

The global drivers of wildfire

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The global drivers of wildfire

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Changes in wildfire regimes are of growing concern and raise issues about how well we can model risks in a changing climate. Process-based coupled fire-vegetation models, used to project future wildfire regimes, capture many aspects of wildfire regimes poorly. However, there is now a wealth of information from empirical studies on the climate, vegetation, topography and human activity controls on wildfire regimes. The measures used to quantify these controls vary among studies, but certain variables consistently emerge as the most important: gross primary production as a measure of fuel availability, vegetation cover as a measure of fuel continuity, and atmospheric humidity as a measure of fuel drying. Contrary to popular perception, ignitions are generally not a limiting factor for wildfires. In this review, we describe how empirical fire models implement wildfire processes, synthesise current understanding of the controls on wildfire extent and severity, and suggest ways in which fire modelling could be improved.

KEYWORDS

wildfire regimes, drivers of wildfire, empirical modelling, fuel availability, fuel continuity, fuel drying, wildfire modelling

Highlights

- Empirical analyses of the controls on wildfires consistently identify vegetation properties associated with fuel availability and continuity and climate factors associated with fuel drying as the most important influences on wildfire extent and severity.
- Ignitions, whether anthropogenic or natural, are generally not limiting.
- Fire size, burnt area and fire intensity are influenced by different factors; current relationships between these aspects of wildfire could become decoupled in an altered climate.
- Some hypotheses embedded in 'process-based' fire-vegetation models are inconsistent with empirical evidence, implying a need for a re-design.

Introduction

Wildfires are unplanned fires that occur in natural ecosystems, although the ignition source can be natural (most often lightning) or anthropogenic. Wildfires occur on all vegetated continents. Current remotely-sensed based estimates suggest that something of the order of $2.6\% \pm 0.3\%$ (GFED4: [Giglio et al., 2013](#)) to $5.9\% \pm 0.5\%$ (GFED5: [Chen et al., 2023](#)) of the global vegetated area burns each year. Wildfires have been the most important cause of disturbance in natural ecosystems for millions of years ([Scott, 2000](#); [Scott and](#)

Glasspool, 2006; Harrison et al., 2010) and indeed are fundamental to the maintenance of many ecosystems and floras (Pausas and Keeley, 2009; Pausas et al., 2017; Harrison et al., 2021; Pausas and Keeley, 2023). The fire regime, the long-term characteristics of wildfires in specific environments (Lavorel et al., 2007; Archibald et al., 2018) as expressed in terms of fire size, intensity, extent or frequency, shapes ecosystem properties and plant reproductive traits. Some ecosystems rely on frequent wildfires for the establishment of dominant plant-types, whilst others can only support infrequent burning (Archibald et al., 2013; Archibald et al., 2018; Harrison et al., 2021; Foster et al., 2018; Simpson et al., 2021).

At a global scale, burnt area has declined in recent decades (Andela et al., 2017; Forkel et al., 2019; Jones et al., 2022; Zubkova et al., 2023). This decline is driven by changes in the tropical savannas of northern Africa and grasslands in Asia, and to a lesser extent by changes in southern Africa and Europe (Zubkova et al., 2023); other regions of the world have shown no significant trends in the past two decades. Nevertheless, recent years have been marked by extreme wildfire seasons, characterised by increased frequency, seasonality, size, intensity or severity of wildfires, in several regions, including Europe (Carnicer et al., 2022; Grünig et al., 2023), Siberia (Kharuk et al., 2022; Ponomarev et al., 2023) and the western United States (Singleton et al., 2019; Mueller et al., 2020; Jones et al., 2022; Wasserman and Mueller, 2023). These extreme wildfires have been widely attributed to anthropogenic climate change (Abatzoglou et al., 2019; Kirchmeier-Young et al., 2019; Williams et al., 2019; Bowman et al., 2020; Abram et al., 2021; van Oldenborgh et al., 2021). Model projections suggest that burnt area will increase by 13%–15% by 2030 and by 20%–40% by 2050 (UNEP, 2022). The focus on future changes in burnt area may be misleading, however, since some studies show that changes in other aspects of the fire regime, such as intensity, may be decoupled from changes in burnt area under altered climate states (Haas et al., 2023; Haas et al., 2024).

Wildfire regimes are controlled by factors related to climate, vegetation, landscape characteristics and human activities (Bowman et al., 2009; Harrison et al., 2010; Bowman et al., 2011). Many of these controls are incorporated in some way in global fire-enabled vegetation models (Rabin et al., 2017) or are implicit in empirically based global fire models. Nevertheless, while these models can predict the broad global patterns of burnt area, they struggle to reproduce fire season length or the interannual variability of wildfires (Hantson et al., 2020). It is unclear how well they reproduce other aspects of wildfire regimes, such as fire intensity, since this has not been a focus of model evaluation. Even though the current generation of fire-enabled vegetation models reproduce modern global patterns of burnt area, there are significant differences between them in even the sign of historic trends in burnt area reflecting differences in the sensitivity to individual forcings (Teckentrup et al., 2019) and an incomplete or inaccurate description of key processes associated with vegetation properties and anthropogenic influences on wildfire (Forkel et al., 2019). There have been many empirical studies analysing the controls on wildfires at a global scale, many conducted since the initial development of the current generation of fire-enabled vegetation models (Forkel et al., 2019) and these could provide a basis for improving model representations of key processes. This

effort would require an assessment of the robustness of the findings across studies, and diagnosis of the underlying mechanisms.

