

The spatial distribution and temporal drivers of changing global fire regimes: a coupled socio-ecological modeling approach

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RESEARCH ARTICLE

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Key Points:

- Representing managed fire in global-scale fire models has represented a substantial research challenge in fire science
- We address this through the offline coupling of a global agent-based model of human fire use with a dynamic global vegetation model
- The coupling improves model performance and allows exploration of drivers of change in global fire regimes of the recent past

Supporting Information:

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

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The Spatial Distribution and Temporal Drivers of Changing Global Fire Regimes: A Coupled Socio-Ecological Modeling Approach

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Abstract The limited capacity of fire-enabled vegetation models to represent human influences on fire regimes is a fundamental challenge in fire science. This limitation places a major constraint on our capacity to understand how vegetation fire may change under future scenarios of climate change and socio-economic development. Here, we address this challenge by presenting a novel integration of two process-based models. The first is the Wildfire Human Agency Model (WHAM!), which draws on agent-based approaches to represent anthropogenic fire use and management. The second is JULES-INFERNO, a fire-enabled dynamic global vegetation model, which takes a physically grounded approach to the representation of vegetation-fire dynamics. The combined model enables a coupled socio-ecological simulation of historical burned area. We calibrate the combined model using GFED5 burned area data and perform an independent evaluation using MODIS-based fire radiative power observations. Results suggest that as much as half of all global burned area is generated by managed anthropogenic fires—typically small fires that are lit for, and then spread according to, land user objectives. Furthermore, we demonstrate that including representation of managed anthropogenic fires in a coupled socio-ecological simulation improves understanding of the drivers of unmanaged wildfires. For example, we show how vegetation flammability and landscape fragmentation control inter-annual variability and longer-term change in unmanaged fires. Overall, findings presented here indicate that both socio-economic and climate change will be vital in determining the future trajectory of fire on Earth.

Plain Language Summary Humans have used fire as a tool to manage land over many thousands of years, and they continue to do so across the world today. However, global-scale models which are used to understand how vegetation fire may respond to climate change in the future have not yet robustly accounted for this core aspect of the system. To address this research gap, we built a new model that represents how humans use and manage fire globally and coupled it with an existing global model that represents the climatic and ecological factors that shape patterns of wildfire. The combined model simulates annual global burned area, directly accounting for human and biophysical factors. We use this coupled model to investigate what factors contributed to historical patterns of burned area in satellite-based observations. We find that improved representation of human impacts on fire significantly improves the model's ability to reproduce observed annual burned area and sheds new light on what is driving change in vegetation fire globally. Our results demonstrate the importance of human-fire interactions for understanding how fire may respond to climate change, and therefore to scientists and practitioners seeking to implement effective adaptation measures.

1. Introduction

Vegetation fire is a coupled socio-ecological process, in which humans are the largest driver of change in its global distribution (Andela et al., 2017; Kelley et al., 2019). Perhaps the central example of this is that, whilst the planet has warmed under recent anthropogenic climate change, the area burned globally each year has decreased, particularly in savannas and grasslands (Chen et al., 2023). Drivers of this phenomenon are complex and uncertain (Zubkova et al., 2023), ranging from cropland conversion (Andela et al., 2017) to changes in anthropogenic fire use (Smith et al., 2022), from increased grazing intensity (Archibald & Hempson, 2016) to the CO₂ fertilization effect (Ripley et al., 2022; Stevens et al., 2016). A lack of clarity around the drivers of declining global burned area has made attribution of changes in global fire regimes a significant challenge (Jones et al., 2022). This, in

turn, limits understanding of how fire may evolve in the future, including its potential role as a positive feedback to climate change (Lasslop et al., 2019).

At the heart of this uncertainty are the huge diversity of ways in which humans use and manage fire. Human fire use ranges from burning of agricultural residues in intensive land use systems (Kumar et al., 2023) to cultural uses such as religious ceremonies (Smith et al., 2022). Human fire management is similarly diverse, ranging from proactive indigenous “patch-burning” methods (Laris, 2002) to industrial fire suppression. As such, fire can broadly be categorized into managed or “landscape” fires—which are typically small, controlled, and can be beneficial to humans—and unmanaged wildfires, which are larger and burn more intensely (UNEP - The United Nations Environment Programme, 2022). Furthermore, human fire use is itself undergoing substantial change, with shifts away from more subsistence-oriented fire uses (Smith et al., 2022) and possibly an overall decline in fire use driven by agricultural intensification (Perkins et al., 2024). Consequently, Shuman et al. (2022) argue that incorporating managed fire into models at all spatial scales is an important step toward equipping fire science for the Anthropocene.

In addition to direct anthropogenic influences on fire, humans also have many indirect influences on fire regimes. For example, multiple authors have argued that anthropogenic fragmentation of vegetated landscapes is a key process shaping the evolution of global fire (Archibald et al., 2012; Driscoll et al., 2021; Harrison et al., 2021). Fragmentation can have opposite effects across ecosystems—with logging and degradation increasing fire in otherwise fire-independent forests, and reduced fuel connectivity decreasing burned area in grassland and savannah ecosystems (Rosan et al., 2022). As such, understanding the drivers of change within global fire regimes requires consideration not only of biophysical factors, but also of both direct and indirect human impacts (Archibald, 2016).

Global-scale fire models have struggled to reproduce the observed decline in global burned area (Hantson et al., 2020). Indeed, in the first intercomparison project of the global fire model community (FireMIP, Rabin et al., 2017), models largely disagreed about both centennial trends, and more recent decadal trends, in global burned area (Teckentrup et al., 2019). Underlying this lack of consensus have been substantial limitations in the representation of human impacts on the fire modules of dynamic global vegetation models (Ford et al., 2021). Typically, these have been restricted to global functions relating population density to numbers of fires in satellite observations (Rabin et al., 2017). This ignores the diversity of human fire use and management, and hence limits the capability of DGVMs to advance understanding of socio-ecological dynamics of present-day fire regimes and how human and biophysical factors may interact in the future (Shuman et al., 2022).

The Wildfire Human Agency Model (WHAM!) is the first formal model to represent present-day anthropogenic fire use and management at global scale. A full model description is given in Perkins et al. (2024), with a brief summary provided here. Drawing on agent-based approaches, WHAM! is a geospatial behavioral model that captures the underlying land system drivers of anthropogenic fire use and management to simulate human fire use decision-making from the bottom-up (Perkins et al., 2022). It does this by modeling the distribution of contrasting land use systems (e.g., different systems of arable and livestock farming, forestry and non-extractive land uses) and representing their empirical relationships to fire use and management decisions. As WHAM! only represents human influences on global fire regimes, it was designed to be integrated with fire-enabled DGVMs, such as the JULES-INFERN0 model (Mangeon et al., 2016), which capture the biophysical drivers of fire. Here we present the first coupling between WHAM! and JULES-INFERN0, such that biophysical, direct and indirect human drivers of fire regimes are all explicitly represented in an integrated simulation for the first time.

WHAM! takes its empirical basis from the Database of Anthropogenic Fire Impacts (DAFI, Perkins & Millington, 2021). DAFI is the product of a literature meta-analysis covering the period 1990–2020 and comprises 1809 case studies of human-fire interactions from 504 academic papers, government and NGO reports (Millington et al., 2022). This data set addresses a previous barrier to improved representation of anthropogenic fire in DGVMs: the lack of a systematic data set on which to base new parameterizations (Forkel et al., 2019). Alongside development of DAFI, the 5th version of the Global Fire Emissions Database (GFED5, Chen et al., 2023) accounts for smaller fires than previous versions and therefore enables more robust evaluation of global-scale modeling of human fire interactions. Previous iterations of GFED have been based on a combination of MODIS for burned area and VIRS for active fire detection (Giglio et al., 2013). As such, they have not been able to systematically detect anthropogenic fires: DAFI suggests that >50% of anthropogenic fires are smaller than the 21 ha threshold above which MODIS can detect (Millington et al., 2022). GFED5 incorporates higher resolution

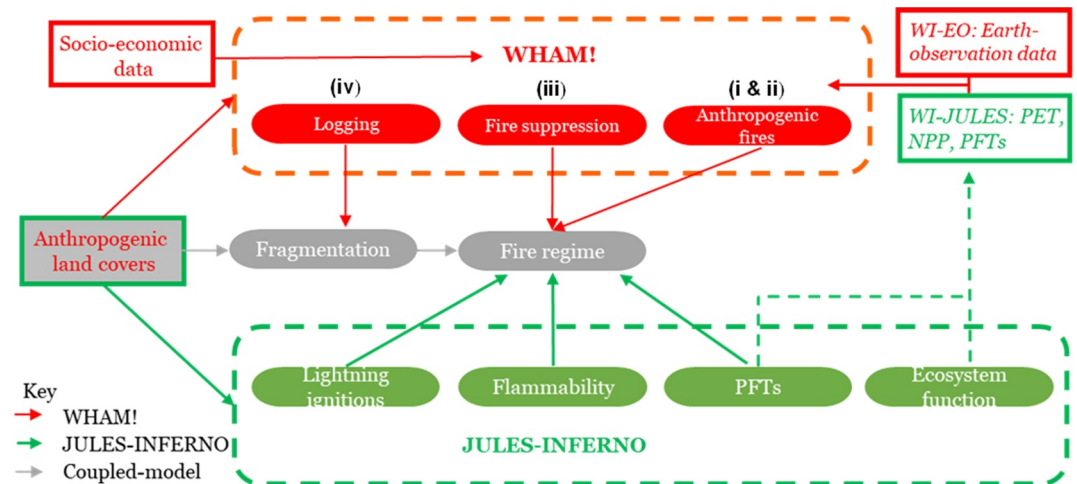


Figure 1. Processes represented in the WHAM-INFERNO combined model. Solid arrows denote dynamic model calculations, whilst dashed lines denote static exchange of information. Socio-economic data and biophysical inputs to WHAM! (Potential Evapotranspiration [PET], Net Primary Production [NPP], and Plant Functional Types [PFTs]) are passed offline. In WHAM-INFERNO-JULES (WI-JULES) these data are taken from JULES outputs, whilst in WHAM-INFERNO-Earth Observation (WI-EO) PET and NPP inputs are taken from remote sensing. Roman numerals (i–iv) correspond to numbers given in Section 2.1.1 of the text.

