monthly BA		Interannual: Fire Season Mean FWI vs. Fire Season Total BA	
		ρ	Significance ($p < 0.05$)	ρ	Significance ($p < 0.05$)
GFED	BONA	0.92	*	0.56	
	TENA	0.57	*	0.58	
	CEAM	0.87	*	0.64	
	NHSA	0.91	*	0.72	
	SHSA	0.89	*	0.49	
	EURO	0.70	*	0.22	
	MIDE	0.67	*	0.32	
	NHAF	0.63	*	-0.45	
	SHAF	0.90	*	0.03	
	BOAS	0.73	*	0.32	
	CEAS	0.76	*	0.45	
	SEAS	0.70	*	0.63	
	EQAS	0.91	*	0.92	*
	AUST	0.56	*	0.28	
Ecoregions	Alaskan Forests	0.82	*	0.91	*
	Pacific Canadian Forests	0.71	*	0.86	*
	Pacific US Forests	0.87	*	0.89	*
	Southern Amazonia	0.73	*	0.58	
	Mediterranean	0.83	*	0.87	*
	North African Savannahs	0.74	*	-0.32	
	South African Savannahs	0.90	*	0.14	
	East Siberian Forests	0.89	*	0.71	
	Indonesian Forests	0.87	*	0.94	*
	Southeast Australian Forests	0.54	*	0.39	

Note. Two types of correlation are calculated: first, the seasonal correlation of monthly mean FWI and monthly BA in each region, and; second, the interannual correlation of the mean FWI and total BA during the annual fire season of each region (each calendar year's fire season is defined as the months in which at least 80% of fire activity occurred). Asterisks denote significant correlations ($p < 0.05$). Colors represent the strength of positive (purple) and negative (green) correlations as in Figure 7. The BA data derive from Giglio et al. (2018; updated through 2019) and the FWI data from Vitolo et al. (2020; see Text A in Supporting Information S1 for methods).

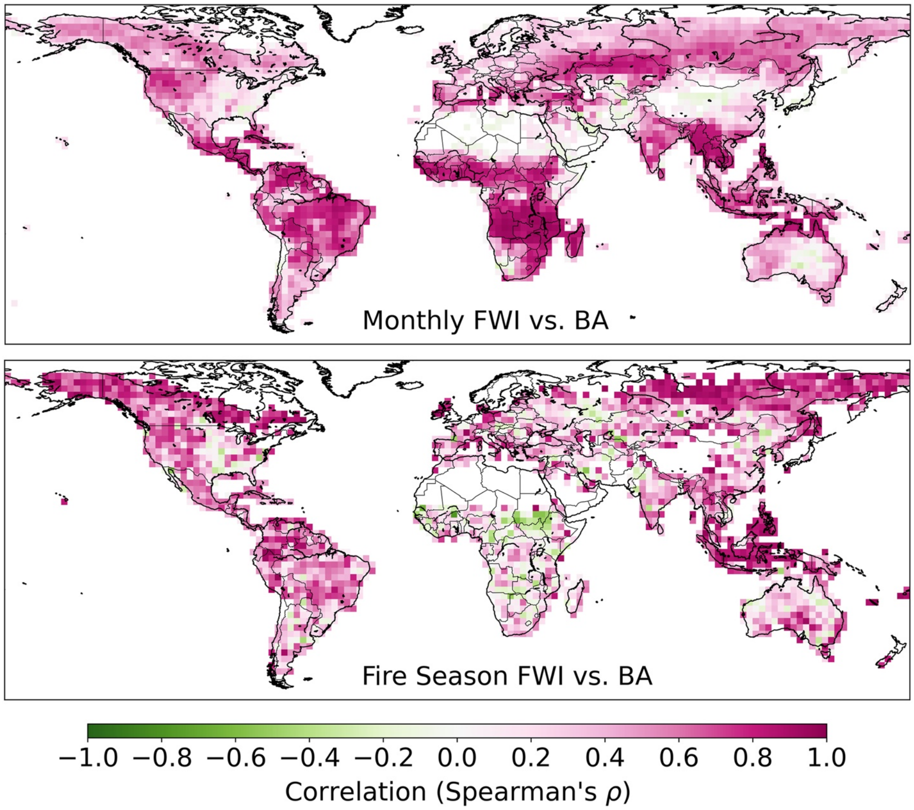

Figure 7. Spearman's correlation (ρ) between burned area (BA) and fire weather index (FWI) on two timeframes. (Upper panel) Interannual correlation between the monthly BA and monthly mean FWI during the fire season. The fire season is defined for each calendar year as the months in which >80% of the BA occurs. (Lower panel) Correlation between monthly BA and monthly mean FWI during the period 2001–2019. The BA data derive from Giglio et al. (2018; updated through 2019) and the FWI data from Vitolo et al. (2020; see Text A in Supporting Information S1 for methods).

in western US forests during 1984–2015 could be explained by variability in fuel dryness as represented by multiple indices including FWI. Williams et al. (2019) found robust interannual relationships between summer VPD and summer BA in western US forests during 1972–2018. Goss et al. (2020) recently found that autumn forest fire extent is particularly sensitive to extreme fire weather episodes and linked the doubling of autumn BA to increases in extreme fire weather frequency during 1979–2018. In our analysis, we observed strong correlations between FWI and BA on monthly and interannual timescales in Pacific US forests during 2001–2019 (Table 3, Figure 7). Overall, fire weather conditions are recognized as the dominant control on variability and trends in fire activity in fuel-rich western US forests, although the influence of antecedent weather conditions and land management on fuel availability has also been shown to modulate the impacts of fire weather (Abatzoglou & Kolden, 2013; Parks et al., 2014; Stephens et al., 2013).

Fire weather has also been identified as the dominant control on forest fire activity in *Canadian and Alaskan forests*, with the majority of annual BA typically occurring during just a few days of extreme fire weather (Barrett et al., 2016; Coogan et al., 2021; Duffy et al., 2005; L. M. Johnston et al., 2020; M. D. Flannigan & Wotton, 2001; M. D. Flannigan et al., 2009; Podur & Wotton, 2011; Wotton et al., 2010; X. Wang et al., 2015). M. D. Flannigan et al. (2005) showed that fuel moisture (represented by FWI components) explained 36%–64% of variance in BA across Canadian ecoregions during 1959–1997. Balshi et al. (2009) later showed that 82% of the interannual variation in BA during 1960–2002 could be explained by similar variables and a more complex statistical model. Girardin and Wotton (2009) showed that the drought code sub-component of FWI alone could explain 63% of the variability in forest BA across Canada (1959–1999). Magnussen and Taylor (2012) showed that lightning-caused fires could be predicted with particular skill using components of the FWI. Barrett et al. (2016) found that fire weather is the only variable required to explain the occurrence of wildfires in Alaskan boreal forest using a machine learning model that accounts for static and varying environmental factors. In our analysis, we observed strong and significant correlations between FWI and BA on monthly and interannual timescales in Pacific Canadian forests during 2001–2019 (Table 3, Figure 7). The strength of the relationship between fire weather and BA is such that many modeling studies have inferred future fire activity based on projected increases in the frequency of FWI thresholds under anthropogenic climate change (M. D. Flannigan et al., 2009; Kirchmeier-Young et al., 2017; Wotton et al., 2010; X. Wang et al., 2015). Overall, fire weather is known to be a critical determinant of fire activity in Canadian forests, though the importance of other factors such as fuel and ignitions availability has also been noted and are discussed in following sections (Cavard et al., 2015; Parisien et al., 2016; Veraverbeke et al., 2017; Walker et al., 2020; X. Wang et al., 2014). Recent work focussed on Siberian boreal forests has identified related weather factors such as contemporaneous water deficit and precipitation as major controls on annual BA (Talucci et al., 2022).

Exceptionally strong relationships have been observed between the FWI and BA in the *Mediterranean* (Carvalho et al., 2008; Fox et al., 2018; Papagiannaki et al., 2020; Parente et al., 2018; Rodrigues et al., 2020; Ruffault et al., 2018; Turco et al., 2017; Urbieta et al., 2015). Carvalho et al. (2008) constructed a stepwise regression model of BA in Portugal during 1980–2004 in which FWI was consistently selected as a predictor variable. The model explained over 80% of the monthly variability in BA. Urbieta et al. (2015) found that models including only long-term water balance variables predict large fire BA considerably less robustly than models that also include contemporaneous fire weather in Portugal, Spain, South France, Italy, and Greece, highlighting that fire weather is a critical trigger for fires in this region irrespective of seasonal-scale droughts. Others have also highlighted the dominant influence of contemporaneous weather conditions, including heatwaves and summer drought on fire activity and BA in the Mediterranean (Parente et al., 2018; Rodrigues et al., 2020; Turco et al., 2017). Fox et al. (2018) found that BA in SE France increases non-linearly with fire weather, with 97% of total BA occurring in weeks with extreme FWI values (FWI > 90). In our analysis, we observed strong and significant correlations between FWI and BA on both monthly and interannual timescales in the Mediterranean during 2001–2019 (Table 3, Figure 7), which is consistent with the especially strong relationships seen in prior work. Pinto et al. (2020) recently highlighted the compounding impact of pyroconvective conditions on fire activity in the Mediterranean. Inclusion of the C-Haines index in predictive models of area burned by large wildfires led to improved model performance. This highlights the need for wider exploration of the compounding effects of extreme fire weather and C-Haines index in regions beyond Australia, where the C-Haines index was originally developed and has been most routinely employed.

Our analysis also indicates that the correlations between FWI and BA are strong in the tropical forests of *southern Amazonia and Indonesia* (Table 3, Figure 7). In the normal range of hydrological conditions seen in Amazonia, moisture is efficiently recycled and hence forests display a general resilience to moderate moisture stresses (Baker & Spracklen, 2019; Betts et al., 2004; Bonan, 2008; Coe et al., 2013; Malhi et al., 2009; Staal et al., 2018; Zemp et al., 2017). A similar ecosystem-level resilience to moderate moisture stresses has been observed in Indonesian forests (Field et al., 2016; Langner & Siegert, 2009; Nikonovas et al., 2020; Pan et al., 2018; Spessa et al., 2014; Wooster et al., 2012). Nonetheless, droughts of sufficient severity and scale can interrupt moisture recycling and cause significant upticks in BA in Amazonia (Aragão et al., 2018; Brando et al., 2008, 2014; Cochrane, 2003; D. Nepstad et al., 2004, 2007; Fonseca et al., 2019; Marengo et al., 2011). The critical influence of drought on pantropical fire activity is also evident globally from the interannual variability in BA caused by the ENSO (Burton et al., 2020; Field et al., 2009; van der Werf et al., 2008; Y. Chen et al., 2017). Most analyses of the relationship between weather conditions and fire in Amazonia and Indonesia have centred on precipitation and drought metrics (Alencar et al., 2015; Aragão et al., 2018; Nogueira et al., 2017; Pan et al., 2018), however, FWI has been shown by Bedia et al. (2015) and Abatzoglou et al. (2018) to correlate positively with fire activity in these regions. Our analysis shows that BA correlates strongly with FWI on monthly timescales in southern Amazonia and Indonesia (Table 3, Figure 7), consistent with the important role of fire weather in priming moist tropical forests to burn and enabling deforestation fires or wildfires to occur. Further, the correlation between BA and FWI is found to be strong and significant in Indonesian forests signifying the particular dependence of fires on weather conditions in this region.

In our analysis, we found that the correlations between BA and FWI were weaker in *southeast Australian forests* than in many other regions of interest (Table 3, Figure 7). This observation is in line with the previous observations of Bedia et al. (2015), who also assessed the relationship between BA and FWI on a linear basis. On the other hand, the observation contrasts with that of Abatzoglou et al. (2018) who found a strong interannual correlation between log-transformed BA and FWI in the region, which indicates that regional BA responds non-linearly to fire weather. The non-linear response of fire weather to BA in southeast Australia has also been highlighted recently by Abram et al. (2021). Several studies have concluded that the largest forest fires in southeast Australia (>0.5 million ha) have occurred almost exclusively in unseasonably dry and hot conditions compounded by extreme pyroconvective conditions (Abram et al., 2021; Di Virgilio et al., 2019; Dowdy et al., 2019).

The insignificant negative correlations seen between fire season BA and fire season FWI in *northern African savannahs* are clear outliers in our analysis. These negative relationships are best explained by strong alternative controls on fire activity in this region, including fuel availability and connectivity as governed by moisture availability and by the fragmentation of natural landscapes by agriculture (Alvarado et al., 2020; Archibald et al., 2009, 2010; van der Werf et al., 2008; Zubkova et al., 2019; see Sections 4.1 and 5.4).

4. Bioclimatic Mediation of the Fire Weather-Burned Area Relationship

Fire weather has become more frequent and intense in the majority of world regions in recent decades, and coincident increases in BA have been seen in some regions (Section 3). Strong positive trends in BA have been observed in fuel-rich mesic forests, and these trends have typically coincided with substantial increases in fire weather (e.g., Pacific US, Pacific Canada, and east Siberia). Fire weather and BA are correlated positively in most regions of the world on seasonal timescales, signifying that climate is a major and pervasive control on the timing of fire activity. In addition, fire weather and BA correlate positively on inter-annual timescales in many mesic ecoregions. Nonetheless, trends in FWI and BA often diverge in regions where other bioclimatic and human factors act as overriding controls on fire activity (e.g., African savannahs, southern Amazonia, and the Mediterranean). The strength of the relationship between BA and fire weather also varies regionally and in some cases, the correlation is negative on interannual timescales (e.g., African savannahs). This variability emphasizes that fire is not an exclusively climatic phenomenon, and that patterns and trends of fire can only be comprehensively explained through consideration of the influence of a broader range of bioclimatic and human factors on fire activity. In this section, we discuss the bioclimatic drivers and constraints that mediate the relationship between fire weather and BA, whereas the human drivers and constraints will be the focus of Section 5.

4.1. Vegetation Distribution and Productivity Mediate Fuel Loads

While the flammability of vegetation is critically limited by moisture deficits that are promoted by fire weather, those fire weather conditions are of little consequence for fire activity unless vegetation stocks are sufficiently dense and connected to sustain the spread of fire. Hence, low fuel availability is a second critical limitation to fire activity in many regions of the world and mediates the relationship between fire weather and BA (Archibald et al., 2009; Bedia et al., 2015; Bistinas et al., 2014; Bradstock, 2010; Forkel, Andela, et al., 2019; Forkel et al., 2017; Kelley et al., 2019; Krawchuk & Moritz, 2011; Pausas & Bradstock, 2007; Pausas & Ribeiro, 2013; van der Werf et al., 2008). The ecoregions of the world can be arranged along a fire limitation continuum ranging from systems where vegetation fuels are too sparse to sustain significant fire spread (fuel production limited) to systems where fuels are rarely dry enough to burn (fuel moisture limited) (Alvarado et al., 2020; Archibald et al., 2009; Kelley et al., 2019; Krawchuk & Moritz, 2011; Pausas & Ribeiro, 2013). Many of the ecoregions that display greatest sensitivity to monthly or interannual variability in fire weather, including most mesic forests, are those without substantial fuel limitations and where fire weather occurs with low to moderate frequency (Abatzoglou et al., 2018; Bedia et al., 2015).

Climate and its variability have fundamentally influenced the global biogeography of forests, savannahs, shrublands, and grasslands and the species traits of vegetation, and fire has also interacted with climate to influence vegetation in many parts of the world (Bond & Keeley, 2005; Bowman et al., 2009; Harrison et al., 2021; Pausas & Keeley, 2009; Pausas et al., 2017; Whitlock et al., 2010). Annual BA peaks globally at around 10%–30% tree cover, where fires typically return every 10–30 years, and falls with tree cover (Archibald et al., 2009; Andela et al., 2017); at 60%–80% tree cover, fires typically return on the timescale of hundreds of years. Figure 8 shows our analysis of spatial correlations at sub-grid scale between BA and tree biomass, non-tree biomass and total biomass during 2019–2020, and Table 4 shows the average of these correlations within each region of interest (see Text A in Supporting Information S1 for methods; the correlation analyses are performed at a spatial resolution of 2.5° based on input data from 100 sub-grid cells with 0.25° spatial resolution). Consistent with the generally

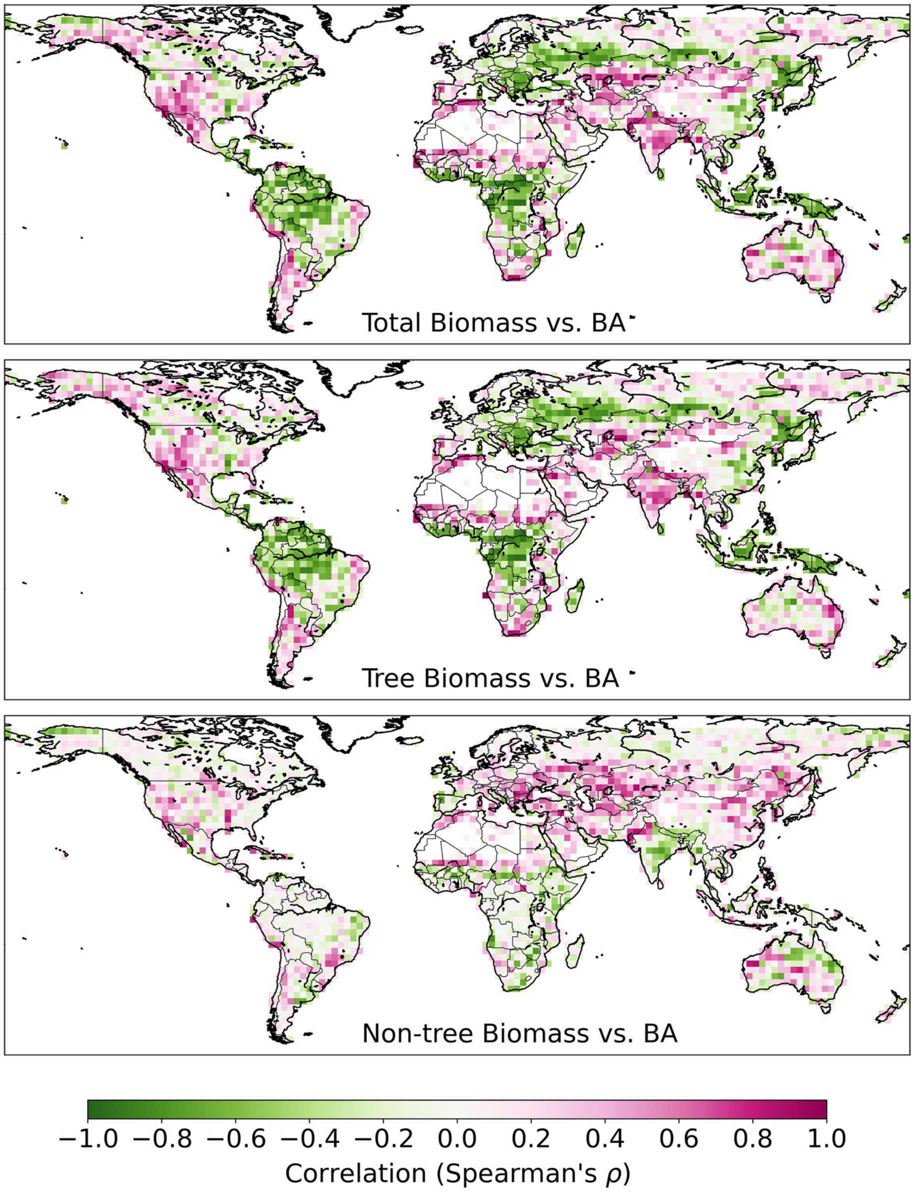

Figure 8. Spearman's correlation (ρ) between mean annual burned area (BA) and biomass fuel stocks (Spawn et al., 2020) during 2001–2019 at 2.5° resolution. Correlations are shown separately for (top panel) total, (middle panel) tree and (bottom panel) non-tree biomass fuel stocks. The correlation analyses are performed at a spatial resolution of 2.5° based on input data from 100 sub-grid cells with 0.25° spatial resolution. The BA data derive from Giglio et al. (2018; updated through 2019) and the biomass data from Spawn et al. (2020; see methods in Text A in Supporting Information S1).

negative relationship seen globally between tree cover and annual BA, we observe negative correlations between tree biomass and BA in the majority of world regions. In contrast, correlations between non-tree biomass and BA are more often positive. These correlations are broadly consistent with the flammable nature of herbaceous fuels, which dry more rapidly during periods of fire weather than woody fuels and so can quickly become flammable (Alvarado et al., 2020; Kahiu & Hanan, 2018; van der Werf et al., 2008; Y. Chen et al., 2017).