The aim of this perspective is to identify key variables needed to model different aspects of wildfire regimes and how these could be incorporated in a global modelling framework. We first review how empirical (data-based) fire models treat key controls on fire processes. We then review global studies of different fire properties to assess whether there is a consensus about the importance of specific drivers of burnt area, occurrence, fire size and fire intensity. Finally, we suggest ways in which current understanding of these empirical relationships could be used to improve models and thus our ability to predict changes in fire regimes under future climate change.

Wildfire modelling: The state-of-the-art

Wildfires are simulated in dynamic global vegetation models (DGVMs) and land-surface models (LSMs) through specific modules (Hantson et al., 2016; Jones et al., 2022). There are two basic types: process-based (see e.g., CTM: Arora and Boer, 2005; Melton and Arora, 2016; SPITFIRE: Thonicke et al., 2010; CLM-Li: Li et al., 2012; Li et al., 2013) and empirical (see e.g., GLOBFIRM: Thonicke et al., 2001; Kloster et al., 2010; SIMFIRE-BLAZE: Knorr et al., 2014; INFERNO: Mangeon et al., 2016) modules. Process-based models simulate the behaviour of individual wildfires using theoretical equations for ignitions and fire spread, alongside parameterisations based on laboratory or field experiments, and typically produce estimates of burnt area by scaling up to the grid-cell level (generally $0.5^\circ \times 0.5^\circ$ or coarser). Although much of the focus of fire modelling has been on burnt area and carbon emission, some process-based models explicitly simulate the number and size of individual fires. Empirical models do not try to simulate individual wildfires but simulate the emergent properties of the fire generally using statistical relationships between assumed drivers and fire properties (usually burnt area) across a grid. Comparisons of process-based and empirical models made in the context of the Fire Modelling Intercomparison Project (FireMIP: Hantson et al., 2016; Rabin et al., 2017) have shown that empirical models perform at least as well as process-based models in simulating global patterns of burnt area under modern conditions (Hantson et al., 2020). Both empirical and process-based fire models are incorporated in LSM components of the climate models used in the sixth phase of the Coupled Model Intercomparison Project (CMIP6), and show comparable performance in simulating modern burnt area and emissions (Li et al., 2024).

Although all the FireMIP models can reproduce the spatial patterns in burnt area under modern conditions reasonably well, they tend to overestimate the length of the fire season and do not capture the interannual variability in wildfires (Hantson et al., 2020). Perhaps more importantly, the models disagreed on the sign and magnitude of the trend in global burnt area over the 20th century (Teckentrup et al., 2019; Jones et al., 2022). Furthermore, although the models captured the emergent observed relationships between burnt area and various climate factors influencing wildfires, they