remote sensing (principally from Landsat and Sentinel-2), and hence is much more effective at capturing small fires: global burned area in GFED5 is a 61% increase over GFED4s (Chen et al., 2023). Therefore, with DAFI providing an empirical-basis for bottom-up modeling of human-fire interactions, and GFED5 better able to detect them from space, a comprehensive and empirically grounded assessment of the role of managed anthropogenic fire in global fire regimes is now possible.

This paper presents the integration of WHAM! with JULES-INFERNO and its application to understand the spatiotemporal drivers of global fire regimes. Section 2 (Methods) focuses on describing the integration of outputs from the two models. Model calibration is described briefly in the main text with further details provided in Supporting Information S1. In Section 3 (Results), we present a brief evaluation of the outputs of the coupled model to establish its credibility, before focusing on understanding how human and biophysical factors combine to produce observed distributions of fire globally. Discussion (Section 4) focuses on insights relevant to the question of declining global burned area, and in particular to understanding the relative contribution of direct human influences (starting and suppressing fires), indirect human influences (i.e., landscape fragmentation) and biophysical factors (i.e., climate and vegetation flammability).

2. Methods

Our methods are presented in five sections, which respectively describe the inputs, structure, calibration, evaluation, and analysis of the WHAM-JULES-INFERNO combined model (hereafter WHAM-INFERNO). A schematic overview of the processes represented in WHAM-INFERNO is presented in Figure 1. Calculations of the fire regime at each timestep combine three elements: (a) WHAM! outputs for managed and unmanaged anthropogenic fires and fire suppression, (b) JULES-INFERNO outputs for lightning ignitions, flammability and plant functional types, and (c) a representation of vegetation fragmentation derived from secondary data and WHAM! outputs for logging. These are each detailed further in Section 2.1.

Importantly, two versions of WHAM-INFERNO are presented and assessed: WHAM-INFERNO-JULES (hereafter WI-JULES) and WHAM-INFERNO-Earth Observation (hereafter WI-EO). The difference between these two versions is that in WI-JULES, WHAM! is parameterized using biophysical inputs directly from JULES, whilst in WI-EO, WHAM! takes these inputs from remote sensing. Specifically, inputs for potential evapotranspiration, net primary production, and the bare soil fraction are replaced with Earth observation data. The differences between these two versions of WHAM! are described in detail in Perkins et al. (2024; Supporting Information S1).

Table 1
Overview of Inputs to the WHAM!-INFERNO Combined Model

Coupled model input	Source	Units	Temporal resolution
Managed burned area	WHAM!	Cell fraction (0–1)	Annual
Unmanaged anthropogenic fires	WHAM!	Fires km ^{−2}	Annual
Fire suppression	WHAM!	Cell fraction (0–1)	Annual
Selective logging	WHAM!	Cell fraction (0–1)	Annual
Distribution of PFTs	JULES-INFERNO	Cell fraction (0–1)	Monthly
Flammability per PFT	JULES-INFERNO	Dimensionless (0–1)	Monthly
Burned area per fire per PFT	JULES-INFERNO	km ²	Fixed (n/a)
Lightning—ground strikes	Christian et al. (2003)	strikes km ^{−2}	Fixed (single daily mean)
Road density	Meijer et al. (2018)	m ² km ^{−2}	Annual
Anthropogenic land cover	Hurt et al. (2020)	Cell fraction (0–1)	Annual

Note. PFT is plant functional type. Data inputs for lightning strikes, road density, and anthropogenic land covers were rescaled to the resolution of WHAM!-INFERNO (1.875° × 1.25°). Differing temporal resolutions of inputs were reconciled as noted in Section 2.1.

The primary purpose of the comparison of WI-JULES and WI-EO is to allow interrogation of the robustness of inferences made about the drivers of global fire regimes. For example, if trends are identified in WI-JULES but not in WI-EO, then they may be attributable to underlying model error in JULES' representation of ecosystem dynamics. Similarly, assessing the difference in performance (as measured against GFED5) allows exploration of how far underlying error in the hydrological and vegetation outputs of DGVMs may constrain the capacity of their fire modules to reproduce remotely sensed observations (Hantson et al., 2020).

Code to run and analyze WHAM-INFERNO is written in R version 4.2.2 (R Core Team, 2022), using the “raster” library version 3.6-20 (Hijmans, 2023). Code and data to run and analyze outputs of both versions of WHAM-INFERNO are made available on Zenodo (Perkins et al., 2023).

2.1. Inputs to the Coupled Model

WHAM-INFERNO takes inputs from WHAM!, JULES-INFERNO and from secondary data sources. Each of these inputs are described in turn below (Sections 2.1.1–2.1.3), and an overview is given in Table 1. WHAM! outputs are currently at an annual timestep, whilst as per results in the sixth coupled model intercomparison project (CMIP6), JULES-INFERNO outputs are aggregated monthly means. Therefore, WHAM-INFERNO runs at a monthly timestep, with WHAM! outputs for a given year assumed to be uniformly distributed across calendar months.

2.1.1. WHAM! Inputs to the Coupled Model

WHAM! inputs to the coupled model comprise (a) managed burned area as a fraction of each cell, (b) numbers of unmanaged fires (count km^{−2} yr^{−1}), (c) fire suppression intensity (0–1), and (d) the presence of selective logging as a fraction of the tree cover in each cell (see corresponding numerals in Figure 1). WHAM! inputs used were those presented in Perkins et al. (2024).

2.1.2. JULES-INFERNO Inputs to the Coupled Model

INFERNO (Mangeon et al., 2016) is the fire module of the JULES DGVM. INFERNO calculates burned area from fires with two key components. The first is mean global burned area per fire per PFT, a set of PFT-specific model free parameters. Model parameters for burned area per PFT were as in Burton et al. (2019). The second component of INFERNO burned area calculations is fuel flammability, which INFERNO calculates as a function of leaf carbon and soil carbon pools, temperature, relative humidity, precipitation, and soil moisture (Mangeon et al., 2016). Flammability is therefore important in capturing the impact of both climate change and spatial heterogeneity in vegetation on fire regimes. Flammability is calculated per PFT in each model pixel at each timestep. JULES outputs are from the model set-up used in CMIP6 (Wiltshire et al., 2020).

2.1.3. Ancillary Inputs to the Coupled Model From Secondary Data

In addition to the calculations from the two models, three sets of secondary data were used as inputs: lightning ground strikes, anthropogenic land covers—cropland, pasture, rangeland, and urban—and road density. First, as in JULES-INFERNO standalone (Mathison et al., 2023), counts of lightning strikes were sourced from the Lightning Imaging Sensor—Optical Transient Detector (LIS/OTD, Christian et al., 2003). Second, as in CMIP6, anthropogenic land cover was taken from the LUH2 data set (Hurtt et al., 2020). Finally, Haas et al. (2022) demonstrated that road density was effective in capturing vegetation fragmentation effects on fire regimes at global scale; road density data were therefore taken from the GRIP global road database (Meijer et al., 2018).

2.2. WHAM-INFERNO Structure

The coupled WHAM-INFERNO model is a “prescribed” model coupling (sensu Robinson et al., 2018) such that whilst simulations of global burned area depend on calculations involving outputs of both models, dynamic information transfer is only one way—from WHAM! to INFERNO (see Section 2.2.1). Specifically, for each simulated year, annual burned area from managed fire is taken directly from WHAM!, with $\frac{1}{12}$ assigned to each calendar month. But to calculate unmanaged fire burned area, the original JULES-INFERNO calculations are modified by the number of anthropogenic fires ($\text{km}^{-2} \text{yr}^{-1}$) provided by WHAM!. Therefore, description of model coupling here first describes calculation of burned area from unmanaged fires (Section 2.2.1). Then, as burned area from unmanaged fires is also impacted by anthropogenic landscape fragmentation, the representation of such processes is then described in Section 2.2.2. Finally, the calculation of overall burned area combining both managed and unmanaged fire is described in Section 2.2.3.