Fire has itself imprinted on the traits of some plant species, which have evolved survival or rejuvenation strategies to deal with fire disturbance. For example, the eucalyptus forests of Southeast Australia are particularly noted for their tolerance of fire, with flammable properties such as leaves with high surface area and volatile oil content (Bond & Keeley, 2005; Cawson & Duff, 2019; Crisp et al., 2011; Rodriguez-Cubillo et al., 2020; Tumino et al., 2019). Eucalyptus species show various evolutionary strategies that protect them from mortality or allow

Table 4
Regional Correlations Between Burned Area (BA) and Aboveground Biomass Carbon Density Based on BA Observations and Biomass Carbon Density

Region		Total Biomass Stocks		Tree Biomass Stocks		Non-tree Biomass Stocks	
		Mean ρ	% of area with significant correlation (p < 0.05) of the same sign	Mean ρ	% of area with significant correlation (p < 0.05) of the same sign	Mean ρ	% of area with significant correlation (p < 0.05) of the same sign
GFED	BONA	-0.07	18	-0.07	16	0.02	7
	TENA	0.06	39	0.05	37	0.17	33
	CEAM	-0.08	27	-0.09	27	0.07	30
	NHSA	-0.51	68	-0.51	68	0.09	9
	SHSA	-0.25	42	-0.25	43	0.02	18
	EURO	-0.29	28	-0.30	28	0.26	29
	MIDE	0.30	42	0.16	33	0.34	47
	NHAF	-0.11	32	-0.06	28	-0.10	28
	SHAF	-0.20	42	-0.18	41	-0.06	25
	BOAS	-0.28	33	-0.28	30	0.19	22
	CEAS	-0.11	32	-0.21	35	0.31	49
	SEAS	0.10	43	0.10	47	-0.07	32
	EQAS	-0.44	51	-0.44	51	-0.02	6
	AUST	0.04	37	-0.01	20	-0.02	26
Ecoregions	Alaskan Forests	0.02	33	0.03	39	0.05	11
	Pacific Canadian Forests	0.00	11	0.00	49	0.03	0
	Pacific US Forests	0.07	35	0.06	35	0.10	30
	Southern Amazonia	-0.39	79	-0.39	78	-0.05	5
	Mediterranean	0.03	21	-0.04	30	0.22	38
	North African Savannahs	-0.10	30	-0.06	29	-0.10	30
	South African Savannahs	-0.19	45	-0.18	45	-0.06	24
	East Siberian Forests	-0.15	24	-0.15	22	0.11	20
	Indonesian Forests	-0.43	47	-0.43	47	-0.01	8
	Southeast Australian Forests	0.34	45	0.33	45	-0.12	28

Note. The regional correlations reflect spatial co-variability in BA and biomass carbon density, expressed as the average of the correlations seen across the 2.5° cells of each region (each 2.5° cell includes a sample of 100 data points for each variable at 0.25° resolution). This approach is based on that used by Andela et al. (2017). We consider regional correlations to be significant in cases where the majority (>50%) of cells show a significant correlation ($p < 0.05$) of the same sign. Colors represent the strength of positive (purple) and negative (green) correlations as in Figure 8. The BA data derive from Giglio et al. (2018; updated through 2019) and the biomass data from Spawn et al. (2020; see methods in Text A in Supporting Information S1).

their communities to re-establish quickly following fire (Burton, Bennett, et al., 2021; Furlaud et al., 2021; Poulos et al., 2018; Rodriguez-Cubillo et al., 2020). In our analysis, correlations between tree cover and BA were usually negative but this differed in the case of southeast Australia and in the Mediterranean climates of the Pacific US and the Iberian Peninsula, where weak positive correlations are seen between tree biomass and BA (Figure 8, Table 4). These spatial correlations suggest that denser forests in these regions support a greater level of fire activity, in contrast to forests in other world regions.

Notably, plant traits can also modulate fire characteristics. Differences in low-severity surface fire and high-severity crown fire dynamics are seen between boreal forests in North America and Eurasia, and they have been associated with the traits of the spruce, pine and larch species that dominate in those regions (Baltzer et al., 2021;

de Groot et al., 2013; Rogers et al., 2015; Wooster & Zhang, 2004). Rogers et al. (2015) suggested that the North American dominant species have evolved to embrace or tolerate high-severity stand-replacing fires as part of their life cycle, whereas the Eurasian dominant species have evolved to promote low-severity fires with low tree mortality. The dominant Eurasian species shed more understory branches (reducing ladder fuels), maintain higher leaf moisture and thicker bark, and have greater survival rates during fires than their North American counterparts (Rogers et al., 2015). Meanwhile, the dominant North American species, most notably black spruce, favor high-intensity crown fires that combust more fuel and lead to higher tree mortality (Rogers et al., 2015). An increase in the coniferous fraction of tree cover with latitude in Canada has also been associated with increased sensitivity to fire weather, consistent with observations that North American coniferous species are less resistant to fire than deciduous species (X. Wang et al., 2014). The importance of species traits is similarly implied in our analysis by the contrasting correlations between tree biomass and BA in the Pacific Canadian and Alaskan forests versus the east Siberian forests, with the latter showing a negative correlation consistent with the fire-resistant properties of dominant subspecies in the region (Figure 8, Table 4). Several studies have shown that including vegetation properties such as stand age and species composition can improve the predictive capacity of fire models in Canadian forests versus those based on fire weather alone (Cavard et al., 2015; Hanes et al., 2019), including in the case of severe fires (Walker et al., 2020). Recently, it has been reported that the regeneration of black spruce communities following fire is beginning to falter in some regions of North America as reductions in moisture availability lessen their competitive advantage over other species (Baltzer et al., 2021). This demonstrates how climate transitions beyond historical windows can alter special composition and alter the fire-adapted traits of the landscape.

Analyses of the relationship between BA and tree fraction or tree biomass provide insights into the role of vegetation biogeography as a control on fire activity, however, they do not represent temporal variability in fuel availability, which exerts important controls on fire activity in many fuel productivity-limited ecoregions of the world. In many savannahs, weather conditions lead to the desiccation and turnover of fuels in virtually every dry season, such that the quantity of vegetation produced during prior wet seasons is a greater control on interannual variability in BA than contemporaneous moisture deficit in the dry season season (Alvarado et al., 2020; Archibald et al., 2009; van der Werf et al., 2008; Y. Chen et al., 2017). A strong positive correlation between precipitation during the wet season and fire activity during the following dry season was observed by van Wilgen et al. (2000) in Kruger national park (South Africa). van der Werf et al. (2008) showed that BA increases with mean annual precipitation in zones of transition between deserts and savannah grasslands (e.g., in the Sahel and northern Australia), also highlighting the dependence of BA on prior vegetation productivity. Archibald et al. (2009) also showed that, in African savannahs, high wet-season rainfall followed by a long dry season supports the greatest fire frequencies. Andela and van der Werf (2014) showed that a reduction in precipitation associated with the ENSO during 2001–2012 affected the wet season productivity of African savannahs and hence also BA, particularly in southern Africa. Chen et al. (2017) later showed that variability in precipitation associated with the ENSO influences fuel availability in northern Australian and African savannahs, with negative emissions responses occurring widely during the second year of El Niño as a result of reduced fuel production. Alvarado et al. (2020) used regression models to understand the long (2 years) and short (6 months) lagged effects of precipitation on fuel load and fuel moisture, respectively, in tropical savannahs. BA was principally controlled by the longer-term accumulation of fuels in Australian savannahs, whereas in African savannahs the effects of fuel loads and fuel moisture conditions were of approximately equal importance, and in South American savannahs BA was principally controlled by fuel moisture levels. Abatzoglou et al. (2018) also highlighted that 2-year precipitation was a stronger covariate of BA than contemporaneous fire weather in northern Australian savannahs. By using machine learning models, it has been shown that monthly BA increases with increasing vegetation photosynthesis in the previous 6 months in many semi-arid regions (Forkel, Andela, et al., 2019; Kuhn-Régnier et al., 2021).

Although fuel limitations are most prominent in savannahs and grasslands, vegetation productivity during prior growing seasons has also been linked with interannual variability in fine fuel availability in forests and shown to influence fire activity in some cases. The Mediterranean can be considered a region with complex constraints on fire activity, where both fuel limitations, affected by spring precipitation, and moisture limitations, affected by contemporaneous fuel drying, impact the interannual variability in fire (Pausas & Paula, 2012; Turco et al., 2014). The annual extent of forest fires has been shown to correlate positively with precipitation in prior years in some parts of France (Ruffault et al., 2016), Greece (Koutsias et al., 2012), and Spain (Turco et al., 2013), although Turco et al. (2017) concluded that antecedent conditions affecting vegetation growth explained a minor fraction of the variability in summer BA at the scale of the Mediterranean. A relationship between prior-year fuel production and BA, consistent with fuel limitation, has also been observed in some forest ecoregions within the mediterranean climate zone in the western US (Keeley et al., 2015; Littell et al., 2009), although these relationships are predominantly restricted to non-forests (Abatzoglou & Kolden, 2013; Keeley et al., 2017; Westerling et al., 2003). Similar observations have been made in southeast Australian forests where BA is notably more limited by fire weather than by fuel accumulation, in contrast to semi-arid grasslands and shrublands (Bradstock, 2010; Russell-Smith et al., 2007). Global-scale analysis has shown that forest BA rarely exhibits a strong positive correlation with rainfall in prior years (Abatzoglou et al., 2018).

4.2. Lightning Is a Key Ignition Source in Wildlands

Lightning is the principal natural ignition source for fire and can be the dominant ignition source in many of Earth's wildlands. In general, human ignitions prevail over lightning ignitions in most urban, peri-urban and rural landscapes, however, numerous studies have shown that lightning strikes are the major source of fire in the most remote parts of the world (Abatzoglou et al., 2016; Balch et al., 2017; Cattau et al., 2020; Ganteaume et al., 2013; Kasischke et al., 2010; Reeve & Toumi, 1999; Stocks et al., 2002).

Due to the paucity of multi-decadal lightning observations at the global scale, most studies of the relationship between lightning activity and fire activity have to date focused on regions where national lightning detection networks have been in operation or where fire causes have been recorded routinely. Stephens (2005) evaluated US national fire statistics from federal forest land during 1940–2000 and found that the majority of fires in the southwest and Pacific coast region, including California, and the upper Rocky Mountains were ignited by lightning. Abatzoglou et al. (2016) also examined records of fire cause in the western US and observed that 40% of all wildfires, representing 69% of all BA, were ignited by lightning. Combining these records with data from the US National Lightning Detection Network and North American Precision Lightning Network, the authors showed that the correlation between lightning activity and BA was weak unless the impacts of fire weather on vegetation dryness were also accounted for. Balch et al. (2017) showed that lightning ignitions dominate over human ignitions in the forest ecoregions of the western US, in stark contrast to the grassland and shrublands of the region. Cattau et al. (2020) showed that ecoregions of the US in which fires are predominantly ignited by lightning experience fires that are on average nine times larger than in areas where human ignitions dominate. Overall, human ignitions usually prevail in the coastal parts of the western US landscape and result in frequent small fires, whereas lightning ignitions are less frequent but tend to result in larger forest fires in remote terrain (Abatzoglou et al., 2016; Balch et al., 2017; Cattau et al., 2020).

In interior Alaska and the Northwest Territories of Canada, Veraverbeke et al. (2017) showed that interannual variability in lightning ignition explained more than 55% of the interannual variability in BA, while in excess of 80% of all BA in these regions could be traced back to lightning ignition points during 1975–2015. Previously, Stocks et al. (2002) examined national fire records of large fires in Canada and revealed a gradient from predominantly human-ignited fires in the more populous south of the country to predominantly lightning-ignited fires in the more remote northern regions. Around 70% of large fires and 85% of large fire BA were associated with lightning during 1959–1997 (Blouin et al., 2016; Stocks et al., 2002). Peterson et al. (2010) found that annual fire counts correlated strongly with lighting strike frequency and that ~40% of satellite-detected hotspots in Interior Alaska were likely caused by lightning strikes during 2000–2006, while Kasischke et al. (2010) showed that lightning-ignited fire BA has increased since the 1940s in contrast to a decrease in the case of human-ignited fires. Magnussen and Taylor (2012) similarly showed that 55% of recorded fires in British Columbia were ignited by lightning, though interannual variability in lightning igitions was twice greater than interannual variability in human ignitions. Hanes et al. (2019) re-examined Canadian records of large fires and showed that the area burned by large lightning-ignited fires increased since 1959–2017, consistent with the findings of Veraverbeke et al. (2017) based on a blend of national records (1975–2000) and satellite detections (2001–2015). Numerous studies have also highlighted that climatic and topographic conditions are favorable for dry lightning occurrence in the North American boreal region (Blouin et al., 2016; Dissing & Verbyla, 2003; Peterson et al., 2010). The distribution of fires across populated and unpopulated regions of Russia infers that forest fires in Siberia are predominantly caused by lightning (Kharuk et al., 2011; Mollicone et al., 2006; Ponomarev et al., 2016), although the explicit separation of human and lightning -ignited fires is pending in the region. In our analysis, we observed strong correlations between monthly BA and monthly lightning activity on a climatological basis in the forests of

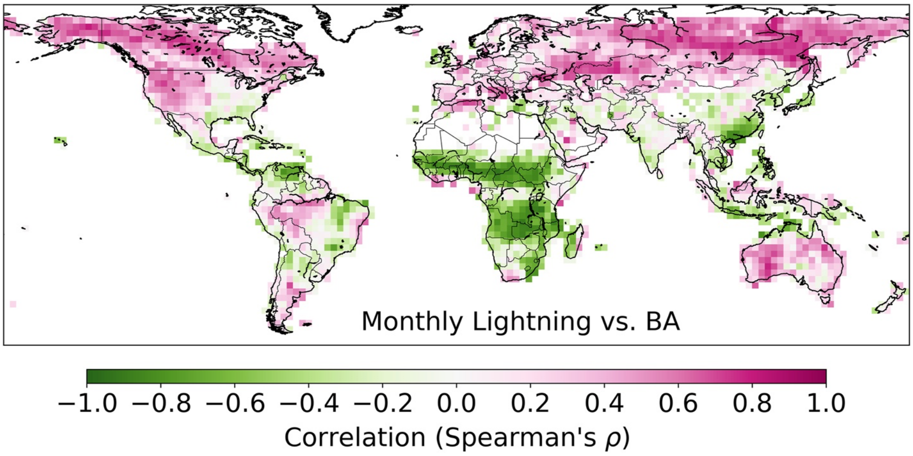

Figure 9. Spearman's correlation (ρ) between burned area (BA) and lightning activity, mapped at 2.5° resolution. Spearman's correlation between climatological monthly BA (2001–2019) and climatological monthly lightning activity in the periods 1995–2000 (extratropics) or 1998–2010 (tropics). Correlations derived at 0.5° are averaged to 2.5° for consistency with other correlation plots. The BA climatology is based on data from Giglio et al. (2018; updated through 2019) and the lightning climatology on data from Cecil et al. (2014; see methods in Text A in Supporting Information S1).

Pacific Canada, Alaska and east Siberia, thus suggesting that lightning plays a key role as a fire ignition source throughout the boreal forest zone (Figure 9, Table 5).

The Mediterranean is a fire-prone region where the majority of fires are associated with human ignitions (Ganteaume et al., 2013; San-Miguel-Ayanz et al., 2013). One study reports that just 5% of all fires in the Mediterranean region are caused by lightning (Camia et al., 2010). Nonetheless, several studies have identified parts of Spain (Amatulli et al., 2007; González-Olabarria et al., 2015; Vazquez & Moreno, 1998), southern France (Curt et al., 2016; Ganteaume & Guerra, 2018) and Italy (Vacchiano et al., 2018) where lightning fires exceed human ignitions, which are typically remote forested areas (Perez-Invernon et al., 2021). Ganteaume et al. (2013), San-Miguel-Ayanz et al. (2013), and Pineda and Rigo (2017) have investigated relationships between lightning ignition and the largest and some of the most severe fires in the Mediterranean.