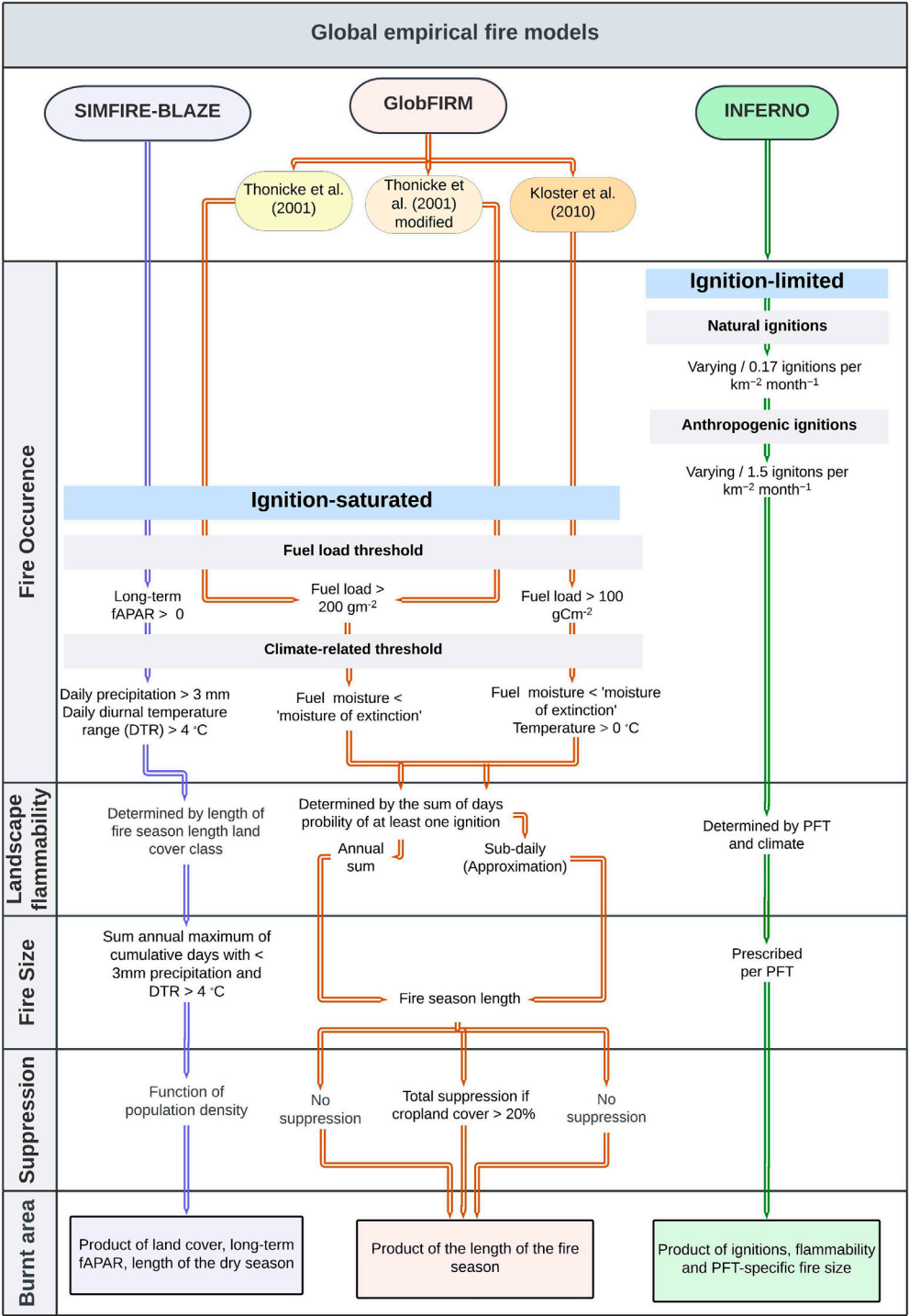
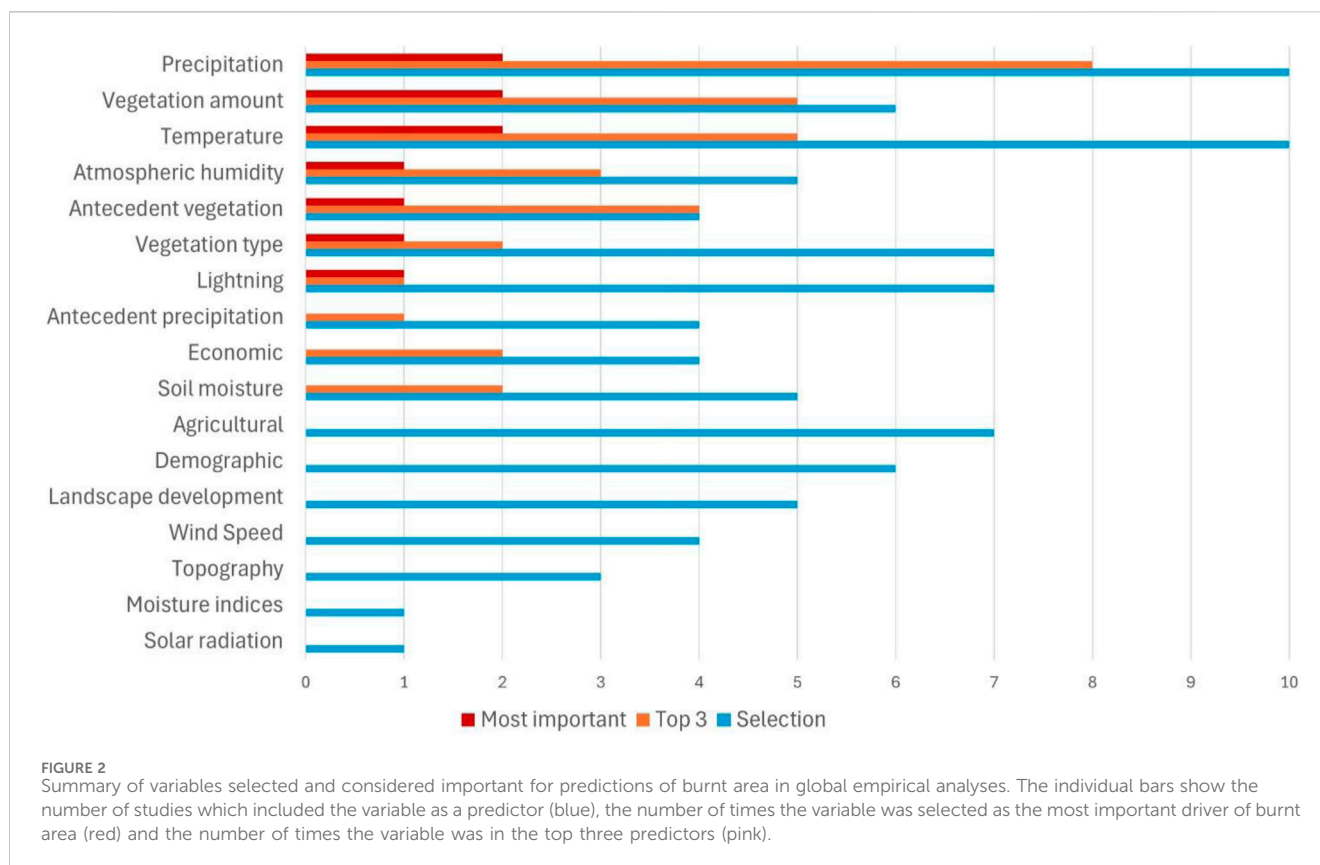


FIGURE 1
Flow diagram showing how processes related to the simulation of burnt area are treated in empirical models from FireMIP.

failed to capture the observed relationships with other drivers (Forkel et al., 2019; Teckentrup et al., 2019). These analyses imply that the incorporation of process understanding in both empirical and process-based models is incomplete.