2.2.1. Unmanaged Fire

The calculation of burned area from unmanaged fires is presented in two parts: first the calculation of numbers of unmanaged fires and second the calculation of their respective burned area. An overview of this process is given in Figure 2.

2.2.1.1. Number of Fires

In the original Mangeon et al. (2016) conception of INFERNO, the numbers of ignitions from lightning strikes are calculated as follows:

$$I_L = 7.7 \times \text{Lightning} \times (1 - \text{Suppression}) \quad (1)$$

where I_L is the number of ignitions from lightning strikes in a given model timestep, Lightning is the number of lightning strikes and Suppression is a population density-dependent suppression function. The structure of this calculation is retained with two changes: first, the suppression function is replaced with an empirically defined representation of suppression intensity (Section 2.2.2) and second the empirically defined linear scaling parameter ($=7.7$) from Mangeon et al. (2016) is replaced with a free parameter (λ) to allow re-calibration. A complete set of model free parameters is given in Table S1 in Supporting Information S1.

In the WHAM-INFERNO combined model, calculation of lightning fires is integrated with unmanaged anthropogenic fire numbers from WHAM! as follows:

$$\text{Fires}_{\text{UM}} = \text{Arson} + \text{Escaped} + (1 - \text{Suppression}) * (\text{Background} + \text{Lightning}) \quad (2)$$

where Fires_{UM} is the annual number of unmanaged fires per grid box per year, Arson and Escaped fire numbers are the number of fires $\text{km}^{-2} \text{yr}^{-1}$ taken from WHAM! outputs, and Lightning is the number of lightning fires calculated from mean daily ground strikes as in Equation 1. Finally, *Background*, is a small globally constant rate used to capture fires that are not arson, lightning or escaped managed fires. The constant rate maintains an aspect of INFERNO, in which a uniform “ignition” rate is an option.

Fire suppression in the coupled model (Section 2.2.2) is applied to background and lightning fires, but not to arson and escaped fires. This is for ontological reasons, as follows. INFERNO assumes that suppressed *ignitions* have no burned area. However, in DAFI, the database used to develop WHAM!'s calculation of arson and escaped *fires*,

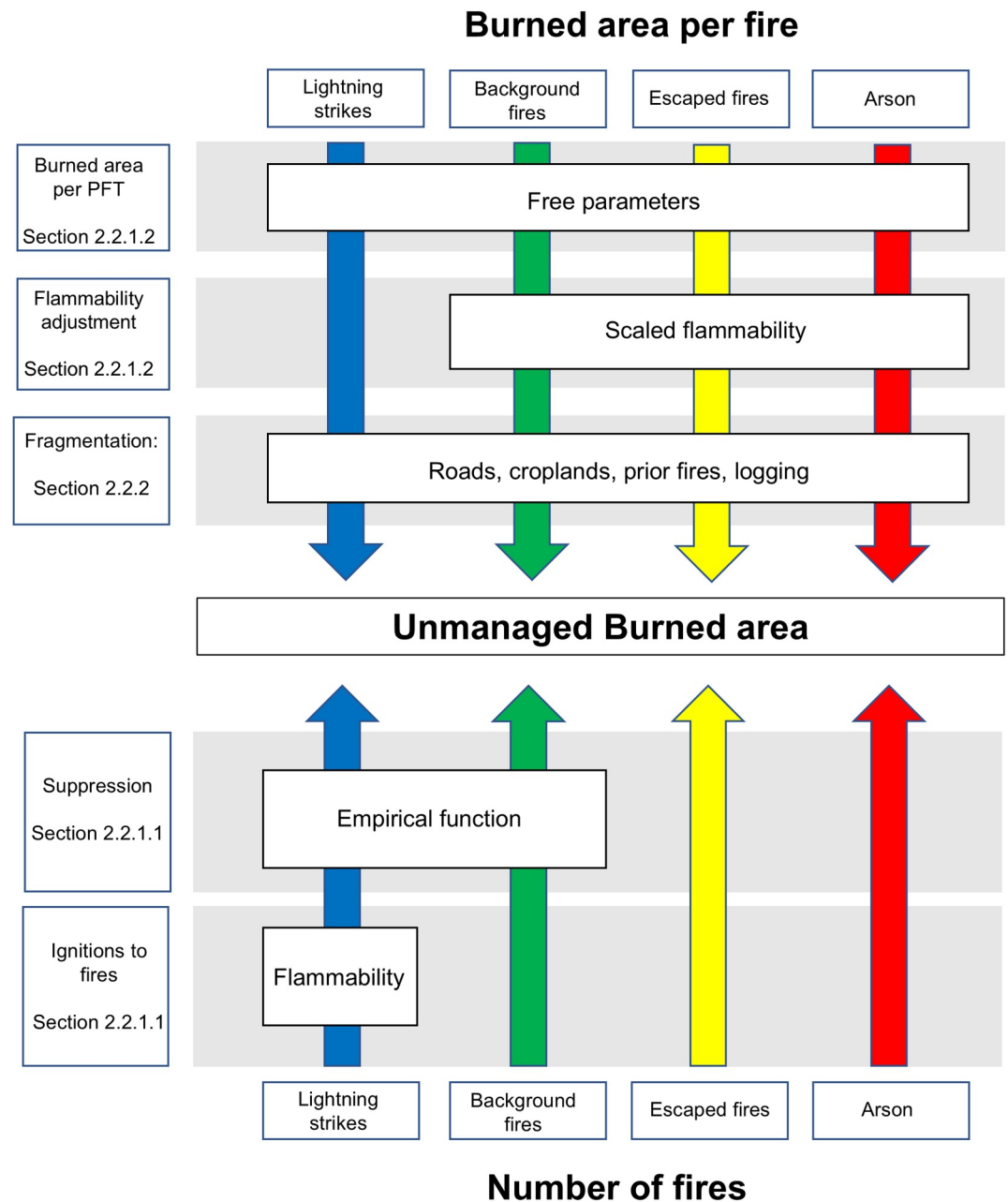


Figure 2. Calculation of burned area from unmanaged fires in the WHAM-INFERNO combined model.

numbers of *fires* are recorded, therefore by definition these have burned area >0. As such, it is illogical to apply modeled suppression to them. By contrast, as the background rate was calculated using a constant, clearly this did not account for the impact of suppression. Similarly, lightning remains calculated based on *ignitions* rather than *fires* and hence could be suppressed before beginning to burn.

2.2.1.2. Burned Area per Unmanaged Fire

After calculation of the numbers of unmanaged fires per pixel ($Fires_{UM}$), these are then converted to burned area. In its original conception, INFERNO calculates the number of fires as:

$$Fires = Ignitions * Flammability \quad (3)$$

In other words, both humans and lightning are conceptualized as producing ignitions, which may or may not become fires based on the flammability of the surrounding vegetation. By contrast, because most human fires are started deliberately, WHAM! does not output numbers of *ignitions*, but numbers of *fires* directly (Figure 2). However, whilst vegetation flammability plays the ontological role of translating ignitions to fires in INFERNO, it also plays an important functional role: capturing geographic variation in the capacity and tendency of the vegetation to sustain unmanaged fire, as well as providing the means by which climate change impacts fire regimes. This is because INFERNO calculates burned area per fire with a simple global mean value per PFT. Therefore, simply removing flammability from the calculation and taking numbers of unmanaged fires from WHAM! was not possible.

The solution adopted is to multiply WHAM! unmanaged fires by INFERNO flammability, but to rescale with a free parameter. This leaves a burned area calculation from unmanaged fires of:

$$BA_{UM} = \text{Fires}_{UM} * \Phi * \sum_{PFT=1}^{PFT=n} PFT * \text{Flammability}_{PFT} * BA_{PFT} \quad (4)$$

where BA_{UM} is the annual burned area from unmanaged fires as a fraction of each model pixel, PFT is the fraction of each model pixel (0–1) occupied by a given PFT, $\text{Flammability}_{PFT}$ is a PFT-specific dimensionless adjustment (0–1) reflecting spatiotemporal differences in the combustibility of vegetation, BA_{PFT} is the PFT-specific mean burned area per fire from JULES-INFERNO, and Φ is a scaling factor reflecting the differing model ontologies of WHAM! and JULES-INFERNO.

2.2.2. Fragmentation

The impact of landscape fragmentation effects was restricted to unmanaged fires; managed burned area was not altered for fragmentation effects, as these would already be implicitly accounted for in the observations captured in DAFI. Representation of fragmentation is done in three ways. First, as WHAM! accounts for anthropogenic cropland fires, to account for the role of cropland conversion in fragmenting more flammable fuels, burned area per unmanaged fire was set to 0 for cropland PFTs.

Second, Haas et al. (2022) demonstrate the importance of road density in reducing both fire sizes and burned area. This finding was implemented in the coupled model by adjusting burned area per fire with a simple negative exponential function:

$$BA_{UM_frag} = BA_{UM} * \left(1 - \frac{\ln(RD)}{\rho} \right) \quad (5)$$

where BA_{UM} and BA_{UM_frag} are annual burned area per pixel (0–1) from unmanaged fire before and after adjustment for fragmentation effects, RD is road density and ρ a free parameter.