Lightning is noted as a key ignition source in southeast Australia, in particular due to the relationship between pyroconvective conditions and fire activity in the region. Some of the most significant wildfire outbreaks in Australian history have been ignited by lightning strikes. For example, during the Black Saturday fires of 2009, which remain the deadliest Australian fire outbreak on record, convection resulting from the initial fires led to the generation of additional lightning strikes that ignited fires in neighboring forests (Dowdy et al., 2017). Penman et al. (2013) showed that lightning becomes an increasingly important contributor to total ignitions with distance from human infrastructure in southeast Australia, and that lightning ignitions tend to cluster on high and forested terrain. Lightning ignition rate is more strongly modulated by contemporaneous fire weather conditions than in the case of human-ignited fires (H. Clarke, Gibson, et al., 2019). Nonetheless, at the scale of Victoria and New South Wales, lightning ignitions of large forest fires are outnumbered by human ignitions of small fires especially in the more populated coastal regions (Attiwill & Adams, 2013; K. M. Collins et al., 2015; Williamson et al., 2016). Many fires occur each year in periods prior to the annual season of significant lightning activity, signifying the influence of humans on the fire regime in southeast Australia; however, peaks in annual fire activity partially coincide with peaks in lightning activity during the late dry season (Williamson et al., 2016). Dowdy (2020) found that the likelihood of dry lightning strikes has increased in all seasons in southeast Australia during 1979–2016, representing an upwards pressure on fire activity.

Many of the studies discussed above have used national records of fire cause to quantify the relative importance of lightning and human ignitions. Our analysis of the correlation between climatological monthly BA and monthly lightning activity complements these earlier studies by evaluating the co-seasonality of fire and lightning in the period 1998–2010 (tropics) and 1995–2000 (extratropics; Figure 9, Table 5; see Text A in Supporting Information S1 for methods). In line with previous reports, we observed spatially varying relationships between BA and lightning activity with a tendency for positive correlations to occur in remote forested regions (Figure 9).

Table 5
Regional Correlations Between Climatological Monthly Burned Area (BA) and Climatological Monthly Lightning Flashes, Averaged Within Each Region

Region		Mean ρ	p < 0.05
GFED	BONA	0.50	0.175
	TENA	0.19	0.352
	CEAM	-0.09	0.400
	NHSA	-0.28	0.338
	SHSA	0.03	0.392
	EURO	0.20	0.361
	MIDE	0.07	0.395
	NHAF	-0.48	0.195
	SHAF	-0.46	0.189
	BOAS	0.50	0.184
	CEAS	0.18	0.301
	SEAS	-0.09	0.417
	EQAS	-0.02	0.397
	AUST	0.25	0.301
Ecoregions	Alaskan Forests	0.60	0.108
	Pacific Canadian Forests	0.45	0.218
	Pacific US Forests	0.41	0.223
	Southern Amazonia	0.21	0.360
	Mediterranean	0.28	0.319
	North African Savannahs	-0.62	0.121
	South African Savannahs	-0.66	0.077
	East Siberian Forests	0.61	0.098
	Indonesian Forests	-0.02	0.399
	Southeast Australian Forests	0.25	0.379

Note. The lightning climatology in the tropics and subtropics is based on OTD data obtained during 1995–2000 and LIS data obtained during 1998–2010, whereas the extratropical climatology is based only on OTD data. We calculated the BA climatology for the period 2001–2019. Colors represent the strength of positive (purple) and negative (green) correlations as in Figure 9. The BA climatology is based on data from Giglio et al. (2018; updated through 2019) and the lightning climatology on data from Cecil et al. (2014; see methods in Text A in Supporting Information S1).

Insignificant positive correlations between lightning activity and BA were seen in many parts of the extratropics, including in the forests of the Pacific US and Canada, Alaska, east Siberia. The strongest and most significant correlations were observed in high latitude forests of Alaska and Siberia. The predominance of positive correlations in the extratropics is consistent with prior studies showing lightning's importance as a fire ignition source in temperate and boreal forests, however, the insignificance of the correlations likely indicates that fire weather or other bioclimatic and human factors have more pronounced impacts on the temporal variability in fire activity.

In contrast to the extratropics, our analysis shows insignificant negative correlations between BA and lightning activity across most of the tropics, including in African savannahs, but excluding some tropical forests. The negative correlation for much of the tropics likely reflects the coincidence of wet season peaks in lightning frequency with the season of greatest vegetation moisture content (and therefore lowest flammability), which determines that lightning strikes predominantly occur at a time when fire ignition and spread are most inhibited.

The positive correlation between lightning and BA in western and central parts of Amazonia is a peculiar regional finding with relatively little precedent from the existing literature (Figure 9, Table 5). Fires in the Amazon are usually considered to result overwhelmingly from deforestation or degradation fires as wet lightning with low ignition efficiency is more common than dry lightning (Alencar et al., 2004; Cochrane, 2003; van Marle, Field, et al., 2017; van der Werf et al., 2017). However, the positive, though insignificant, correlation seen here implies that lightning may be a more important ignition source than is typically considered. We note that the annual peak in lightning activity occurs around August-September in Amazonia, which coincides with the typical deforestation season of July-October (Aragão et al., 2018). Hence, the correlation between lightning and BA may be an artifact caused by covariance between lightning activity and human ignitions. In addition, lightning and deforestation fires may not be mutually exclusive as it has been suggested that smoke emitted from deforestation fires can promote lightning activity in Amazonia through pyroconvection and the supply of smoke particles to the atmosphere (Altaratz et al., 2010; Cochrane, 2003; W. A. Lyons et al., 1998).

5. Human Mediation of the Climate-Fire Relationship

5.1. Human Relationships With Fire Are Spatially Diverse

Humans have used fire throughout much of our history as a species, and aside from some of the more remote regions of the world (see Section 4.2) it is generally thought that humans dominate ignitions globally (Balch et al., 2017; Le Page et al., 2010). How and where humans today use fire intentionally as a tool of land stewardship, for deforestation, and for agricultural purposes creates distinct global patterns of high fire activity where climatic controls are secondary (Archibald et al., 2013; Syphard et al., 2017). Further, human management of the landscape feeds back to patterns of fire extent, frequency, and seasonality. Contemporary human suppression of fire through direct control (i.e., firefighting), land use or land management has created novel fire regimes, many of which are exacerbated by the changing climate (Archibald et al., 2013; Bowman et al., 2011; Kelley et al., 2019).

Global fire ignitions by humans today generally fall into three categories: human-caused wildfires that are usually accidental (but also include arson); intentional deforestation fires set to clear existing forests, and; intentional agricultural fires set annually to support cultivation of crops and pastoralism. Efforts to parse out whether human-caused fires are intentional or accidental focus on departures from natural fire regimes (seasonality and intensity), land use/land cover linkages, and syntheses of regional ethnographic literature, although these have primarily been regional in nature and there is no global human fire data set to date (Lauk & Erb, 2009; Lavorel et al., 2007).

To summarize all variants of the human-fire relationships, which are inherently local in nature, would be an elusive task (Ford et al., 2021). Nonetheless, some of the great spatial diversity of human relationships with fire has been distilled into regional patterns by global-scale studies of the co-variability between satellite-observed BA and population density and land use (Andela et al., 2017; Kelley et al., 2019). Here, we highlight some of the better-documented impacts of humans on global patterns of fire in relation to their influence on ignition opportunities, land cover, fuel loads and connectivity, and we consider how the spatial and temporal variability in these effects mediates the climate-fire relationship. To complement this discussion, we analyzed the spatial correlation between mean annual BA (2001–2019) and human population density at sub-grid scale, following the approach of Andela et al. (2017) with BA observations (see Text A in Supporting Information S1 for methods). Correlations are highly variable on these spatial scales (e.g., holding a mixture of positive and negative values; Figure 10) such that they can average to weak values even within ecoregions (Table 6).

5.2. Human Population and Infrastructure Mediate Wildfire Ignitions

Human ignitions, both accidental and related to arson, are most evident and tractable in European countries and some of their previous colonies, where intensive wildfire suppression is the dominant mode of management and deforestation and agricultural fires set by rural landowners are less prominent, including in the US, Canada, Australia, and much of Europe. Across these regions, human-caused wildfire distribution relates strongly to spatial proximity to human infrastructure and density in general. This includes increased ignitions with higher proximity to roads (Catry et al., 2009; Curt et al., 2016; Ganteaume et al., 2013; Gralewicz et al., 2011; H. Clarke, Gibson, et al., 2019; Oliveira et al., 2017; Silva et al., 2019; Syphard et al., 2017), with increased settlement in rural areas (Radeloff et al., 2018), and with higher population density (Clarke, Gibson, et al., 2019; Gralewicz et al., 2011; K. M. Collins et al., 2015, 2016), while rural abandonment coincides with a reduction in fire incidence (Oliveira et al., 2017; Silva et al., 2019). Spatial variability in human ignition opportunities can strongly

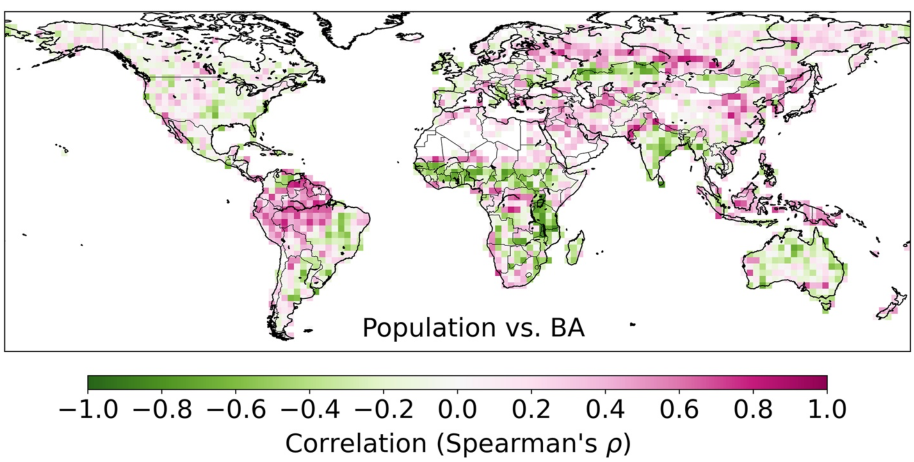

Figure 10. Spearman's correlation (ρ) between mean annual burned area (BA) and population density, gridded at 2.5° resolution. The correlation analysis is performed at a spatial resolution of 2.5° based on input data from 100 sub-grid cells with 0.25° spatial resolution. The BA data derives from Giglio et al. (2018; updated through 2019) and the data for population density follow Andela et al. (2017; see methods in Text A in Supporting Information S1).

Table 6
Regional Spearman's Correlations (ρ) Between Mean Annual Burned Area (BA) and Population Density

Region		Population Density	
		Mean ρ	% of area with significant correlation (p < 0.05) of the same sign
GFED	BONA	0.00	11
	TENA	-0.06	25
	CEAM	0.02	25
	NHSA	0.22	53
	SHSA	0.09	36
	EURO	0.02	17
	MIDE	0.18	44
	NHAF	-0.07	39
	SHAF	-0.12	43
	BOAS	0.12	33
	CEAS	0.05	31
	SEAS	-0.07	37
	EQAS	0.10	42
	AUST	-0.10	35
Ecoregions	Alaskan Forests	0.04	25
	Pacific Canadian Forests	-0.01	14
	Pacific US Forests	-0.11	48
	Southern Amazonia	0.29	69
	Mediterranean	0.05	26
	North African Savannahs	-0.15	50
	South African Savannahs	-0.21	51
	East Siberian Forests	0.11	28
	Indonesian Forests	0.08	38
	Southeast Australian Forests	-0.16	52

Note. The regional correlations are expressed as the average of the correlations seen across the 2.5° cells within each region (see Figure 10). We consider regional correlations to be significant in cases where the majority (>50%) of cells show a significant correlation ($p < 0.05$) of the same sign. Colors represent the strength of positive (purple) and negative (green) correlations as in Figure 10. The BA data derive from Giglio et al. (2018; updated through 2019) and the data for population density follow Andela et al. (2017; see methods in Text A in Supporting Information S1).

determine if a spell of fire weather translates to fire incidence, particularly in regions where lightning ignitions are rare.

Temporally, human-caused wildfires expand wildfire seasons well beyond the peak burning period of the natural fire regime (Balch et al., 2017; Le Page et al., 2010). Perhaps the starkest example of human-caused ignition anomalies is the >200% increase in mean daily ignitions in the US on its 4 July Independence day, linked to widespread use of fireworks (Balch et al., 2017). Notably, in regions with strong fire suppression and education campaigns (e.g., North America), the number of human-caused fires has declined significantly over the last half-century (Coogan et al., 2021; Prestemon & Butry, 2005).

5.3. Fire Is Integral to Tropical Deforestation

Fire is regularly used for the process of deforestation and land clearing for agriculture in the tropics, where modern land use changes have been most concentrated in recent decades (Hansis et al., 2015; Houghton & Nassikas, 2017). The so-called "slash-and-burn" agriculture practice has principally been concentrated in the tropical forests of southern Amazonia and Indonesia (Aragão et al., 2018; Silva Junior et al., 2021; Curtis et al., 2018; D. Nepstad et al., 2014; van der Werf et al., 2017). Fire is integral to the deforestation process in Amazonia and hence deforestation rates are highly correlated with fire incidence (Aragao & Shimabukuro, 2010; Aragão et al., 2008). The annual window of fire is constrained by the length and intensity of the dry season which vary from year to year, highlighting the underlying role of meteorology in controlling the timing of deforestation activities (Carvalho et al., 2021). Amazonian BA trends have changed in sign several times since the 1990s in response to policy implementation, regulation and recent relaxation (Aragão et al., 2018; D. Nepstad et al., 2014; Libonati et al., 2021; Tyukavina et al., 2017; Silva Junior et al., 2021; see Section 3.2). Notably, fire incidence is concentrated along legal and illegal roads and waterways, and at the periphery of existing agriculture, reflecting a mixture of expanding agricultural frontiers and unintentional fire escape from agriculture into the degraded edges of neighboring forest (Aldersley et al., 2011; Azevedo-Ramos & Moutinho, 2018; Cano-Crespo et al., 2015; Cochrane & Barber, 2009; D. Nepstad et al., 2001; Kumar et al., 2014).

Deforestation has legacy effects on the susceptibility of tropical forest edges to fire. Forest edges are less productive and hold lower stocks of biomass than intact forests, and they also experience increased rates of tree mortality and reduced rates of plant reproduction (Chaplin-Kramer et al., 2015; Pütz et al., 2011). Forest edges are more susceptible to desiccation and fire during droughts because they are better-ventilated and warmer due to reduced canopy cover and evaporative cooling, and because the penetration of light to the forest floor facilitates the enhanced growth of herbaceous vegetation that is sensitive to fire weather (Aragão et al., 2008, 2014, 2018; Alencar et al., 2015; Balch et al., 2015; Brando et al., 2014; Cochrane & Barber, 2009; Cochrane & Laurance, 2002; Coe et al., 2013; Silva Junior et al., 2018; Davidson et al., 2012; Fonseca et al., 2019; Hardwick et al., 2015; Laurance & Williamson, 2001; Nikonovas et al., 2020; Phillips et al., 2009). Understory vegetation can facilitate the spread of fire into forests from neighboring agricultural land, and even in regions of Amazonia with declining deforestation rates, the regular occurrence of agricultural fires near forest edges has been found to increase the incidence of wildfires in recent decades, especially during droughts (Alencar et al., 2004; Aragão et al., 2008, 2014; Barlow et al., 2020; Silva Junior et al., 2018; Nepstad et al., 2008). Selective logging has also been shown to increase forest temperatures, increase ventilation and foster the ingress of herbaceous vegetation in the forest interior, similarly leading to an elevated risk of fire occurrence in these areas (D. C. Nepstad et al., 1999, 2008). Hence, the positive correlations between BA and population density and agricultural activity in southern Amazonia (Andela et al., 2017; Figure 10, Table 6) are likely linked to a mixture of deforestation fires and fire escape from agricultural land. Negative correlations between BA and tree biomass in Amazonia also support a link between forest degradation and fire incidence in the region (Figure 8; see Text A in Supporting Information S1 for methods).

While many studies have focused on the impacts of humans on fire activity in Amazonia, similar dynamics are seen in Indonesian tropical forests. Indonesian forest fires predominantly occur in proximity to human infrastructure (Field et al., 2009; Nikonovas et al., 2020). Field et al. (2009) showed that large fire events were recorded in some Indonesian forests during drought years only once the human population had expanded into those regions, despite equally strong droughts being recorded in the years prior. Deforestation fires are generally ignited at the climatological driest point of the year in order to maximize tree mortality and consumption of biomass (Field et al., 2016; Le Page et al., 2010). In addition, Nikonovas et al. (2020) have shown that forest edges are vulnerable to fire during drought periods in Indonesia and that the dense network of human infrastructure and large extent of fragmented forest edges in Indonesia mean that only ~3% of forest area remains insensitive to fire. In common with Amazonia, positive correlations are seen between BA and population density and agricultural activity in Indonesian forests (Andela et al., 2017; Figure 10, Table 6), while negative correlations are seen between BA and tree biomass (Figure 8). Similar dynamics have also been reported recently in African tropical forests (Z. Zhao et al., 2021).