This incompleteness is illustrated by differences in the three empirically based models (Figure 1; Supplementary Table 1) that have been used in FireMIP: GLOBFIRM (Thonicke et al., 2001;

Kloster et al., 2010), SIMFIRE-BLAZE (Knorr et al., 2014) and INFERNO (Mangeon et al., 2016). Fire occurrence is determined by ignitions in INFERNO, where the number of natural and anthropogenic ignitions is prescribed. However, ignitions are not considered to be limiting in GLOBFIRE and SIMFIRE-BLAZE and occurrence is therefore entirely determined by fuel load and climate conditions. SIMFIRE-BLAZE uses a threshold of climatological



values of the fraction of absorbed photosynthetically active radiation (fAPAR) as an index of fuel load, whereas the variants of GLOBFIRM use thresholds of fuel load explicitly to determine fire occurrence. SIMFIRE-BLAZE also uses thresholds for daily precipitation and diurnal temperature range to determine fire occurrence, while GLOBFIRM only allows fire to occur when fuel moisture content is less than the moisture of extinction. The Kloster et al. (2010) variant of GLOBFIRM also imposes a daily minimum temperature threshold on occurrence. All three models consider landscape flammability, determined by plant functional type (PFT) in INFERNO, by the length of the fire season and landcover class in SIMFIRE-BLAZE and by the total number of days with a probability of fire ignition greater than one in GLOBFIRM. Fire size is also determined differently by the three models: by climate conditions in SIMFIRE-BLAZE, fire season length in GLOBFIRM and by PFT in INFERNO. The standard version of GLOBFIRM does not account for fire suppression, but the other models take account of this either through population density (SIMFIRE-BLAZE, the Kloster et al. (2010) version of GLOBFIRM and INFERNO) or through cropland area (the modified version of GLOBFIRM in Thonicke et al., 2001). The final estimate of burnt area is the product of land cover, longterm fAPAR and the length of the dry season in SIMFIRE-BLAZE, whereas it is determined by the number of ignitions, flammability and PFT-specific fire size in INFERNO, and determined by the length of the fire season in GLOBFIRM. These differences in the processes considered and in the final simulation of burnt area between the empirical models clearly highlight the uncertainties in understanding of the empirical controls on fire.

Empirical studies of the controls on burnt area

A review of the literature identified 10 empirical global studies that examined the controls on wildfires, using either machine-learning or more traditional regression-based approaches, and ranked them according to their relative importance in determining burnt area (Supplementary Table 2). Although these studies used different analytical approaches, and included different numbers of explanatory variables, they all provide an assessment of which variables are significant and a quantitative ranking of the importance of these variables (see Supplementary Table 3), allowing at least a qualitative comparison of the consistency of the results. Several other studies looked at the influence of specific controls (e.g., Knorr et al., 2014; Lasslop et al., 2015; Krawchuk and Moritz, 2011) or have derived predictions based on optimizing multiple controls without prioritizing them (e.g., Boer et al., 2021); or examined controls on interannual variability rather than burnt area (e.g., Abatzoglou et al., 2018). These studies do not provide a ranking of the importance and are therefore not considered here.

The initial selection of variables reflects hypotheses about the mechanisms involved in wildfire occurrence and spread. It is therefore not surprising that variables related to climate (often some measure of precipitation and temperature) are selected in most studies (Figure 2). More surprisingly, the relative importance of these variables does not reflect the frequency with which they are included in analyses. In particular, atmospheric humidity is consistently shown to be an important variable although it is included in analyses only half as frequently as temperature and

precipitation. Field studies indicate that atmospheric humidity is a strong control on both live and dead fuel moisture (Dickman et al., 2023) and this probably explains its emergence as an important variable. However, in a modelling context, fuel moisture is more often represented by soil moisture (only indirectly related to humidity) or some kind of moisture index - both of which are shown to be relatively unimportant in these empirical analyses. Variables related to fuel availability, such as the current vegetation amount and vegetation type, are included equally frequently in these global analyses. The current amount of vegetation has a different influence on burnt area from the amount during antecedent periods (Kuhn-Régner et al., 2021) and thus these two variables should be considered separately. Variables related to the instantaneous amount of vegetation, which impacts both fuel availability and fuel continuity, emerge as more diagnostic than vegetation type. When considering both instantaneous and antecedent conditions, vegetation amount emerges as the single most important control on burnt area, being the most important predictor in a third of the studies (Figure 2). This suggests that models that explicitly consider fuel loads or measures such as fAPAR that are closely related to vegetation production are more likely to capture the processes involved in modulating burnt area than models that rely on PFT-specific parameterisations. A number of variables related to ignitions (lightning, demographic measures) or to fire spread (wind speed, topography) are routinely included in these empirical analyses, but turn out to be less important determinants of burnt area at a global scale. This helps to explain why models that assume that ignitions are saturated perform as well as those that explicitly try to estimate the frequency of natural and human ignitions. Factors relating to landscape fragmentation (e.g., measures of agricultural activity or landscape development) are also less important than climate and vegetation factors in determining burnt area. Landscape fragmentation has an impact on limiting fire spread, but this impact is complex and depends on the nature of the fragmentation and the vegetation type (Armenteras et al., 2017; Harrison et al., 2021; Rosan et al., 2022; Harrison et al., 2024). Current measures of and assumptions about the role of fragmentation, both in empirical and process-based models, are likely over-simplified. More generally, no variable representative of human activity and its impact emerges as a strong control on burnt area. This highlights that the current ways in which we represent this impact in global models are most likely inadequate and unable to capture the desired human effects.