By contrast, logging of wet, fire-prone forests can lead to increased fire (both numbers of fires and fire size), as gaps in the canopy lead to drying on the forest floor (Cochrane & Barber, 2009; Lapola et al., 2023). A simple representation of this was implemented by increasing the mean burned area per fire for broadleaf tree PFTs given the presence of the Logging AFT in WHAM! outputs. The values of mean burned area for broadleaf tree PFTs therefore become:

$$BA_{broadleaf|logging} = BA_{broadleaf} * \Lambda(\text{Logging}) \quad (6)$$

where $BA_{broadleaf}$ is the burned area per fire for broadleaf tree PFTs, $BA_{broadleaf|logging}$ is this parameter value when adjusted for logging, Logging is the fraction of tree cover in a cell occupied by WHAM's logging AFT, and Λ a free parameter.

2.2.3. Combining Managed and Unmanaged Fire

JULES-INFERNO typically runs at a timestep of between 30 and 60 min (Clark et al., 2011). This is required for the stability of model equations and has the advantage of capturing temporal fluctuations in vegetation

flammability. As such, INFERNO increases the amount of bare soil in a given model pixel when a fire burns, which reduces fuel availability and the amount of area burned from subsequent fires until vegetation resprouts (Burton et al., 2019). However, as it is not meaningful to model human land use decision-making at such short durations (Arnell et al., 2014), managed fire is output at an annual timestep by WHAM!. For these reasons, calculating the combined burned area of managed and unmanaged fires requires an adjustment to account for the effect of preceding fires:

$$BA_{\text{tot}} = BA_{\text{Managed}} + BA_{\text{UM}} * \gamma \quad (7)$$

where BA_{Managed} is burned area from managed fire, BA_{tot} is total burned area, and γ a function representing the impact of preceding fires on unmanaged burned area. Managed fire was not adjusted for effects of antecedent fire for several reasons: first, because WHAM! has its own internal calculation for including fuel limitations in agent calculations; second, because WHAM! outputs are empirically grounded, derived from data that would capture such limitations to a degree. Third, many managed anthropogenic fires are lit to reduce the intensity and spread of unmanaged fire (e.g., prescribed fire or indigenous patch burning mosaics). The γ function was calculated using a linear function after a threshold:

$$\gamma = \begin{cases} 1 & \text{if } BA_{\text{UM}} \leq \alpha \\ \beta & \text{otherwise} \end{cases} \quad (8)$$

where α is a free parameter representing a threshold burned fraction of a cell below which fuel availability is not limiting, whilst β is a further free parameter capturing the rate of decay in burned area once this threshold is reached. This functional form was chosen as it approximates the behavior observed by Archibald et al. (2012), who explored the impact of fragmentation on burned area in flammable ecosystems.

2.3. WHAM-INFERNO Calibration

The model structure set out in Section 2.2 resulted in 20 free parameters (Table S1 in Supporting Information S1), which formed the basis of a perturbed parameter ensemble for model calibration. A total of 10,000 perturbed parameter sets were created with a maximin latin hypercube sampling design (Carnell, 2022). Using the resulting parameter sets, 10,000 model runs were conducted (i.e., one for each perturbed parameter combination) for both versions of the WHAM-INFERNO ensemble.

The outputs of each run were compared with the recent GFED5 global burned area product (Chen et al., 2023). First, “implausible” parameter sets were ruled using history matching with the overall magnitude of global burned area in GFED5. Remaining parameter sets were then treated as “not ruled out yet” (NROY, Rougier & Beven, 2013). Second, as well as global burned area, Pearson's correlation (r) was calculated with a square root transformation applied. These two metrics were those used in the FireMIP (Teckentrup et al., 2019), and hence were adopted here to define a pareto-optimal parameter space capturing the trade-offs in maximizing performance against each metric. This approach allows, first, the evaluation of different model processes in capturing observed fire regimes of the recent past and second overall evaluation of the performance of the WHAM-INFERNO ensemble. The mean outputs of WI-JULES and WI-EO in the pareto parameter space then formed the basis of further analysis. Fuller detail of model calibration is given in Supporting Information S1.

2.4. WHAM-INFERNO Evaluation

WHAM-INFERNO is evaluated in three broad ways, first by output corroboration through comparison of model outputs with remotely sensed burned area from GFED5 (as described above), second by model benchmarking against a null or baseline model, and third by comparison of model outputs with (unseen) fire radiative power (FRP) data. The baseline model used in the second evaluation step was an offline version of INFERNO (as presented in Mangeon et al. (2016)). As INFERNO was originally calibrated using GFED4 data, in which burned area was 49% lower than the more recent GFED5 burned area product, a process of recalibration required. The recalibration of this INFERNO offline model (hereafter, “baseline model”) followed broadly the same steps as WHAM-INFERNO combined model: 10,000 parameter sets were used to define a perturbed parameter ensemble, from which both NROY and pareto-optimal parameter spaces were defined using GFED5 burned area. Detailed

description of the setup of the baseline model, including how its free parameters differ from WHAM-INFERNO, is described in Supporting Information S1.

WHAM-INFERNO provides the first global estimate of how burned area breaks down between managed and unmanaged fire. This relationship is not measured in remote sensing products, and so evaluating the separate modeled distributions of managed and unmanaged fire is challenging. However, we would expect managed anthropogenic fires to tend to be smaller and less intense on average (Kasoar et al., 2024; Millington et al., 2022). As such, in our third evaluation step, we use the MODIS FRP product (i.e., MCD14 ML, Giglio et al., 2006) as a means of evaluating the plausibility of the managed and unmanaged fire breakdown projected by WHAM-INFERNO. FRP data were processed as in Haas et al. (2022) with the median FRP of all fires in a pixel calculated per calendar year and pixels filtered for those containing vegetation fire with >50% confidence.

We hypothesized that where managed fire forms a greater proportion of the total burned area in a pixel the FRP will be lower, and vice versa. To test this hypothesis, we fit linear models of FRP with two independent variables. The first of these was the proportion of the total modeled burned area (managed and unmanaged) that was generated by managed fire (Mfrac) and the second was simply the fraction of the pixel burned by managed fire. A log transformation was applied to FRP data to ensure independence of residuals.

2.5. Historical Run Setup and Analysis

As with the WHAM! standalone historical simulations presented in Perkins et al. (2024), WHAM-INFERNO runs span 1990–2014. These two years mark the beginning of the data recorded in the DAFI database of global anthropogenic fire impacts (i.e., 1990, Millington et al., 2022) that was used to parameterize WHAM!, and the end of the CMIP6 historical period (i.e., 2014), respectively. Both models were run at the spatial resolution that JULES-INFERNO adopted in the FireMIP ($1.875^\circ \times 1.25^\circ$). Model outputs are evaluated during the overlapping period in WHAM-INFERNO historical runs and the GFED5 record (2001–2014); GFED5 data were aggregated to the spatial resolution of WHAM-INFERNO.

Analysis of outputs focuses on understanding spatial and temporal variation in the drivers of global fire regimes. Spatial analysis focuses on understanding how managed anthropogenic fire and unmanaged fire combine to produce observed fire regimes across global regions. Similarly, temporal analysis first assessed how far managed fire and unmanaged fire contribute to interannual variability in fire regimes. This was calculated by detrending the global total burned area from GFED5 and WHAM-INFERNO model outputs before calculating the correlation and standard deviation of the residual variabilities.

Then, drivers of longer-term (decadal) change were assessed. Perkins et al. (2024) present analysis of the drivers of change in WHAM! managed fire outputs. Results pointed to land use intensification as a global dampening effect on fire use, whilst conversely land use extensification—particularly for livestock farming—led to increased fire use. Therefore, analysis of temporal trends here focuses on change in unmanaged fire in relation to the human and physical drivers represented in the coupled models. These are annual changes in numbers of unmanaged fires, road density (fragmentation, Haas et al., 2022), vegetation flammability, fire suppression, and cropland conversion. The relative influence of these drivers was assessed at a pixel-level first by comparing the Kendall's Tau correlations of their interannual changes with interannual change in unmanaged burned area (for each of WI-JULES and WI-EO). Second, using these same independent variables, linear models of pixel-level change in unmanaged burned area were fit for both interannual and overall change between 2001 and 2014. *t*-Values of the independent variables were used to assess the relative strength of their relationships to changes in unmanaged burned area.