5.4. Landscape Fragmentation by Agriculture Restricts Wildfire in Fire-Prone Regions

Landscape burns continue to be ignited frequently by humans in some agricultural and pastoral systems to maintain productivity, and there is strong regionality in the use of fire for agricultural management (Barlow et al., 2020; Bernardi et al., 2019; Korontzi et al., 2006; Rabin et al., 2015). In some regions, this is a continuation of millennia of pastoral cultures, while in other regions it stems from colonialism and the replacement of Indigenous and lightning-ignited fires with intentional human ignitions. In agricultural systems, particularly where monoculture cereal crops dominate, humans tend to use fire to remove the crop residues from the prior growing season before planting or after harvest (Aguiar et al., 2011; Hall et al., 2016; McCarty et al., 2007; Korontzi et al., 2006; Moreira & Pe'er, 2018). Agricultural fires also influence fire patterns in regions that have been recently deforested, such as in Amazonia, which can lead to unintended ignitions of forest fires during drought periods (Aragão et al., 2018; Barlow et al., 2020; Libonati et al., 2021).

In tropical and temperate pastoral rangelands, such as the *cerrado* and *pampas* of South America, the tropical savannahs of Africa and Australia and the temperate prairies and steppe of mid-North America, southeast Australia, and central Asia, pastoralists have ignited fires near annually for millennia to remove material from the prior growing season and stimulate new growth of native, fire-adapted herbaceous species (Bernardi et al., 2019; Le Page et al., 2010, 2017; Magi et al., 2012). Today, these burns are conducted early in the growing season in most regions (Le Page et al., 2010), and the fires provide a short-lived fertilizing effect (San Emeterio et al., 2016). In many of these regions, such pastoral fires are the dominant source of fire activity, and ultimately serve to limit wildfires by modifying the availability and connectivity of fuel (Eloy, Bilbao, et al., 2019; Eloy, Schmidt, et al., 2019).

The fragmentation of natural fire-prone landscapes by expansion of agricultural land can lead to major shifts in the type and timing of fires. While early dry season agricultural burns are applied to maintain agricultural productivity and workability of the land, the removal of natural vegetation excludes wildland fires that would otherwise be more expansive and occur later in the dry season. Fire is excluded from croplands by irrigation, which maintains sufficiently high moisture levels to retard combustion (Moreira & Pe'er, 2018; Moreira et al., 2011; Oliveira et al., 2014). The maintenance of dry croplands, such as cereal crops and legumes, also reduces BA by altering fuel structure, timing of harvest (i.e., removing fuel prior to peak fire potential), and the speed and efficacy of fire suppression efforts in valuable croplands (Cruz et al., 2020; Moreira et al., 2009). In contrast to annual crops, agricultural forestry plantations can increase fire activity and severity, both through increasing the density of fuel and introducing non-native species with high flammability (Bowman et al., 2019; Moreira et al., 2009; Thompson et al., 2007). The herding of livestock, which consume herbaceous biomass and thus prevent fuel build-up, can result in the exclusion of fire from some areas; indeed, livestock are specifically used for this purpose in some fire-prone regions (Archibald & Hempson, 2016; Bernardi et al., 2019; Bond, 2008; Hempson et al., 2017; Scholes, 2009; Stevens et al., 2017). However, in some semi-arid regions where BA was historically low, overgrazing has been cited as the source of land cover conversion from relatively fire-resistant shrublands to high-flammability exotic grasslands, leading to significant increases in fire frequency and BA (Balch et al., 2013; D'Antonio & Vitousek, 1992; Olsson et al., 2012).

As more than half of global BA occurs in African savannahs, the drivers of fire in these regions are largely responsible for the overall declining trend of global BA. Several factors have received attention as potential drivers of the significant decline in BA in the African savannahs during recent decades, including changing precipitation patterns which variably affect fuel build-up and fuel moisture levels, but also including a shift towards high-capital agricultural production (Alvarado et al., 2020; Andela & van der Werf, 2014; Forkel et al., 2017; Zubkova et al., 2019). A widespread transition from nomadic pastoralism on common land to permanent cropland systems has been invoked by some studies as a key driver of the significant decline in BA during recent decades

(Andela et al., 2017; Arora & Melton, 2018; Grégoire et al., 2012; Houghton et al., 2000). This explanation is consistent with previous reports that fire timing and frequency are controlled by management practices employed in permanent croplands, that unplanned fires tend to be suppressed actively, and that the landscape tends to be more fragmented thus inhibiting the spread of fire, in contrast to nomadic pastoralism which often promotes burning as a tool for land management (Archibald et al., 2009; Grégoire et al., 2012; Tiffen, 2006; Turner, 2011; Van Wilgen, 1997). Supporting these accounts of the socioeconomic dynamics of agriculture affecting fire in the African savannahs, Andela et al. (2017) evaluated how the relationship between BA and population and land use varies across gradients of economic development. The relationships seen between BA and the density of humans, cropland and livestock were found to conform to a conceptual framework describing the socioeconomic drivers of fire in Africa: As landscapes are converted from common land with low economic productivity to permanent agriculture with higher economic productivity, open canopy savannah-grasslands become more fragmented and BA reduces in both the remaining intact savannahs and on the farmed land. Further, the authors showed that BA falls most rapidly during the initial phases of transition from common to low-capital permanent agriculture, and more slowly during the later transition from low- to high- capital permanent agriculture.

Beyond the studies of the socioeconomic drivers of fire activity in the African savannahs, the impacts of temporal variability and trends in climate and land use on BA have also been investigated. Andela and van der Werf (2014) used a statistical model describing the dependence of annual BA on antecedent precipitation as well as change in cropland extent. The model indicated that 24% of the decline in BA is explained by reductions in precipitation and 20% was explained by cropland expansion in northern hemisphere savannahs. Meanwhile, in southern hemisphere savannahs, trends in BA were driven predominantly by changing patterns of precipitation. Employing the same statistical model, Andela et al. (2017) adjusted annual BA estimates to filter out the effect of precipitation on BA in Africa during the 1998–2016, finding that the significant decline in BA persisted even after accounting for precipitation trends. This result implicated human effects such as cropland expansion and the fragmentation of the natural fire-prone landscape as the predominant driver of the decline in BA during 1998–2016. However, other studies have debated the importance of cropland expansion to trends in African savannahs. Earl and Simmonds (2018) showed that weekly cycles of fire activity are weak in African savannahs, suggesting a lesser human imprint on fire activity than in other world regions. They instead considered the reduction in fire activity in northern Africa to result from a combination of agricultural expansion and declines in vegetation productivity which had been reported by others (Giglio et al., 2013; M. Zhao & Running, 2010). Zubkova et al. (2019) studied the contribution of trends in effective rainfall (precipitation minus evapotranspiration) and soil moisture to BA trends at the ecoregional scale in African savannahs, finding that these metrics were stronger predictors of BA than precipitation alone in all ecoregions. The results indicated that climate variables can explain 70% of the BA decline in Africa, a higher proportion that the 24% found by Andela and van der Werf (2014), most likely because the variables used as predictors reflect the landscape-level hydrological balance making them better indicators of the moisture available to vegetation (for either fuel production or the maintenance of vegetation moisture levels).

In summary, most studies suggest a mix of bioclimatic and human factors are responsible for the decline in BA in African savannahs during recent decades. Spatial correlations imply that human activities including the agricultural extent and landscape fragmentation are important drivers of variability in BA in African savannahs, consistent with understanding of socioeconomic processes affecting fire in the region, particularly in the northern hemisphere (Figure 10). Some studies have also suggested that the effect of human activities can be detected in the temporal trend in BA in the north African savannahs. On the other hand, the impact of humans is clearly heterogenous, and for example, positive correlations between human activities and BA are seen in the Sahel and many parts of Southern African savannahs (Figure 10). In addition, climate trends including reductions in rainfall have been shown to suppress vegetation productivity, reduce fuel stocks and thus generally reduce BA, and these trends have also been implicated as important drivers of the decline in BA in some parts of the African savannahs. Hence, it is likely that humans and bioclimatic factors are both important drivers of BA in African savannahs, and that these factors have both contributed to the substantial regional decline in BA during recent decades. Machine learning models attribute temporal variability in BA in African savannahs to humans and bioclimatic factors, with high spatial variability in the relative importance of each factor (Forkel et al., 2017; Kelley et al., 2019). This highlights the complexity of the controls on fire in the region and that the decline in BA during recent decades is likely to be explained by interacting human and bioclimatic phenomena.

5.5. Humans Suppress Fire to Protect Lives and Assets

Aside from deforestation fires and agricultural burning, intentional fire suppression is the globally prevalent response to wildfires caused by natural or unwanted human ignitions, especially in developed nations strongly influenced by European colonial attitudes to fire (Burrows & McCaw, 2013; Doerr & Santín, 2016; Marlon et al., 2012; North et al., 2015). The concept of fire control was initially brought to the Americas, Australia, and Africa by European colonizers, who fundamentally changed fire use by Indigenous peoples (Greenlee & Langenheim, 1990; Head, 1994; Mensing et al., 1999), although it was still used by white settlers in rural areas as a primary tool for clearing land for farming and to establish communities. This changed rapidly in the latter half of the nineteenth century in concert with the industrial revolution, as railroads expanded globally (and steam engines became a vector for ignitions in dry regions), timber became a highly valued commodity for building the rapidly expanding post-colonial cities, and machinery began to replace landscape fire as a more controllable and efficient tool (Bowman et al., 2011). Government-organized wildfire suppression expanded throughout the twentieth century, and became particularly effective in the aftermath of World War II, when military techniques and equipment were adopted (Pyne, 1982).

Modern suppression techniques have been effective in limiting the spread of fire in many fuel types globally for over a century, particularly where low- and moderate-intensity fires dominate the fire regime. Suppression has been less effective in regions dominated by high-intensity, stand-replacing fires associated with extreme fire weather conditions; as those conditions occur more frequently with climate change, the efficacy of suppression has declined and larger, longer-burning fires have occurred. Several studies have concluded that reductions in BA in the Mediterranean are associated with increased suppression capability (Duane & Brotons, 2018; Forzieri et al., 2016; Fréjaville & Curt, 2017; Turco et al., 2016; Urbieta et al., 2019). By contrast, BA in North America declined in the mid-twentieth century with effective suppression, but has increased over the last four decades as both an accumulation of fuel and more extreme fire weather conditions have resulted in increased fire size and difficulty of control (Barbero et al., 2015; Littell et al., 2009). This aptly demonstrates the unintended consequence of effective fire suppression, which can increase the risk of extreme fires in the long term by allowing the undisturbed accumulation of aboveground biomass in the absence of other fuel management interventions (Allen et al., 2002; A. M. S. Smith et al., 2016; Schoennagel et al., 2017). In the western US, fire suppression policies have resulted in excessive fuel accumulation, an increase in fire severity and fire size in some regions and has left many forest types out of sync with their historic fire regimes (Hagmann et al., 2021; Hurteau et al., 2014; Marlon et al., 2012).

Intentional burns have been carried out by Indigenous peoples for millennia to promote biodiversity, food security, facilitate mobility of human populations, protect against wildfires, and even conduct warfare (Bird et al., 2008; Bowman et al., 2009). In the modern period, controlled or "prescribed" fire has been co-opted by post-colonial western societies to achieve some of these same goals. In some regions, the magnitude of prescribed fire has increased to the point where it contributes substantially to regional BA (Kolden, 2019). We found that population correlates negatively with BA in coastal regions of California, southeast Australia and the Mediterranean (Figure 10, Table 6). This may reflect, in part, a combination of intensive wildfire suppression, the maintenance of agricultural or urban landscapes, and the fragmentation of natural land cover with impacts on the connectivity of fuels across the landscape (Bell & Oliveras, 2006; Fernandes et al., 2013; Kolden, 2019; Prichard et al., 2021).

Controlled burning in contemporary western societies has its roots in ecological restoration but today it is used increasingly to manage fuel loads and with the aim to reduce the severity of wildfires, particularly in seasonally dry temperate forests in North America, the Mediterranean, and Australia. Controlled burns are conducted when weather conditions offer a low risk of fire spread (Burrows & McCaw, 2013; Doerr & Santín, 2016; Fernandes & Botelho, 2003; Fernandes et al., 2013; H. Clarke, Gibson, et al., 2019; Clarke, Tran, et al., 2019; Price et al., 2015). In the USA, between 2001 and 2019 an annual average area of 12,900 km^2 was treated with controlled burns compared to 27,500 km^2 by wildfires, however, >90% of the area treated was in the relatively low population density portions of the eastern and southeastern US (Kolden, 2019). Negative correlations between population density and BA may indicate the effectiveness of controlled burning programmes in these parts of the US (Figure 10, Table 6). Similarly, cooperative prescribed fire informed by aboriginal cultural practices in northern Australia is extensive and has shifted the peak of the burning period over a month earlier and reduced wildfire risks (Liu et al., 2021). The reduction in overall fire activity as a result of controlled burning programmes may contribute to the negative correlation between population density and BA in this region (Figure 10).

Controlled burning is considered effective in reducing the risk of damage to infrastructure and, to various degrees, to reduce fire frequency and intensity (Bradstock et al., 2012; Hiers et al., 2020; Moritz et al., 2014; O. F. Price et al., 2015). However, its effectiveness could be diminished by lengthening FWSL in some regions (O. F. Price et al., 2015; Tolhurst & McCarthy, 2016). For example, extended wildfire seasons in the western US and southeast Australia have resulted in a perceived reduction in the number of days suitable for controlled burning amongst operational services (Prichard et al., 2017; Ximenes et al., 2017). In the southeast US, Kupfer et al. (2020) used climate models to project that the future frequency of suitable days for prescribed burning will decrease substantially in the summer months by the end of the twenty-first century compared with historical conditions. Similar efforts using regional climate models in Australia have also pointed toward a more constrained burn window in southeast Australia in future climates (Di Virgilio et al., 2020), however, the projections also vary regionally and with definition of suitable conditions for prescribed burning (H. Clarke, Gibson, et al., 2019; Clarke, Tran, et al., 2019). Other work has suggested that suppression capacity could be exceeded more regularly in future due to climate change in parts of Canada (Wotton et al., 2017). As more extreme environmental conditions occur and fire frequencies change across seasonally dry biomes, questions have begun to arise about the trade-offs between controlled burning and other ecosystem services such as air quality and carbon storage (Hunter & Robles, 2020).

6. Century-Scale Changes in Fire Weather and Burned Area

6.1. Fire Weather Is Escalating as the Climate Warms

Increases in fire weather during the past four decades have exerted an upwards pressure on fire activity in virtually all regions of the world (Section 3; Figure 7). This pressure influences the risk of fires where fuels and ignition sources are available, and it is linked to variability in fire activity in many forest ecoregions with ample fuel loads. This raises critical questions related to fire risk in fuel-rich regions: To what extent has fire weather increased due to anthropogenic climate change, and will this continue in future? To help address the question, a host of global and regional studies have used climate model simulations of past and future change in temperature, precipitation, humidity and wind to simulate change in fire weather indices (Abatzoglou et al., 2019; Bowman et al., 2017; M. Flannigan et al., 2013).

M. Flannigan et al. (2013) used three climate models and three emission scenarios to evaluate how cumulative severity rating (CSR), a component of the FWI, will change in the mid-century (2041–2050) and late century (2091–2100) relative to the 1971–2000 baseline. They observed significant increases in CSR that are initially most pronounced in high northern latitudes but encompass most of the Earth by the end of the century. Bowman et al. (2017) calculated the future frequency of extreme (93rd percentile) fire weather based on 23 CMIP5 climate models running RCP 8.5, finding increases on the order of 20%–50% by the mid-21st century in many regions that are historically prone to disastrous fires (e.g., the western US and southeast Australia) and larger increases in the Mediterranean and the subtropical Southern Hemisphere. Abatzoglou et al. (2019) used a 17-model ensemble of CMIP5 climate models to assess trends in four metrics of fire weather including FWSL and the annual frequency of extreme fire weather (FWI_{95d}), also applying the temperature of emergence framework to distinguish modern and future fire weather from that seen in the pre-industrial period (see Section 6.2). Son et al. (2021) recently highlighted that fire weather increases markedly between the 1.5°C and 2.0°C increments of global MAT in many regions, most notably in the Mediterranean, Amazonia and African savannah. While their results highlight the potential benefits to mitigating avoided fire risk of meeting the 1.5°C ambitious target of the Paris Agreement rather than the 2.0°C commitment, our results further indicate that weather-related fire risks could also rise substantially if the 2.0°C commitment is not achieved.

As an extension to the global modeling exercise of Abatzoglou et al. (2019), we used the same 17-model ensemble of CMIP5 models to estimate the regional impacts of climate change on modeled mean annual FWSL and mean annual FWI_{95d} for the modern period (1980–2019) and for policy-relevant MAT increments (1.5°C, 2.0°C, 3.0°C, and 4.0°C) relative to the pre-industrial period (1860–1910; see Text A in Supporting Information S1 for methods; Tables 7 and 8, Figure 11). In general, the majority of models agree on the sign and significance of trends in FWSL and FWI_{95d} at temperature increments of 1.5°C and above (Tables 7 and 8).