Even in the broad categories related to climate and vegetation, there are differences in the specific metrics employed in different empirical studies. Precipitation, for example, can be represented by average monthly values, total precipitation within the typical burn period or a specific season, or precipitation during an antecedent period of varying length. However, these different choices frequently relate to different processes: average monthly data is largely a measure of the immediate impact of precipitation on fuel moisture whereas antecedent precipitation is more likely to be related to the control of aridity on vegetation growth and fuel accumulation. Both the instantaneous and antecedent measures of precipitation emerge as important controls of burnt area, and they have been shown to have different (and contrasting) effects (Kuhn-Régner et al., 2021). This poses problems in empirical analyses since the inclusion of more than one predictor variable

to represent a key process means that the influence of both may be down-weighted. There is no ideal solution to this problem since there are still uncertainties about which specific processes need to be considered and which predictive variables would best represent these processes. One approach that has been used is systematic variable selection, in which a large number of individual variables are tested for their contribution in a large number of models constructed by systematically including or excluding individual variables (e.g., Tracy et al., 2018; Keeping et al., 2024).

Systematic variable selection analyses provide support for the importance of climate, vegetation and human parameters in driving fire occurrence. Figure 3 shows the frequency of variable selection, using a forward-backward selection algorithm (Keeping et al., 2024), for the prediction of fires >0.25 acres for the contiguous United States in a 12-variable model, given the selection of one initial variable, in a suite of 1,000 variable selection runs (see Supplementary Figure 1 for full matrix). Diurnal temperature range is consistently chosen in all of the runs, even when other temperature variables are selected as the initial variable. Similarly, 5-day precipitation, snow cover, antecedent GPP and rural population density are consistently selected as important in more than 90% of the selection runs. This analysis confirms the importance of the factors that emerge as important controls on fire in global analyses - including factors influencing fuel load (such as vegetation cover or GPP), fuel drying (such as relative humidity, precipitation), and fire spread (such as population density or crop cover). However, some factors that have been used as predictors of fire occurrence in regional empirical studies, such as minimum temperature or the presence of powerlines, are never selected in this analysis. This shows that some factors that might be thought of as influencing fire occurrence have no additional predictive power in the model and are thus not important at a global scale.

Few studies have examined the global controls on fire properties other than burnt area. Three studies were identified that explicitly looked at the environmental controls of fire occurrence (Shmuel and Heifetz, 2022; 2023; Mukunga et al., 2023; Zhang et al., 2023) and four that examined the global controls of fire size (Hantson et al., 2015; Shmuel and Heifetz, 2022; Haas et al., 2022; Zhang et al., 2023). Despite the limited number of studies, factors relating to human activity were shown to have a less significant effect on fire occurrence than authors expected (Zhang et al., 2023; Shmuel and Heifetz, 2022) although gross domestic product (GDP) did emerge as a significant control (Mukunga et al., 2023). Cropland fraction was shown to increase ignitions in one study (Mukunga et al., 2023); this contradicts the assumption that croplands have a consistent, suppressing effect on wildfire activity as registered by fire size and burnt area. Wind speed was also shown to have a negative effect on fire occurrence above a threshold of 3–4 m/s-1 (Shmuel and Heifetz, 2023). Fire size follows a power-law (Randerson et al., 2012), and Hantson et al. (2015) used this assumption to investigate the drivers of fire size. They showed that there is a negative linear relationship between cropland cover and fire size but the relationship with population density was humped, with fire size peaking at intermediate levels of population density. Similar assumptions underpin the study of Andela et al. (2017), which suggests that agricultural expansion has been a key driver of the reduction in fire size (and the number of fires and global total burnt area) in recent decades. Zhang et al. (2023) also showed the dominant role of