3. Results

3.1. Model Evaluation

Measured by correlation with the GFED5 record during 2001–2014, both WI-JULES and WI-EO perform significantly better than the baseline model (Z Tests; both $p < 0.001$, $n = 10, 14$). Specifically, the mean correlation of the pareto-optimal parameter space is 0.81 for WI-EO and 0.76 for WI-JULES, compared with 0.58 for the baseline model (Figure 3). This result also compares favorably with INFERNO v1.0 presented in the FireMIP, in which INFERNO had a correlation of 0.70 against GFEDv4 and 0.64 against GFEDv4s (Teckentrup et al., 2019). As such, inclusion of WHAM! seemingly improves INFERNO both in an absolute sense, when

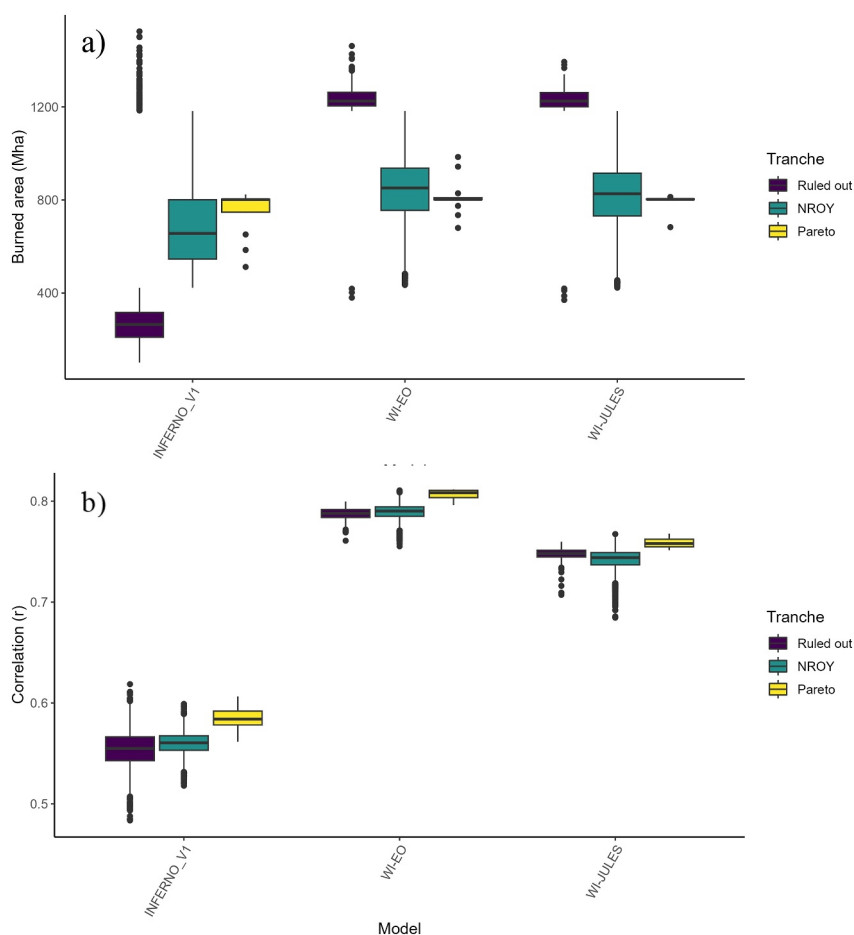


Figure 3. Outputs of WHAM-INFERNO in comparison with a baseline model (INFERNO_V1): (a) simulated global burned area and (b) Pearson correlation with GFED5. For burned area, the baseline model has many runs ruled out for burned area being too low in comparison with GFED5, whilst in both versions of WHAM-INFERNO a smaller number of runs are ruled out. The two versions of WHAM-INFERNO both produce higher correlations than the baseline model across all three tranches of parameter sets (ruled out, NROY and pareto-optimal). NROY refers to “not ruled out yet.”

compared to GFED5, but also relatively against INFERNO's performance based on the observational data available at the time of its original development.

Furthermore, almost 70% of the baseline model ensemble's runs are ruled out, primarily due to simulating burned area too low to achieve acceptable coherence with the GFED5 record (mean of ruled out runs was 276 vs. 802 Mha in GFED5). By contrast, only 182 of WI-EO and 124 of WI-JULES runs are ruled out. In the pareto parameter space, WI-EO has a slight overprediction bias (+11 Mha) and WI-JULES has a slight underprediction bias (−10 Mha), compared to a bias of −52 Mha in the baseline model. Overall, we conclude that the WHAM integration improves the structural capacity of INFERNO to capture the magnitude and distribution of global fire regimes.

Both WI-EO and WI-JULES capture significant effects in the global distribution of FRP (Figure S3 in Supporting Information S1). Specifically, linear models of FRP with a single independent variable—the fraction of the total burned area contributed by managed fire—have r^2 of 0.18 for WI-EO and 0.12 for WI-JULES (both $p < 0.001$, Table S3 in Supporting Information S1). Two parameter models, using the managed fraction of the total burned area per pixel and the pixel fraction burned from managed fire as independent variables perform marginally better (WI-EO: $r^2 = 0.20$, WI-JULES: $r^2 = 0.15$; both $p < 0.001$). This indicates first that the modeled distribution of managed fire and its relationship to unmanaged fire in WHAM-INFERNO capture meaningful processes in global fire regimes, and second that the improved burned area projection of WI-EO over WI-JULES results in improved explanatory power of the global distribution of FRP.

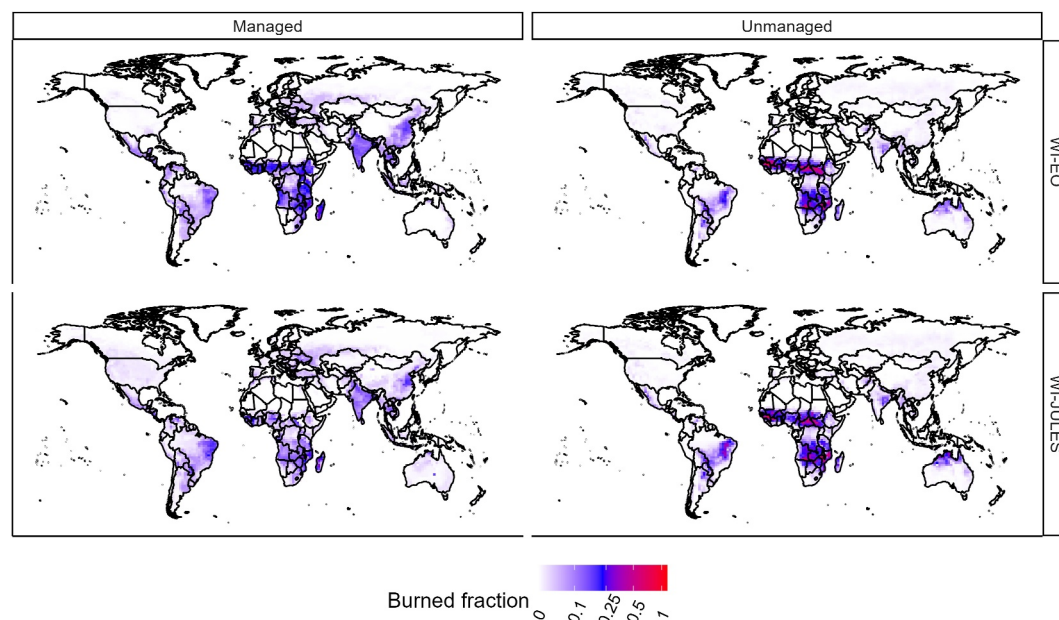


Figure 4. Distribution of managed and unmanaged fire in WHAM-INFERNO-Earth Observation (WI-EO) and WHAM-INFERNO-JULES (WI-JULES) shown as the burned fraction of each pixel. The arithmetic mean of model outputs was taken across the historical model run period (1990–2014). Principle differences between the two versions of WHAM-INFERNO are seen in the managed fire outputs of WI-EO in sub-Saharan Africa, which have a more homogeneous distribution than WI-JULES's more sporadic spatial pattern. Other anomalies between models are seen in the Caatinga region of Brazil and in the Northern Territories of Australia.

3.2. Analysis of WHAM-INFERNO Outputs

3.2.1. Spatial Analysis

Across the pareto parameter runs, simulated burned area in both coupled models is split approximately evenly between managed and unmanaged fires. Over the historical period (1990–2014) in WI-JULES a mean of 441 Mha (54%) comes from unmanaged fires and 379 Mha (46%) from managed fires. Similarly, in WI-EO, 404 Mha (47%) comes from unmanaged fires, and 453 Mha (53%) comes from managed fires.

Furthermore, there is substantial heterogeneity in the spatial location of burned area due to managed versus unmanaged fires (Figure 4). For example, across 1990–2014 at the level of World Bank regions, in sub-Saharan Africa WI-JULES suggests 69% of mean annual burned area is from unmanaged fires (57% in WHAM-EO, Figure 5). Conversely, in South Asia (which includes India), WI-JULES suggests just 31% of burned area is from unmanaged fires (23% in WI-EO, Figure 5). The predominance of managed fire is driven by large-scale crop-residue burning in the region (Hall et al., 2024; Perkins et al., 2024). Furthermore, there is also regional heterogeneity in the trends in managed and unmanaged fire. For example, in both WI-JULES and WI-EO, managed fire is increasing in South Asia, whilst decreasing in Latin America and the Caribbean (Figure 5).

Perhaps the two most notable differences in sources of burned area between the two models' (WI-JULES and WI-EO) simulations come in Latin America & the Caribbean and sub-Saharan Africa. The difference in Latin America is that WI-JULES simulates higher unmanaged burned area than WI-EO (76 vs. 57 Mha) particularly in the Caatinga region of Brazil (Figure 6), which is due to a known anomaly in JULES' hydrological cycle in the region (Perkins et al., 2024). By contrast, in sub-Saharan Africa WI-EO simulates higher managed burned area than WI-JULES (208 vs. 124 Mha), attributable to the more homogeneous spatial distribution in WI-EO outputs—particularly in the Guinean Savanna—compared to the comparatively heterogeneous WI-JULES outputs (Figures 4 and 6).