The modeled historical changes in FWSL varied across our focus ecoregions, with the greatest proportional changes occurring in Alaskan forests (+28%), southern Amazonia (+22%) and the Mediterranean (+20%) and

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the greatest absolute changes in Pacific US forests (+7 days year^{-1}), the Mediterranean (+8 days year^{-1}), and African savannahs (+5–6 days year^{-1}). FWSL is projected to increase particularly rapidly in Amazonia as higher temperature increments are breached, from +74% at 1.5°C, to +136% at 2.0°C, +282% at 3.0°C and +414% at 4.0°C. FWSL is also projected to increase steeply in Alaskan forests, the Mediterranean, Pacific Canadian forests and Indonesian forests, increasing by 37%–73% at temperature increments of 1.5°C–2.0°C and approximately doubling at 3.0°C above the baseline (Figure 11, Table 7). Similar patterns of change in FWI_{95d} are also seen across most of these regions, although typically the relative changes are larger in magnitude (Table 8). For example, FWI_{95d} is predicted to increase 2–3 times more rapidly than FWSL in the Mediterranean and Pacific US forest at all future temperature increments, and 4–7 times more rapidly than FWSL in African savannahs. Son et al. (2021) recently highlighted that fire weather increases markedly between the 1.5°C and 2.0°C increments of global MAT in many regions, most notably in the Mediterranean, Amazonia and African savannah. While their results highlight the potential benefits to mitigating avoided fire risk of meeting the 1.5°C ambitious target of the

Table 7
Fire Weather Season Length (FWSL) Modeled by 17 CMIP5 Models (Multi-Model Mean) During a Baseline Period of 1860–1910, and Change in FWSL in the Modern Period (1990–2019) and at Four Future Temperature Increments (1.5°C, 2.0°C, 3.0°C, and 4.0°C; 10 Models Only for 4.0°C)

Region		1860-1910 mean FWSL (days year^{-1})	Absolute Change in mean FWSL (year^{-1})					Relative Change in mean FWSL (%)					Multi-model Agreement on Sign and Significance of Change (%)					Period of emergence
			1990-2019	1.5°C	2.0°C	3.0°C	4.0°C (10 models only)	1990-2019	1.5°C	2.0°C	3.0°C	4.0°C (10 models only)	1990-2019	1.5°C	2.0°C	3.0°C	4.0°C (10 models only)	
Global	Global	43	5	10	14	22	31	11	24	32	51	72	100	100	100	100	100	Already emerged
GFED	BONA	11	1	3	4	9	15	9	27	39	86	137	47	76	88	88	100	Already emerged
	TENA	33	6	9	12	19	32	18	27	35	56	95	76	94	100	100	100	Already emerged
	CEAM	68	14	22	26	41	47	21	33	39	61	69	88	88	94	100	100	Already emerged
	NHSA	16	3	6	9	16	25	18	40	56	96	153	59	82	82	100	100	Already emerged
	SHSA	27	5	11	17	25	39	21	42	63	95	148	71	94	100	100	100	Already emerged
	EURO	17	4	10	14	19	34	22	61	84	115	205	88	100	100	100	100	Already emerged
	MIDE	104	11	17	23	33	44	11	17	22	32	43	88	100	100	100	100	Already emerged
	NHAF	119	4	5	6	10	9	3	4	5	9	8	47	53	65	65	70	3.0C
	SHAF	87	10	20	25	35	42	11	23	28	40	49	88	100	100	100	100	Already emerged
	BOAS	9	0	2	5	7	15	3	24	50	73	164	53	82	88	88	100	Already emerged
	CEAS	29	2	6	8	12	21	7	21	27	43	74	47	94	100	100	100	Already emerged
	SEAS	65	5	6	7	10	18	7	9	11	15	27	65	71	82	82	100	2.0C
	EQAS	3	0	2	2	4	4	14	65	54	117	130	24	65	71	82	100	3.0C
	AUST	97	4	15	18	27	40	4	15	19	28	41	29	76	82	82	100	2.0C
Ecoregions	Alaskan Forests	6	2	3	3	7	10	28	51	57	119	174	41	76	76	88	100	2.0C
	Pacific Canadian Forests	10	2	4	6	13	18	18	37	62	136	177	41	59	82	94	100	2.0C
	Pacific US Forests	58	7	9	14	23	29	12	16	23	39	50	41	71	88	100	100	2.0C
	Southern Amazonia	9	2	7	12	26	38	22	74	136	282	414	35	71	82	94	90	Already emerged
	Mediterranean	43	8	20	28	42	58	20	47	65	97	135	82	100	100	100	100	Already emerged
	North African Savannahs	141	5	7	8	11	11	4	5	6	8	8	59	76	76	76	70	1.5C
	South African Savannahs	90	6	9	14	20	28	6	10	15	23	31	71	82	94	100	100	Already emerged
	East Siberian Forests	10	0	1	2	5	14	-2	8	24	54	137	24	47	65	82	100	2.0C
	Indonesian Forests	3	1	2	2	3	4	16	73	57	106	132	12	65	71	71	80	3.0C
	Southeast Australian Forests	37	1	10	12	18	20	2	27	34	48	54	24	71	76	88	100	3.0C

Note. Significant changes in FWSL are assessed using a *t*-test for each model, and here, we show the degree of model agreement (% of models) on the sign and significance of the reported changes. The timing of the emergence of FWSL beyond pre-industrial variability is identified via a strict signal-to-noise criterion. All data and methods follow those of Abatzoglou et al. (2019; see methods in Text A in Supporting Information S1). Colors represent the strength of positive (red) and negative (blue) relative changes in fire weather as in Figure 11.

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Table 8
The Frequency of Extreme Fire Weather (FWI_{95d}) Modeled by 17 CMIP5 Models (Multi-Model Mean) During a Baseline Period of 1860–1910, and Change in FWI_{95d} in the Modern Period (1990–2019) and at Four Future Temperature Increments (1.5°C, 2.0°C, 3.0°C, and 4.0°C; 10 Models Only for 4.0°C)

Region		1860-1910 mean FWI_{95d} (days year^{-1})	Absolute Change in mean FWI_{95d} (days year^{-1})					Relative Change in mean FWI_{95d} (%)					Multi-model Agreement on Sign and Significance of Change (%)					Period of emergence
			1990-2019	1.5°C	2.0°C	3.0°C	4.0°C (10 models only)	1990-2019	1.5°C	2.0°C	3.0°C	4.0°C (10 models only)	1990-2019	1.5°C	2.0°C	3.0°C	4.0°C (10 models only)	
Global	Global	15	3	6	9	16	25	17.5	40.3	58.4	103.9	165.4	94	100	100	100	100	Already Emerged
GFED	BONA	16	2	5	8	15	24	15.8	33.3	52.8	95.1	153.7	65	88	88	88	100	Already Emerged
	TENA	15	3	6	8	16	27	22.5	41.3	54.3	109.0	176.1	76	88	100	100	100	Already Emerged
	CEAM	12	6	13	16	23	27	51.6	104.3	128.8	187.2	222.4	82	88	88	100	100	Already Emerged
	NHSA	14	4	8	10	20	26	25.3	54.9	69.9	138.7	180.8	53	76	82	100	100	Already Emerged
	SHSA	14	4	12	16	24	39	27.1	82.7	111.1	170.1	274.5	65	94	100	100	100	Already Emerged
	EURO	15	4	8	12	21	34	24.7	55.1	83.8	139.6	227.5	82	100	100	100	100	Already Emerged
	MIDE	14	5	11	16	24	35	35.1	78.5	118.3	180.2	256.0	71	100	100	100	100	Already Emerged
	NHAF	16	2	3	4	7	9	11.6	19.6	25.2	45.4	57.3	47	65	76	88	80	2.0C
	SHAF	15	3	8	13	21	27	23.1	56.7	90.7	139.7	182.8	59	100	100	100	100	Already Emerged
	BOAS	16	2	5	7	13	21	15.3	30.5	44.9	83.0	129.5	59	88	88	88	100	Already Emerged
	CEAS	16	2	5	8	12	20	10.8	32.8	48.8	73.2	119.6	53	100	100	100	100	Already Emerged
	SEAS	14	4	6	8	14	22	30.6	46.8	60.5	100.8	158.0	65	94	100	100	100	Already Emerged
	EQAS	15	1	4	6	7	12	9.3	23.5	40.8	46.6	77.6	18	59	71	82	100	3.0C
	AUST	18	0	4	7	11	14	2.4	20.4	36.3	61.4	76.6	35	71	82	82	100	1.5C
Ecoregions	Alaskan Forests	15	3	5	6	12	17	18.8	30.5	37.6	77.2	112.3	47	76	76	88	100	1.5C
	Pacific Canadian Forests	16	3	4	7	13	23	16.2	27.5	43.9	81.6	144.1	41	65	88	94	100	2.0C
	Pacific US Forests	14	4	7	11	18	26	28.2	51.2	72.7	122.8	182.9	47	82	82	100	100	2.0C
	Southern Amazonia	16	2	10	13	34	56	13.7	65.0	84.7	219.0	361.0	41	71	76	94	90	Already Emerged
	Mediterranean	12	6	14	20	36	54	51.3	114.6	162.0	295.3	438.5	82	100	100	100	100	Already Emerged
	North African Savannahs	16	2	4	5	7	9	14.0	24.2	31.8	46.4	59.1	53	71	71	76	70	1.5C
	South African Savannahs	16	2	7	10	19	19	12.2	40.6	62.4	117.2	120.0	53	82	94	100	100	Already Emerged
	East Siberian Forests	17	1	2	4	9	19	5.5	12.1	25.2	54.1	108.3	29	59	76	88	100	1.5C
	Indonesian Forests	15	1	4	5	6	10	8.3	24.5	34.1	38.1	64.8	18	59	76	82	80	3.0C
	Southeast Australian Forests	17	1	5	8	14	15	8.0	27.9	46.8	83.1	90.2	29	71	82	88	90	3.0C

Note. Significant changes in FWI_{95d} are assessed using a *t*-test for each model, and here, we show the degree of model agreement (% of models) on the sign and significance of the reported changes. The timing of the emergence of FWI_{95d} beyond pre-industrial variability is identified via a strict signal-to-noise criterion. All data and methods follow those of Abatzoglou et al. (2019; see methods in Text A in Supporting Information S1). Colors represent the strength of positive (brown) and negative (purple) relative changes in fire weather as in Figure 11. See methods in Text A in Supporting Information S1.

Paris Agreement rather than the 2.0°C commitment, our results further indicate that weather-related fire risks could also rise substantially if the 2.0°C commitment is not achieved 12.

Substantial increases in future fire weather have previously been modeled in *North American boreal regions* where MATs are increasing at a faster rate than elsewhere in the world (Coogan et al., 2019; de Groot et al., 2013; Kirchmeier-Young et al., 2017, 2019; M. D. Flannigan et al., 2005, 2009, 2013; Wotton et al., 2017). De Groot et al. (2013) used several models and concentration scenarios to simulate the impacts of climate change on daily severity rating, a component of the FWI representing the degree to which a fire could be suppressed, in two large boreal study areas in Canada and Russia. All models and climate change scenarios indicated that future fire weather conditions will become more severe in both regions by up to a factor of 4–5 during the peak of the fire season in the late twenty-first century relative to the late twentieth Century, with the largest increases occurring in western Canada. The annual number of spread days, defined according to operational thresholds that are deemed

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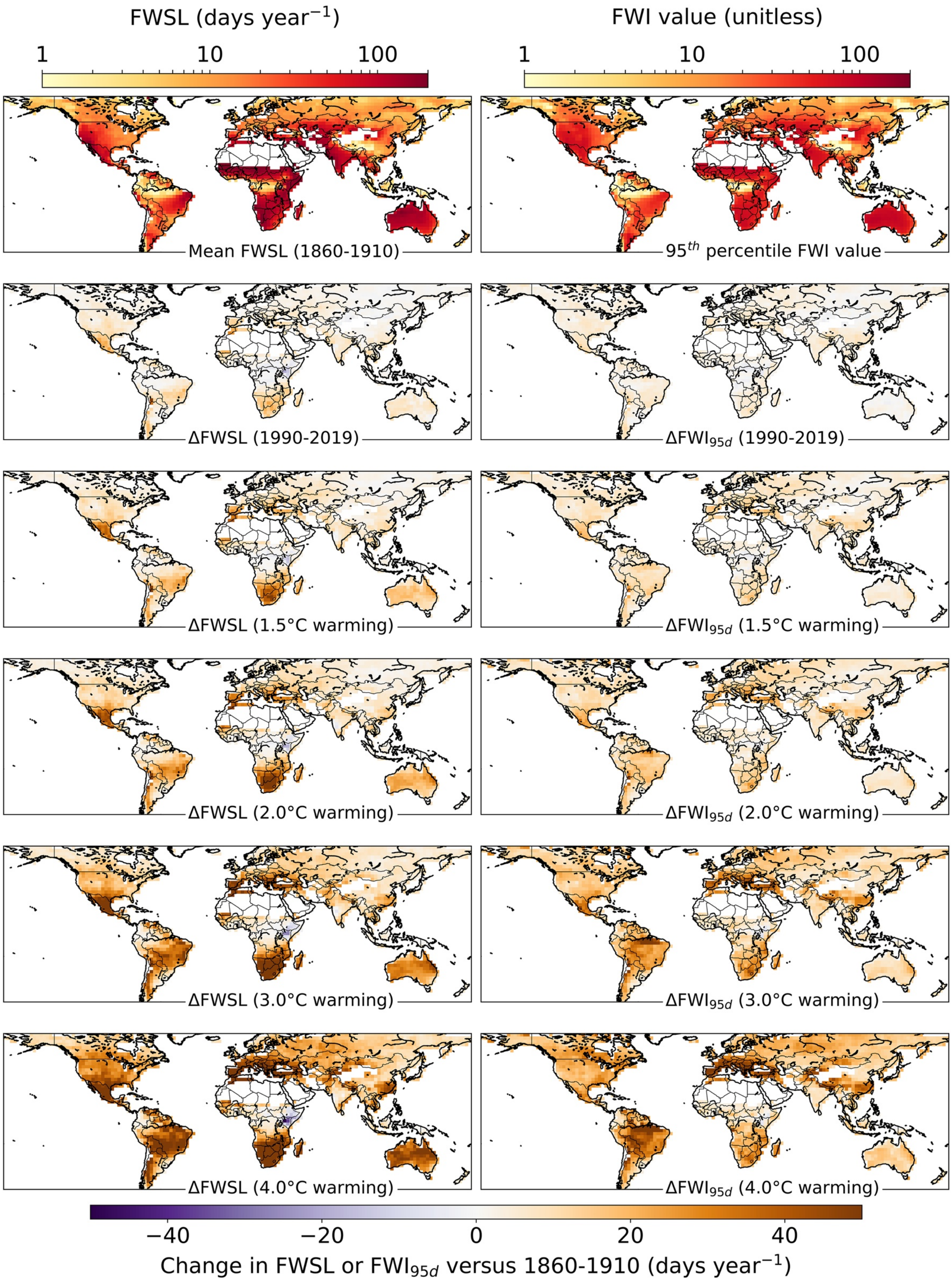

Figure 11. Global patterns and trends in fire weather based on multi-model statistics from 17 CMIP5 models (10 models for +4.0°C), gridded at 2.5° resolution. Multi-model mean estimates of (top row) mean and (other rows) change in (left panels) fire weather season length (FWSL) and (right panels) days exceeding the 95th percentile fire weather index (FWI_{95d}) relative to the baseline period (1861–1910). Changes are shown for the modern period (1990–2019) and for each of four global mean annual temperature increments as indicated. All data and methods follow those of Abatzoglou et al. (2019; see methods in Text A in Supporting Information S1).

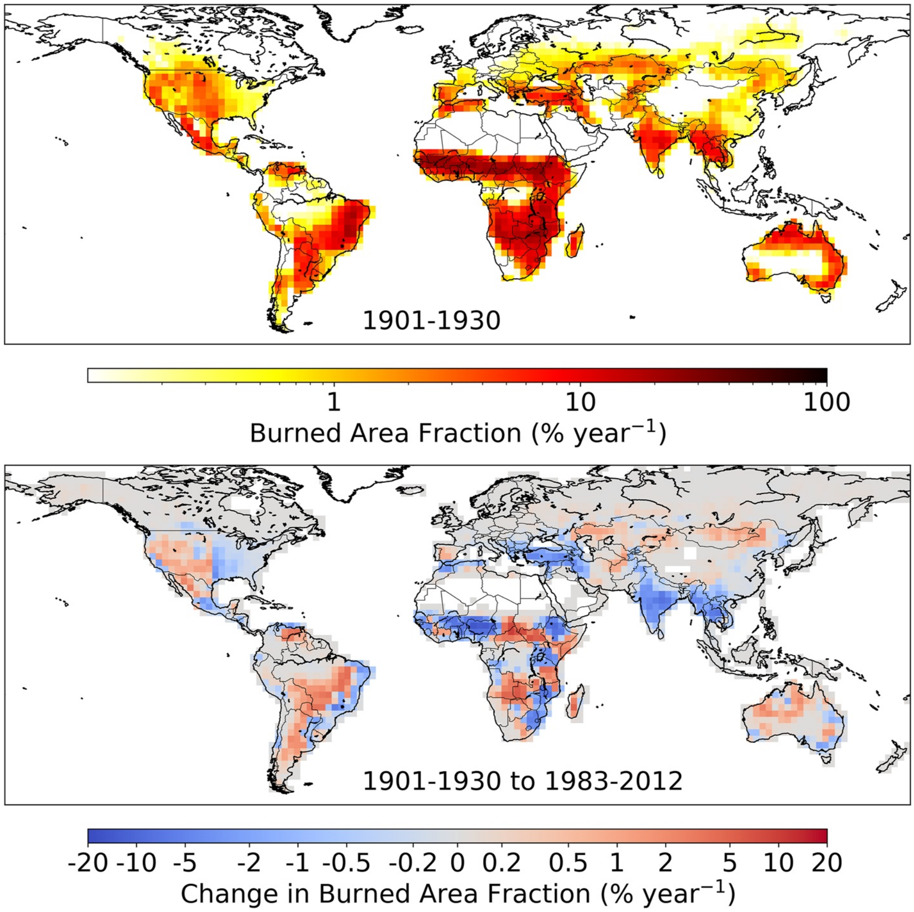

Figure 12. Multi-model median simulations of burned area (BA) fraction during 1901–1930 (% year^{-1}) and change in BA fraction between the periods 1901–1930 and 1983–2012 (% year^{-1}) from the ensemble of six Fire Model Intercomparison Project models, gridded at 2.5° resolution. (Top panel) Multi-model median estimate of mean annual BA fraction in the baseline period 1901–1930. (Right panel) Change in the multi-model median estimate of mean annual BA fraction between baseline and modern (1983–2012) periods. The model simulation data derives from Teckentrup et al. (2019) with updates to two models after Lasslop, Hantson, Harrison, et al. (2020) and Burton et al. (2019; see Text A in Supporting Information S1 for methods).

by practitioners to be supportive of fire spread, will increase by 35%–400% by mid-to-late century across Canada relative to the late twentieth century conditions (Wang et al., 2015, 2017). Wotton et al. (2017) analyzed projections from three climate models, which showed progressive increases in both fuel dryness and the potential intensity of fires that occur in Canadian boreal forests during the twenty-first century. The number of days with greatest potential of intense, and often unmanageable, crown fires was simulated to increase due to changes in moisture availability in aboveground biomass. The projections of future fire weather and its interannual variability vary across ecosystems (Kitzberger et al., 2017; Young et al., 2017). Alaskan Arctic tundra and boreal forest edge environments are projected to experience the largest increases in fire weather, where the 30 years fire probability is projected to increase four-fold by 2100 under RCP6.0 based on change in climatic conditions (Young et al., 2017).