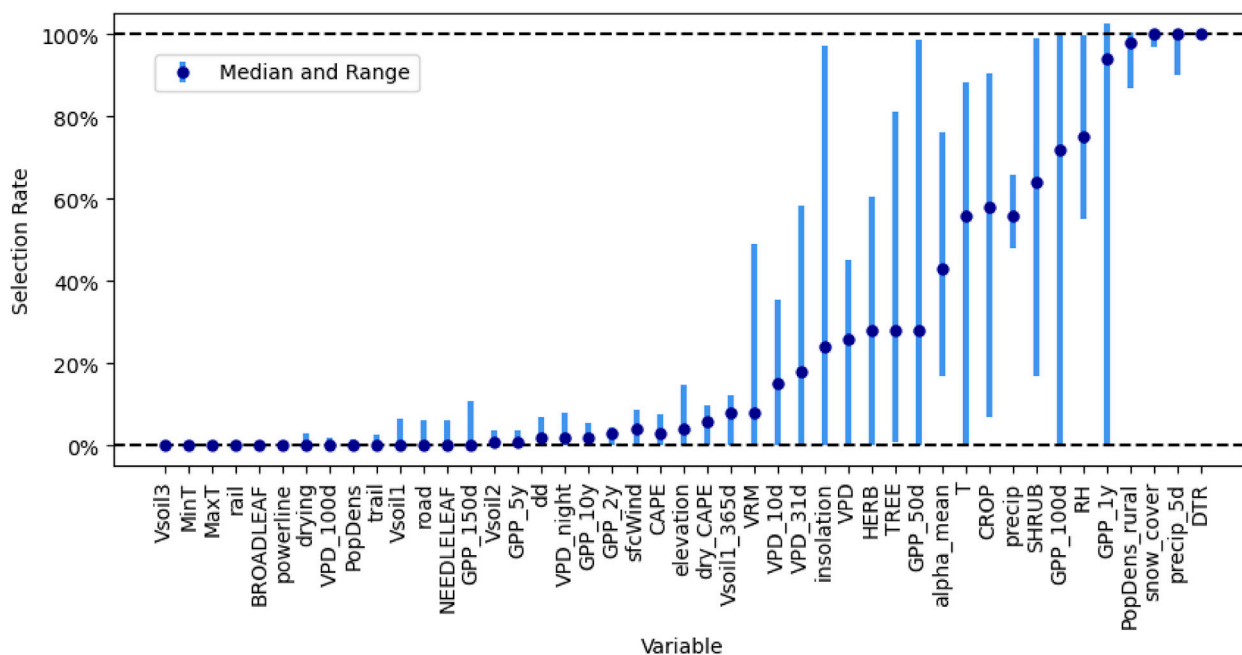


FIGURE 3

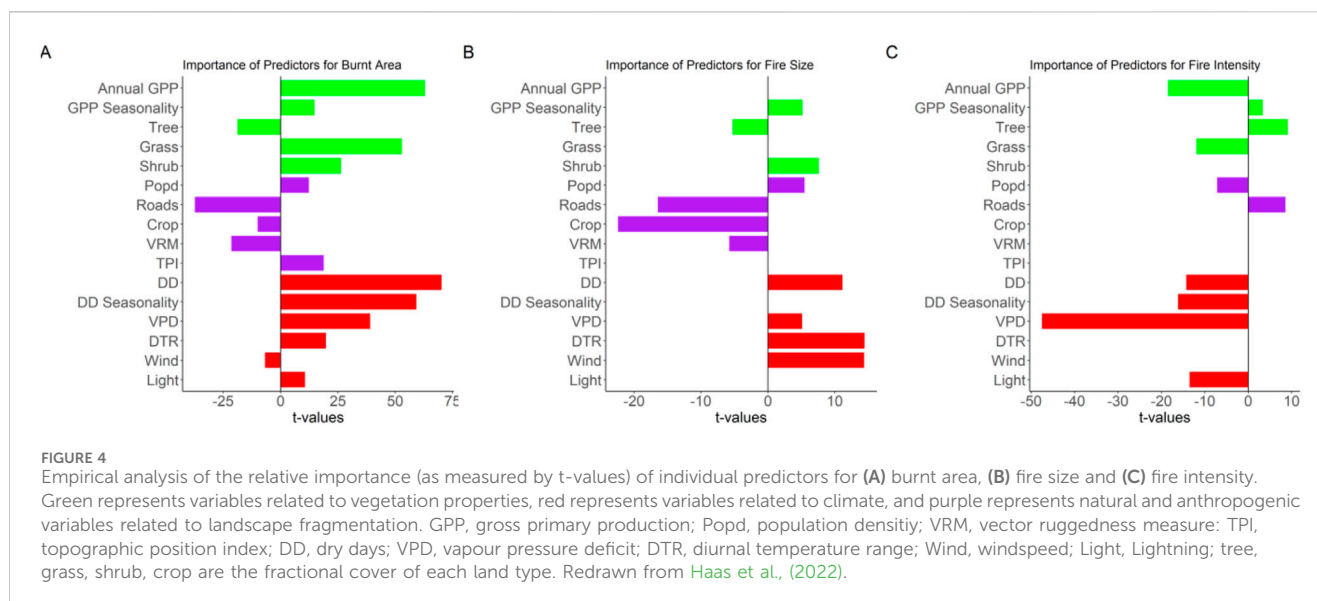
Outcome of systematic variable selection, showing the initial variable included in the model and the median and range of the number of times it was selected. The variables are: Vsoil3 – daily soil water volume in second layer (28–100 cm) (m^3/m^3), MinT–minimum daily temperature ($^{\circ}\text{C}$), MaxT–maximum daily temperature ($^{\circ}\text{C}$), rail–total length of rail lines per km^2 (km/km^2), BROADLEAF–the fraction of broadleaf plants (%), powerline–total length of powerlines per km^2 (km/km^2), drying–cumulated vapour pressure deficit in prior dry spell (Pa days), VPD_100d–mean vapour pressure deficit over prior 100 days (Pa), PopDens–population density (people/ km^2), trail–total length of walking trails per km^2 (km/km^2), road–total length of roads per km^2 (km/km^2), Vsoil1 – daily soil water volume in top layer (0–7 cm) (m^3/m^3), NEEDLELEAF–the fraction of needleleaf plants (%), GPP_150d–Gross Primary Production in prior 150 days ($\mu\text{gC}/\text{m}^2/\text{s}$), Vsoil2 – daily soil water volume in second layer (7–28 cm) (m^3/m^3), GPP_5y–Gross Primary Production in prior 5 years ($\mu\text{gC}/\text{m}^2/\text{s}$), dd–prior dry days ($<0.1\text{ mm}$ precipitation) (days), VPD_night–mean vapour pressure deficit in night-time (Pa), GPP_10y–Gross Primary Production in prior 10 years ($\mu\text{gC}/\text{m}^2/\text{s}$), GPP_2y–Gross Primary Production in prior 2 years ($\mu\text{gC}/\text{m}^2/\text{s}$), sfcWind–surface windspeed (m/s), CAPE–convective atmospheric potential energy (J/kg), elevation–elevation (m, dry_CAPE–convective atmospheric potential energy if day is dry (J/kg), Vsoil1_365d–soil water volume in top layer (0–7 cm) averaged over prior 365 days (m^3/m^3), VRM–vector roughness metric (unitless), VPD_10d–mean vapour pressure deficit over prior 10 days (Pa), VPD_31d–mean vapour pressure deficit over prior 31 days (Pa), solar_insolation–downwelling shortwave solar radiation ($\text{J}/\text{m}^2/\text{s}$), VPD–daily mean vapour pressure deficit (Pa), HERB–the fraction of herbaceous plants (%), TREE–the fraction of forest (%), GPP_50d–Gross Primary Production in prior 50 days ($\mu\text{gC}/\text{m}^2/\text{s}$), alpha_mean–the average annual ratio of actual to potential evapotranspiration (kg/kg), T–daily mean temperature ($^{\circ}\text{C}$), CROP–the fraction of cropland (%), precip–daily precipitation (kg), SHRUB–the fraction of shrubland (%), GPP_100d–Gross Primary Production in prior 100 days ($\mu\text{gC}/\text{m}^2/\text{s}$), RH–relative humidity (%), GPP_1y–Gross Primary Production in prior 1 year ($\mu\text{gC}/\text{m}^2/\text{s}$), popDens_rural–population density clipped at 25 people per km^2 (people/ km^2), snow_cover–snow cover fraction (%), precip_5d–precipitation in prior 5 days (kg), DTR–diurnal temperature range ($^{\circ}\text{C}$).