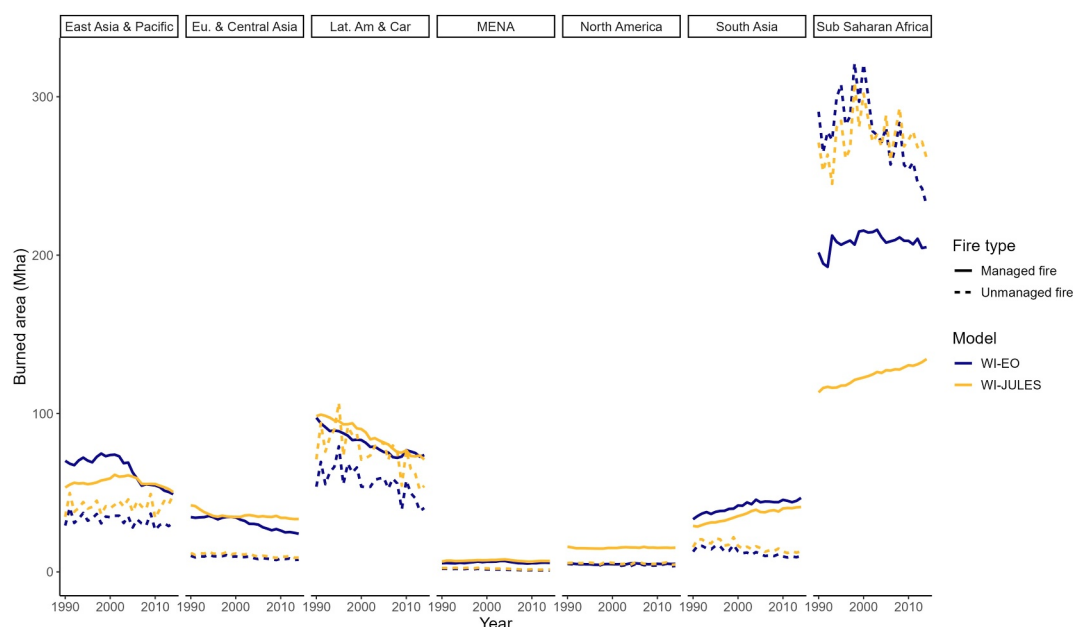


Figure 5. Trends in managed and unmanaged fire across the World Bank global regions. The largest gap between managed and unmanaged fire is seen in sub-Saharan Africa, where unmanaged fire dominates. Conversely, South Asia (including India) is dominated by managed fires, particularly crop residue fires (as shown in Perkins et al. (2024)). Key: Eu. & Central Asia = Europe & Central Asia; Lat. Am & Car = Latin America & Caribbean; and MENA = Middle East and North Africa.

3.2.2. Temporal Analysis

Across the overlapping period with GFED5 (2001–2014), total burned area (i.e., the sum of managed and unmanaged fire) in WI-EO global burned area declines by 139 Mha, WI-JULES total burned area declines by 56 Mha, and the baseline model declines by 30 Mha. This compares with a decline of 193 Mha in GFED5. In WI-EO, this global decline is primarily attributable to the trend in sub-Saharan Africa (Figure 7), where burned area declines by 78 Mha (compared to 112 Mha in GFED5). By contrast, in WI-JULES burned area in sub-Saharan Africa declines by just 14 Mha (Figure 7). This lack of decline in sub-Saharan Africa is in part due to managed fires, which increase by 11 Mha as crop residue burning increases in the region in this model. A similar trend is seen in sub-Saharan African crop-residue burning in WI-EO, but this is offset by a steeper decline in pasture fires (Perkins et al., 2024). Further, WI-JULES seemingly overestimates the rate of declining burned area in Latin America & Caribbean (−35 Mha; GFED5 −18 Mha), whilst WI-EO captures a similar rate of decline to GFED5 (−21 Mha). As such, WI-EO is best able to reproduce the observed decline in burned area, followed by WI-JULES, and then the baseline model. The drivers of this modeled decline are explored in detail below.

Globally, both WI-JULES and WI-EO underestimate the magnitude of interannual variability (IAV) in burned area. The standard deviation of detrended model outputs (i.e., with mean = 0) was 9.5 Mha in WI-EO and 9.7 Mha in WI-JULES. However, the correlation of the detrended outputs with GFED5 was 0.81 in WI-EO and 0.41 in WI-JULES: indicating that although the magnitude of IAV is underestimated in both models, WI-EO is substantially better at capturing the direction of fluctuations in burned area. IAV in both models is driven by unmanaged fire. Detrended global outputs for unmanaged fire correlate with detrended global burned area in GFED5 (WI-EO: $r = 0.74$ and WI-JULES: $r = 0.53$); however there is no meaningful relationship for IAV in GFED5 and detrended outputs for managed fire ($r \leq 0.11$).

Based on the variable with the strongest Kendall's Tau correlation in each pixel, inter-annual change in burned area due to unmanaged fire is most strongly associated with flammability (Figure 8). In WI-JULES, flammability has the highest Tau value across 9,644 Mha (~70% of global land area; Table 2), whilst cropland conversion, which has the strongest relationship over the second largest area, has the highest Tau value across 1,037 Mha (~8% of global land area). A similar trend is seen in WI-EO, where flammability has the highest Tau value across 9,414 Mha and cropland conversion has the highest Tau value across 1,052 Mha.

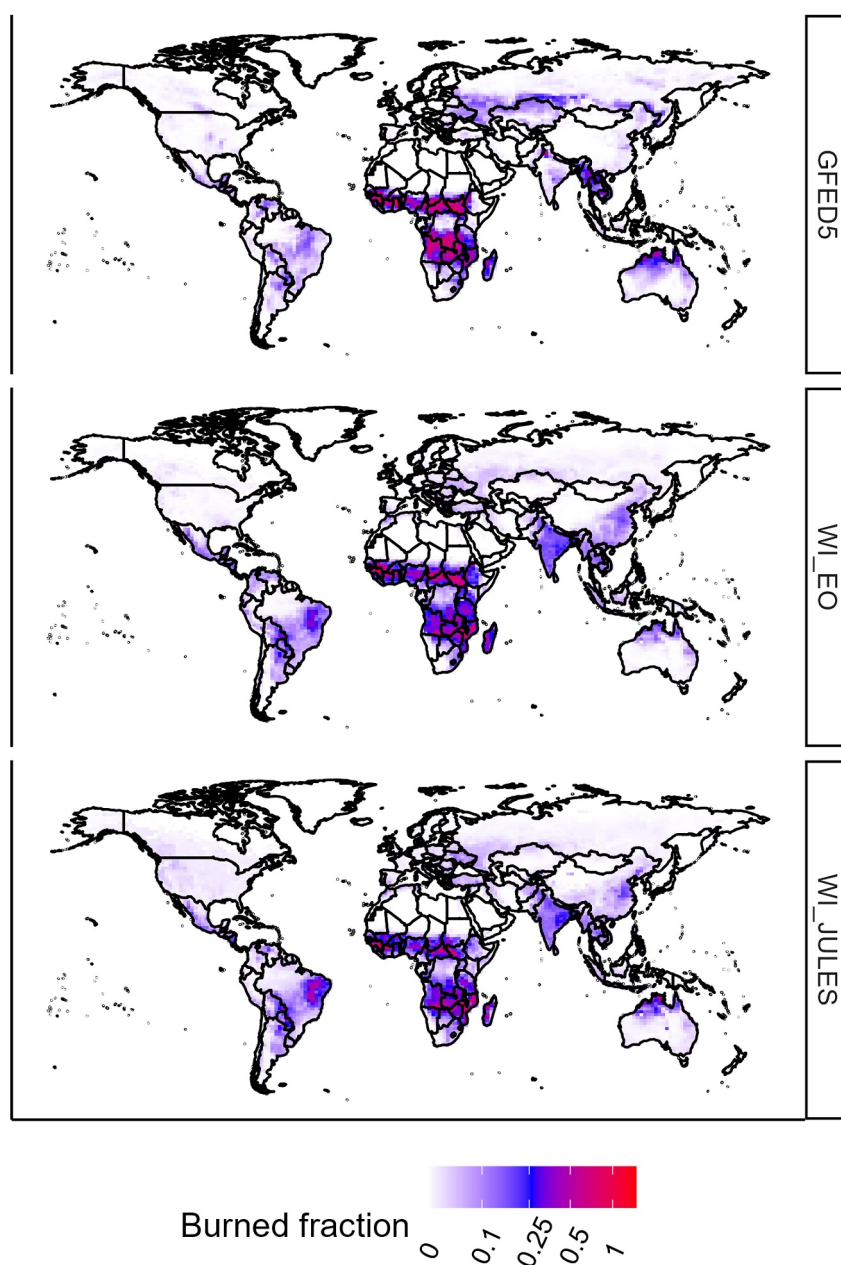


Figure 6. Total annual burned area in GFED5 WI-EO and WI-JULES as a fraction of each pixel. Values shown are the mean of the overlapping period (2001–2014). Three clear anomalies between models and GFED5 are present: first in the Caatinga region of Brazil, second in southern Russia, and third in India. This latter discrepancy is due to differences in burned area from crop residue burning between WHAM! and GFED5 (Perkins et al., 2024). Model outputs shown are the sum of managed and unmanaged fire.