According to our analysis, FWSL has historically increased by 18%–28% (~2 days year^{-1}) and FWI_{95d} by 16%–19% (~3 days year^{-1}) in Alaskan and Pacific Canadian forests since the pre-industrial period (1860–1910), with the majority of models agreeing on the sign and the significance of these changes in the case of FWSL. In these regions, the simulated increases in FWSL rise to 37%–62% (3–6 days year^{-1}) at global MAT increments of 1.5–2.0°C, to 136% (7–13 days year^{-1}) at 3.0°C and to 174%–177% (10–18 days year^{-1}) at 4.0°C. Meanwhile, FWI_{95d} is simulated to increase to 28%–44% (4–7 days year^{-1}) at global MAT increments of 1.5–2.0°C, to 72%–82% (12–13 days year^{-1}) at 3.0°C and 112%–144% (17–23 days year^{-1}) at 4.0°C. These results support previous work in suggesting that unabated warming of the climate will lead to substantial increases in the frequency and extremity of fire weather in the North American boreal region, especially beyond 2.0°C of global MAT increase.

Modeling assessments of change in fire weather have also been completed for the *western US*. Barbero et al. (2015) used an ensemble of climate models to project change in the frequency of fire weather conditions prone to producing large fire events (90th percentile BA) under the RCP8.5 scenario. The models projected an increase in the likelihood of large fires across most historically fire-prone regions of the western US, with the largest increases in the northwest US. Goss et al. (2020) showed ubiquitous, albeit heterogenous, increases in extreme fire weather days (FWI_{95d}) in Autumn (September-November, when the largest wind-driven fires tend to occur) through 2100 in the western US under RCP4.5 and RCP8.5. The models indicated that the magnitude of the trend in Autumn FWI_{95d} is not likely to be spatially uniform, yet increases are essentially ubiquitous across all vegetated areas of California. In some regions, relative increases in extreme FWI frequency are projected to exceed 50% by the late-twenty-first century under RCP4.5 and approach 100% under RCP8.5 by the late-twenty-first century relative to 1950–1979. Abatzoglou et al. (2021) used an 18-model model ensemble to project the future likelihood of fire weather conditions linked to spatially synchronous large fire outbreaks across much of the western US under both RCP4.5 and RCP8.5. The models projected that such prolonged spatially synchronous extremes, which have occurred on average in one-in-three years during 1991–2020, will occur in the majority of years during 2050–2100 regardless of the RCP scenario. According to our analysis, FWI_{95d} has already increased by 28% since the pre-industrial period, and it is projected to increase to 51% above the pre-industrial at 1.5°C and to more than double at 3.0°C warming (Table 8).

Numerous studies have also modeled an increase in the frequency of extreme fire weather in *Australia*. Models run by Clarke et al. (2011) projected increases in the annual number of days with extreme fire weather in southeast Australia of 30%–200% by 2100 relative to the modern period under a high emissions scenario (SRES A2). Clarke et al. (2016) noted that projections of future fire weather can be highly model-dependent in Australia, specifically due to diverging simulations of future precipitation across models. Sharples et al. (2016) projected the future occurrence of pyroconvective conditions, which are strongly associated with the most extreme bushfires based on simulations from an ensemble of regional climate models, in southeast Australian forest. On average, the models indicated a 30% increase in the occurrence of extreme C-Haines index values of 30% by 2070 relative to the modern period under SRES A2. Dowdy et al. (2019) modeled the future frequency of extreme FFDI and C-Haines index values using global and regional climate models under RCP8.5, which indicated that increases in extreme FFDI across Australia could be modulated by a reduction in the frequency of pyroconvective extremes in the northeast and a contrasting increase in most other regions. Di Virgilio et al. (2019) modeled the future occurrence of days when both the FFDI and C-Haines indices are very high to severe using regional climate model simulations under SRES A2, identifying significant increases in spring and lesser increases in summer by 2060–2079. Herold et al. (2021) recently showed that 1-in-20 years FFDI values observed in recent decades will return at least twice as frequently by 2060–2079 across much of southeast Australia, with strong agreement across an ensemble of 12 regional climate models under SRES A2. In broad agreement with these previous studies, our analysis suggests that FWSL and FWI_{95d} will increase in southeast Australian forests to 34% and 47%, respectively, above the pre-industrial period at a global MAT increment of 2.0°C, and further to ~50% and ~60%–70%, respectively, above the pre-industrial period at 3.0°C–4.0°C warming (Tables 7 and 8).

Increases in the frequency of extreme fire weather episodes have also been projected to increase in the *Mediterranean* region. Moriondo et al. (2006) used a single climate model to show increases in mean FWI, FWSL and extreme fire weather frequency (week-long episodes of FWI > 45) lead to an increase in fire risk even in a relatively low emission scenario (SRES B2). Several studies have also projected increase in temperature, precipitation and drought and heatwaves and evaluated their effects on the likelihood of fire occurrence and BA in the Mediterranean (Parente et al., 2018; Turco et al., 2014). Fargeon et al. (2020) used three regional climate models under RCP4.5 and RCP8.5 to project that, by the end of the century, mean summer FWI will increase by +24% to 67% and the frequency of 90th percentile FWI will increase by +19% to 50% in France with greater rates of change in southern regions. Using an 8-model ensemble of regional climate models under RCP4.5 and RCP8.5, Ruffault et al. (2020) projected that the frequency of fire weather conditions linked to the largest fire types ("heatwave" and "hot drought" fires) in France, Portugal, Greece and Tunisia will increase by 14% and 30% by the end of the century under the RCP4.5 and RCP8.5, respectively. Calheiros et al. (2021) used projections from 11 regional climate models under RCP4.5 and RCP8.5 to reveal significant increase in future fire weather on the Iberian Peninsula that will be temporally pronounced in late spring and early autumn, and spatially pronounced in southern and eastern parts of the region. Our analyses indicate that FWSL has already increased by 20% and FWI_{95d} by 51% since the pre-industrial period, with the majority of models in agreement on the sign and significance of the historical change. The analysis also suggests that FWSL will rise by 47%–65% above the pre-industrial average at 1.5°C–2.0°C warming, and by 97%–135% at 3.0°C–4.0°C warming. FWI_{95d} is projected to rise far more steeply, by 115%–162% at 1.5°C–2.0°C warming and 295%–439% at 3.0°C–4.0°C warming.

6.2. Fire Weather Is Increasingly Distinguishable From Its Natural Variability

In addition to producing CMIP5 model simulations of historical and future BA, Abatzoglou et al. (2019) applied the time of emergence framework (Stott et al., 2016) to determine if simulated fire weather has shifted beyond its simulated pre-industrial ("natural") variability. Time of emergence is identified according to a strict signal-to-noise criterion to detect the contribution of climate change to changes in FWSL and the frequency of extreme fire weather (FWI_{95d}) versus that which would solely arise due to natural variability in climate. Abatzoglou et al. (2019) used a 17-model ensemble of CMIP5 models to show that FWI_{95d} has already emerged on 22% of global land area in the year 2019, and that the global extent of emergence increases exponentially with global MAT. The area experiencing emergence was modeled to double between 2°C and 3°C above pre-industrial levels.

Extending the analysis of Abatzoglou et al. (2019; see Text A in Supporting Information S1 for methods), we find that both FWSL and modeled FWI_{95d} have emerged above pre-industrial variability in southern African savannahs, the Mediterranean and southern Amazonia (Tables 7 and 8). Emergence becomes increasingly widespread as global MAT rises. At 1.5°C above pre-industrial global MAT, FWSL emerges above pre-industrial variability in northern African savannahs, while FWI_{95d} emerges in northern African savannahs, Alaskan forests, and east Siberian forests. At 2.0°C above pre-industrial global MAT, FWSL emerges in Alaskan forests, east Siberian forests, Pacific US forests, and Pacific Canadian forests, while FWI_{95d} emerges in Pacific US forests and Pacific Canadian forests. At 3.0°C above pre-industrial global MAT, FWSL, and FWI_{95d} emerge above pre-industrial variability in Indonesian forests and southeast Australian forests. Overall, the models indicate that fire weather has already emerged beyond pre-industrial variability in some regions and that continued warming will cause increasingly pervasive shifts in fire weather.

Here, as in prior regional studies, we found that fire weather is yet to emerge beyond pre-industrial variability in the Pacific US forests or in southeast Australia where large pre-industrial variability obscures the signal of anthropogenic climate change despite visible trends in FWSL and FWI_{95d} (Abatzoglou & Williams, 2016; Dowdy, 2018; Head et al., 2014; Williams et al., 2019; Figures 3, 4 and 11). The distinction between anthropogenic and natural signals is particularly challenging to unravel in the case of southeast Australia due to the strong pre-industrial variability imposed by several large-scale climate oscillations (ENSO, the IOD, and SAM) (Abram et al., 2021; Dowdy, 2018; Clarke et al., 2013; Harris & Lucas, 2019; Lewis et al., 2020; van Oldenborgh et al., 2021). Our analysis of the CMIP5 model simulations indicates that FWSL and FWI_{95d} will emerge at a global MAT increment of 2.0°C in Pacific US forests and 3.0°C in southeast Australian forests, signifying that unabated warming will likely shift fire weather conditions to a state outside their natural range as noted previously by others (Sharples et al., 2016; van Oldenborgh et al., 2021; Williamson et al., 2016; Yoon et al., 2015).

In contrast, the impact of anthropogenic climate change on fire weather has already emerged beyond pre-industrial variability in the Mediterranean region according to our analysis. Barbero et al. (2020) recently reported that fire weather in France has emerged beyond pre-industrial variability. The detectable impact of climate change on fire weather is consistent with the broader concept of Mediterranean amplification of climate change marked by strong emergent increases in the frequency of hot and dry summers (Fargeon et al., 2020; Turco, Rosa-Cánovas, et al., 2018).

6.3. Climate Change Has Raised the Likelihood of Recent Wildfires

Several studies have sought to quantify the impact of climate change on the likelihood of some major fire events that have occurred in recent years. These studies typically take one of two approaches to quantify the differences in likelihood of the observed fire weather conditions relative to a scenario without anthropogenic climate change. Some have run climate models in two scenarios; one with natural forcings only, and one with natural plus anthropogenic forcings (Lewis et al., 2020; Partain et al., 2016; van Oldenborgh et al., 2021). Others have isolated the climate trend from the model-derived time series using time series decomposition, and thereafter subtracted the trend from model simulations (Barbero et al., 2020; Kirchmeier-Young et al., 2017, 2019; Williams & Abatzoglou, 2016).

The greatest concentration of attribution studies has been placed on wildfires in *North America*. The 2015 Alaskan wildfires occurred amidst fire weather conditions that were 34%–60% more likely due to anthropogenic effects on temperature and moisture availability, although lightning strikes were the dominant ignition source and the effect of anthropogenic climate change on lightning activity was not established (Partain et al., 2016). Kirchmeier-Young et al. (2017) demonstrated that anthropogenic climate change increased the likelihood of the 2016 Fort McMurray fires in Canada by a factor of 1.5–6 due to increases in FWI. Kirchmeier-Young et al. (2019) later found that anthropogenic climate change increased the probability of extreme fire weather by 2–4 times during record BA in British Columbia during 2017, while 95% of the temperature anomaly at the time of the event was attributed to anthropogenic climate change. Kirchmeier-Young et al. (2019) further used empirical relationships between weather metrics and fire activity in the region, and estimated that 86%–91% of the BA in British Columbia during 2017 was attributable to anthropogenic climate change.

Several event attribution studies have also been conducted in *Australia* and parts of *Europe*. Lewis et al. (2020) suggested that extreme temperatures at the time of the 2018 bushfires in northern Queensland were 4.5 times more likely due to anthropogenic climate change and the rainfall deficit was 1.5 times more likely, enhancing the risk of an event on the scale of the 2018 bushfires. Climate models run by van Oldenborgh et al. (2021) suggested that the FWI values seen during the 2019/2020 bushfires in southeast Australia were at least 30% more likely as a result of anthropogenic climate change. Krikken et al. (2021) found that the FWI values present during the 2018 wildfires in Sweden were around 10% more likely as a result of anthropogenic climate change and that the likelihood of the fire weather conditions seen at that time will double under 2.0°C of warming above pre-industrial levels. Barbero et al. (2020) used a 17-model ensemble of CMIP5 models to show that fire weather conditions that triggered fires in the 2003 fire season in France would have *a* <0.2% annual probability of occurrence in the absence of anthropogenic climate change, compared to a probability of ∼10% (return interval ∼10 years) under today's climate.

Other attribution studies have focussed on quantifying the contribution of climate change to trends in fire weather, rather than individual events. Abatzoglou and Williams (2016) showed that anthropogenic climate change accounted for ∼55% of observed increases in fuel dryness from 1979 to 2015 across western US forests. By accounting for strong relationships between BA and fire weather in western US forests, the authors estimated that anthropogenic climate change has doubled the forest fire area. Based on dual runs of the climate models, Barbero et al. (2020) concluded that anthropogenic climate change was responsible for nearly half of the observed increases in fire weather across the Mediterranean region of France.

6.4. Uncertainty in Past and Future Trends in Fire

While the upwards pressure of climate change on fire weather has risen in recent decades (Section 4) and is set to rise in future, multiple bioclimatic and human factors affect BA by controlling fuel availability, fuel flammability and ignitions (Sections 4 and 5). Hence, trends in fire weather alone do not necessarily translate into an increase in fire activity in all regions, and most notably in fuel-limited regions such as grasslands and savannahs, or regions where humans have a dominant influence on fire patterns through ignition and suppression.

Many empirical models have been developed to simulate fire activity as a function of climate, vegetation productivity, population and land use (Archibald et al., 2009; Knorr et al., 2014; Krawchuk & Moritz, 2011; Krawchuk et al., 2009; Le Page et al., 2015; Moritz et al., 2012; Pechony & Shindell, 2009, 2010; Thonicke et al., 2010; Turco, Jerez, et al., 2018). However, these models are typically used for diagnosis of the controls on fire and few empirical models have been used in a stand-alone manner to make projections of future fire activity. Moritz et al. (2012) used logistic regression to predict fire probability derived from observable predictors (net primary production, precipitation, and temperature), and simulated future fire activity using simulations of those predictors from 16 climate models. Their results generally indicated increases in fire probability in already warm biomes, but the trends were highly variable across climate models for the first half of the twenty-first century. Although empirical models generally produce realistic simulation of current fire activity, a key limitation is that they omit feedbacks between fire and carbon storage or surface albedo which arise through fire impacts on vegetation distribution and productivity (Hantson et al., 2016; Rabin et al., 2017; Williams & Abatzoglou, 2016). Hence, the development of fire models for application within fire-enabled DGVMs has been a key step towards the prediction of future fire activity on centennial timescales.

Some fire-enabled DGVMs were used in CMIP5 to predict future fire activity, however, these models drastically underestimated global BA, by on the order of 90%, and also failed to reproduce the observed spatial distribution of fire activity (Kloster & Lasslop, 2017). A key shortfall in fire modeling capacity in the CMIP5 era of models is that the fire models had been developed before the period of consistent global monitoring of BA by satellites (e.g., MCFIRE and GlobFIRM) and so they were tuned to reproduce the BA from incomplete data sets (Hantson et al., 2020; Kloster & Lasslop, 2017; Mouillot & Field, 2005). A simplistic representation of human impacts on ignitions and fuel loads was also noted in the case of some models (Bistinas et al., 2014; Hantson et al., 2016; Knorr et al., 2014). A persistent dilemma in process-based fire model development is that they are required to make some assumptions based on incomplete or low-resolution data about processes that are not yet well understood (Hantson et al., 2016; Rabin et al., 2017; Williams & Abatzoglou, 2016).

The growing availability of satellite BA observations and long-term charcoal records has since helped to improve and optimize models to reproduce observations (Arora & Melton, 2018; Forkel et al., 2017; Marlon et al., 2008, 2016; van Marle, Kloster, et al., 2017). For example, Knorr et al. (2014) developed the empirical SIMFIRE model which uses the Nesterov index, vegetation cover, and population density to simulate BA. It was calibrated against satellite observations of BA and later coupled with the LPJ-GUESS DGVM and the BLAZE combustion model (LPJ-GUESS-SIMFIRE-BLAZE; Knorr et al., 2016). Arora and Melton (2018) optimized the CLASS-CTEM model to reproduce charcoal indices and satellite BA observations. Based on these models, Knorr et al. (2016) and Arora and Melton (2018) estimated ~15%–25% reductions in BA since 1900–1930. Primary explanations given for the reduction in fire activity during the recent century are changes in population density, since humans tend to suppress wildfire on balance (Knorr et al., 2014, 2016), and the expansion of cropland area, which restrict the area of intact vegetation available to burn (Arora & Melton, 2018). Knorr et al. (2016) also showed that climate factors alone would cause a significant increase in fire activity of ~15%–40% in the twenty-first century, depending on the future emissions pathway. However, these increases are offset by changes in vegetation productivity under elevated atmospheric CO_2 concentration and by the moderation of fire activity by humans in tropical savannahs.

The FireMIP is a collaborative global effort to improve fire-enabled DGVMs through the systematic comparison of models and sharing of knowledge across the modeling community Figure 12; Forkel, Andela, et al., 2019; Hantson et al., 2016; Li et al., 2019; Rabin et al., 2017; Teckentrup et al., 2019). Hantson et al. (2020) recently conducted a benchmarking exercise of the FireMIP models in which the vegetation and fire properties (e.g., leaf area index, vegetation productivity, BA and its timing, fire count and fire size) simulated by nine FireMIP models were compared with observations from multiple satellite products. The nine models simulated a wide range in global BA (0.5–5 million km^2) but the majority fell within the observational range of 3–5 million km^2 during 2002–2012. Models that explicitly simulate individual fires (e.g., SPITFIRE and RegFIRM) were found to outperform those taking empirical approaches (e.g., GlobFIRM) with respect to the simulation of fire counts, whereas fire sizes were often underestimated by those models in key regions of tropical savannah (Hantson et al., 2020). In addition, the models with the strongest simulation of vegetation growth and its seasonality also tended to provide the best predictions of BA, emphasizing the importance of good fuel modeling for the representation of fire especially in fuel-limited regions. DGVMs which incorporated older fire modules were found to reproduce poorly the observed global-scale distribution of fire activity.