human activity in decreasing global BA through suppressing fire size rather than fire numbers as well as a limited effect of climate and vegetation in driving fire size (Zhang et al., 2023). This finding is in line with work showing that road density and cropland cover have a strong limiting effect on fire size, but that vegetation predictors had a less significant effect (Haas et al., 2022). These various studies make it clear that human activities influence different fire properties in different ways and that factors that increase ignitions may have the opposite impact on overall burnt area or fire intensity.

Some previous studies have focused on the relationship between different aspects of fire regimes (e.g., size, frequency, intensity) and grouped distinct clusters of these properties into fire regimes (e.g., Archibald et al., 2013; Pereira et al., 2022; Fan et al., 2023; Pias et al., 2023; Garcia et al., 2022; Yang et al., 2023). Luo et al. (2017) proposed that there is a humped relationship between fire frequency and fire intensity, with the highest-intensity fires occurring at intermediate levels of fire occurrence. This finding presumably reflects the fact that frequent fires fragment the landscape (Laurent et al., 2019) and reduce fuel load and fuel

continuity (Archibald et al., 2013; Luo et al., 2017), whereas environments characterised by low fire frequency may have high fuel loads but must inevitably be too wet to burn.

Only one study (Haas et al., 2022) has separately examined the role of individual predictors on different aspects of the fire regime, comparing the drivers of burnt area, fire size and fire intensity. Starting from a common set of 16 predictors, that study showed that some variables were important for one property but either had no influence or had the opposite effect on the others. For example, both annual GPP and the seasonality of dry days have a positive effect on burnt area, but no influence on fire size and reduce fire intensity (Figure 4). Overall, whereas burnt area is primarily driven by factors influencing fuel availability and fuel dryness and is reduced by landscape fragmentation, fire size is increased by factors promoting fire spread such as wind speed but is also reduced by landscape fragmentation. Fire intensity is primarily driven by tree cover; the strong positive relationship with road density probably reflects deforestation fires. These results are broadly compatible with the emergent relationships between different fire properties shown in



previous studies. However, they have strong implications for process-based fire modelling since they imply that changes in fire properties could be decoupled under changed climates (Haas et al., 2023; Haas et al., 2024) and so the processes underlying burnt area, fire size and fire intensity need to be distinguished.

Lessons for fire science and modelling

Consistent patterns are emerging from empirical analyses that are leading to an improved understanding of wildfire regimes and their environmental controls. These provide a basis for improving the treatment of wildfire in a modelling context. Here, we summarise the lessons learnt from these empirical analyses about what factors are important and suggest ways in which these lessons could be incorporated into process-based models.

GPP consistently emerges as the most important control on wildfires. Both total GPP and the seasonality of GPP have a positive impact on burnt area. The influence of seasonality is consistent with studies that show that antecedent GPP has an opposite effect from the GPP during the wildfire season (Forkel et al., 2017; Kuhn-Régner et al., 2021): high GPP in the period before the fire season means that fuel loads are high, whereas high GPP at the time of a fire could only be sustained if climate conditions were favourable, i.e., the fuel is likely too wet to burn. Studies that have included measures of antecedent conditions have generally found them to be important controls on wildfires. This is also consistent with the negative impact of GPP on fire intensity. These various measures of GPP appear to be reasonably good surrogates for fuel loads. Given the limited field information available globally about fuel loads (see e.g., Pettinari and Chuvieco, 2016; McNorton and Di Giuseppe, 2024), this suggests that GPP (or net primary production, NPP) can usefully serve as a surrogate in a modelling context. However, this means that it is important to ensure that the vegetation component of process-based wildfire models simulate GPP (or NPP) accurately to ensure an accurate simulation of wildfire regimes (Forkel et al., 2019).

Vegetation cover emerges from the empirical analyses as an important influence on wildfire, particularly the relative abundance of trees versus herbaceous plants. The nature of the vegetation cover is a crucial factor in influencing fuel continuity and fire spread. Globally, grass-dominated landscapes tend to lower fire intensity but produce more burnt area. However, empirical analyses that include PFTs as predictors do not show that they have an influence on wildfire properties. Many fire models have PFT-specific parameterisations, but this arises largely because of inheriting the PFT concept from the dynamic vegetation models used to provide vegetation characteristics (Cranko Page et al., 2024). Since this multiplies the number of, often poorly specified, parameters needed, simplifying the linkages between vegetation properties and wildfire processes would be useful. There are studies suggesting that individual species are fire-promoting but, at the scale of global modelling, it seems more likely that the traits which promote fire spread, such as the presence of volatile oils or ladder-fuel structure (Blaauw et al., 2017; Popović et al., 2021; Rodman et al., 2021; Chen et al., 2023a; Chen et al., 2023b), should be explicitly represented in fire-enabled vegetation models.