However, whilst change in burned area is most closely correlated with flammability over the largest area, these areas are seemingly weighted toward model pixels with less overall change in burned area. For both WI-EO and WI-JULES, in linear regression models of interannual variability absolute t -values for flammability are more than twice as large as any other variable (Table 2). By contrast, for the overall change over 2001–2014, t -values are closer between variables, with ignitions having the largest absolute t -values for both models. Similarly, variables with a negative impact on burned area have a larger impact on the overall 2001–2014 change than interannual variation (Table 2). Road density seemingly has the largest impact on declining burned area (t -values: -21.7 and

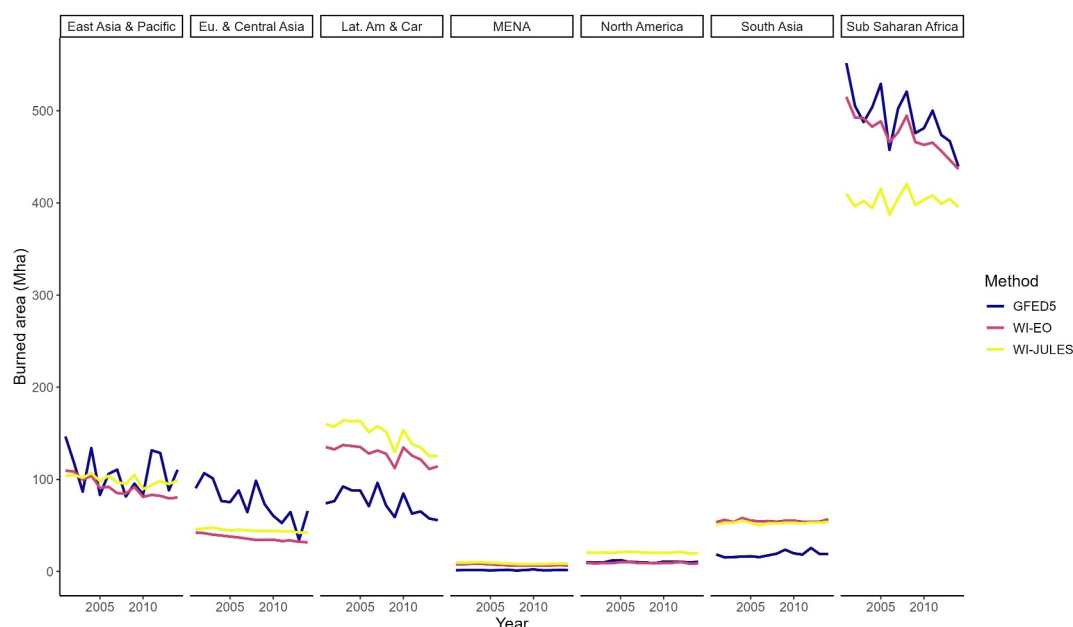


Figure 7. Burned area by World Bank region in GFED5 and the two versions of the WHAM-INFERNO model ensemble (WHAM-EO and WI-JULES). WI-EO is best able to reproduce the observed decline in burned area in sub-Saharan Africa, with WI-JULES showing an essentially static burned area. Conversely, both WI-EO and WI-JULES overestimate burned area in Latin America, though the trend of declining burned area is captured strongly. Both models show generally poor performance in Europe & Central Asia, showing limited discernible trend. Model outputs for WI-EO and WI-JULES are the sum of the managed and unmanaged burned area presented in Figure 5. Key: Lat. Am & Car = Latin America & Caribbean and MENA = Middle East and North Africa.

−19.3), followed by cropland conversion (t -values: −16.1 and −19.1), respectively. Fire suppression has only a marginal influence and indeed shows little relationship with the long-term trend in WI-JULES ($t = 0.433$).

4. Discussion

This paper has presented the first integration of a global-scale behavioral model of human fire use and management coupled with a DGVM. Discussion focuses on advances made for global understanding of human drivers of vegetation fire regimes through this technical advance, before addressing its limitations and possible future directions for development of WHAM-INFERNO.

4.1. WHAM-INFERNO: Insights for Global-Human Fire Interactions

The WHAM-INFERNO model integration reveals both the extent and the diversity of the socio-ecological dynamics of global fire regimes. In pareto model runs of WHAM-INFERNO, managed and unmanaged fire contribute approximately equal amounts of global burned area. Furthermore, the spatiotemporal distribution of anthropogenic managed fire, and its relationship with unmanaged (“wild”) fires differs substantially across space. Whilst anthropogenic fire use, primarily for crop residue burning, dominates the South Asian World Bank Region, in sub-Saharan Africa more than half of burned area is from unmanaged fires (Figure 5). The modeled distribution of managed fire presented here is given additional support by the lower FRP measured in pixels in which WHAM-INFERNO outputs have a larger proportion of fire generated by managed anthropogenic fire use.

Such findings have profound implications for understanding of global fire regimes and illustrate that effective fire management policies and climate adaptation strategies must be based on detailed understanding of how human livelihoods and associated fire use systems contribute to existing fire regimes. Scientific advice on fire management in the context of a changing climate must account for such human dimensions, or risk giving inappropriate or unworkable recommendations (e.g., Croker et al., 2023). At the very least, the large extent of managed anthropogenic fire around the world implied by these results is demonstration of the inadequacy of

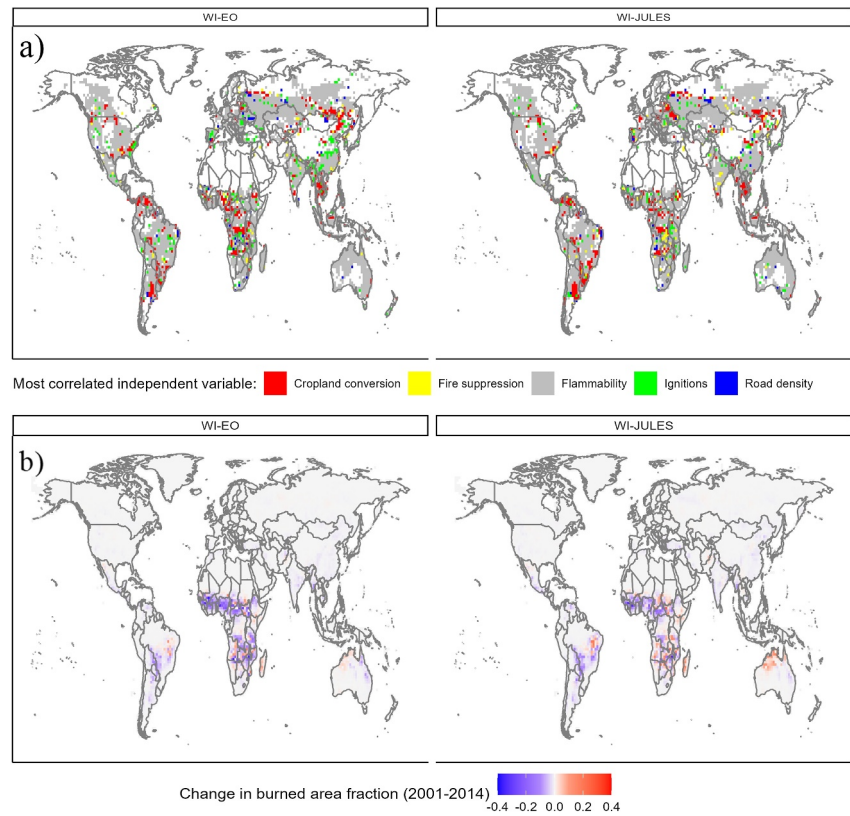


Figure 8. Relationship of changes in unmanaged burned area to independent variables. (a) Variable with highest absolute correlation (r) with change in burned area from unmanaged fire; values were filtered for pixels with at least 0.1% of the land area burned. (b) Change in burned area between 2001 and 2014. Although flammability is most closely correlated with changes in burned area across the largest geographic space, the influence of other factors—particularly cropland conversion—is clustered toward pixels with the largest changes in burned area. A non-linear stretch was applied to the color scale in panel (b) to show differences between smaller absolute values.

model approaches seeking to represent direct anthropogenic influence on fire regimes as simple functions of population density (Rabin et al., 2017).