In addition to the model benchmarking exercise, Forkel, Andela, et al. (2019) used a machine learning approach to identify relationships between climate, vegetation and human-related predictors of fire and monthly BA in satellite observations and simulations from FireMIP models. They showed that most models reproduce observation-derived relationships between BA and climate variables adequately, however, they poorly reproduce relationships with plant productivity and land cover, and they show diverse relationships with population density. These results suggest that FireMIP models need to be specifically improved with respect to effects of fuel build-up, land cover and human effects on fire behavior.

To supplement these prior model comparison studies, we compared the global and regional BA simulated by six FireMIP models with satellite observations from the MODIS Collection 6 BA product MCD64A1 (Giglio et al., 2018; see Text A in Supporting Information S1 for methods). At the global scale, the median FireMIP model simulates global BA to within 3% of observations during 2001–2012, however, the median model underpredicts BA by 33% in southern African savannahs and 11% in northern African savannahs, representing large absolute errors totaling more than 0.5 million km^2 (22%) across the two regions. On the other hand, the median model substantially overestimates BA in several macroregions and focus ecoregions, including by ∼400%–700% in southeast Australian forests, the Mediterranean and Pacific US forests (Table 9, Figure 13). The median model simulations of BA were within 66% of observations in Alaskan forests, southern Amazonia, east Siberian forests and Indonesian forests. These results suggest that BA is typically underestimated in tropical savannahs and overestimated elsewhere, notably in some key forest environments with large stocks of carbon, in broad agreement with the more comprehensive benchmarking exercise of Hantson et al. (2020).

Taken as an ensemble, the FireMIP models indicate that reductions in BA seen in recent decades are not a new phenomenon, but rather a continuation of a decline in BA seen over the past century (Table 9, Figure 13). Our comparison of the median model estimate for the initial and final 30-year periods of the FireMIP model runs (1901–1930 and 1983–2012, respectively; see Text A in Supporting Information S1 for methods) suggests that BA declined by around 14% (−680,000 km^2 year^{-1}) during the twentieth century, with 4 of the 6 models agreeing on the direction and significance of the trend. Nonetheless, the FireMIP models included in our analysis simulate diverse trends in global BA (Table 9, Figure 13), with three models showing a decline (CLASS-CTEM, JSBACH-SPITFIRE, and LPJ-GUESS-SIMFIRE-BLAZE), one model showing a considerable increase (LPJ-GUESS-SPITFIRE), and two models showing little trend or a mid-twentieth Century peak (JULES-INFERNO and CLM). The models showing neutral or positive trends in global BA are more consistent with the reconstructed BA trends that were being reported at the time of development of earlier models (Mouillot & Field, 2005). The multi-model median trend in global BA since 1901–1930 (−14%) is consistent with the ∼15%–25% reductions in BA since 1900–1930 reported by Knorr et al. (2016) and Arora and Melton (2018).

Despite disagreeing on the global trend in BA during the past century, the FireMIP models did show a majority agreement on a significant reduction in BA in the Mediterranean (−39%), Indonesian forests (−28%), Pacific US forests (−20%), and northern African savannahs (−19%; Figure 13). Meanwhile, the FireMIP models suggested that BA increased by 101% in Alaskan forests and 38% in southern Amazonia. Also, at macroregional scales, the majority of models were in agreement on significant negative trends in southeast Asia (−41%), the Middle East (−26%), northern hemisphere Africa (−20%), equatorial Asia (−18%), and North America (−16%) and Europe (−18%). However, we note that BA was simulated with large errors relative to MODIS BA observations during 2001–2012 in some of these regions (see Table 9), and that the modeled regional trends in BA were also not always consistent with those observed in the MODIS BA data set. For example, visual assessment of Figure 5 indicates that the sign of the modeled and observed trends varies on sub-regional scales; boreal and temperate North America, southern Africa, the Brazilian *cerrado* and South American *pampas*, northern China, the borders of Russia and Kazakhstan, the Iberian Peninsula, and southeast Australia were poorly captured in the models. Another intriguing feature of the FireMIP trends is the modeled increase in BA in the Sahel region, which is not present in the MODIS BA data set.

Upcoming phases of FireMIP will seek to project BA under various emission scenarios for the twenty-first century. However, the capacity of models to reproduce the regional BA observations in the modern period must be considered when interpreting their future projections (Hantson et al., 2020), and the disagreement amongst models in the twentieth Century means that individual model projections must be interpreted with some caution. Given their contrasting simulations of historical BA, fire-enabled DGVMs are expected to simulate a wide range of trends in future BA. Projections of future BA have thus far only been published for LPJ-GUESS-SIMFIRE-BLAZE (Knorr et al., 2016) and JULES-INFERNO for South America (Burton, Kelley, et al., 2021), however, a multi-model ensemble approach encouraged by FireMIP is needed to prevent over-reliance on projections from any individual model in isolation. Exemplifying the advantages of a multi-model approach, the IPCC Special Report on Climate Change and Land (Jia et al., 2019) was only able to present the simulations of future BA from LPJ-GUESS-SIMFIRE-BLAZE and, therefore, is unlikely to capture the full diversity of trends from fire-enabled DGVMs. Hence, simulations of future fire activity from fire-enabled DGVMs are needed to provide insights into the potential impacts of climate change on wildfire risks and to inform international policymaking.

Table 9

Burned Area (BA) and Burned Area Fraction (BAF) Modeled by the Six Model Fire Model Intercomparison Project (FireMIP) Ensemble for the Pre-Industrial Baseline (1901–1930 Multi-Model Median) and the Modern Period (1983–2012 Multi-Model Median) and Change Between the Two Periods

Region Source	Region	Baseline Mean Annual BA (km^2 year^{-1})	Modern Mean Annual BA (km^2 year^{-1})	Baseline Mean Annual BAF (% year^{-1})	Modern Mean Annual BAF (% year^{-1})	Relative Change (%)	Model Agreement on Sign and Significance of Change (%)	MODIS Mean Annual BA during overlap (2001-2012) (km^2 year^{-1})	FireMIP Mean Annual BA during overlap (2001-2012) (km^2 year^{-1})	Over/under - estimation of MODIS BA by FireMIP (%)
Global	Global	4,806,243	4,126,399	3.2	2.8	-14.15	67	4,538,747	4,400,527	3
GFED	BONA	22,660	20,573	0.1	0.1	-9.21	50	15,868	21,111	-25
	TENA	215,522	181,261	2.1	1.7	-15.9	67	182,994	27,933	555
	CEAM	99,238	96,482	1.9	1.9	-2.78	50	118,948	29,136	308
	NHSA	53,135	56,553	1.5	1.6	6.43	33	72,222	53,636	35
	SHSA	564,839	572,447	3.2	3.3	1.35	50	845,176	314,874	168
	EURO	52,167	42,653	0.5	0.4	-18.24	67	50,052	11,688	328
	MIDE	211,730	157,148	1.3	0.9	-25.78	83	131,148	13,606	864
	NHAF	1,191,746	956,959	7.2	5.7	-19.7	67	1,135,647	1,342,363	-15
	SHAF	1,021,620	962,083	8.6	8.1	-5.83	50	1,131,258	1,557,035	-27
	BOAS	54,243	61,917	0.3	0.3	14.15	50	49,106	98,656	-50
	CEAS	232,928	250,638	1	1.1	7.6	50	349,429	217,685	61
	SEAS	322,406	190,916	3.7	2.1	-40.78	100	133,338	136,143	-2
	EQAS	14,048	11,521	0.1	0.1	-17.98	83	5,677	15,099	-62
	AUST	344,071	335,861	3.1	3.1	-2.39	50	374,900	560,618	-33
Ecoregions	Alaskan Forests	699	1,407	0.1	0.1	101.18	83	2,105	3,065	-31
	Pacific Canadian Forests	3,357	3,648	0.2	0.2	8.69	50	2,698	1,229	120
	Pacific US Forests	33,501	26,916	2.5	2	-19.66	67	26,896	3,499	669
	Southern Amazonia	44,243	60,960	1.1	1.5	37.78	83	71,250	44,075	62
	Mediterranean	67,275	41,071	2.3	1.4	-38.95	67	43,061	5,476	686
	North African Savannahs	1,077,252	871,917	11.8	9.3	-19.06	67	1,049,866	1,179,139	-11
	South African Savannahs	712,191	702,665	11	10.8	-1.34	50	792,821	1,190,145	-33
	East Siberian Forests	15,404	17,390	0.3	0.3	12.89	50	13,252	18,620	-29
	Indonesian Forests	9,094	6,589	0.1	0.1	-27.54	83	4,771	10,984	-57
	Southeast Australian Forests	60,140	50,357	3.8	3.3	-16.27	50	45,327	9,299	387

Note. Significant changes in BA are assessed using a *t*-test for each model, and here, we show the degree of model agreement (% of models) on the sign and significance of the reported changes. A comparison of FireMIP modeled BA is made with moderate resolution imaging spectroradiometer (MODIS) BA data for the period in which the two data sets overlap (2001–2012). The FireMIP model simulation data derives from Teckentrup et al. (2019) with updates to two models after Lasslop, Hantson, Harrison, et al. (2020) and Burton et al. (2019; see Text A in Supporting Information S1 for methods). The MODIS BA data derive from Giglio et al. (2018). See methods in Text A in Supporting Information S1.

7. Frontiers in Predicting Fire's Future

7.1. Optimizing Global Models Using Machine Learning

Although fire-enabled DGVMs are increasingly calibrated against satellite observations, even the most proactively optimized models (e.g., LPJ-GUESS-SIMFIRE-BLAZE; Knorr et al., 2014) have not shown a dramatically superior performance in comparison with other models in FireMIP comparison studies (Forkel, Andela, et al., 2019; Hantson et al., 2020). A possible reason might be that empirical fire model structures continue to be predefined and do not consider the potential predictive performance of alternative, and potentially stronger,

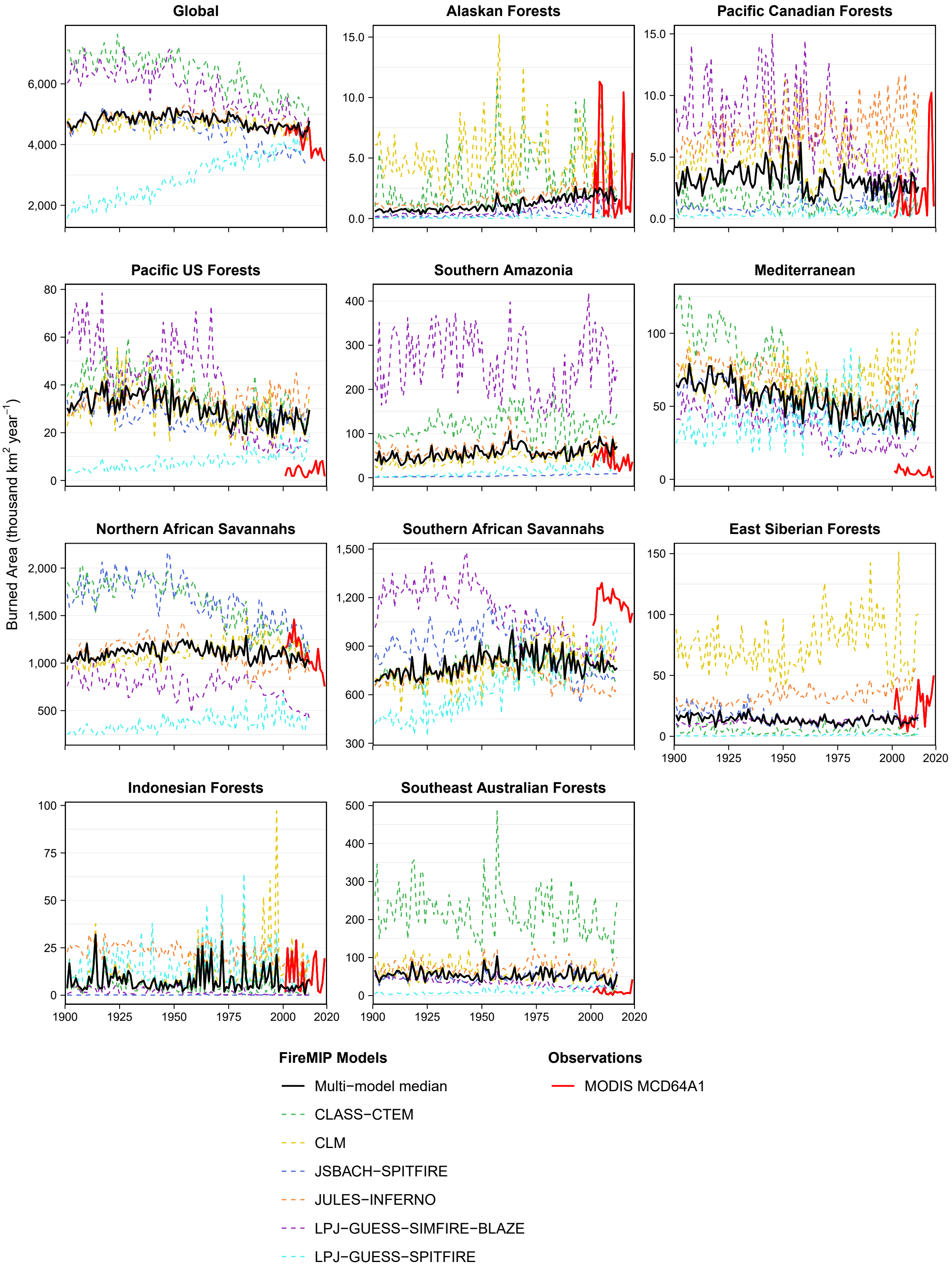
Global
Alaskan Forests
Pacific Canadian Forests
Pacific US Forests
Southern Amazonia
Mediterranean
Northern African Savannahs
Southern African Savannahs
East Siberian Forests
Indonesian Forests
Southeast Australian Forests
Burned Area (thousand km^2 year^{-1})
1900 1925 1950 1975 2000 2020
FireMIP Models
Multi−model median
CLASS−CTEM
CLM
JSBACH−SPITFIRE
JULES−INFERNO
LPJ−GUESS−SIMFIRE−BLAZE
LPJ−GUESS−SPITFIRE
Observations
MODIS MCD64A1

Figure 13.

predictor variables for fire activity. Secondly, in a coupled setup, fire-enabled DGVMs rely on the vegetation simulations from the DGVMs themselves, which might not agree with observed vegetation conditions on which the stand-alone fire model is trained (Hantson et al., 2020; Teckentrup et al., 2019). Consequently, global process-based fire models are likely to benefit from the use of strict data-model integration approaches informed by machine learning throughout all phases of model development, including formulation of empirical fire model structures, parameter calibration and model evaluation (Forkel, Andela, et al., 2019; Forkel et al., 2017). By using various climate, vegetation and human predictor variables, fire activity can be estimated with generalized linear models, logistic regression, general additive models, random forests, or neural networks, enabling the most important predictors and their underlying relationships and sensitivities to be identified, including on regional scales (Archibald et al., 2009; Bistinas et al., 2014; Forkel, Andela, et al., 2019; Jain et al., 2020; Joshi & Sukumar, 2021; Moritz et al., 2012). Although such machine learning models have shown a strong predictive capacity for BA, they are usually too complex to be implemented as fire modules within DGVMs.

Nonetheless, machine learning can help to select the best model that remains sufficiently simple for implementation in DGVMs. For example, Forkel et al. (2017) developed an empirical fire model approach that estimates BA under a large number of climate, vegetation and human factor combinations. Under this approach, model structures with different combinations of predictors are generated and each optimized against observed BA, and the best-performing model is thereafter selected after optimization. Forkel et al. (2017) found that the best models always include fuel moisture and fuel availability as predictors. Moreover, the optimal fire model can be recalibrated once coupled to a DGVM to avoid biases in the simulated vegetation properties. For example, Drüke et al. (2019) calibrated the LPJmL-SPITFIRE model against satellite data sets of BA and vegetation biomass within South America. The recalibrated model showed improved regional simulation of both BA and vegetation distribution relative to the optimal offline model. Despite the value of such formal data-model integration approaches for model development, these approaches are not yet frequently used by all modeling groups because they are computationally exhaustive, and they require knowledge and computational skills to link modeling, observations and optimization techniques.

An overarching challenge for future fire model optimization will be to avoid overfitting human ignition and suppression algorithms to observations, since there are various limitations to the accuracy and agreement between satellite BA products (see Section 2.1). Similarly, charcoal records are not distributed evenly across the world and they disproportionately represent the burning of woody vegetation as opposed to herbaceous vegetation and so their use as reference data representing historical fire activity may result in the over-tuning of parameters to regions with high woody biomass (Jones et al., 2019; Marlon et al., 2016; van Marle, Kloster, et al., 2017). Using multiple satellite BA reference data sets with varying satellites, methods and detection algorithms and being mindful of the large uncertainties in proxy data will likely help to avoid some of these over-tuning issues (Forkel, Andela, et al., 2019; Forkel et al., 2017).

7.2. Improving Representation of Ignition and Suppression in Global Models

Fire processes are necessarily simplified in fire-enabled DGVMs due to the computational demands of modeling fire, amongst a large number of other processes, at the global scale and on timescales of hundreds of years. A general principle of modeling many environmental processes in DGVMs is that all processes can be expressed using universal algorithms with parameter values allowed to vary across plant functional types. While this approach is reasonable in the case of many physical and biogeochemical processes, the simplicity of the models can lead to the omission of variables that are known, based on regional modeling, to exert important influences on the ignition, suppression and spread of fires. An additional shortfall of modeling fire in DGVMs is that the influence of some controls on fire varies considerably at sub-grid scales. Innovative ways of integrating processes from regional models into DGVMs in a simplified form, including those with influence at sub-grid scale, is likely to be a critical step toward the improved modeling of fire at the global scale for past and future centuries.