The empirical analyses show that climatic variables that influence atmospheric humidity, and hence fuel drying, such as vapour pressure deficit (VPD) or the diurnal temperature range consistently emerge as an important control on wildfires. Precipitation, as such, is likely chiefly influential in so far as it is a surrogate for the more direct influence of atmospheric humidity on fuel drying. In studies that include precipitation and some measure of atmospheric dryness, precipitation may also be a reflection of direct fuel wetting. Soil moisture has been widely used in a modelling context to account for fuel dryness, but empirical studies which have tested this, or used aridity indices, indicate that these are not good predictors. In the absence of explicit simulation of the fuel bed and fuel moisture, models could replace soil moisture with parameterisations based on climatic factors such as VPD, which are more closely aligned to the process of fuel drying.

Empirical analyses indicate that ignitions are not a limiting factor for wildfire occurrence at a global scale. Lightning is

important for ignitions in many ecosystems. Lightning initiates ca 90% of wildfires in Siberia (Ivanov and Ivanova, 2010) and the majority of fires in Alaska (Kasischke et al., 2010) and northern Canada (Coogan et al., 2020). Changes in the incidence of lightning have been associated with increases in wildfires in these regions during the historical and recent past (e.g., Vachula et al., 2022; Veraverbeke et al., 2017). Nevertheless, even in these regions, climate and vegetation factors that influence fuel load and fuel drying play an important part in determining the occurrence of wildfires. Given this, models that prescribe anthropogenic and lightning ignitions, such as the empirical model INFERNO (Mangeon et al., 2016) and virtually all process-based models (Rabin et al., 2017), are likely focusing on the wrong process. As the differences in the prescribed relationships used by different models show (Teckentrup et al., 2019), the relationships are also poorly constrained. Most models use population density to encapsulate both anthropogenic ignitions and (direct and indirect) suppression (Rabin et al., 2017; Li et al., 2024), but this conflates two distinct processes which are influenced by different factors. Remote-sensed fire products are now available at much higher resolution, and this means that they now capture small fires, many of which are explicitly set for agricultural purposes such as preparing fields or removing waste (Millington et al., 2022). The use of total population density as a measure of anthropogenic ignitions for both wildfires and agricultural fires, ignores both differences between these two types of fire and the complexity of the cultural uses of fire.

Empirical analyses do not support the hypotheses about human impacts on wildfire currently embedded in process-based models. The peaked relationship between burnt area and population density used in many models (Rabin et al., 2017; Li et al., 2024) is an emergent property of the system and not a causal mechanism (Bistinas et al., 2014). Including other factors reflecting human transformation of the landscape, such as road density for example, transforms the relationship between burnt area and population density from negative (Bistinas et al., 2014) to positive (Haas et al., 2022). There have been attempts to provide a more nuanced picture of human impacts, through the inclusion of economic measures such as GDP (e.g., Mukunga et al., 2023), but while these factors may influence the number of ignitions they rarely turn out to be important predictors of other properties such as burnt area and do not improve the predictions of wildfire regimes. Cultural differences in human influence on fire (Pyne, 2014; Huffman, 2013; Millington et al., 2022) need to be expressed in a way that takes account of the intent and practice of deliberate and managed burning. Separate treatments of wildfires and agricultural fires are required in a modelling context, since their controls are very different.

Fragmentation is important in limiting fire spread, and this is reflected in the importance of factors such as crop cover and population density, which are indirect measures of fragmentation of the landscape, in the empirical analyses. However, a more nuanced approach to measuring fragmentation is needed if this is to be implemented in a modelling context. There is a growing understanding that the impacts of fragmentation differ between ecosystems (Armenteras et al., 2017; Harrison et al., 2021; Rosan et al., 2022; Harrison et al., 2024), and that this can be broadly

explained in terms of the degree to which an ecosystem is adapted to frequent fires or not. However, more systematic analyses are required before these insights can be properly incorporated into models.

Empirical analyses of the controls on wildfire need to be more explicit about which processes are hypothesised to be controlled by specific variables. This will ensure that the variables tested are not redundant and/or acting on two different aspects of the wildfire regime. It would also be useful to adopt more systematic approaches to the evaluation of the inclusion/exclusion of specific variables and their contributions. Nevertheless, although there are gaps in our understanding of the controls on wildfires, especially related to the role of humans and the influence of landscape fragmentation, empirical analyses at the global scale already provide insights that could be used to improve process representations in process-based fire-vegetation models. The most obvious improvements are to use variables more closely aligned to the processes of generating fuel loads and of fuel drying. Separating the treatment of different aspects of the fire regime, most particularly by simulating fire intensity separately from fire size and overall burnt area, would also be a useful improvement. While the existing empirical models themselves can be useful in projecting the response of wildfires to future climate change (e.g., Haas et al., 2024), improved process-based models will be necessary in the long run to be able to examine feedbacks from fire to the climate system.

Author contributions

OH: Conceptualization, Investigation, Writing–review and editing. TK: Conceptualization, Investigation, Writing–review and editing. JG-D: Conceptualization, Investigation, Writing–review and editing. IP: Conceptualization, Investigation, Writing–review and editing. SH: Conceptualization, Formal Analysis, Investigation, Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenvs.2024.1438262/full#supplementary-material>

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