Furthermore, combined global-scale simulations of both managed and unmanaged fire presented here add weight to the finding from Earth observation that small fires have declined less than larger ones (Chen et al., 2023). Managed fire declines by just 35% and 52% of the rate of unmanaged fire in WI-JULES and WI-EO, respectively. Data from empirical studies indicates that the two largest sources of burned area from managed human fires—

Table 2
Relationship of Changes in Burned Area From Unmanaged Fires to Explanatory Variables

	WI-EO (area, Mha)	WI-EO (t -value, IAV)	WI-EO (t -value, trend)	WI-JULES (area, Mha)	WI-JULES (t -value, IAV)	WI-JULES (t -value, trend)
Cropland conversion	1,052	−10.4	−16.1	1,037	−13.8	−19.1
Fire suppression	244	−2.78	3.26	377	−1.9	0.43
Flammability	9,414	162.3	24.4	9,644	267.2	46.0
Ignitions	736	70.61	25.7	522	87.5	46.6
Road density	206	−5.1	−21.7	209	−8.0	−19.3

Note. Area gives the total land surface over which each variable was most strongly correlated with changing burned area. t -Values are from linear models of change in burned area to change in the independent variable; interannual variation (IAV) is for linear models of year-on-year change between 2001 and 2014, whilst trend denotes overall change during the same period.

crop residue burning and pasture management—have mean sizes of 5 and 34 ha, respectively (Millington et al., 2022), whilst in JULES-INFERNO mean burned area per fire for unmanaged fires varies from 170 to 320 ha. This result seems to give weight to findings of Smith et al. (2022) and Perkins et al. (2024), that managed fire is changing in line with socio-ecological forces that are distinct from those driving change in unmanaged fire.

In addition, the finding that unmanaged fire is primarily responsible for interannual variability in burned area (Section 3.2.2) is consistent with the findings of Randerson et al. (2012), who find less fluctuation in small fires than those detectable by MODIS (i.e., <21 ha). This is intuitive, as crop residue fires, for example, occur annually according to the logic of cropping systems rather than fluctuations in climate (Millington et al., 2022). However, this opens an intriguing possibility for fire-enabled DGVMs, which have typically struggled with interannual variability whilst also not including representation of managed human fires—the more static part of the regime (Li et al., 2019). In effect, DGVMs may have been *doubly* underestimating the sensitivity of burned area from unmanaged fires to interannual climate variability. This underrepresentation of the sensitivity of unmanaged fires to climate volatility may contribute to the difficulty of attributing changes in global fire regimes to global warming (Jones et al., 2022), although a lack of representation of peat fires may also be a partial explanation (Blackford et al., 2024; Li et al., 2019).

By accounting for the less temporally variable and more spatially homogeneous signal of burned area due to managed fires (Figures 4 and 5), the WHAM-INFERNO integration advances understanding of the drivers of declining global burned area. Whilst interannual variability is primarily driven by changes in vegetation flammability, longer-term change in burned area highlights the important role played by the fragmentation of natural and semi-natural vegetation through road building and cropland conversion (Figure 8). This result coheres strongly with that of Andela et al. (2017) who find that interannual variability is closely linked to precipitation, whilst cropland fraction is strongly associated with declining burned area. Furthermore, WHAM-INFERNO can identify the processes underlying the finding of Andela that cropland has a spatially heterogeneous impact on burned area. For example, increased burned area in croplands in South Asia and Northeastern China is due to large-scale agricultural residue burning, whilst decreased fire in savanna grasslands is due to landscape fragmentation and the subsequent reduced capacity of savanna grasslands to sustain unmanaged fires.

4.2. Model Performance and Limitations

Both versions of the WHAM-INFERNO ensemble represent a significant improvement in the capacity of INFERNO to reproduce historical global annual burned area over the baseline model (Figure 3), and indeed over the performance of INFERNO against GFED4 presented in FIREMIP ($r = 0.70$, Mangeon et al., 2016; Teckentrup et al., 2019). This demonstrates the fundamental importance of a process-based approach to understanding and representing human-fire interactions in global modeling. Furthermore, the improvements made in WHAM-INFERNO over the baseline version allow the impact of landscape fragmentation in global burned area to be incorporated and understood (Figures 2 and 8). Indeed, the WHAM-INFERNO integration, and particular WI-EO seems to advance capacity for DGVMs to reproduce the observed decline in global burned area (Hantson et al., 2020).

However, representation of landscape fragmentation, its interaction with different ecosystem types, and other anthropogenic pressures remains incomplete. One way that WHAM-INFERNO represents fragmentation is through the role of roads in reducing fire size (Haas et al., 2022), by applying a road density correction to fire sizes per PFT. Although useful in constraining the model parameter space through restricting burned area in more densely populated areas (Figure S1 in Supporting Information S1) this single global function is a somewhat simplistic way of capturing such effects, resulting in a substantially larger impact on WHAM-INFERNO burned area outputs than on correlation with GFED5 (Figure S2 in Supporting Information S1). Hence, the road density parameterization in WHAM-INFERNO employed to capture fragmentation effects is analogous to representations of anthropogenic “ignitions” as a global function of population density in previous fire-enabled DGVMs: they are both a first step with outstanding issues to be addressed. By contrast, the representation of selective logging on the flammability of fire-prone tropical forests in WHAM-INFERNO has been more successful. Although having a small impact on global burned area, including this process leads to an improved global correlation between WHAM-INFERNO outputs and GFED5 (Figure S2 in Supporting Information S1). Representation of logging was derived from WHAM! outputs, hence illustrating the value of process-based representation of anthropogenic impacts on fire regimes, as opposed to the top-down road density parameterization.

Whilst many landscape fragmentation effects emerge as a spillover of wider economic activity (road building, logging etc.), the WHAM-INFERNO ensemble also indicates that managed fire use directly serves to reduce the radiative power of fires. This is a significant finding, as the 1 km² resolution of the FRP observations is too coarse to detect many managed fires (Giglio et al., 2006; Millington et al., 2022). Hence, human fire use seems to reduce the FRP of larger unmanaged fires, whether through fuel load reduction or intentional fuel fragmentation (Laris, 2002). Nevertheless, the modest relationship detected between managed fire use and FRP ($r^2 \leq 0.2$), points to the fact that numerous other biophysical factors influence fire intensity. For example, Haas et al. (2022) identify the vapor pressure deficit, fuel dryness and land cover as important global controls. The impact of such drivers can be seen in the southeastern USA. Here, the hypothesis that managed fire use reduces FRP suggests FRP should decline in the grasslands and agricultural areas toward the Gulf of Mexico, but observations show the opposite (Figure S3 in Supporting Information S1). Rather, it seems evident that lower temperatures and forested land cover are reducing FRP as we move inland to the north. Further studies can incorporate our managed fire parameterization into wider models of FRP to understand its interactions with additional biophysical factors.

In addition to limitations in the WHAM-INFERNO ensemble, underlying limitations in the two models (i.e., WHAM! and JULES-INFERNO) constrain the certainty of our results. The major limitation in WHAM! is that it runs at an annual timestep (Perkins et al., 2024). This is particularly important for the representation of escaped fires, as the spread of these fires will be impacted by the seasonal cycle of flammability in INFERNO, but they are currently necessarily assumed to be lit uniformly throughout the year. Capturing the seasonal cycle of managed anthropogenic fire is a major technical and research challenge, requiring account of decisions to light early or late-dry season fires depending on land user objectives, as well as the bimodal distributions that may arise from double and triple cropping (Liu et al., 2019). The primary limitation in INFERNO evident here is that fire size is assumed to be a fixed function of plant functional types. Consequently, we were not able to use the fire size distribution implied by the breakdown of managed and unmanaged fire to calibrate or evaluate our model outputs.

Similarly, it is notable that WI-EO performs more strongly than WI-JULES at reproducing the magnitude, spatial distribution, and temporal dynamics of burned area found in GFED5. On one hand, this illustrates the benefits of a well-specified parameterization of managed human fire: by better accounting for this aspect of the observed burned area signal, WI-EO is better able to reproduce the inter-annual variability of unmanaged fire, and its pronounced global decline. Yet the weaker performance of WI-JULES perhaps also illustrates the potential for underlying error in the representation of ecosystems within DGVMs to lead to misleading conclusions being drawn from their fire modules (Hantson et al., 2020). Continued model intercomparison projects and use of model ensembles are likely to remain the most effective means to apply the fire outputs of DGVMs. Overall, the large scale of anthropogenic managed fire entails that careful consideration should be given to how future socioeconomic scenarios, and their limitations, inform our projections of how global fire regimes may evolve under a warming climate (Keys et al., 2024).

5. Conclusion

This paper has presented the first integration of a global behavioral model of human fire use and management with a DGVM. Overall, model evaluation highlights the strong benefits of coupled socio-ecological modeling approaches for reproducing the observed spatial and temporal patterns of burned area globally. Furthermore, findings demonstrate the extent and complexity of human-fire interactions. Results imply that managed anthropogenic fire accounts for as much as half of all global burned area, whilst the trends and distribution of, and relationship between, managed and unmanaged fires is highly spatially heterogeneous. Such complexities demonstrate that socio-ecological modeling is vital to advance understanding of present-day and future fire regimes. A key area for future work identified here is in developing more nuanced representation of landscape fragmentation, particularly in grazing lands in sub-Saharan Africa, which remain a central contributor to global burned area.

Conflict of Interest

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

Data Availability Statement

Data and code necessary to reproduce the results in this paper, as well as analysis and figures presented are made available on zenodo: <https://zenodo.org/doi/10.5281/zenodo.8319445> (Perkins et al., 2023). Code to run the WHAM-INFERNO ensemble are also made available on GitHub: https://github.com/OliPerkins1987/WHAM_INFERNO. All data and code are made available under a Creative Commons License.

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