Figure 13. Regional time series of global and regional burned area (BA) modeled by six fire-enabled dynamic global vegetation models run offline as part of Fire Model Intercomparison Project (FireMIP) (dashed lines for individual models) (Teckentrup et al., 2019). The solid black lines plot the multi-model median annual BA from the FireMIP models. The solid red lines (2001–2019) plot observed BA from the moderate resolution imaging spectroradiometer BA product (Giglio et al., 2018). The model simulation data derives from Teckentrup et al. (2019) with updates to two models after Lasslop, Hantson, Harrison, et al. (2020) and Burton et al. (2019; see Text A in Supporting Information S1 for methods).

The human controls on fire are particularly local in nature. Substantial variability in the relationships between fire and population, agriculture and GDP per capita is seen at fine scales, especially with respect to the balance of ignitions and suppression in regions of low population density (Andela et al., 2017; Archibald et al., 2010; Balch et al., 2017; Knorr et al., 2014; Parisien et al., 2016; Syphard et al., 2009; Vannière et al., 2016). Existing DGVM algorithms typically express human ignition and suppression of fires as a function of population density (Ford et al., 2021; Hantson et al., 2016; Pechony & Shindell, 2009; Teckentrup et al., 2019): ignitions are broadly modeled to increase at low population densities up to a threshold, and reduce thereafter, while suppression is broadly modeled to increase with population density. However, these high-level indicators of human activity generally fail to capture the spectrum of socioeconomic and cultural factors that influence the relationship between humans, fire, and the landscape (Coughlan, 2015; Coughlan & Petty, 2012). These complexities can lead to very different relationships between humans and fire even in places with similar population densities and economic productivity. Consequently, the representation of socioeconomic factors affecting the human-fire relationship must become more sophisticated in global models if these models are to reliably reproduce and predict the ignition and suppression of fires by humans.

A variety of local- to regional-scale models have been constructed to represent the interactions between humans and fire (Ford et al., 2021). Economic models have also been developed to express the interactions between land users (agents) and fire, treating the most likely actions of each agent as a function of the costs and benefits to that agent in a range of environmental and socioeconomic circumstances, while recognizing that fire can represent a cost to one agent while synchronously providing economic benefits to another (Ford et al., 2021; Prestemon et al., 2013; Purnomo et al., 2017). These models are quantitative in their structure and thus particularly promising for integration in numerical process-based models. However, valuable lessons about the relationship between agents, their land and their use of/interactions with fire have been learned by employing qualitative modeling techniques such as place- or agent-based models. These models formalize and synthesize local knowledge into a conceptual framework that explains how humans respond to particular environmental or socioeconomic changes, for example, by constructing a network of causal chains that explain the response of agents to an environmental or socioeconomic change (C. Smith et al., 2007; Hulse et al., 2016; McKemey et al., 2020; Medrilzam et al., 2014; Monzón-Alvarado et al., 2014; Spies et al., 2017). Often, these models are specialized to a particular locale or region, providing intricate knowledge of the human controls on fire in the circumstances; that is, the agents present and the economy, culture, and environment in which they are embedded (Barlow et al., 2020; Bilbao et al., 2019; Carmenta et al., 2017).

To transfer these complex socioeconomic models to global models is challenging for a variety of reasons. First, qualitative models cannot feasibly be integrated into the numeric structure of a fire-enabled DGVM. Second, a complex socioeconomic model could place excessive computational demand on a fire-enabled DGVM. Third, data sets of observations or equivalent data layers are not always available at the global scale for predictors that emerge as important controls on fire in a specific region. Fourth, it may be unclear how to aggregate diverse relationships seen at sub-grid scales to the coarse global grid of a fire-enabled DGVM. Fifth, the extrapolation of local or regional models beyond a specific region, with a particular set of agents and circumstances, may not be appropriate and is sometimes considered unethical in cases where generalizations are made across societies, especially Indigenous peoples. This list is not particularly exhaustive but serves to illustrate the plethora of challenges to integrating lessons from regional models into global models.

In recognition of these challenges, there have been calls for greater interaction between social scientists, economists and natural scientists with the view to foster a new era of fire models that are sufficiently complex to robustly represent human controls on fire, but also sufficiently simple to implement in DGVMs (Ford et al., 2021; Hantson et al., 2016). There are promising signs that using regional parameter values for human ignitions and suppression in fire-enabled DGVMs can represent a "quick win," improving model performance versus the native DGVM running with global parameter values (Le Page et al., 2017; Zou et al., 2019, 2020). Also, some fire-enabled DGVMs have begun to include the human development index to represent the impacts of living standards and education on fire ignition opportunities, with signs of improved performance as a result (Teixeira et al., 2020). Ford et al. (2021) proposed a step-change in the way that human impacts on fire are represented in DGVMs, advocating for the addition of "agent functional types" to fire-enabled DGVMs. Agent functional types would act as a categorical variable across which the fire ignition and suppression parameters could vary, in a manner akin to the selection of different parameter values across plant functional types as an expression of processes in DGVMs. Pfeiffer et al. (2013) made some early progress in line with this ethos by incorporating fire ignition parameterizations for three groups of global actors (hunter-gatherer, pastoralist, and farming populations) in the SPITFIRE model.

Aside from the need to better-represent the interactions between humans and the landscape that influence fire, some quick progress in ignition modeling might also be made by mapping human infrastructure more effectively in models. Ignitions in semi-remote regions consistently center around transport routes and other human infrastructure in diverse environments (D. Nepstad et al., 2001; Oliveira et al., 2017; Silva et al., 2019; Syphard et al., 2019). For example, the statistical modeling work of Syphard et al. (2017, 2019) has highlighted the significant impact of including future scenarios of rural and urban land cover, infrastructure, and land use change on climate model projections of future fire activity in the western US. While it may not be feasible to explicitly represent sub-grid infrastructural features in a DGVM model, it may well be feasible to represent the density of such features as a probabilistic predictor of the ignition frequency. This ethos could similarly apply to the mapping of human infrastructure and assets that are priorities for protection using fire suppression techniques.

Other insufficiencies of DGVM models likely emerge when they are coupled with the atmospheric components of ESMs. Lightning is notably a strong covariate of BA in wildland environments (Section 4.2) and this means that the lightning scheme employed alongside fire models can strongly influence the simulated patterns and trends in fire activity. In climate models, lightning occurrence is typically parameterized as a function of cloud top height (C. Price & Rind, 1994; Hantson et al., 2016), as the product of convective available potential energy and precipitation (CAPE×P; Romps, 2019; Romps et al., 2014; Tippett et al., 2019), or as a function of cloud ice flux (Finney et al., 2014, 2018). When applied in climate models, the cloud top height and CAPE×P lightning schemes predict large increases in future lightning activity over most of the globe, whereas the cloud ice flux scheme predicts a decline in tropical lightning activity and an increase at high latitudes (Finney et al., 2018; Romps, 2019). Hence, the choice of lighting scheme has major implications for future regional trends and the global distribution of lightning ignitions including in remote regions where lightning is known to be an important control on fire activity. The dependence of simulated BA patterns and trends on choice of lightning scheme is yet to be vigorously assessed across fire-enabled DGVMs, however, this step will be critical to understanding the robustness of projections of BA especially in wildlands (Felsberg et al., 2018; Gordillo-Vázquez et al., 2019; Krause et al., 2014; Teckentrup et al., 2019). The improved availability and accessibility of lightning observations should aid this task by providing key reference data sets to evaluate lightning model performance (e.g., Cecil et al., 2014, 2015; Holzworth et al., 2021; Kaplan & Lau, 2021; Velde et al., 2020).

7.3. Improving Representation of Fire Spread in Global Models

There are also opportunities to improve the model representation of human and natural factors that affect the spread of fire in DGVMs, principally including controls on fuel continuity across the landscape. Physical barriers such as lakes, waterways, roads, railway lines and utility corridors can act as unintended fire breaks that constrain the spread of surface fires, yet many of these features are not represented at the coarse grid scale of fire-enabled DGVMs. A range of fire spread models have been produced at local to regional scales to represent the physics of the combustion process, energy transfer, fluid dynamics, and turbulence, or to empirically simplify the physics of these processes at regional scales (Finney, 1998; Rothermel, 1972; Tymstra et al., 2010). A consistent lesson from the application of such models is that the physical breaks in the landscape act to prevent the spread of fire and ultimately constrain the footprint of a fire (Cochrane et al., 2012; Finney, 1998; Narayanaraj & Wimberly, 2011; Tymstra et al., 2010). While DGVMs account for land cover and incorporate the impacts of agricultural land use on the spread of fire across natural landscapes, they do not typically account for finer-scale features that fragment the landscape and interrupt fire spread (X. Wang et al., 2014). Consequently, the fragmentation of the landscape via the building of human infrastructure has a real-world capacity to influence fire spread that is not represented in fire-enabled DGVMs. Although these features occur on sub-grid scales with respect to fire-enabled DGVMs and so cannot be represented explicitly, a representation of the density of physical barriers is feasible and could prove a useful addition to models of fire spread.

One process that may overcome physical barriers in the landscape is the near-surface transport of hot embers, which can lead to downwind spot fire ignitions if deposited to dry vegetation surfaces especially during periods of extreme fire weather (Cruz et al., 2012; Lecina-Diaz et al., 2014; Penman et al., 2013; Storey et al., 2020; Zigner et al., 2020). However, the process of ember transport and spot fire ignition are also challenging to model at the global scale because the distance over which spotting occurs is far smaller than the resolution of the wind field generated by climate models (100 km). As in the case of physical barriers, a statistical approximation of spotting processes may be feasible in DGBMs, but the uncertainties involved would likely be substantial.

Regional assessments have similarly shown that slope and aspect can influence the occurrence and spread of fires in some regions with complex terrain, either because the topographical variation itself affects the dynamics of energy transfer or because topographical variation is a proxy for microclimatic conditions or ignition opportunities (Blouin et al., 2016; Cavard et al., 2015; Dillon et al., 2011; Fang et al., 2015; Iniguez et al., 2008; Oliveira et al., 2014; P. J. Clarke et al., 2014). Topography has not always been found to significantly affect fire dynamics, especially in cases where other factors have overriding effects, and the relationships can also be highly scale-dependent (Cary et al., 2006; Parisien et al., 2011). At present, the majority of fire-enabled DGVMs do not include topographic effects on fire spread (Hantson et al., 2016), though some incorporate limits to fire spread due to the fragmentation of the landscape by mountainous terrain (Pfeiffer et al., 2013). More work is required to understand the ranging impact of topography on fire spread across environments before a more sophisticated treatment of topographic effects can be implemented in fire-enabled DGVMs.

8. Conclusions

We have reviewed the latest insights into global and regional trends in fire weather during recent decades, over the past century, and for potential future temperature increments ranging from 1.5°C to 4.0°C above the pre-industrial period. We have also reviewed the diverse drivers of trends and variability in fire activity, as represented by BA, and the capacity of current fire models to reproduce regional patterns of BA. In addition, we have presented a series of supplemental analyses of published data sets in order to evaluate how patterns of BA relate to fire weather and various other bioclimatic and human controls on fire.

There have been increases in the length of the fire weather season and the frequency of extreme fire weather in most world regions during 1979–2019, priming landscapes to burn more frequently, especially in the case of mesic environments. For example, 27%–94% increases in FWSL have been observed in southern Amazonia, the Mediterranean region and forests of southeast Australia, Alaska, east Siberia, Pacific Canada and the Pacific US during 1979–2019. Increases in extreme fire weather in these regions were typically larger than increases in FWSL, ranging from 17% to 163%.

During 2001–2019, we observed significant positive correlations between fire weather and BA in all ecoregions that we studied on a seasonal basis, indicating that fire weather strongly determines the annual timing of fires. Inter-annual correlations between fire weather and BA also suggest that fire weather is a significant control on annual BA in some regions, specifically the Mediterranean, the Pacific US and high latitude forests. Overall, correlations between BA and fire weather indicate that fire activity peaks in the seasons when fire weather is most conducive to vegetation flammability, and in some places the years with greatest BA also tend to coincide with the years of greatest fire weather. No other human or bioclimatic control on fire shares such a consistent relationship with BA as fire weather, signifying the key role of fire weather as a pervasive enabler of fire. In mesic forests of the Pacific US and the high latitudes, notable increases in BA on the order of 49%–93% have occurred in tandem with significant increases in fire weather. The robustness of these trends in BA is uncertain at present due to high inter-annual variability in BA. Nonetheless, the significant inter-annual correlation between BA and fire weather, the significant increases in fire weather, and the sizable increases in BA in these regions are symptomatic of the upwards pressures of climate change on fire activity in mesic forests.

Fire activity is not controlled exclusively by fire weather, but also by a range of other bioclimatic and human factors affecting the ignition and spread of fires. Particularly important factors include variability in vegetation productivity in fuel-limited regions, as well as human impacts on patterns of fire ignition and connectivity of fuels. For example, land use suppresses BA in some places (e.g., by fragmenting savannah vegetation), whereas human activities are associated with elevated ignition frequency in other places (e.g., in tropical forests that are not naturally fire-prone). Similarly, BA tends to increase with vegetation biomass in regions with low vegetation productivity (productivity-limited regions, e.g., savannah-grasslands) but reduce with biomass in regions with high vegetation productivity (e.g., forests). These factors can either compound or counteract the relationship between fire weather and fire activity, explaining the non-significant interannual relationships between BA and fire weather and the divergence of trends in BA from those of increasing fire weather in many regions, particularly in the tropics. Overall, the link between BA and fire weather is overridden by the effects of other human and bioclimatic factors in many regions.

Globally, BA decreased by 1.1 million km^2 year^{-1} or 27% during 2001–2019. Around half of this decline is explained by a significant decline in BA in African savannahs. The African savannahs are a prime example of a region where fire weather has a weaker influence on fire activity than other bioclimatic or human factors, such that trends in BA and fire weather diverged strongly in recent decades. Reductions in vegetation productivity, related to changing hydrology, and fragmentation of the naturally flammable landscape by agricultural expansion have been invoked as key drivers of declining BA in African savannahs. The impacts of these factors have outweighed the role of increases in fire weather in these regions to drive the observed decline in BA. Similarly, humans exert a dominant control on BA patterns in Amazonian forests through their ignition of deforestation fires and their degradation of forest edges. During recent decades, trends in BA in tropical forests have related strongly to trends in deforestation, with fire weather generally acting as a secondary control. While the annual timing of fires is tied to fire weather in African savannahs and Amazonian forests, interannual variability in BA and fire weather are related less strongly and hence trends in fire weather and BA have diverged. These examples highlight that the controls on BA are highly region-specific, and that increases in fire weather do not always translate to positive trends in BA despite the upwards pressure placed on vegetation flammability.

According to CMIP5 climate model projections, the prevalence and extremity of fire weather have already emerged beyond their pre-industrial variability in the Mediterranean and southern Amazonia due to climate change. Increases in fire weather are projected to escalate and become more widespread with further warming. The CMIP5 models suggest that fire weather (either FWSL or FWI_{95d}) will emerge at 1.5°C above the pre-industrial MAT in Alaskan forests and east Siberian forests and at 2°C in Pacific US forests and Pacific Canadian forests. At 3°C above the pre-industrial MAT, both FWSL and FWI_{95d} emerge beyond pre-industrial variability in all of the focus ecoregions and macroregions that we studied. Emergence signifies a fundamental shift in the occurrence of fire weather relative to a world without anthropogenic climate change and marks a discernible upwards pressure of climate change on fire in these regions. It remains unclear if the dominant controls on fire activity will shift in some regions as fire weather enters uncharted territory.

The simulated increases in fire weather tend to accelerate with each added increment of warming, and extreme fire weather is generally projected to increase more sharply than FWSL. Moreover, several studies have shown that some of the wildfire outbreaks experienced in recent years have occurred amidst fire weather conditions that would have been considerably less likely in the absence of climate change. As in the observational period, other bioclimatic and human factors can be expected to mediate the response of fire activity to changes in fire weather in region-specific ways; however, all else being equal, climate change is increasing the flammability of landscapes globally and thus enhancing the likelihood of fires in environments where neither fuel nor ignition opportunities are limited.

Process-based fire models are key to understanding how the impacts of change in fire weather, bioclimatic factors, and human controls on fire activity will interact to influence BA patterns in future under various scenarios of climate change. An ensemble of state-of-the-art FireMIP models reproduce global BA to within 3% of observational data, and they collectively indicate that BA has declined by 14% globally over the past century. However, this ensemble also shows a tendency to underestimate contemporary BA in African savannahs and to overestimate BA in forest ecoregions, and there is poor agreement amongst the models on the sign and magnitude of historical changes in BA at global and regional scales.

Process-based models of fire broadly oversimplify and over-generalize the relationships between fire and its bioclimatic and human controls, omitting the regional complexity of these relationships. Machine learning can help to optimize the selection of fire model variables that have already been trialled as predictors of BA, however, it is likely that the addition of under-represented factors such as landscape fragmentation, the density of human infrastructure, and traditional or cultural relationships with fire are needed to address the regionality of human ignitions and suppression in fire models. Uncertainty in the response of lightning to climate change must also be constrained, especially for the modeling of fire in wildlands where lightning is a major ignition source.

Overall, we conclude that climate change is exerting a pervasive upwards pressure on fire activity globally through its impacts on fire weather, and this upwards pressure will escalate with each increment of global warming. Continued investments in fire model development are required if we are to foresee the regions in which escalating fire weather will materialize as rising fire activity and to mitigate against the impacts of these changes on human livelihoods and ecosystem services such as biodiversity or carbon storage.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

A data set containing the results of all analyses presented here will be made available via the article web page as a Supporting Information S1. The contents of our Data Set S1 are outlined in Text B in Supporting Information S1. Our input data derive chiefly from Abatzoglou et al. (2019), Andela et al. (2017), Cecil et al. (2014), Giglio et al. (2018), Hersbach et al. (2020), Spawn et al. (2020), Teckentrup et al. (2019), and Vitolo et al. (2020) as described in the methods section (Text A in Supporting Information S1) and readers are guided to those studies for access to the relevant data.

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